

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 in the US between the years of 1999 and 2017 [1]. These deaths are related to the overprescription of medication and are arguably for the sake of increased profits of pharmaceutical companies, at the cost of human life. This has 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 in 2010), Texas (2007), Washington State (2012).

2. Data

Data Handling

Three datasets were combined in preparation for analysis: the ARCOS drug tracking database, mortality data to identify causes of death, and population data from the U.S. Census Bureau. These datasets were cleaned and merged together, with the intermediate goal for each dataset to be merged onto a schema crosswalk to provide a uniform unique identifier. In the case for these three datasets, each county in the US has a FIPS (Federal Information Processing Standards) Code [3], which was merged onto each table prior to all three tables being merged together using their FIPS code.

(a) ARCOS Dataset

This data was downloaded by State from the Washington Post. Each file was reduced down to the following columns:

State	County	Transaction Date	Calc Base Weight in Grams	MME Conversion Factor
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“Calc Base Weight in Gram” is a value that is generated by ARCOS database that is a value that identifies the final gram conversion of the controlled drug substance, taking into effect of Quantity, Dosage Unit and Dosage Strength information. Each opioid was scaled to a Morphine Milligram Equivalent using its “MME Conversion Factor”. A new value, “MME Strength” was calculated by multiplying “Calc Base Weight in Gram” and “MME Conversion Factor” [2].

After calculating MME Conversion Factor, the Transaction Date was converted to the transaction year, and finally a groupby function was applied on State, County, and Year to have an output table “State”, “County”, “Year”, and “MME Strength”.

These files were concatenated together and then merged with the FIPS table on the “State” and “County” columns for later analysis. The merge was validated using an outer join and 1:1 matching. The final ARCOS Table was:

FIPS	State	County	Year	MME Strength
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(b) Mortality

Mortality data was gathered from 2003 to 2015. The data came in 13 files, one for each year and was merged into one dataframe. The important columns in the source file is shown in the table below:

County	State	Year	Drug/Alcohol Induced Cause	Deaths
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All non-drug related deaths were filtered out of the dataframe because this study was interested in only deaths due to drug-related causes. A group-by operation was performed

to aggregate the data by “County”, “State”, and “Year” to generate the total number of deaths due to all drug-related causes. This table was then merged onto the related FIPS code. We performed a validation test by performing checking that the number of rows of the new table after joining the aggregated mortality table with the FIPS codes would be the same as the number of rows we had in the aggregated mortality table.

(c) Population

The population data was used to generate per capita data. The two original data frames contained population data on a county level from 2000 to 2010 and 2010 to 2018. The important columns in the source file is shown in the table below:

County Code	State Code	State Name	County Name	Census 2000/2010	Pop Estimate 2001/2011	...
-------------	------------	------------	-------------	------------------	------------------------	-----

The U.S. Census Bureau conducts the census every 10 years. The last census was conducted in 2010. Based on the 2000 Census and 2010 Census, the Census Bureau estimates the population data from 2001 to 2009 and 2011 to 2018. Thus we used the official census and estimations as population data [4]. Unrelated columns for years not in the 2003 to 2015 time frame were removed. The FIPS code was included in the Census data.

To make merging and analysis process easier for other datasets, we rearranged, renamed some columns and melted the data according to “FIPS”, “County Name” and “State Name”. This allowed us to reshape the data frame by pivoting objects and make an index of years identify individual observations

(d) Missing Data

Several counties did not have reported fatalities or drug shipments. We did not assign zero or other values to this missing data. For our analysis we want to only consider counties that are affected by this particular crisis so we only consider counties with relevant data.

3. Methods and Metrics

Pre-post Comparison

Pre-post comparison aims to achieve summary statistics for two different time periods. Since we want to see how the opioid policy affected the prescription and overdose death, pre-post analysis shows us a general intuitive change in state. Take Florida as an example: if the prescription and overdose death decreases after applying the policy in 2010, this opioid policy is more likely to be determined successful. If the trend of prescription and overdose death remain unchanged, the policy is possibly ineffective.

We completed the pre-post comparison analysis for overdose deaths were performed for Washington and Texas, and pre-post comparisons for both overdose deaths and for prescriptions were performed for Florida. Analysis for prescriptions were not performed for Washington and Texas due to the lack of opioid shipment data. The analysis aims to directly show the changes of overdose deaths and prescription in the pre-post graphs.

Difference-in-difference

Samples of different groups may have prior differences before the implementation of the policy. A single pre-post comparison may ignore these differences, which lead to a biased estimation of the effect of the policy implementation. The DID model is based on observed data. It effectively controls the pre-existing differences between the research objects through modeling, and separates the true results of policy influences. Still taking Florida as an example, we assume there would be a decrease in prescription and overdose deaths in Florida after policy change. We also want to estimate if there also exist large difference after that period of policy change in other states, which have a similar trend before but with no policy change. To ensure that the findings of our pre-post analysis were not just capturing the national differences, we use the difference-in-difference model to compare the effects in the state versus the whole country. This will isolate any effects particular to the state.

In this project, we chose the whole USA as control group to complete the DID analysis, which indicates the average level and has almost parallel trends before policy year. Also, we completed the DID analysis for overdose deaths in Washington, Texas and Florida, and only for prescription in Florida, based on both graphs and regressions.

The assumptions of DID model:

- 1) The treatment groups (Florida, Texas and Washington) and control group (the USA) have parallel trends in outcome (have similar trend in overdose deaths and prescription before policy year).
- 2) The composition of both treatment groups and control group is stable.
- 3) The policy changes for all the three states have no spillover effects (the policy would only produce the expected effect, no other effects on the people or society outside the states).

