Mandatory Jail Sentence Policy and Traffic Fatalities

1. Introduction

According to the National Highway Traffic Safety Administration, 36560 fatalities due to motor vehicle crashes occurred in the United States in 2018, in which drunk-driving crash accounted for 29 percent. Many researches have focused on controling traffic fatalities. Wagnenaar et al (2007) reported that the mandatory minimum jail sentence is associated with the decrease in nighttime traffic fatalities by 5 percent per year. Some research also showed that arresting drunk driving offenders can significantly affect the drunk driving fatalities(Chang & Yeh, 2004; Rogers & Shoenig, 1994). Morrisey & Grabowski (2011) reported that 10 percent higher beer taxes could decrease traffic fatalities among young drivers by 1.3 percent. It was reported that income is negatively related to traffic fatality rate while alcohol consumption and unemployment rate are positively associated with state traffic fatality (Greenwalt, 2006; Wilkinson, 1987). Based on previous research, our project focused on the effects of per capita income, unemployment rate, spirit consumption, tax on beer and whether having a mandatory jail sentence on traffic fatalities.

2. Exploratory Data Analysis

This study used a balanced panel data of 48 states in United States (excluding Alaska, Hawaii, and the District of Columbia) from 1982 to 1988, with 336 observations in total. The vehicl fatality rate per year of each state was calculated by dividing the number of vehicle fatalities by state population, then multiplying by 10000 to represent the average fatality every 10000 people. As shown in the plot of average fatality rates over 1982 through 1988 across United States (*Figure 1* left), the average fatality rates over 7 years are quite different across the country. Rhode Island has the lowest fatality rate (1.11) while New Mexico has the highest (3.65).

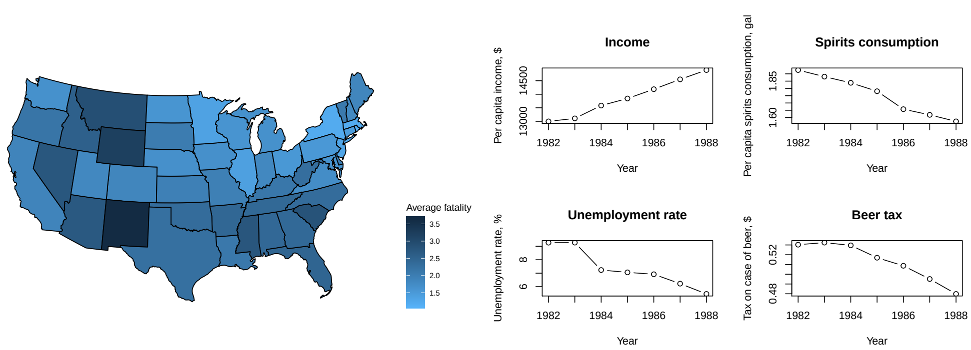

Figure 1: Fatality and covariates over year

Unemployment rate (unemp), spirits consumption (spirits), per capita income (income), tax on beer (beertax) and mandatory jail sentence for DUI conviction (jail) were considered as independent variables in this study. As shown in Trends Plot (*Figure 1* right), the average per capita income across the country kept increasing from 1982 to 1988, while spirits consumption,unemployment rate and tax on beer decreased. Average fatality stayed rather stable over 7 years, and states having mandatory jail sentence seems to have higher average fatality than those not (As shown in *Figure 2* left), which is surprising and will be analyzed in the following.

There was one missing value of mandatory jail sentence status for California in 1988, which was replaced with "no" by referring to the California Drunk-driving Legislation (Laurence, 1988). Per capita income was removed from the statistic model to avoid collinearity because it has a high correlation (-0.55) with unemployment rate, and is more correlated to other variables than unemployment rate (*Figure 2* right). In order to avoid the multicollinearity, we choose the unemployment rate, beer tax and spirits consumption as covariates

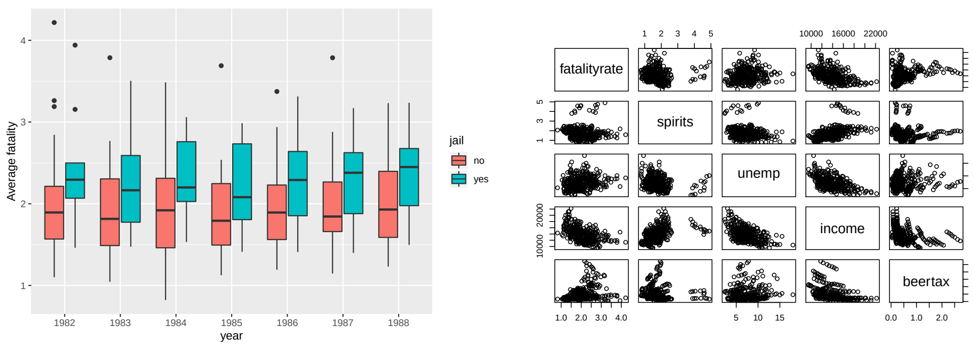

Figure 2: The effect of mandatory jail (Left) and Pairwise correlation plot (Right)

3. Propensity Score Matching

3.1 Propensity score estimation

The data we collected from National Highway Traffic Safety Administration is observational data, which means it is not like a randomized experimental data where the investigator did not decide which unit would receive the treatment and which one would be treated as the control group. In order to make inferences about the causal effect of an active treatment versus a control treatment based on the observational data, a useful way is to use logistic regression to estimate the probability of being treated as a function of covariates for each unit.

