The Effect of Cannabis Legalisation on Drug Abuse: a quantitative analysis

Alice Madama, Github: https://github.com/AliceMadama/Effects-of-Cannabis-Legalisation-on-Overdose-Deaths[a]

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Abstract

Michigan has been a trailblazer for Cannabis legalization in the United States. Initially it was only permitted for medical purposes. However, with the Michigan Regulation and Taxation of Marihuana Act of 2018, it is now also available for recreational use. The potential benefits and drawbacks of marijuana legalization are constantly discussed in diverse legal, medical, and sociological domains. Would it have a positive impact on our society, or would the negative aspects outweigh the positives? In this study, we focus on the age-long stereotype that views Cannabis as a "getaway drug" for opioid addiction. Through the use of both inferential and descriptive statistics, we observe the overdose levels, prior to and after the enactment of the Law, and conclude whether the legalization of this substance has caused a raise in the overdose rates in Michigan.

Keywords: Difference in Difference, Cannabis, Drug abuse, Legalisation

1. Introduction

Cannabis is the most popular illegal substance in the United States, with about 18 % of Americans being frequent users (National Institute on Drug Abuse (2021)). While some States may allow its application for both medical and recreational purposes, it's crucial to recognize that cannabis containing over 0.3% THC is still illegal under Federal Law. This is largely due to the potential health and social risks associated with consuming marijuana. Long-term smoking can result in lung and brain damage, and negatively impact attention, memory, and learning. Additionally, recent studies suggest that smoking marijuana may increase a person's risk of heart attack by nearly five times their usual risk in the first hour after use (National Institute on Drug Abuse (2021)).

In addition to the proven risks, usually marijuana is viewed as a "breakthrough drug" for heavier opiates such as heroin, fentanyl, and cocaine. Although cannabis use is considered to have been associated with the development of various addictions, most of the results are connected with alcohol dependence disorders, and it is noted that many other factors are crucial in defining the risk of drug addiction, not just biological mechanisms (National Institute on Drug Abuse (2021)). To attain a more comprehensive understanding of this issue, the following analysis examines the fluctuations in fatalities linked to opioids by employing both descriptive and inferential statistical methods. During the period from 2018 to 2020, this study concentrates on the states of Michigan and Wisconsin. Its primary objective is to ascertain whether the implementation of legal recreational cannabis in Michigan has been associated with elevated rates of opioid-related fatalities.

2. Data

The Center for Disease Control and Prevention was founded in 1946 with the purpose of preventing the spread of Malaria across the United States. Nowadays it is the most relevant organization regarding health and prevention in the USA, partnering with the Government to better the welfare of citizens. The data used for this research references the database for "Multiple Causes of Death (Final)", specifically "Current Final Multiple Causes of Death" from 2018 to 2021 (CDC (2021)). The dataset is so built:

- `State`, either Michigan or Wisconsin in this case
- `State.Code`, identifying code for the State
- `Month`, Month and year in which the data has been collected
- `Month.Code`, identifying code for the month
- `Gender`, gender of the deceased individual
- `Gender.Code`, binary code identifying "Male" as M and "Female" as F
- `Single.Race.6`, race of the deceased individual, out of the 6 available options, specifically "African American and Black" and "White"
- `Single.Race.6.Code`, identifying code for the race of the individual
- `Deaths`, number of deaths occurred due to drugs
- `Population`, overall Population for that state in said Year. This is not applicable the data used was collected monthly.
- `Crude.Rate`, the proportion of yearly Deaths over the entire population of said State. This is not applicable the data used was collected monthly.

Ulterior filtering was carried out regarding Deaths and Underlying causes of death, the following codes were chosen:

- `Drug poisonings (overdose), Unintentional (X40-X44)`
- `Drug poisonings (overdose) Undetermined (Y10-Y14)`
- `All other drug-induced causes`

- `Drug poisonings (overdose) Suicide (X60-X64)`,
- `Drug poisonings (overdose) Homicide (X85)`,

2.1. Data cleaning and Pre-Processing

The Center for Disease Control and Prevention provides the WONDER tool, enabling efficient feature engineering on the website, prior to exporting the data. However, managing the data-set's size required ulterior data cleaning and filtering.

Firstly, data was reduced to the fundamental variables for the analysis, to avoid future biases and confusion. Moreover, it was cleansed from missing data to ensure the accurate processing of information. Eliminating flawed data instead of collecting the median for those values helped avoid evaluation errors. To simplify the analysis, four dummy variables were created to define the experiments: Treatment Status, Gender Dummy, Race Dummy, and Period. The resulting information was stored in a data-set for data visualization and computation purposes.

3. Experiments

3.1. Shapiro-Wilk Test

The Shapiro-Wilk test is a test of normality that assesses whether a sample is likely to originate from a normal distribution. (1)

$$W = \frac{(\sum_{i=1}^{n} a_i x_{(i)})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{1}$$

The null hypothesis for the Shapiro-Wilk test assumes that the population from which the sample is drawn follows a normal distribution. If the calculated p-value from the test is less than the chosen significance level (alpha), it indicates that there is enough evidence to reject the null hypothesis. In other words, if the p-value is low, it suggests that the data being tested do not come from a population that follows a normal distribution. On the other hand, if the p-value is greater than the chosen alpha level, there isn't enough evidence to reject the null hypothesis.

Statistical significance tests, including the Shapiro-Wilk test, can detect even minor deviations from the null hypothesis when the sample size is large. Therefore, it's recommended to supplement such tests with additional analyses, such as investigating the effect size, and graphical methods like Q-Q plots to assess the distribution of the data.

Verifying normality of distribution is a requirement for running several of the well-known statistical tests such as Student's t-test and ANOVA, and it's exactly why it is needed in the context of the analysis.

3.2. T-test

A T-test is a statistical methodology that compares the means of two groups. It is a widely utilized technique in hypothesis testing to determine the effectiveness of a treatment on the population or to identify any differences between two entities (Kim (2015)). T-tests do assume that:

- The data are continuous
- The sample data have been randomly sampled from a population
- There is homogeneity of variance (i.e., the variability of the data in each group is similar)
- The distribution is approximately normal

T-tests can be divided into three types, sharing the same assumptions:

- Independent sample t-test, also known as two samples t-test, which can be used when the two groups under comparison are independent of each other. It can be used both in categorical and continuous data and it evaluates if the mean of two different groups is equal or not.
- One sample t-tests, also known as "Student t-tests". It helps decide if the population mean is equal to a specific value or not and it is commonly only used for continuous values.
- Paired t-tests indicate if the difference between paired measurements for a population is null.

In this case study, the Welch's a variation of Student's t-test was used. Welch's assumes a difference in variance between the two samples. This allows for better accuracy in the calculations, as it takes into account the difference in variances while defining the degrees of freedom of the statistic. Naturally, if the two variances were to be equal, then the degrees of freedom would be the same both for the Student t-test and the Welch's t-test.

3.3. Difference in Difference

Difference-in-differences (DiD) is a popular econometric method for estimating causal relationships in empirical research. Developed originally in the field of economics, DiD has since gained traction across various disciplines due to its ability to address endogeneity and selection biases commonly encountered when studying treatment effects. By analyzing the distinct impact of a treatment on a "treatment group" as compared to a "control group" within a natural experiment, the Difference-in-Differences method assesses the influence of a treatment variable (explanatory or independent) on an outcome variable (response or dependent). This is accomplished by contrasting the average temporal alteration in the outcome variable for the treatment group with the average temporal alteration for the control group (University (2022)).

The assumptions that underlie the Ordinary Least Squares (OLS) model apply equally to the Difference-in-Differences (DiD) method. Additionally, DiD relies on a crucial assumption known as the "parallel trend" assumption. This assumption posits that the difference in differences ($\lambda_2 - \lambda_1$) remains consistent across both $s = 1$ and $s = 2$.

