DREW UNIVERSITY / MADISON NJ

Chicago Insurance Redlining

(Regression Analysis Report)

By

Malik Hassan Qayyum

Supervisor

Dr. Ellie Small

Table of Contents

Background

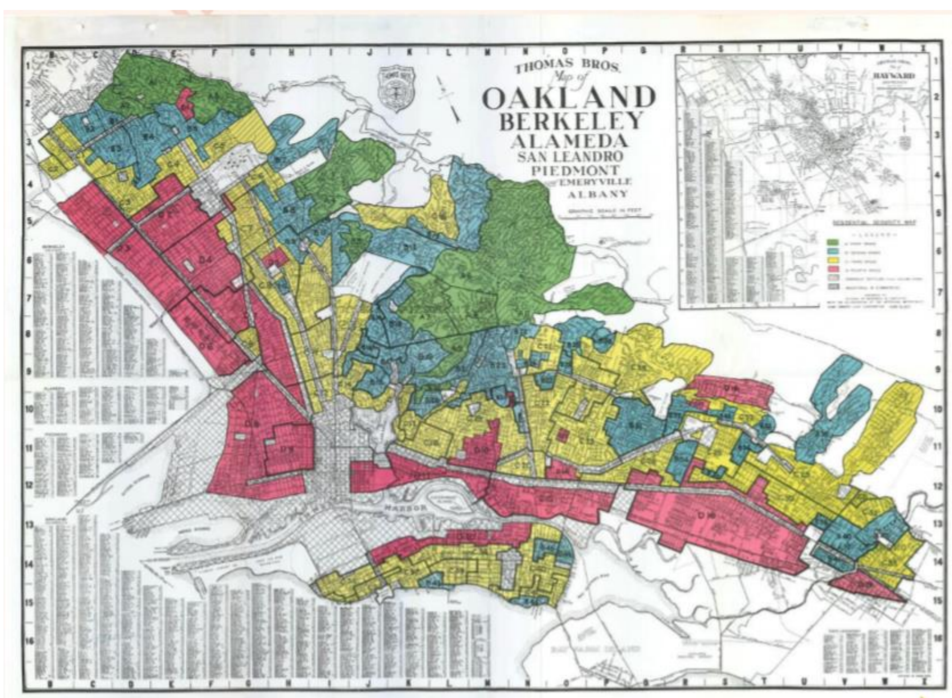
The term redlining originates from the 1930s practice of color-coding maps of cities based on different neighborhoods' eligibility to receive a loan or mortgage. The lowest ranked neighborhoods were often literally lined in red and were almost always a community of color or other marginalized identity.

Redlining began in 1935 when the Home Owner's Loan Corporation began producing maps of virtually every major city upon request of the Federal Home Loan Bank Board.

Neighborhoods were color coded based on their desirability, from "A - First Grade" to "D - Fourth Grade." Most often the "D" ranking neighborhoods were black communities, or other communities of minorities, while the "A" ranking neighborhoods were affluent white suburbs.

The maps were used by both public and private banks and loan offices to directly discriminate and refuse loans to residents of the "D" neighborhoods.

The Fair Housing Act of 1968 made discrimination during the process of selling a house illegal, yet redlining was not effectively outlawed until 1977. The Home Mortgage Disclosure Act of 1975 required transparency thus making redlining unfeasible, and was followed by the Community Reinvestment Act of 1977 that finally prohibited it



A red lined map of Oakland, California, created by Home Owner's Loan Corporation.

Data Source

In a study of insurance availability in Chicago, the U.S. Commission on Civil Rights attempted to examine charges by several community organizations that insurance companies were redlining their neighborhoods, i.e. canceling policies or refusing to insure or renew.

First the Illinois Department of Insurance provided the number of cancellations, non-renewals, new policies, and renewals of homeowners and residential fire insurance policies by ZIP code for the months of December 1977 through February 1978. The companies that provided this information account for more than 70% of the homeowner's insurance policies written in the City of Chicago. The department also supplied the number of FAIR plan policies written a renewed in Chicago by zip code for the months of December 1977 through May 1978. Since most FAIR plan policyholders secure such coverage only after they have been rejected by the voluntary market, rather than as a result of a preference for that type of insurance, the distribution of FAIR plan policies is another measure of insurance availability in the voluntary market.

Secondly, the Chicago Police Department provided crime data, by beat, on all thefts for the year 1975. Most Insurance companies claim to base their underwriting activities on loss data from the preceding years, i.e. a 2-3-year lag seems reasonable for analysis purposes. the Chicago Fire Department provided similar data on fires occurring during 1975. These fire and theft data were organized by zip code.

Finally, the US Bureau of the census supplied data on racial composition, income and age and value of residential units for each ZIP code in Chicago. To adjust for these differences in the populations size associated with different ZIP code areas, the theft data were expressed as incidents per 1,000 population and the fire and insurance data as incidents per 100 housing units.

Variables

Following are the variables of the data source.

race racial: composition in percent minority

fire: fires per 100 housing units

theft: theft per 1000 population

age: percent of housing units built before 1939

volact: new homeowner policies plus renewals minus cancellations and non-renewals per 100 housing units

involact: new FAIR plan policies and renewals per 100 housing units

income: median family income

Goal

To compute the effect of different parameters on insurance redlining in 1975, in which race has been a dominant contributor. To Creating a Linear model for the involuntary market activity variable (the number getting FAIR plan insurance) based on the other parameters. Hence, we can compare the parameters who effects the redlining most in the past vs the one's which are affecting it now. This regression analysis will give a comparison matric to the policy maker to measure the changes of insurance redlining now and then.