The DID model only allowing for level changes:

$$Y_{c,t} = \alpha + \beta_1 post_t + \beta_2 post_t * policy_state_c + \epsilon_{c,t}$$

$Y_{c,t}$: overdose deaths or opioid shipment per capita

$post_t$: an indicator for whether we are in a period of after implementation of the policy change

$policy_state_c$: an indicator for whether a given county is in a state that experienced a policy change

In this regression model, we would like to interpret the coefficient β_2 to show the effect of policy change. The coefficient β_2 includes two levels of difference. This first one is the difference of whether the group is the state of a policy implementation, which could be calculated by $\beta_2 - \beta_1$ mathematically. The second one is the difference of whether the group is after the year of policy change, which could be indicated by $\beta_1 - 0$. If we calculate these two differences together, it will give us a “difference-in-difference” estimate including both of them, which could be calculated by $\beta_2 - \beta_1 + \beta_1 - 0 = \beta_2$.

The DID model allowing for both changes in levels and for changes in trends:

$$Y_{c,t} = \alpha + \beta_1 policy_state_c + \beta_2 year_t + \beta_3 post_t + \beta_4 post_t year_t + \beta_5 post_t policy_state_c + \beta_6 year_t policy_state_c + \beta_7 post_t year_t policy_state_c + \epsilon_{c,t}$$

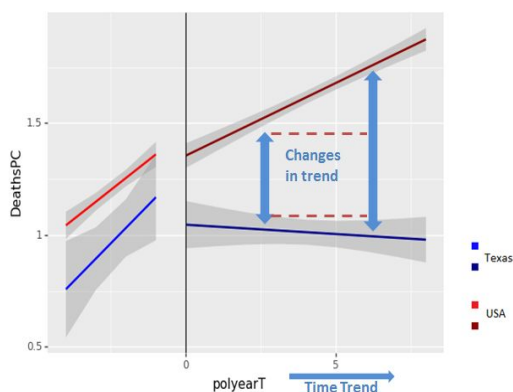
$year_t$: adjust year, which has a value of 0 in the year the policy goes into effect

In this regression model, we would like to interpret difference-in-difference in time trend. The two difference-in-difference coefficients should be β_5 and β_7 . While β_5 indicates

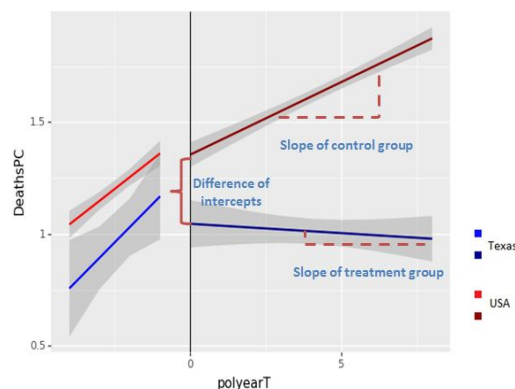
the estimate of change in intercepts (level shift) at the time point of switch (the policy year), β_7 gives us the estimate of change in slopes (see **figure (2)** below). The differences of intercepts should be calculated right before or after the policy change period ($t=0$). The differences of slopes should be generated from “ $year_t$ ”, which could be treated as a continuous variable in our second DID model.

β_5 could be calculated by $\beta_5 + \beta_1$ (the difference in intercepts at $t=0$ for the post-policy change period) minus β_1 (the difference in intercepts at $t=0$ for the pre-policy change period). We could also get β_7 by $\beta_6 + \beta_7$ (the difference in slopes in the post-policy change period) minus β_6 (the difference in intercepts in the pre-policy change period). The DID including time trend enables us to calculate the special differences at some points after policy implementation. We could compare and analyze the results at different time points (different values of $year_t$) (see **figure (1)** below). If there is a huge difference in slopes between control and treated groups, the effect of whether the group is the state of a policy implementation could grow increasingly larger as time goes by.

Figure (1) and (2):



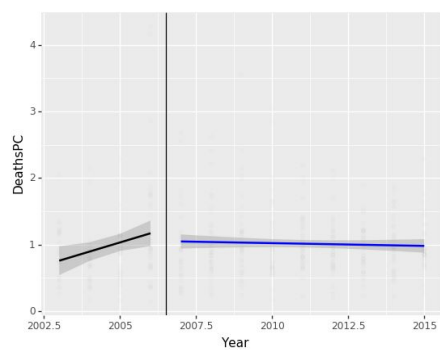
(1)



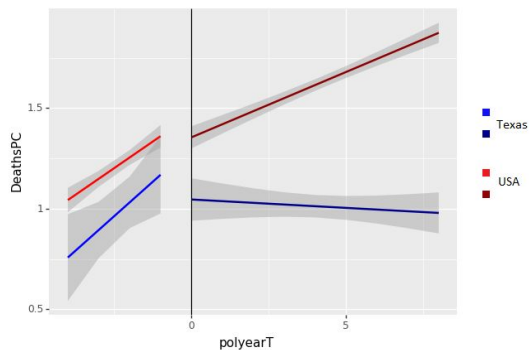
(2)

4. Findings

Texas: Pre-post Comparison and DID graphs for overdose deaths



Pre-Post Analysis



Diff-in-Diff Analysis

In Texas we see that there is a change. The slope changes after the policy (indicated by the black line). In the Difference in Difference graph we can see that the US has a clear upward trend while Texas shows a downward trend after the policy.

This means we can interpret these results as evidence for the policy having a causal effect in the decrease of these drug-related deaths in Texas.

Washington: DID Regression Analysis for overdose deaths

OLS Regression Results						
=====						
Dep. Variable:	DeathsPC	R-squared:	0.004			
Model:	OLS	Adj. R-squared:	0.003			
Method:	Least Squares	F-statistic:	14.29			
Date:	Sun, 10 Nov 2019	Prob (F-statistic):	6.40e-07			
Time:	15:19:18	Log-Likelihood:	-11838.			
No. Observations:	7917	AIC:	2.368e+04			
Df Residuals:	7914	BIC:	2.370e+04			
Df Model:	2					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	1.5137	0.025	60.731	0.000	1.465	1.563
Policy_T	0.0087	0.029	0.302	0.763	-0.048	0.065
Policy_T:State_T	0.3528	0.067	5.276	0.000	0.222	0.484
=====						
Omnibus:	5512.832	Durbin-Watson:	0.672			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	104455.185			
Skew:	3.129	Prob(JB):	0.00			
Kurtosis:	19.658	Cond. No.	7.10			
=====						

