Effect of State Regulations on Opioid Shipment and Overdose Deaths

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1. Introduction

1.1 The motivation for the project:

While legal settlements with opioid companies have been dominating recent headlines, the opioid crisis is still actively affecting millions of Americans. Between 2000 and 2019, opioid overdose deaths in the United States rose by more than 300%, while overall deaths rose only by 19% (CDC Wonder data). Action on this crisis may be especially critical now, as preliminary data suggests that the COVID-19 pandemic may be exacerbating the opioid epidemic (CDC, 2021). In this context, it is clear that policymakers must implement effective public policies quickly, at multiple levels of government (i.e., federal, state, and local). However, there is significant debate about which specific policies are the most effective at combating the opioid crisis—specifically, the question is which policies are effective at reducing (a) the number of opioid drug prescriptions and (b) mortality from drug overdoses. Examining these outcomes concurrently is important because it is possible for policy changes to affect them in opposite directions. While reducing the number of opioid drug prescriptions can reduce the number of people with incident addiction to opioids, it may also drive an increase in opioid mortality, as currently addicted persons turn to alternative, and potentially more dangerous, forms of opioids. Therefore, the goal of this project is to identify policy interventions that are effective at reducing opioid mortality, as well as the number of prescribed opioids, in order to inform policymakers hoping to act further on the opioid crisis. Specifically, we examine three policy changes, all made at the state government level, in three different states across the country: Florida, Texas, and Washington.

1.2 The motivation for the research design being used:

The goal of the research design implemented here is to demonstrate whether or not the policy changes in Florida, Texas, and Washington affected the number of deaths related to opioid abuse and the number of prescription opioids shipped into the state. Therefore, the motivation for the research design was to establish a causal relationship between policy change and opioid abuse parameters. We achieved this by using two strategies in tandem: pre-post comparison and difference-in-difference analysis. Pre-post comparison simply visualizes what opioid abuse parameters look like before and after the policy change. In difference-in-difference analysis, the pre-and post-periods in the policy state of interest are compared to a control group with no policy change. This analysis is intended to eliminate the causal effects of any potential confounding variables, such as policy changes at a federal or regional level, or general shifts in the trend of opioid abuse parameters.

1.3 Description of Data Used

We used three datasets in this analysis:

- All opioid prescription drug shipments in the US from 2006-2012 (from US Drug Enforcement Agency, obtained by Washington Post).
- Mortality due to drug and non-drug-related causes in the US from 2003-2015 (from US Vital Statistics records).
- Population and population estimates for each US county from 2003-2015 (from the US Census).

The opioid shipment data originally contained detailed information for each transaction that happened, including the locations of the buyers and the sellers, the drug type and dose, and the date. For our analysis, we're interested in where the opioids went instead of who sold them, so we used the location of the buyers and dropped information of the sellers. To measure the number of opioids shipped, we used morphine milligram equivalents (MME), which is a long-established numerical standard for measuring opioids. The data set does not include MME but it includes information that allows us to calculate MME. Specifically, we used dosage strength (dos_str), dosage unit (DOSAGE_UNITS), and the MME conversion factor of the drug (MME_Conversion_Factor). We used the formula below, which is in accordance with guidelines provided by the CDC.

$$MME = dos\_str \times DOSAGE\_UNITS \times MME\_Conversion\_Factor$$

We then aggregated opioid shipment by county by month to create the sum of MME shipped to each county each month.

For the mortality data set, data for each year was contained in separate files. For each year of mortality data, the file was read in and stacked by row to create a single data set. Because the data contained death data from multiple causes, we limited the data to only categories including opioid overdoses, which are unintentional overdoses, intentional overdoses (suicide), and unknown overdoses. All three of these categories were included in order to be consistent with the CDC classification of opioid deaths. Then, similarly to the shipment data, the data was aggregated by state, county, and year, so that the data was in tidy format and every observation could be interpreted as the number of opioid deaths in a county year.

Subsequently, the population data was cleaned and exported to an intermediate format. Here, the data was in two files, one containing population estimates from 2000 to 2010 and the other containing Estimates from 2010 to 2020. Initially, the information was in "wide" format, with each observation representing a county and columns for each year of population. This data was also converted to tidy format, with each observation representing population in a county year. The years were limited to 2003-2015, the relevant years for the analysis. After cleaning these three datasets, the next step was to merge the population data frame to both mortality and opioid shipment data.

For both mortality and shipment datasets, we performed an outer merge with the population data, merging on year, state, and county. There were significant discrepancies between county names, which were fixed using string replacement and regular expressions. Interestingly, there were counties that changed names and boundaries between the 2000 Census and the 2010 Census, which meant that there were some observations in which we had a population for only some years between 2003 and 2015. Because the boundary changes could also affect population changes, and therefore lead to artificial inflation or deflation of trends, the states which contained these counties were dropped: Alaska, Louisiana, South Dakota, and Virginia. Continually, observations from U.S. territories (besides Washington, D.C.) were also dropped. Performing the outer merge, in both cases, created null values in the shipment and mortality datasets. In the case of mortality, counties with fewer than 10 deaths in a given category are not reported, so these missing values represent counties with fewer than 27 deaths (given all three combined mortality categories). This information is important to include in the analysis, as counties with few mortality deaths are potentially very important to assessing change. Thus, an attempt was made to impute reasonable values for these counties. For each county-year missing data, we used the average mortality rate in its state in that specific year to impute this value. In the case that no counties in a specific state had opioid deaths in that year, we used the average mortality rate in that state, regardless of year. In the shipment data, the missing values were replaced with 0, on the assumption that data that was missing was due to the fact that there were simply no shipments to that specific county in that specific month. Following the successful merge, columns for opioid mortality per 100,000 residents and opioid shipments in MME per resident were created. These final datasets were used for analysis.

Histograms in the appendix are to help visualize the distribution of data in opioid mortality per 100,000 residents and opioid shipments in MME per resident columns for each state. One additional histogram is for the US county population dataset which we included in the appendix as a point of reference and which we used for normalizing the merged opioid shipment and mortality datasets. US county population histogram (Figure A1) indicates that most counties had populations of less than 200,000 in 2003-2015.

State-specific histograms display mortality and annual/monthly opioid shipment data over the years in the respective dataset. Distributions of annual and monthly opioid shipment-per-resident data are right-skewed and non-uniform for all three states, in which Florida has the highest maximum shipment-per-resident values for both annual and monthly data. The distribution of opioid deaths per 100,000 residents has higher symmetricity than shipment data for all three states. In the appendix are also statistical value tables for state-specific datasets and the county population dataset.

2. Analysis Methods:

2.1 Summary

We employed two methodologies to investigate the effect of opioid regulations on the volume of opioids prescribed and the number of opioid-related mortalities. First, we conducted a pre-post comparison to compare the metrics before and after the regulations went into effect in each of the three states studied. While this method provides a straightforward view of the effect of opioid regulations, it does not account for the impact of national-level changes or regulations. For example, a national crackdown could decrease opioid prescriptions and opioid overdose deaths. If the national regulation concurred with the state-level regulations, a pre-post analysis would not be able to isolate the effects of the state-level regulations. As such, we also performed a difference-in-difference analysis to more concretely quantify the effects of the state-level regulations.

2.2 Pre-Post Comparison

We first performed a pre vs. post analysis to compare the volume of opioids shipped as well as the number of opioid-related deaths before and after the policy regulations took effect. Since we did not have access to data on opioid prescriptions, we used opioid shipment as a proxy for opioid prescriptions.

2.2.1 Time Period

The data for the opioid shipments is available monthly, while the overdose data is annual. As such, we examined opioid shipments in each state on a monthly interval while we examined opioid overdoses on an annual interval.

The pre-period of each analysis includes all years before the regulation took effect in the state. The year that the regulation took effect and onwards are the post-period. Each of the three states we investigated implemented regulations in different years. In addition, the opioid shipment and drug overdose death data sets used in this analysis include different time periods. As such, the pre-and post-periods differ by analysis and by state.

We laid out the pre-and post-periods for each analysis below to bring more clarity to the time periods.

State	Analysis	Regulation Date	Pre-Period	Post-Period
Florida	Opioid Shipment	February, 2010	2006 - 2009	2010 - 2012
Florida	Opioid Overdose Death	February, 2010	2003 - 2009	2010 - 2015
Texas	Opioid Shipment	January, 2007	2006	2007 - 2012
Texas	Opioid Overdose Death	January, 2007	2003 - 2006	2007 - 2015
Washington	Opioid Shipment	January, 2012	2006 - 2011	2012
Washington	Opioid Overdose Death	January, 2012	2003 - 2011	2012 - 2015

Table 1 periods of each analysis

2.2.2 Methodology

For each analysis for each state, we created an indicator variable that marked whether each observation was from the pre-period or the post-period. We then ran linear regressions for the pre-period and the post-period separately, using the year and month as the independent variable and the metric of interest (opioid shipment or opioid overdose death) as the dependent variable. We also calculated the 95% confidence interval for each regression.

To visualize the effect of regulations, we plotted the regression line and the confidence band of the pre-period and the post-period on the same plot by state. In each plot, the x-axis represents time, and the y-axis represents the metric of interest.

