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ECONOMETRICS & TIME SERIES ANALYSIS

PROJECT ON: HOW DO DRUNK DRIVING LAWS AFFECT TRAFFIC DEATHS

PROJECT BY:

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ABSTRACT

Millions of people get injured or die due to traffic accidents every year. Hence, traffic accidents are a major cause of concern in the present world. There are many causal factors for traffic accidents. Few of the factors that could influence the fatality rate of a state could be night hours, speeding laws, tax on alcohol, state laws (seat belt law, community service), economic conditions, population of the state, the religious beliefs and other social and economic indicators over different geographical regions.

In this project, we are estimating the effects of drunk driving laws on traffic fatality rates based on the economic theory. The data has been collected from the U.S. Department of Transportation Fatal Accident Reporting System, the Department of Transportation, U.S. Bureau of Economic Analysis and U.S. Bureau of Labor Statistics. The data present is for 48 states in US over the timeframe of 1982 to 1988. Using this data, we are trying to analyze the impact that the drunk driving laws can have on traffic fatality rates.

Here we are considering the traffic fatality rate to be the dependent variable that is regressed on all the independent variables that could affect the traffic fatality rate. The regression is compared over different models to find the best suitable model.

DESCRIPTIVE DATA ANALYSIS

To understand the impact of drunk driving laws on fatality rates, we check for the different variables and the effects these have in different regions over the fatality rate.

From the data given, we find that the traffic fatalities vary every year and in every state. Below graph shows us the average fatality rate over all the years for different states. We find that New Mexico (NM) has the highest fatality rate per 10,000 people living in that state in that year (mrall) and New York (NY) has the lowest fatality rate.

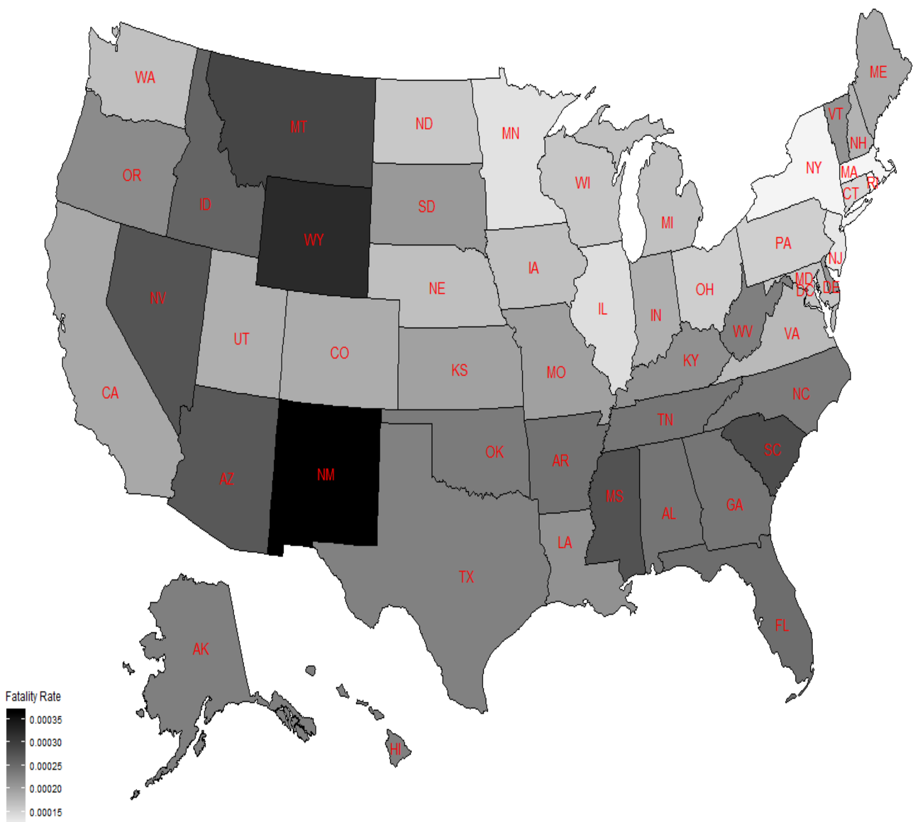

Figure showing the average fatality rate for different state

We use the economic theory and economic models to analyze the data and to estimate the fatality rate value and the changes in it.

From the data present for the years 1982 to 1988, we try to analyze each factor to decide which factor to include in our model. We consider all the relevant factors that could influence the fatality rate.

TOTAL VEHICLE FATALITY vs NIGHT TIME VEHICLE FATALITY

To begin with, let us compare the total number of vehicle fatalities (ALLMORT) and vehicle fatalities that occur in the night (ALLNITE) to check if driving during the night has any significant impact on overall vehicle fatality rate. Plotting the graph of vehicle fatality rate and vehicle fatality rate that occurs during night, we find that the number of fatalities that occur during the night is comparatively very less when compared to the total fatalities. It is almost less than 20% over all the states throughout all the years. Therefore, we can conclude that driving during night has no significant impact overall and we use the total vehicle fatality rate (MRALL) throughout our model.