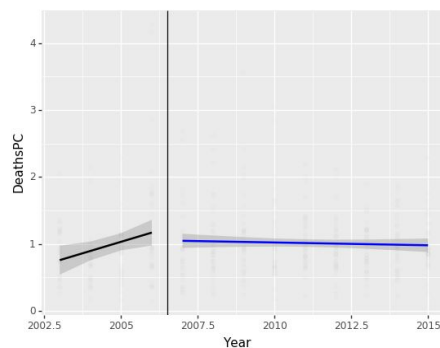
Pre-Post Analysis

OLS Regression Results						
=====						
Dep. Variable:	DeathsPC	R-squared:	0.008			
Model:	OLS	Adj. R-squared:	0.007			
Method:	Least Squares	F-statistic:	10.02			
Date:	Sun, 10 Nov 2019	Prob (F-statistic):	4.70e-11			
Time:	15:21:31	Log-Likelihood:	-11823.			
No. Observations:	7917	AIC:	2.366e+04			
Df Residuals:	7910	BIC:	2.371e+04			
Df Model:	6					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

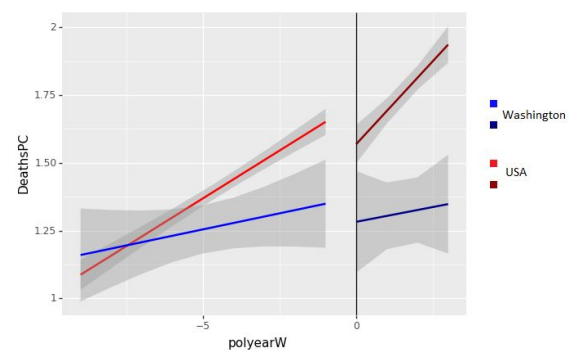
Intercept	1.5175	0.060	25.475	0.000	1.401	1.634
adj_year_T	-0.0048	0.023	-0.214	0.831	-0.049	0.039
Policy_T	0.0703	0.065	1.074	0.283	-0.058	0.199
Policy_T:State_T	0.6792	0.122	5.551	0.000	0.439	0.919
Policy_T:adj_year_T	-0.0108	0.023	-0.467	0.640	-0.056	0.035
State_T:adj_year_T	0.1252	0.044	2.828	0.005	0.038	0.212
Policy_T:State_T:adj_year_T	-0.2076	0.051	-4.060	0.000	-0.308	-0.107
=====						
Omnibus:	5509.892	Durbin-Watson:	0.674			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	104728.294			
Skew:	3.125	Prob(JB):	0.00			
Kurtosis:	19.686	Cond. No.	64.1			
=====						

Diff-in-Diff Analysis

Washington: Pre-post Comparison and DID graphs for overdose deaths



Pre-Post Analysis



Diff-in-Diff Analysis

Since we have little proof for the policy effect according to the DID graph, the difference in level change could not be explained by regression.

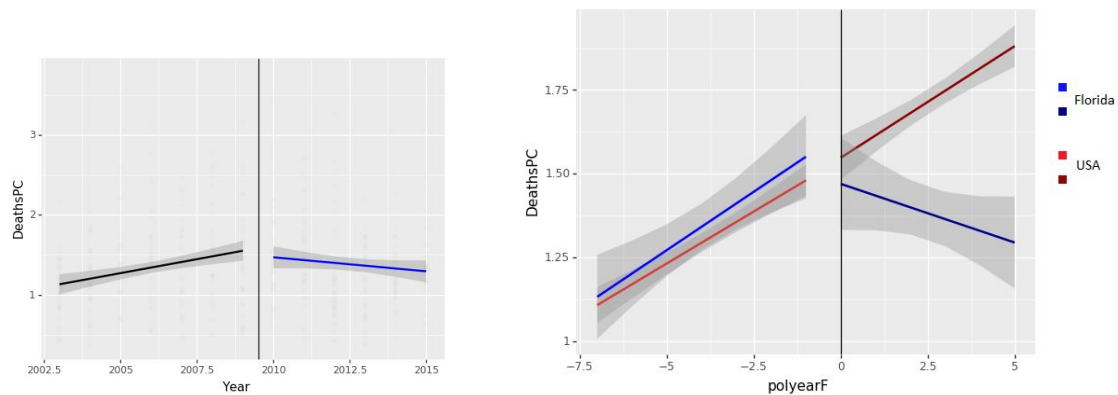
Before the policy, Washington shows different behavior than the rest of the country. Due to the nature of scale in the graph we see a little shift in the two graphs but this is not as important. With the confidence or error margins we can see that there is a good chance that there is no difference between the Washington trend before and after the policy. The fact that we can draw a line that can go straight through both intervals indicates that there is a reasonable chance that there is no difference from the policy.

OLS Regression Results						
=====						
Dep. Variable:	DeathsPC	R-squared:	0.003			
Model:	OLS	Adj. R-squared:	0.002			
Method:	Least Squares	F-statistic:	4.241			
Date:	Sun, 10 Nov 2019	Prob (F-statistic):	0.000287			
Time:	15:25:12	Log-Likelihood:	-11840.			
No. Observations:	7917	AIC:	2.369e+04			
Df Residuals:	7910	BIC:	2.374e+04			
Df Model:	6					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	1.5951	0.031	51.041	0.000	1.534	1.656
adj_year_W	0.0069	0.006	1.157	0.247	-0.005	0.019
Policy_W	-0.1021	0.047	-2.167	0.030	-0.194	-0.010
Policy_W:State_W	-0.8421	0.343	-2.453	0.014	-1.515	-0.169
Policy_W:adj_year_W	-0.0094	0.019	-0.486	0.627	-0.047	0.029
State_W:adj_year_W	0.0680	0.024	2.792	0.005	0.020	0.116
Policy_W:State_W:adj_year_W	0.1776	0.185	0.960	0.337	-0.185	0.540
=====						
Omnibus:	5514.488	Durbin-Watson:	0.671			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	103743.276			
Skew:	3.133	Prob(JB):	0.00			
Kurtosis:	19.590	Cond. No.	136.			