Opioid shipment and overdose death increased overtime in Florida, Texas, and Washington before the respective state-level regulations took effect. As such, if the regulations did mitigate opioid prescriptions or opioid overdose death, we'd expect the post-period regression line to have a smaller slope than the pre-period regression line. If the post-period and pre-period slopes are similar, then the regulations likely did not have a meaningful impact.

2.3 Difference-in-Difference

The pre-post comparison method described above is an easy and straightforward way to visualize the effects of regulations on opioids. However, as described in “2.1 Summary”, it is difficult to attribute the changes of pre- vs. post-period slopes to state-level regulations alone because the method does not account for confounding variables such as changes at the national level.

To overcome this limitation, we next performed a difference-in-difference analysis, in which we compared counties in Florida, Texas, and Washington to similar counties in other states. This method assumes counties in Florida, Texas, and Washington should behave comparably to the similar counties selected. Therefore, similar counties could provide insights into what would have happened in those three states had the regulations not taken place. To make things easier, we'll refer to counties in each of Florida, Texas, and Washington as "test groups," and the group of similar counties selected for each test group the "control groups". The process we used to select the control group for each test group is described below.

2.3.1 Control Group Selection

To ensure that the difference-in-difference methodology measures the effect of state-level regulations instead of the effects of confounders, we'd need to find control counties that are as similar to the test group as possible. Most importantly, we must ensure that the control group has an equal pre-period slope as the test group. To achieve this, we used the below process to select control counties for each test group.

1. Calculate the pre-period slope of the measured metric (shipment/mortality) for counties in the test group and counties in the rest of the country

2. Calculate the pre-period average population of counties in the test group and counties in the rest of the country

3. For each county in the test group, select two counties in the control group whose pre-period slope is the most similar to that of the test county

4. If there are ties, narrow down to 2 counties whose pre-period average population is the most similar to that of the test county

5. Draw with replacement

Following the process above, we selected two similar counties for each county in the three test groups. Counties were first selected based on the pre-period slope of the measured metric. There were many counties in the test groups whose pre-period slope was 0 – for those counties. We selected control counties whose pre-period slope was also 0 and had a similar population as the test county.

We drew with replacement so that if a particular county were selected as the control multiple times, then we'd give the county a higher weight in the control group accordingly.

2.3.2 Time Period

The pre-and post-period of each analysis is the same as the time periods listed out in the table under the previous section. For each analysis, we used the same time periods for the test group and the control group. Similar to the pre-post comparison, opioid shipment was investigated using a monthly interval while opioid overdose was investigated using an annual interval.

2.3.3 Methodology

Similar to the pre-post comparison analysis, we created an indicator variable to mark whether an observation was from the pre-period or the post-period. For each analysis in each state, we ran four regressions, one each for the test and control groups in the pre-and post-periods. We then plotted the regression lines as well as the 95% confidence bands.

We plotted each analysis in a separate plot. On each plot, there are four lines – test group in the pre-period, test group in the post-period, control group in the pre-period, and control group in the post-period. To distinguish the test group from the control group, we applied different colors for each group. If we had performed the control selection appropriately, we'd expect to see similar slopes for the regression lines of the test group and the control group in the pre-period. If the regulation had a meaningful impact on the opioid shipment or overdose death, then we'd expect the slope of the test group in the post-period to decrease while the slope of the control group in the post-period remains constant or decreases by a smaller magnitude.

3. Analysis Results

3.1 Pre-Post Analysis

As discussed in the methods section, the first analysis conducted was a pre-post analysis, simply looking at the trend in either opioid prescription shipments or opioid overdoses in states with a policy change before and after that policy change. Therefore, four relevant graphs were generated: opioid shipments in Florida and opioid overdoses in Florida, Texas, and Washington, individually. These graphs visually demonstrate whether there was a change in the trend of opioid shipments or mortality per year before and after the state's policy change.

3.1.1 Florida Analysis (Mortality & Shipment)

First off, Figure 1 and Figure 2 display opioid shipments per capita and mortality per capita, respectively.

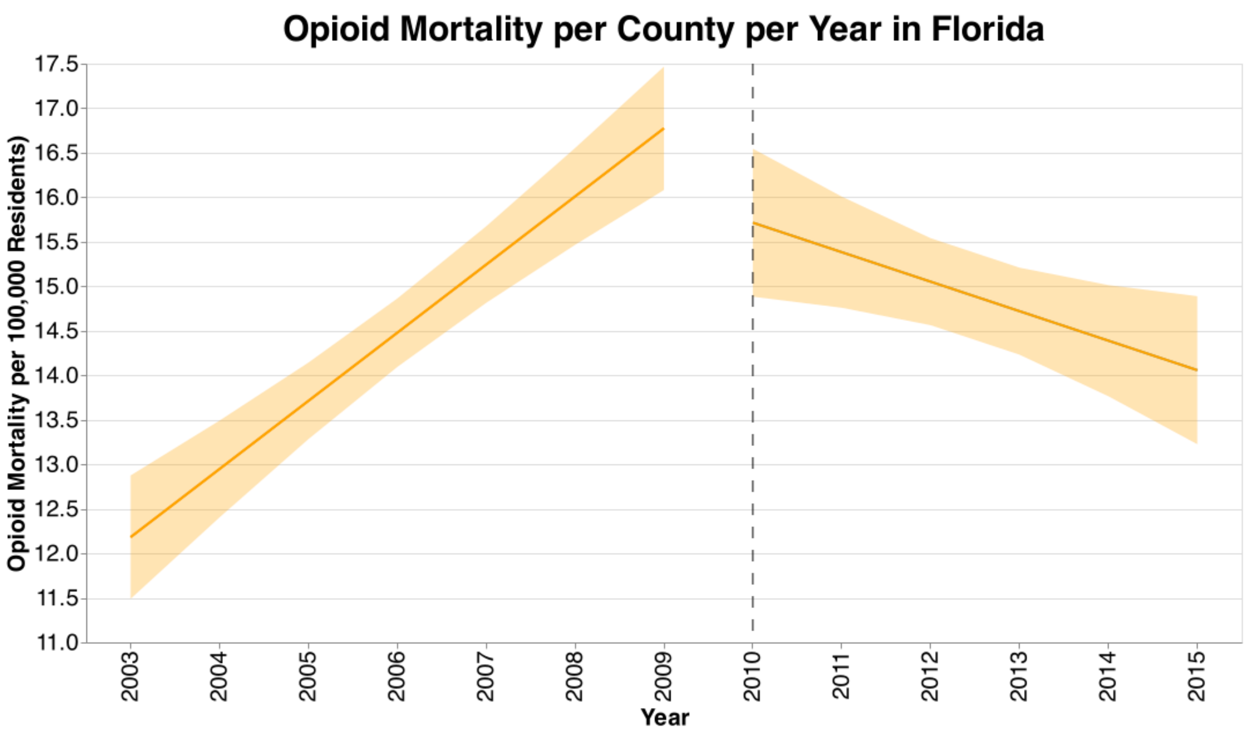

Figure 1 opioid mortality per county per year in Florida

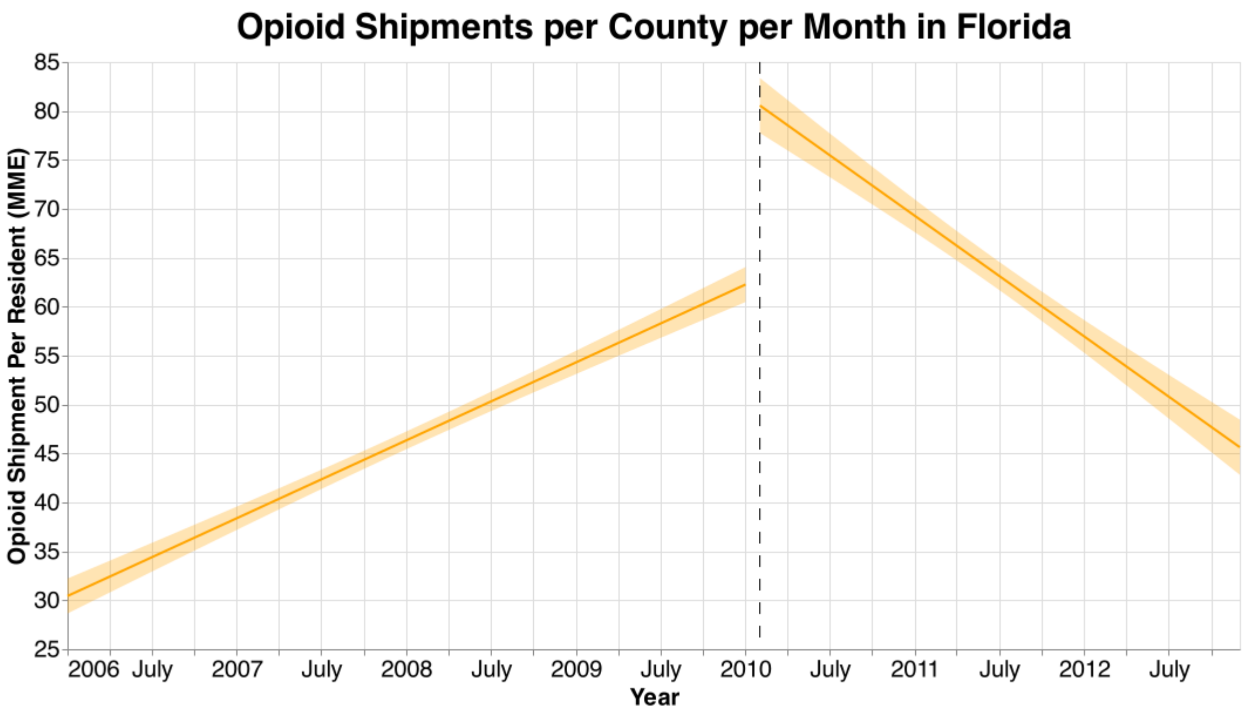

Figure 2 opioid shipments per county per month in Florida

Interestingly, there is a clear increasing trend in both opioid shipments and opioid mortality before 2010, which is reversed. However, as visualized by the 95% confidence bands, there is more significant uncertainty (i.e., more spread) in the mortality data. Overall, from these graphs, we can assert relatively confidently that there was a change in the trend of opioid shipments per capita in Florida after the policy change, and mortality also appears to display a different trend.

