

1. Introduction

Background

Opioids are a drug class that are primarily used for pain relief, but are highly addictive and can result in fatal overdose. Opioids are “controlled substances”, meaning that they are regulated by the government. However, due to addiction and illicit use coupled with malfeasance from drug manufacturers, distributors and doctors there have been 399,212 opioid related deaths between the years of 1999 and 2017 (Source: CDC). These deaths are related to the overprescription of medication for the sake of increased profits of pharmaceutical companies and the medical industry at the cost of human life. This has led to a declaration of an opioid “epidemic” and the implementation of public policies aimed at reducing the amount of opioid-related deaths by controlling over-prescription.

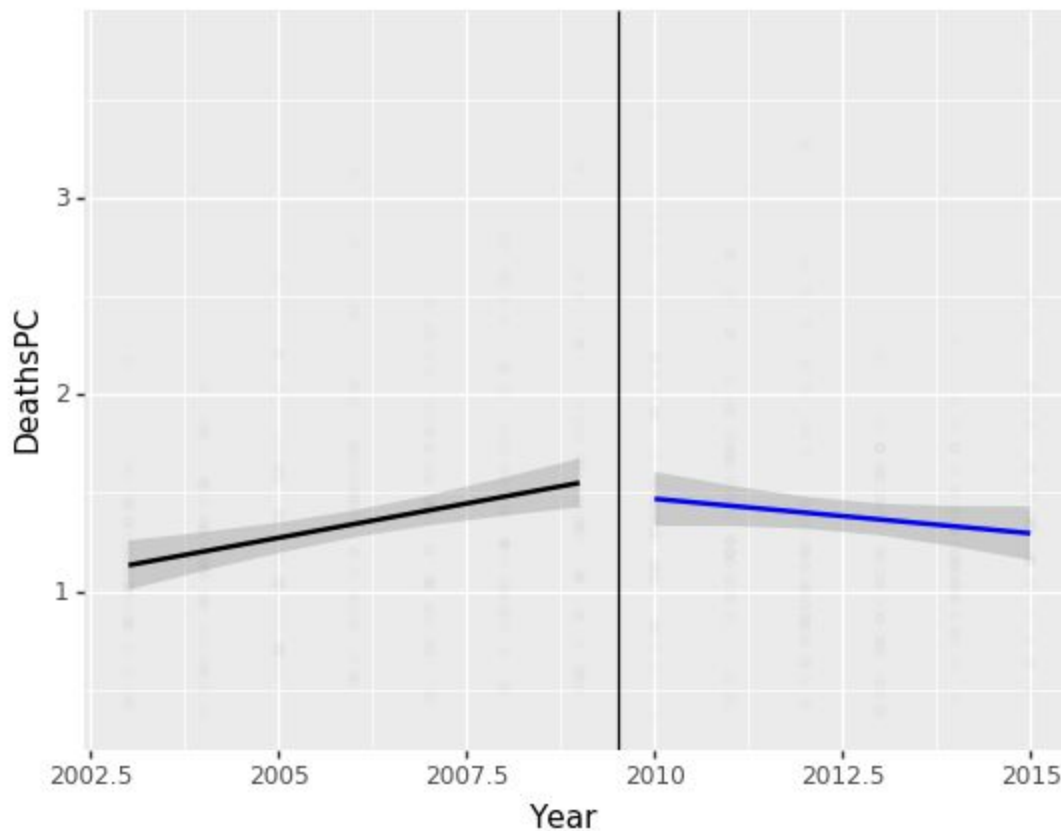
The motivation for the project

A database maintained by the Drug Enforcement Administration that tracks pain pills was recently made available as a result of a court order from the Washington Post and HD Media, who publishes the Charleston Gazette-Mail in West Virginia.

From the Automation of Reports and Consolidated Orders System (ARCOS), all opioid pills that were distributed from 2006 to 2012 were recorded. Using this data in comparison with other metrics, causal analysis will be performed to evaluate the effectiveness of opioid policies implemented in three states: Florida (implemented 2010), Texas (2007), Washington State (2012).