The outcome is defined as the temporal difference between pre- and post-treatment periods and matching units based on their pre-treatment characteristics, the resulting Average Treatment Effect (ATE) offers a robust estimate of treatment effects.

The treatment effect signifies the discrepancy between the observed value of y and the value y would have taken if parallel trends persisted without treatment. When employing

the DiD model, potential issues like autocorrelation should be thoughtfully addressed to uphold the reliability of the results.

In this experiment I have run the following regression:

$$\begin{aligned}\text{Deaths} = \beta_0 + \beta_1 \times \text{Period} + \beta_2 \times \text{Treatment\_Status} \\ + \beta_3 \times (\text{Period} \times \text{Treatment\_Status}) + \epsilon\end{aligned} \tag{2}$$

To ensure the reliability of the model, a sensitivity analysis is conducted. This method is aimed at assessing the stability of the results when confronted with variations in the model specifications. Additionally, the data will be visually represented through graphical techniques, enhancing the interpretability of the findings (RPu (n.d.)).

4. Results

4.1. Descriptive Statistics and Overview

Before addressing the core research question, it is imperative to analyze the available data and derive informative insights from the descriptive statistics at disposal.

As depicted in Table 1, similar trends emerge in both Wisconsin and Michigan, which is a promising indication for the purpose of conducting a Difference-in-Differences (DiD) analysis. Notably, the highest average deaths recorded in Michigan were observed in July 2018, amounting to 78, whereas in Wisconsin, the peak averages were attained in December 2018, reaching 46. Furthermore, following the treatment (Table 2), the pinnacle of deaths in Wisconsin was noted in August 2020, while in Michigan, it occurred in May 2020. Although there is an observable increase in means, it is rather marginal. While it is undeniable that there has been an elevation, it remains unlikely that this uptick would qualify as a substantial and significant change that could be attributed to the legislative intervention as its primary cause.

Figure 1 also offers a visual perspective on these shifts. Beyond merely identifying similar trends, although not quite overlapping, the graph reveals several distinct peaks both before and after treatment.

An equally crucial visualization pertains to the data's distribution. To proceed with the analysis, it is fundamental to confirm that the data adheres to a Normal Gaussian distribution. For this purpose, we leverage QQ-plots. Figure 2 showcases the QQ-plot developed from the data (Figure 8-10) , focusing on the untreated category. A cursory observation suggests an approximate Gaussian resemblance, yet a more in-depth examination is warranted.

Thus, to refine the analysis, we compute the logarithm of deaths.

4.2. Shapiro-Wilk Test and T-Test

Based on the findings derived from the initial exploration, it appears prudent to opt for the logarithm of the data as the most appropriate approach for conducting the t-test.

First, to confirm the results of the QQ-plot, the Shapiro-Wilk test is over the logarithm of the data.

$$\begin{cases} H_0 : \ population \sim N(\mu, \sigma^2) \\ H_1 : \text{The population does not follow a normal distribution} \end{cases}$$

As depicted in Table 3, the test yields a p-value of 0.0004, a value that crosses the threshold of statistical significance. Consequently, it decisively rejects the hypothesis of the data conforming to a normal distribution. It is noteworthy, however, that the Shapiro-Wilk test, when applied to extensive data-sets, tends to exhibit hypersensitivity.

In light of this, an exploration is undertaken involving smaller sample sizes to evaluate the test's sensitivity to changes in data volume. Intriguingly, this maneuver results in an increase of the p-value (Table 4-5). This phenomenon strongly suggests that the Shapiro-Wilk Statistic is susceptible to such heightened sensitivity, particularly when confronted with substantial data sets.

Thanks to the previously conducted data visualization, it was possible to collect valuable insights to better understand the results of the test. Through this visual exploration, it was highlighted that minor deviations from normality do not significantly disrupt the approximate normal distribution of the data.

It is now possible to conduct the statistical test.

$$\begin{cases} H_0 : \mu_1 = \mu_2 \\ H_1 : \mu_1 \neq \mu_2 \end{cases}$$

The outcomes, as presented in Table 6, confirm the hypothesis proposed during the initial analysis that the two groups are not significantly different after treatment.

4.3. Difference in Difference Analysis

Based on the comprehensive analysis thus far, it is reasonable to anticipate that the Difference in Difference analysis will yield analogous conclusions. The evidence suggests that the introduction of Cannabis legalization, which constitutes the treatment, is not likely to be a contributing factor in elevating the levels of overdose deaths for the respective states.

The experiment is led using as date of beginning of Treatment 01/12/2019, which corresponds to the first licensed selling of Cannabis in Michigan. Michigan is the Treated Subject, while Wisconsin is instead the Control Group. Wisconsin was chosen due to its similarities to Michigan according to the Similarity Index, having quite close geography and government (Jones (2022))

In the results, as shown in Table 7, "Period", the coefficient representing the moving from the pre-treatment period to the post-treatment period in the control group, is not statically significant. It suggests that there is no significant change in the control group over time. Moreover, the estimated Interaction Effect between the treatment status and the period is also not

statistically significant, indicating there is no significant difference in the change over time between the Treatment and control group.

These results are coherent with the previous findings.

To ensure the respect of the Parallel Trend assumption, it is necessary to refer back to the descriptive analysis of the data. Although the graphs seem to show similarities among the two States, and standardization of the data does not yield to strikingly different results, it is impossible to conclude the presence of trends (Figure 4-7). Thus the Spearman's rank correlation coefficient is used instead. As shown by Table 10, the coefficient exhibits a small positive monotonic relationship between the variable Deaths and the Treatment.

To check for robustness we conducted a sensitivity analysis, adding also Gender and Race to the regression model. T able 8 shows the results of the model, considering also the Gender variable. Such change does not lead to significant differences in the outcome, most importantly it does not variate the relationship between Period and Treatment Status. Thus so far, the Difference-in-Difference analysis seems robust.

On the contrary, adding the Race variable into the regression model does heavily influence the outcome of the analysis, leading to believe that White and African Americans in the observed States do not share the same statistics regarding drug abuse. When taking into consideration the race of the deceased individuals, we get new insights into the data: belonging to the African American group (also defined as Black) increases the effects of the Treatment, effectively increasing the deaths by overdose over time (Table 10).

5. Conclusions

The findings of the analysis do not provide sufficient evidence to support the notion that the legalization of Cannabis has a inflating impact on the number of overdose deaths in the State of Michigan. Both the t-test and the Difference-in-difference analysis fail to consistently demonstrate a significant disparity between the treated and untreated groups. Although the Difference-in-difference analysis indicates a marginal increase in overdose deaths, aligning with the observed data, such an increase is due to the observed variable "Race".

However, this study has helped uncover an important relationship between the racial background of individuals involved in drug abuse: African Americans are much more effected by the opioid epidemic than White Americans.

It is imperative to acknowledge that these conclusions are influenced by the inherent limitations of this study. Firstly, a more comprehensive understanding of the characteristics of individuals struggling with addiction could enhance the sensitivity analysis, thereby reinforcing the robustness of the findings. Furthermore, it is crucial to recognize that the timing of the treatment coincides with the beginning of the COVID-19 pandemic, a factor that potentially influence drug abuse data.

In summary, the study's outcomes underscore the complexity of attributing changes in overdose deaths only to the legalization of Cannabis. The study's limitations, ranging from the need for more nuanced demographic insights to the impact of external events, underscore the intricacies of drawing definitive causal inferences from observational data.

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	Month.Code	Michigan	Wisconsin
1	2018/01	59.00	27.00
2	2018/02	55.00	42.00
3	2018/03	62.00	42.00
4	2018/04	63.00	27.00
5	2018/05	45.00	33.00
6	2018/06	54.00	39.00
7	2018/07	78.00	34.00
8	2018/08	52.00	29.00
...	...		

