IDS 720: Mid Semester Project Report
Team IV

Project Motivation
Since 1999, the U.S. has experienced a tremendous increase in the abuse of opioids for two decades. The continuing abuse of opioid prescriptions led to a 6% increase in the opioid-related death rate and an increased death rate from non-opioids drugs such as Heroin. To reduce opioid abuse, several states launched opioid regulation laws during the last decade. In this project, we are interested in examining if such regulations effectively reduce the opioids prescriptions in those states. In addition, we are also interested in the effect of opioid regulation laws on the mortality rate resulting from drug overdose.

If the result of our study shows that state regulations on opioids do reduce the opioid prescriptions and mortality rate, we can conclude that there is a positive effect of those regulations and we should recommend states that have not implemented opioid regulations to implement similar policies.

Research Design
The research goal is to determine whether state regulation on opioids reduced the amount of opioid prescription and the drug-overdose mortality rate.

In this study, we want to evaluate the effects of three policy changes:

1. Florida, effective February, 2010
2. Texas, effective January, 2007
3. Washington, effective January, 2012

The basic strategy to evaluate whether a change is effective is the Pre-Post Analysis. By examining the trend of outcome variables that we are interested in before and after the treatment takes effect, we can imply the effectiveness of the treatment as we would assume that the trend will stay similar if there is no treatment or the treatment is ineffective.

However, the main downside of the Pre-Post Analysis is there might be confounders that also affect the outcome variable that we are not able to capture. Therefore, we also conducted a Difference in Difference (DID) approach. The DID analysis compares the changes in outcome overtime between a population received the treatment and a population that did not receive the treatment. Such an approach removes the bias that was due to the permanent difference between treatment and control group but also the treatment effect resulted from confounders.

Hence, a larger decrease in a state with policy intervention in comparison to the decrease in other states without policy changes over the same period would indicate an effective policy intervention. In this way, we can exclude confounding variables such as nationwide changes and we would be more confident in making such causal inferences.

Additionally, it’s worth noting that we will need assumptions to ensure that our difference-in-difference analysis is valid: the trend before the policy change in the two groups we are comparing should be similar. Otherwise, we cannot infer the effectiveness of a policy change even if we observe a large difference between the two groups after the policy intervention because they are not comparable.
Three criteria that we focused on when we are selecting control states:

1. Have similar GDP per capita with the corresponding treatment state
2. Have similar total population with the corresponding treatment state
3. Did not have any state regulation policy change within our window of experiment (3yrs before and after treatment state’s policy change)

For control states, we decided to select three states as the control group for each state we are interested in investigating the policy changes so that any idiosyncratic shocks to individual control states will tend to average out.

Based on the above criteria, the control states we selected for each state with policy intervention are as following:

- Policy intervention state: Florida 2010; Comparison states: Michigan, Georgia, Arizona
- Policy intervention state: Texas 2007; Comparison states: Pennsylvania, Ohio, Virginia
- Policy intervention state: Washington 2012; Comparison states: Massachusetts, Illinois, Maryland

Data and Data Wrangling:

Population Dataset

The population data is obtained from the United States Census Bureau website, which contains county-level population data from 2000 to 2019. It is worth noting that since the US Census occurs once every 10 years, the population data of the years in between is the estimation produced by the census bureau's own interpolations using data they collect between censuses. We will also use those population estimations for our following analysis.

Since the population dataset serves as a complement data source for our future calculation of per capita data, the pre-processing of this dataset is aimed to format it in a way that aligns with the prescription and mortality data. First of all, to use the county FIPS code as an ideal key for the merge, we achieved the consistency in county code format from the two datasets by filling the county code with zero to the left if the county code is less than 3 digits in the population dataset and concatenating it with the state code. Next, we subset the data to the states and corresponding years we need for the analysis and renamed columns for the ease of use. Lastly, we reshaped the dataframe to convert the columns of year into rows.

Prescription Dataset

For the prescription difference-in-difference analysis, we downloaded the state-wise datasets made available by the Drug Enforcement Administration. The data tracks every opioid pill sold in the United States. This data was available from 2006-2014. We loaded the data for our treatment state (Florida) and our control states (Michigan, Georgia, Arizona) as zip files because the datasets were huge (> 6 GB) and read them as pandas dataframes. We are using a product of the total active weight of the drug (mg), strength of the drug (mg) and morphine milligram equivalent to estimate the number of prescriptions that were given out in a particular county and year. We labeled this product as `MME`. After this we wrote a function to clean the prescription datasets. The function basically groups the data by buyer county and year and sums `MME` for the grouped observations.

Because we do not have county FIPS code in the prescription data for merging, we will use county name as the join key. To avoid the potential issue with counties of the same name in different states, we chose to merge the prescription data with population data for each state separately before we finally combine all the states together.

To merge the prescription data with corresponding population data, we went through the data wrangling steps as following:

1. Created a new column for abbreviation of state name in population dataset in order to match the column of state name in prescription data.
2. Aligned county name to match. In the merging process, we found that several county's names are not consistent in the two datasets. For example, counties named with "SAINT" in the prescription data are named as "ST." in the population dataset. So we change names for all unmatched counties in the population dataset to have them matched with prescription dataset.
3. Outer merge. We observed that prescription data do not contain all the counties as population data do. Thus, we use outer merge to keep all the counties in our final dataset rather than simply dropping counties that do not have prescription data.
4. Missing value imputation. Since we roughly have ⅓ to ¼ counties without prescription data, we assume that these counties simply did not have any prescription shipments

during the period we are investigating. Therefore, we imputed zero for counties without prescription data.

After merging we proceeded to make the intermediate variables which were needed to plot the difference-in-difference plots. After reading in the data for both treatment (Florida) and control (Michigan, Georgia, Arizona) states, we dropped unwanted columns which were a result of the merge. Next we appended the merged control data to the merged treatment data. Then we calculated the number of prescriptions given out per capita (`pres_per_capita`) for county-year pairs by dividing the number of prescriptions given out by population of that county for that year. We used this variable to plot the difference-in-difference plot from 2008-2010 (pre-treatment) and 2011-2013 (post-treatment). We intentionally left a one year gap in between i.e. we did not plot data for 2010-2011 as that is when the effect came into place and results for such interventions take some time to take effect.

