Effect of mandatory jail sentence on State vehicel fatality rate

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## 1.0 Introduction

#### 1.1 Background

Traffic accidents cause thousands of deaths in the United States every year. Data pertinent to US traffic fatalities from the years 1982 to 1988 can be easily accessed in the “Fatalities” dataset. The data was obtained from sources such as the US Department of Transportation Fatal Accident Reporting System (FARS) and the US Bureau of Labor Statistics. The dataset includes panel data for 48 states (Alaska and Hawaii not included), containing demographic variables such as population, income per capita, religious belief, and unemployment rate. In addition, features that are commonly associated with traffic accidents and its regulation, such as average miles per driver, percentage of young drivers, tax collected per case of beer, presence of a preliminary breath test law, and whether the state implemented mandatory jail sentences or community service for an initial drunk driving conviction, were also presented in the dataset. Finally, the number of vehicle fatalities and its numerous subsets, such as night-time or single-vehicle fatalities, were introduced. The observations were recorded for each state annually. In total, there are 336 observations recorded for 34 distinct variables.

Due to the observational nature of the data, obtaining causal effects may pose a challenge. In observational studies, treatment selection is often influenced by subject characteristics. In the context of our study, “treatment assignment” refers to whether a state has a mandatory jail sentence for an initial drunk driving conviction. It is not difficult to imagine that demographic characteristics of a state can influence both its traffic legislations as well as its traffic fatality rate, causing confounding effects that obscure the impact of legislation on traffic fatality. As a result, systematic differences in baseline characteristics between states with and without mandatory jail sentences must be taken into account when estimating its effect on outcomes. The **propensity score** is the probability of treatment assignment conditional on observed baseline characteristics. The propensity score allows one to analyze an observational study so that it mimics some of the particular characteristics of a randomized controlled trial. In particular, conditional on the propensity score, the distribution of observed baseline covariates will be similar between treated and untreated subjects, allowing the estimation of the average treatment effect (Austin, 2011). In this report, we will attempt to discover the potential causal relationship between a mandatory jail sentence for an initial drunk driving conviction and the traffic fatality rate of the state using the **propensity score matching** technique, followed by **mixed-effect ANOVA modeling**. The primary objective of this analysis is to educate State legislators on whether a mandatory jail sentence is a proper current and will result in lower automobile fatality rates.

#### 1.2 Questions of Interest

* Are there demographic features that correlate with a state’s mandatory jail sentence law?
* Is a state’s mandatory jail sentence law associated with its annual traffic fatality rate, without adjusting for potential covariating demographic variables?
* Is a state’s mandatory jail sentence law associated with its annual traffic fatality rate, after adjusting for potential covariating demographic variables?
* Can we draw a causal conclusion regarding the relationship between a state’s mandatory jail sentence law and its annual traffic fatality rate?

## 2.0 Analysis Plan

From data collected by the National Highway Traffic Safety Administration’s FARS, we plan to conduct a propensity score analysis followed by mixed-effect ANOVA modeling to isolate the average effect of required jail time on automobile fatality rates.

#### 2.1 Population and study design

The response variable used in this analysis is the yearly traffic fatality rate per 10,000 population. This statistic will be calculated by dividing a state’s total traffic fatality count within a given year by its population of the year, multiplied by 10,000.

The “Fatalities” dataset is a longitudinal dataset, also know as “panel dataset”, with a “year” index that delineates the temporal order of entries. In a typical panel dataset, each individual has multiple entries, some of which correspond to pre-treatment records while others post-treatment. In this regard, the vehicle fatality dataset is atypical, because only six out of 48 states had pre- and post-treatment records (*Figure X*). Most states did not change their mandatory jail sentence policy between 1982 and 1988. Due to this limitation, common panel data analysis techniques are not applicable. In response, we will follow a bench-marked pipeline for analyzing non-panel observational data under a propensity score matching framework (Smith, 1997), while closely monitoring the behavior of the temperal variable throughout the analysis, and address any potential issues that might arise.

