

Regression_Analysis_Housing_Electricity

2024-01-18

```
### import libraries
```

```
library(car)
```

```
## Loading required package: carData
```

```
library(MASS)  
library(dplyr)
```

```
##
```

```
## Attaching package: 'dplyr'
```

```
## The following object is masked from 'package:MASS':
```

```
##
```

```
##      select
```

```
## The following object is masked from 'package:car':
```

```
##
```

```
##      recode
```

```
## The following objects are masked from 'package:stats':
```

```
##
```

```
##      filter, lag
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
##      intersect, setdiff, setequal, union
```

```
library(tidyr)  
library(fastDummies)  
library(lubridate)
```

```
##
```

```
## Attaching package: 'lubridate'
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
##      date, intersect, setdiff, union
```

```
library(coefplot)
```

```
## Loading required package: ggplot2
```

```
library(ggplot2)
library(leaps)
library(lmtest)
```

```
## Loading required package: zoo
```

```
##
```

```
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
##      as.Date, as.Date.numeric
```

Loading the data

```
df = read.csv("data_cleaned_R_final.csv", head = TRUE)
```

```
head(df, 10)
```

```
##      X age income      political_party
## 1  25  65  3000      CDU/CSU
## 2  26  59   800      Keine Angabe
## 3  27  60  1750      Keine Angabe
## 4  28  73  2500      SPD
## 5  30  43  2500 Einer anderen Partei
## 6  31  49  2300      CDU/CSU
## 7  32  57   600      CDU/CSU
## 8  33  39  5000      SPD
## 9  34  62    0      Keine Angabe
## 10 36  45  2600      Keine Angabe
##
##                                     education
## 1 (Fach-) Hochschulabschluss (Bachelor, Master, Magister, Diplom, Staatsexamen)
## 2      Allgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS)
## 3      Berufsausbildung, Lehre oder Ausbildung an einer Fachschule
## 4      Realschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss
## 5      Berufsausbildung, Lehre oder Ausbildung an einer Fachschule
## 6      Berufsausbildung, Lehre oder Ausbildung an einer Fachschule
## 7      Realschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss
## 8 (Fach-) Hochschulabschluss (Bachelor, Master, Magister, Diplom, Staatsexamen)
## 9 (Fach-) Hochschulabschluss (Bachelor, Master, Magister, Diplom, Staatsexamen)
## 10      Berufsausbildung, Lehre oder Ausbildung an einer Fachschule
##      EUROSTAT      RLK2022      KTU2022
## 1      PU      zentral      Städtischer Kreis
## 2      PU sehr zentral      kreisfreie Großstadt
## 3      IN      peripher Ländlicher Kreis mit Verdichtungsansätzen
```

| | | | | | | |
|-------|----------------------|------------------|---------------------------------|-------------------------|----------|-----------------------|
| ## 4 | IN sehr zentral | | Städtischer Kreis | | | |
| ## 5 | PU sehr zentral | | kreisfreie Großstadt | | | |
| ## 6 | IN zentral | | kreisfreie Großstadt | | | |
| ## 7 | IN zentral | | Städtischer Kreis | | | |
| ## 8 | PU sehr zentral | | kreisfreie Großstadt | | | |
| ## 9 | PU sehr zentral | | kreisfreie Großstadt | | | |
| ## 10 | PU sehr zentral | | kreisfreie Großstadt | | | |
| ## | federal_state | C02_housing | C02_electricity | C02_housing_electricity | | |
| ## 1 | Saarland | 5038.2000 | 1053.000 | 6091.2000 | | |
| ## 2 | Hessen | 1785.0000 | 487.500 | 2272.5000 | | |
| ## 3 | Bayern | 200.1024 | 663.000 | 863.1024 | | |
| ## 4 | Bayern | 648.4800 | 975.000 | 1623.4800 | | |
| ## 5 | Berlin | 1923.4862 | 390.000 | 2313.4862 | | |
| ## 6 | Sachsen-Anhalt | 2793.0960 | 663.000 | 3456.0960 | | |
| ## 7 | Baden-Württemberg | 1620.0000 | 112.000 | 1732.0000 | | |
| ## 8 | Berlin | 902.6745 | 26.320 | 928.9945 | | |
| ## 9 | Nordrhein-Westfalen | 2340.0000 | 825.825 | 3165.8250 | | |
| ## 10 | Hessen | 868.1526 | 47.600 | 915.7526 | | |
| ## | C02_cruise | C02_flight | C02_public_transport | C02_car1 | C02_car2 | C02_car3 |
| ## 1 | 0 | 2440.0 | 0.0 | 1432.728 | 0.000 | 0 |
| ## 2 | 2710 | 5985.0 | 107.8 | 1944.608 | 1037.124 | 0 |
| ## 3 | 0 | 598.5 | 107.8 | 0.000 | 0.000 | 0 |
| ## 4 | 0 | 2287.6 | 0.0 | 1432.728 | 0.000 | 0 |
| ## 5 | 0 | 0.0 | 107.8 | 0.000 | 0.000 | 0 |
| ## 6 | 0 | 532.0 | 107.8 | 3581.820 | 0.000 | 0 |
| ## 7 | 0 | 0.0 | 0.0 | 0.000 | 0.000 | 0 |
| ## 8 | 4878 | 2074.8 | 107.8 | 5185.620 | 5185.620 | 0 |
| ## 9 | 0 | 0.0 | 107.8 | 2226.012 | 2782.515 | 0 |
| ## 10 | 0 | 3894.0 | 107.8 | 0.000 | 0.000 | 0 |
| ## | C02_car4 | C02_car5 | C02_car_total | C02_mobility | C02_food | C02_other_consumption |
| ## 1 | 0 | 0 | 1432.728 | 3872.728 | 1494.628 | 3766.100 |
| ## 2 | 0 | 0 | 2981.731 | 11784.531 | 1731.025 | 1444.879 |
| ## 3 | 0 | 0 | 0.000 | 706.300 | 1180.241 | 2433.480 |
| ## 4 | 0 | 0 | 1432.728 | 3720.328 | 1709.007 | 4152.125 |
| ## 5 | 0 | 0 | 0.000 | 107.800 | 1735.132 | 3766.100 |
| ## 6 | 0 | 0 | 3581.820 | 4221.620 | 1033.474 | 2317.600 |
| ## 7 | 0 | 0 | 0.000 | 0.000 | 1295.785 | 1520.925 |
| ## 8 | 0 | 0 | 10371.240 | 17431.840 | 2384.497 | 1216.740 |
| ## 9 | 0 | 0 | 5008.527 | 5116.327 | 1790.341 | 1376.075 |
| ## 10 | 0 | 0 | 0.000 | 4001.800 | 1407.010 | 3398.905 |
| ## | public_emission | C02_total | belief_diff_housing_electricity | | | |
| ## 1 | | 1152 | 16376.656 | | | -31 |
| ## 2 | | 1152 | 18384.935 | | | -38 |
| ## 3 | | 1152 | 6335.123 | | | 40 |
| ## 4 | | 1152 | 12356.940 | | | -2 |
| ## 5 | | 1152 | 9074.518 | | | -43 |
| ## 6 | | 1152 | 12180.790 | | | -6 |
| ## 7 | | 1152 | 5700.710 | | | -1 |
| ## 8 | | 1152 | 23114.072 | | | 5 |
| ## 9 | | 1152 | 12600.568 | | | -48 |
| ## 10 | | 1152 | 10875.468 | | | -1 |
| ## | belief_diff_mobility | belief_diff_food | belief_diff_other_consumption | | | |
| ## 1 | | -14 | 5 | | | -68 |
| ## 2 | | -42 | -26 | | | 23 |

| | | | |
|-------|-------------------|-----|-----|
| ## 3 | 11 | 49 | 9 |
| ## 4 | -31 | -9 | -36 |
| ## 5 | -2 | -26 | -53 |
| ## 6 | 22 | 93 | 24 |
| ## 7 | 72 | 60 | 37 |
| ## 8 | -67 | -61 | 12 |
| ## 9 | -34 | -5 | 18 |
| ## 10 | -48 | 11 | -64 |
| ## | belief_diff_total | | |
| ## 1 | -15 | | |
| ## 2 | -76 | | |
| ## 3 | 57 | | |
| ## 4 | -8 | | |
| ## 5 | -1 | | |
| ## 6 | 13 | | |
| ## 7 | 68 | | |
| ## 8 | -66 | | |
| ## 9 | -16 | | |
| ## 10 | -2 | | |

Hypotheses for the regression model

1. The first dependent variable: actual CO2 emission H1a: age makes differences in the actual CO2 emission from everyday activity.

H1b: income makes differences in the actual CO2 emission from everyday activity.

H1c: education level makes differences in the actual CO2 emission from everyday activity.

H1d: the place of residence (city or countryside) in the actual CO2 emission from every day activity. H1e: the region (the federal state) makes differences in the actual CO2 emission from everyday activity.

H1f: the political party that the respondent supports makes differences in the actual CO2 emission from everyday activity.

2. The second dependent variable: cons H2a: age makes differences in the consumers' belief about CO2 emission from everyday activity.

H2b: income makes differences in the consumers' belief about CO2 emission from everyday activity.

H2c: education level makes differences in the consumers' belief about CO2 emission from everyday activity.

H2d: the place of residence (city or countryside) makes differences in the consumers' belief about CO2 emission from everyday activity.

H2e: the region (the federal state) makes differences in the consumers' belief about CO2 emission from everyday activity.

H2f: the political party that the respondent supports makes differences in the consumers' belief about CO2 emission from everyday activity.

Independent variables in the dataset

1. age: age, numerical variable
2. income: monthly net income in Euro, numerical variable, less than 10,000 EUR only (outlier removed)
3. education: categorical variable
4. urban_rural_class: categorical variable
5. federal_state: federal state, categorical variable
6. political_party: political_party, categorical variable

Dependent variables in the dataset

1. Actual CO2 from housing, electricity, mobility, food, other consumption

- 1) CO2_housing_electricity
- 2) CO2_mobility
- 3) CO2_food
- 4) CO2_other_consumption
- 5) CO2_total

2. Belief about CO2

- 1) belief_diff_housing_electricity
- 2) belief_diff_mobility
- 3) belief_diff_food
- 4) belief_diff_other_consumption
- 5) belief_diff_total

Data preparation

```
# change into categorical variable
```

```
df$education <-as.factor(df$education)
df$EUROSTAT <-as.factor(df$EUROSTAT)
df$RLK2022 <-as.factor(df$RLK2022)
df$KTU2022 <-as.factor(df$KTU2022)
df$political_party <-as.factor(df$political_party)
df$federal_state <-as.factor(df$federal_state)
```

```
## Select the classification for the urban_rural
```

```
#df1_1<- subset(df, select = -c(KTU2022, RLK2022) #EUROSTATS
```

```
df1_1<- subset(df, select = -c(KTU2022, EUROSTAT)) #RLK2022
```

```
#df1_1<- subset(df, select = -c(RLK2022, EUROSTAT)) #KTU2022
```

```
names(df1_1)[names(df1_1) == 'RLK2022'] <- 'urban_rural_class' #change the variable name!!
```

```
head(df1_1)
```

```
##      X age income      political_party
## 1 25  65   3000          CDU/CSU
## 2 26  59    800        Keine Angabe
## 3 27  60   1750        Keine Angabe
## 4 28  73   2500             SPD
## 5 30  43   2500 Einer anderen Partei
## 6 31  49   2300          CDU/CSU
##
##                                     education
## 1 (Fach-) Hochschulabschluss (Bachelor, Master, Magister, Diplom, Staatsexamen)
## 2      Allgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS)
```

```

## 3          Berufsausbildung, Lehre oder Ausbildung an einer Fachschule
## 4          Realschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss
## 5          Berufsausbildung, Lehre oder Ausbildung an einer Fachschule
## 6          Berufsausbildung, Lehre oder Ausbildung an einer Fachschule
##  urban_rural_class  federal_state C02_housing C02_electricity
## 1          zentral      Saarland   5038.2000      1053.0
## 2      sehr zentral      Hessen    1785.0000      487.5
## 3          peripher      Bayern    200.1024      663.0
## 4      sehr zentral      Bayern    648.4800      975.0
## 5      sehr zentral      Berlin    1923.4862      390.0
## 6          zentral Sachsen-Anhalt 2793.0960      663.0
##  C02_housing_electricity C02_cruise C02_flight C02_public_transport C02_car1
## 1          6091.2000          0      2440.0          0.0 1432.728
## 2          2272.5000      2710      5985.0          107.8 1944.608
## 3          863.1024          0      598.5          107.8 0.000
## 4          1623.4800          0      2287.6          0.0 1432.728
## 5          2313.4862          0          0.0          107.8 0.000
## 6          3456.0960          0      532.0          107.8 3581.820
##  C02_car2 C02_car3 C02_car4 C02_car5 C02_car_total C02_mobility C02_food
## 1      0.000          0          0          0      1432.728      3872.728 1494.628
## 2 1037.124          0          0          0      2981.731      11784.531 1731.025
## 3      0.000          0          0          0          0.000      706.300 1180.241
## 4      0.000          0          0          0      1432.728      3720.328 1709.007
## 5      0.000          0          0          0          0.000      107.800 1735.132
## 6      0.000          0          0          0      3581.820      4221.620 1033.474
##  C02_other_consumption public_emission C02_total
## 1          3766.100          1152 16376.656
## 2          1444.879          1152 18384.935
## 3          2433.480          1152 6335.123
## 4          4152.125          1152 12356.940
## 5          3766.100          1152 9074.518
## 6          2317.600          1152 12180.790
##  belief_diff_housing_electricity belief_diff_mobility belief_diff_food
## 1          -31          -14          5
## 2          -38          -42         -26
## 3          40          11          49
## 4          -2          -31          -9
## 5          -43          -2         -26
## 6          -6          22          93
##  belief_diff_other_consumption belief_diff_total
## 1          -68          -15
## 2          23          -76
## 3          9          57
## 4          -36          -8
## 5          -53          -1
## 6          24          13

```

```
## Creating a demo-dataset for a quick regression model building
```

```

# Independent variables: age, income, political_party, education, urban_rural, federal_state
# Dependent variables: C02_housing_electricity