Firstly, we can check the mean for each covariate including unemployment rate, beer tax and spirits consumption by treatment status.

Table 1: Mean of covariates in each group

Mandatory Jail Sentence	Unemployment Rate	Beer Tax	Spirits Consumption
0	7.116942	0.5243991	1.774380
1	7.938298	0.4845684	1.700425

Note: There is mandatory jail sentence if 1; there is no mandatory jail sentence if 0.

From the *Table 1* above, we can find that those means of the same covariate are quite different in the situation when there is no mandatory jail sentence and when there is mandatory jail sentence. It means that when we compare the influence of jail sentence policy on traffic facilities, we cannot ignore the influence of other covariates. Therefore, we need to reconstruct our data set by creating some blockings of observations based on the covariates, and then we can calculate propensity score of having jail sentence in a certain state by logistic regression.

3.2 Executing the matching algorithm

After calculating the propensity score, we could use some methods to restrict the sample to observations within the region of common support and then estimate the mean difference of facilities with and without jail sentence. Rubin and others have argued that this is sufficient to eliminate 95% of the bias due to confounding of treatment status with covariates. The method we use is to find pairs of observations that have very similar propensity scores but differ in their treatment status, and then we match the pairs and put the matched observations in a new data. Through this method we can reconstruct out data set and we can use this data set to fit our model without worrying about the confounding effect. We can evaluate covariate balance in the matched sample by calculating the mean of each covariate.

Table 2: Mean of covariates in each group after matching

Mandatory Jail Sentence	Unemployment Rate	Beer Tax	Spirits Consumption
0	7.853192	0.4868655	1.723936
1	7.938298	0.4845684	1.700425

Note: There is mandatory jail sentence if 1; there is no mandatory jail sentence if 0.

From *Table 2* we can see that the means of the same covariate are almost same. In addition, the distribution of propensity scores in the group with jail sentence to the distribution of scores in the group without jail sentence is similar.(See *Figure 3*) We attain a high degree of balance on the covariates included in the model. In the following analysis process, we use the new matching data to fit regression model and make causal inference.

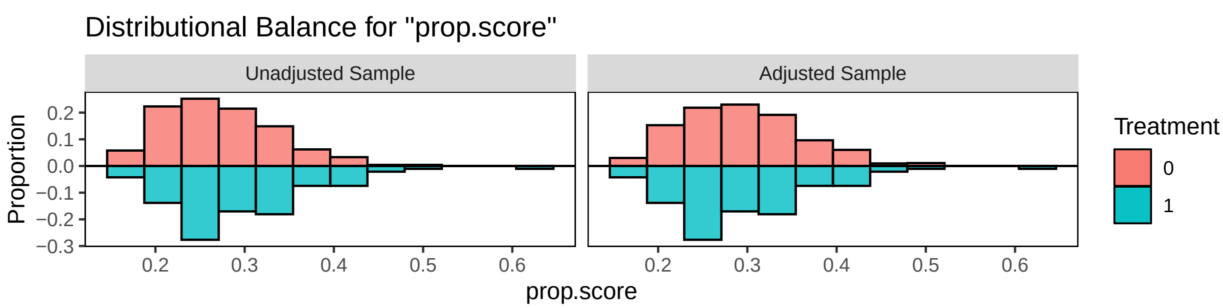

Figure 3: Distributions of propensity scores before and after matching

4. Fixed Effect Panel Model

4.1 Model Building

Fixed effect panel model is efficient since it controls for all time-invariant differences between the individuals. For instance, the transportation industry or the climate of specific state are fixed over short time, but they actually influence the fatality rate of traffic accident. In this case, fixed effect panel model is used to reduced the omitted variable biases of not accounting for these variables.