#### 2.2 Descriptive Analysis

#### 2.3 Propensity Score Analysis

##### 2.3.1 Propensity Score Estimation

We will estimate the propensity score through a logistic regression model. The dependent variable of the logistic regression model is a binary variable indicating treatment status, whether or not a State has a mandatory jail sentence. There is a lack of consensus in the applied literature as to which variables to include in the propensity score model (Austin, 2001). Brookhart et al. (2006) suggested that for practical purposes, it is safe to include all potential confounding covariables in propensity score estimation. In this study, 14 independent variables were included in the logistic regression model to account for demographic characteristics that could potentially influence whether a state mandates such a jail sentence. These variables include year, population, gross state product (GSP), spirits consumption, unemployment rate, per capita income, tax on a case of beer, percentage of baptists, percentage of Mormons, minimum drinking age, percent residing in dry counties, percentage of drivers younger than 24, average miles per driver, and preliminary breath test upon initial drunk driving conviction.

The output of this model is the propensity score, which equals to the probability that a State has a mandatory jail sentence given the set of covariates. The logistic regression model we used to estimate the propensity score is as follows:

Where , is the indicator variable for mandatory jail sentence upon initial drunk driving conviction. when the state has mandatory jail sentence, and other wise. is a vector of length 14, indicating the realized value of the 14 independent variables of the i-th subject in the logistic regression model. .

##### 2.3.2 Matching

To match observations with mandatory jail sentences to observations without, we will use the nearest neighbor matching algorithm based upon propensity score.

##### 2.3.3 Examining covariate balance in the matched sample

After the propensity score matching, we would check whether our propensity score model has been adequately specified using the following steps:

1. we would assess the standardized differences of each covariate between treatment groups.
2. we would assess the distributions of propensity scores by treatment.
3. we would compare distributions of the covariates between treatments.

##### 2.3.4 Estimate Treatment Effect

To estimate the effect of mandatory jail sentences on a State’s traffic fatality rate, we will fit the following linear regression relating the binary treatment variable to Fatality Rate:

for and .

Where  
- represents the yearly traffic fatality rate of a given State in a given year.  
- represents the overall sample mean of yearly traffic fatality rates.  
- represents the fixed effect of mandatory jail sentence law. when the state has mandatory jail sentence, and other wise.  
- represents the random effect of State , and  
- the residuals.

The model is constrained such that , , and .

#### 2.4 Model Diagnostics

We will use Q-Q plot, histogram and the Shapiro-Wilk test inspect the normality of residuals. A scatter plot and a fitted-value-versus-residual scatter plot and the Levene test will be used to examine equality of residual variance. Independence of residuals and outlying data points will also be discussed.

##### 2.5 Causal Inferece Assumptions

The legislative measures to reduce fatal collisions, such as mandatory jail sentences, are determined at the State level. A State legislature’s decision to implement this treatment, is, however, based upon much of the information contained within our dataset, which creates a dependence between the treatment level and our other predictor variables. We can control for this dependence by making use of the covariates which affect the outcome and treatment selection by performing a propensity score matching procedure (Sasidharan, 2013).

To make causal inferences with propensity score analysis, we make the following assumptions:

*1.* **Stable unit treatment value assumption (SUTVA)** (Rubin, 1990): This assumption states that the treatment applied to one entity does not affect the outcome of any other (i.e., no interference among the entities). In our case, it is challenging to make this assumption for two primary reasons. First, the fatality rates are likely correlated between states who share a geographic boundary. For example, the fatality rate of New York is likely highly correlated with New Jersy’s as much of New Jersy’s population commutes into New York, and vice-a-versa. Mediating this spatial correlation is outside the scope of this class, and we will continue under the assumption that the fatality rate of states is not geographically correlated with one another. Secondly, there is a likely correlation in a State’s fatality rate across time. For example, we would expect California’s 1982 fatality rate having a strong correlation with the 1983 rate. While we attempted to control for this correlation across time through a three-point moving average model. Applying this model to our data resulted in a 33% loss of data, since each state only has six observations. Given the time constraints of this project, we decided to ignore the correlations across time, and assume that the effect of time is independent across all observations.

While it is clear that our data fails to strictly meet the SUTVA assumptions for causal inference. To continue the project, we will satisfy this assumption by ignoring the effects of time and geographic proximity.