```

```
df1 <- as_tibble(df1_1)
```

```
head(df1)
```

```
## # A tibble: 6 x 29
##       X   age income political~1 educa~2 urban~3 feder~4 C02_h~5 C02_e~6 C02_h~7
##   <int> <int>   <dbl> <fct>      <fct>   <fct>   <fct>   <dbl>   <dbl>   <dbl>
## 1    25    65   3000 CDU/CSU    (Fach-- zentral Saarla~  5038.   1053   6091.
## 2    26    59    800 Keine Anga~ Allgem~ sehr z~ Hessen    1785    488.   2272.
## 3    27    60   1750 Keine Anga~ Berufs~ periph~ Bayern     200.    663    863.
## 4    28    73   2500 SPD          Realsc~ sehr z~ Bayern     648.    975   1623.
## 5    30    43   2500 Einer ande~ Berufs~ sehr z~ Berlin   1923.    390   2313.
## 6    31    49   2300 CDU/CSU    Berufs~ zentral Sachse~  2793.    663   3456.
## # ... with 19 more variables: C02_cruise <dbl>, C02_flight <dbl>,
## #   C02_public_transport <dbl>, C02_car1 <dbl>, C02_car2 <dbl>, C02_car3 <dbl>,
## #   C02_car4 <dbl>, C02_car5 <dbl>, C02_car_total <dbl>, C02_mobility <dbl>,
## #   C02_food <dbl>, C02_other_consumption <dbl>, public_emission <dbl>,
## #   C02_total <dbl>, belief_diff_housing_electricity <dbl>,
## #   belief_diff_mobility <dbl>, belief_diff_food <dbl>,
## #   belief_diff_other_consumption <dbl>, belief_diff_total <dbl>, and ...
```

```
df1 <- df1 %>% select(2, 3, 4, 5, 6, 7, 10) #10, 20, 21, 22, 24
```

```
df1
```

```
## # A tibble: 588 x 7
##       age income political_party      education      urban~1 feder~2 C02_h~3
##   <int>   <dbl> <fct>      <fct>      <fct>   <fct>   <dbl>
## 1    65   3000 CDU/CSU    (Fach-) Hochschula~ zentral Saarla~  6091.
## 2    59    800 Keine Angabe Allgemeine oder fa~ sehr z~ Hessen    2272.
## 3    60   1750 Keine Angabe Berufsausbildung, ~ periph~ Bayern     863.
## 4    73   2500 SPD          Realschulabschluss~ sehr z~ Bayern   1623.
## 5    43   2500 Einer anderen Partei Berufsausbildung, ~ sehr z~ Berlin   2313.
## 6    49   2300 CDU/CSU    Berufsausbildung, ~ zentral Sachse~  3456.
## 7    57    600 CDU/CSU    Realschulabschluss~ zentral Baden~  1732.
## 8    39   5000 SPD          (Fach-) Hochschula~ sehr z~ Berlin    929.
## 9    62     0 Keine Angabe (Fach-) Hochschula~ sehr z~ Nordrh~  3166.
## 10   45   2600 Keine Angabe Berufsausbildung, ~ sehr z~ Hessen    916.
## # ... with 578 more rows, and abbreviated variable names 1: urban_rural_class,
## #   2: federal_state, 3: C02_housing_electricity
```

```
## Creating a demo-dataset for a quick regression model building
```

```
# Independent variables: age, income, political_party, education, urban_rural, federal_state
# Dependent variables: belief_diff_housing_electricity
```

```
df2 <- as_tibble(df1_1)
```

```
head(df1_1)
```

```
##       X age income      political_party
## 1 25  65   3000          CDU/CSU
## 2 26  59    800          Keine Angabe
```

```

## 3 27 60 1750 Keine Angabe
## 4 28 73 2500 SPD
## 5 30 43 2500 Einer anderen Partei
## 6 31 49 2300 CDU/CSU
##
## 1 (Fach-) Hochschulabschluss (Bachelor, Master, Magister, Diplom, Staatsexamen)
## 2 Allgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS)
## 3 Berufsausbildung, Lehre oder Ausbildung an einer Fachschule
## 4 Realschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss
## 5 Berufsausbildung, Lehre oder Ausbildung an einer Fachschule
## 6 Berufsausbildung, Lehre oder Ausbildung an einer Fachschule
## urban_rural_class federal_state CO2_housing CO2_electricity
## 1 zentral Saarland 5038.2000 1053.0
## 2 sehr zentral Hessen 1785.0000 487.5
## 3 peripher Bayern 200.1024 663.0
## 4 sehr zentral Bayern 648.4800 975.0
## 5 sehr zentral Berlin 1923.4862 390.0
## 6 zentral Sachsen-Anhalt 2793.0960 663.0
## CO2_housing_electricity CO2_cruise CO2_flight CO2_public_transport CO2_car1
## 1 6091.2000 0 2440.0 0.0 1432.728
## 2 2272.5000 2710 5985.0 107.8 1944.608
## 3 863.1024 0 598.5 107.8 0.000
## 4 1623.4800 0 2287.6 0.0 1432.728
## 5 2313.4862 0 0.0 107.8 0.000
## 6 3456.0960 0 532.0 107.8 3581.820
## CO2_car2 CO2_car3 CO2_car4 CO2_car5 CO2_car_total CO2_mobility CO2_food
## 1 0.000 0 0 0 1432.728 3872.728 1494.628
## 2 1037.124 0 0 0 2981.731 11784.531 1731.025
## 3 0.000 0 0 0 0.000 706.300 1180.241
## 4 0.000 0 0 0 1432.728 3720.328 1709.007
## 5 0.000 0 0 0 0.000 107.800 1735.132
## 6 0.000 0 0 0 3581.820 4221.620 1033.474
## CO2_other_consumption public_emission CO2_total
## 1 3766.100 1152 16376.656
## 2 1444.879 1152 18384.935
## 3 2433.480 1152 6335.123
## 4 4152.125 1152 12356.940
## 5 3766.100 1152 9074.518
## 6 2317.600 1152 12180.790
## belief_diff_housing_electricity belief_diff_mobility belief_diff_food
## 1 -31 -14 5
## 2 -38 -42 -26
## 3 40 11 49
## 4 -2 -31 -9
## 5 -43 -2 -26
## 6 -6 22 93
## belief_diff_other_consumption belief_diff_total
## 1 -68 -15
## 2 23 -76
## 3 9 57
## 4 -36 -8
## 5 -53 -1
## 6 24 13

```



```
df2 <- df2 %>% select(2, 3, 4, 5, 6, 7, 25) #25, 26, 27, 28, 29
```

```
df2
```

```
## # A tibble: 588 x 7
##   age income political_party education urban~1 feder~2 belie~3
##   <int> <dbl> <fct> <fct> <fct> <fct> <dbl>
## 1 65 3000 CDU/CSU (Fach-) Hochschule~ zentral Saarla~ -31
## 2 59 800 Keine Angabe Allgemeine oder fa~ sehr z~ Hessen -38
## 3 60 1750 Keine Angabe Berufsausbildung, ~ periph~ Bayern 40
## 4 73 2500 SPD Realschulabschluss~ sehr z~ Bayern -2
## 5 43 2500 Einer anderen Partei Berufsausbildung, ~ sehr z~ Berlin -43
## 6 49 2300 CDU/CSU Berufsausbildung, ~ zentral Sachse~ -6
## 7 57 600 CDU/CSU Realschulabschluss~ zentral Baden-- -1
## 8 39 5000 SPD (Fach-) Hochschule~ sehr z~ Berlin 5
## 9 62 0 Keine Angabe (Fach-) Hochschule~ sehr z~ Nordrh~ -48
## 10 45 2600 Keine Angabe Berufsausbildung, ~ sehr z~ Hessen -1
## # ... with 578 more rows, and abbreviated variable names 1: urban_rural_class,
## # 2: federal_state, 3: belief_diff_housing_electricity
```

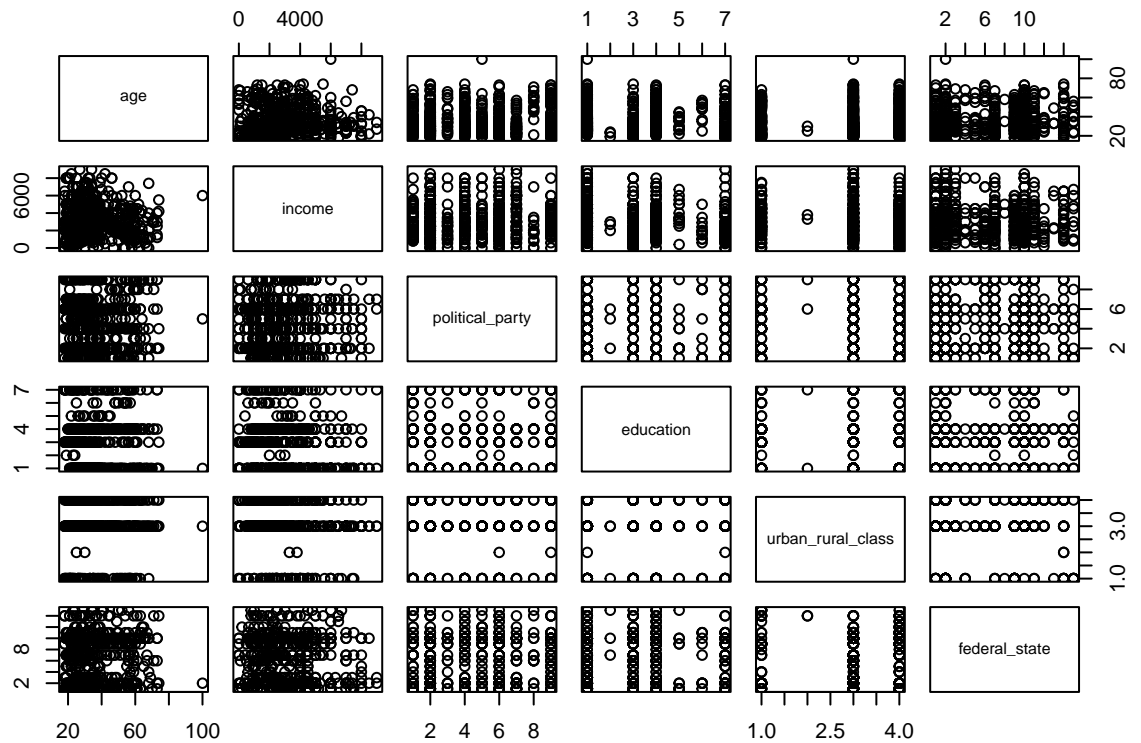
I. Exploratory Data Analysis

Check the Jupyter notebook: EDA_scatter_plot_actual_belief

II. Multivariate Regression: CO2 housing electricity

```
# Checking the possible correlation in the data
```

```
plot(df1[1:6])
```



1. Modeling

```
table(df1$political_party)
```

```
##
##           AfD      Bündnis 90/Die Grünen Bündnis Sarah Wagenknecht
##           58           143           23
##      CDU/CSU      Die Linke      Einer anderen Partei
##           75           44           111
##           FDP      Keine Angabe      SPD
##           48           15           71
```

```
table(df1$education)
```

```
##
## (Fach-) Hochschulabschluss (Bachelor, Master, Magister, Diplom, Staatsexamen)
##                                     253
##                                     (Noch) kein Abschluss
##                                     3
## Allgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS)
##                                     131
## Berufsausbildung, Lehre oder Ausbildung an einer Fachschule
##                                     118
##                                     Doktorgrad oder Habilitation
##                                     13
## Hauptschulabschluss (Volksschulabschluss) oder gleichwertiger Abschluss
##                                     11
```

```
##           Realschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss
##                                                    59
```

```
table(df1$urban_rural_class)
```

```
##
##      peripher sehr peripher  sehr zentral      zentral
##          79             2        350        157
```

```
table(df1$federal_state)
```

```
##
##      Baden-Württemberg      Bayern      Berlin
##             94             100             44
##      Brandenburg      Bremen      Hamburg
##             8             15             25
##      Hessen Mecklenburg-Vorpommern  Niedersachsen
##             50             2             58
##      Nordrhein-Westfalen  Rheinland-Pfalz  Saarland
##             117            30             10
##      Sachsen-Anhalt      Schleswig-Holstein  Thüringen
##             4             22             9
```

```
## defining a reference level
```

```
df1$political_party <- relevel(df1$political_party, ref='Bündnis 90/Die Grünen')
df1$education <- relevel(df1$education, ref='(Fach-) Hochschulabschluss (Bachelor, Master, Magister, D
df1$urban_rural_class <- relevel(df1$urban_rural_class, ref='sehr zentral')
df1$federal_state <- relevel(df1$federal_state, ref='Nordrhein-Westfalen')
```

```
# regression model with all variables
```

```
modell1 <- lm(CO2_housing_electricity ~ age + income + political_party + education + urban_rural_class
summary(modell1)
```

```
##
## Call:
## lm(formula = CO2_housing_electricity ~ age + income + political_party +
##      education + urban_rural_class + federal_state, data = df1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2671.4  -762.0  -235.4   437.8 13841.0
##
## Coefficients:
##                                     Estimate
## (Intercept)                    1444.32318
## age                           12.94510
## income                         -0.05536
## political_partyAfD              325.16106
## political_partyBündnis Sarah Wagenknecht 166.97042
```

| | |
|--|------------|
| ## political_partyCDU/CSU | 17.13978 |
| ## political_partyDie Linke | -142.15689 |
| ## political_partyEiner anderen Partei | 33.17008 |
| ## political_partyFDP | 504.59733 |
| ## political_partyKeine Angabe | 119.44216 |
| ## political_partySPD | 118.45958 |
| ## education(Noch) kein Abschluss | -608.98577 |
| ## educationAllgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS) | 83.56266 |
| ## educationBerufsausbildung, Lehre oder Ausbildung an einer Fachschule | -91.19049 |
| ## educationDoktorgrad oder Habilitation | 9.27019 |
| ## educationHauptschulabschluss (Volksschulabschluss) oder gleichwertiger Abschluss | -494.68473 |
| ## educationRealschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss | -19.29133 |
| ## urban_rural_classperipher | 300.42781 |
| ## urban_rural_classsehr peripher | -876.89481 |
| ## urban_rural_classzentral | -237.95096 |
| ## federal_stateBaden-Württemberg | -330.23463 |
| ## federal_stateBayern | -203.80324 |
| ## federal_stateBerlin | -144.95052 |
| ## federal_stateBrandenburg | -279.64348 |
| ## federal_stateBremen | 391.75815 |
| ## federal_stateHamburg | -361.35209 |
| ## federal_stateHessen | 338.73305 |
| ## federal_stateMecklenburg-Vorpommern | -581.97535 |
| ## federal_stateNiedersachsen | 141.91428 |
| ## federal_stateRheinland-Pfalz | 696.83833 |
| ## federal_stateSaarland | 1485.10203 |
| ## federal_stateSachsen-Anhalt | 1259.44507 |
| ## federal_stateSchleswig-Holstein | 283.79099 |
| ## federal_stateThüringen | 660.92693 |
| ## | Std. Error |
| ## (Intercept) | 289.24263 |
| ## age | 5.12072 |
| ## income | 0.03422 |
| ## political_partyAfD | 245.00273 |
| ## political_partyBündnis Sarah Wagenknecht | 343.40265 |
| ## political_partyCDU/CSU | 220.04990 |
| ## political_partyDie Linke | 265.22422 |
| ## political_partyEiner anderen Partei | 196.85985 |
| ## political_partyFDP | 254.85140 |
| ## political_partyKeine Angabe | 441.43510 |
| ## political_partySPD | 224.08098 |
| ## education(Noch) kein Abschluss | 896.49641 |
| ## educationAllgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS) | 174.26340 |
| ## educationBerufsausbildung, Lehre oder Ausbildung an einer Fachschule | 177.77469 |
| ## educationDoktorgrad oder Habilitation | 434.56494 |
| ## educationHauptschulabschluss (Volksschulabschluss) oder gleichwertiger Abschluss | 496.05145 |
| ## educationRealschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss | 226.07717 |
| ## urban_rural_classperipher | 227.82185 |
| ## urban_rural_classsehr peripher | 1127.83798 |
| ## urban_rural_classzentral | 167.02552 |
| ## federal_stateBaden-Württemberg | 216.97097 |
| ## federal_stateBayern | 222.76807 |
| ## federal_stateBerlin | 270.62556 |
| ## federal_stateBrandenburg | 568.41886 |