Initial Data Analysis

Summary

```
summary(chicago)
##       race             fire            theft              age
##  Min.   : 1.00   Min.   : 2.00   Min.   :  3.00   Min.   : 2.00
##  1st Qu.: 3.75   1st Qu.: 5.65   1st Qu.: 22.00   1st Qu.:48.60
##  Median :24.50   Median :10.40   Median : 29.00   Median :65.00
##  Mean   :34.99   Mean   :12.28   Mean   : 32.36   Mean   :60.33
##  3rd Qu.:57.65   3rd Qu.:16.05   3rd Qu.: 38.00   3rd Qu.:77.30
##  Max.   :99.70   Max.   :39.70   Max.   :147.00   Max.   :90.10
##      volact          involact          income
##  Min.   : 0.50   Min.   :0.0000   Min.   : 5583
##  1st Qu.: 3.10   1st Qu.:0.0000   1st Qu.: 8447
##  Median : 5.90   Median :0.4000   Median :10694
##  Mean   : 6.53   Mean   :0.6149   Mean   :10696
##  3rd Qu.: 9.65   3rd Qu.:0.9000   3rd Qu.:11989
##  Max.   :14.30   Max.   :2.2000   Max.   :21480
```

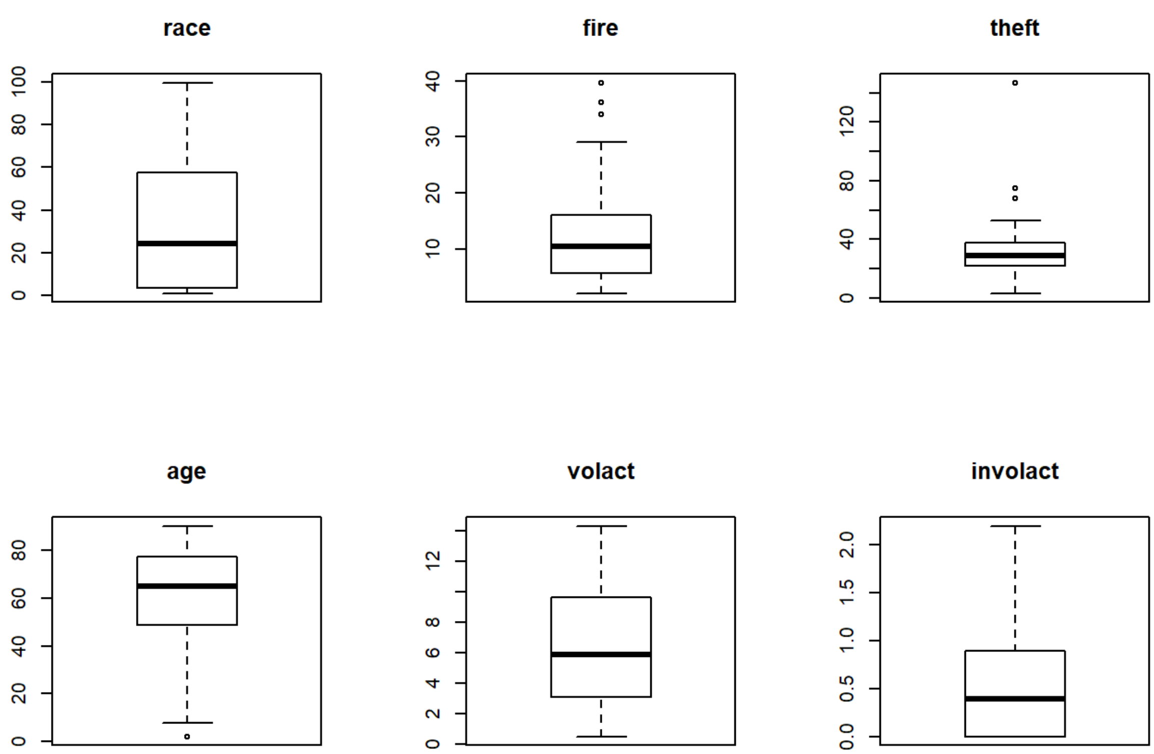
Income has much bigger numbers then other parameters. It would have greater weight in the regression model. Hence, to avoid this we standardize the income variable.

Scaling Income variable

```
ch = chicago
ch$income = ch$income/1000
summary(ch)
##       race             fire            theft              age
##  Min.   : 1.00   Min.   : 2.00   Min.   :  3.00   Min.   : 2.00
##  1st Qu.: 3.75   1st Qu.: 5.65   1st Qu.: 22.00   1st Qu.:48.60
```

```
##  Median :24.50   Median :10.40   Median : 29.00   Median :65.00
##  Mean   :34.99   Mean   :12.28   Mean   : 32.36   Mean   :60.33
##  3rd Qu.:57.65   3rd Qu.:16.05   3rd Qu.: 38.00   3rd Qu.:77.30
##  Max.   :99.70   Max.   :39.70   Max.   :147.00   Max.   :90.10
##      volact          involact          income
##  Min.   : 0.50   Min.   :0.0000   Min.   : 5.583
##  1st Qu.: 3.10   1st Qu.:0.0000   1st Qu.: 8.447
##  Median : 5.90   Median :0.4000   Median :10.694
##  Mean   : 6.53   Mean   :0.6149   Mean   :10.696
##  3rd Qu.: 9.65   3rd Qu.:0.9000   3rd Qu.:11.989
##  Max.   :14.30   Max.   :2.2000   Max.   :21.480
```

```
par(mfrow=c(2,3))
for(i in 1:6)
boxplot(chicago[,i],main=names(chicago)[i])
```

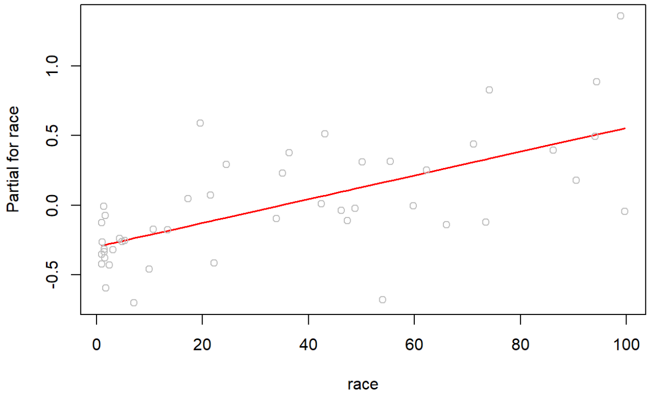


Boxplots show some unusual observations, that we are later going to deal with.