Analysis: Florida

Part 1: Overdose-related Deaths



Analysis

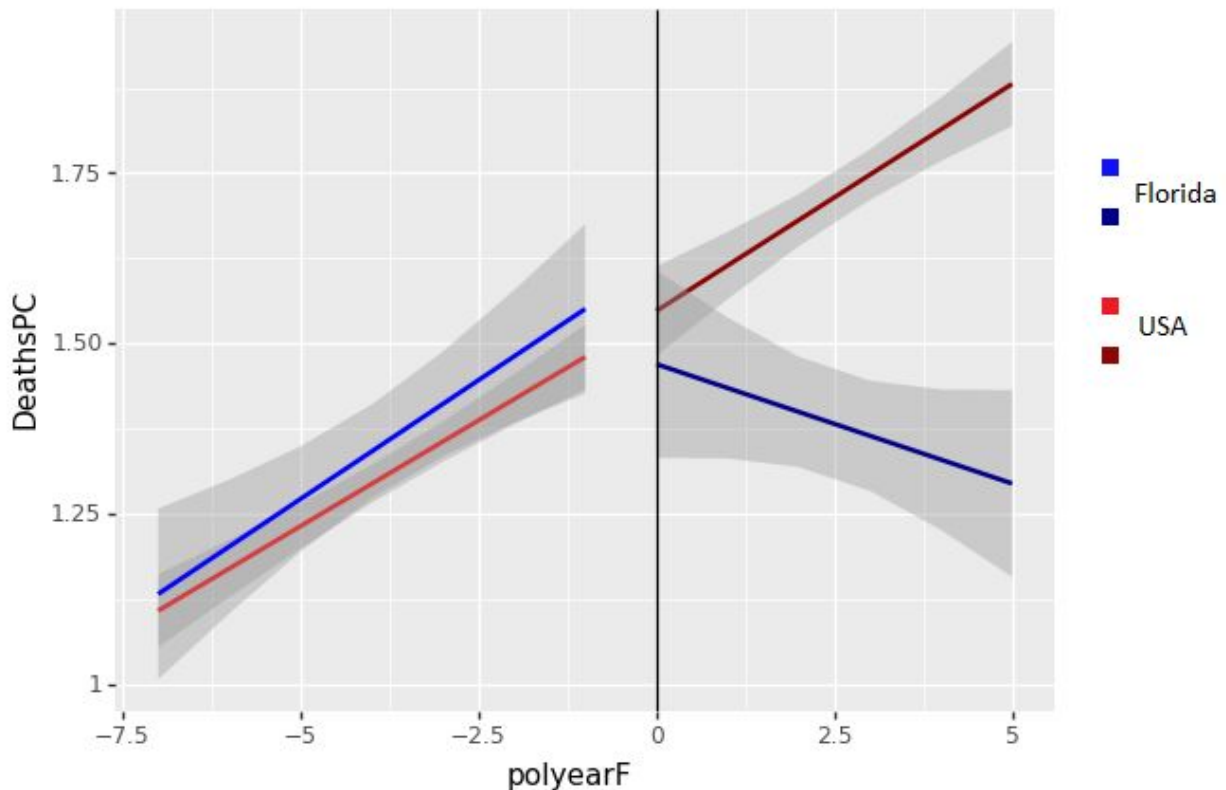
The above graph displays an analysis of the situation in Florida before and after the policy was enacted.

Firstly, the statistic DeathsPC is the number of drug overdose deaths for every 10,000 inhabitants in a county. The higher this number, the higher the rate of these kinds of deaths in a county. The black line depicts an average result per county, and it depicts a rising trend before 2010.

The statistics after the policy enactment are shown in blue. We can see that it has changed from an upward trend to a downward one.