*2.* **Positivity**: This assumption requires that there be a non-zero probability of receiving every level of treatment for the combination of values of exposure and covariates that occur among entities in the population (Rubin, 1978). Since each state can pass legislation for and against mandatory jail sentences at any time, the probability of receiving both levels of the treatment is, in fact, positive.

*3.* **Unconfoundedness**: The treatment assignment mechanism is said to be unconfounded if the treatment status is conditionally independent of the potential outcomes, given a set of covariates (Rubin, 1990). This assumption is not satisfied by our original data since a clear dependence exists between a State’s decision to implement mandatory jail sentences is based upon much of the data we plan to use in our analysis. However, through the use of propensity score matching, we can control for this since the propensity score is conditioned on all potential covariates (Rosenbaum, 1983).

*4.* **Observation of all Covariates**: This assumption, unique to propensity score, requires we observe all possible covariates in the assignment of a treatment (Rosenbaum, 1983). Unfortunately, with such a complex decision such as implementing a required jail sentence, it is impossible to assume that our data is a complete case of all covariates used in this decision. However, since we are limited with both the data and time at hand, we will make this assumption in order to continue the project.

##### 2.6 Mixed Linear Models Assumptions

After propensity score matching, we plan to construct a mixed linear model to capture the average causal effect of mandatory jail sentences while accounting for the random effect due to each individual state. To use this type of model, the following assumptions must be satisfied.

*1.* **Normality & Equal Variance**: The model residuals approximately follow a distribution.

*2.* **Independence**: The model residuals follow no detectable pattern and appear to unrelated to one another.

*3.* **Outliers**: The data does not contain any major outliers.

*4.* **State Effect**: The effect due to each state follows a distribution.

## 3.0 Results

#### 3.1 Descriptive Analysis

The data set contains the US traffic fatalities panel data for the 48 contiguous states from 1982 to 1988, where each state is observed in seven time periods. There are 336 rows and 34 columns in the data set. Each row represents an observation for a state in a time point and each column represents a variable for the observation.

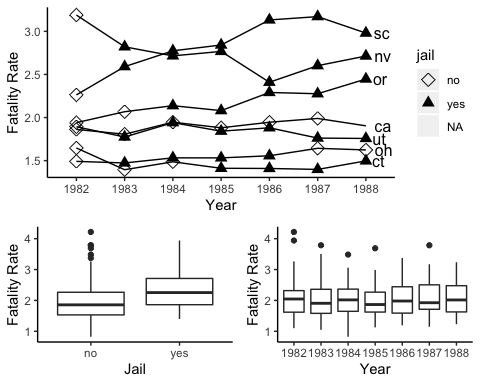
To compare the traffic deaths across the different states and times, we use the fatality rate here, which is the number of annual traffic death in every 10,000 people of that state.

First, we found out there is two missing values in the data set, which are the variable that whether the state had a mandatory jail sentence or not and the variable that whether the state had a mandatory community service or not for Califonia in 1988. Besides, there are 41 states did not change their policy in the mandatory jail sentence from 1982 to 1988. The relationship between the fatality rate and the policy in the mandatory jail sentence for the other seven states is shown in the Figure @ref(fig:fatal)(a). From Figure @ref(fig:fatal)(a), both South Carolina and Nevada changed their policy in the mandatory jail sentence from no to yes in 1983, but their fatality rates changed in the opposite direction after that. Similarly, we could also observe this situation in Oregon, Utah, and Connecticut. Given this plot, we may also need to consider the effects of other variables in the data set or the effects of unobserved variables. Also, because of the existence of missing values, for the analysis in the following part, we drop the observation for California in 1988.

Then, we explore the distribution of fatalities rate for all the observations. Figure @ref(fig:fatal)(b) shows that overall, observations that had the mandatory jail sentence had a higher fatality rate than observations that did not have the mandatory jail sentence had a higher fatality rate, but the difference in medians is not significant. Figure @ref(fig:fatal)(c) shows that distributions of fatalities rate for different years are roughly the same.