Diff-in-Diff Analysis

Florida: Pre-post Comparison and DID graphs for overdose deaths



Pre-Post Analysis

Diff-in-Diff Analysis

Here we can see that Florida seems to have turned an upward trend to a downward one after the policy enactment. It becomes even clearer in the DID graph. With the Florida counties and USA counties seemingly following the same trend before the policy we can reasonably assume that they have matching behavior in a lot of respects. After the policy, it seems that the USA trend continues while Florida has a complete change. The difference in differences is very stark here. This graph is strong evidence that the policy caused there to be less of these specific kinds of drug-related deaths in Florida.

Florida: DID Regression Analysis for overdose deaths

OLS Regression Results						
=====						
Dep. Variable:	DeathsPC	R-squared:	0.001			
Model:	OLS	Adj. R-squared:	0.001			
Method:	Least Squares	F-statistic:	3.331			
Date:	Sun, 10 Nov 2019	Prob (F-statistic):	0.0358			
Time:	15:14:44	Log-Likelihood:	-11849.			
No. Observations:	7917	AIC:	2.370e+04			
Df Residuals:	7914	BIC:	2.373e+04			
Df Model:	2					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

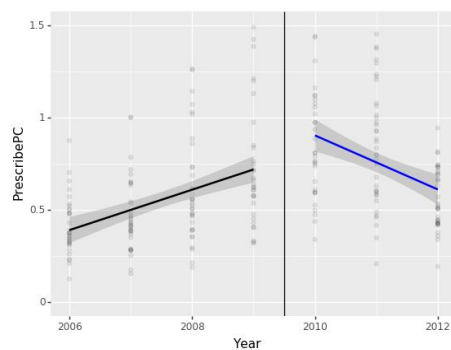
Intercept	1.5599	0.018	88.058	0.000	1.525	1.595
Policy	-0.0567	0.025	-2.308	0.021	-0.105	-0.009
Policy:State	0.1266	0.087	1.457	0.145	-0.044	0.297
=====						
Omnibus:	5512.206	Durbin-Watson:	0.670			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	103839.972			
Skew:	3.131	Prob(JB):	0.00			
Kurtosis:	19.601	Cond. No.	8.30			

Pre-Post Analysis

OLS Regression Results						
=====						
Dep. Variable:	DeathsPC	R-squared:	0.004			
Model:	OLS	Adj. R-squared:	0.003			
Method:	Least Squares	F-statistic:	5.061			
Date:	Sun, 10 Nov 2019	Prob (F-statistic):	3.42e-05			
Time:	15:14:45	Log-Likelihood:	-11837.			
No. Observations:	7917	AIC:	2.369e+04			
Df Residuals:	7910	BIC:	2.374e+04			
Df Model:	6					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

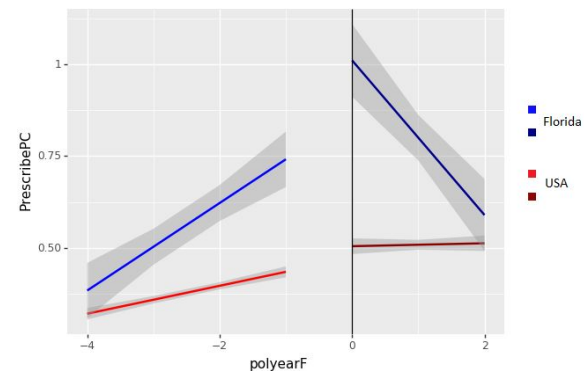
Intercept	1.6393	0.038	43.432	0.000	1.565	1.713
adj_year	0.0186	0.009	2.049	0.041	0.001	0.036
Policy	-0.0946	0.049	-1.945	0.052	-0.190	0.001
Policy:State	0.3842	0.156	2.460	0.014	0.078	0.690
Policy:adj_year	-0.0347	0.013	-2.582	0.010	-0.061	-0.008
State:adj_year	0.0588	0.019	3.071	0.002	0.021	0.096
Policy:State:adj_year	-0.1593	0.054	-2.944	0.003	-0.265	-0.053
=====						
Omnibus:	5491.417	Durbin-Watson:	0.672			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	102512.515			
Skew:	3.117	Prob(JB):	0.00			
Kurtosis:	19.489	Cond. No.	53.4			
=====						

Florida: Pre-post comparison and DID graphs for prescription



Pre-Post Analysis

With prescriptions we see similar behavior than the deaths. In the PrePost graph we can identify the same switch in slope, where after the policy it becomes negative. When we continue to the DID graph we have a similar comparison but it seems that Florida counties have a much more exaggerated behavior than that of the rest of the US. When we consider the post-policy years, Florida has a negative slope while the US slope seems to be somewhat flat. This means that the policy managed to change the trend to negative. We cannot know yet, however, whether this effect is sustainable or if Florida is approaching USA levels of prescribed opioids.



Diff-in-Diff Analysis

Florida: DID Regression Analysis for prescription

OLS Regression Results						
Dep. Variable:	PrescribePC	R-squared:		0.019		
Model:	OLS	Adj. R-squared:		0.019		
Method:	Least Squares	F-statistic:		543.2		
Date:	Sun, 10 Nov 2019	Prob (F-statistic):		2.34e-234		
Time:	15:30:47	Log-Likelihood:		-5490.0		
No. Observations:	55419	AIC:		1.099e+04		
Df Residuals:	55416	BIC:		1.101e+04		
Df Model:	2					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.4417	0.002	263.774	0.000	0.438	0.445
Policy	-0.0319	0.002	-13.850	0.000	-0.036	-0.027
Policy:State	0.2216	0.007	31.703	0.000	0.208	0.235
Omnibus:	28868.651	Durbin-Watson:		0.265		
Prob(Omnibus):	0.000	Jarque-Bera (JB):		249011.523		
Skew:	2.370	Prob(JB):		0.00		
Kurtosis:	12.240	Cond. No.		7.19		