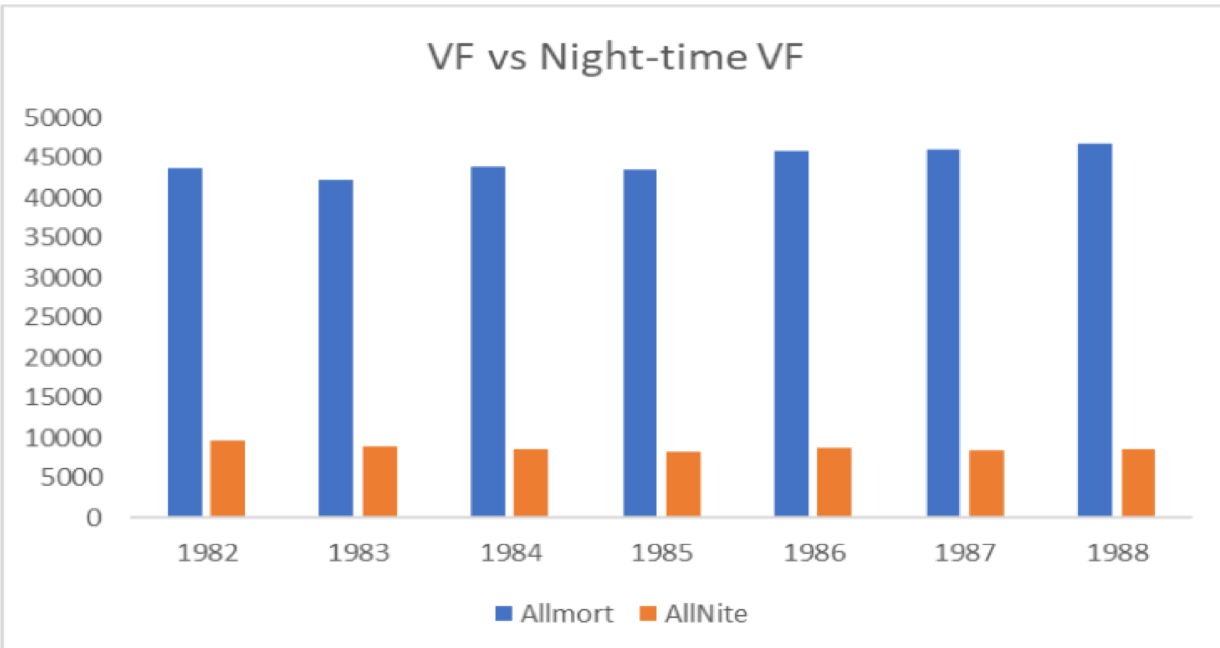

Figure showing the bar graph of Overall Vehicle Fatalities (VF) Vs Night-time VF

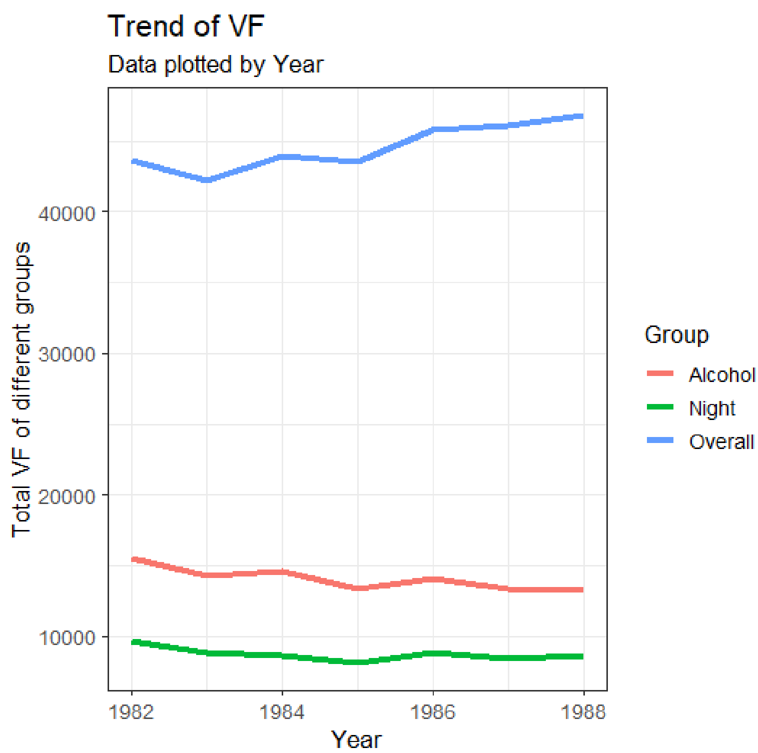

Figure showing graph of Total Vehicle Fatalities for different groups Vs Year

ALCOHOL INVOLVED VEHICLE FATALITY RATE

Vehicle fatalities can occur due to many reasons. Alcohol consumption is one of the reasons that could cause vehicle fatalities but there are other causal factors that could result in vehicle fatalities as well.

Here, we plot the total fatalities that occurred (ALLMORT) and the fatalities that were caused due to alcohol (MRAIDALL) to check if alcohol had any major impact in causing the fatality rates. From the graph, we find that at least 30% of the accidents were caused due to alcohol over all the years. 30% is a significant number and we cannot reject the fact that alcohol is one of the major factors impacting fatality rate.

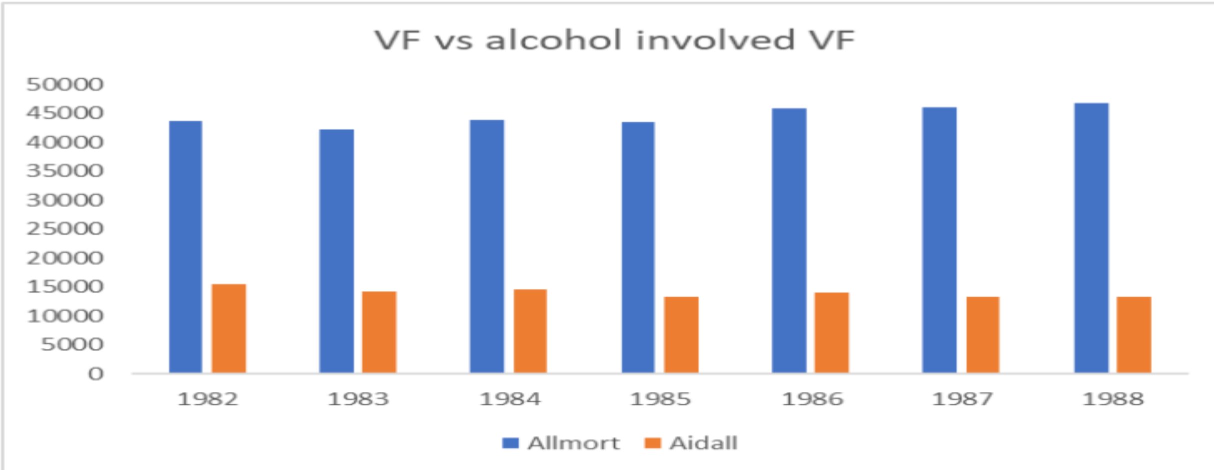

Figure showing the bar graph of Overall Vehicle Fatalities (VF) Vs alcohol involved VF

We can also see below that there is a huge gap between alcohol involved fatalities and total vehicle fatalities in the years 1982 to 1988. This tells us that alcohol is not a major factor in causing vehicle fatalities but does play a significant role.