Through propensity score matching procedure, a balanced and complete matching group is acquired. The new matching data are beneficial in causal inference since it alleviates the effect of potential confounders. In addition, whether there is mandatory jail sentence in the state seems to affect the reduced traffic fatality rate in each state. Since the unemployment rate, tax on case of beer and spirits consumption are correlated to the traffic fatality rate of the year in each state, we consider them as the time-variant variables in our fixed effect panel model. In this case, we set the model notations as below:

- Response variable Y_{it}: the traffic fatality rate of state i in time t. In this case, we have $Y_{it} = log[(10000 \times F_{it})/P_{it}]$, where F_{it} represents the number of vehicle fatalities of the state i in year t and P_{it} is the population of the state i in year t. In this report, the traffic fatality rate can be interpreted as the logarithm of the number of deaths caused by traffic per 100,000 population;
- Time fixed effect α_t: time specific intercept. It represents any change over time (1982-1988) that affects all observational units in the same way. The level of time effect is 7;
- Mandatory jail sentence indicator X_{it}: $X_{it} = 1$ when there is mandatory jail sentence of state i in time t; $X_{it} = 0$ when there is no mandatory jail sentence of state i in time t;
- Covariates vector Z_{it}: potential time-varying covariates. In this case, we mainly focus on three variables: the unemployment rate, beer tax and spirits consumption.
- State fixed effect S_i: In this case, each level of S_i represents one of 48 states in US excluding Alaska and Hawaii.

The fixed effect model equation is: $Y_{it} = \alpha_t + \beta X_{it} + \gamma Z_{it} + S_i + \epsilon_{it}$

where β and vector γ are regression coefficients and ϵ_{it} is error term. In fixed effect model, we assume that: (1) The normality of error terms: the error terms are normally distributed; (2) The homogeneity of variance assumption: the error terms have the constant variance; (3) Independent assumption: in time series data, the error terms are allowed to be autocorrelated within states, which means that there is autocorrelation relationship across time in one specific state. However, in a fixed time, the error terms should be independent across states.

4.2 Fitting result

We use R to fit fixed effect panel model which is shown above. We see that there is no the same number of observations for each state over 48 subjects (states) and 7-year periods (for a total of 188 observations). By taking non-mandatory jail sentence as reference group, the *Table 3* shows the fitting result of fixed effect panel model.

Table 3: Fitting Result of Fixed Effect Panel Model

	Estimate Effect	Standard Error
Mandatory Jail Sentence	-0.01	0.04
Unemployment Rate	-0.03	0.01
Beer Tax	-0.04	0.11
Spirits Consumption	0.24	0.08

The results show the estimates of each effect on traffic fatality rate. The estimate of effect of unemployment rate is -0.03, which means that the higher the unemployment rate, the lower the traffic fatality rate. The estimate of spirits consumption effect is 0.24, which means that there is a period of high traffic fatality rate when spirits consumption is high. The estimate of beer tax effect is -0.04, and it seems that the higher beer tax tends to associate with the lower traffic fatality rate. In addition, if there is a policy of mandatory jail sentence, it seems that the traffic fatality rate is relatively higher since the estimate is -0.01. However, we are more interested in the causal effect of mandatory jail sentence. After the model diagnostics and causal inference, we can draw the final conclusion in the following part.

4.3 Model Diagnostics

4.3.1 Normality

The normality assumption of error terms is checked by Q-Q plot. From the Q-Q plot (*Figure 4* left) we can see that the most of points are on the diagonal line, which means that the error terms are mostly normally distributed. The normality assumption is sufficed.

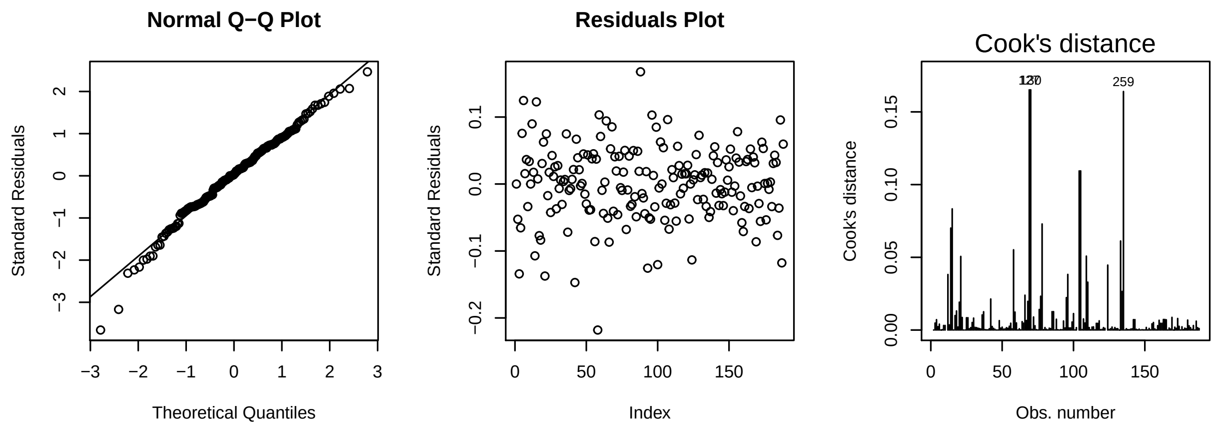

Figure 4: Model Diagnostic Plots

4.3.2 Homogeneity of Variance

The assumption homogenity of variance is checked by the residuals plot. From the Residuals Plot (*Figure 4* middle) we can see that there is no obvious pattern of the residuals, which suggests that the error terms have the constant variance. The assumption of homogeneity of variance is satisfied.