library("AER")  
library(tidyverse)  
data(Fatalities)  
  
library("directlabels")  
library(gridExtra)  
  
data = Fatalities %>%   
 mutate(fatal\_rate = fatal/pop\*10000)  
  
state\_1 <- c('ca', 'ct', 'nv', 'oh', 'or', 'sc', 'ut')  
  
plot1 <- data %>%   
 filter(state %in% state\_1) %>%   
 ggplot(aes(x = year, y = fatal\_rate, group = state)) +  
 geom\_line()+  
 geom\_point(aes(shape = jail), size = 3)+  
 scale\_shape\_manual(values=c(5, 17))+  
 geom\_dl(aes(label = state), method = list("last.points", hjust = -.5)) +  
 theme(panel.grid.major = element\_blank(), panel.grid.minor = element\_blank(),  
 panel.background = element\_blank(), axis.line = element\_line(colour = "black")) +  
 labs(y = "Fatality Rate", x = "Year")  
  
#data[data$state == "ca" & data$year == "1988",]$jail = "no"  
data <- data %>% drop\_na()  
  
plot2 <- data %>%   
 ggplot(aes(x = jail, y = fatal\_rate))+  
 geom\_boxplot(na.rm = TRUE) +  
 theme(panel.grid.major = element\_blank(), panel.grid.minor = element\_blank(),  
 panel.background = element\_blank(), axis.line = element\_line(colour = "black")) +  
 labs(y = "Fatality Rate", x = "Jail")  
  
plot3 <- data %>%   
 ggplot(aes(x = year, y = fatal\_rate))+  
 geom\_boxplot(na.rm = TRUE) +  
 theme(panel.grid.major = element\_blank(), panel.grid.minor = element\_blank(),  
 panel.background = element\_blank(), axis.line = element\_line(colour = "black")) +  
 labs(y = "Fatality Rate", x = "Year")  
  
grid.arrange(plot1, arrangeGrob(plot2, plot3, ncol = 2), ncol = 1, heights = c(.4/4, .3/4))

## Warning: Removed 1 rows containing missing values (geom\_point).



(a) Fatality rate for states that changed their policy in the mandatory jail sentence from 1982 to 1988 (b) Boxplot of the fatality rate for different policies in the mandatory jail sentence (c) Boxplot of the fatality rate for different years

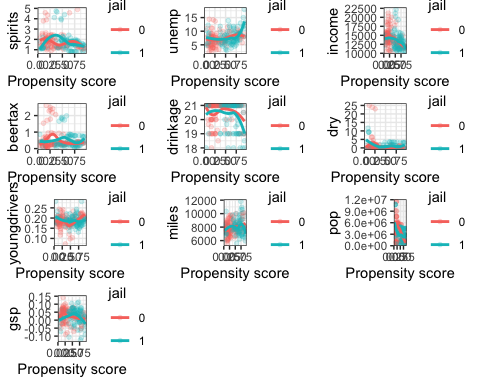
#### 3.2 Propensity Score Analysis

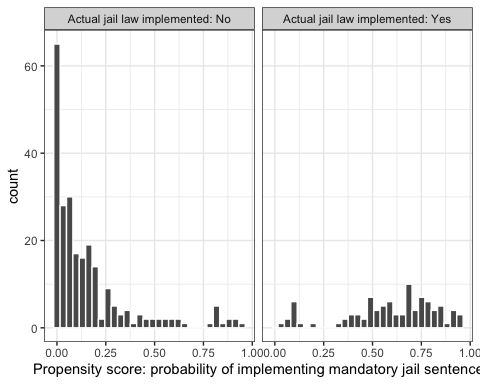
##### 3.2.1 Propensity Score Estimation

A logistic regression model was fit to estimate propensity score for matching treated and untreated samples. Distribution of the estimated propensity scores are displayed in *Figure Y*.

*Figure T*: Distribution of quantitative dependent variables by propensity score:

## Warning: Removed 19 rows containing missing values (geom\_smooth).



*Figure Y*: Propensity score distribution across two treatment groups 

##### 3.2.2 Matching

Nearest neighbor matching algorithm resulted in a new dataset of 188 entires, with 94 original entries with mandatory jail sentence matched with their respective non-treated entry with the most similar propensity score.