3.1.2 Texas Analysis (Mortality & Shipment)

Next, displayed are opioid mortality and shipment trends in Texas, again, before and after policy changes.

In the case of mortality, there is a visible reversal of trend. However, with regards to opioid shipments, it is clear that opioid shipments are increasing both before and after the policy change. However, the rate at which shipments increase post-policy is lower.

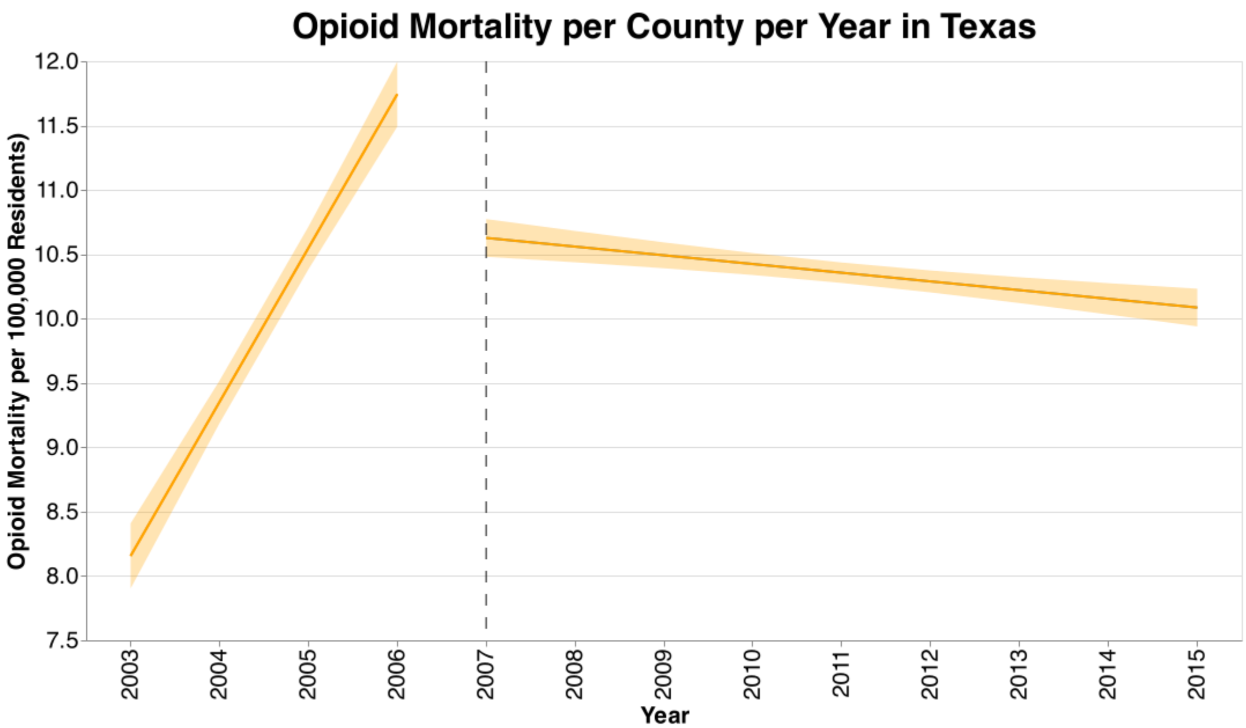

Figure 3 opioid mortality per county per year in Texas

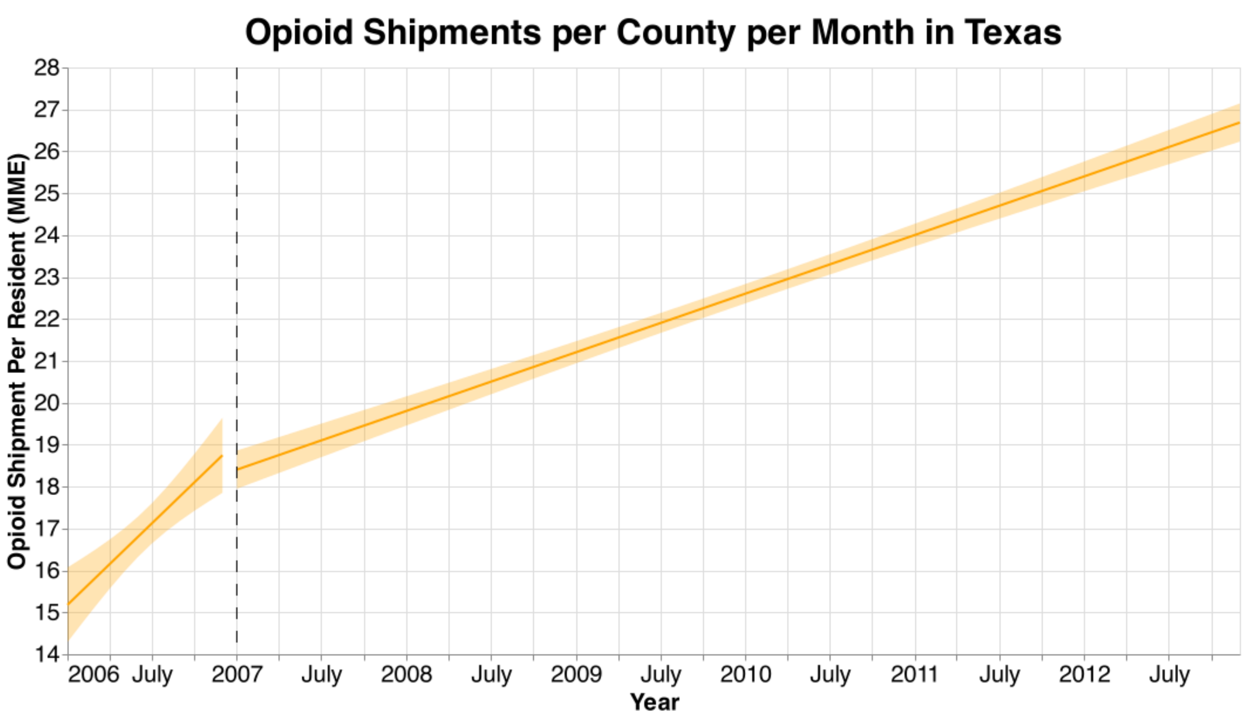

Figure 4 opioid shipments per county per month in Texas

3.1.2 Washington Analysis (Mortality & Shipment)

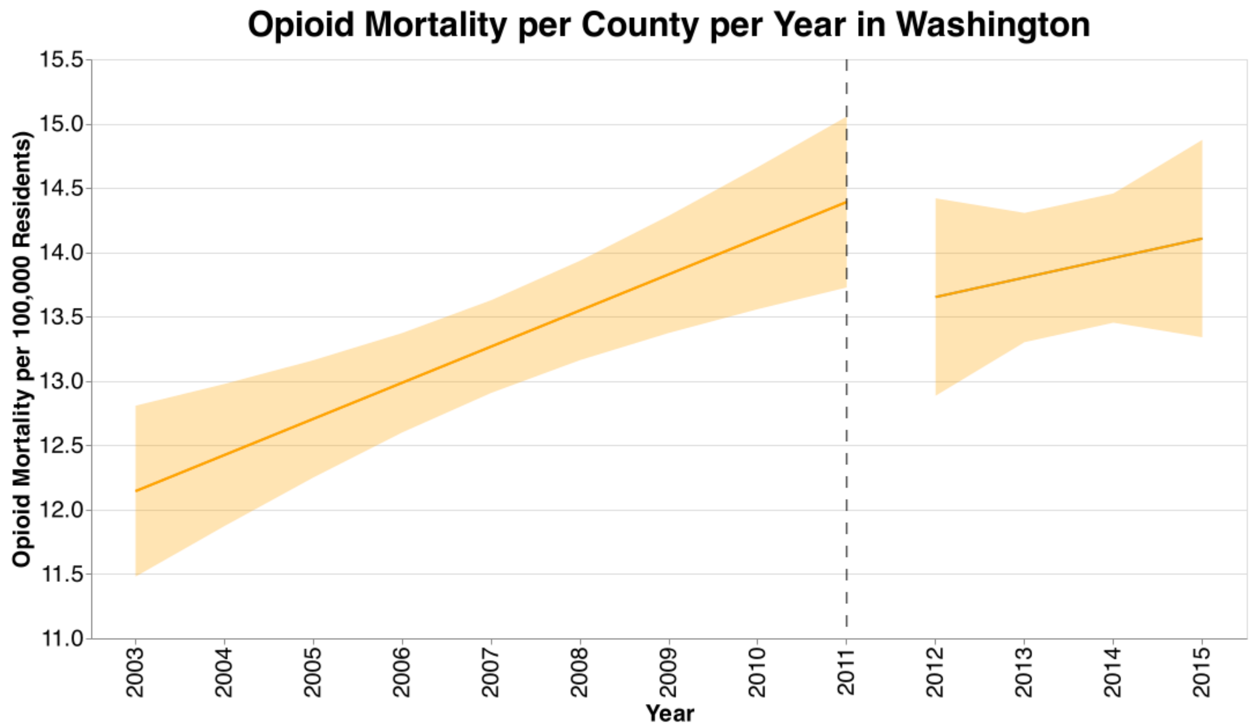

Figure 5 opioid mortality per county per year in Washington

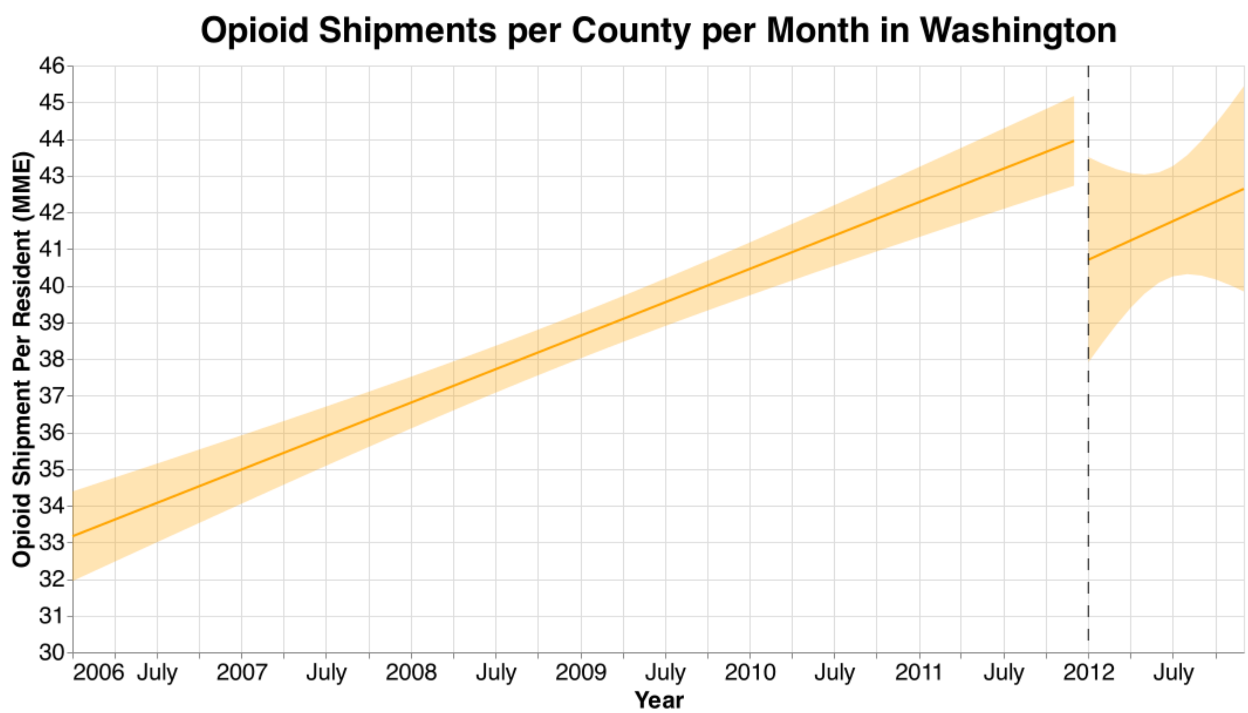

Figure 6 opioid shipments per county per year in Washington

Lastly, the results for Washington are displayed above. Given the width of the confidence bands, interpretation of results is trickier here. In both shipment and mortality, like the other states, there is a visible increasing trend by month before the policy change. While the regression lines suggest a continuation of these trends, the confidence bands width easily demonstrate that we are not confident about either the direction or the magnitude of the trend post policy change. In short, more data is needed here.

3.2 Difference-in-Difference Analysis