| | |
|--|------------|
| ## federal_stateBremen | 414.60387 |
| ## federal_stateHamburg | 337.40376 |
| ## federal_stateHessen | 258.86887 |
| ## federal_stateMecklenburg-Vorpommern | 1086.61583 |
| ## federal_stateNiedersachsen | 263.35516 |
| ## federal_stateRheinland-Pfalz | 324.81836 |
| ## federal_stateSaarland | 510.04738 |
| ## federal_stateSachsen-Anhalt | 786.22894 |
| ## federal_stateSchleswig-Holstein | 379.91939 |
| ## federal_stateThüringen | 575.85538 |
| ## | t value |
| ## (Intercept) | 4.993 |
| ## age | 2.528 |
| ## income | -1.618 |
| ## political_partyAfD | 1.327 |
| ## political_partyBündnis Sarah Wagenknecht | 0.486 |
| ## political_partyCDU/CSU | 0.078 |
| ## political_partyDie Linke | -0.536 |
| ## political_partyEiner anderen Partei | 0.168 |
| ## political_partyFDP | 1.980 |
| ## political_partyKeine Angabe | 0.271 |
| ## political_partySPD | 0.529 |
| ## education(Noch) kein Abschluss | -0.679 |
| ## educationAllgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS) | 0.480 |
| ## educationBerufsausbildung, Lehre oder Ausbildung an einer Fachschule | -0.513 |
| ## educationDoktorgrad oder Habilitation | 0.021 |
| ## educationHauptschulabschluss (Volksschulabschluss) oder gleichwertiger Abschluss | -0.997 |
| ## educationRealschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss | -0.085 |
| ## urban_rural_classperipher | 1.319 |
| ## urban_rural_classsehr peripher | -0.778 |
| ## urban_rural_classzentral | -1.425 |
| ## federal_stateBaden-Württemberg | -1.522 |
| ## federal_stateBayern | -0.915 |
| ## federal_stateBerlin | -0.536 |
| ## federal_stateBrandenburg | -0.492 |
| ## federal_stateBremen | 0.945 |
| ## federal_stateHamburg | -1.071 |
| ## federal_stateHessen | 1.309 |
| ## federal_stateMecklenburg-Vorpommern | -0.536 |
| ## federal_stateNiedersachsen | 0.539 |
| ## federal_stateRheinland-Pfalz | 2.145 |
| ## federal_stateSaarland | 2.912 |
| ## federal_stateSachsen-Anhalt | 1.602 |
| ## federal_stateSchleswig-Holstein | 0.747 |
| ## federal_stateThüringen | 1.148 |
| ## | Pr(> t) |
| ## (Intercept) | 7.96e-07 |
| ## age | 0.01175 |
| ## income | 0.10630 |
| ## political_partyAfD | 0.18500 |
| ## political_partyBündnis Sarah Wagenknecht | 0.62700 |
| ## political_partyCDU/CSU | 0.93794 |
| ## political_partyDie Linke | 0.59218 |
| ## political_partyEiner anderen Partei | 0.86625 |

| | |
|--|---------|
| ## political_partyFDP | 0.04820 |
| ## political_partyKeine Angabe | 0.78682 |
| ## political_partySPD | 0.59726 |
| ## education(Noch) kein Abschluss | 0.49723 |
| ## educationAllgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS) | 0.63176 |
| ## educationBerufsausbildung, Lehre oder Ausbildung an einer Fachschule | 0.60819 |
| ## educationDoktorgrad oder Habilitation | 0.98299 |
| ## educationHauptschulabschluss (Volksschulabschluss) oder gleichwertiger Abschluss | 0.31908 |
| ## educationRealschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss | 0.93203 |
| ## urban_rural_classperipher | 0.18782 |
| ## urban_rural_classsehr peripher | 0.43720 |
| ## urban_rural_classzentral | 0.15482 |
| ## federal_stateBaden-Württemberg | 0.12857 |
| ## federal_stateBayern | 0.36066 |
| ## federal_stateBerlin | 0.59244 |
| ## federal_stateBrandenburg | 0.62294 |
| ## federal_stateBremen | 0.34512 |
| ## federal_stateHamburg | 0.28465 |
| ## federal_stateHessen | 0.19124 |
| ## federal_stateMecklenburg-Vorpommern | 0.59246 |
| ## federal_stateNiedersachsen | 0.59019 |
| ## federal_stateRheinland-Pfalz | 0.03236 |
| ## federal_stateSaarland | 0.00374 |
| ## federal_stateSachsen-Anhalt | 0.10975 |
| ## federal_stateSchleswig-Holstein | 0.45539 |
| ## federal_stateThüringen | 0.25158 |
| ## | |
| ## (Intercept) | *** |
| ## age | * |
| ## income | |
| ## political_partyAfD | |
| ## political_partyBündnis Sarah Wagenknecht | |
| ## political_partyCDU/CSU | |
| ## political_partyDie Linke | |
| ## political_partyEiner anderen Partei | |
| ## political_partyFDP | * |
| ## political_partyKeine Angabe | |
| ## political_partySPD | |
| ## education(Noch) kein Abschluss | |
| ## educationAllgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS) | |
| ## educationBerufsausbildung, Lehre oder Ausbildung an einer Fachschule | |
| ## educationDoktorgrad oder Habilitation | |
| ## educationHauptschulabschluss (Volksschulabschluss) oder gleichwertiger Abschluss | |
| ## educationRealschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss | |
| ## urban_rural_classperipher | |
| ## urban_rural_classsehr peripher | |
| ## urban_rural_classzentral | |
| ## federal_stateBaden-Württemberg | |
| ## federal_stateBayern | |
| ## federal_stateBerlin | |
| ## federal_stateBrandenburg | |
| ## federal_stateBremen | |
| ## federal_stateHamburg | |
| ## federal_stateHessen | |

```
## federal_stateMecklenburg-Vorpommern
## federal_stateNiedersachsen
## federal_stateRheinland-Pfalz
## federal_stateSaarland
## federal_stateSachsen-Anhalt
## federal_stateSchleswig-Holstein
## federal_stateThüringen
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1497 on 554 degrees of freedom
## Multiple R-squared:  0.08865,    Adjusted R-squared:  0.03436
## F-statistic: 1.633 on 33 and 554 DF,  p-value: 0.01562
```

```
# Checking the VIFs for multicollinearity
```

```
vif(model1)
```

```
##              GVIF Df GVIF^(1/(2*Df))
## age          1.313360 1          1.146019
## income       1.099357 1          1.048502
## political_party 1.794759 8          1.037231
## education    1.848270 6          1.052520
## urban_rural_class 2.066166 3          1.128568
## federal_state 3.002832 14          1.040051
```

```
# threshold for multicollinearity
# Calculating the threshold
```

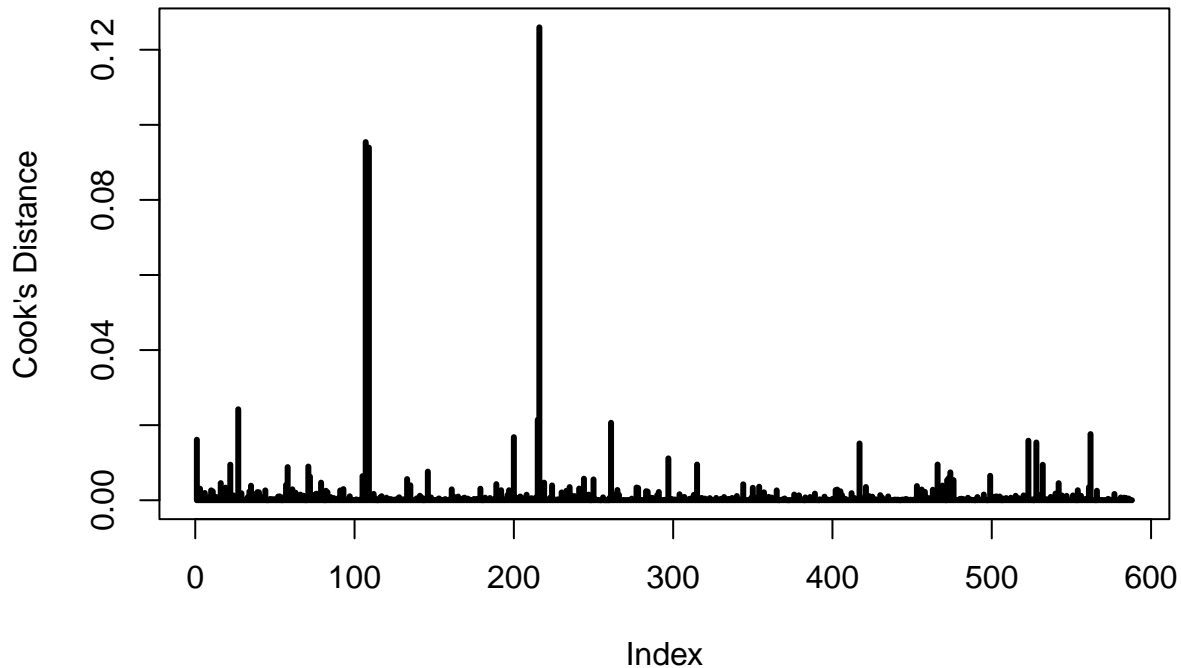
```
max(10, 1/(1-summary(model1)$r.square))
```

```
## [1] 10
```

```
# Checking outliers: estimate of the influence of data point; summary of how much a regression model ch
```

```
cook = cooks.distance(model1)
plot(cook,
      type="h",
      lwd=3,
      ylab = "Cook's Distance",
      main="Cook's Distance")
abline(h = 1)
```

Cook's Distance



```
influential = cooks.distance(model1)[which(cook > 3*mean(cook, na.rm=TRUE))]  
influential
```

```
##          1          22          27          58          71          72  
## 0.016127624 0.009480507 0.024224697 0.008826271 0.008973082 0.006299245  
##          105          107          109          133          146          200  
## 0.006429258 0.095412252 0.093940930 0.005639933 0.007636482 0.016803997  
##          215          216          244          250          261          297  
## 0.021428641 0.125965406 0.005741790 0.005549451 0.020633259 0.011149565  
##          315          417          466          472          473          474  
## 0.009513089 0.015125598 0.009513787 0.005364578 0.005906450 0.007422763  
##          476          499          523          528          532          562  
## 0.005368812 0.006519123 0.015858419 0.015381180 0.009444404 0.017618512
```

```
influential = influential[!is.na(influential)]  
influential_vector = c(as.numeric(rownames(data.frame(influential))))
```

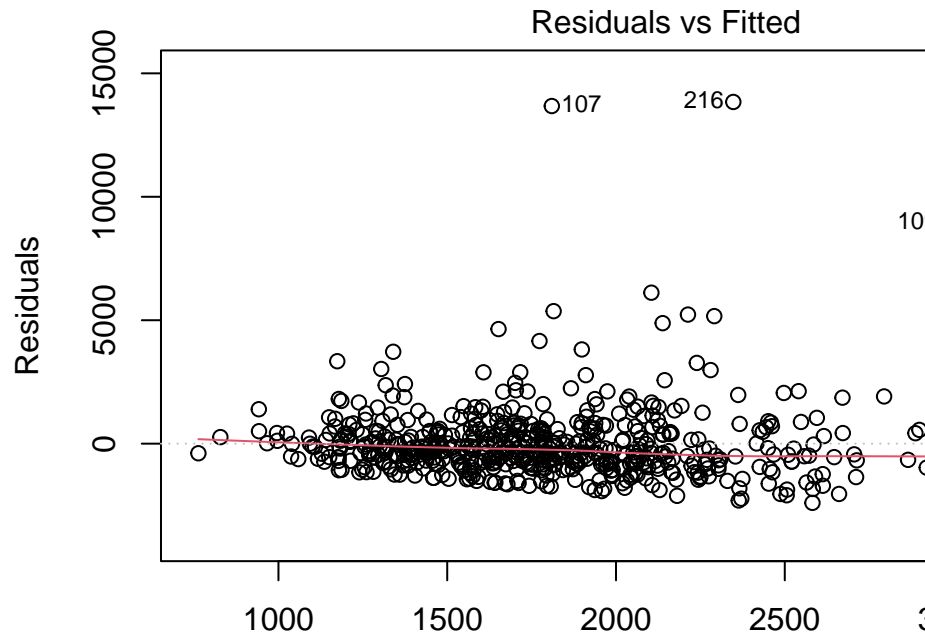
```
df1[influential_vector, ]
```

```
## # A tibble: 30 x 7  
##   age income political_party education urban~1 feder~2 CO2_h~3  
##   <int> <dbl> <fct>          <fct>    <fct>    <fct>    <dbl>  
## 1    65   3000 CDU/CSU      (Fach-) Hochs~ zentral Saarla~ 6091.  
## 2    52   4800 Die Linke    (Fach-) Hochs~ periph~ Thürin~ 4534.
```



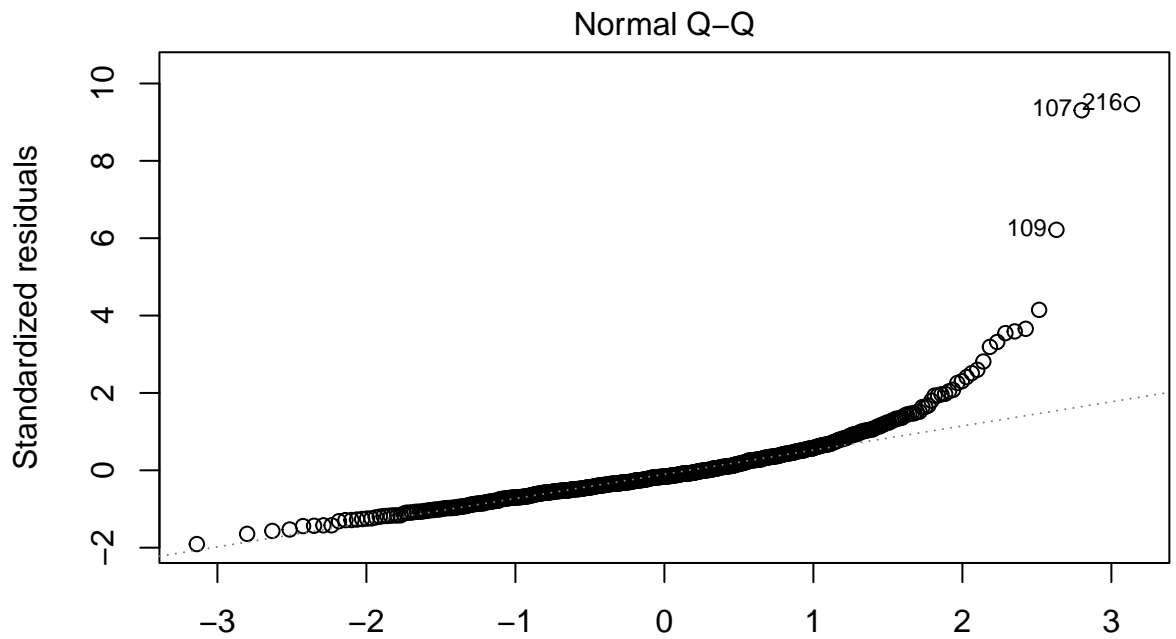
```
## 3 36 1000 AfD Berufsausbild~ zentral Saarla~ 6713.
## 4 53 1500 AfD Hauptschulabs~ periph~ Bayern 4093.
## 5 56 1000 Keine Angabe Berufsausbild~ periph~ Thürin~ 4700.
## 6 49 2000 Keine Angabe Berufsausbild~ sehr z~ Baden~ 3771.
## 7 49 3000 Bündnis 90/Die Grünen Berufsausbild~ zentral Rheinl~ 5261.
## 8 32 7000 Bündnis 90/Die Grünen (Fach-) Hochs~ sehr z~ Hessen 15486.
## 9 22 600 FDP Allgemeine od~ sehr z~ Rheinl~ 11925
## 10 29 1900 Bündnis Sarah Wagenknecht Berufsausbild~ sehr z~ Rheinl~ 451.
## # ... with 20 more rows, and abbreviated variable names 1: urban_rural_class,
## # 2: federal_state, 3: CO2_housing_electricity
```

```
plot(model1)
```