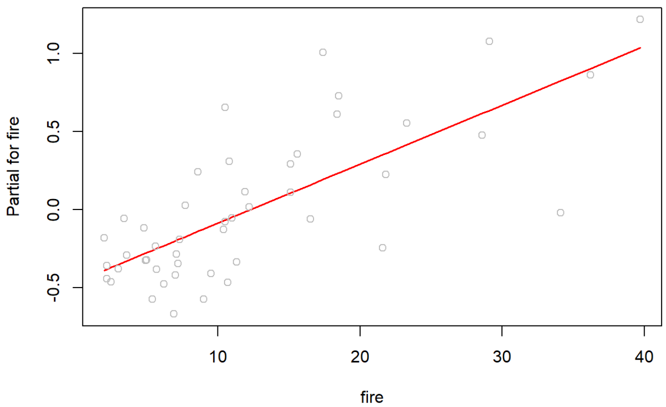
Assumptions

Checking the linear Structure of the model

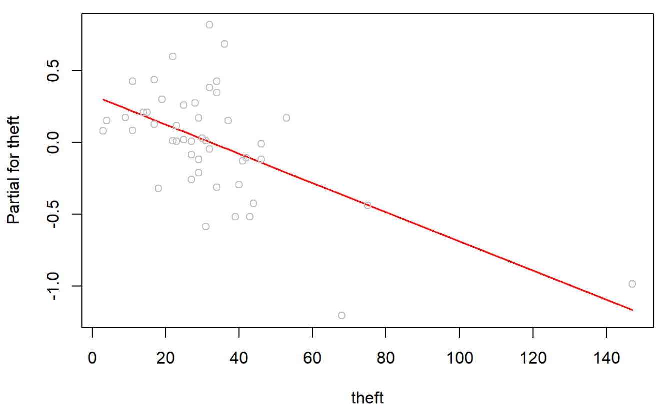
```
ch= data.frame(ch)
lmod_full <- lm(involact~., ch)
lmod_full$rank
## [1] 7
summary(lmod_full)
##
## Call:
## lm(formula = involact ~ ., data = ch)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.84296 -0.14613 -0.01007  0.18386  0.81235
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.486201   0.602048  -0.808 0.424109
## race         0.008527   0.002863   2.978 0.004911 **
## fire         0.037780   0.008982   4.206 0.000142 ***
## theft       -0.010160   0.002908  -3.494 0.001178 **
## age          0.007615   0.003330   2.287 0.027582 *
## volact      -0.010180   0.027734  -0.367 0.715519
## income       0.025685   0.032199   0.798 0.429759
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3387 on 40 degrees of freedom
## Multiple R-squared:  0.7517, Adjusted R-squared:  0.7144
## F-statistic: 20.18 on 6 and 40 DF,  p-value: 1.072e-10
termplot(lmod_full, partial.resid = T, terms=1)
```



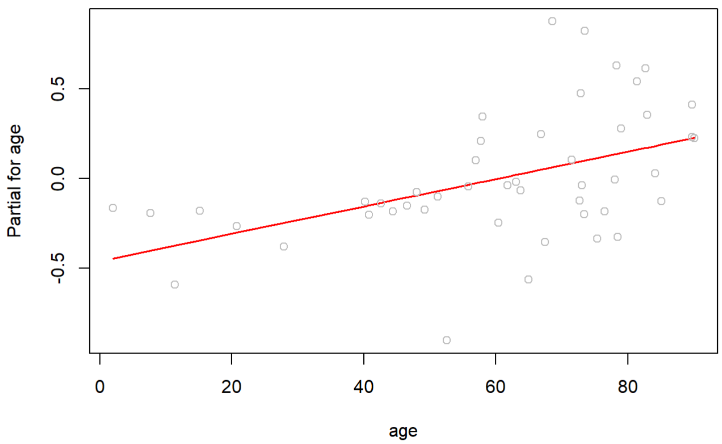

```
termplot(lmod_full, partial.resid = T, terms=2)
```



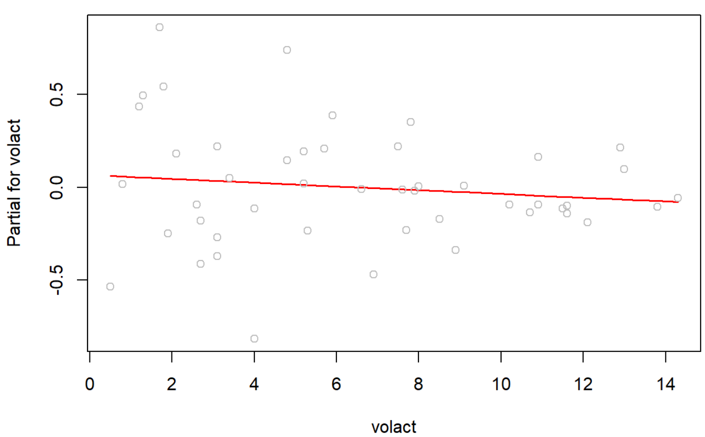

```
termplot(lmod_full, partial.resid = T, terms=3)
```



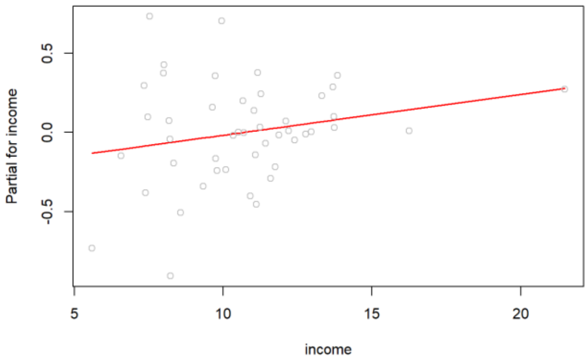
```
termplot(lmod_full, partial.resid = T, terms=4)
```




```
termplot(lmod_full, partial.resid = T, terms=5)
```



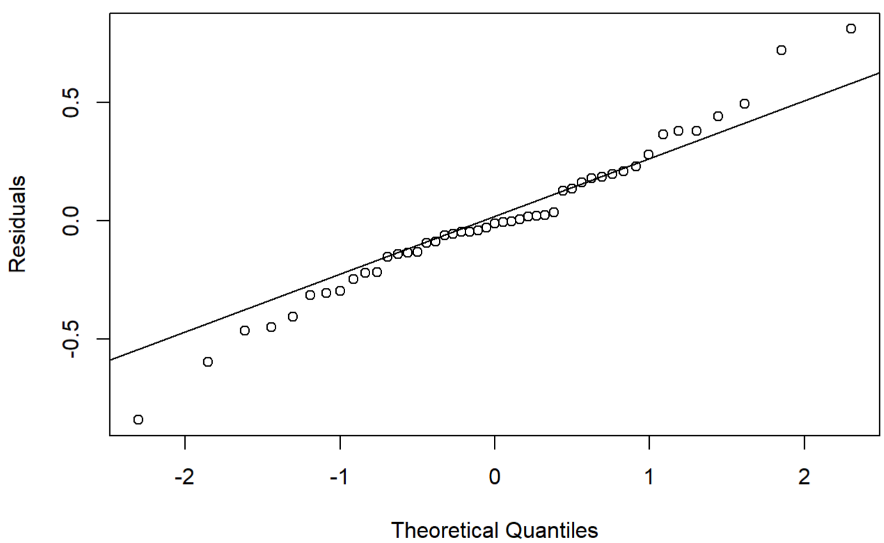

```
termplot(lmod_full, partial.resid = T, terms=6)
```



Structure is linear as we checked for every predictor.