Here are displayed the results of the difference-in-difference analysis. As previously, there are the same four graphs, but in this case, the graphs also include the selected control counties before and after the policy change.

3.2.1 Florida Analysis (Mortality & Shipment) Vs. Controls

Here, the results of the previously seen pre-post graph for Florida's opioid mortality are strengthened by addition of the controls. Visibly, the control counties experienced nearly the same rate of increase after the policy change, potentially indicating that the trend observed is accountable to the policy change in Florida. For Florida's opioid shipment data, the same is true. While it is visible that control counties also experience a change (in this case, a flattening) in the rate of opioid shipments over time, the effect is clearly much stronger in Florida.

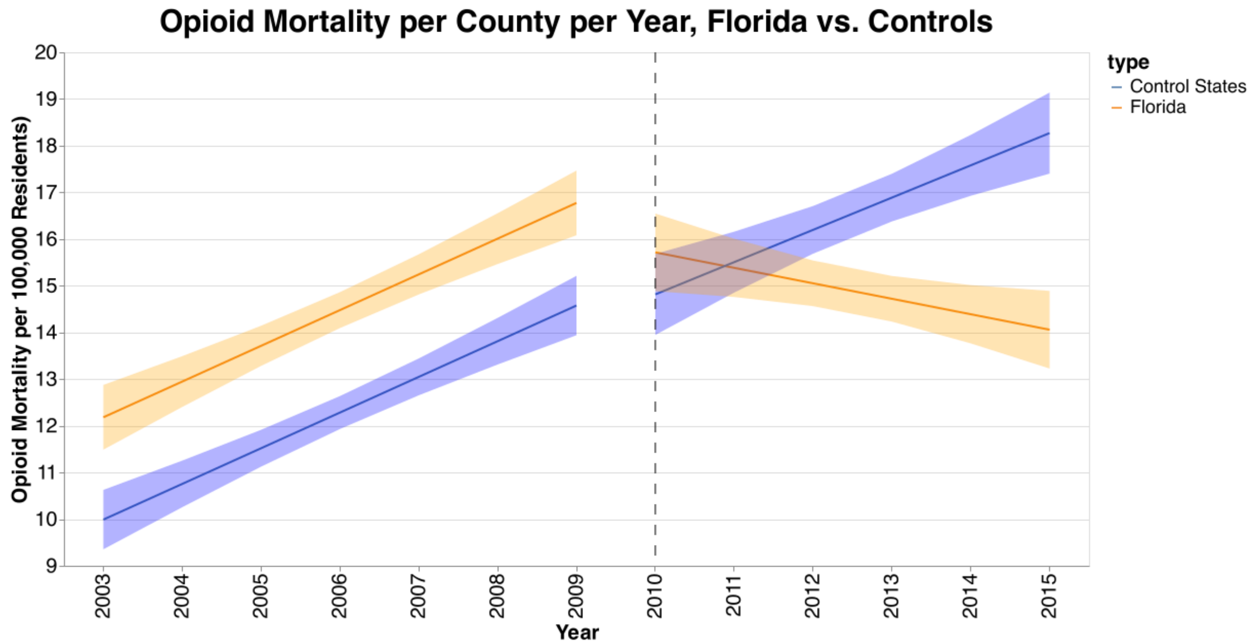

Figure 7 opioid mortality per county per year in Florida vs. controls

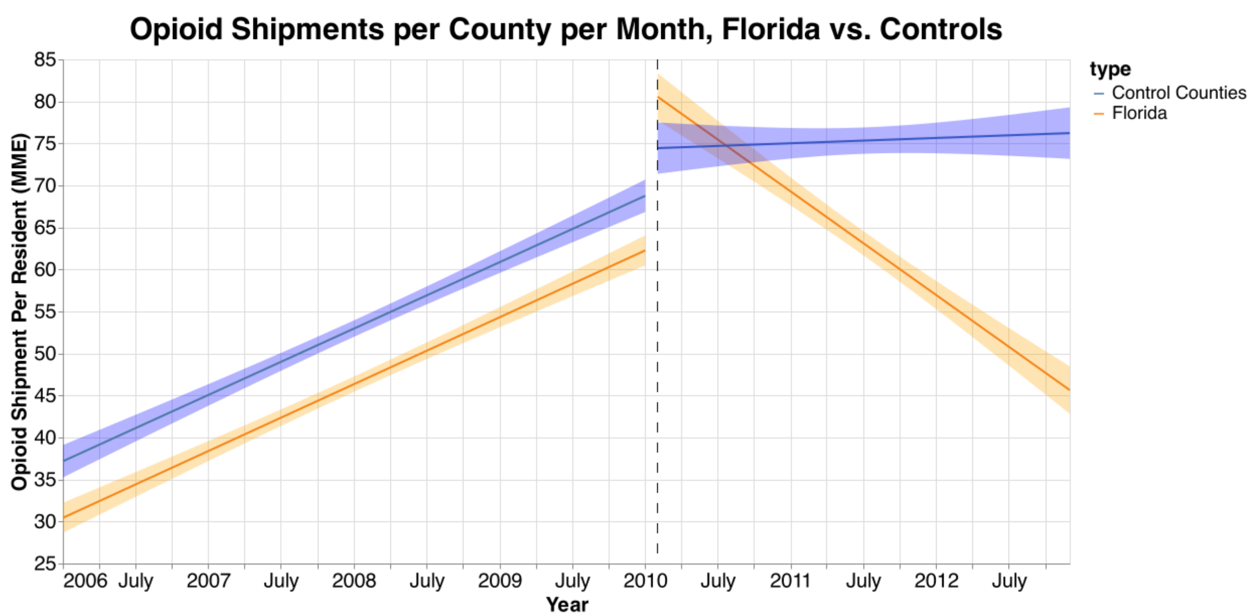

Figure 8 opioid shipment per county per month in Florida vs. controls

3.2.2 Texas Analysis (Mortality & Shipment) VS Controls

Similarly, below are the graphs for mortality and shipment in Texas. Here, the control states show a clear continuation of trends in opioid mortality, with very little change, while Texas's flattening (and perhaps reversal) is clear. With Shipment data, the picture is less clear. It does appear that Texas's policy change may have altered the slope of the increasing trend in shipment, but the change is minimal.