ALCOHOL CONSUMPTION

Let us consider the variable of annual alcohol consumption (spircons) for our analysis. This variable provides us with information on annual per capita consumption of pure alcohol. We check the comparison of spircons against the fatality rate (mrall). We expect the fatality rate to go higher as alcohol consumption increases if any strict laws have not been implemented in the state.

UNEMPLOYMENT RATE

Next, we consider the unemployment rate (UNRATE). When a person is unemployed, a person tends to be depressed and hence consumption of alcohol is high. Also, the person tends to be frustrated in general and due to these we expect that the fatality rate to be higher. From the graph above, we can conclude that as unemployment rate increases, the fatality rate increases, and it is one of the variables that we consider in our model.

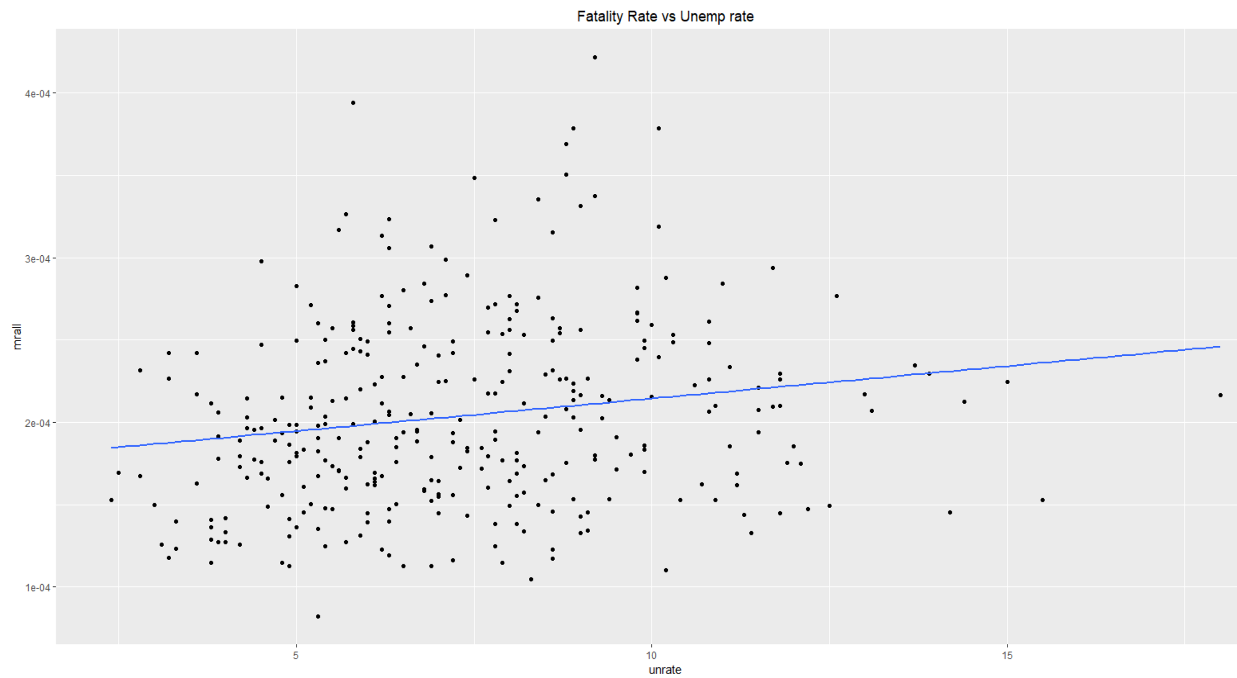

Figure showing graph of Vehicle Fatality Rate (mrall) Vs unemployment rate(unrate)

PER CAPITA INCOME

Another factor that could affect the fatality rate is the per capita income (PERINC), if an individual has better income then he has a better standard of living with better safety conditions and better vehicles. This results in lower fatality rate for high income people. We notice the same effect even in the graph.

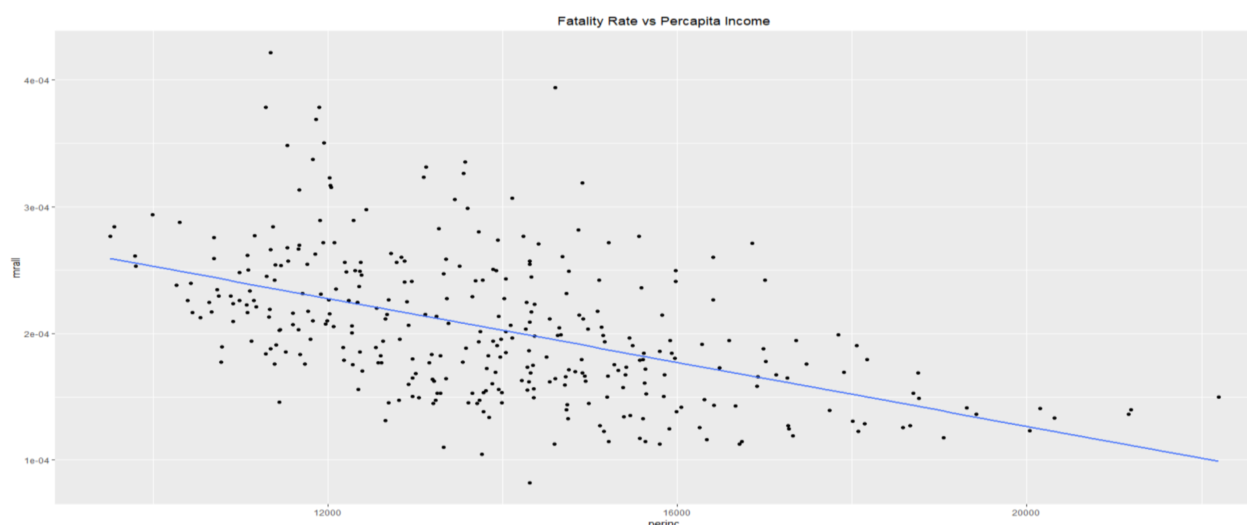

Figure showing graph of Vehicle Fatality Rate (mrall) Vs Per Capital Personal Income (perinc)

TAX ON ALCOHOL

Tax in case of beer tells us a different story from the below graph. As the beer tax (BEERTAX) increases, the fatality rate increases. But the interpretation is possibly wrong. This could be because as fatality increases, there could be a increase in beer tax as well because of simultaneity bias. When the beer tax increases, we assume that the quantity of alcohol consumed by people would automatically decrease. This would result in a decrease in the fatality rate.