Table .1: Average Deaths Pre-Treatment Per Month

	Month.Code	Michigan	Wisconsin
1	2019/12	47.00	33.00
2	2020/01	45.00	46.00
3	2020/02	51.00	41.00
4	2020/03	53.00	35.00
5	2020/04	58.00	52.00
6	2020/05	80.00	50.00
7	2020/06	70.00	42.00
8	2020/07	59.00	40.00
...	...		

Table .2: Average Deaths Pre-Treatment Per Month

	Variable	Test_Statistic	P_Value
W	Deaths	0.98	0.0004

Table .3: Shapiro-Wilk Test Results

	Variable	Test_Statistic	P_Value
W	Deaths	0.98	0.12

Table .4: Shapiro-Wilk Test Results- Untreated

	Variable	Test_Statistic	P_Value
W	Deaths	0.97	0.002

Table .5: Shapiro-Wilk Test Results- Untreated

Statistic	p-value
T-Value	1.04932039301889
p-value	0.295644816248226

Table .6: T-Test Results

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3.3792	0.0898	37.62	0.0000
Period	0.1681	0.1456	1.15	0.2495
Treatment_Status	0.3323	0.1151	2.89	0.0042
Period:Treatment_Status	-0.0858	0.1882	-0.46	0.6489

Table .7: Difference In Difference Regression Model Summary

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3.1366	0.0989	31.71	0.0000
Period	0.1473	0.1389	1.06	0.2898
Treatment_Status	0.3584	0.1098	3.26	0.0013
Gender_Dummy	0.4191	0.0856	4.90	0.0000
Period:Treatment_Status	-0.0620	0.1794	-0.35	0.7299

Table .8: Difference In Difference Sensitivity Analysis, Gender Dummy

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	3.3028	0.0335	98.50	0.0000
Period	0.2314	0.0462	5.01	0.0000
Treatment_Status	0.6848	0.0417	16.41	0.0000
Gender_Dummy	0.6207	0.0292	21.24	0.0000
Race_Dummy	-1.4663	0.0559	-26.22	0.0000
Treatment_Status:Race_Dummy	0.2309	0.0665	3.47	0.0006
Period:Treatment_Status	-0.1360	0.0596	-2.28	0.0235