4.3.3 Independence and Outliers

From the Residuals Plot (*Figure 4* middle), it does not show a specific pattern of the scatter of points, which means that the error terms are independently distributed.

In addition, from the Residuals Plot (*Figure 4* middle), no point is significantly away from the middle, which means that there is no outlier in the model. The Cook's distance is used to check if there is any high influential point. The higher the Cook's distance, the more likely that the point is high influential to the model. From the plot of Cook's distance (*Figure 4* right), all the Cook's distance of observations are lower than 0.1, which means that they are not high influential points.

5. Statistical Testing

From the diagnostics of fixed effect panel model, most of the assumption are satisfied. For the new matching data, the factor effect component of the sum of squares are no longer orthogonal. Therefore, we will use the general linear F-test to test if the effect of mandatory jail is significant. We use the same notations as mentioned above:

Null hypothesis $H_0 : \beta = 0$ v.s. Alternative hypothesis $H_a : \beta \neq 0$

Full model: $Y_{it} = \alpha_t + \beta X_{it} + \gamma Z_{it} + S_i + \epsilon_{it}$

Reduced model: $Y_{it} = \alpha_t + \gamma Z_{it} + S_i + \epsilon_{it}$

From the F-test, since the p-value is 0.76, given the significant level 0.05, we cannot reject the null hypothesis. It means that the the effect of mandatory jail sentence is not significant.

Similar F-test ($H_0 : \gamma = 0$) can be done with the same method to test the effect of covariates including the unemployment rate, beer tax and spirits consumption. However, in this report we mainly focus on the effect of mandatory jail, other detailed test results are stated in the appendix.

6. Causal Inference

Through the propensity score matching process, states with or without mandatory jail sentences have identical distributions on the measured confounders. (See *Figure 3*) Therefore, differences between states with/without mandatory jail sentences with the same propensity scores can be used to estimate the average effect of a treatment. Since our propensity score estimates are reasonably close to the true probabilities of being treated (given the covariates). In this case, the assumptions of causal inference can be sufficed as following:

- The stable unit treatment value assumption: The traffic fatality rate of one state is unaffected by the particular assignment of all other states.
- Unitary treatment assumption: In a fixed year, each state has one policy of whether it executes mandatory jail sentence.
- Positivity assumption: Since the distribution of propensity scores in the state with mandatory jail to the distribution of scores in the state without mandatory jail is similar, all states have some probability of executing the policy.
- Ignorability assumption: Each unit's probability of being treated does not depend on its unobserved potential outcomes. Since the fixed effect model can balance all the time-invariant unobserved effect, the ignorability assumption holds in this analysis. (Rubin, 2003)

In conclusion, the results by the fixed effect panel model can be used to make causal inference. However, since the effect of mandatory jail on the traffic fatality rate is not significant from the result of the F-test, it is most likely that the mandatory jail does not cause the reduction of the traffic fatality rate from 1982 to 1988.

7. Conclusion and Suggestion

Although we adopt propensity score methods to mimic randomized studies to reduce the effects of confounders, we still do not find evidence to support our initial expectation that having mandatory jail sentences can significantly reduce traffic fatalities rate. However, we do not recommend to abolish or ban mandatory jail sentences because several possible obstacles might undermine the power of mandatory jail sentences. One obstacle is that the credibility of mandatory jail sentences for initial drunk drivers is different across the states. The minimum sentence time from 1 to 10 days or no minimum sentence time in some states (Comoreanu, 2017). Another obstacle is that drunk drivers may not perceive the mandatory jail sentence is severed. For instance, some defense attorneys state that license suspension is more threatening to their clients than mandatory jail sentences (Ross, McCleary & LaFree, 1990). Furthermore, the awareness of the mandatory jail sentences might be low among the targeted population, especially young drivers. Besides, due to incomplete information of the data, we do not know the factors that are very different across the states such as road maintenance status and weather conditions, which could significantly affect traffic fatalities rates. Therefore, future studies need to focus on the effectiveness of procedures for enforcement and implementation of mandatory jail sentences. We also suggest that it is better to combine other alcohol control policies to help drivers make better and wiser decisions about drunk driving.

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Appendix: additional F-test

	Estimate Effect	Standard Error	P-value for F-test
Mandatory Jail Sentence	-0.01	0.04	0.76
Unemployment Rate	-0.03	0.01	<0.01
Beer Tax	-0.04	0.11	0.72
Spirits Consumption	0.24	0.08	<0.01