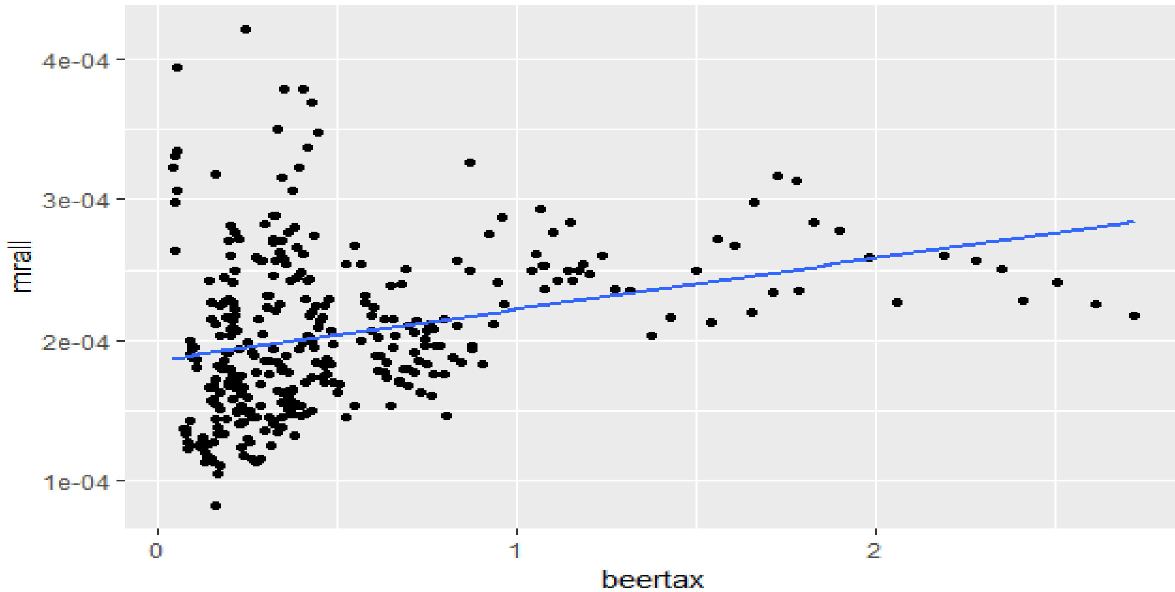

Figure showing graph of Vehicle Fatality Rate (mrall) Vs beertax

AVERAGE MILES PER DRIVER

Another factor that could affect is the average miles driven by a person (VMILES). Higher the number of miles driven, the person tends to be exhausted and hence the fatality rate is expected to go high. This is the same impact that we find in the graph shown below.

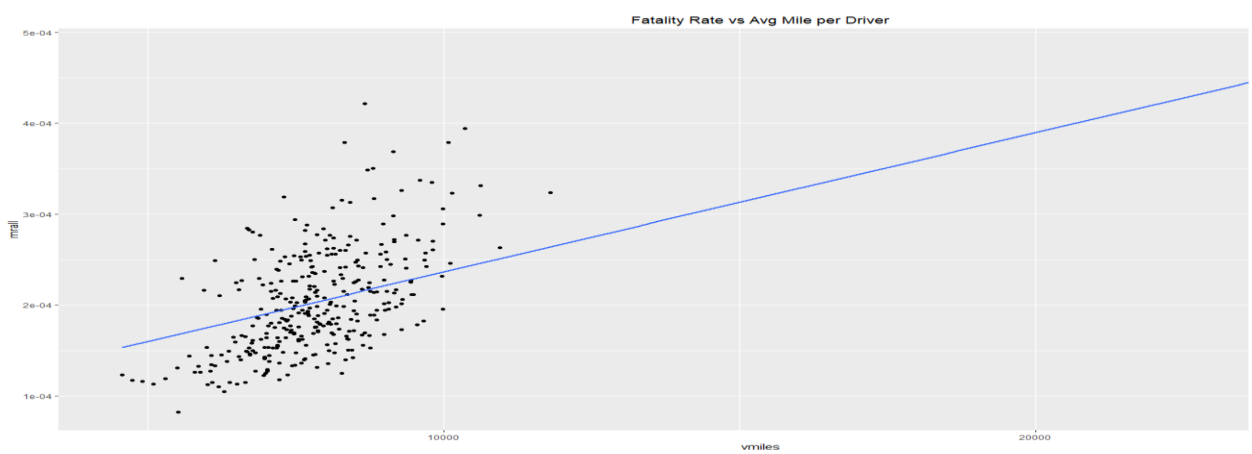

Figure showing graph of Vehicle Fatality Rate (mrall) Vs Average Miles per driver

MANDATORY JAIL SERVICE

When the laws are strict, people tend to be more conscious and be wary of their surroundings while driving. Hence, the fatality rate is expected to go down. For example, one of the laws we could consider as a variable in our model is the mandatory jail (JAILD). This is an indicator variable that denotes 1 if the mandatory jail law was applicable during that year in that state and it denotes 0 otherwise. From the below graph we see that, every year from 1982 to 1988, we find that the fatality rate is higher if the mandatory jail has not been implemented.