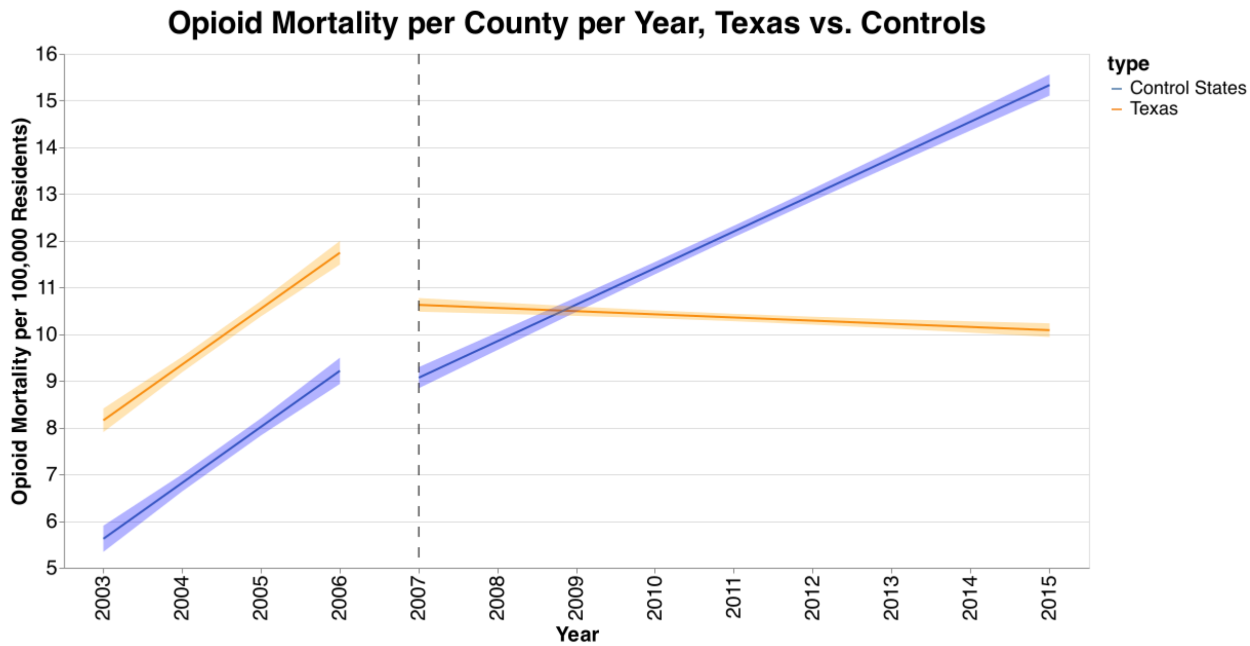

Figure 9 opioid mortality per county per year in Texas vs. controls

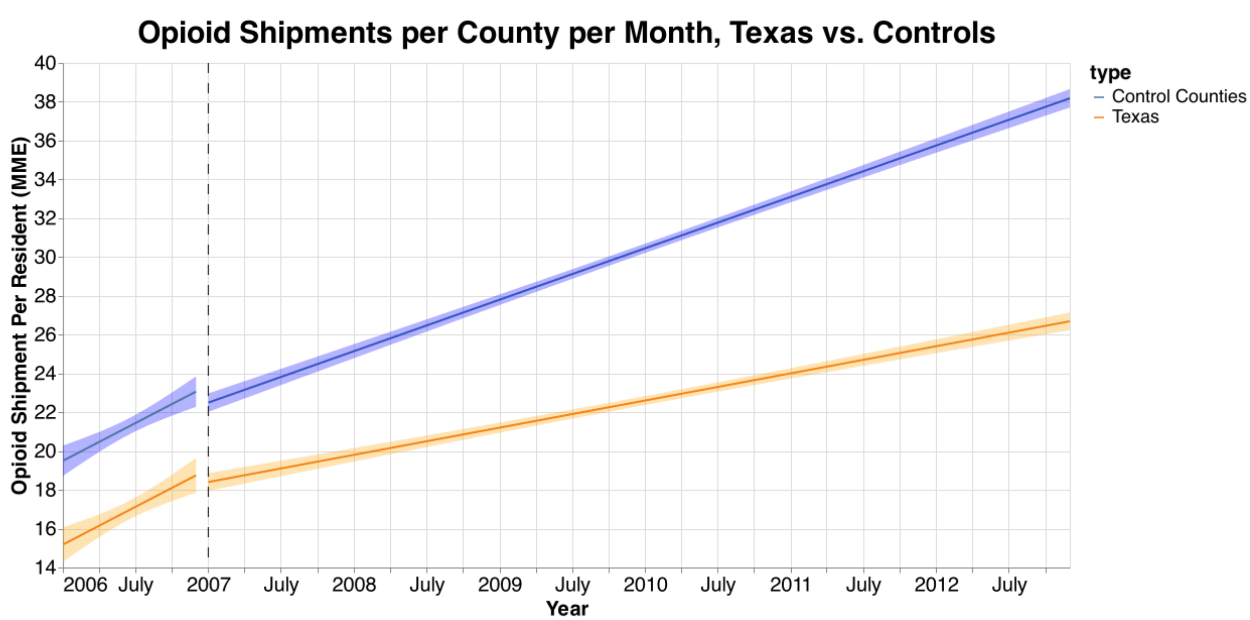

Figure 10 opioid shipments per county per month in Texas vs. controls

3.2.3 Washington Analysis (Mortality & Shipment) Vs. Controls

The last graphs displayed here are the difference-in-difference analyses for Washington.