##### 3.2.3 Examining covariate balance in the matched sample

1. The standardized differences of each covariate between treatment groups.

Table @ref(tab:stdf) shows the results of standardized differences and the 95% confidence interval for covariates. It can be seen that all the confidence intervals include 0, we are 95% confidence that there is no differences between treatment groups for covariates.

library(stddiff)  
library(cobalt)

## cobalt (Version 4.0.0, Build Date: 2020-01-08 14:20:10 UTC)  
## Please read the documentation at ?bal.tab to understand the default outputs.  
## Submit bug reports and feature requests to https://github.com/ngreifer/cobalt/issues  
## Install the development version (not guaranteed to be stable) with:  
## devtools::install\_github("ngreifer/cobalt")  
## Thank you for using cobalt!

##   
## Attaching package: 'cobalt'

## The following object is masked from 'package:MatchIt':  
##   
## lalonde

#bal.tab(mod\_match, m.threshold = .1)  
stdf <- stddiff.numeric(dta\_m, 15, c(3:13, 27, 34))  
colnames(stdf) <- c("Mean(jail = 0)","Sd(jail = 0)","Mean(jail = 1)","Sd(jail = 1)","missing.c","missing.t", "Standardized difference", "Lower bound", "Upper bound")  
stdf <- stdf %>% as.tibble()

## Warning: `as.tibble()` is deprecated, use `as\_tibble()` (but mind the new semantics).  
## This warning is displayed once per session.

knitr::kable(stdf[,c(1:4,7:9)], caption = "Standardized differences of covariates between treatment groups.")

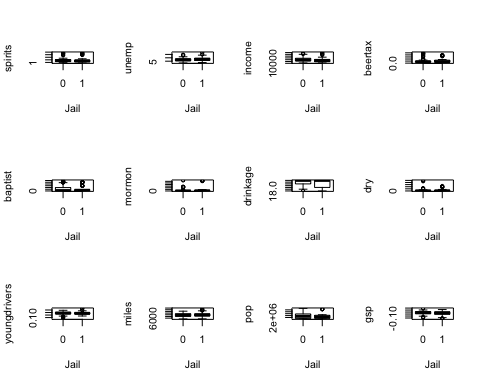
Standardized differences of covariates between treatment groups.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Mean(jail = 0) | Sd(jail = 0) | Mean(jail = 1) | Sd(jail = 1) | Standardized difference | Lower bound | Upper bound |
| 1.852 | 0.790 | 1.700 | 0.792 | 0.192 | -0.094 | 0.479 |
| 7.179 | 2.452 | 7.938 | 2.747 | 0.292 | 0.004 | 0.579 |
| 14281.939 | 2428.093 | 13326.736 | 2203.751 | 0.412 | 0.123 | 0.701 |
| 61.603 | 3.694 | 59.924 | 5.756 | 0.347 | 0.059 | 0.635 |
| 0.534 | 0.603 | 0.485 | 0.417 | 0.095 | -0.191 | 0.381 |
| 6.523 | 9.555 | 5.898 | 8.423 | 0.069 | -0.217 | 0.355 |
| 3.180 | 9.141 | 6.184 | 15.231 | 0.239 | -0.048 | 0.526 |
| 20.457 | 0.816 | 20.298 | 1.017 | 0.172 | -0.114 | 0.459 |
| 1.489 | 4.299 | 1.106 | 2.229 | 0.112 | -0.174 | 0.398 |
| 0.185 | 0.030 | 0.186 | 0.026 | 0.038 | -0.248 | 0.324 |
| 7845.093 | 1046.807 | 8057.946 | 1162.624 | 0.192 | -0.094 | 0.479 |
| 3812797.327 | 2724177.761 | 2883446.331 | 2170402.655 | 0.377 | 0.089 | 0.666 |
| 0.029 | 0.043 | 0.021 | 0.048 | 0.176 | -0.111 | 0.462 |

1. Distributions of propensity scores by treatment.
2. Distributions of the covariates between treatments.

Figure @ref(fig:cov\_bp) shows that distributions of the covariates are similar between treatments.

data\_cov = c("spirits" , "unemp" , "income" , "beertax" , "baptist" , "mormon" , "drinkage" , "dry" , "youngdrivers" , "miles" , "pop" , "gsp")  
par(mfrow = c(3,4))  
for (i in 1:length(data\_cov)){  
 boxplot(dta\_m[,data\_cov[i]]~dta\_m$jail, xlab = "Jail", ylab = data\_cov[i])  
}