Pre-Post Analysis

OLS Regression Results						
Dep. Variable:	PrescribePC	R-squared:		0.043		
Model:	OLS	Adj. R-squared:		0.043		
Method:	Least Squares	F-statistic:		417.3		
Date:	Sun, 10 Nov 2019	Prob (F-statistic):		0.00		
Time:	15:31:34	Log-Likelihood:		-4803.3		
No. Observations:	55419	AIC:		9621.		
Df Residuals:	55412	BIC:		9683.		
Df Model:	6					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.4231	0.004	119.062	0.000	0.416	0.430
adj_year	-0.0012	0.001	-1.394	0.163	-0.003	0.000
Policy	0.0001	0.005	0.029	0.977	-0.009	0.009
Policy:State	0.2413	0.012	19.716	0.000	0.217	0.265
Policy:adj_year	-0.0040	0.001	-3.181	0.001	-0.006	-0.002
State:adj_year	-0.0544	0.002	-36.069	0.000	-0.057	-0.051
Policy:State:adj_year	0.0463	0.004	10.775	0.000	0.038	0.055
Omnibus:	28815.198	Durbin-Watson:		0.272		
Prob(Omnibus):	0.000	Jarque-Bera (JB):		253345.452		
Skew:	2.356	Prob(JB):		0.00		
Kurtosis:	12.355	Cond. No.		45.9		

Diff-in-Diff Analysis

References

- [1] “Overdose Death Rates.” *NIDA*, National Institute on Drug Abuse, 29 Jan. 2019, www.drugabuse.gov/related-topics/trends-statistics/overdose-death-rates.
- [2] “ARCOS Registrant Handbook.” *ARCOS Registrant Handbook - Appendix 5*, www.deadiversion.usdoj.gov/arcos/handbook/appendix5.htm.
- [3] “FIPS Code.” *NRCS*, www.nrcs.usda.gov/wps/portal/nrcs/detail/national/home/?&cid=nrcs143_013697.
- [4] “US Census Population Data.” *Index of /Programs-Surveys/Popest/Datasets*, www2.census.gov/programs-surveys/popest/datasets/.

1. Introduction

Background

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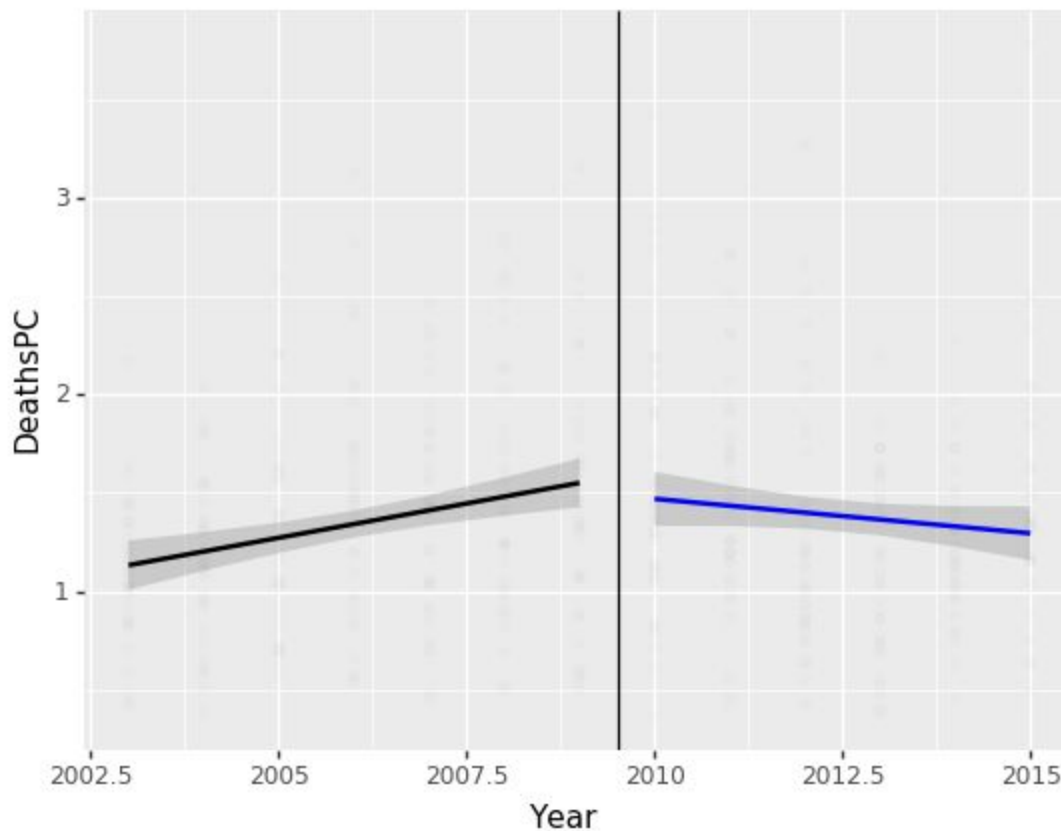
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A database maintained by the Drug Enforcement Administration that tracks pain pills was recently made available as a result of a court order from the Washington Post and HD Media, who publishes the Charleston Gazette-Mail in West Virginia.