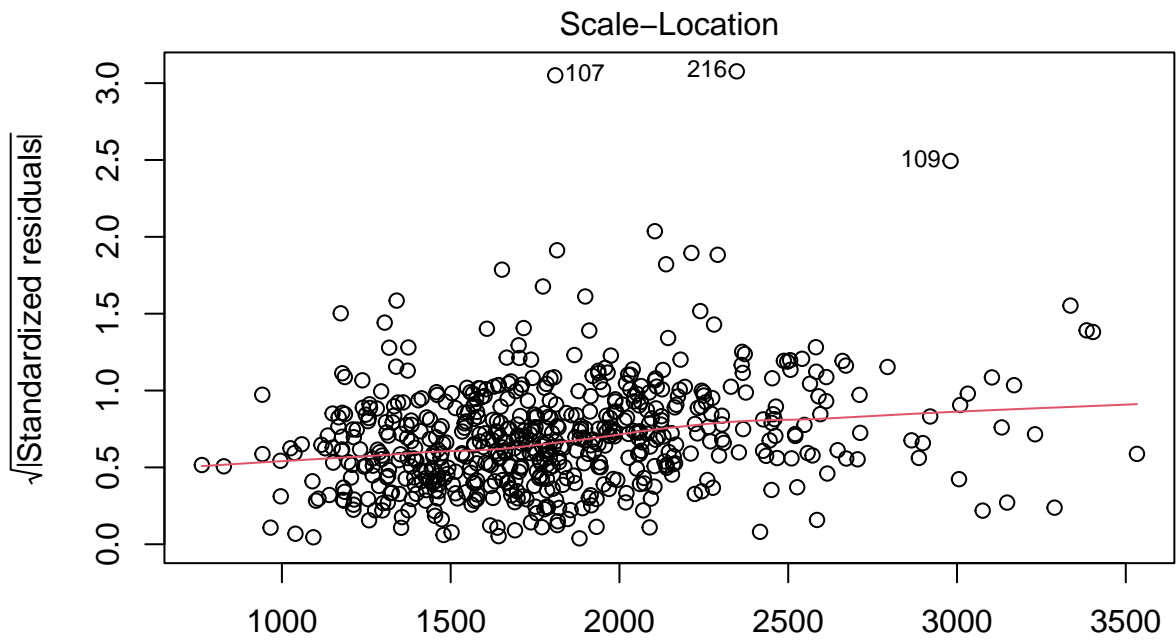


lm(CO2_housing_electricity ~ age + income + political_pa

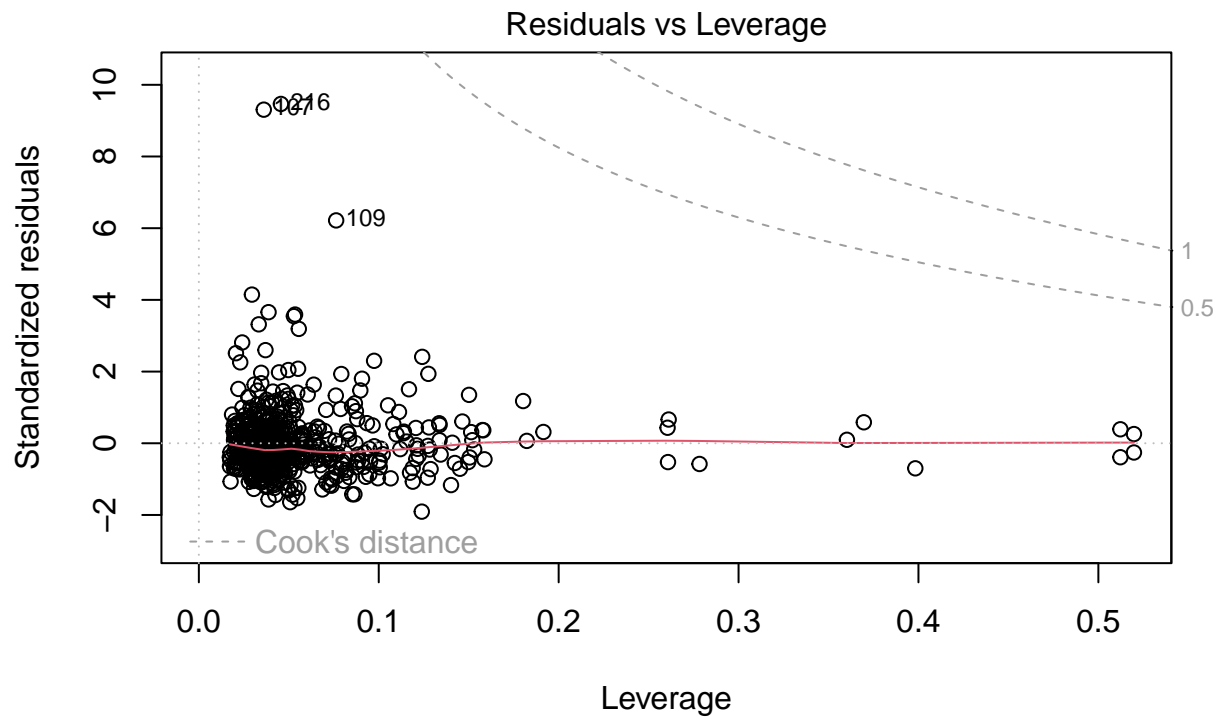
2. Assumptions check in the residuals



lm(CO2_housing_electricity ~ age + income + political_party + education + u ...



Fitted values
 $\text{lm}(\text{CO2_housing_electricity} \sim \text{age} + \text{income} + \text{political_party} + \text{education} + \text{u} \dots)$

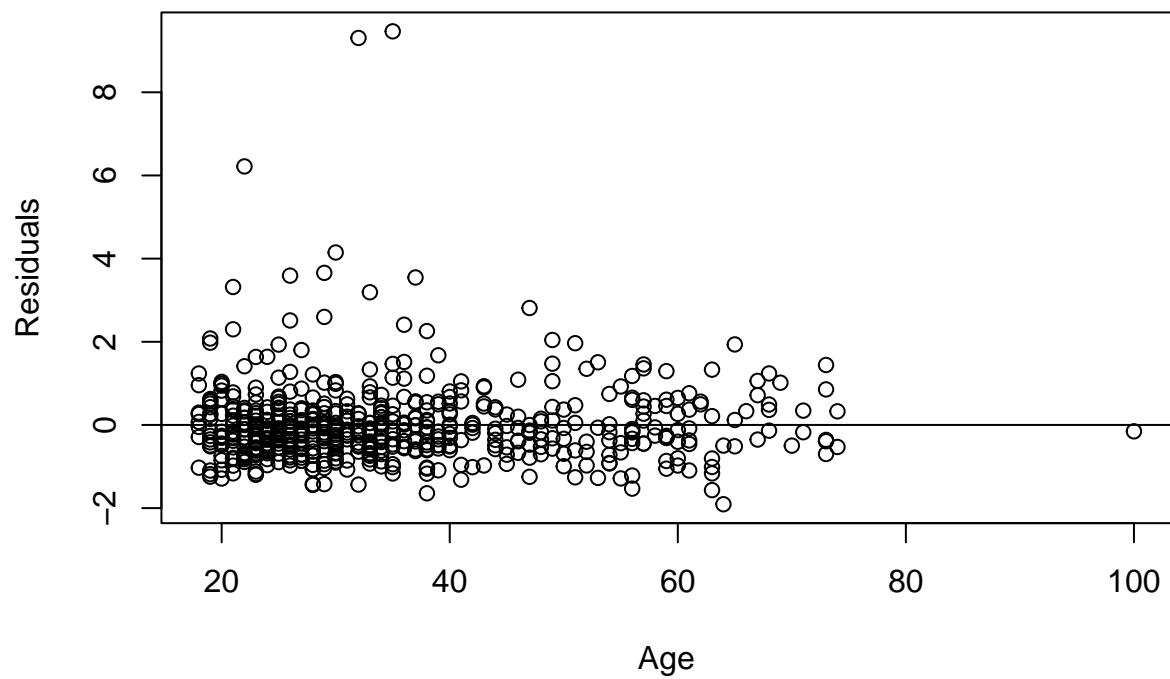


lm(CO2_housing_electricity ~ age + income + political_party + education + u ...

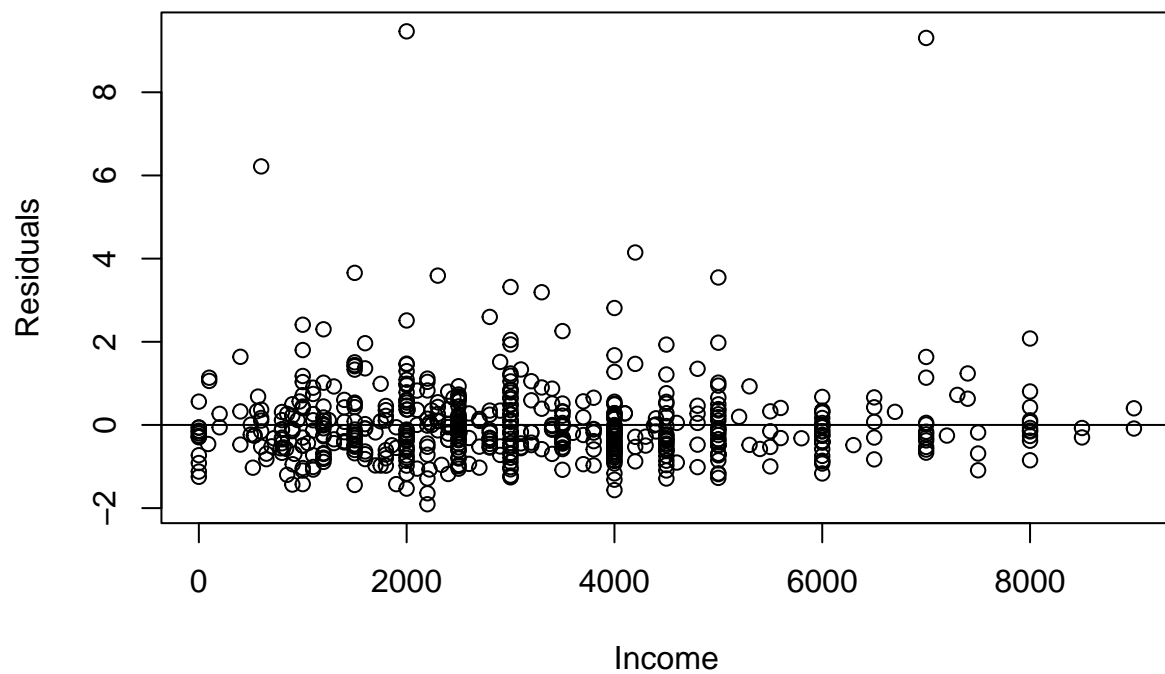
```
res1 = stdres(model1) ## (Standardized) Residuals

# Linearity assumption/Mean zero assumption

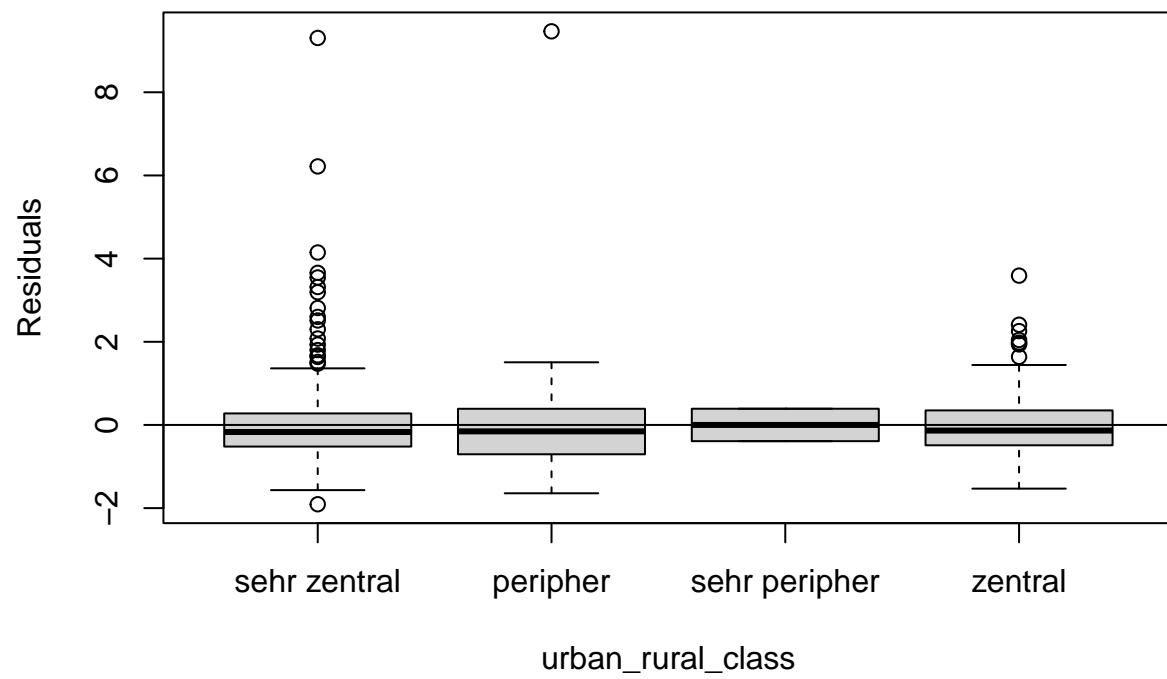
plot(df1$age, res1, xlab = "Age", ylab = "Residuals")
abline(h = 0)
```



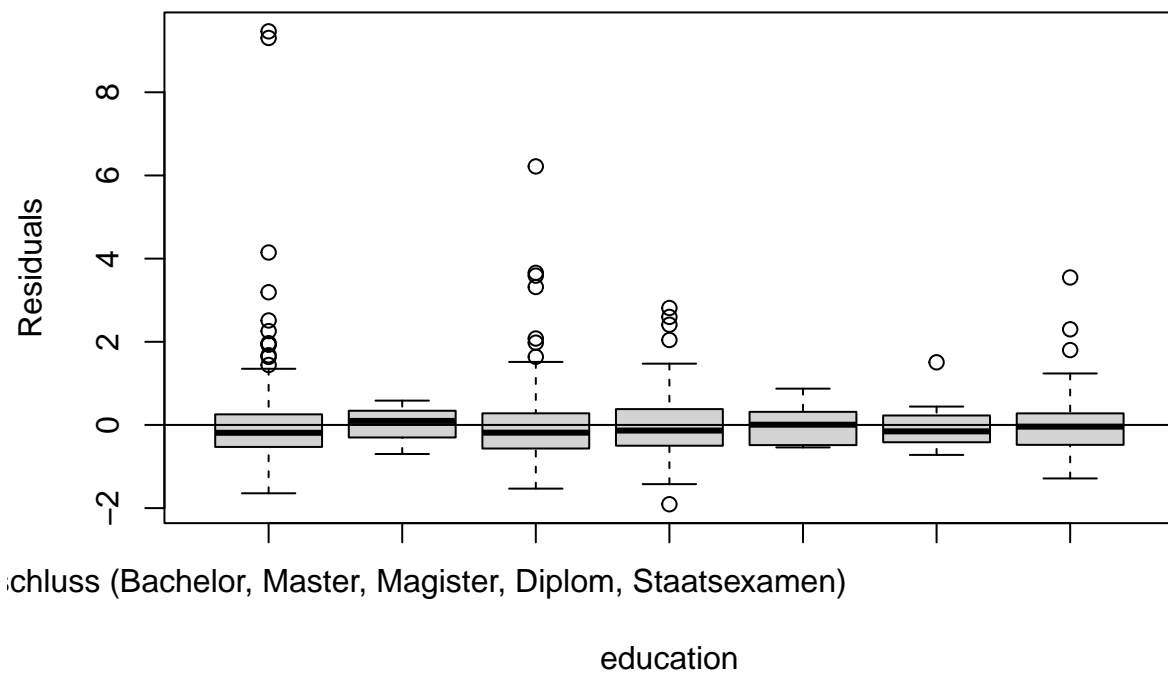
```
plot(df1$income, res1, xlab = "Income", ylab = "Residuals")  
abline(h = 0)
```