	Treatment_Status	Deaths
Treatment_Status	1.00	0.21
Deaths	0.21	1.00

Table .9: Spearman Correlation

	Race_Dummy	Deaths
Race_Dummy	1.00	-0.72
Deaths	-0.72	1.00

Table .10: Spearman Correlation, Race and Deaths

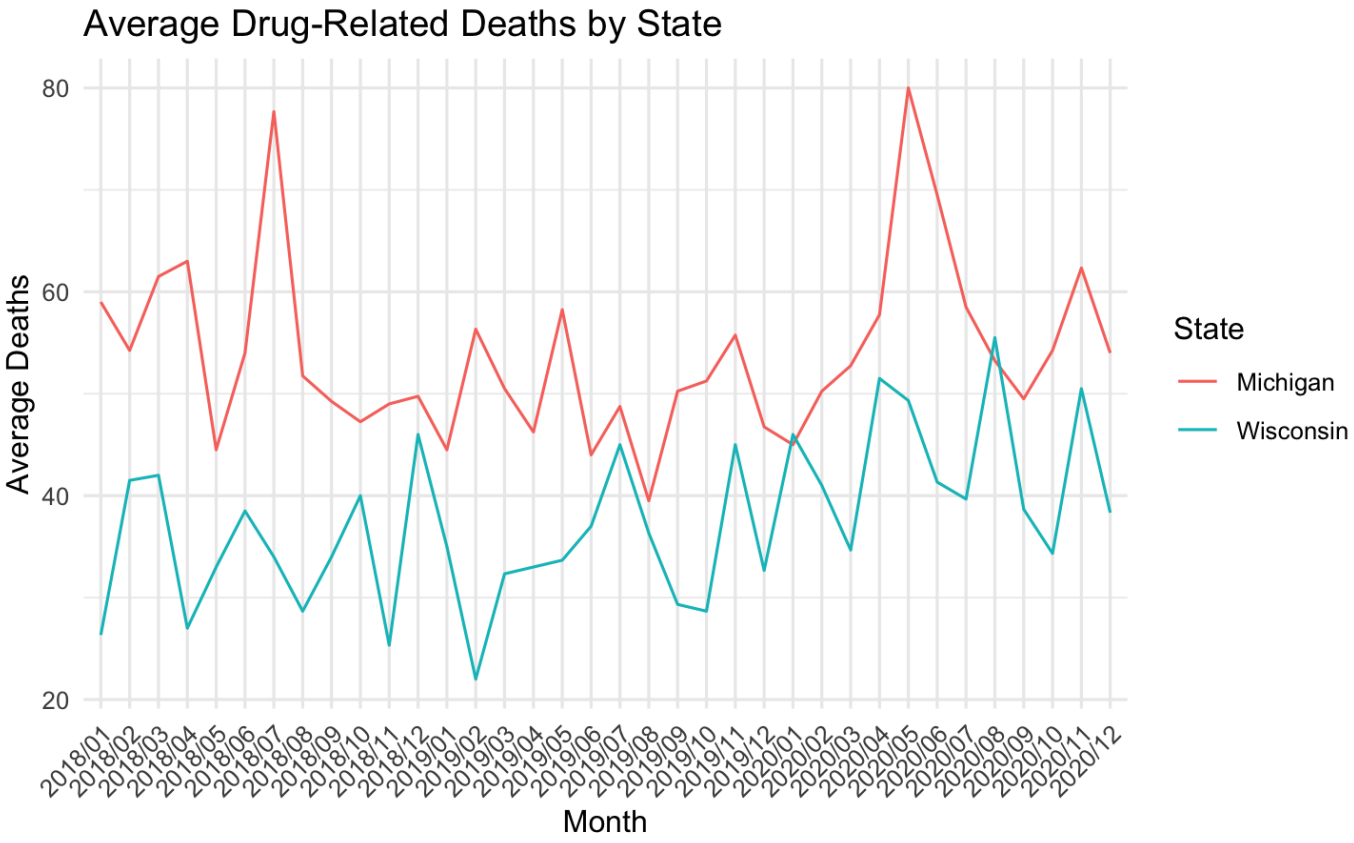

Figure .1: Graph of Average Deaths per Month for Wisconsin and Michigan

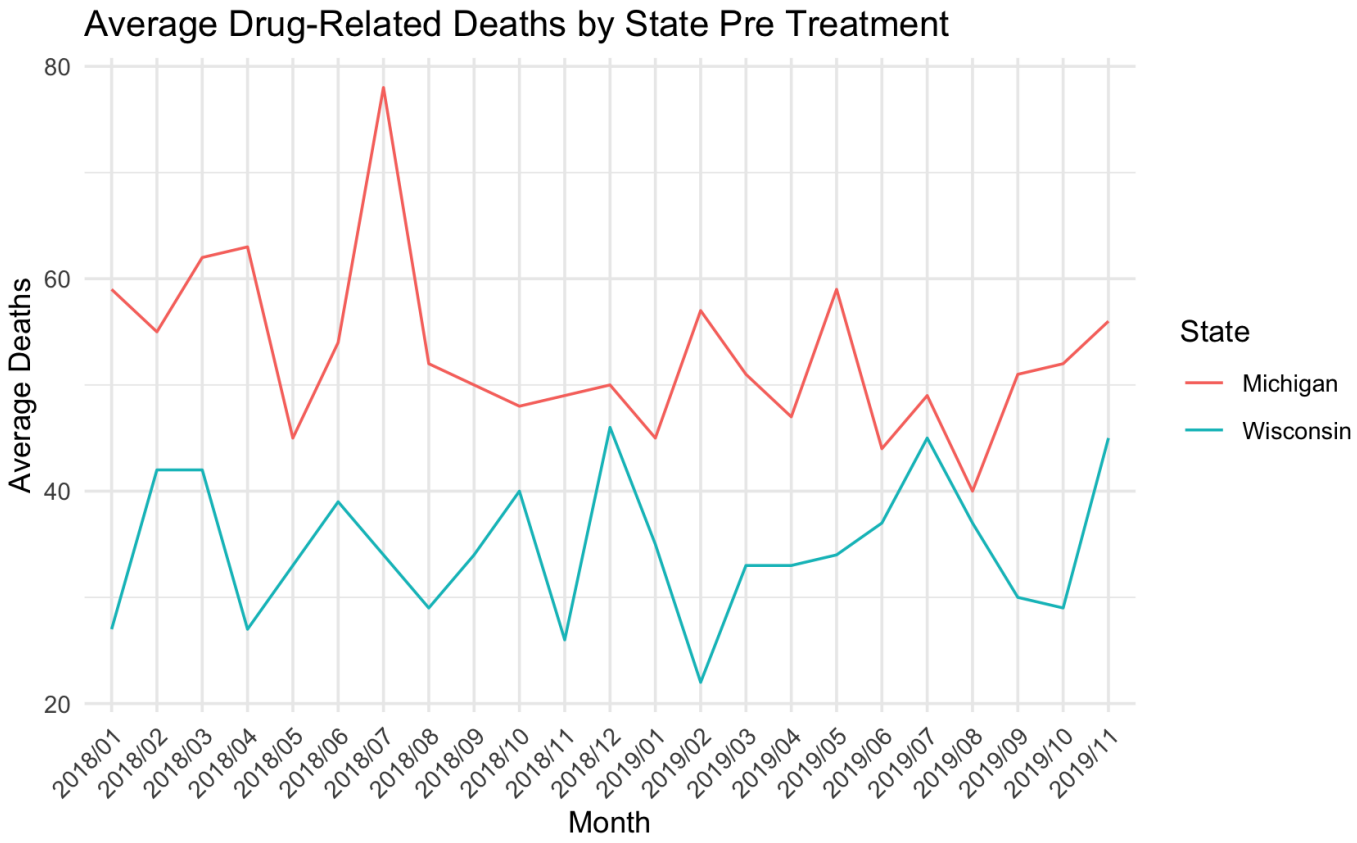

Figure .2: Graph of Average Deaths per Month for Wisconsin and Michigan Pre-Treatment

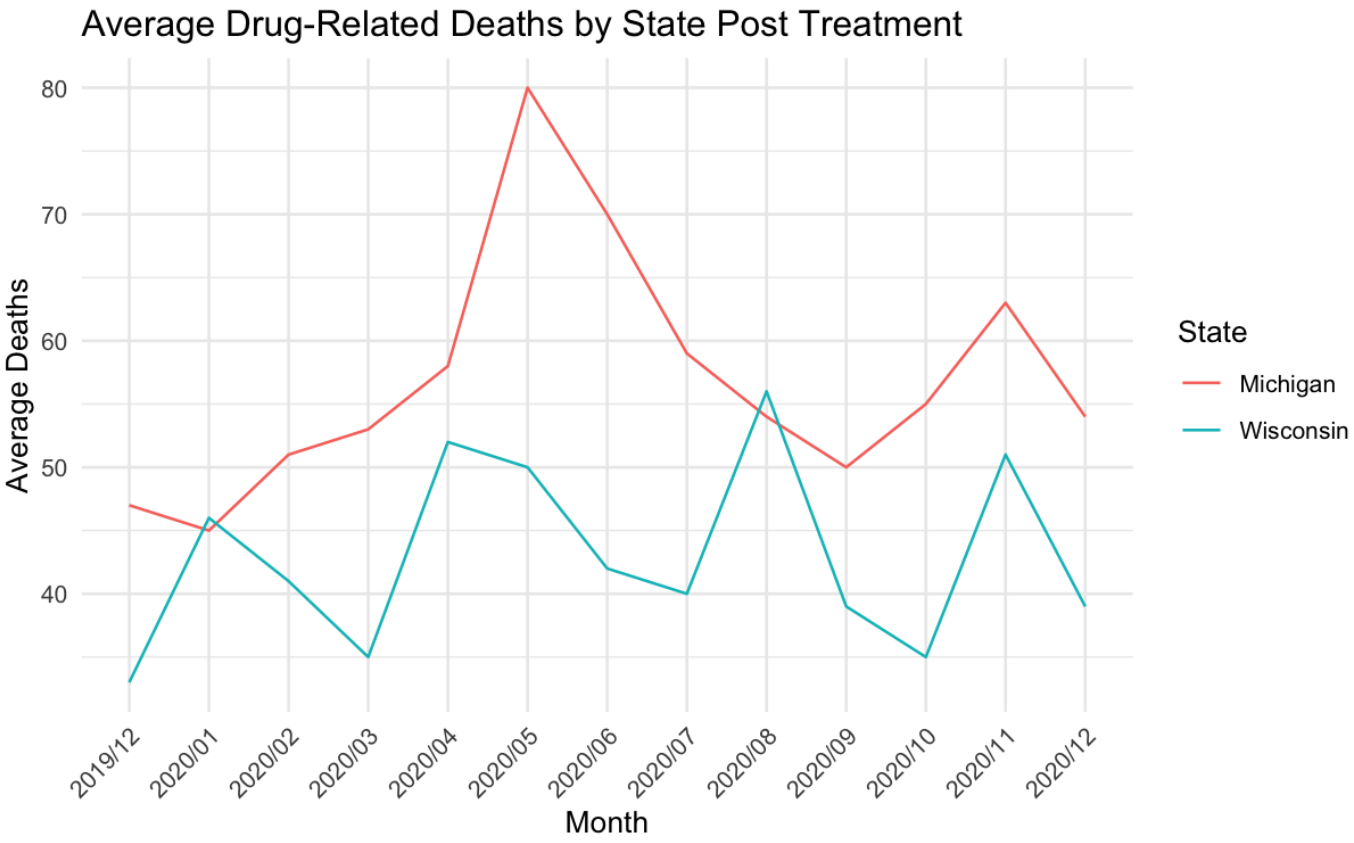

Figure .3: Graph of Average Deaths per Month for Wisconsin and Michigan Post-Treatment