Distributions of the covariates

par(mfrow = c(1,1))

##### 3.2.4 Estimate Treatment Effect

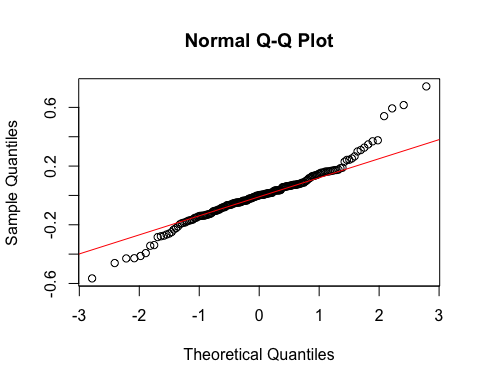
#### 3.3 Model Diagnostics

##### 3.3.1 Goodness-of-fit of logistic regression model

Unlike linear regression with ordinary least squares estimation, there is no statistic which explains the proportion of variance in the dependent variable that is explained by the predictors. The most notable pseudo metric commonly used for assessing goodness-of-fit in logistic regression is McFadden’s , which is defined as where is the log likelihood value for the fitted model and is the log likelihood for the null model with only an intercept as a predictor. The propensity-score-generating logistic regression model used in this study has a McFadden’s of 0.39, indicating effective removal of a large portion of confounded samples through the propensity score matching process.

##### 3.3.2 Mixed Effect model

The two crucial assumptions for a mixed effect model are normally distributed residuals and constant variance of the residuals across the fitted values, which will be discussed below. Influential observations will also be discussed.





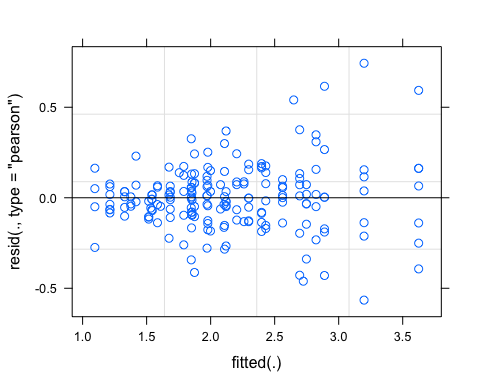




Figure ..: Visual diagnostics of Mixed Effect model assumptions. (a). Normal Q-Q plot of residuals. (b) Histogram of model residuals. (c) Residuals-versus-fitted value scatter plot.

##### Normality:

From the Q-Q plot of the residuals (Figure ..a), we can see that the probability mass on the left and right tails are higher than what is expected from a normal distribution. The distribution of the residuals seem to be heavy-tailed. Thus, the normality assumption is not satisfied from the Q-Q plot. A histogram is used to visualize the distribution of the residuals (Figure ..b). From the histogram, it is not easily noticeable that the residuals do not follow a normal distribution.

To further test for normality of the errors, a Shapiro-Wilk test will be used on the distribution of the residuals. A Shapiro-Wilk test is used to test whether a distribution of data follows a normal distribution.

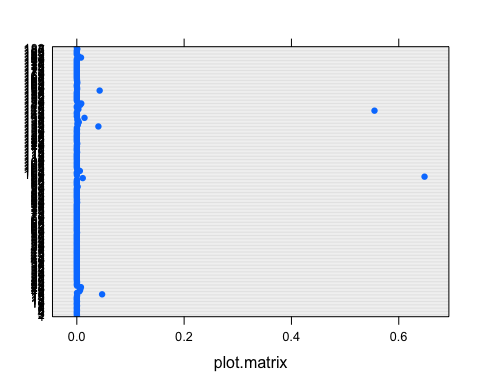
The null and alternative hypotheses of the Shapiro-Wilk test are:  
: The residuals are normally distributed.  
: The residuals are not normally distributed.

The p-value is essentially 0, and thus we reject the null hypothesis. Thus, there is evidence that the distribution of the residuals do not follow a normal distribution.