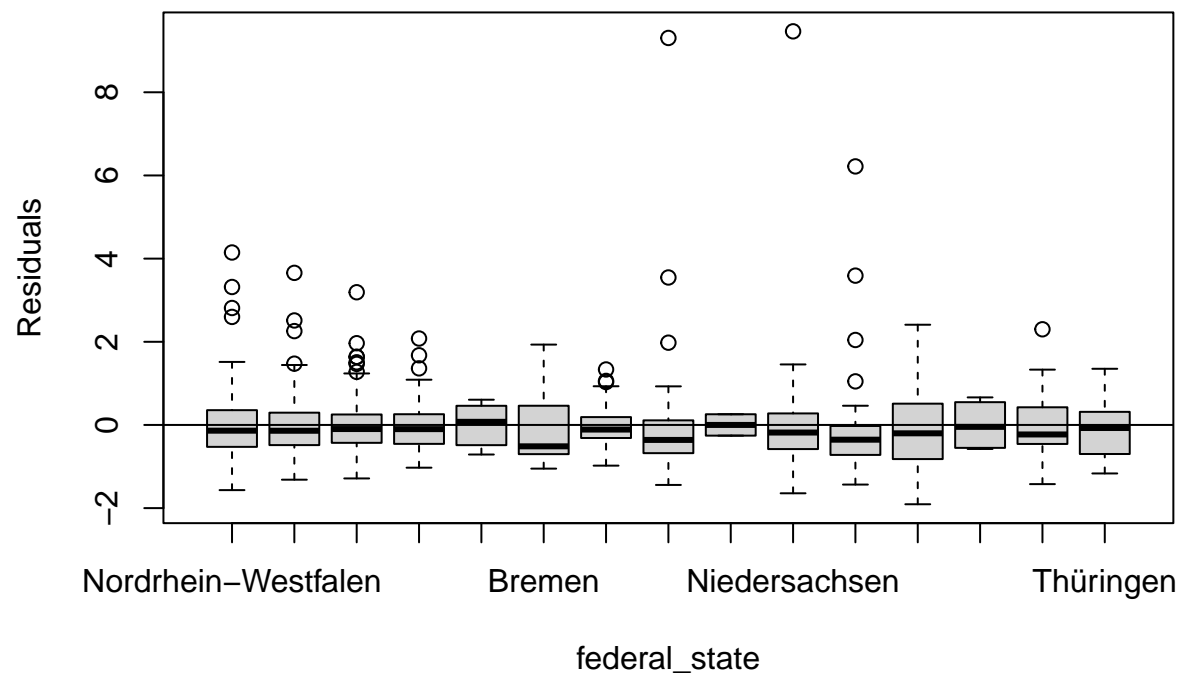
```
plot(df1$urban_rural_class, res1, xlab = "urban_rural_class", ylab = "Residuals")  
abline(h = 0)
```



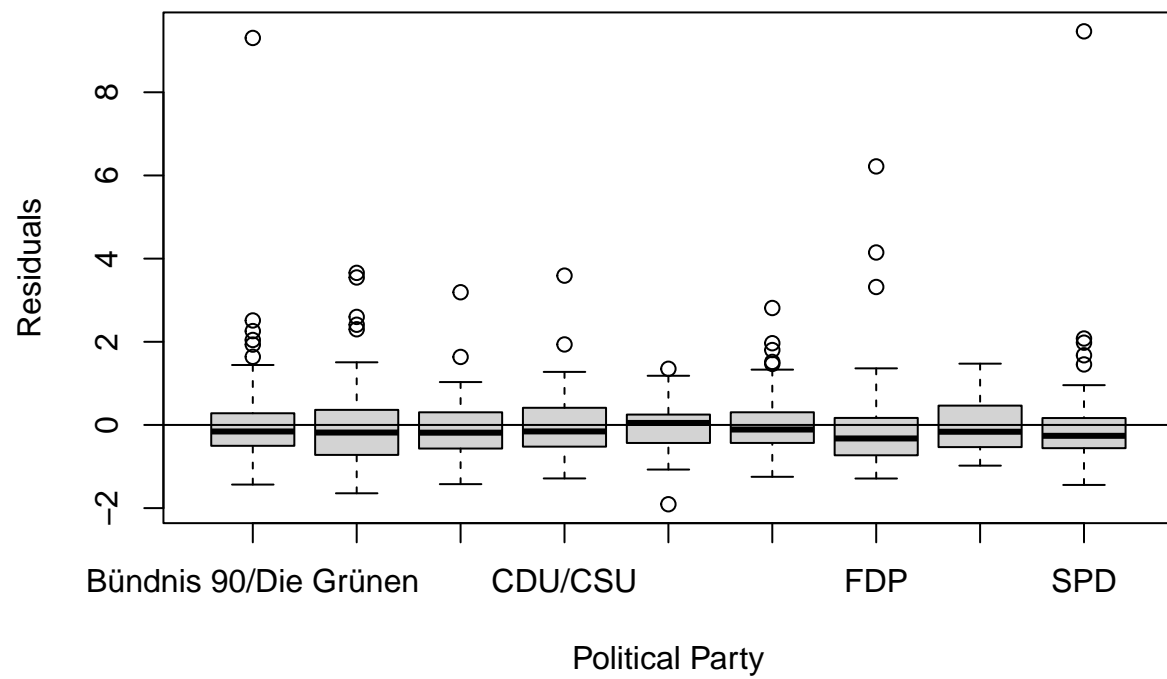
```
plot(df1$education, res1, xlab = "education", ylab = "Residuals")  
abline(h = 0)
```



```
plot(df1$federal_state, res1, xlab = "federal_state", ylab = "Residuals")  
abline(h = 0)
```

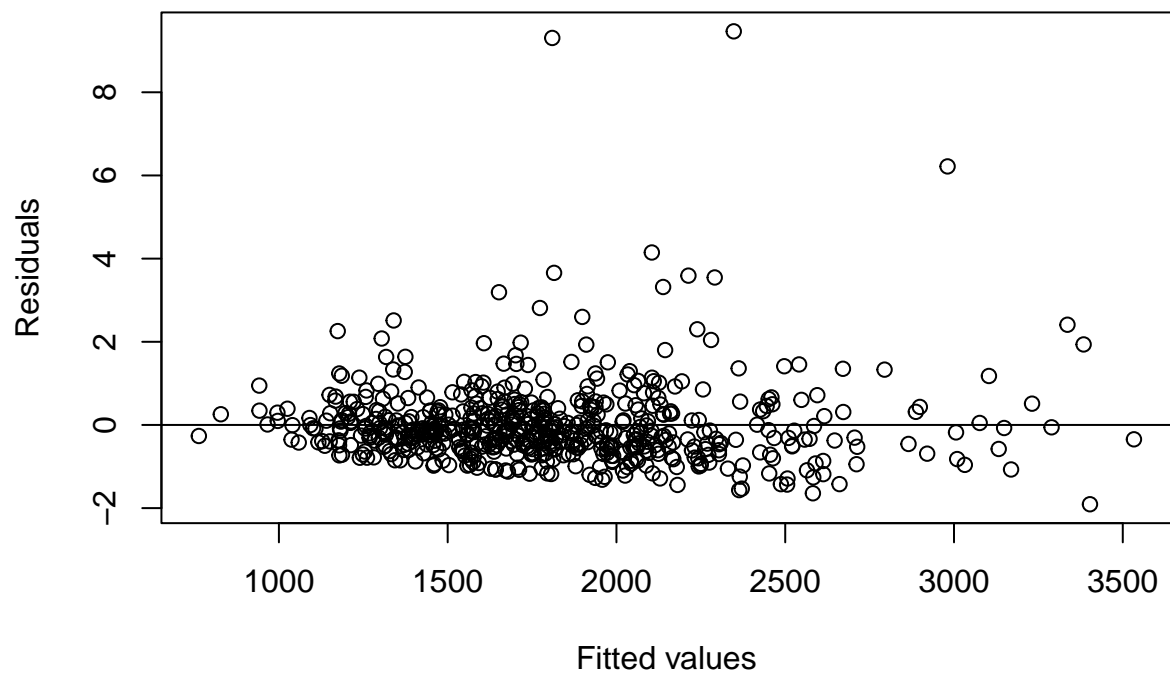



```
plot(df1$political_party, res1, xlab = "Political Party", ylab = "Residuals")
abline(h = 0)
```



Constant variance and independent error term assumption

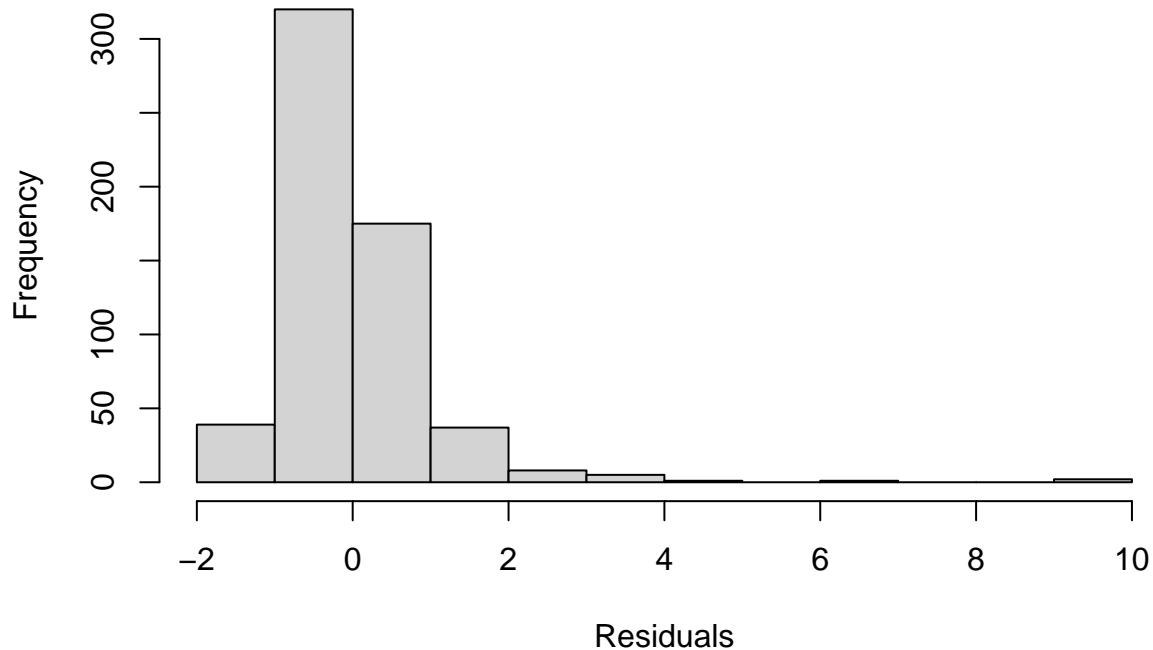
```
plot(fitted(model1), res1, xlab = "Fitted values", ylab = "Residuals")
abline(h = 0)
```



```
# Normality assumption
```

```
hist(res1, xlab="Residuals", main= "Histogram of Residuals")
```

Histogram of Residuals



```
### Backward regression using AIC: starting with all of the variables
```

```
step_model1 <- stepAIC(model1, trace=TRUE, direction= "backward")
```

3. Variable Selection, model outcome and assumption check

```
## Start: AIC=8630.84
```

```
## CO2_housing_electricity ~ age + income + political_party + education +
```

```
##   urban_rural_class + federal_state
```

```
##
```

```
##           Df Sum of Sq      RSS   AIC
```

```
## - education    6  4723490 1245963158 8621.1
```

```
## - political_party    8  15175336 1256415003 8622.0
```

```
## <none>                1241239667 8630.8
```

```
## - income          1   5863257 1247102924 8631.6
```

```
## - urban_rural_class  3  14793184 1256032851 8631.8
```

```
## - age              1  14318420 1255558087 8635.6
```

```
## - federal_state    14  71384514 1312624181 8635.7
```

```
##
```

```
## Step: AIC=8621.07
```

```
## CO2_housing_electricity ~ age + income + political_party + urban_rural_class +
```

```
##   federal_state
```

```
##
```

```

##              Df Sum of Sq      RSS      AIC
## - political_party    8  14763817 1260726974 8612.0
## <none>                  1245963158 8621.1
## - urban_rural_class   3   13808719 1259771877 8621.6
## - income              1    5688390 1251651548 8621.7
## - age                 1   12719286 1258682444 8625.0
## - federal_state      14   70692591 1316655748 8625.5
##
## Step: AIC=8612
## CO2_housing_electricity ~ age + income + urban_rural_class +
##   federal_state
##
##              Df Sum of Sq      RSS      AIC
## - urban_rural_class   3  12154533 1272881508 8611.6
## <none>                  1260726974 8612.0
## - income              1    4948920 1265675894 8612.3
## - federal_state      14   67372513 1328099487 8614.6
## - age                 1   13065133 1273792107 8616.1
##
## Step: AIC=8611.64
## CO2_housing_electricity ~ age + income + federal_state
##
##              Df Sum of Sq      RSS      AIC
## <none>                  1272881508 8611.6
## - income              1    4916171 1277797679 8611.9
## - federal_state      14   65378580 1338260087 8613.1
## - age                 1   13498518 1286380025 8615.8

```

summary(step_model1)