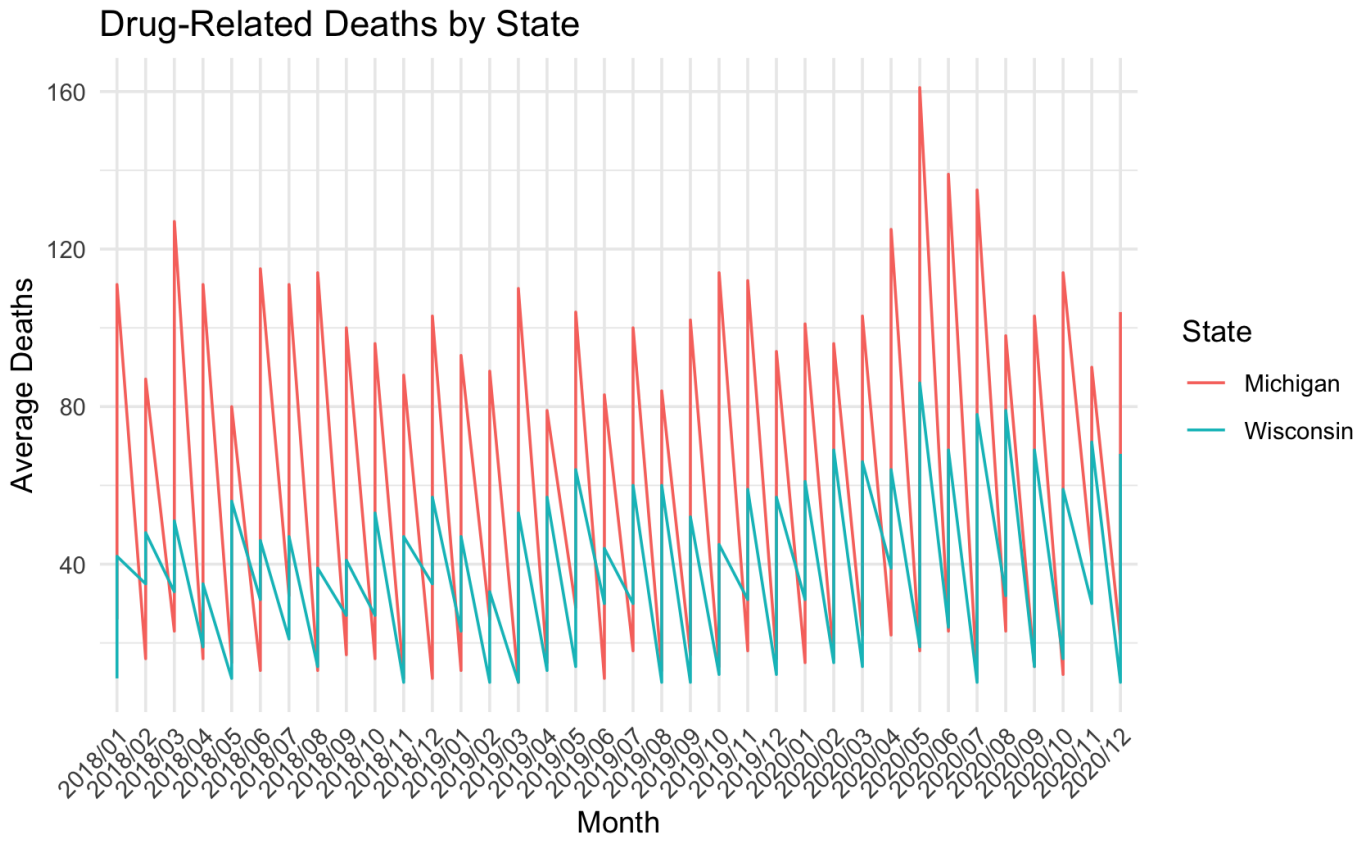

Figure .4: Drug Related Deaths by State

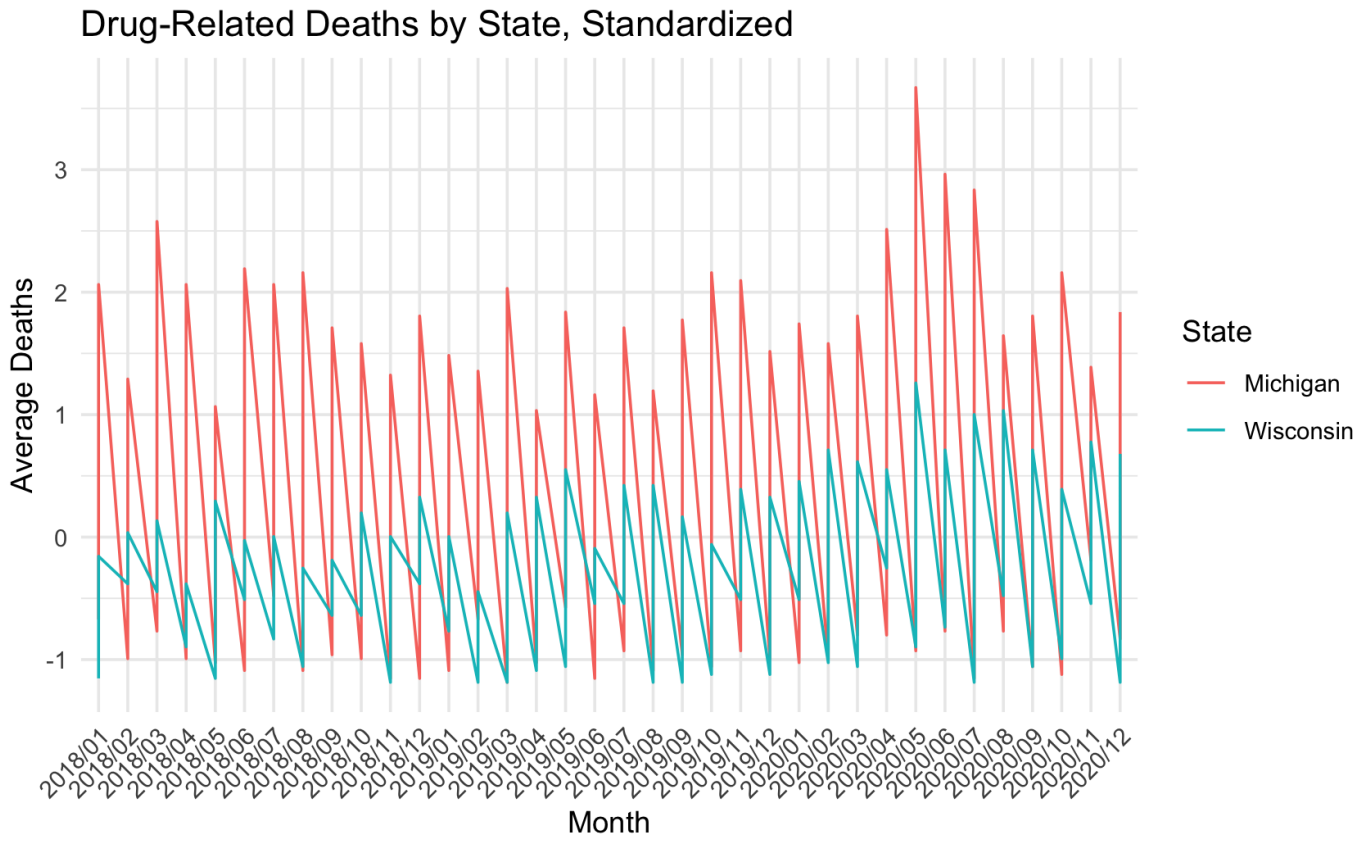

Figure .5: Drug Related Deaths by State, Standardized

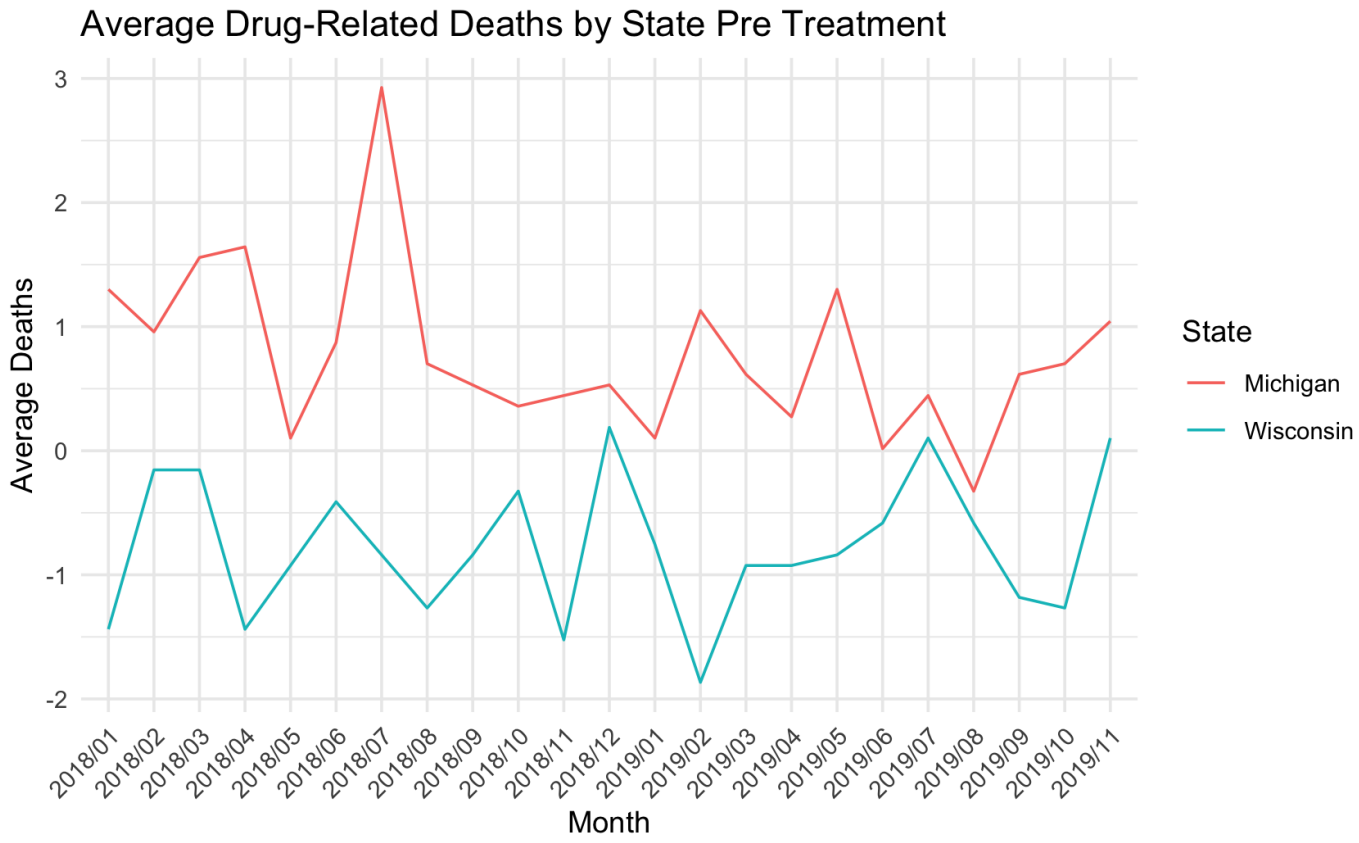