Mortality Dataset

For the mortality difference-in-difference, we downloaded the 'US Vital Statistic Records' data set which includes data on every death in the U.S. The data is available from 2003-2015. We use this data to analyze the effect of state-wise policy on opioids on the mortality rate for three sets of treatment state and control states.

We then proceed to our data wrangling part:

1. Cleaned the NA's. After filtering out all rows that contain at least one NA's, we found that resulting rows have NAs for all columns. We decided to drop those rows because they do not contain any information. The rationale is consistent within all years.
2. Type of Death Selection. Since we are interested in drug-related overdose deaths, we filtered out deaths related to drugs. The types of death we selected are Drug poisonings (overdose) due to unintentional, suicide, undetermined, homicide and all other drug-induced causes.
3. Group by County and Year. We are interested in the mortality rate on a county-year basis; therefore, we aggregated our cleaned dataset using a unit of observation of 'county-year' and summed up the number of deaths.
4. Outer merge with Population dataset. To avoid situations where the county does not exist in the mortality dataset, we used full join with county code and year as connectors and it turns out that a lot of counties are missing mortality data.
5. Calculate Mortality Rate. We then calculate the drug overdose mortality rate by dividing the number of drug-related deaths by total population for each county in each year.
6. Impute Mortality Rate. We used the state-year level average drug overdose mortality rate to impute the mortality rate for counties that have 'Deaths' column missing.

a. For FL’s final dataset, we imputed 1,651 observations.
b. For TX’s final dataset, we imputed 3,113 observations
c. For WA’s final dataset, we imputed 865 observations.

Summary Statistics:

Prescription

In our merged dataset for Florida, we have 600 observations of Florida, 1366, 738, 135 observations of Georgia, Michigan and Arizona respectively. The average prescription per capita before treatment (2010) is 442.27 for Florida. The average prescription per capita after 2010 is 530.54 for Florida. Although the mean has gone up we can see from the difference-difference plot below that the trend goes down after the drug regulation comes into effect. This increase in mean can be attributed to the fact that the intervention took some time to actually take effect in Florida. For example if I calculate the same statistic for 2012 and after, it is 421.13 which is a considerable decrease from the pre-treatment statistic.

Mortality

In our final dataset for Florida’s analysis, we have 816 observations of Florida. The average drug overdose mortality rate before treatment(2010) is 0.000149 for Florida. The average drug overdose mortality rate after 2010 is 0.000145 for Florida. There is a minor drop in drug overdose mortality rate after the treatment in Florida.
In our final dataset for Texas’s analysis, we have 3,060 observations of Texas. The average drug overdose mortality rate before treatment(2007) is 0.000101. The average drug overdose mortality rate after 2007 is 0.000104 for Texas. Although there is a slight increase in the mortality rate, we can interpret it as it took some time for the policy to take effect. As we can see from the DID figure for TX, there was a sudden drop in mortality rate from 2006 to 2007 in Texas, and later the mortality rate increased steadily over years. It might be due to the reason that people then quickly reacted to the policy change and found new sources for drugs.
In our final dataset for Washington’s analysis, we have 480 observations of Washington. The average drug overdose mortality rate before treatment(2012) is 0.000137. The average drug overdose mortality rate after 2012 is 0.000138 for Washington. The mortality rate almost stayed the same for Washington and it aligns with our DID graph for Washington that the trend of mortality rate stays the same before and after treatment.

Analysis:

Prescription

Below are the pre-post and difference-in-difference plots for the prescriptions per capita (MME/capita) given out from 2008-2013. The drug regulation was enforced by the DEA in 2010 which we're using as our marker for post-treatment analysis.

<u>Pre-Post</u>

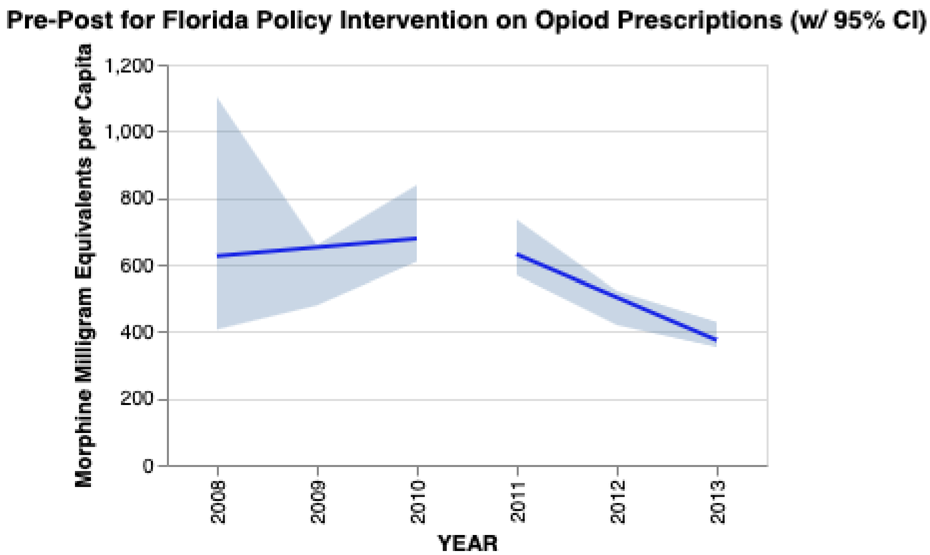

Figure 1. Pre-Post analysis on Florida for a State Regulation effective in 2010

Since the decreasing trend in the above plot could be attributed to a number of factors such as: the shipments weren't being recorded correctly, the drugs were being prescribed off paper (illegally), or the US Customs service reduced the import of the drugs in question. If this were to be the case and we were just comparing Florida in 2008-2010 to Florida in 2011-2013 we would see a decline in trend even if the policy intervention was not effective. To be confident that the decrease in trend was due to the policy intervention by the DEA, we did a difference in difference analysis. In this method, we don't just compare Florida in 2008-2010 to Florida in 2011-2013, we see if a similar decreasing trend was observed in other comparable states of the US. If not, we can be more certain that this decline in the prescription of drugs was due to aforementioned policy intervention.