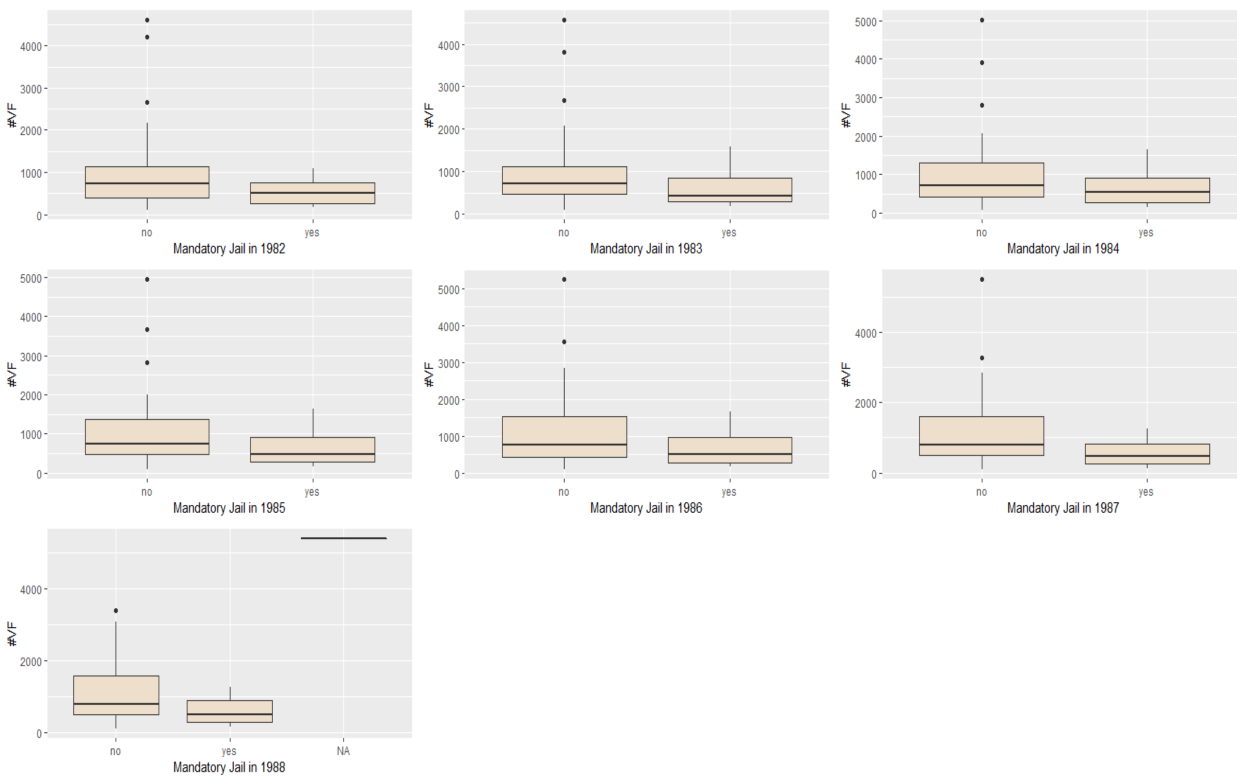

Figure showing box plots of No. of Vehicle Fatalities Vs mandatory jail time over different years

HYPOTHESIS

To test this, we also run a hypothesis. The hypothesis is as stated below:

Null Hypothesis: Ho: Mandatory jail has no impact on fatality rate ($\mu 1 - \mu 2 = 0$)

Alternate Hypothesis: H1: Mandatory jail has impact on fatality rate ($\mu 1 - \mu 2 \neq 0$)

We conduct a t-test to check the hypothesis. The results of the t-test at 95% confidence interval are as below.

```
        Welch Two Sample t-test

data:  allmort by jaild
t = 5.5518, df = 332.9, p-value = 5.787e-08
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 274.0155 574.7542
sample estimates:
 mean in group no mean in group yes
        1034.4274          610.0426
```

From the t-test, we reject the null hypothesis as the p value is low.

Hence, we conclude that the mandatory jail has an impact on fatality rate.

YOUNG DRIVERS

With age, we expect the person to be more responsible and hence avoid rash driving, which results to low fatality rate. Hence, when the population of young drivers in a population is high, then the fatality rate is expected to be high. This is what we notice even in our graph as well.