Checking Normality

```
qqnorm(residuals(lmod_full),ylab = "Residuals", main ="")
qqline(residuals(lmod_full))
```



It looks we have fatter tails distribution.
We use Shapiro Test for verification.

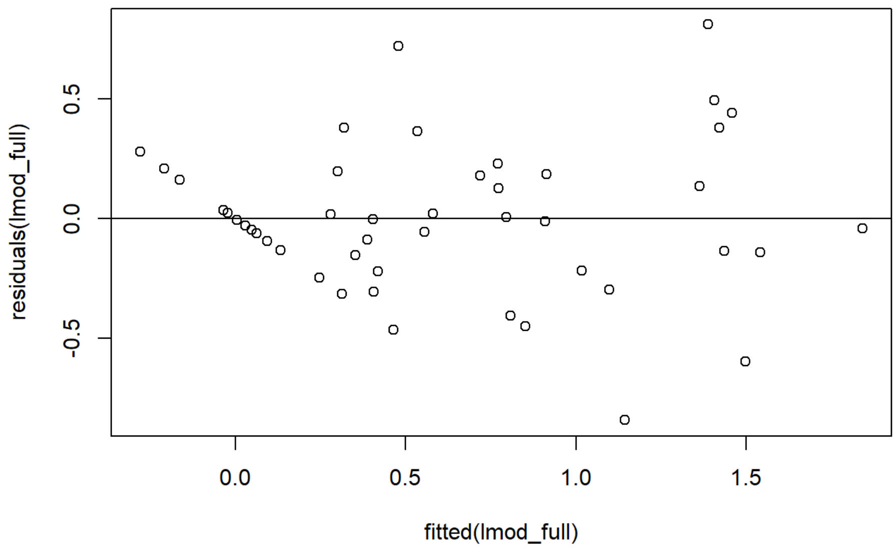
```
#Checking using Shapiro Test
shapiro.test(residuals(lmod_full))
##
##  Shapiro-Wilk normality test
```

```
##
## data:  residuals(lmod_full)
## W = 0.98095, p-value = 0.6317
```

P-value High, Accepting Null hypotheses. Dist. is Normal.

Checking Error Variance

```
plot(fitted(lmod_full),residuals(lmod_full))
abline(h=0)
```



Looks constant variance with few anomalies.

Checking Collinearity

```
X = model.matrix(lmod_full)[,-1]
cor(X)
```

```
##              race       fire      theft        age     volact     income
## race    1.0000000  0.5927956  0.2550647  0.2505118 -0.7594196 -0.7037328
## fire    0.5927956  1.0000000  0.5562105  0.4122225 -0.6864766 -0.6104481
## theft   0.2550647  0.5562105  1.0000000  0.3176308 -0.3116183 -0.1729226
## age     0.2505118  0.4122225  0.3176308  1.0000000 -0.6057428 -0.5286695
## volact -0.7594196 -0.6864766 -0.3116183 -0.6057428  1.0000000  0.7509780
```

```
## income -0.7037328 -0.6104481 -0.1729226 -0.5286695  0.7509780  1.0000000
vif(X)
##     race     fire    theft      age   volact   income
## 3.491088 2.798840 1.684571 2.266203 4.851903 3.153110
```

Every Predictor is under 5. we are safe. (volact has relatively high correlation with other predictors
Building model without volact:

```
lmod1_without_volcat = lm(involact ~  race + fire + theft + age + income, ch )
summary(lmod1_without_volcat)
##
## Call:
## lm(formula = involact ~ race + fire + theft + age + income, data = ch)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.84428 -0.15804 -0.04093  0.18116  0.80828
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.608979   0.495260  -1.230 0.225851
## race         0.009133   0.002316   3.944 0.000307 ***
## fire         0.038817   0.008436   4.602    4e-05 ***
## theft       -0.010298   0.002853  -3.610 0.000827 ***
## age          0.008271   0.002782   2.973 0.004914 **
## income       0.024500   0.031697   0.773 0.443982
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3351 on 41 degrees of freedom
## Multiple R-squared:  0.7508, Adjusted R-squared:  0.7204
## F-statistic: 24.71 on 5 and 41 DF,  p-value: 2.159e-11
```

Model without volcat performs better.

Now, Checking this using anova().

```
anova(lmod1_without_volcat,lmod_full)
## Analysis of Variance Table
##
## Model 1: involact ~ race + fire + theft + age + income
## Model 2: involact ~ race + fire + theft + age + volact + income
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1     41 4.6047
## 2     40 4.5892  1  0.015457 0.1347 0.7155
```

H0: Beta(r) = 0
H1: Beta(r) != 0

High p-value accept Null Hypotheses.
simple words: volcat is not significant.

Checking Summary of the model

```
summary(lmod1_without_volcat)
##
## Call:
## lm(formula = involact ~ race + fire + theft + age + income, data = ch)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.84428 -0.15804 -0.04093  0.18116  0.80828
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.608979   0.495260  -1.230 0.225851
## race         0.009133   0.002316   3.944 0.000307 ***
## fire         0.038817   0.008436   4.602    4e-05 ***
## theft       -0.010298   0.002853  -3.610 0.000827 ***
## age          0.008271   0.002782   2.973 0.004914 **
## income       0.024500   0.031697   0.773 0.443982
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3351 on 41 degrees of freedom
## Multiple R-squared:  0.7508, Adjusted R-squared:  0.7204
## F-statistic: 24.71 on 5 and 41 DF,  p-value: 2.159e-11
```

P-value of income is high. means it insignificant.