Difference-in-Difference

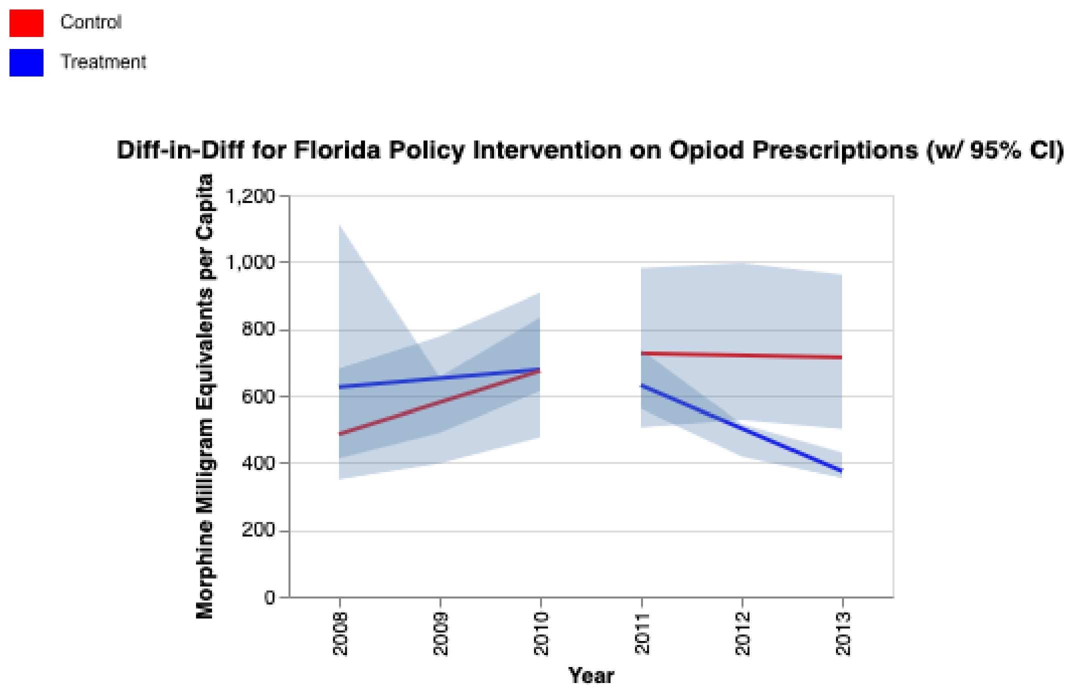

Figure 2. Difference in Difference Analysis on Florida for a State Regulation effective in 2010 compared to group of states (Arizona, Georgia, Michigan) 2008-2013

From Figure 2, we can see that pre-treatment both Florida and the control states both have increasing trend over years but post-treatment the trend line for our control states has a very week downward slope (if you look closely enough), whereas the trend line for Florida has a steep downward slope indicating that the number of prescriptions given out for opioid drugs per capita in Florida did decrease after the drug regulation came into effect.

Mortality

Pre-Post

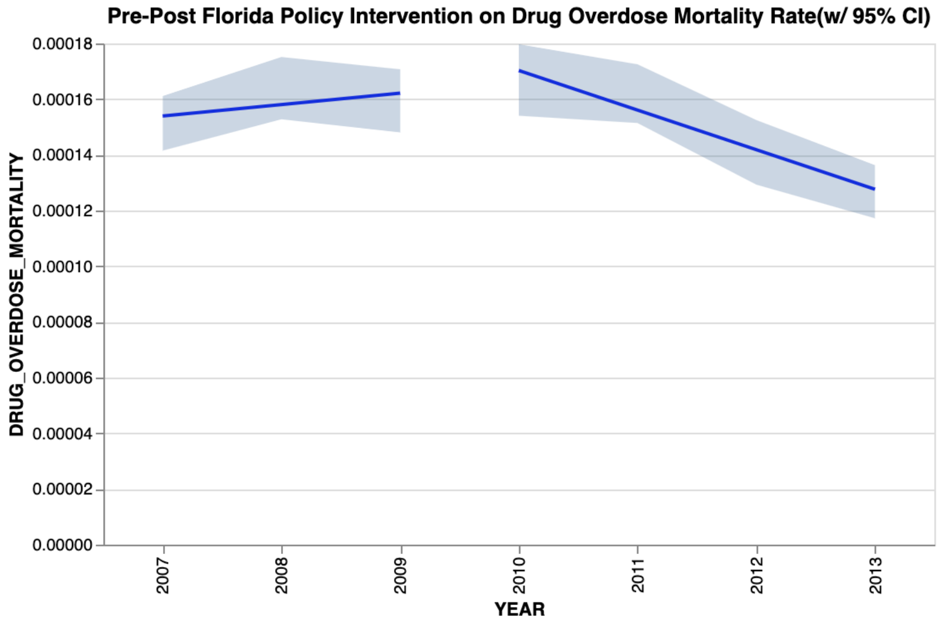

Figure 3. Pre-Post analysis on Florida for a State Regulation effective in 2010

Florida's Policy change in opioids regulations was launched in 2010. From the plot above, we can see that before the policy change, there is an upward trend in drug overdose mortality rate. And after the policy change, the trend became downward with a larger slope. The graph indicates that opioid policy changes took effect in 2010 reduced drug-overdose mortality rate.