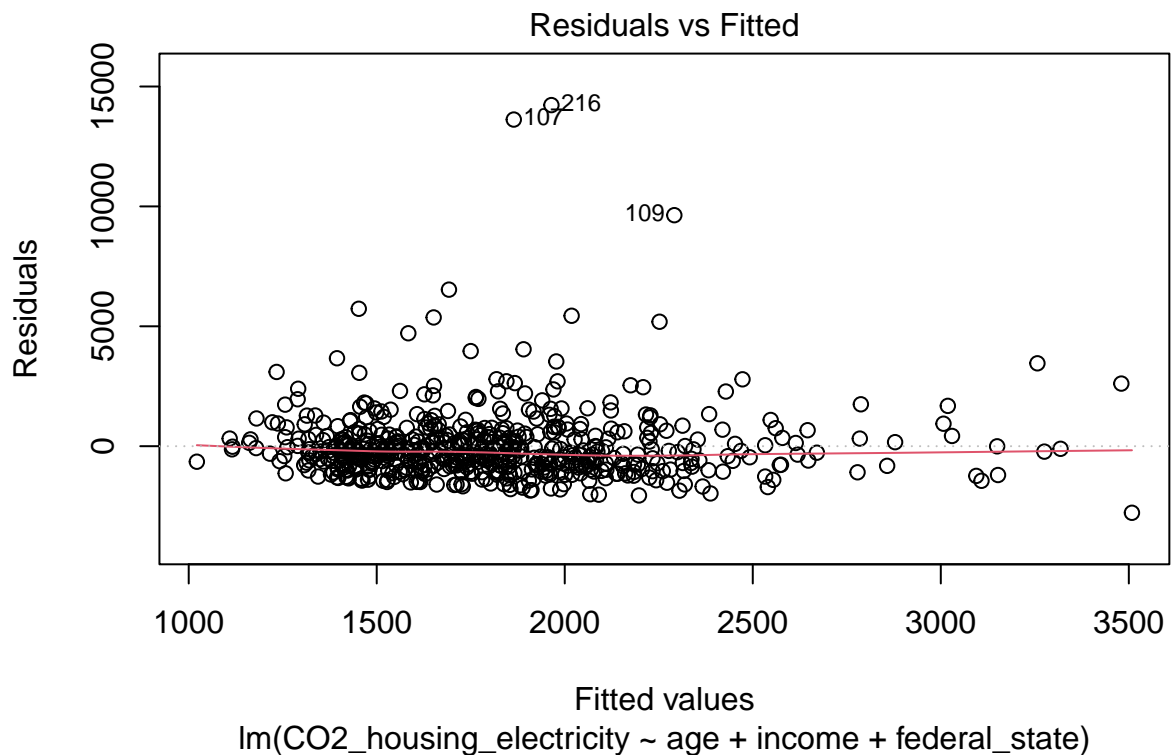
```

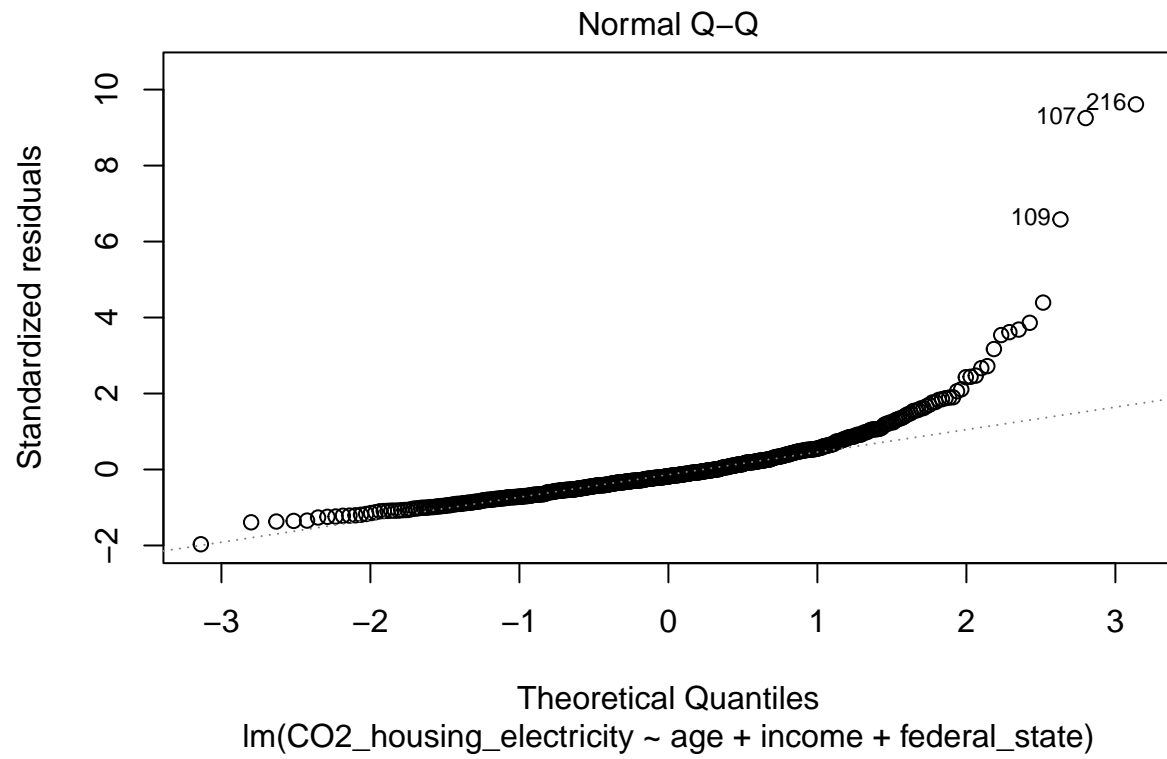
##
## Call:
## lm(formula = CO2_housing_electricity ~ age + income + federal_state,
##     data = df1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2777.0  -790.1  -270.1   388.5 14224.0
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1566.08603   235.44154   6.652 6.79e-11 ***
## age           11.08721     4.50563    2.461  0.01416 *
## income       -0.04919     0.03312   -1.485  0.13809
## federal_stateBaden-Württemberg -361.59221   206.92024   -1.747  0.08109 .
## federal_stateBayern -185.65602   204.01227   -0.910  0.36319
## federal_stateBerlin -149.43881   264.20237   -0.566  0.57187
## federal_stateBrandenburg -288.91151   546.44541   -0.529  0.59721
## federal_stateBremen  358.99164   409.57688    0.876  0.38113
## federal_stateHamburg -312.66275   329.59330   -0.949  0.34321
## federal_stateHessen  287.88789   252.48782    1.140  0.25468
## federal_stateMecklenburg-Vorpommern -591.65061  1067.01177   -0.554  0.57946
## federal_stateNiedersachsen  108.76419   240.33453    0.453  0.65104
## federal_stateRheinland-Pfalz  510.89852   305.78884    1.671  0.09532 .

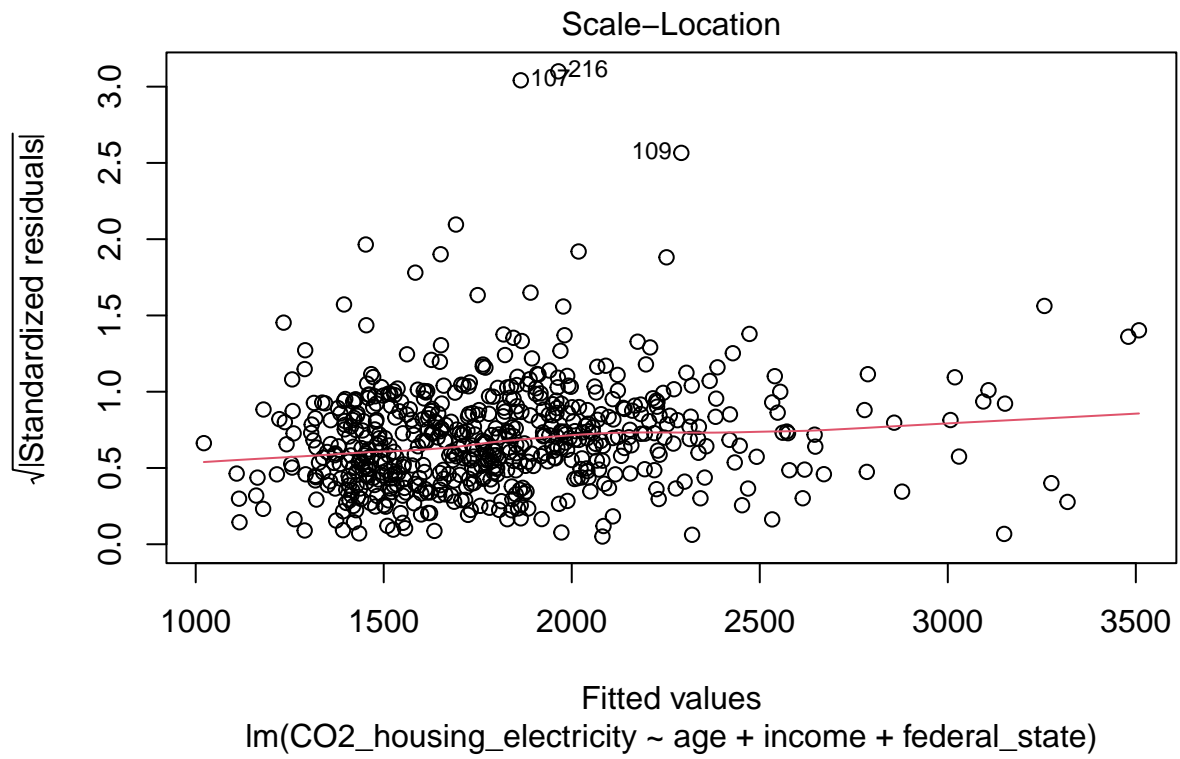
```

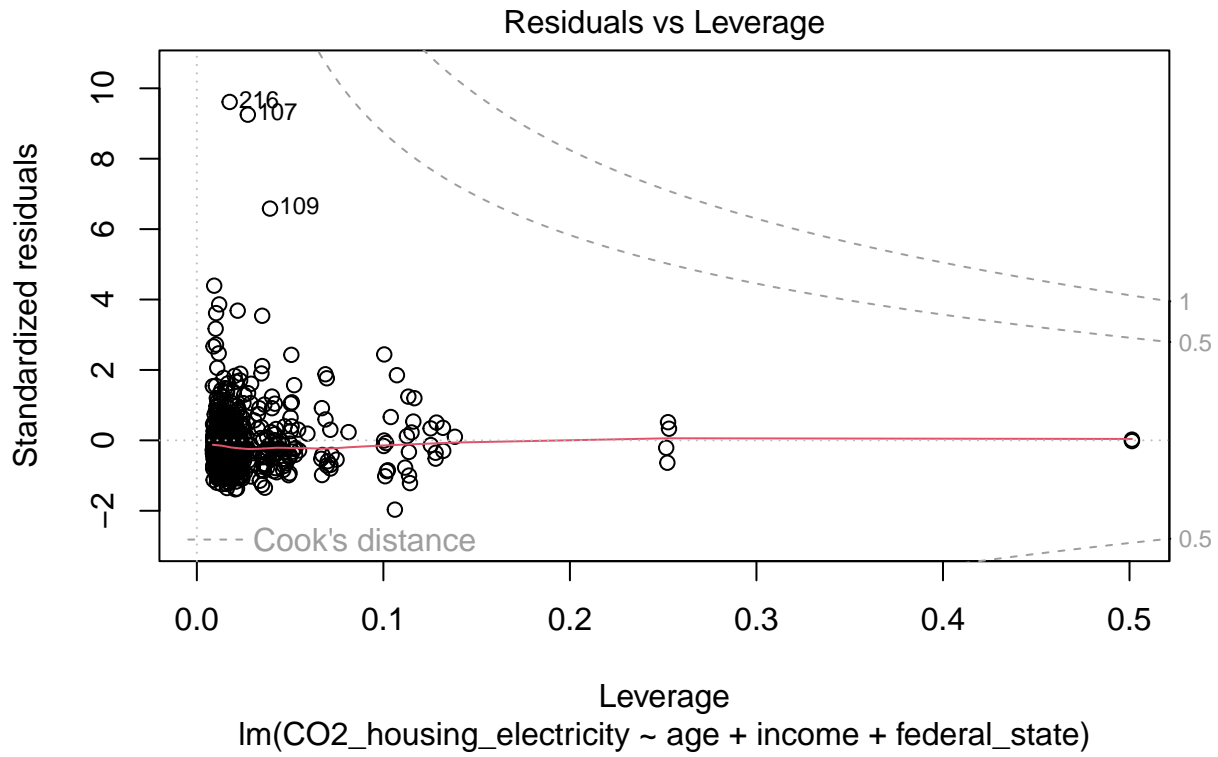
```
## federal_stateSaarland          1340.90572  493.76640   2.716  0.00681 **
## federal_stateSachsen-Anhalt    1033.62431  760.13352   1.360  0.17443
## federal_stateSchleswig-Holstein 237.61095  347.47597   0.684  0.49437
## federal_stateThüringen         880.97153  517.04822   1.704  0.08895 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1493 on 571 degrees of freedom
## Multiple R-squared:  0.06541,    Adjusted R-squared:  0.03923
## F-statistic: 2.498 on 16 and 571 DF,  p-value: 0.001053
```

```
plot(step_model1)
```





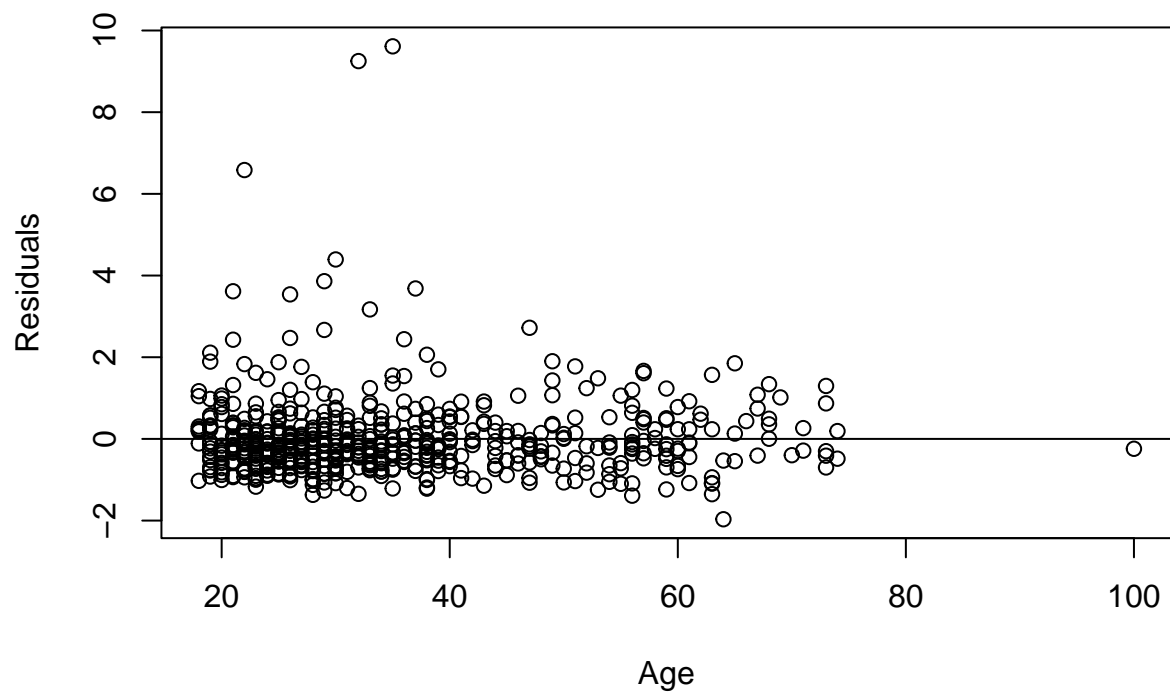




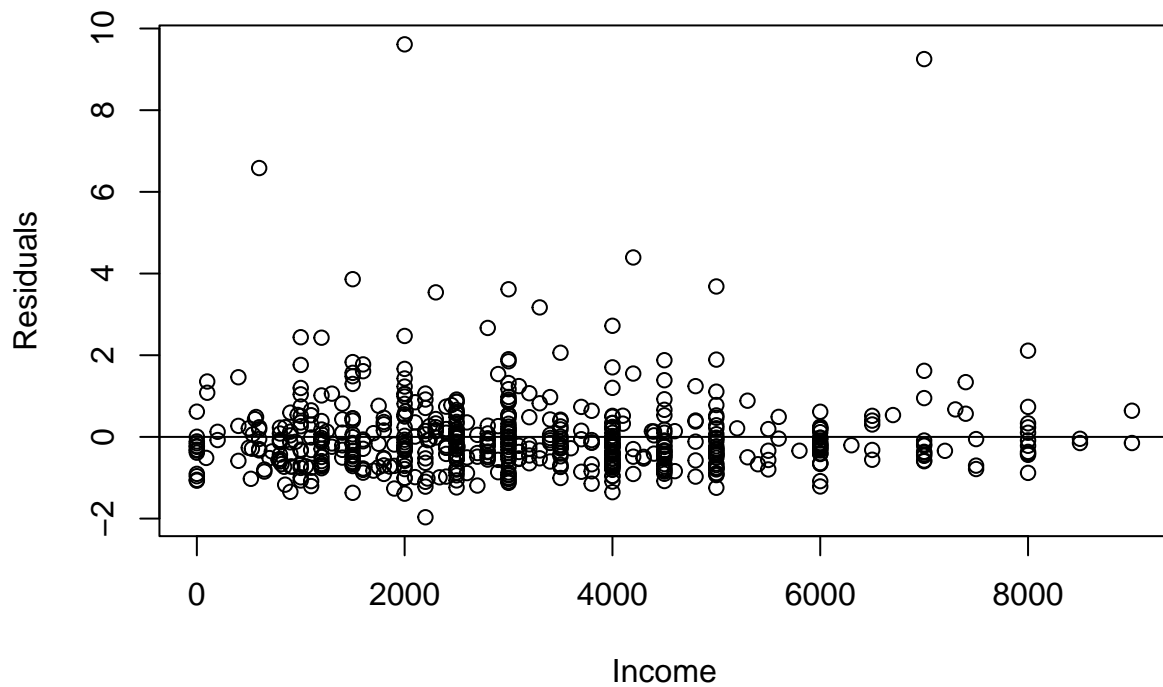
```
res1 = stdres(step_model1) ## (Standardized) Residuals

# Linearity assumption/Mean zero assumption

plot(df1$age, res1, xlab = "Age", ylab = "Residuals")
abline(h = 0)
```