Let's try removing income.

```
lmod2_without_volcat_income = lm(involact ~ race + fire + theft + age, ch)
summary(lmod2_without_volcat_income)
##
## Call:
## lm(formula = involact ~ race + fire + theft + age, data = ch)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.87108 -0.14830 -0.01961  0.19968  0.81638
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.243118   0.145054  -1.676 0.101158
## race         0.008104   0.001886   4.297 0.000100 ***
## fire         0.036646   0.007916   4.629 3.51e-05 ***
## theft       -0.009592   0.002690  -3.566 0.000921 ***
## age          0.007210   0.002408   2.994 0.004595 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3335 on 42 degrees of freedom
## Multiple R-squared:  0.7472, Adjusted R-squared:  0.7231
## F-statistic: 31.03 on 4 and 42 DF,  p-value: 4.799e-12
```

Removing income does not make much of the difference

Comparing models using anova():

```
anova(lmod2_without_volcat_income,lmod1_without_volcat)
## Analysis of Variance Table
##
## Model 1: involact ~ race + fire + theft + age
## Model 2: involact ~ race + fire + theft + age + income
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1     42 4.6718
## 2     41 4.6047  1  0.067101 0.5975  0.444
```

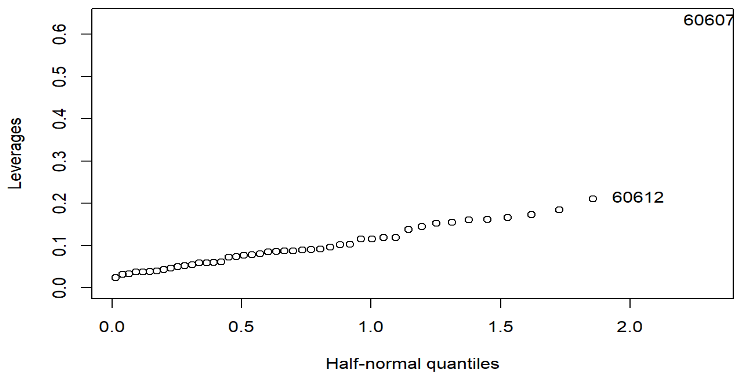
H0: Beta(r) = 0
H1: Beta(r) != 0

Significance level = 5%
High p-value accept Null Hypothesis.
simple words: income is not significant.

Checking Unusual Observations

Checking Leverage Points

```
zips = row.names(ch)
hat_vals = hatvalues(lmod2_without_volcat_income)
halfnorm(hat_vals,labs = zips, ylab = "Leverages")
```



Zip Code: 60607 seems to be high leverage point.

Checking this observation:

```
row1 = which(rownames(ch) == 60607)
ch[row1,]
##        race fire theft age volact involact income
## 60607 50.2 39.7   147  83    5.2      0.9  7.459
```

We can observe high theft in this observation

See what's happens if we remove this observation.

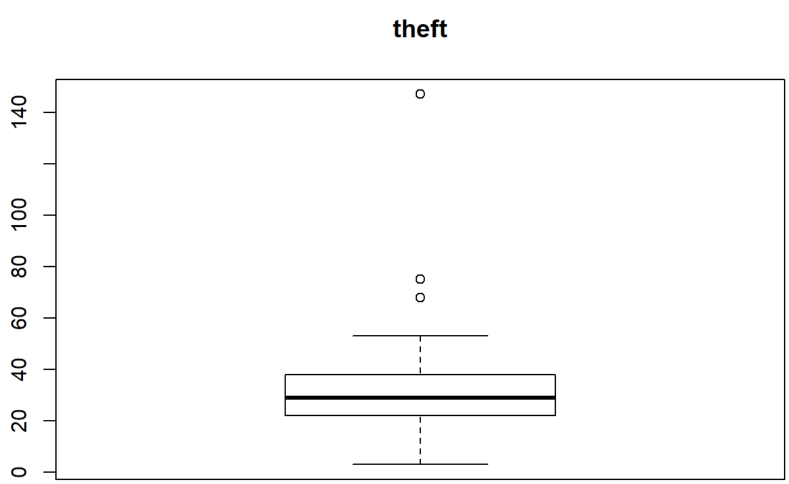
```
lmod3_modified_1 = lm(involact ~ race + fire + theft + age ,ch[-row1])
summary(lmod3_modified_1)
##
## Call:
## lm(formula = involact ~ race + fire + theft + age, data = ch[-row1])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.87108 -0.14830 -0.01961  0.19968  0.81638
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.243118   0.145054  -1.676 0.101158
## race         0.008104   0.001886   4.297 0.000100 ***
```

```
## fire          0.036646   0.007916   4.629 3.51e-05 ***
## theft        -0.009592   0.002690  -3.566 0.000921 ***
## age           0.007210   0.002408   2.994 0.004595 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3335 on 42 degrees of freedom
## Multiple R-squared:  0.7472, Adjusted R-squared:  0.7231
## F-statistic: 31.03 on 4 and 42 DF,  p-value: 4.799e-12
```

No Effect. As it is not affecting the model let it be in the model but report the case.

Further Investigation:

```
theft = 3
boxplot(ch[,theft],main=names(ch)[theft])
```



This observation theft value is far higher than other observation. it must be reported.