Difference-in-Difference

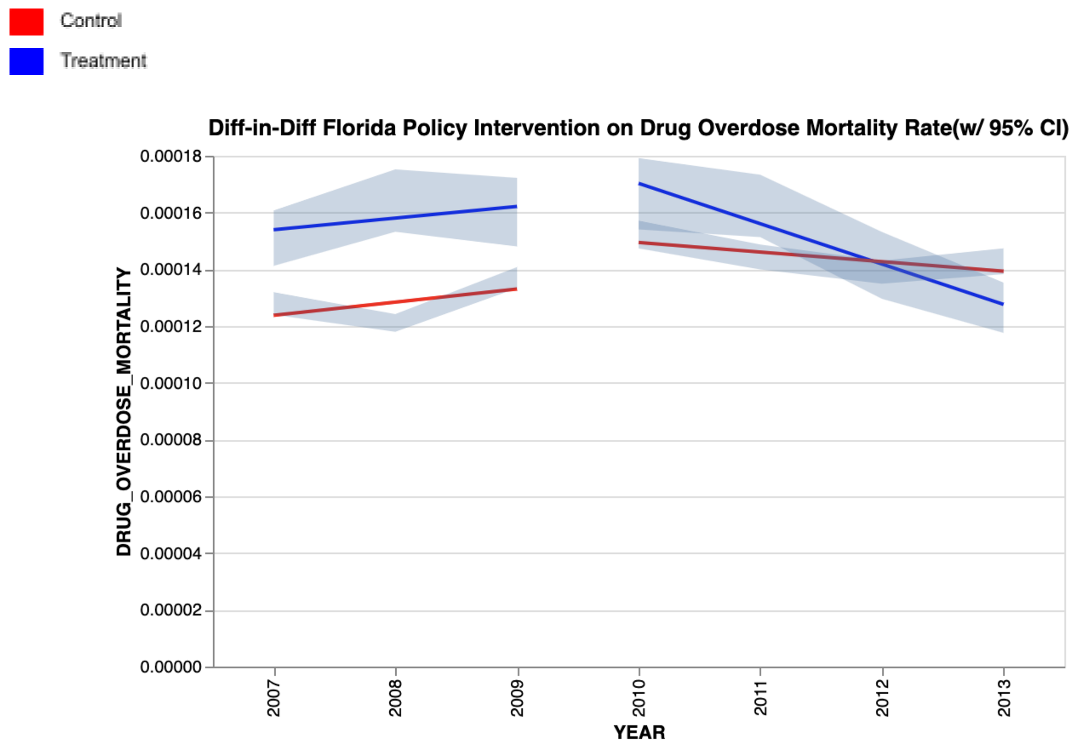

Figure 4. Difference in Difference Analysis on Florida for a State Regulation effective in 2010 compared to group of states (Arizona, Georgia, Michigan) 2007-2013

From Figure 4, we can observe that before the policy change in Florida in 2010, the drug-overdose mortality rate in Florida and three control states exhibited parallel trends and increased over years. However, after the policy took effect in 2010 in Florida, we can see a significant downward trend of drug overdose mortality rate in Florida. While for control states, there was barely a decreasing trend over the years. The result shows that not only we can observe a decreasing trend of drug overdose mortality rate in Florida, the deviations in trends are significant between Florida and its comparison states where we assume there were no drug-related policy changes. It can be concluded that Florida’s policy changes truly had an effect on reducing drug-overdose mortality rate eliminating other potential factors.

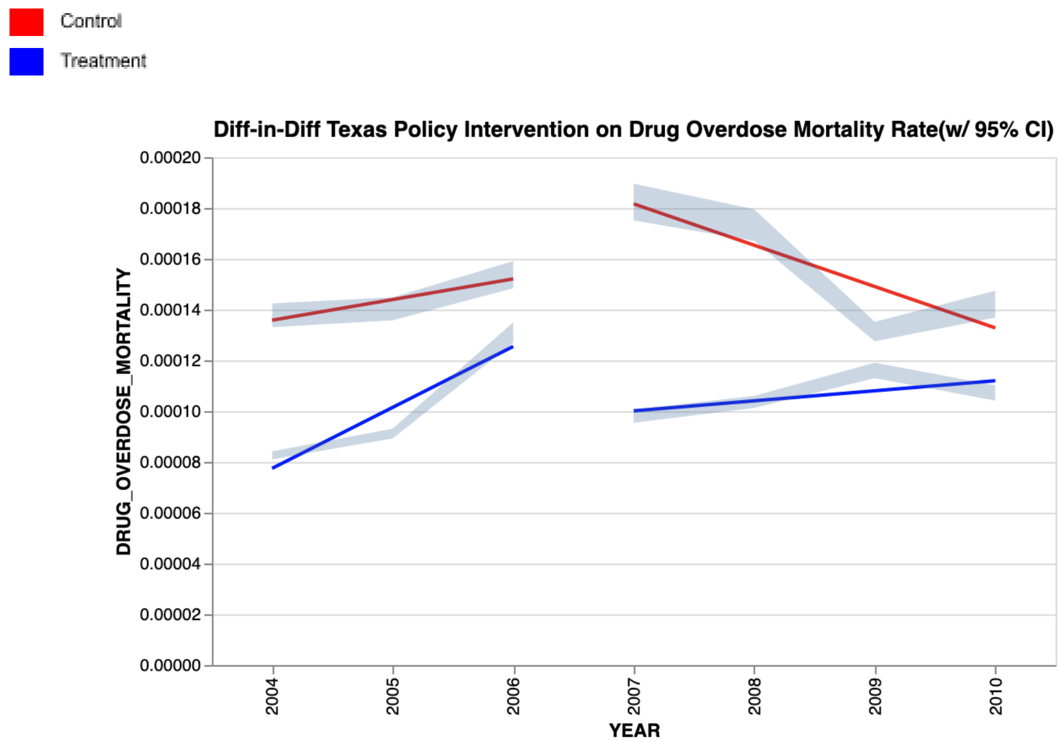

Figure 5. Difference in Difference Analysis on Texas for a State Regulation effective in 2007 compared to group of states (Ohio, Pennsylvania, Virginia) 2004-2010

Texas's policy changes took effect in 2007. Before the policy change, drug-overdose mortality rate in Texas and three control states all exhibited upward trends, and Texas's increasing slope is steeper than those control states. However, after the policy took effect in 2007 in Texas, while control states' trend exhibited a decreasing trend, we can see that there was an initial drop in drug-overdose mortality rate and the increasing trend became flatter compared to pre-policy changes period. The result indicates that, although opioid policy changes in Texas did not turn the drug-overdose mortality rate to a negative trend, it did successfully lower the speed of increasing since the policy took effect.