##### Equal Variances:

The spread of the residuals seem to increase along the x-axis in the residuals-versus-fitted value scatter plot (Figure ..c), indicating unequal variance of the residuals across the fitted values. Thus, the equal variance assumption is not satisfied.

#### Influential Observations:



Since the Cook’s distance for every observation is less than 1, we conclude that there are no highly influential observations.

##### Response Variable Transformation:

In an attempt to remedy the departures of the assumptions of the mixed effect model, we used a log transformation of the response variable, fr. After the transformation, we concluded that the distribution of the residuals did not follow a normal distribution after looking at a Normal Q-Q plot and performing a Shapiro-Wilk test. The residuals did seem to have more equal variance across the fitted values after the transformation. Overall, a log transformation of the response variable did not remedy the departures of the assumptions of the mixed effect model.

## 4.0 Discussion

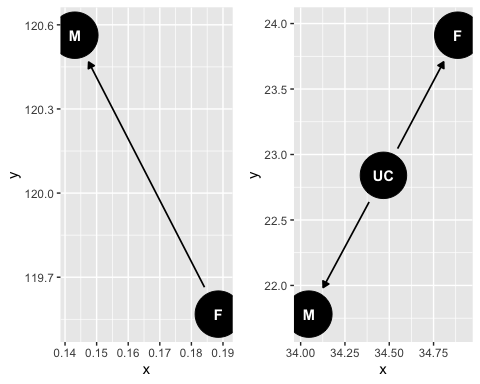
### Propensity Score Matching

In this report, we highlight the usage of propensity score matching for isolating average treatment effect of implementing mandatory jail sentence upon initial conviction of driving under influence. Rosenbaum and Rubin (1983) defined treatment assignment to be strongly ignorable if the following two conditions hold: (a) treatment assignment is independent of the potential outcomes conditional on the observed baseline covariates, and (b) every subject has a nonzero probability to receive either treatment. They demonstrated that if treatment assignment is strongly ignorable, conditioning on the propensity score allows one to obtain unbiased estimates of average treatment effects. We achieved these conditions through propensity score matching.

### Causal Inference

We cannot confidently draw causal conclusions using the result from this analysis. This is because of the violation of these assumptions necessary for causal inference:

1. The stable unit treatment value assumption (SUTVA):  
   SUTVA states that the treatment assignment of one experimental unit cannot interfere with the outcome of a separate experimental unit. This is violated in this dataset because
2. temporal correlations across records taken from the same State, and
3. spacial correlations among states that are geographically close to each other.  
   The implementation of mandatory jail sentence in one state is very likely to influence the vehicle fatality of an adjacent state. And the historic state of the legislation is very likely to influence the vehicle fatality of the same state in the years to come.
4. Exogeneity: The exogeneity assumption states that the independent variable (implementation of mandatory jail sentence) cannot be dependent on the dependent variable (vehicle fatality rate). This assumption is likely to be violated in this dataset because legislations can arise from existing conditions (*Figure Za*).
5. Ignorabilty of unobserved potential confounding variables: Although this expansive dataset captures many prominent variables that are associated with vehicle fatality rate, many more economic and social factors come into play in impacting the interactions between the implementation of mandatory jail sentence and vehicle fatality rate. We cannot confidently exclude the possiblity of the existence of many of such variables (*Figure Zb*).

*Figure Z: directed acyclic graphs of scenarios where direction of causal inference changes. a. Violation of exogeneity. b. Violation of ignorability of unobserved confounding variables. M: mandatory jail sentence; F: vehicle fatality rate; UC: unobserved confounding variable*  


Ultimately, our analysis makes very improbable assumptions in order to analyze this observational data. Due to this lack of strong assumptions around SUTVA and observation of all covariates, we fail to make any strong causal conclusions regarding the effect of mandatory jail sentences on State fatality rates.

Due to this lack of clear causality, we propose State legislators focus their energy and capital on measures directly correlated with the probability of entering a fatal collision. Better seatbelt enforcement, speeding enforcement, and drunk driver intervention have all demonstrated their effectiveness at better-protecting citizens and reducing the risk of a fatal accident (Morley, 2016). Legislators should focus on active measures to combat fatal automobile collisions instead of hoping to find a strong causal effect in passive measures like mandatory jail sentencing.

## 5.0 Reference

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