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

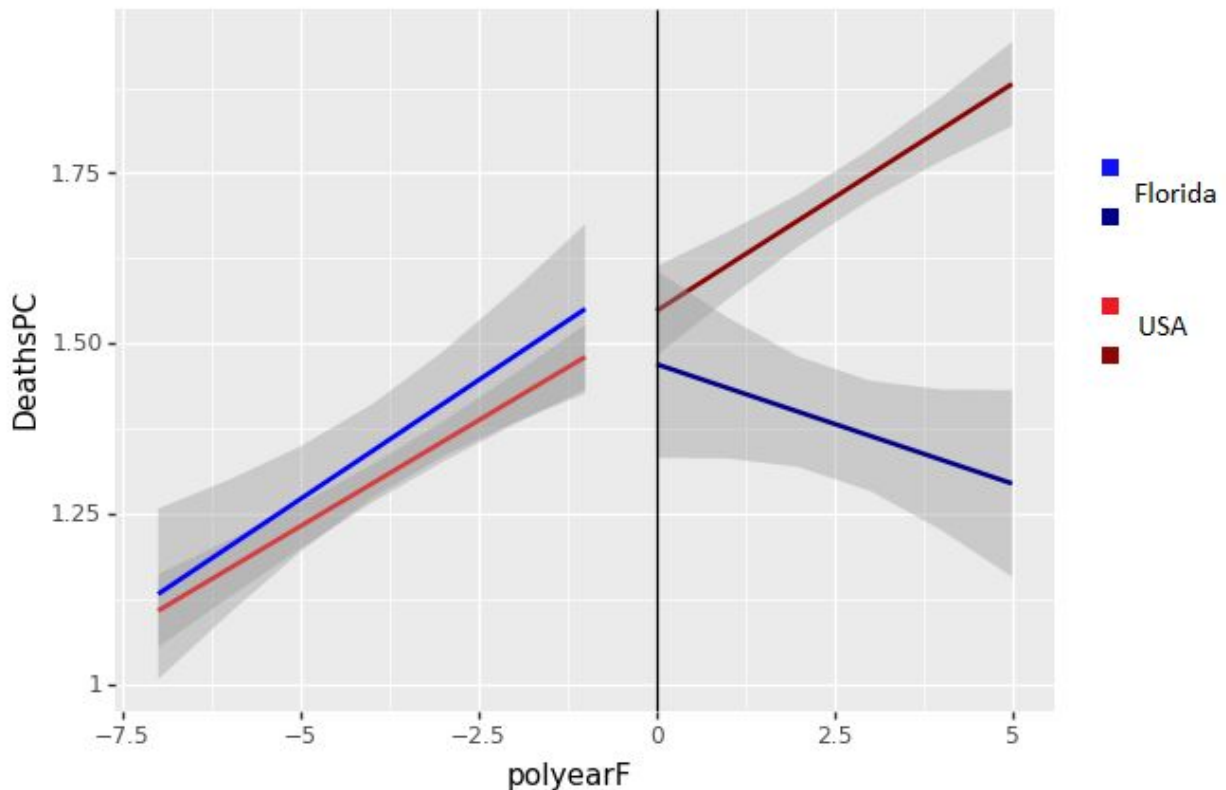
The above graph displays an analysis of the situation in Florida before and after the policy was enacted.

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.



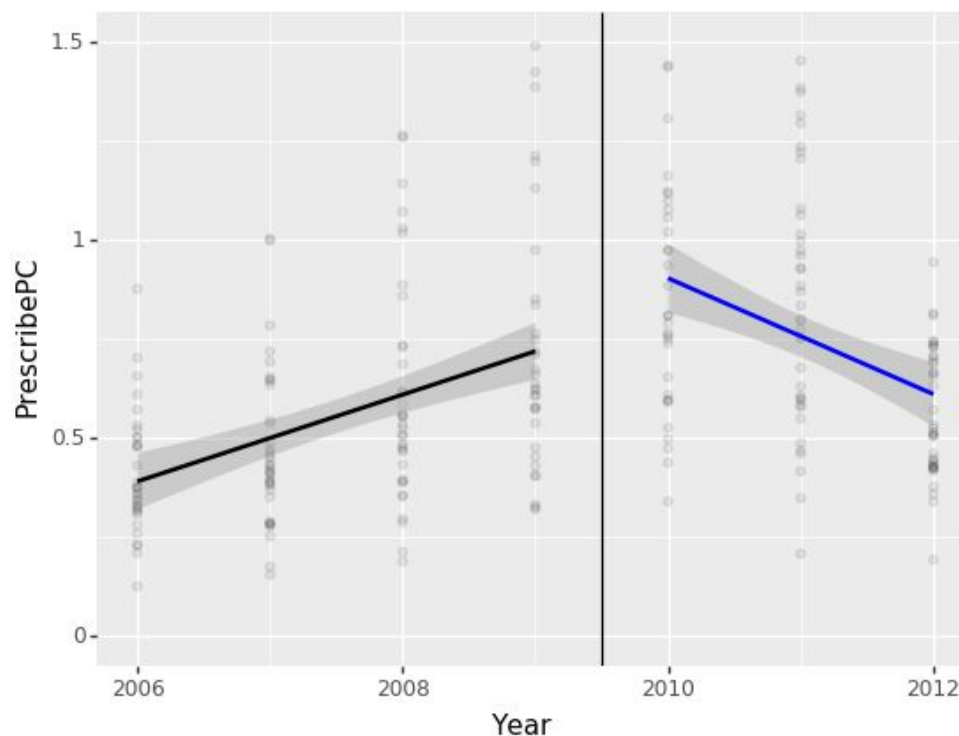
The above graph, called a Difference in Difference graph, shows more information. Firstly, we see that at the bottom we are now tracking polyyearF. This name is a stand in for the number of years before or after the policy came into effect, where 1 means a year later and -1 means a year earlier.

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.