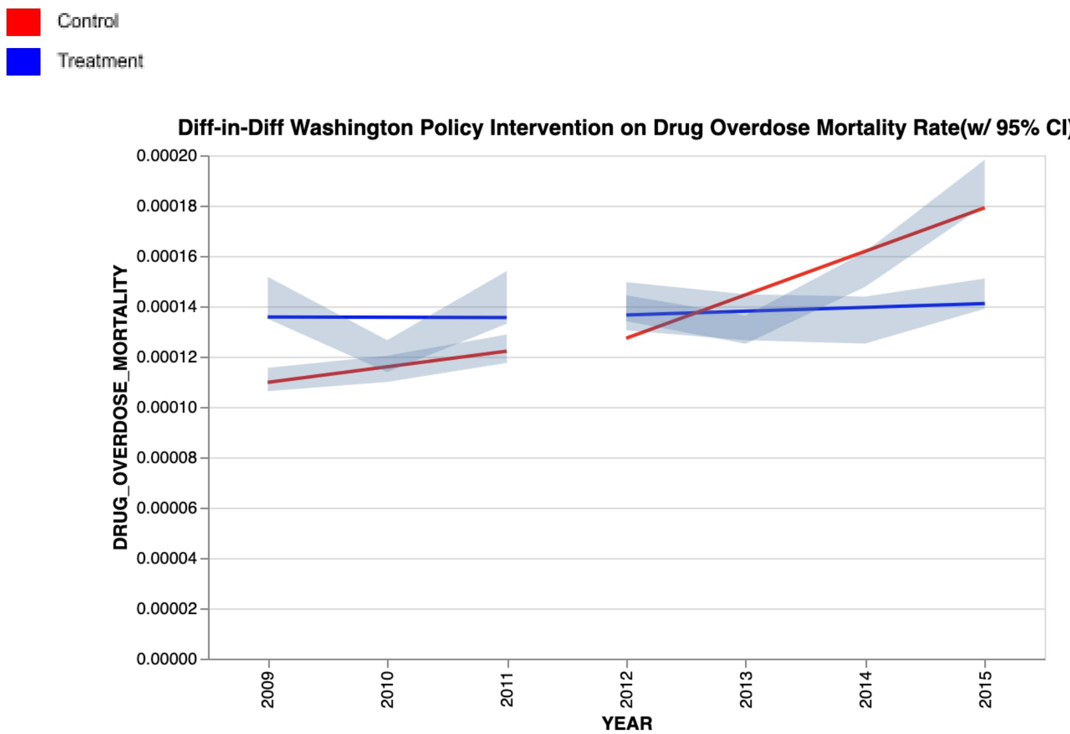

Figure 6. Difference in Difference Analysis on Washington for a State Regulation effective in 2012 compared to group of states (Illinois, Massachusetts, Maryland) 2009-2015

Washington's policy changes took effect in 2012. Before the policy change, the mortality rate due to drug overdose in Washington and three control states all had a similar parallel trend. While Washington had a flat trend, three control states had a slight increasing trend. However, after the policy took effect in 2012 in Washington, we can see Washington's drug-overdose mortality rate remained the same, while for control states, there was a significantly increasing trend for drug-overdose mortality rate. The above result shows that Washington's opioid policy changes effectively maintained the drug-overdose mortality rate. Comparable states with similar GDP per capita and total population all exhibited an increasing trend, and we can conclude that there was a positive effect of the policy.

Conclusions:

To examine the effect of state regulation on opioid prescription and drug-overdose mortality rate in Florida. We conducted a pre-post analysis and the result shows that opioid state regulations do have an effect on reducing opioids prescription and drug-overdose mortality rate in Florida. However, pre-post analysis can be biased if there are confounders also affecting the outcome variable. Thus, we also utilized a difference-in-difference(DID) analysis, which compares the difference of changes between with policy changes states and without policy changes states. Such a method can remove biases of original difference between those two groups but also biases caused by confounders. The most important findings of the DID analysis is that Florida's state regulation on opioids in 2010 did effectively reduce both opioid prescription and drug-overdose mortality rate. Similarly, Texas's state regulation in 2007 flattened the trend of drug-overdose mortality rate and Washington's state regulation in 2012 maintained the trend of drug-overdose mortality rate at a steady level. We conclude that there is a certain degree of positive effect of opioid state regulation and we recommend states that did not have drug regulation to implement similar policies.

Limitations:

1. Both opioid prescription data and mortality data have missing values at county-year level. Especially for mortality dataset, a large portion of counties (roughly ⅔ to ¾ of all counties) do not have mortality data due to small county size. Therefore, using the state-year level average calculated from available data as imputation may not be representative enough for those counties with missing data and may lead to a bias in our evaluation.
2. For some states (such as Texas), the assumption for difference in difference analysis that the trend line pre-treatment for the control and treatment groups should be parallel is being violated. This makes it harder for the treatment and control states to be perfectly comparable.
3. We tried to find the best possible match for our treatment states but finding a perfect control state is close to impossible

IDS 720: Mid Semester Project

Policy Maker

Team IV

Project Motivation

Since 1999, the U.S. has experienced a tremendous increase in the abuse of opioids for two decades. The continuing abuse of opioid prescriptions not only led to an increase in opioid-related deaths but also induced people to be addicted to other drugs that also drove up the overdose mortality rate. In fact, according to the CDC, increasing abuse of opioids has led to a 6% increase in the opioid-related death rate and an increased death rate from non-opioids drugs such as Heroin.

To reduce opioid abuse, several states have launched opioid regulation laws during the last decade, and it is important to study the result of such policy changes. There are two factors we could use to measure the effectiveness of the policy, amount of opioid prescription and drug-overdose mortality rate. This study aims to examine policy's effect and if the policy truly had an effect, we expect to see downward trends of both opioids prescription and drug-overdose mortality rate.

If the result of our study shows that state regulations on opioids do reduce the opioid prescriptions and mortality rate, we can conclude that those regulations were effective. Abuse of drugs is still prevalent in the U.S. and people are dying because of drug addiction, and if regulations truly have an effect, we recommend states that have not implemented opioid regulations to implement similar policies.

Design

The basic approach to evaluate the effectiveness of the policy is a pre-post comparison. In pre-post analysis, we will compare our interested outcome variable before and after the policy went into effect. Assuming the overall trend will stay similar if there is no policy intervention, a decreasing trend in the quantity of drug prescriptions will thus indicate that the policy is effective in reducing drug consumption. In other words, if the trend still follows the general trend before the policy took effect, we can conclude that the policy intervention is not effective as expected.

However, we cannot take other factors that may also have the impact on the interested outcome variable into account in a simple pre-post comparison. Since there are a lot of other things that can happen meanwhile when the policy intervention starts, for example, there may be a nationwide decline in drug overdose mortality rate due to a national regulation policy at the same time, we cannot attribute the decline in drug prescriptions to the policy intervention in that specific state only. Therefore, to solve this potential problem, we will also adopt difference-in-difference analysis for our evaluation.