These results show that the policy seemingly has had a useful effect in curbing the growth of these types of deaths in Florida. Although the trends are slight, the policy seems to have at least stabilized the trend if not turned it around.

To continue this analysis we should now compare Florida to the United States. This comparison is done to guarantee that the cause of this trend switch is the policy in Florida and not some other effect that happened across the country.



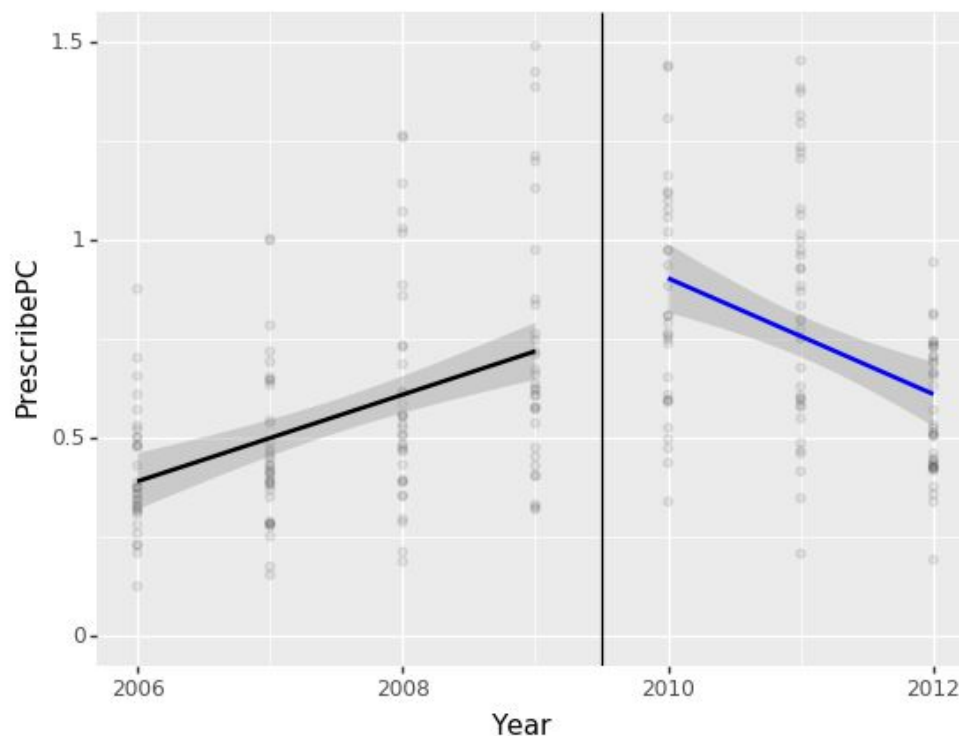
The above graph, called a Difference in Difference graph, shows more information. Firstly, we see that at the bottom we are now tracking polyyearF. This name is a stand in for the number of years before or after the policy came into effect, where 1 means a year later and -1 means a year earlier.

Like in the previous graph, the black line shows us the year the policy was enacted. To its left we see two similar lines, blue and red. The blue line depicts a stat we are already familiar with, DeathsPC in Florida, but the red line depicts this statistic as an average for the whole United States. Clearly, Florida seemed to be following the overall trend in the US, though at a slightly higher level.

What is most interesting comes to the right of the black line. Unlike the previous pair, these two are going in opposite directions. The dark blue is our Florida line and the dark red our USA line. If you connected the red and dark red lines, you could make a nearly straight red line; this means that there was no significant change between the before and after policy years for the US. With Florida, however, the lines have changed directions; the before and after are clearly different.

We can interpret these results as a clearly effective policy change. Clearly the year 2010 caused an impactful change for this statistic that was not felt in the whole country; only in Florida. This can be considered evidence to suggest that not only was there an effective decrease in deaths after 2010 but that the cause was the policy in 2010.