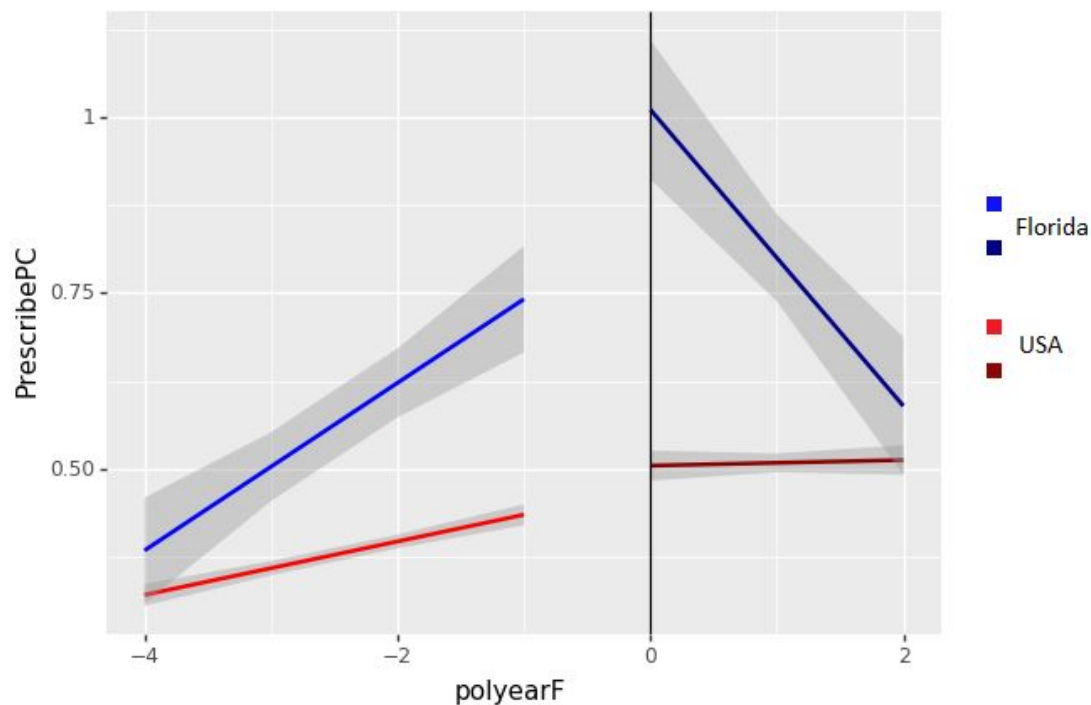
Part 2: Prescriptions of Opioids



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:

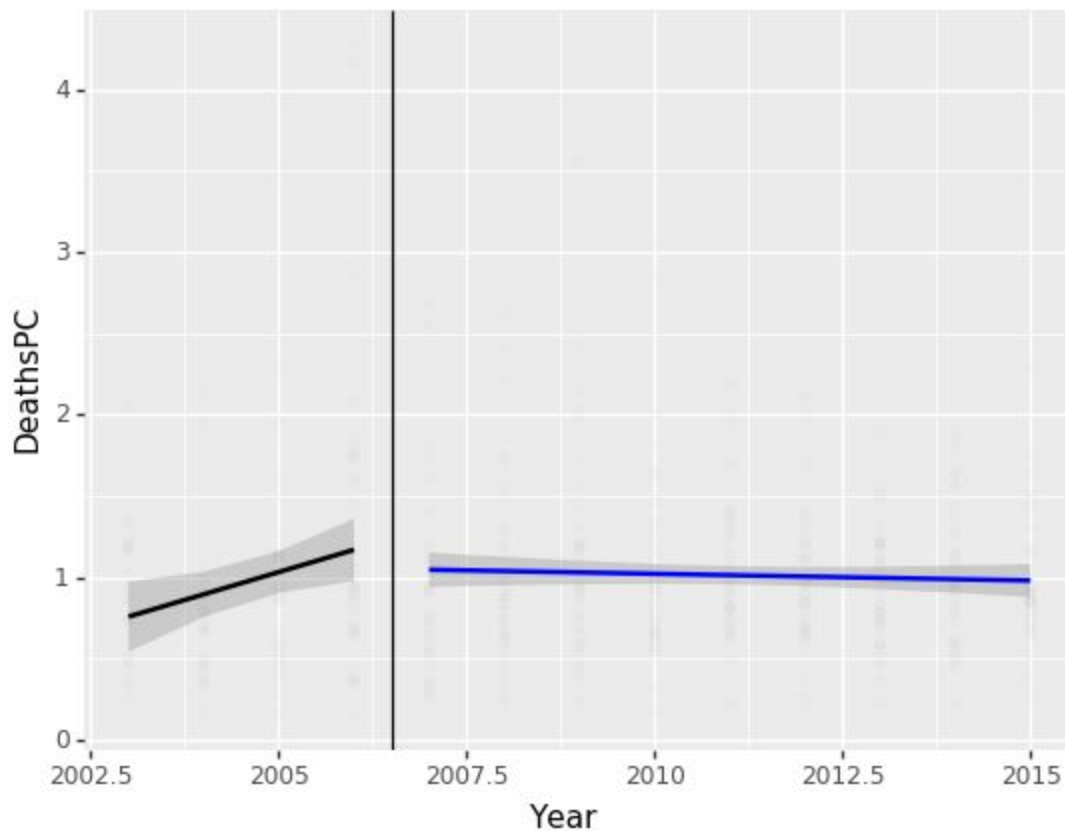


Once again we see blue lines for Florida and red lines for US counties. If we consider that the average US county is what we should normally expect, we can see a clear difference with the behavior of this statistic in Florida counties.

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.