In the difference-in-difference approach, we will incorporate trends from other states for a more comprehensive comparison in order to rule out potential external confounding variables. Hence, a larger decrease in a state with policy intervention in comparison to the decrease in other states without policy changes over the same period would indicate an effective policy intervention. In this way, we can exclude confounding variables such as nationwide changes and we would be more confident in making such causal inferences.

Additionally, it's worth noting that we will need assumptions to ensure that our difference-in-difference analysis is valid: the trend before the policy change in the two groups we are comparing should be similar. Otherwise, we cannot infer the effectiveness of a policy change even if we observe a large difference between the two groups after the policy intervention because they are not comparable.

Therefore, we will select states that are as similar to the states with policy changes as possible to make valid comparisons in our difference-in-difference analysis. To define and achieve this similarity between states, we followed these three criterias for selection:

1. There are not any drug-related policy changes in these states during the years of our evaluation
2. Similar GDP per capita
3. Similar population

Based on the criteria above, we choose the following states as the comparison group for the three states which had policy interventions on drugs that we are evaluating, respectively:

- Policy intervention state: Florida 2010; Comparison states: Michigan, Georgia, Arizona
- Policy intervention state: Texas 2007; Comparison states: Pennsylvania, Ohio, Virginia
- Policy intervention state: Washington 2012; Comparison states: Massachusetts, Illinois, Maryland

We will treat the three states together as a single comparison group for each state with policy change to average out any idiosyncratic shocks to individual states.

Data Overview

Our data come from three datasets:

1. 'Population Census data' from United States Census Bureau: containing county-level population data from the year 2000 to 2019
2. 'Opioid Prescriptions data' from the Drug Enforcement Administration: containing all prescription opioid drug shipments in the United States from the year 2006 to 2014
3. 'Mortality Data' from the US Vital Statistic Records: containing data on every death in the United States from the year 2003 to 2015

The unit of observation is on the county-year level while we will visualize the analysis on a per state per year level and two indicators we focused on are:

1. 'Prescriptions Given out per Capita': divide the number of opioid prescriptions given out by population
2. 'Drug-Overdose Mortality Rate': divide the number of drug-related deaths by population

Data Analysis:

Prescription

The drug regulation was enforced by the DEA in 2010 which we're using as our marker to see the change in the number of opioid pills being given out in Florida pre and post the intervention.

The quantity that helps us measure the number of pills being given out is MME (Morphine Milligram Equivalent). MME is a value that represents the potency of a drug, in our case Hydrocodone and Oxycodone, relative to Morphine. Hydrocodone and Oxycodone make upto nearly three quarters of the total opioid shipments in the United States.

We have divided the data we want to analyse into two segments: pre-intervention and post-intervention. By pre-intervention we mean the MME of the above-mentioned drugs that were being prescribed in Florida by pain clinics before the implementation of the policy i.e. from 2008-2010. Post-intervention on the other hand means the MME of the above-mentioned drugs that were being prescribed in Florida by pain clinics after the implementation of the policy i.e. from 2010-2013. If the policy was effective, we would ideally see a decline in the MME being prescribed after the policy implementation.

<u>Pre-Post</u>

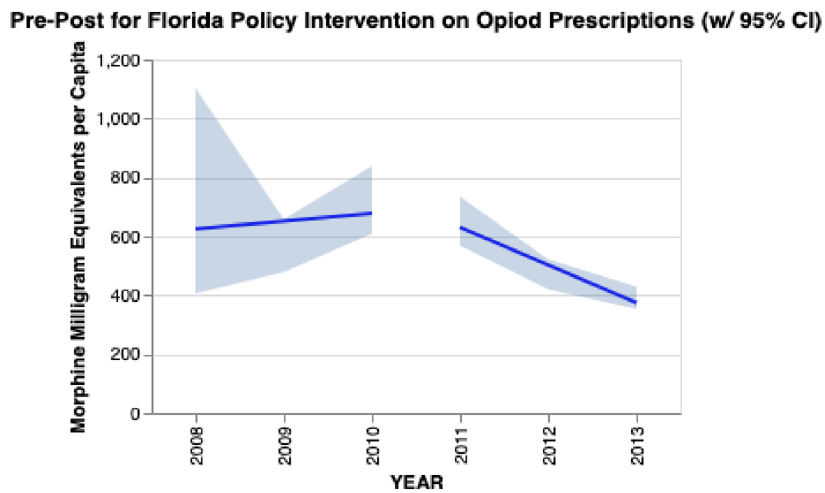

Figure 1. Pre-Post analysis on Florida for a State Regulation effective in 2010

From Figure 1, we can see that pre-intervention there is an upward trend in the MME being prescribed. However, after the implementation of the policy there is a steep downward trend. But to be sure that this downward trend was due to the policy and not due to other confounding factors such as a ban implemented by the US customs service on the import of these drugs or incorrect documentation of shipments, we look at how other states (similar to Florida) were behaving during the same time period.

Difference-in-Difference

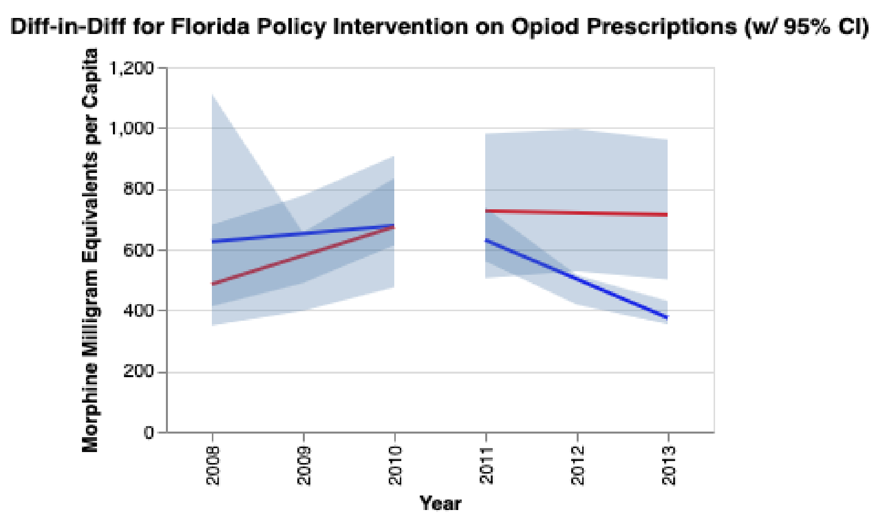

Figure 2. Difference in Difference Analysis on Florida for a State Regulation effective in 2010 compared to group of states (Arizona, Georgia, Michigan) 2008-2013

In Figure 2, the red line is for comparable states of Florida and the blue line is for Florida. As we can see, the trend for other states has a very very weak downward slope whereas Florida exhibits a very steep downward slope. This confirms that the policy implemented in Florida resulted in a decrease in the number of MME that were being prescribed.