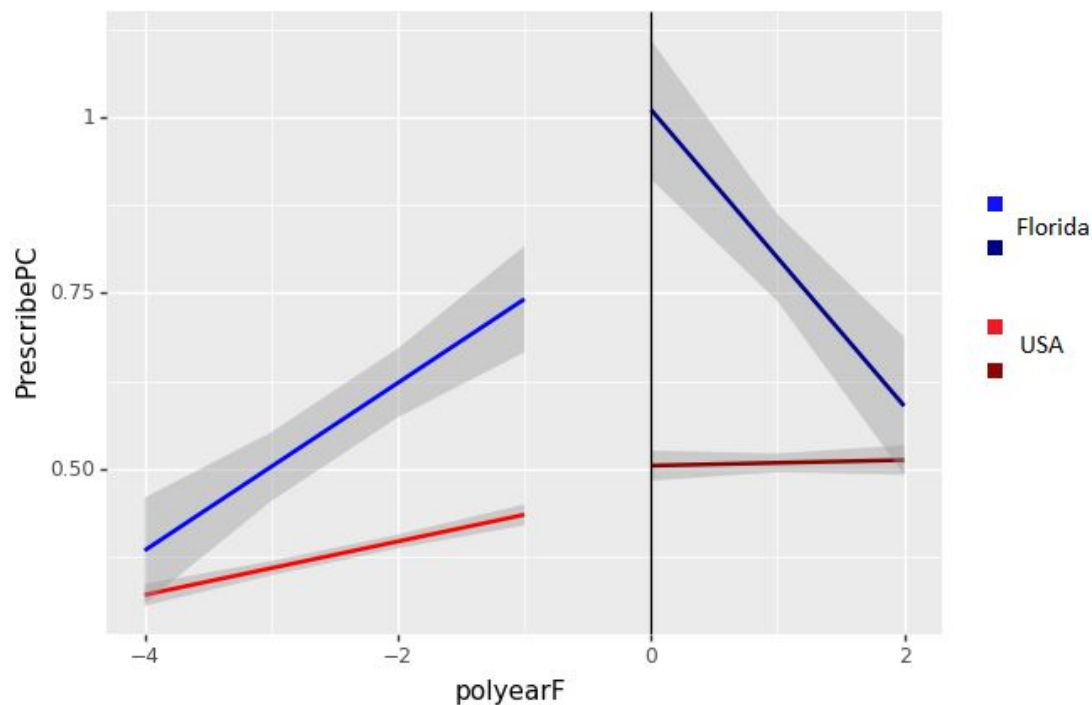
Part 2: Prescriptions of Opioids



We now switch to observing opioid prescriptions in Florida. The statistic PrescribePC is a number that describes MME per capita in a state. MME stands for Morphine Milligram Equivalents and it is a way to standardize the amount of opioids sold in an area; MME accounts also for the strength of each opioid. After standardizing MME by each county we take an average that can be seen by each of the two lines above. The black line once again represents the period of time the policy was enacted. Before the policy, we see that the prescriptions had an upward trend in the black line. After the policy this trend switched to a negative one, we can

interpret that the policy was likewise effective in causing a change in the statistics. If the trend continues, we can see that opioids will continue to be prescribed less.

Let's continue to the Difference in Difference graph to continue our analysis:

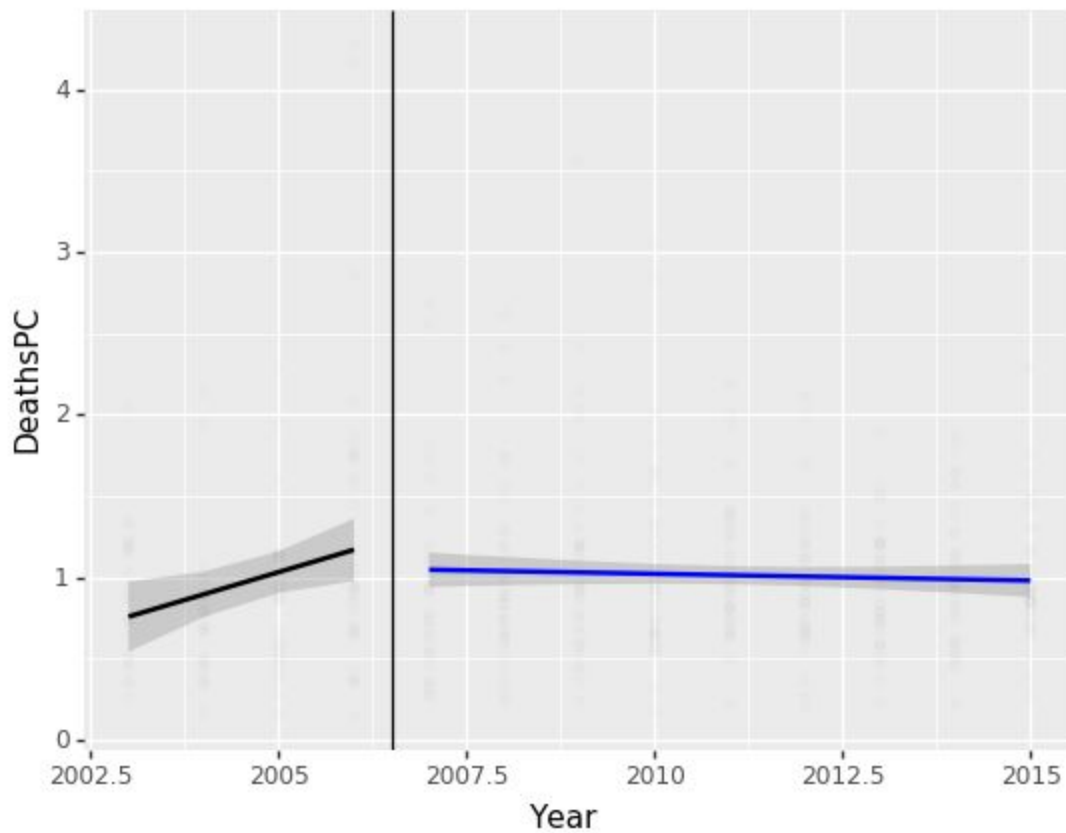


Once again we see blue lines for Florida and red lines for US counties. If we consider that the average US county is what we should normally expect, we can see a clear difference with the behavior of this statistic in Florida counties.

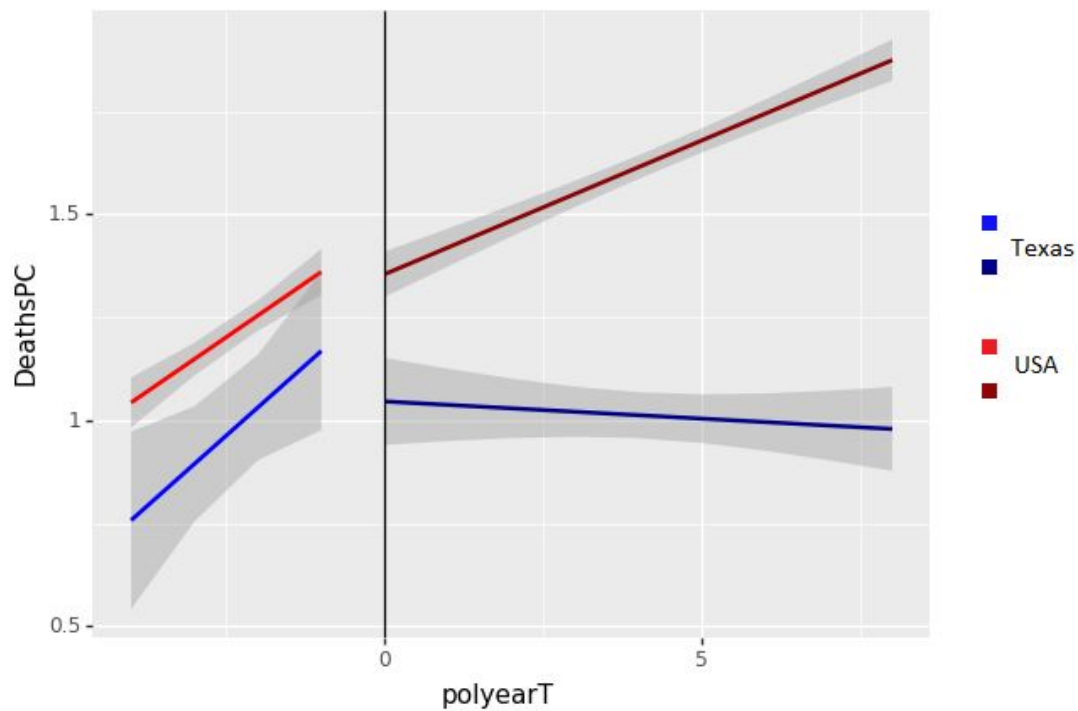
This time, it seems that prior to 2010 we see a trend upwards in the amount of opioids prescribed in the country. After 2010, we see the amount per capita stabilizing. For Florida, however, we see a far steeper upwards trend in the data. After 2010, we see that it turns into a steep decline comparatively.