Figure .6: Drug Related Deaths by State Standardized Pre-Treatment

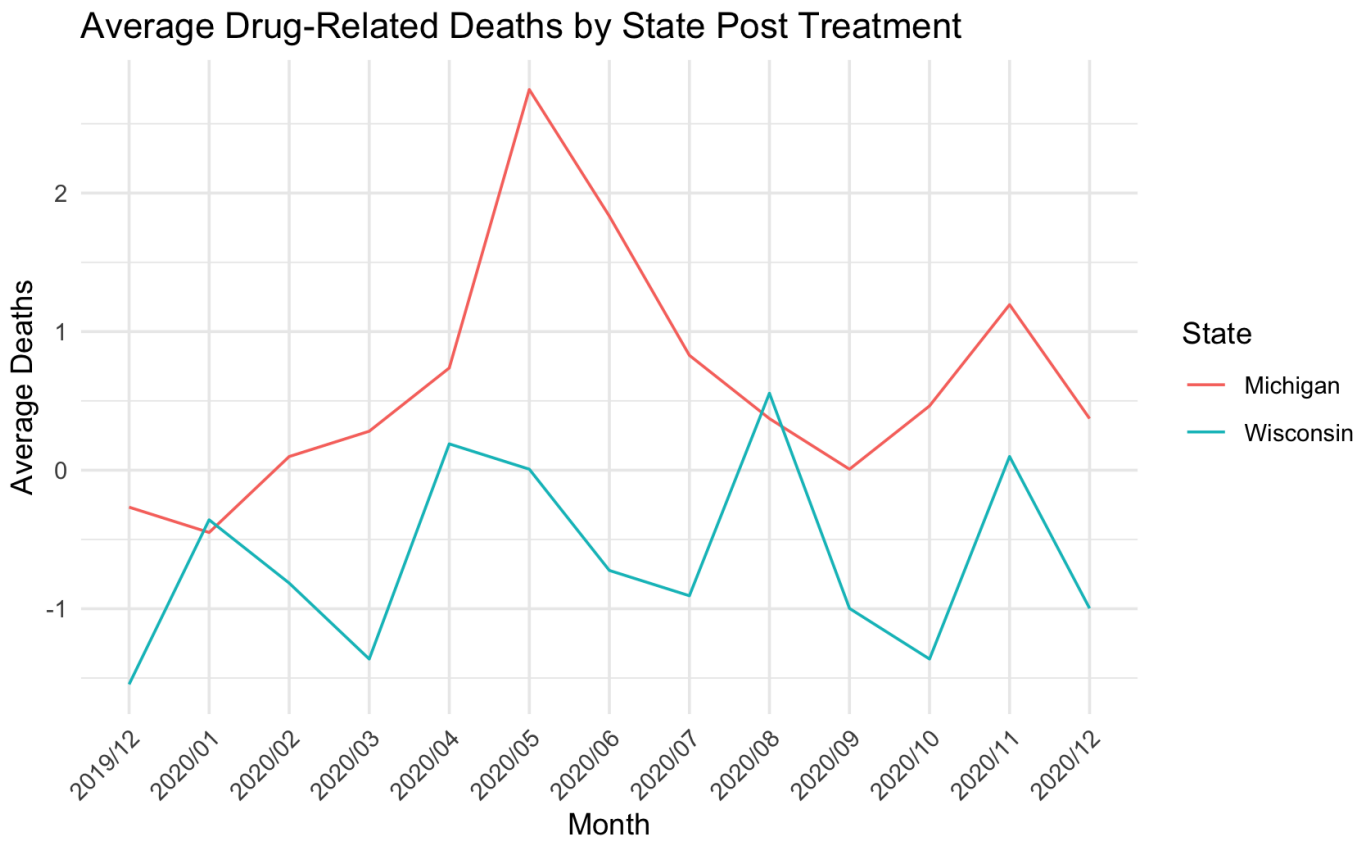

Figure .7: Drug Related Deaths by State Standardized Post-Treatment