Checking Outliers

```
sort(abs(residuals(lmod2_without_volcat_income)))
##        60631       60619       60632       60616       60638       60618
## 0.001966931 0.004373166 0.007351602 0.013648913 0.018400932 0.019607322
```

```
##       60651       60643       60645       60612       60646       60635
## 0.021481962 0.036764563 0.038561267 0.043673115 0.069513114 0.079401224
##       60634       60629       60607       60636       60630       60609
## 0.085058456 0.090890292 0.093118206 0.104531778 0.110429605 0.118843923
##       60633       60655       60608       60620       60639       60644
## 0.126700197 0.131776158 0.148096306 0.160332787 0.169898411 0.186612598
##       60657       60656       60647       60611       60626       60628
## 0.193319018 0.206048996 0.207880464 0.212589033 0.222429899 0.238847285
##       60627       60652       60637       60640       60641       60614
## 0.250934003 0.255827264 0.308243446 0.314421019 0.323936345 0.350925819
##       60649       60617       60624       60615       60622       60625
## 0.358846125 0.360328508 0.385193257 0.451842984 0.457316717 0.460601200
##       60623       60653       60613       60621       60610
## 0.510361779 0.627657515 0.714891996 0.816376747 0.871077427
```

Following are the outlier observations

60653	60613	60621	60610
0.990274659	1.127907196	1.288022823	1.374325778

Now Let’s Try by removing them

```
#Getting Outlier Rows
rn = rownames(ch)
rows_outliers = subset(ch, rn == 60610 | rn == 60621 | rn == 60613 | rn == 60653)
rows_outliers
##       race fire theft  age volact involact income
## 60613 19.6 10.5    36 73.5    4.8      1.2  9.948
## 60610 54.0 34.1    68 52.6    4.0      0.3  8.231
## 60653 99.7 21.6    31 65.0    0.5      0.9  5.583
## 60621 98.9 17.4    32 68.6    1.7      2.2  7.520
#buliding model with out them
lmod2_without_volcat_income_outlier_removed = lm(involact ~ race + fire + theft + ag
e, data = ch[-c(60653,60613,60621,60610),])
summary(lmod2_without_volcat_income)
```

```
##
## Call:
## lm(formula = involact ~ race + fire + theft + age, data = ch)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.87108 -0.14830 -0.01961  0.19968  0.81638
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.243118   0.145054  -1.676 0.101158
## race         0.008104   0.001886   4.297 0.000100 ***
## fire         0.036646   0.007916   4.629 3.51e-05 ***
## theft       -0.009592   0.002690  -3.566 0.000921 ***
## age          0.007210   0.002408   2.994 0.004595 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3335 on 42 degrees of freedom
## Multiple R-squared:  0.7472, Adjusted R-squared:  0.7231
## F-statistic: 31.03 on 4 and 42 DF,  p-value: 4.799e-12
```

```
summary(lmod2_without_volcat_income_outlier_removed)
```

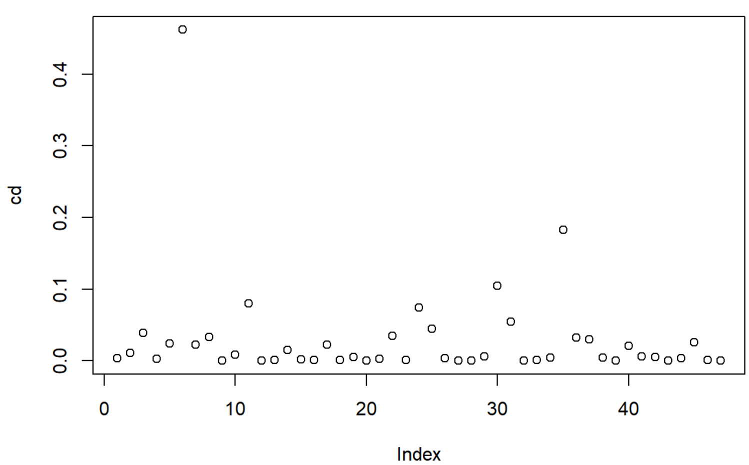
```
##
## Call:
## lm(formula = involact ~ race + fire + theft + age, data = ch[-c(60653,
##     60613, 60621, 60610), ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.87108 -0.14830 -0.01961  0.19968  0.81638
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.243118   0.145054  -1.676 0.101158
```

```
## race          0.008104   0.001886   4.297 0.000100 ***
## fire          0.036646   0.007916   4.629 3.51e-05 ***
## theft        -0.009592   0.002690  -3.566 0.000921 ***
## age           0.007210   0.002408   2.994 0.004595 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3335 on 42 degrees of freedom
## Multiple R-squared:  0.7472, Adjusted R-squared:  0.7231
## F-statistic: 31.03 on 4 and 42 DF,  p-value: 4.799e-12
```

Does not make any difference in the result. Hence, we let them in the model.

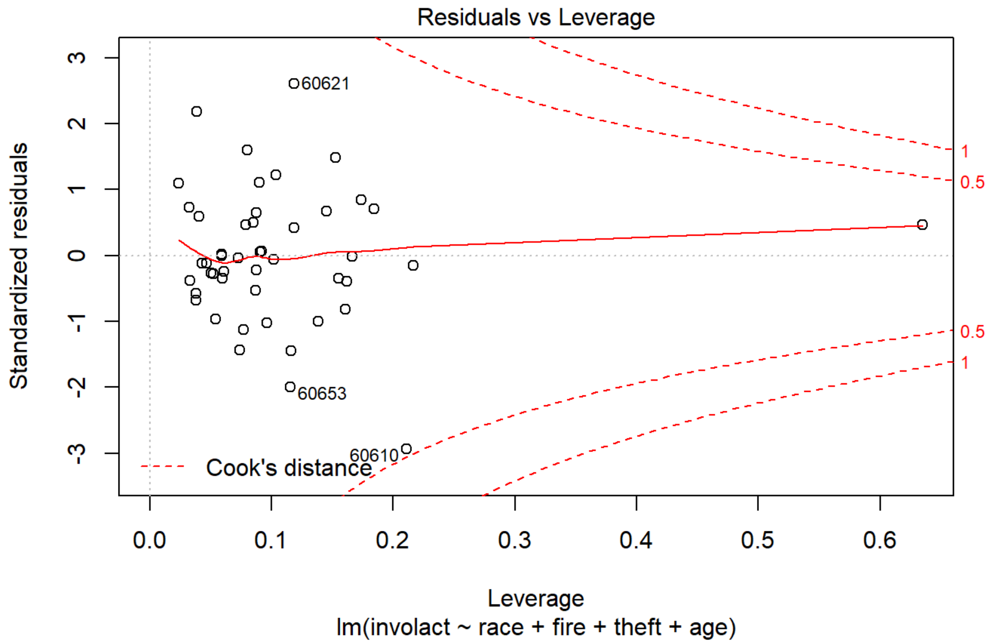
Checking Influential Observations

```
cd = cooks.distance(lmod2_without_volcat_income)
plot(cd)
abline(h=0.5)
```



2nd method

```
plot(lmod2_without_volcat_income)
```



No point is Over 0.5.