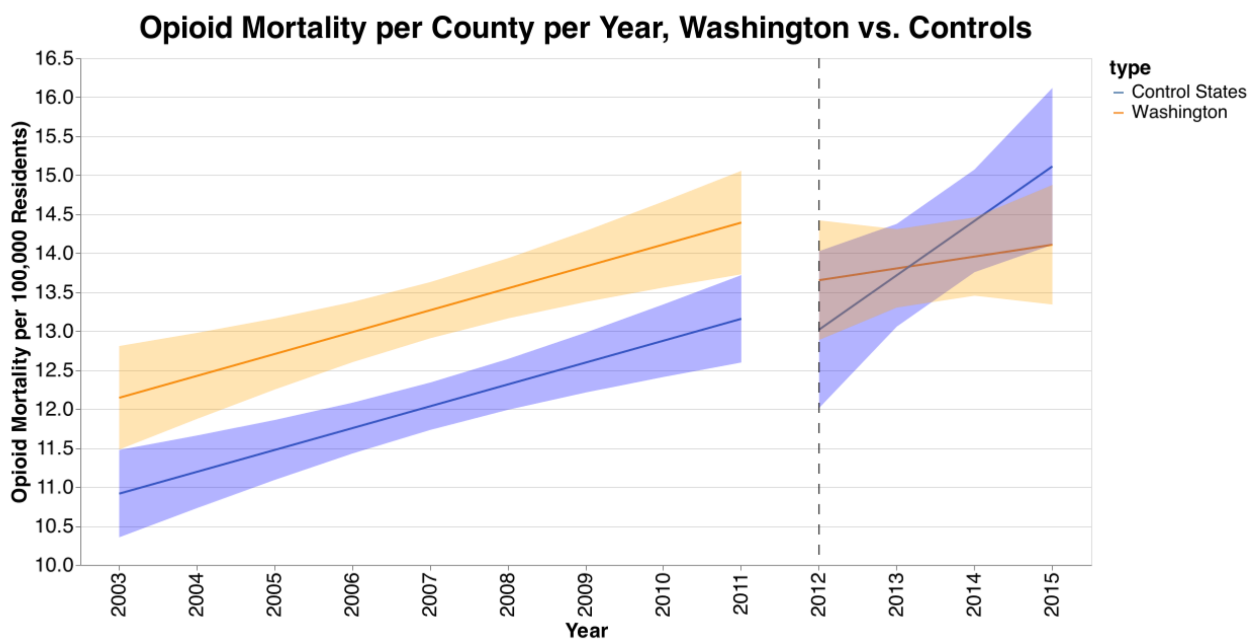

Figure 11 opioid mortality per county per year in Washington vs. controls

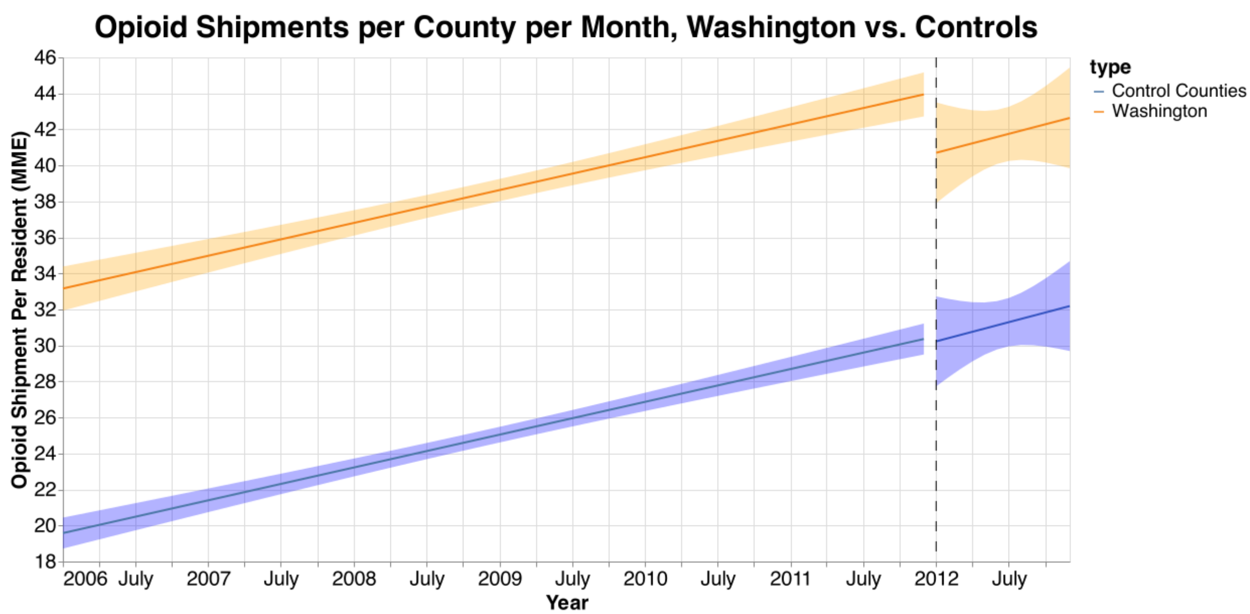

Figure 12 opioid shipments per county per month in Washington vs. controls

While the control counties add needed context to Washington's policy change, meaningful analysis is unfortunately still made challenging by the confidence bands. Without more data, the results are uncertain.

4. Conclusion

4.1 Discussion

The investigations conducted in this project analyzed data on opioid lethality and opioid shipments in three states between 2003-2013 in regards to the impact of specific and distinct opioid restriction policies after their release. We assessed the effect of these policies to some extent by comparing the variable control states. Ultimately, the results suggest that Florida's policy change was effective in reducing opioid shipments to the state as well as opioid mortality within the state. Continually, Texas's policy change was effective in reducing opioid mortality. Unfortunately, the data is not clear enough to evaluate the effect of Washington's policy change.

4.2 Limitations of the current study

Given that the objective of the project is the mortality and transport of opioids for different counties, we face some limitations. The first is the lack of data. Most of the counties in the analysis had suppressed data for opioid mortality, indicating less than 10 deaths in each mortality category. While we imputed these points in our analysis, it is plausible that the imputed values are hiding a confounding variable contained in the actual data. Also, ideally, more categories of data could increase the confidence of this analysis. There are many potential state-specific confounding variables that could be causing changes in trends. The limitations of the data are also reflected in the fact that if we want to analyze the effectiveness of policies, it is necessary to include more policy categories to represent. It is clear that policies of different types and intensities are unlikely to have similar results. Comparing shipments, data on whether prescription opioids were used for consumption in institutions such as hospitals could be added to the discussion. In particular, policy and control groups may have different trends in outcomes over time, or the composition of state populations may change significantly over time.

The field still faces significant methodological challenges and considerations, including standardized classification of opioid policies, identifying optimal control groups, and tightly controlling for differences between policy and control groups, and identifying variables that better capture the impact of policies. Improving the methodology of opioid policy evaluation studies is critical to the final government being able to implement policies that are most effective in reducing harm during the ongoing opioid epidemic.

5. Appendix

5.1 Histograms

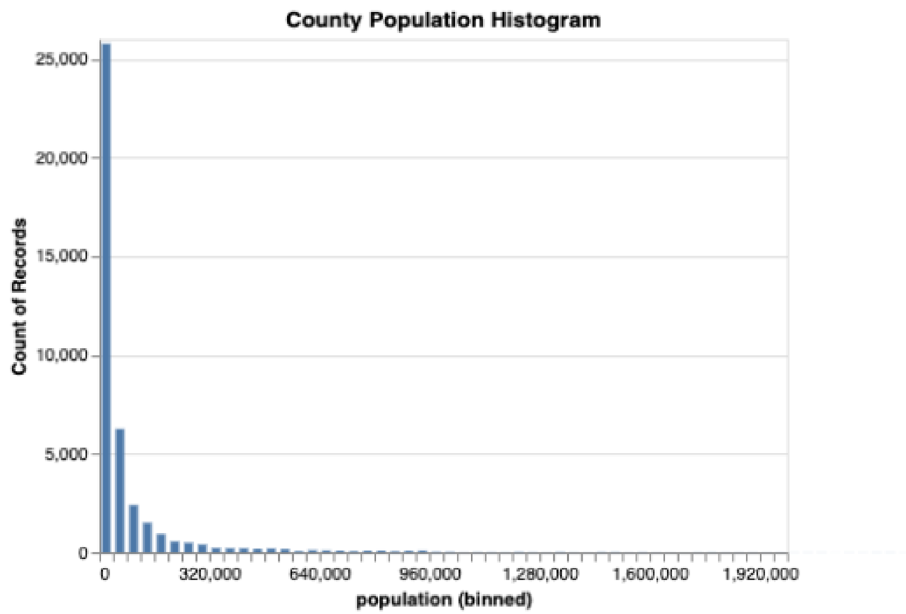

Figure A1 Distribution of population over years in all counties in the US

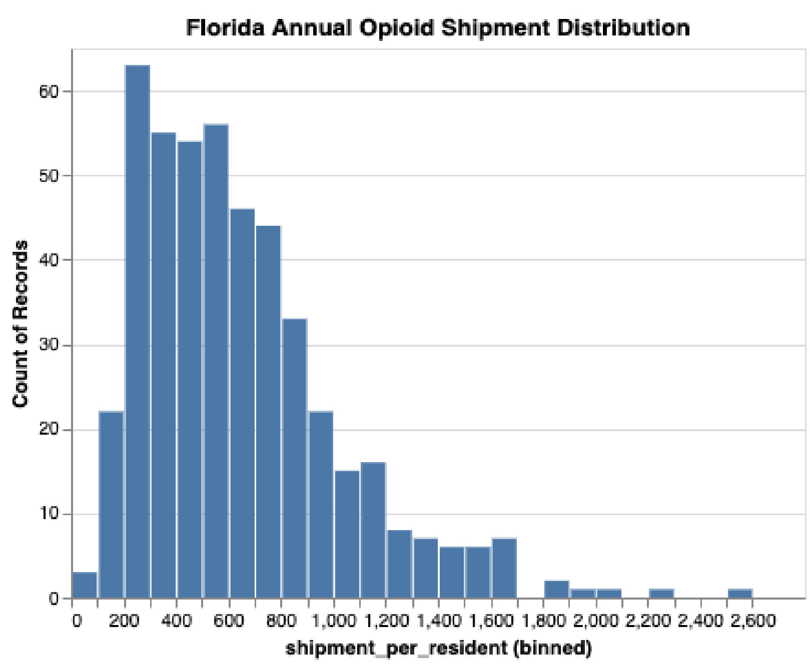

Figure A2 Distribution of annual opioid shipment per resident over years in Florida

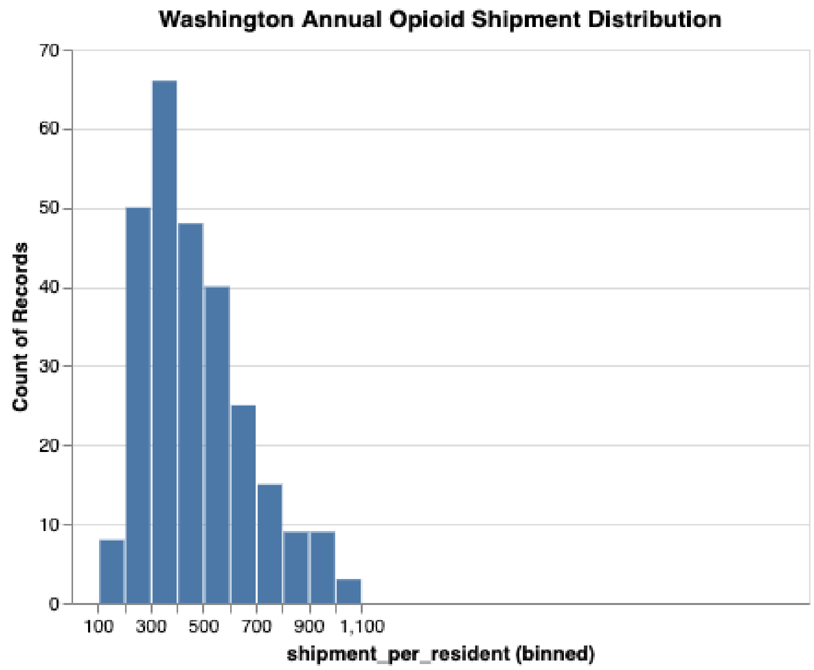

Figure A3 Distribution of annual opioid shipment per resident over years in Washington