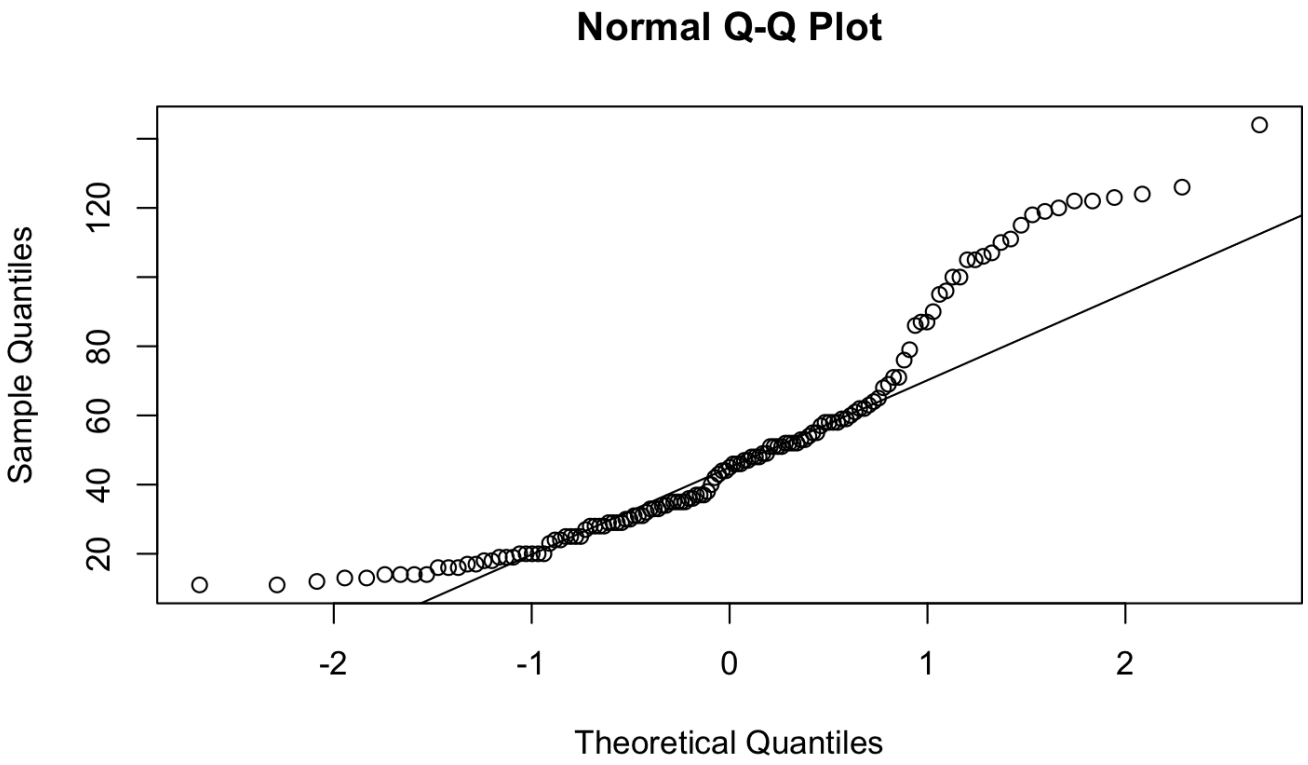

Figure .8: QQ-Plot of Untreated Data

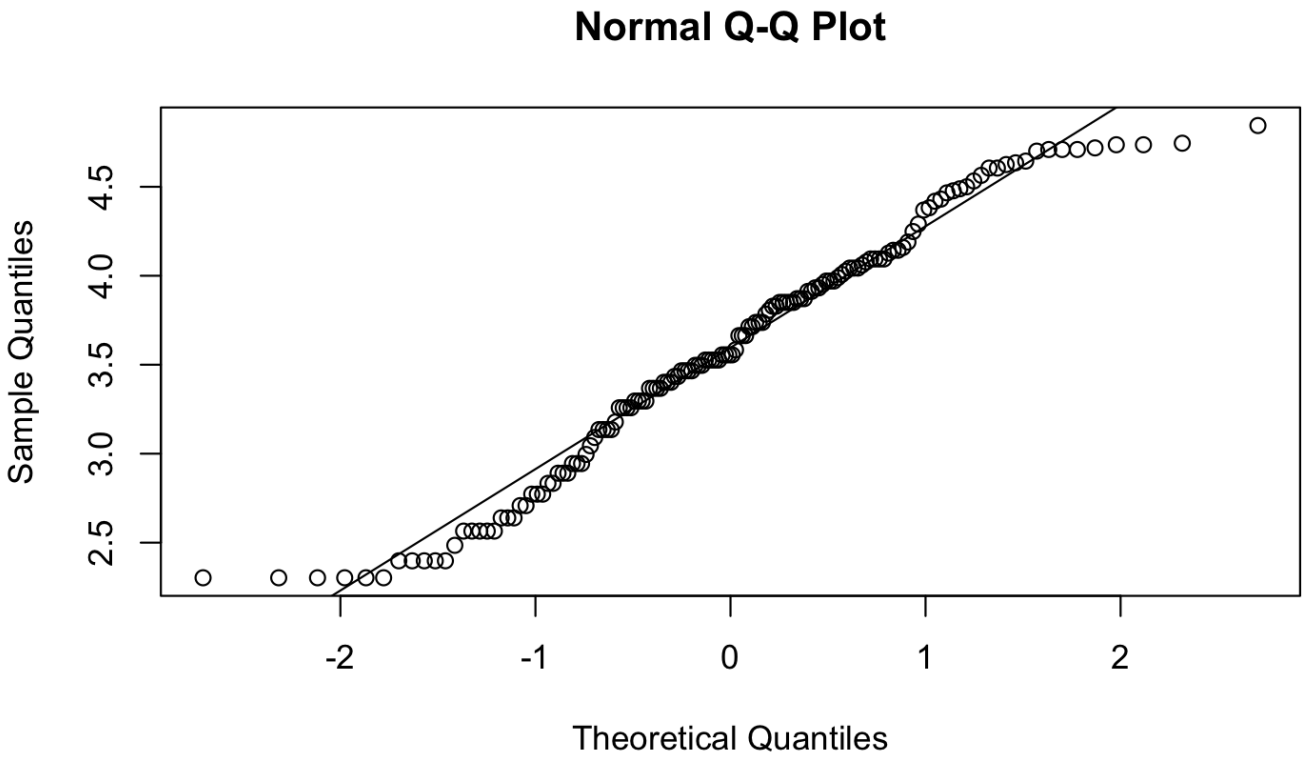

Figure .9: QQ-Plot of Untreated Data, in logarithmic form

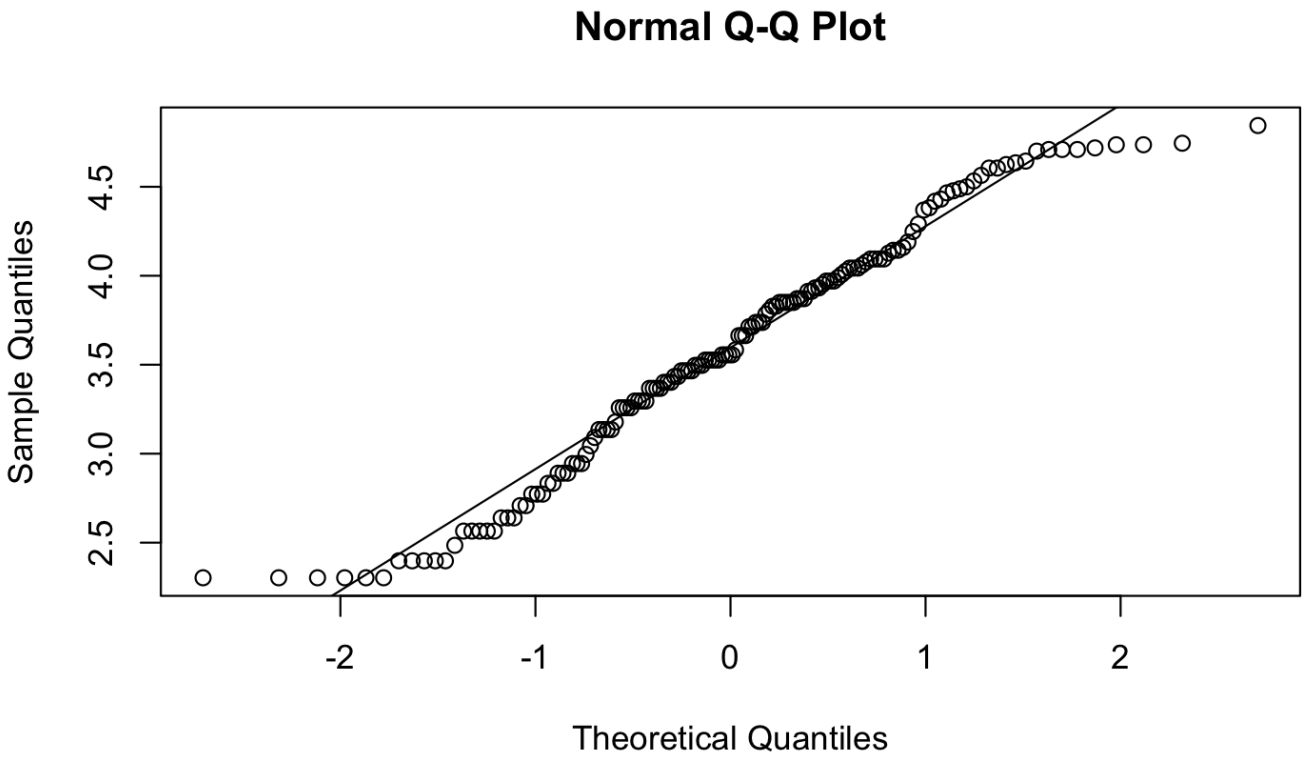