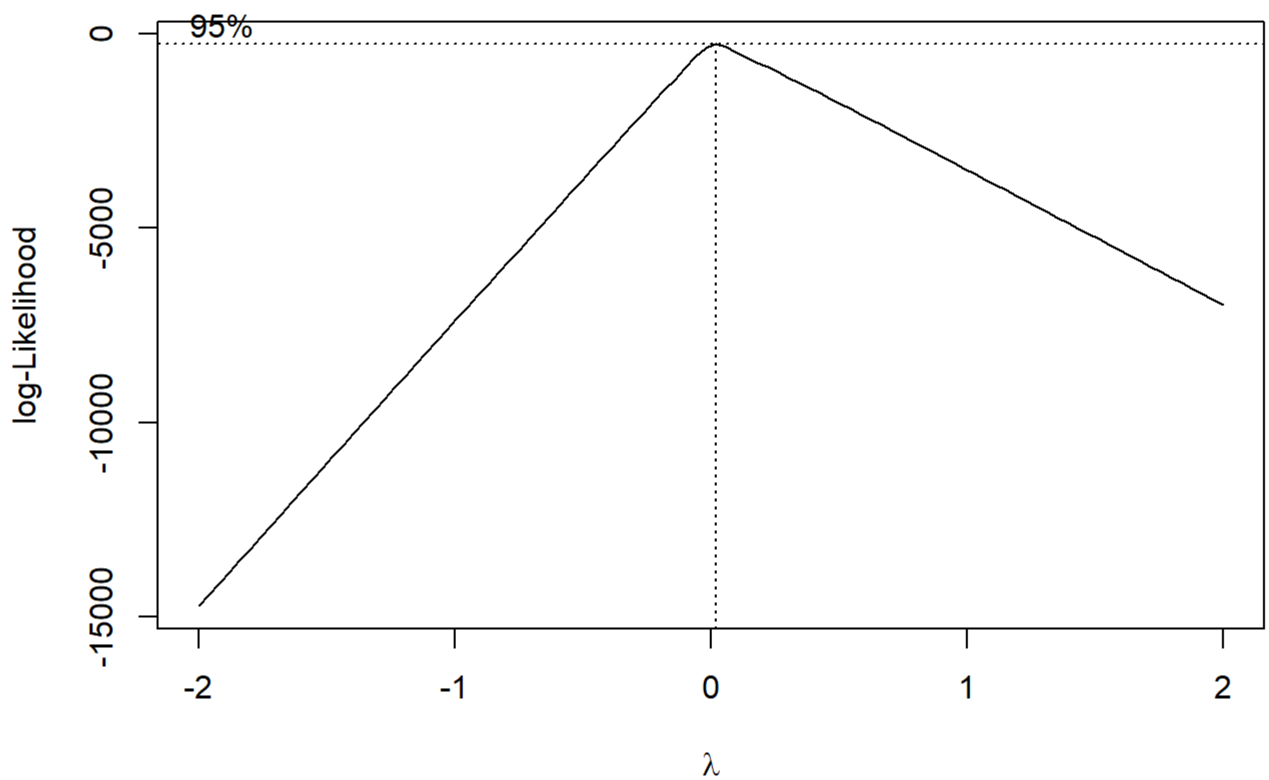
No Influential Observations.

Transformations

Power Transformation

```
# Reponses do not have strictly positive number
unique(ch$involact)

##  [1] 0.0 0.1 1.2 0.5 0.7 0.3 0.4 1.1 1.9 0.2 0.8 1.8 0.9 1.5 0.6 1.3 1.4 2.2 1.0

which(ch$involact == 0.0)

##  [1]  1  7  8 12 13 14 15 16 17 18 32 33 37 42 47


#scale response by adding 10^-100
ch2 = ch
ch2$involact =  ch$involact + (10^-100)


#creating new model with scaled response
lmod4_without_volcat_income_resposeScaledPositive = lm(involact ~ race + fire + thef
t + age, ch2)


summary(lmod2_without_volcat_income)$r.squared
```

```
## [1] 0.7471912
summary(lmod4_without_volcat_income_resposeScaledPositive)$r.squared
## [1] 0.7471912
#doesnt not makes much of the difference


#Ploting boxcox
bc = boxcox(lmod4_without_volcat_income_resposeScaledPositive, plotit=T)
```



Unable to interpret the diagram. Let's try the transform directly if the model works better then fine else revert.

```
bc$x[which.max(bc$y)]
## [1] 0.02020202
```

Best possible Power transformation is ^0.0202

Applying Transformation:

```
lmod5_without_volcat_income_resposeScaledPositive_powerT = lm(involact^0.0202 ~ race
+ fire + theft + age, ch2)

summary(lmod4_without_volcat_income_resposeScaledPositive)

##

## Call:

## lm(formula = involact ~ race + fire + theft + age, data = ch2)

##

## Residuals:

##      Min       1Q   Median       3Q      Max

## -0.87108 -0.14830 -0.01961  0.19968  0.81638

##

## Coefficients:

##              Estimate Std. Error t value Pr(>|t|)

## (Intercept) -0.243118   0.145054  -1.676 0.101158

## race         0.008104   0.001886   4.297 0.000100 ***

## fire         0.036646   0.007916   4.629 3.51e-05 ***

## theft       -0.009592   0.002690  -3.566 0.000921 ***

## age          0.007210   0.002408   2.994 0.004595 **

## ---

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##

## Residual standard error: 0.3335 on 42 degrees of freedom

## Multiple R-squared:  0.7472, Adjusted R-squared:  0.7231

## F-statistic: 31.03 on 4 and 42 DF,  p-value: 4.799e-12

summary(lmod5_without_volcat_income_resposeScaledPositive_powerT)

##

## Call:

## lm(formula = involact^0.0202 ~ race + fire + theft + age, data = ch2)

##

## Residuals:

##     Min      1Q  Median      3Q     Max

## -0.5646 -0.2323 -0.0291  0.2607  0.5683

##
```

```
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.0787021  0.1312383  -0.600  0.55194
## race         0.0072822  0.0017063   4.268  0.00011 ***
## fire         0.0076946  0.0071624   1.074  0.28882
## theft       -0.0006683  0.0024339  -0.275  0.78499
## age          0.0071348  0.0021785   3.275  0.00212 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3018 on 42 degrees of freedom
## Multiple R-squared:  0.6134, Adjusted R-squared:  0.5765
## F-statistic: 16.66 on 4 and 42 DF,  p-value: 2.992e-08
```

Before Transformation R2 was 0.7472
After Transformation R2 is 0.6134
Model works better without Transformation. Hence continuing with model 2.