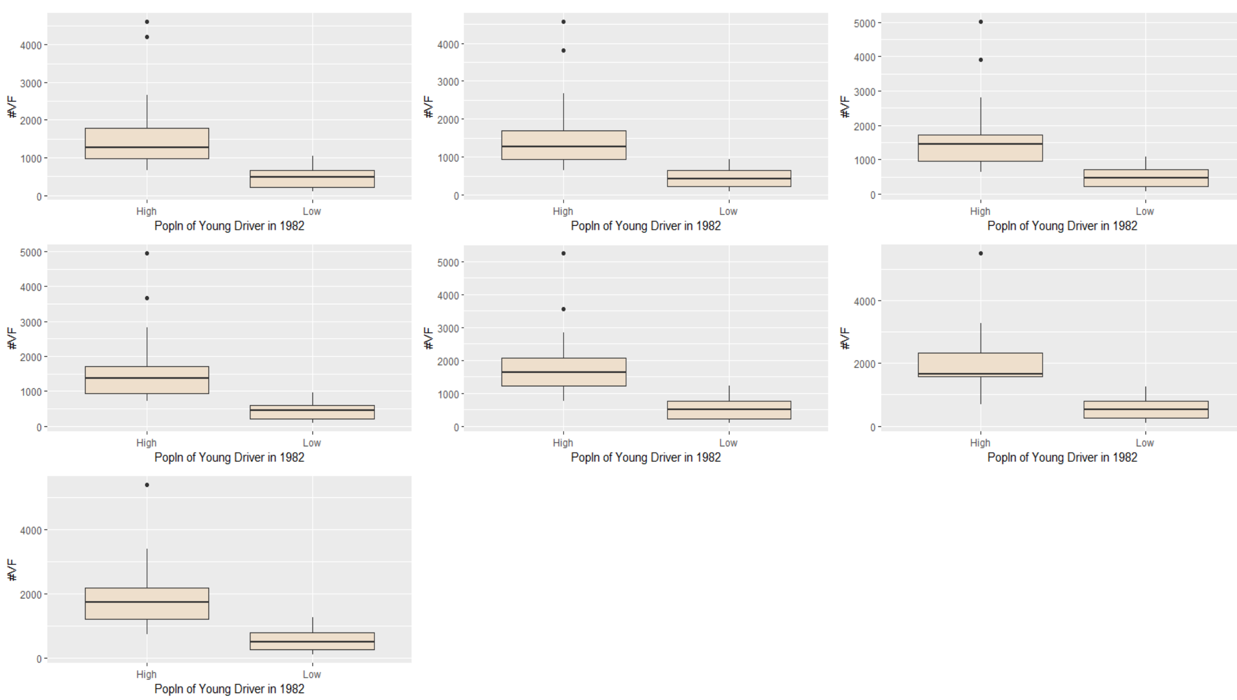

Figure showing box plots of No. of Vehicle Fatalities Vs Population of young drivers over different years

HYPOTHESIS

To test this, we also run a hypothesis. The hypothesis is as stated below:

Null Hypothesis: Ho: Population of young drivers has no impact on fatality rate ($\mu 1 - \mu 2 = 0$)

Alternate Hypothesis: H1: Population of young drivers has impact on fatality rate ($\mu 1 - \mu 2 \neq 0$)

We conduct a t-test to check the hypothesis. The results of the t-test at 95% confidence interval are as below

```
        Welch Two Sample t-test

data:  allmort by yngdrv1
t = 11.833, df = 119.94, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 1078.166 1511.484
sample estimates:
mean in group High  mean in group Low
         1788.0265           493.2018
```

As the p-value is low in this case, we reject the null hypothesis and conclude that population of young drivers has an impact on fatality rate.

MINIMUM LEGAL DRINKING AGE

On similar logic, minimum legal drinking age (MLDA) can be another factor that could influence the fatality rate. If the legal drinking age limit is less, the combination of young drivers and drinking could prove to be lethal. But from the plotted data, we see that there is no trend or effect that is followed by mlda.

POPULATION/TOTAL VEHICLE MILES

Population (POP) and vehicle miles(MILES) are other factors that can impact the fatality rate. As their value increases, we expect the fatality rate also to increase. When the population increases, then the number of vehicles in the area increases which results in an increase in the number of accidents in the area. Similarly, more the number of miles covered, the driver is at a higher risk of fatalities.

CORRELATION MATRIX

To confirm all the speculations made till now and to finalize on the list of variables to use in the model, we check the correlation between the various variables to see if they are highly correlated. If the 2 independent variables are highly correlated in the model, then it could result in multicollinearity. To prevent multicollinearity in the model, we need to ensure that we do not include both the highly correlated terms as our independent variables.

Below is the correlation matrix of the variables we discussed till now:

	spircons	unrate	perinc	beertax	mlda	dry	yngdrv	vmiles	mrall	mralln	mraidall	pop	miles
spircons	1	-0.24	0.45	-0.09	-0.08	-0.27	-0.06	-0.06	-0.06	-0.05	-0.12	-0.07	-0.09
unrate	-0.24	1	-0.55	0.06	-0.26	0.26	0.39	-0.28	0.18	0.26	0.28	0.08	0.04
perinc	0.45	-0.55	1	-0.4	0.2	-0.34	-0.48	-0.08	-0.5	-0.36	-0.54	0.37	0.35
beertax	-0.09	0.06	-0.4	1	-0.06	0.18	0.25	0.14	0.31	0.12	0.29	-0.09	-0.03
mlda	-0.08	-0.26	0.2	-0.06	1	0.14	-0.28	0.06	-0.09	-0.21	-0.16	0.07	0.09
dry	-0.27	0.26	-0.34	0.18	0.14	1	0.06	-0.08	0.13	-0.02	0.22	0.03	0.03
yngdrv	-0.06	0.39	-0.48	0.25	-0.28	0.06	1	-0.06	0.23	0.29	0.31	-0.22	-0.23
vmiles	-0.06	-0.28	-0.08	0.14	0.06	-0.08	-0.06	1	0.4	0.23	0.21	-0.24	-0.1
mrall	-0.06	0.18	-0.5	0.31	-0.09	0.13	0.23	0.4	1	0.77	0.75	-0.27	-0.19
mralln	-0.05	0.26	-0.36	0.12	-0.21	-0.02	0.29	0.23	0.77	1	0.68	-0.15	-0.1
mraidall	-0.12	0.28	-0.54	0.29	-0.16	0.22	0.31	0.21	0.75	0.68	1	-0.24	-0.19
pop	-0.07	0.08	0.37	-0.09	0.07	0.03	-0.22	-0.24	-0.27	-0.15	-0.24	1	0.97
miles	-0.09	0.04	0.35	-0.03	0.09	0.03	-0.23	-0.1	-0.19	-0.1	-0.19	0.97	1

From the correlation matrix, we can see that the 2 variables pop(population) and miles travelled(miles) are highly correlated with the correlation of 0.97 between them. Hence, we need to make sure that both the variables are not included in our model

REGRESSION ANALYSIS

Based on our intuition and all the descriptive analysis performed earlier, we decide on the following independent variables for our model: [unemp, beertax, spircons, perinc, mlda, yngdrv, vmiles, jaild, dry, pop]