Mortality

Pre-Post

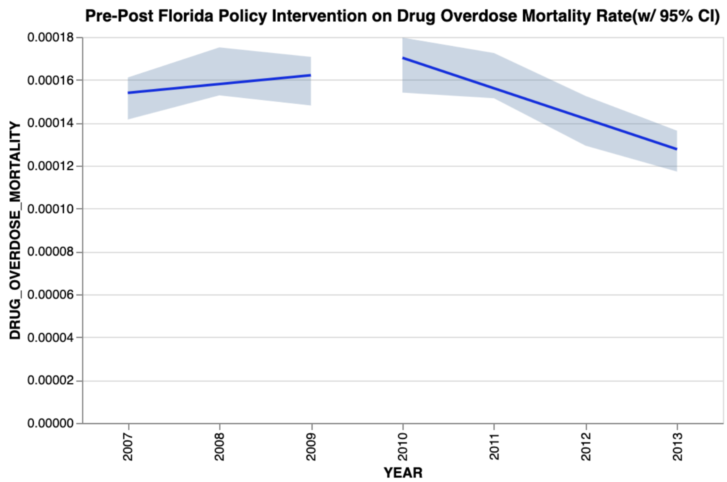

Figure 3. Pre-Post analysis on Florida for a State Regulation effective in 2010

Florida's Policy change in opioids regulations was launched in 2010. From Figure 3, we can see that before the policy change, there was an increasing trend in drug overdose mortality rate. After 2010, the trend became downward and the drug-overdose mortality rate decreased steadily. The graph indicates that opioid policy changes took effect in 2010 reduced drug-overdose mortality rate.

Difference-in-Difference

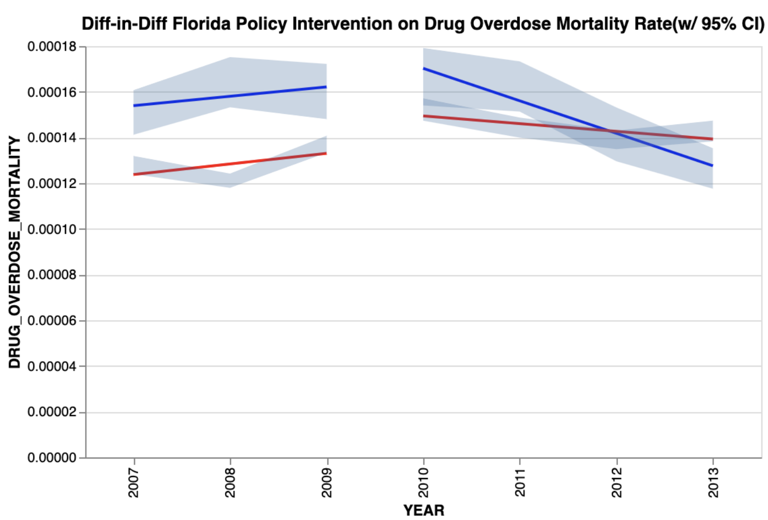

Figure 4. Difference in Difference Analysis on Florida for a State Regulation effective in 2010 compared to group of states (Arizona, Georgia, Michigan) 2007-2013

From Figure 4, we see that before the policy change in 2010, the drug-overdose mortality rate in Florida(blue) and three comparable states(red) both had an increasing trend over years. However, after the policy took effect in 2010 in Florida, we can see a significant decreasing trend of drug-overdose mortality rate in Florida. While for comparable states, the decreasing trend was slower. Florida's drug-overdose mortality rate dropped below the comparable state's average in 2012. It can be concluded that Florida's policy changes truly had an effect on reducing drug-overdose mortality rate eliminating other potential factors.

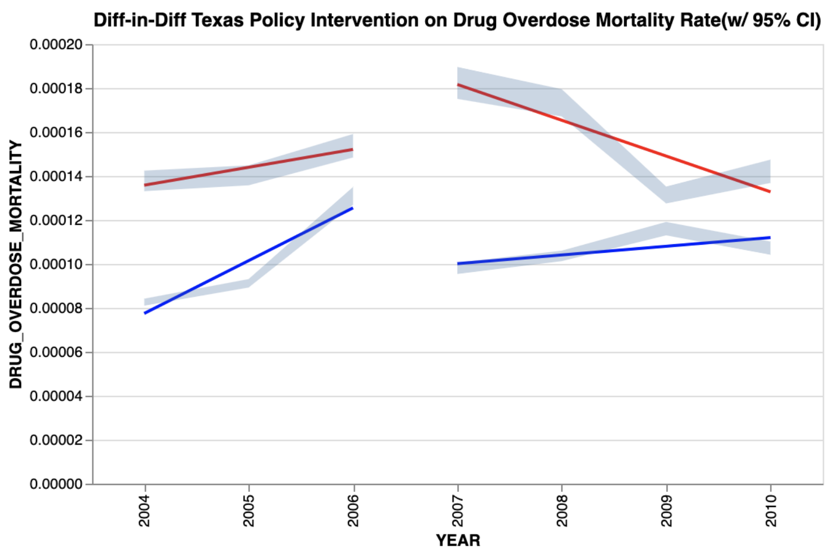

Figure 5. Difference in Difference Analysis on Texas for a State Regulation effective in 2007 compared to group of states (Ohio, Pennsylvania, Virginia) 2004-2010

Texas's policy changes took effect in 2007. Before the policy change, drug-overdose mortality rate in Texas(blue) and comparable states(red) all exhibited an increasing trend. In addition, Texas's increasing slope is steeper than those comparable states. However, after the policy took effect in 2007 in Texas, while comparable states' trend exhibited a decreasing trend, we can see that there was an initial drop in drug-overdose mortality rate and the increasing trend became flatter over years compared to pre-policy changes period in Texas. The result indicates that, although opioid policy changes in Texas did not turn the drug-overdose mortality rate to a negative trend, it did successfully lower the speed of increasing and we believe eventually the trend will become negative.