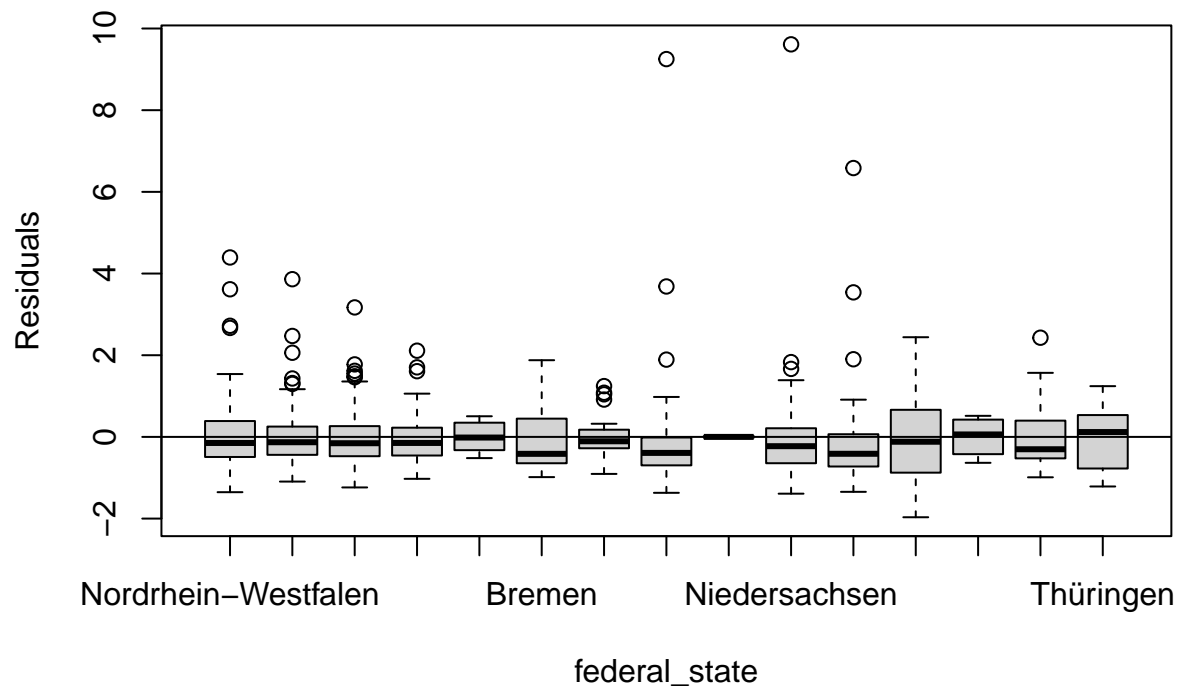
```
plot(df1$income, res1, xlab = "Income", ylab = "Residuals")  
abline(h = 0)
```



```
#plot(df1$urban_rural_class, res1, xlab = "urban_rural_class", ylab = "Residuals")  
#abline(h = 0)
```

```
#plot(df1_scaled$education, res1, xlab = "education", ylab = "Residuals")  
#abline(h = 0)
```

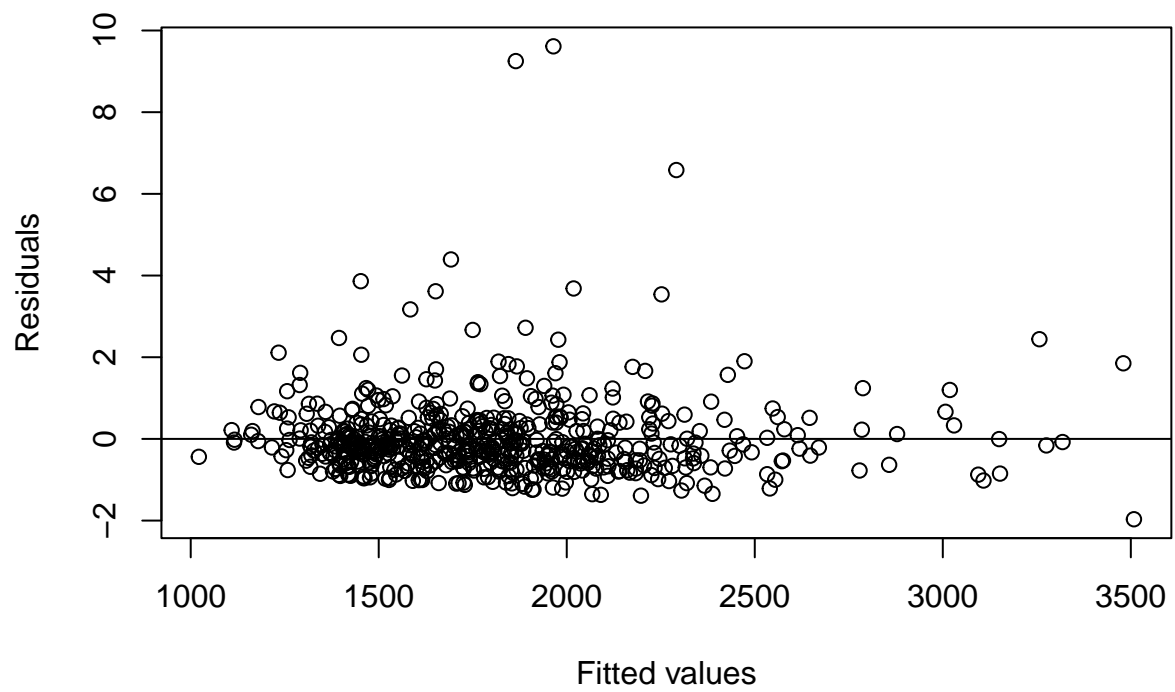
```
plot(df1$federal_state, res1, xlab = "federal_state", ylab = "Residuals")  
abline(h = 0)
```



```
#plot(df1_scaled$political_party, res1, xlab = "Political Party", ylab = "Residuals")
#abline(h = 0)
```

```
# Constant variance and independent error term assumption
```

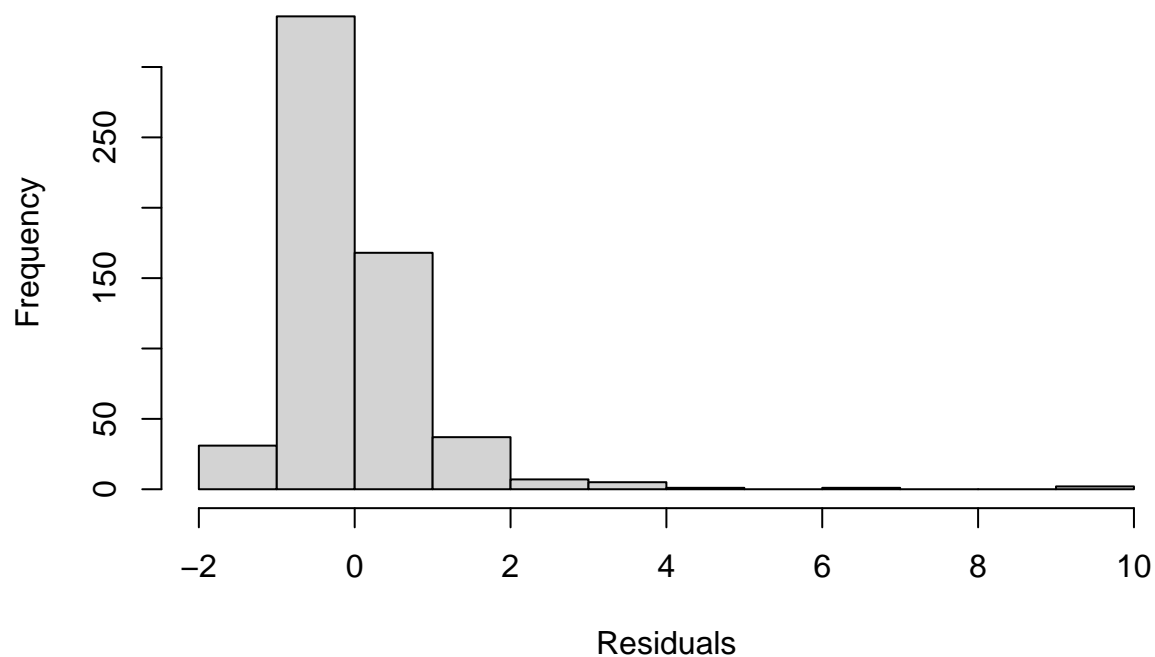
```
plot(fitted(step_model1), res1, xlab = "Fitted values", ylab = "Residuals")
abline(h = 0)
```



```
# Normality assumption
```

```
hist(res1, xlab="Residuals", main= "Histogram of Residuals")
```

Histogram of Residuals



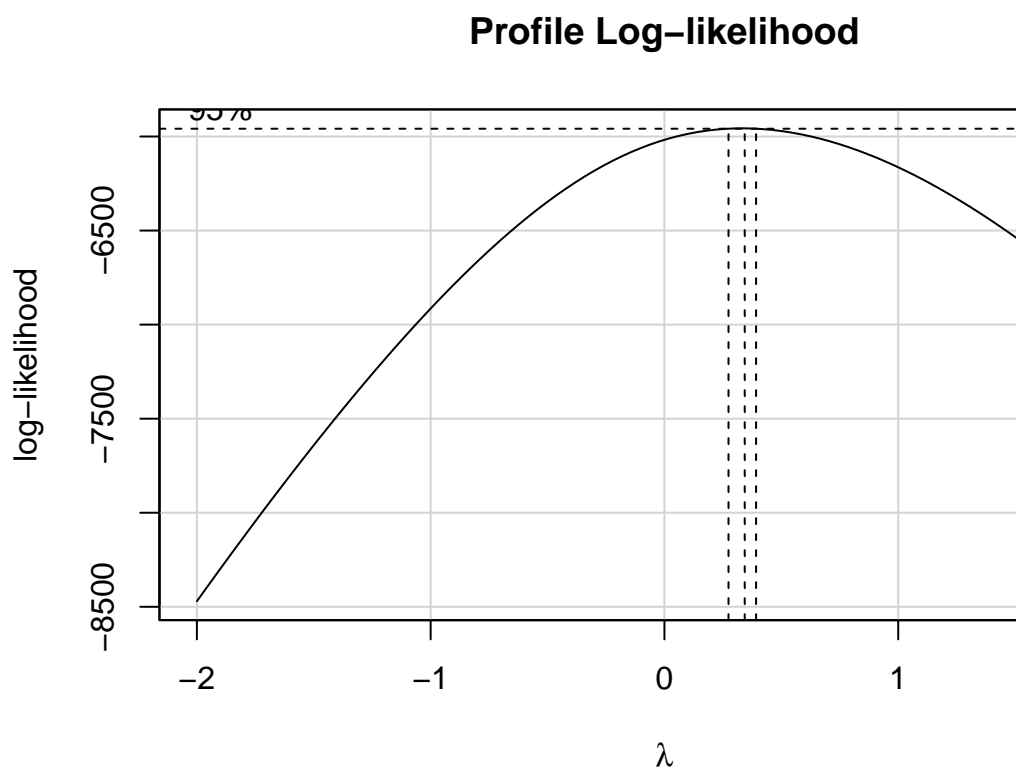
```
## normality test using shapiro-test: reject the H0, not normally distributed  
#H0: the sample comes from a normal distribution
```

```
res1_num = res1[is.finite(res1)]  
shapiro.test(res1_num)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: res1_num  
## W = 0.71431, p-value < 2.2e-16
```

```
# Box-cox transformation
```

```
bc = boxCox(step_model1)
```



4. Improving the regression fit

```
opt.lambda = bc$x[which.max(bc$y)]
round(opt.lambda/0.5)*0.5 # round it to the nearest 0.5
```

```
## [1] 0.5
```

FINAL MODEL

```
# Non-linear transformation with the lambda 0.5

options(scipen = -2)

model1_trans = lm(sqrt(CO2_housing_electricity) ~ age + income + federal_state, data = df1)

summary(model1_trans)
```

```
##
## Call:
## lm(formula = sqrt(CO2_housing_electricity) ~ age + income + federal_state,
##     data = df1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -35.436  -8.123  -0.712   6.929  86.427
```

```
##
## Coefficients:
##
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)      3.715e+01  2.331e+00  15.938 < 2e-16 ***
## age              1.379e-01  4.460e-02   3.093 2.08e-03 **
## income           -6.080e-04  3.279e-04  -1.854 6.42e-02 .
## federal_stateBaden-Württemberg -5.137e+00  2.048e+00  -2.508 1.24e-02 *
## federal_stateBayern -2.337e+00  2.019e+00  -1.157 2.48e-01
## federal_stateBerlin -2.027e+00  2.615e+00  -0.775 4.39e-01
## federal_stateBrandenburg -1.917e+00  5.409e+00  -0.354 7.23e-01
## federal_stateBremen  4.646e+00  4.054e+00   1.146 2.52e-01
## federal_stateHamburg -3.296e+00  3.263e+00  -1.010 3.13e-01
## federal_stateHessen  2.198e+00  2.499e+00   0.880 3.79e-01
## federal_stateMecklenburg-Vorpommern -5.289e+00  1.056e+01  -0.501 6.17e-01
## federal_stateNiedersachsen  5.000e-02  2.379e+00   0.021 9.83e-01
## federal_stateRheinland-Pfalz  4.405e+00  3.027e+00   1.455 1.46e-01
## federal_stateSaarland  1.334e+01  4.888e+00   2.730 6.53e-03 **
## federal_stateSachsen-Anhalt  1.295e+01  7.524e+00   1.721 8.59e-02 .
## federal_stateSchleswig-Holstein  3.160e+00  3.440e+00   0.919 3.59e-01
## federal_stateThüringen  9.924e+00  5.118e+00   1.939 5.30e-02 .
## ---
## Signif. codes:  0 '***' 1e-03 '**' 1e-02 '*' 5e-02 '.' 0.1 ' ' 1
##
## Residual standard error: 14.78 on 571 degrees of freedom
## Multiple R-squared:  0.08588,    Adjusted R-squared:  0.06026
## F-statistic: 3.353 on 16 and 571 DF,  p-value: 1.139e-05
```

```
# Checking the VIFs for multicollinearity
```

```
vif(model1_trans)
```

```
##               GVIF Df GVIF^(1/(2*Df))
## age           1.021943  1      1.010912
## income        1.035322  1      1.017508
## federal_state 1.056661 14      1.001970
```

```
# threshold for multicollinearity
```

```
# Calculating the threshold
```

```
max(10, 1/(1-summary(model1_trans)$r.square))
```

```
## [1] 10
```

```
# Checking outliers: estimate of the influence of data point; summary of how much a regression model changes
```

```
cook = cooks.distance(model1_trans)
```

```
plot(cook,
```

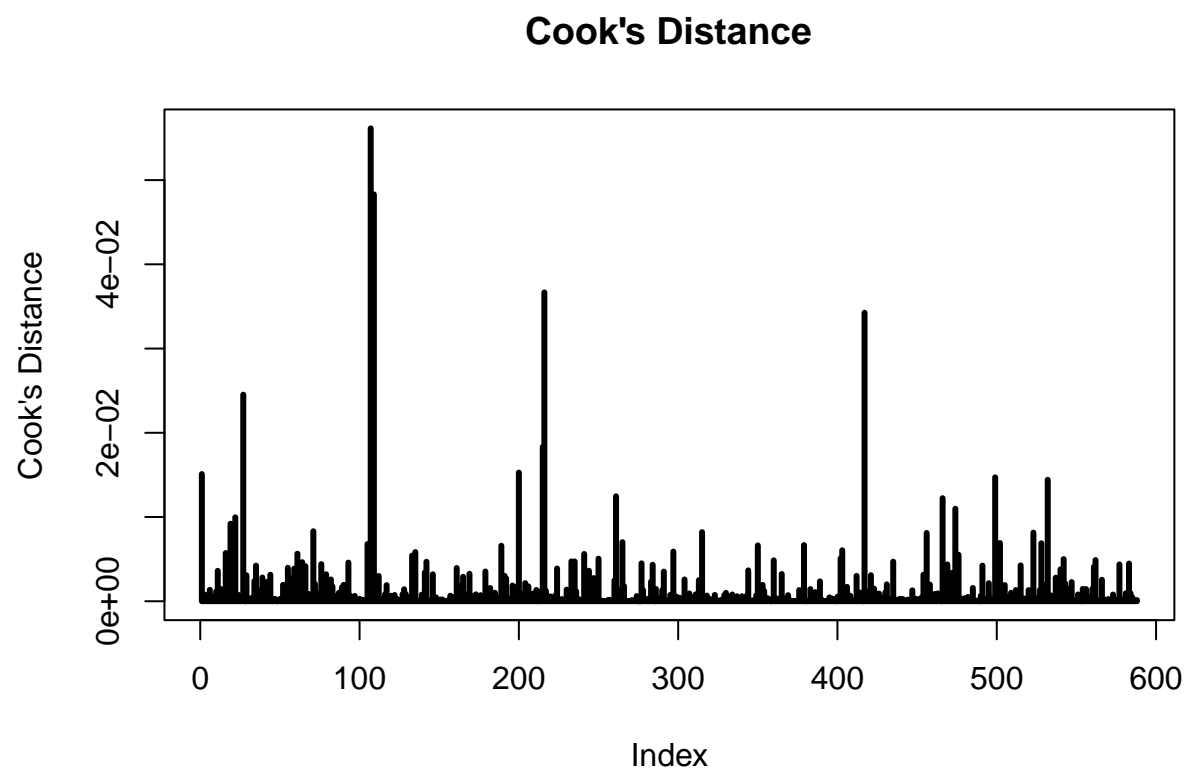
```
  type="h",
```

```
  lwd=3,
```

```
  ylab = "Cook's Distance",
```

```
  main="Cook's Distance")
```