MODEL 1: POOLING MODEL

To begin our analysis, we start our regression analysis with the pooling model. Here we consider all the above-mentioned variables as the independent variables and the traffic fatality rate as our dependent variable. We get the following output on running the Pooled OLS model.

```
Pooling Model

Call:
plm(formula = mrall ~ spircons + unrate + perinc + beertax +
    mlda + yngdrv + vmiles + I(jaild) + dry + pop, data = dataplm,
    model = "pooling")

Balanced Panel: n = 7, T = 48, N = 336

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-2.6795e-04 -2.4845e-05 -2.5427e-06  2.1934e-05  1.9017e-04

Coefficients:
               Estimate  Std. Error t-value  Pr(>|t|)
(Intercept)  1.8249e-04  7.4762e-05  2.4410   0.01518 *
spircons     1.9927e-05  4.1854e-06  4.7610 2.905e-06 ***
unrate      -7.6252e-07  1.3617e-06 -0.5600   0.57590
perinc      -1.3663e-08  1.9581e-09 -6.9775 1.692e-11 ***
beertax      7.3466e-06  5.6409e-06  1.3024   0.19371
mlda         1.8700e-06  2.8374e-06  0.6591   0.51033
yngdrv       7.1846e-05  1.1412e-04  0.6296   0.52940
vmiles       1.4031e-08  1.7404e-09  8.0617 1.456e-14 ***
I(jaild)     2.9449e-05  5.7071e-06  5.1601 4.305e-07 ***
dry          4.3448e-07  2.8559e-07  1.5213   0.12915
pop          1.1484e-12  5.9227e-13  1.9390   0.05336 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1.0892e-06
Residual Sum of Squares: 5.8617e-07
R-Squared:      0.46181
Adj. R-Squared: 0.44525
F-statistic: 27.8878 on 10 and 325 DF, p-value: < 2.22e-16
```

Below is the result of our regression:

mrall = 1.8249e-04 + 1.9927e-05 * spircons - 7.6252e-07 * unrate - 1.3663e-08 * perinc + 7.3466e-06 * beertax + 1.8700e-06 * mlda + 7.1846e-05 * yngdrv + 1.4031e-08 * vmiles + 2.9449e-05 * I(jaild) + 4.3448e-07 * dry + 1.1484e-12 * pop

From the Pooled OLS model, we find that the variables spircons, beertax, mlda, yngdrv, vmiles, jaild, dry and pop are positively related with the independent variable fatality rate and the variables unrate and perinc are negatively related. Based on our assumptions, we find that the variables Beertax, mlda, jaild, dry are not as expected.

From the entire model, we find that only the variables spircon, perinc, vmiles, jaild are significant. Rest all the variables are insignificant.

These results are not as expected. A pooled model leads to heterogeneity due to unobserved characteristics. The unobserved characteristics could be because of different cultural preferences between different states. These characteristics can be correlated with the dependent variables which in turn will result in endogeneity in the model. To control for the unobserved heterogeneity, we use the fixed effects model

MODEL 2: FIXED EFFECTS MODEL

The fixed effects model helps us control unobserved heterogeneity we observed earlier and thus obtain unbiased and consistent estimators. Below is the fixed effects model which is including the time invariant characteristics.

```
Oneway (individual) effect Within Model

Call:
plm(formula = mrall ~ spircons + unrate + perinc + beertax +
    mlda + yngdrv + vmiles + I(jaild) + dry + pop, data = dataplm,
    model = "within")

Balanced Panel: n = 7, T = 48, N = 336

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-2.3166e-04 -2.5281e-05  3.7518e-07  2.0191e-05  1.9175e-04

Coefficients:
            Estimate  Std. Error t-value  Pr(>|t|)
spircons  2.5601e-05  4.4042e-06  5.8129 1.489e-08 ***
unrate    2.0500e-07  1.4378e-06  0.1426   0.88671
perinc   -1.4747e-08  1.9464e-09 -7.5763 3.883e-13 ***
beertax   4.5437e-06  5.5968e-06  0.8118   0.41749
mlda     -6.3669e-07  2.8648e-06 -0.2222   0.82427
yngdrv    2.9667e-04  1.2956e-04  2.2898   0.02269 *
vmiles    1.2795e-08  1.7528e-09  7.3000 2.308e-12 ***
I(jaild)  2.7256e-05  5.7222e-06  4.7631 2.898e-06 ***
dry       3.7372e-07  2.8241e-07  1.3233   0.18668
pop       1.4086e-12  5.8696e-13  2.3997   0.01698 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1.0842e-06
Residual Sum of Squares: 5.5589e-07
R-Squared:      0.48728
Adj. R-Squared: 0.46157
F-statistic: 30.3177 on 10 and 319 DF, p-value: < 2.22e-16
```

Below is our estimated regression equation:

mrall = 2.5601e-05 * spircons + 2.0500e-07 * unrate - 1.4747e-08 * perinc
+ 4.5437e-06 * beertax - 6.3669e-07 * mlda + 2.9667e-04 * yngdrv
+ 1.2795e-08 * vmiles + 2.7256e-05 * I(jaild) + 3.7372e-07 * dry + 1.4086e-12 * pop

From the Fixed effects model, we find that the variables spircons, beertax, mlda, yngdrv, vmiles, jaild, dry and pop, unrate are positively related with the independent variable fatality rate and the variables mlda and perinc are negatively related. Based on our assumptions, we find that the variables Beertax, jaild, dry are not as expected.

From the entire model, we find that only the variables spircon, perinc, yngdrv, vmiles, jaild and pop are significant. Rest all the variables are insignificant.

TEST FOR SIGNIFICANCE OF THE MODEL

To test the significance of both the models and check for the better model, we conduct a test

Null Hypothesis: Ho: Pooling model is better than the fixed model

Alternated Hypothesis: Fixed model is better than the Pooling model.

```
        F test for individual effects

data:  mrall ~ spircons + unrate + perinc + beertax + mlda + yngdrv +  ...
F = 2.8958, df1 = 6, df2 = 319, p-value = 0.009197
alternative hypothesis: significant effects
```

Since p value is less than 0.05, we conclude that the fixed effects model is the better model.