Figure .10: QQ-Plot of Treated Data

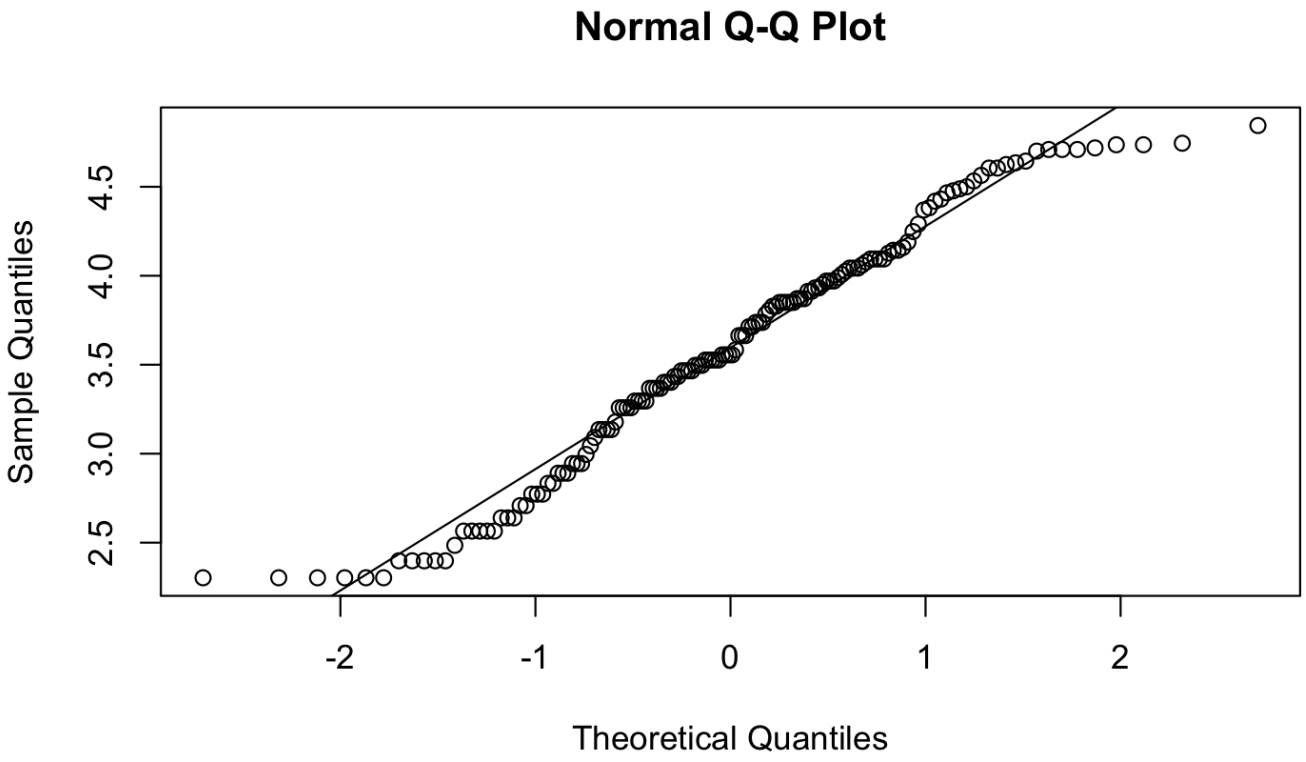

Figure .11: QQ-Plot of Treated Data, logarithmic form

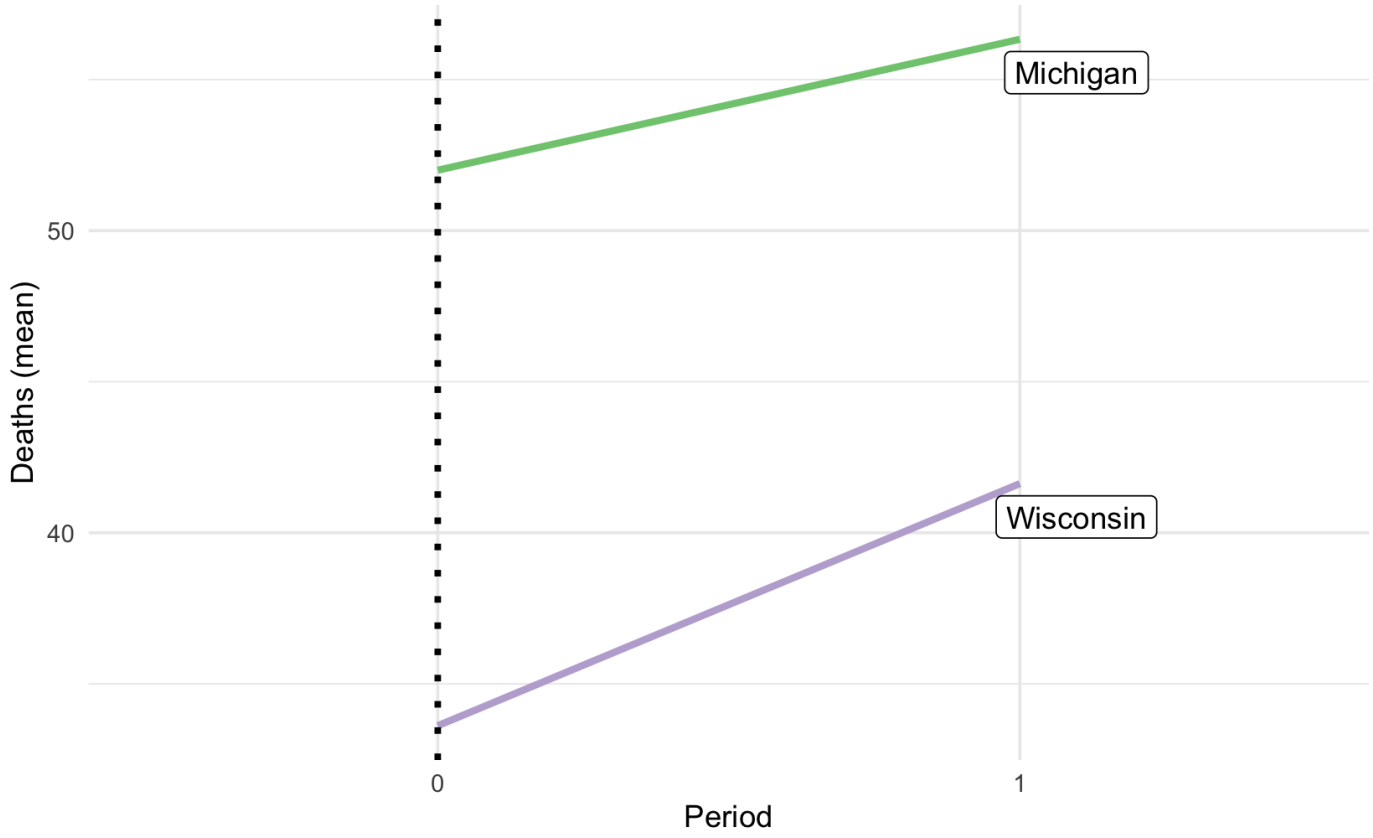

Figure .12: Difference in Difference Graph