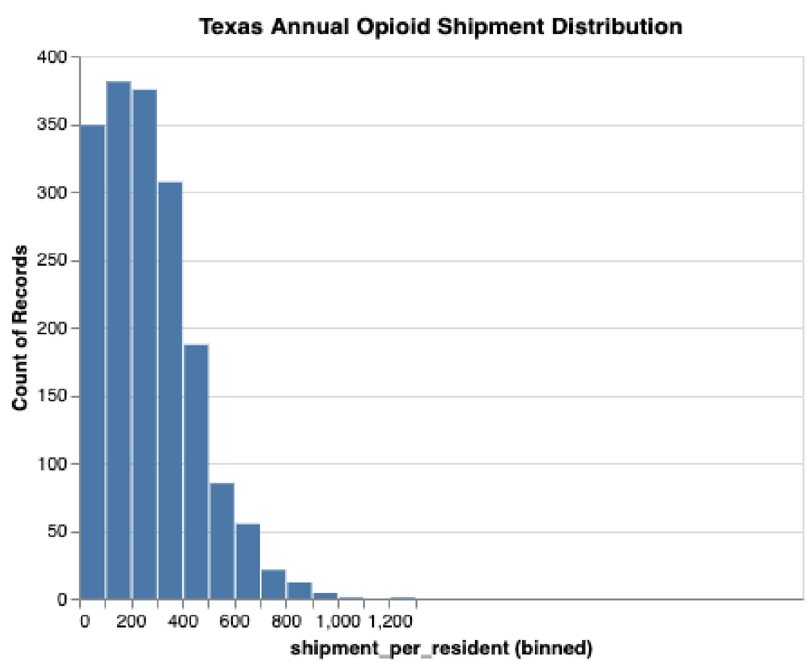

Figure A3 Distribution of annual opioid shipment per resident over years in Texas

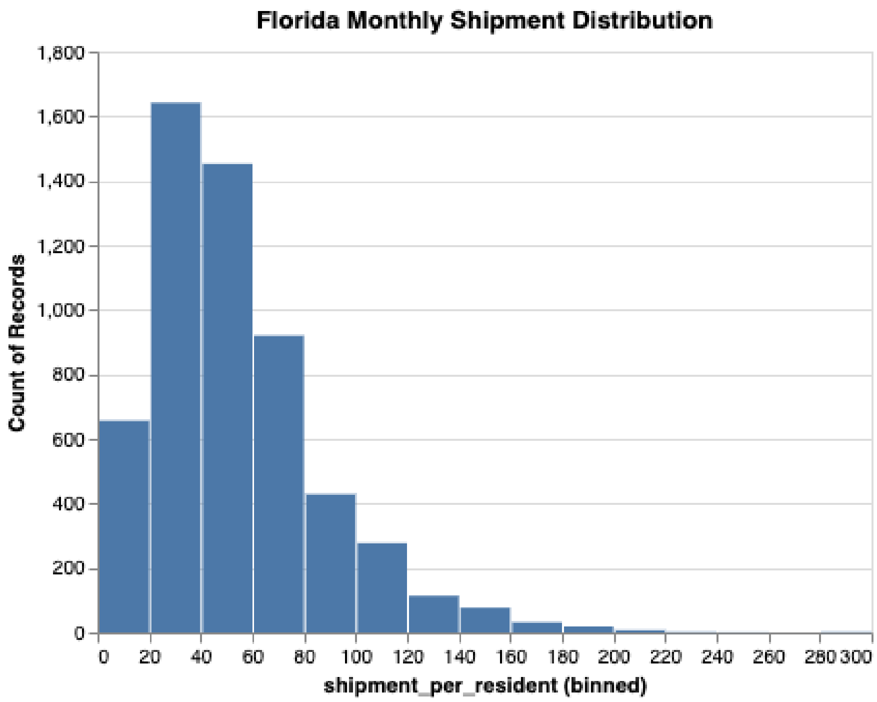

Figure A4 Distribution of monthly opioid shipment per resident over years in Florida

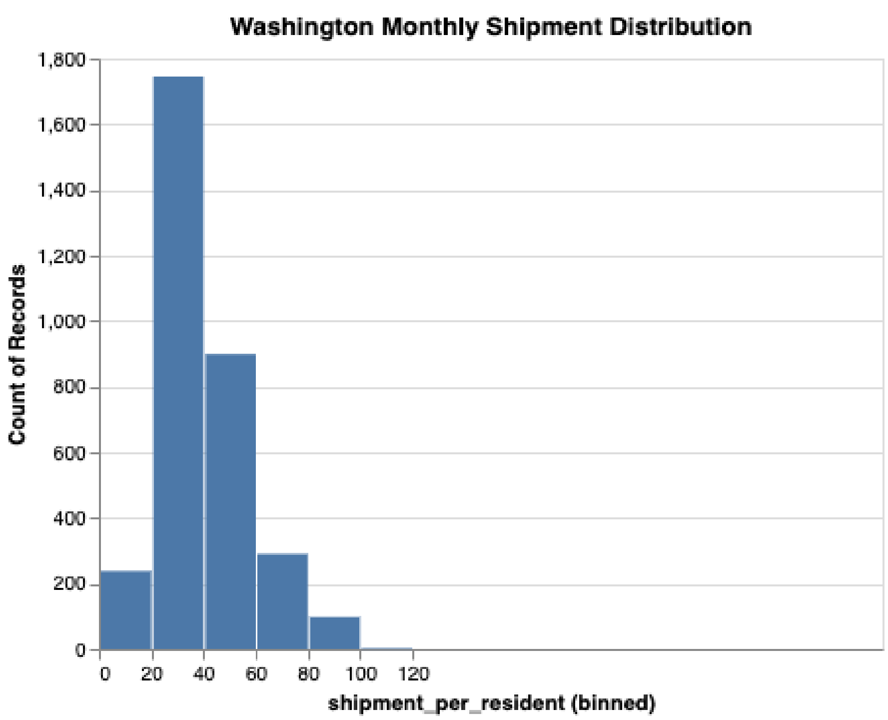

Figure A5 Distribution of monthly opioid shipment per resident over years in Washington

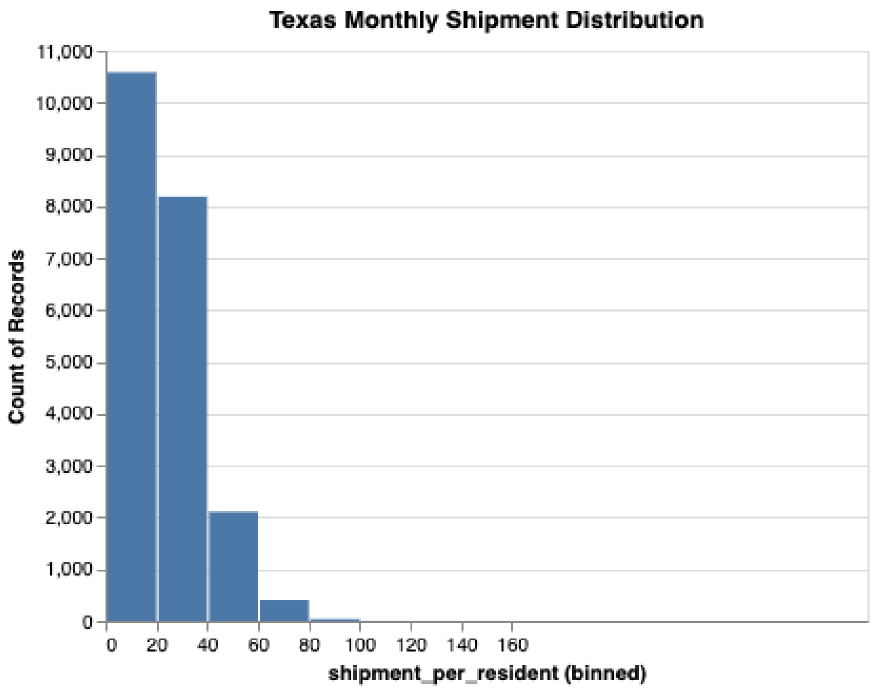

Figure A6 Distribution of annual opioid shipment per resident over years in Texas