MODEL3: FIXED TIME EFFECTS MODEL

There could still be presence of variables which can vary over time but are constant over entities. To check for the effect of variables over time, we run the regression on the time fixed effects model.

```
Oneway (time) effect Within Model

Call:
plm(formula = mrall ~ as.factor(year) + spircons + unrate + perinc +
    beertax + mlda + yngdrv + vmiles + I(jaild) + dry + pop,
    data = dataplm, effect = "time", model = "within")

Balanced Panel: n = 7, T = 48, N = 336

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-3.5893e-05 -8.2390e-06  2.9379e-07  7.7725e-06  4.6359e-05

Coefficients:
                       Estimate  Std. Error t-value  Pr(>|t|)
as.factor(year)1983 -5.8849e-06  3.1097e-06 -1.8925  0.059491 .
as.factor(year)1984 -1.7551e-05  4.0584e-06 -4.3246 2.147e-05 ***
as.factor(year)1985 -2.0902e-05  4.6778e-06 -4.4683 1.158e-05 ***
as.factor(year)1986 -6.7198e-06  5.9262e-06 -1.1339  0.257828
as.factor(year)1987 -1.2096e-05  6.9192e-06 -1.7482  0.081552 .
as.factor(year)1988 -1.5911e-05  8.1584e-06 -1.9502  0.052177 .
spircons             8.2772e-05  1.1405e-05  7.2577 4.129e-12 ***
unrate              -5.4493e-06  1.0395e-06 -5.2424 3.186e-07 ***
perinc               8.3814e-09  2.0709e-09  4.0472 6.761e-05 ***
beertax             -4.3003e-05  1.5576e-05 -2.7608  0.006159 **
mlda                 1.4189e-06  1.6769e-06  0.8461  0.398214
yngdrv              -1.3137e-05  8.2343e-05 -0.1595  0.873358
vmiles               1.2272e-09  8.2218e-10  1.4927  0.136680
I(jaild)             4.2429e-06  5.6260e-06  0.7541  0.451412
dry                  2.0772e-06  1.2185e-06  1.7047  0.089387 .
pop                  2.1821e-12  4.1398e-12  0.5271  0.598542
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1.0785e-07
Residual Sum of Squares: 5.7675e-08
R-Squared:      0.46522
Adj. R-Squared: 0.34136
F-statistic: 14.789 on 16 and 272 DF, p-value: < 2.22e-16
```

Below is the estimated regression equation:

mrall = -5.8849e-06 * d83 - 1.7551e-05* d84 - 2.0902e-05 * d85 - 6.7198e-06 * d86 - 1.2096e-05 * d87 - 1.5911e-05 * d88 + 8.2772e-05 * spircons - 5.4493e-06 * unrate + 8.3814e-09 * perinc - 4.3003e-05 * beertax + 1.4189e-06 * mlda - 1.3137e-05 * yngdrv + 1.2272e-09 * vmiles + 4.2429e-06 * I(jaild) + 2.0772e-06 * dry + 2.1821e-12 * pop

From the time fixed effects model, we notice that the variables spircons, mlda, vmiles, jaild, dry and pop, perinc are positively related with the independent variable fatality rate and the variables unrate, beertax, yngdrv are negatively related. Based on our assumptions, we find that the variables unrate, perinc, mlda, yngdrv, jaild are not as expected. The variables spircons, unrate, perinc, beertax are the only significant variables.

The R squared value we get for this model is 0.46522.

WHITE TEST FOR HETEROSKADASTICITY

To control for the heteroskedasticity, we run white test on the model. After running the white test, we find that there is presence of heteroskedasticity which has been corrected. Along with the variables that were significant in the previous model (spircons, unrate, beertax, mlda), we find that even the dry variable is significant.

```
t test of coefficients:

                       Estimate  Std. Error t value  Pr(>|t|)    
as.factor(year)1983 -5.8849e-06  8.5597e-07 -6.8751 4.233e-11 ***
as.factor(year)1984 -1.7551e-05  3.4198e-06 -5.1321 5.460e-07 ***
as.factor(year)1985 -2.0902e-05  3.9299e-06 -5.3186 2.185e-07 ***
as.factor(year)1986 -6.7198e-06  4.9998e-06 -1.3440  0.180069    
as.factor(year)1987 -1.2096e-05  6.0804e-06 -1.9894  0.047658 *  
as.factor(year)1988 -1.5911e-05  7.5229e-06 -2.1150  0.035342 *  
spircons             8.2772e-05  9.6694e-06  8.5602 8.425e-16 ***
unrate              -5.4493e-06  1.4720e-06 -3.7019  0.000259 ***
perinc               8.3814e-09  1.3454e-09  6.2298 1.768e-09 ***
beertax             -4.3003e-05  1.3535e-05 -3.1771  0.001659 ** 
mlda                 1.4189e-06  8.1607e-07  1.7387  0.083212 .  
yngdrv              -1.3137e-05  9.7851e-05 -0.1343  0.893296    
vmiles               1.2272e-09  7.2849e-10  1.6846  0.093207 .  
I(jaild)             4.2429e-06  3.4262e-06  1.2384  0.216651    
dry                  2.0772e-06  4.1289e-07  5.0309 8.883e-07 ***
pop                  2.1821e-12  2.1870e-12  0.9978  0.319286    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

TEST FOR SIGNINFICANCE OF THE MODEL

To test the significance of both the models and check for the better model, we conduct a test

Null Hypothesis: Ho: Time fixed effects is unnecessary

Alternate Hypothesis: Time fixed effects model is the better model

```
        F test for time effects

data:  mrall ~ as.factor(year) + spircons + unrate + perinc + beertax +  ...
F = 49.993, df1 = 47, df2 = 272, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Since p value is less than 0.05, we reject the null hypothesis and conclude that the time fixed effects model is the better model.

CONCLUSION

Fixed effects model with entity and time fixed effects is our best model.

From the above analysis, we can infer that the drunk driving laws (jaild and mlda) may have an impact on vehicle fatalities but here we cannot clearly conclude drunk driving laws affect traffic deaths using our model.

We also conclude that variables spircons, unrate, perinc, beertax and dry are significant at 5% significance level.

Hence, from the fixed effects model with entity and time fixed effects, and from the data given to us, we conclude that drunk driving laws have the following effects on fatality rate:

- For a 1$ increase in beertax per year on a case of beer, the fatality rate decreases by 0.4 x e^-5. % (Significant at 5%) for each state.

Therefore, other variables such as unemployment rate, Per Capita Alcohol consumption, Per Capita Personal income and dry have a larger effect on fatality rate than just the drunk driving laws as our model shows us that these variables are highly significant.