When we compare the two behaviors we see that instead of seeing a somewhat stable effect in Florida we saw a decline. This can be interpreted as a change thanks to the policy; the policy decreased the amount of prescriptions per capita.

Analysis: Texas - Overdose-related Deaths

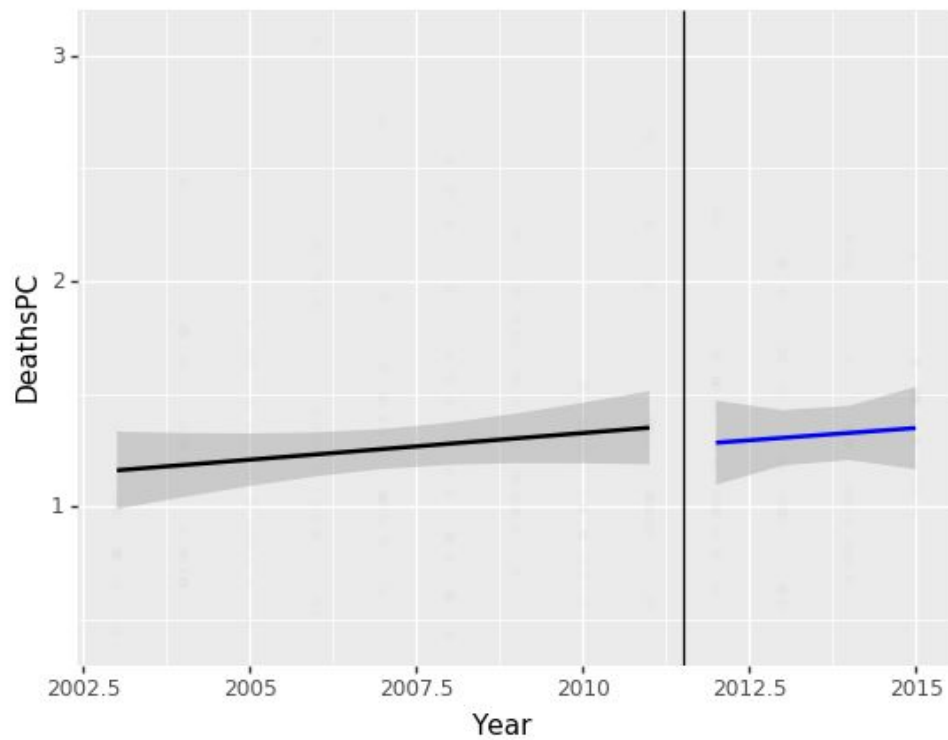


For Texas we see a trend upwards before the policy, that seems to at least flatten out after the policy enactment. There could be evidence of a change thanks to policy but it isn't obvious yet.