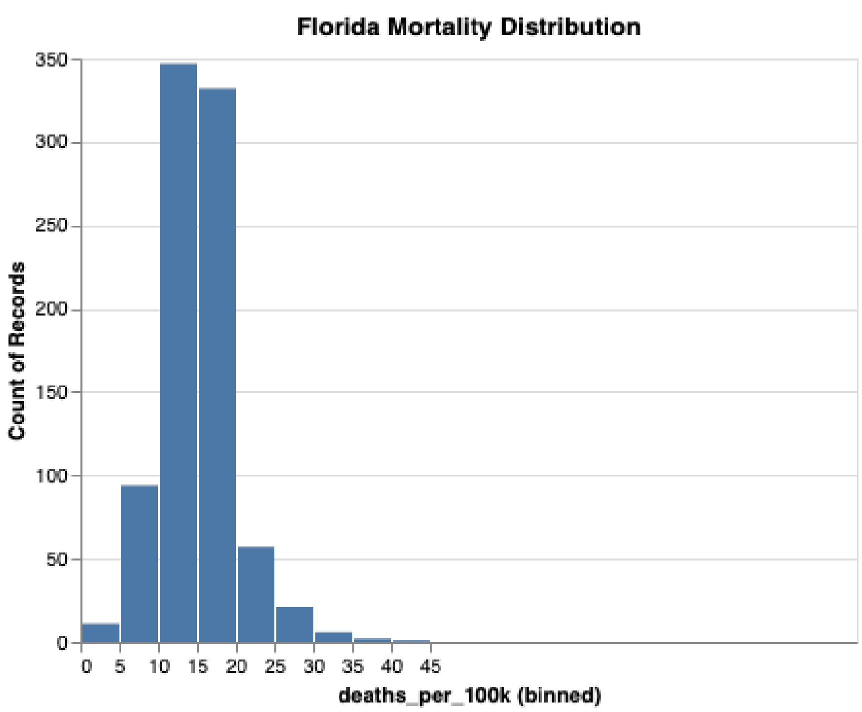

Figure A7 Distribution of drug related deaths per 100,000 residents over years in Florida

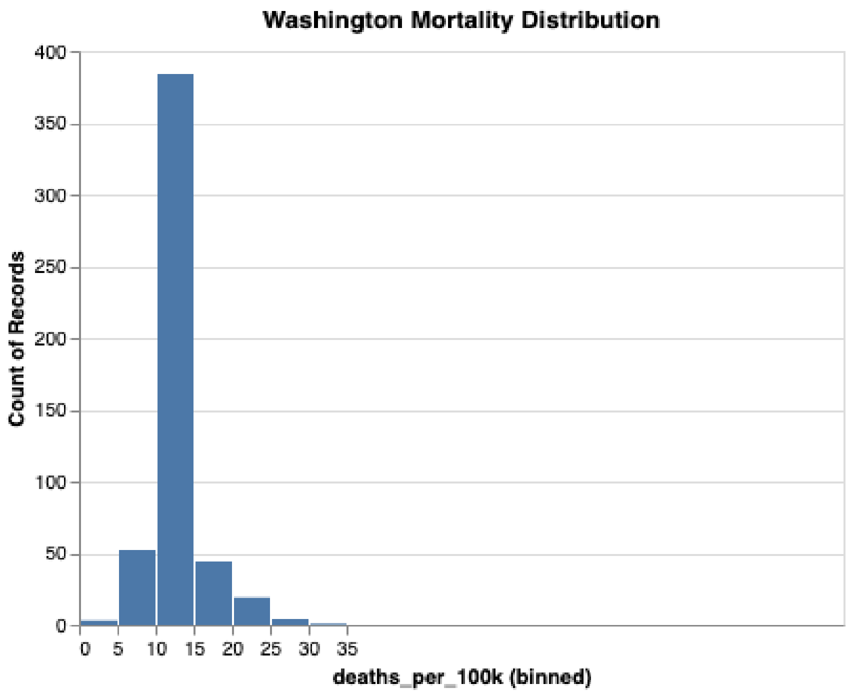

Figure A8 Distribution of drug related deaths per 100,000 residents over years in Washington

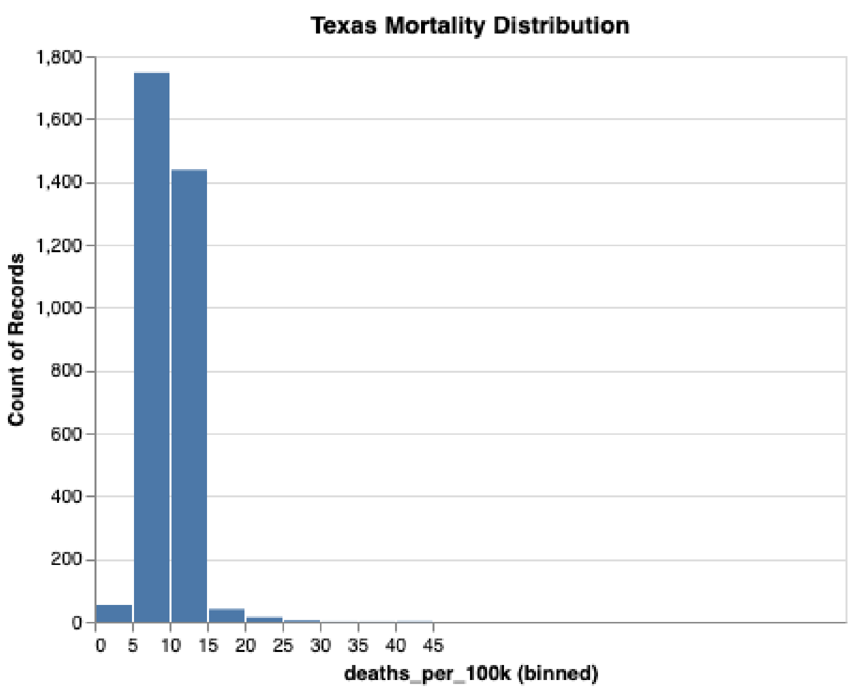

Figure A9 Distribution of drug related deaths per 100,000 residents over years in Texas

5.2 Statistical Summary of Data

Data Statistics for Florida Mortality Distribution :

	Death (total)	**deaths_per_100k**
count	871	871
mean	37.4263	14.6665
std	63.4655	4.64608
min	0.086385 9	3.90227
25%	0.40555	12.5642
50%	11	14.5381
75%	40.5	16.3985
max	326	40.8222

Table A1 Florida mortality data statistics

Data Statistics for Washington Mortality Distribution :

	Deaths (total)	deaths_per_100k
count	507	507
mean	20.4532	13.4558
std	48.3154	3.335
min	0.0232961	4.2504
25%	0.274741	12.0201
50%	0.814898	13.6818
75%	16	14.3425
max	309	30.685

Table A2 Washington mortality data statistics

Data Statistics for Texas Mortality Distribution :

	Deaths (total)	deaths_per_100k
count	3302	3302
mean	7.09966	10.2316
std	34.9609	2.24658
min	0.000454319	1.43812
25%	0.0676432	9.36017
50%	0.18248	9.95264
75%	0.496975	10.6828
max	528	42.7442

Table A3 Texas mortality data statistics

Data Statistics for Florida Annual Opioid Shipment Distribution :

	shipment (total)	shipment_per_resident
count	469	469

mean	2.26374e+08	640.032
std	4.41328e+08	385.64
min	0	0
25%	1.24526e+07	356.089
50%	6.77975e+07	572.974
75%	2.22017e+08	816.735
max	3.43323e+09	2582.39

Table A4 Florida annual opioid shipment data statistics

`Data Statistics for Washington Annual Opioid Shipment Distribution :`

	shipment (total)	**shipment_per_resident**
count	273	273
mean	7.62184e+07	467.972
std	1.39873e+08	197.039
min	1.03975e+06	137.011
25%	9.268e+06	319.47

50%	2.48922e+07	416.167
75%	6.43875e+07	581.359
max	7.86435e+08	1082.66

Table A5 Washington annual opioid shipment data statistics

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Data Statistics for Texas Annual Opioid Shipment Distribution :
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	shipment (total)	**shipment_per_resident**
count	1778	1778
mean	3.0085e+07	260.959
std	1.18823e+08	185.31
min	0	0
25%	1.08372e+06	128.189
50%	4.29198e+06	240.878
75%	1.78259e+07	373.066
max	1.82396e+09	1247.6

Table A6 Texas annual opioid shipment data statistics

Data Statistics for Florida Monthly Shipment Distribution :

	shipment (total)	shipment_per_resident
count	5628	5628
mean	1.88645e+07	53.336
std	3.73027e+07	33.1503
min	0	0
25%	1.03512e+06	29.2221
50%	5.70403e+06	47.17
75%	1.79521e+07	68.2473
max	3.95105e+08	293.004

Table A7 Florida monthly opioid shipment data statistics

Data Statistics for Texas Monthly Shipment Distribution :

	shipment (total)	shipment_per_resident
count	21336	21336
mean	2.50708e+06	21.7466
std	9.93162e+06	15.8343
min	0	0
25%	86500	10.2439
50%	361263	20.1635
75%	1.49206e+06	30.9853
max	1.81066e+08	157.198

Table A8 Texas monthly opioid shipment data statistics

```
Data Statistics for Washington Monthly Shipment Distribution :
```

	shipment (total)	shipment_per_resident

count	3276	3276
mean	6.35154e+06	38.9976
std	1.16649e+07	16.9282
min	40750	8.33754
25%	727212	26.3117
50%	2.10206e+06	34.9091
75%	5.47547e+06	48.2707
max	7.15086e+07	110.665

Table A9 Washington monthly opioid shipment data statistics

`Data Statistics for the population dataset:`

	population
count	40853
mean	97386.9
std	312310

min	55
25%	11061
50%	25580
75%	65964
max	1.00854e+07

Table A10 County population data statistics