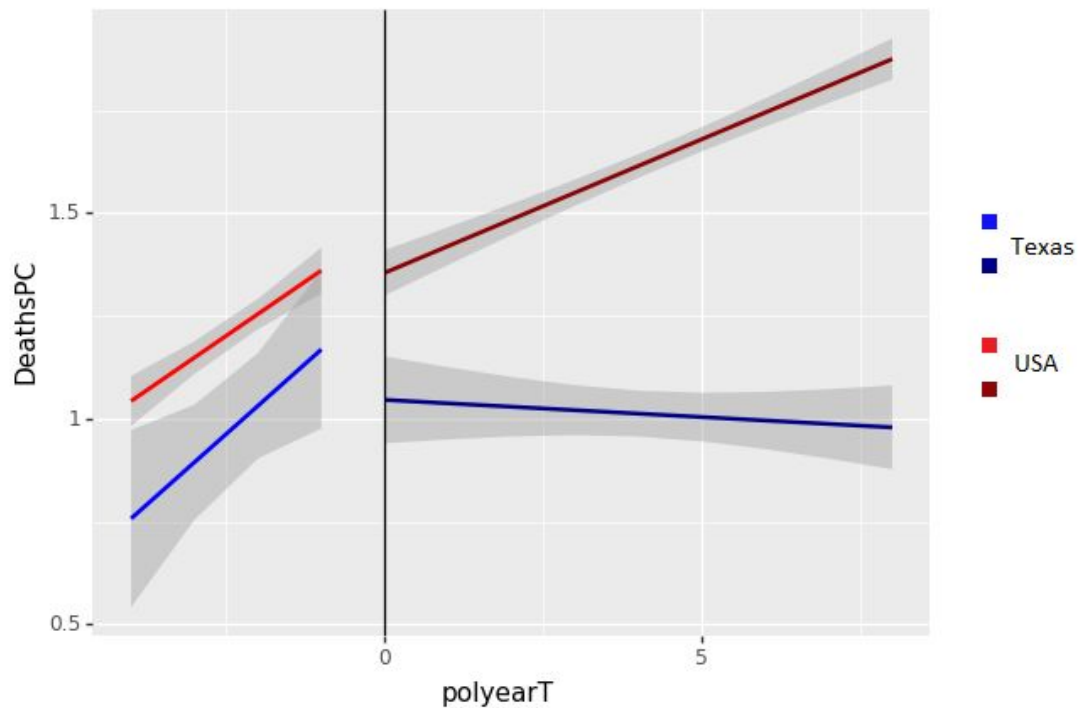
When we compare the two behaviors we see that instead of seeing a somewhat stable effect in Florida we saw a decline. This can be interpreted as a change thanks to the policy; the policy decreased the amount of prescriptions per capita.

Analysis: Texas - Overdose-related Deaths



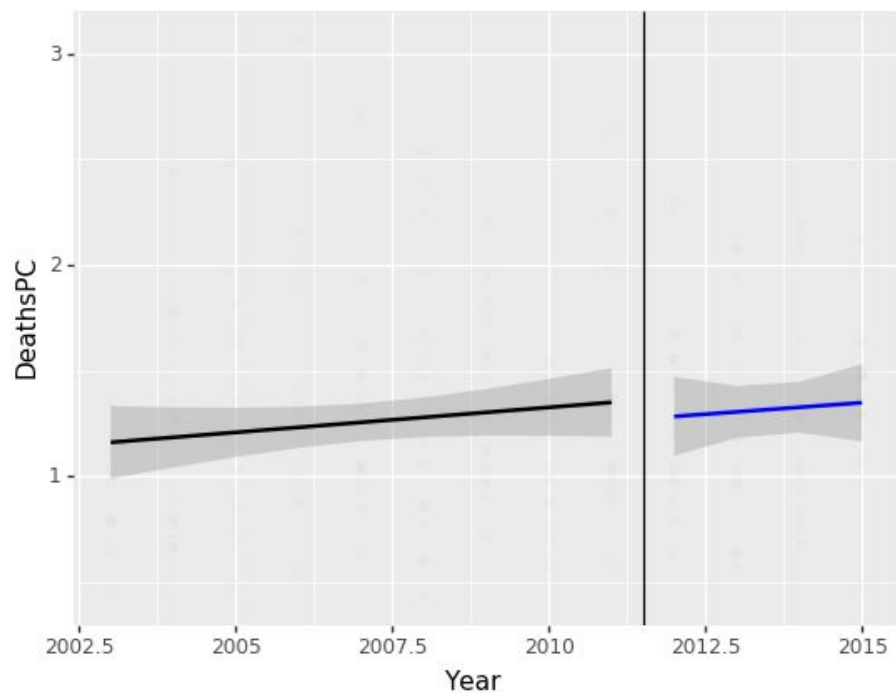
For Texas we see a trend upwards before the policy, that seems to at least flatten out after the policy enactment. There could be evidence of a change thanks to policy but it isn't obvious yet.

Analysis: Washington - Diff-in-Diff Graph

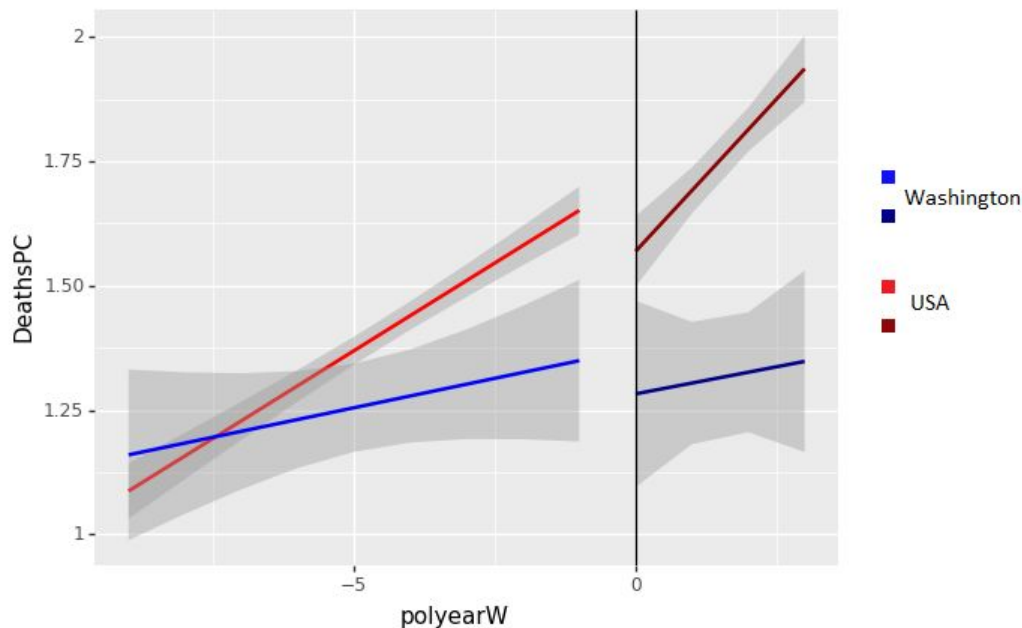


When we look at the Difference in Difference graphs however, we can see a clearer story. Before the policy, Texas counties followed a trend similar to other US counties. After the policy, we see that Texas has its statistic turned into a downward trend while the USA seems to maintain a trend where the 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.