Polynomials

Let's try polynomial on "theft":

```
#Previous model
summary(lmod2_without_volcat_income)$r.squared
## [1] 0.7471912
summary(lmod2_without_volcat_income)$adj.r.squared
## [1] 0.7231142
#model with poly 2
lmod7_without_volcat_income_poly2 = lm(involact ~ race + fire + poly(theft,2) + age,
ch2)
summary(lmod7_without_volcat_income_poly2)$r.squared
## [1] 0.7472763
summary(lmod7_without_volcat_income_poly2)$adj.r.squared
## [1] 0.7164564
#model with poly 3
lmod8_without_volcat_income_poly3 = lm(involact ~ race + fire + poly(theft,3) + age,
ch2)
summary(lmod8_without_volcat_income_poly3)$r.squared
```

```
## [1] 0.76032
summary(lmod8_without_volcat_income_poly3)$adj.r.squared
## [1] 0.724368
#model with poly 4
lmod9_without_volcat_income_poly4 = lm(involact ~ race + fire + poly(theft,4) + age,
ch2)
summary(lmod9_without_volcat_income_poly4)$r.squared
## [1] 0.7606418
summary(lmod9_without_volcat_income_poly4)$adj.r.squared
## [1] 0.71768
```

3rd polynomial of theft makes model better. Hence, continue with model 8.

Evaluating the model

Train and Test data

```
##Test_data
#Selecting Few random rows from data
test_data = ch2[sample(nrow(ch2), 5), ]
options(scipen = 999) #disabling Scintific notation
round(test_data,2)
##        race fire theft  age volact involact income
## 60630  1.6  2.5    22 63.8   10.7      0.0  12.40
## 60609 46.2 21.8     4 73.1    2.6      1.3   8.33
## 60643 42.5 10.4    25 40.8   10.2      0.5  12.96
## 60607 50.2 39.7   147 83.0    5.2      0.9   7.46
## 60639  2.5  7.2    29 84.2    8.5      0.2  11.08
##Train_data
rows= as.numeric(row.names(test_data))
train_data = ch2[-rows,]
head(round(train_data,2))
##        race fire theft  age volact involact income
## 60626 10.0  6.2    29 60.4    5.3      0.0  11.74
## 60640 22.2  9.5    44 76.5    3.1      0.1   9.32
## 60613 19.6 10.5    36 73.5    4.8      1.2   9.95
```

```
## 60657 17.3  7.7    37 66.9    5.7       0.5  10.66
## 60614 24.5  8.6    53 81.4    5.9       0.7   9.73
## 60610 54.0 34.1    68 52.6    4.0       0.3   8.23
```

Training the model

```
#Training the model
lmod_final = lm(involact ~ race + fire + poly(theft,3) + age, data = train_data)
summary(lmod_final)
##
## Call:
## lm(formula = involact ~ race + fire + poly(theft, 3) + age, data = train_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.71209 -0.16182 -0.01792  0.17004  0.79694
##
## Coefficients:
##                   Estimate Std. Error t value  Pr(>|t|)
## (Intercept)      -0.450491   0.174390  -2.583  0.013550 *
## race              0.007628   0.002036   3.747  0.000564 ***
## fire              0.039080   0.008425   4.639 0.0000372 ***
## poly(theft, 3)1 -1.415081   0.406476  -3.481  0.001221 **
## poly(theft, 3)2 -0.074267   0.380385  -0.195  0.846193
## poly(theft, 3)3  0.562725   0.381402   1.475  0.147931
## age               0.005282   0.002882   1.833  0.074258 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3328 on 40 degrees of freedom
## Multiple R-squared:  0.7603, Adjusted R-squared:  0.7244
## F-statistic: 21.15 on 6 and 40 DF,  p-value: 0.00000000005386
```

Testing the model

```
#Testing the model
```

```
test_data_with_removed_varibles = test_data[,-c(5,6,7)]
predict(lmod_final,test_data_with_removed_varibles )
##     60630     60609     60643     60607     60639
## 0.1252968 1.2089165 0.6096953 0.9044523 0.3797168
round(test_data,2)
##        race fire theft  age volact involact income
## 60630   1.6  2.5    22 63.8   10.7      0.0  12.40
## 60609  46.2 21.8     4 73.1    2.6      1.3   8.33
## 60643  42.5 10.4    25 40.8   10.2      0.5  12.96
## 60607  50.2 39.7   147 83.0    5.2      0.9   7.46
## 60639   2.5  7.2    29 84.2    8.5      0.2  11.08
```

Predicted values are almost same as the actual values. Hence, Our Model Performs Well.

Amendment:

Transformed *theft* to various polynomial degrees and also tried power transformations. It turned out that non of them improves the model performance.

```
lmod2_without_volcat_income = lm(involact ~ race + fire + theft + age, ch)
```

Hence, this is our final model.

Conclusion:

We can conclude that racial composition, fire, theft and age of housing drives the redlining. However, the family income was not a significant contributor. Taking these factors into account policy makers can make sure to make better polices and laws to outlaw redlining especially the racial composition factor. Resulting, providing equal opportunities for every USA national.

Furthermore, we can question that is the *involact* a true representative of redlining or we can come up with a better measure? How redlining have changed over the period of time? How these analyses can be used for better policy making?

References

Jackson, Kenneth T. Crabgrass Frontier: The Suburbanization of the United States. New York: Oxford UP, 1985. Print.

Squires, Gregory D. “Racial Profiling, Insurance Style: Insurance Redlining and the Uneven Development of Metropolitan Areas.” Journal of Urban Affairs 25.4 (2003): 391-410. Print.

Badger, Emily. “Redlining: Still a thing.” The Washington Post. WP Company, 28 May 2015. Web. 19 Dec. 2016.

Tootell, G. M. B. “Redlining in Boston: Do Mortgage Lenders Discriminate Against Neighborhoods?” The Quarterly Journal of Economics 111.4 (1996): 1049-079. Print.