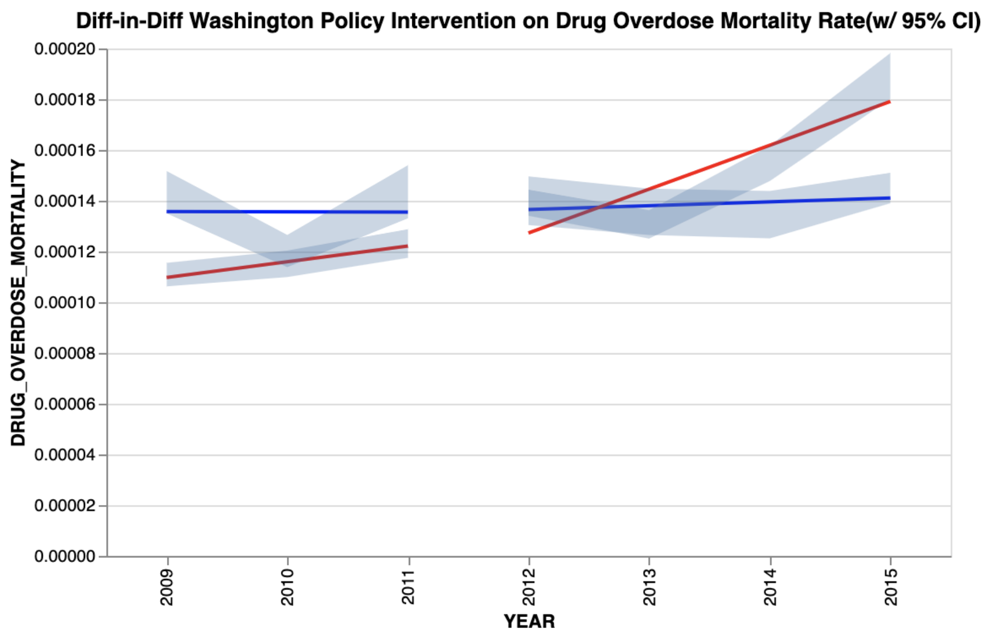

Figure 6. Difference in Difference Analysis on Washington for a State Regulation effective in 2012 compared to group of states (Illinois, Massachusetts, Maryland) 2009-2015

Washington’s policy changes took effect in 2012. Before the policy change, the drug-overdose mortality rate in Washington(blue) and three comparable states(red) all had a similar static trend. While Washington’s drug-overdose mortality rate did not fluctuate over years, comparable states exhibited an increasing trend. However, after the policy took effect in 2012 in Washington, we can see Washington's drug-overdose mortality rate remained the same, while for comparable states there was a significantly increasing trend. The above result shows that Washington’s opioid policy changes effectively maintained the drug-overdose mortality rate. Comparable states with similar GDP per capita and total population all exhibited an increasing trend.

Conclusion

To examine the effect of state regulation on opioid prescription and drug-overdose mortality rate in Florida. We conducted a pre-post analysis and the result shows that opioid state regulations do have an effect on reducing opioids prescription and drug-overdose mortality rate. However, pre-post analysis can be biased if there are confounders also affecting the outcome variable. Thus, we also utilized a difference-in-difference(DID) analysis, which compares the difference of changes between with policy changes states and without policy changes states. The most important findings of the DID analysis is that Florida’s state regulation on opioids in 2010 did effectively reduce the opioid prescription and drug-overdose mortality rate. Similarly, Texas's state regulation in 2007 flattened the trend of drug-overdose mortality rate and Washington's state regulation in 2012 maintained the trend of drug-overdose mortality rate at a steady level.

Policy Recommendation

Opioid Prescription Analysis

1. Conduct regular statewide raids in pain clinics
2. Put programs in place to identify illegal pain clinics
3. This policy has not only had a significant impact on the number of pills being prescribed but also the deaths resulting from overdose of opioid pills in Florida. Keeping this in mind, policymakers looking to significantly decrease opioid prescriptions and related overdose deaths should consider whether Florida's 2010 policy works in their jurisdictions
4. Policy makers looking to reduce drug related crime and violence should also consider working with the government in reducing prescription of opioid drugs

Drug-Overdose Mortality Rate Analysis

1. Instead of setting regulations on opioids regulation, should also consider implementing regulations on other drugs such as Heroin and Fentanyl.
2. Improve regulation of blackmarket to prevent merchants who take the advantages of the regulations to make profit
3. Recommend states that did not implement any regulations to implement regulations
4. Some results we might not see immediately. Do not look at the result right after the regulation took effect, but focus on the long term improvements.
5. To deal with cases such as Texas where there was a significant drop right after the policy intervention and slightly increased later, policy makers should update policies regularly to adapt with those newly come out issues but not just release the policy once and finished.

While providing the above recommendations for future policy design, it's also important to understand the limitations in our analysis as following:

1. Ideally we should choose states that are the most similar to the state with policy change in the difference-in-difference analysis to make them comparable. The only difference between them should be whether there was a policy change or not. However, it's almost impossible to find a perfect match in reality. Therefore, there could be some underlying patterns that are different among states that may potentially affect the results.

2. The assumption for the difference-in-difference analysis that the two groups should exhibit similar (ideally parallel) trends before the policy change took effect is not perfectly met for all the states we are evaluating. As we can see from the plots, although the general direction is similar, some of the trends still have some deviation. This makes it harder for us to draw a conclusion from perfect comparisons.
3. We have a large portion of missing value for mortality data for counties with a small size. Although we imputed the missing mortality rate with the state-year level average calculated from the counties with available data, the results may be biased since the imputed value may not be representative enough for these counties.
4. The analysis and comparison we conducted is at the state level and may not be directly applicable for other states. Policymakers should also be cautious when generalizing these implications from our analysis to other states or nationwide because different regions may have different underlying patterns that need to be taken into consideration.