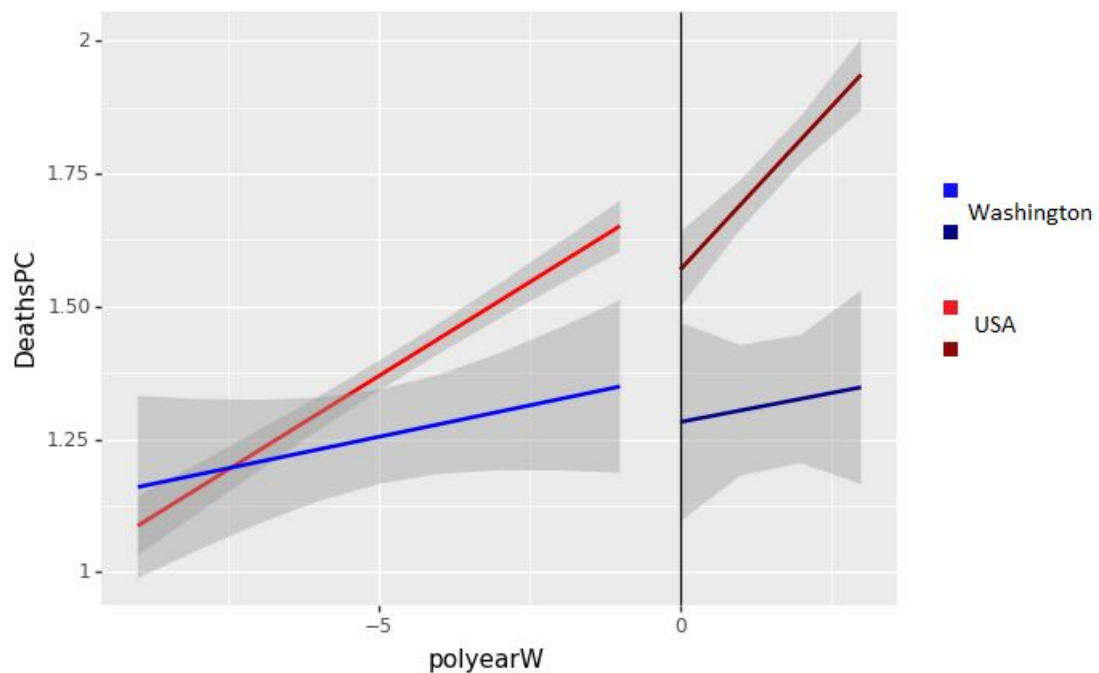


When we look at the Difference in Difference graphs however, we can see a clearer story. Before the policy, Texas counties followed a trend similar to other US counties. After the policy, we see that Texas has its statistic turned into a downward trend while the USA seems to maintain a trend where the amount of deaths per capita increases. This difference in trends can be seen as evidence for an effective policy in curbing the upward trend in these drug-related deaths.

Analysis: Washington - Overdose-related Deaths



Unlike in the previous states, we do not see any discernible difference between the amount of drug-related deaths per capita in Washington. Both lines seem to follow similar trends and are close enough in position; there is no indication here that the policy caused any change.



When we come to the Difference in Difference graph we can compare Washington counties to the average USA counties. Looking first at the red lines, we see that that after the break there is a shift downward and then a higher trend upward than before. The shift downward isn't important but the trend upward is. In Washington's blue lines we see a lack of apparent change in the trend or slope of the line. The grey area around each line is the margin of error; it shows where we could conceivably place the line. For the Washington lines, these space show us that these lines could be one continuous line (as there is a line that can traverse these two grey areas easily).

Essentially, there is little evidence to conclude that the policy created a change in Washington. Though the state behaves differently than the USA, it does not seem to change in behavior after the policy switch. Compared to the average US state could show that Washington states resisted a worse overall US trend but there is no evidence to assume that the policy is the cause for this resistance.