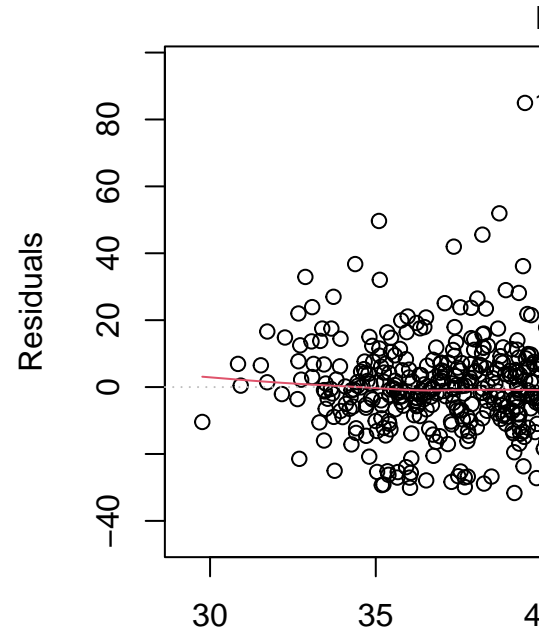
```
abline(h = 1)
```

```
influential = cooks.distance(model1_trans)[which(cook >1)]  
influential
```

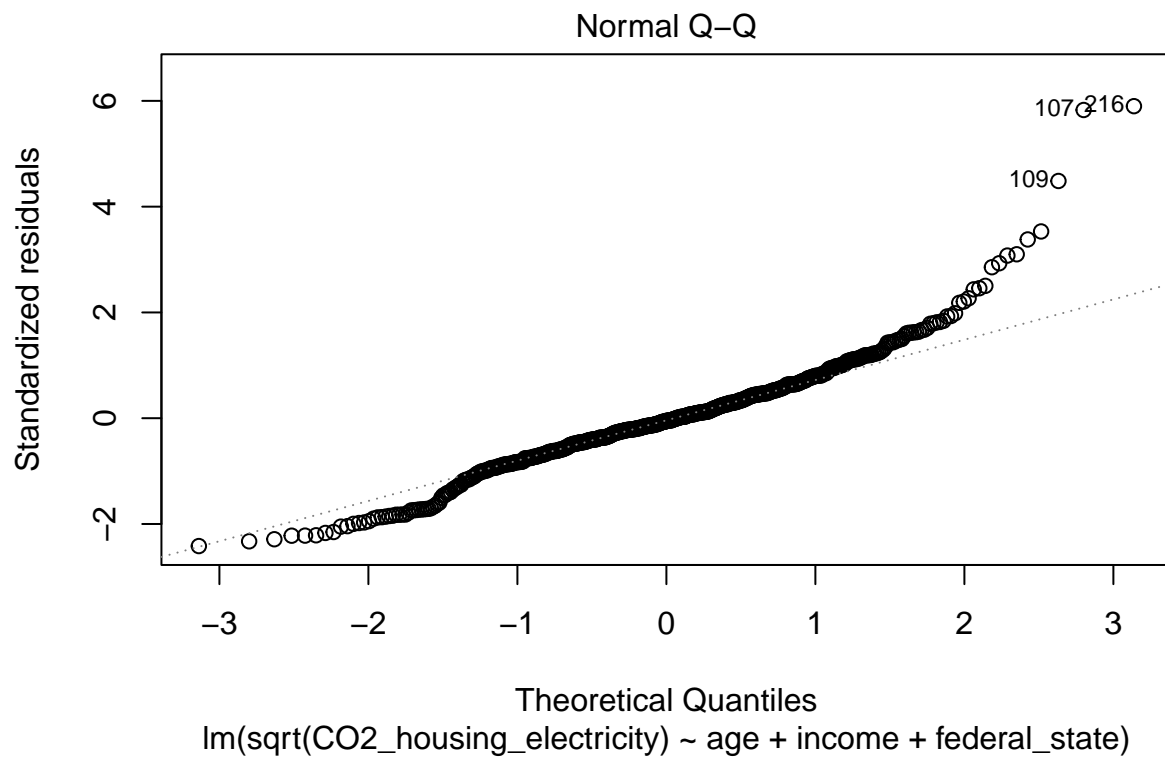
```
## named numeric(0)
```

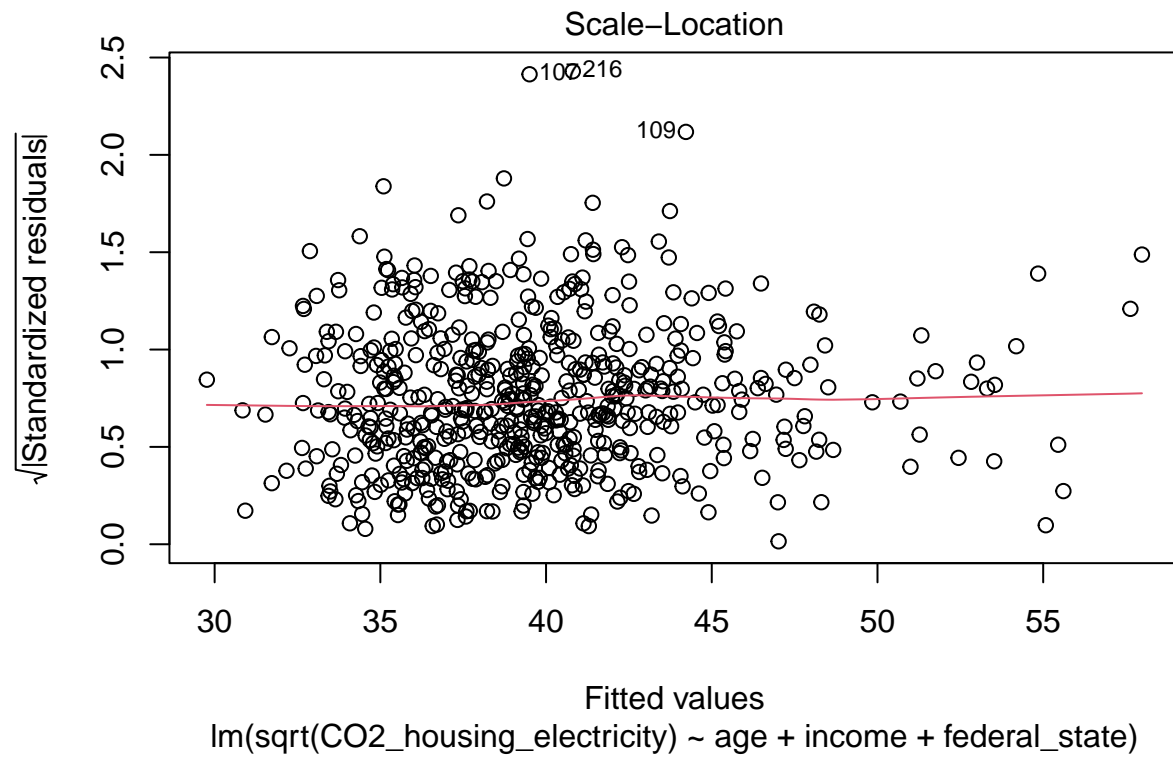
```
plot(model1_trans)
```

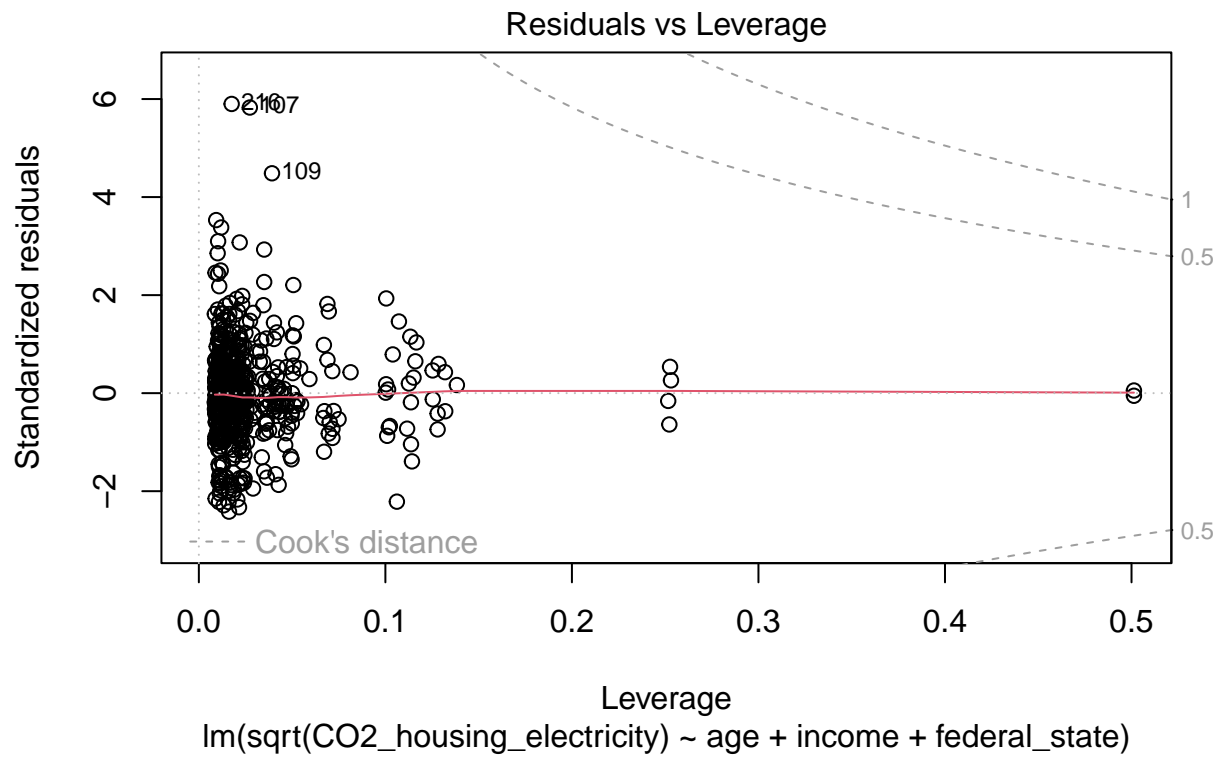


5. Assumptions check in the residuals of the transformed regression

$\ln(\sqrt{\text{CO2_housing_electricity}}) \sim \text{age} + \text{income} + \text{federal_state}$



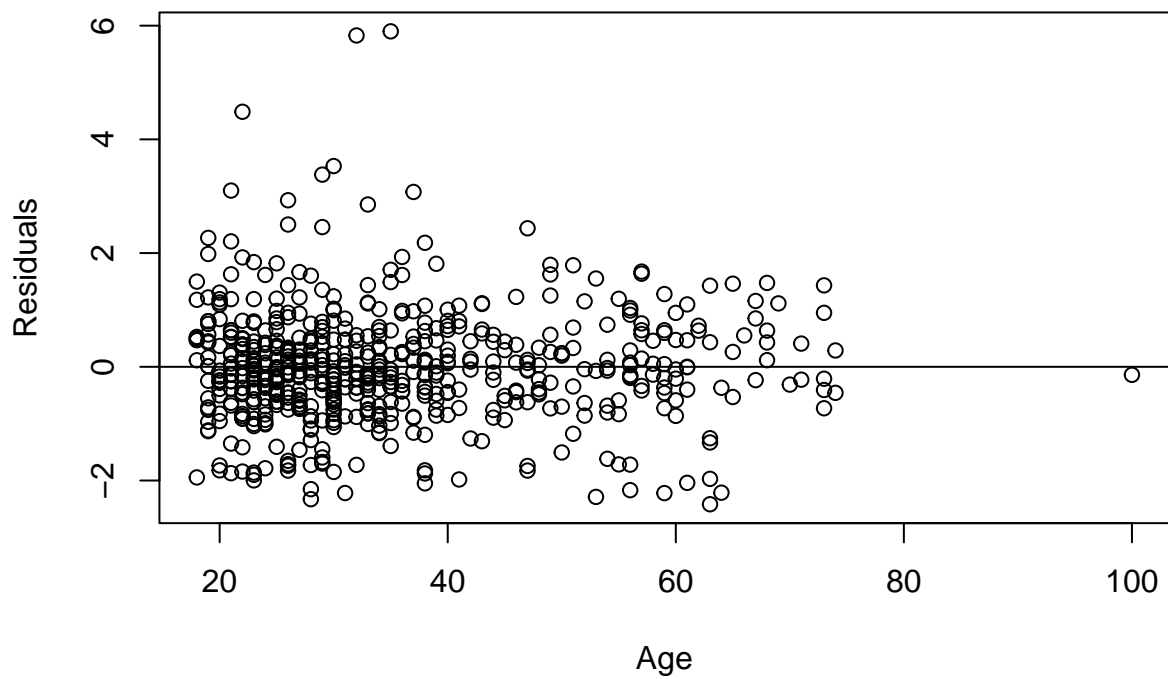




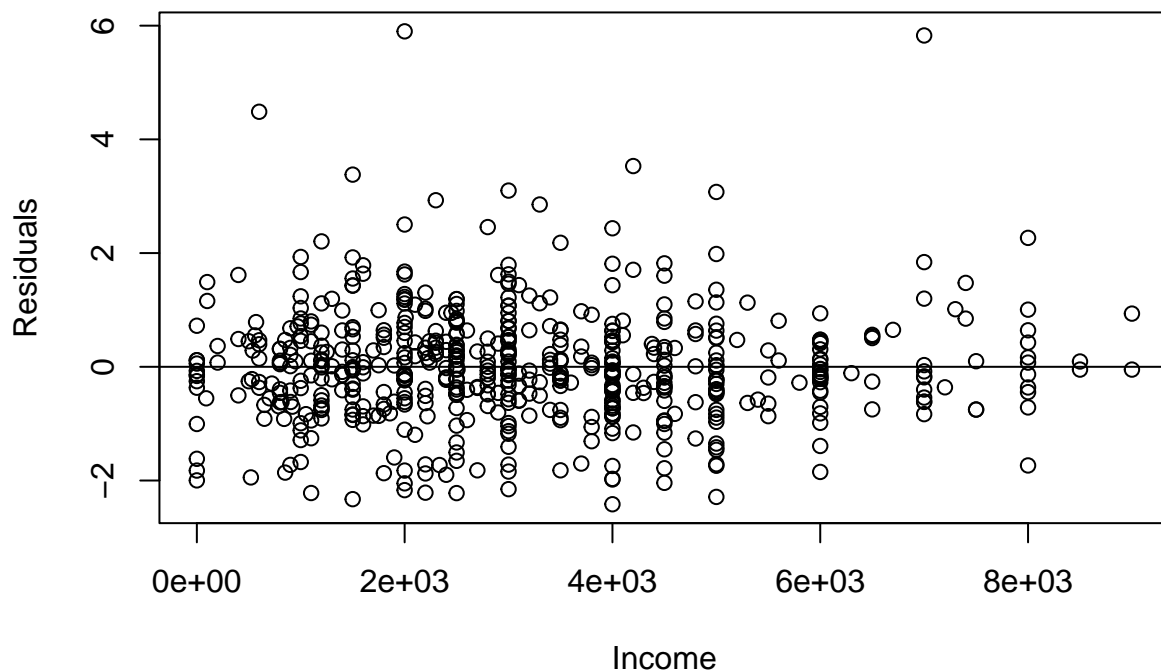
```
res1 = stdres(model1_trans) ## (Standardized) Residuals

# Linearity assumption/Mean zero assumption

plot(df1$age, res1, xlab = "Age", ylab = "Residuals")
abline(h = 0)
```



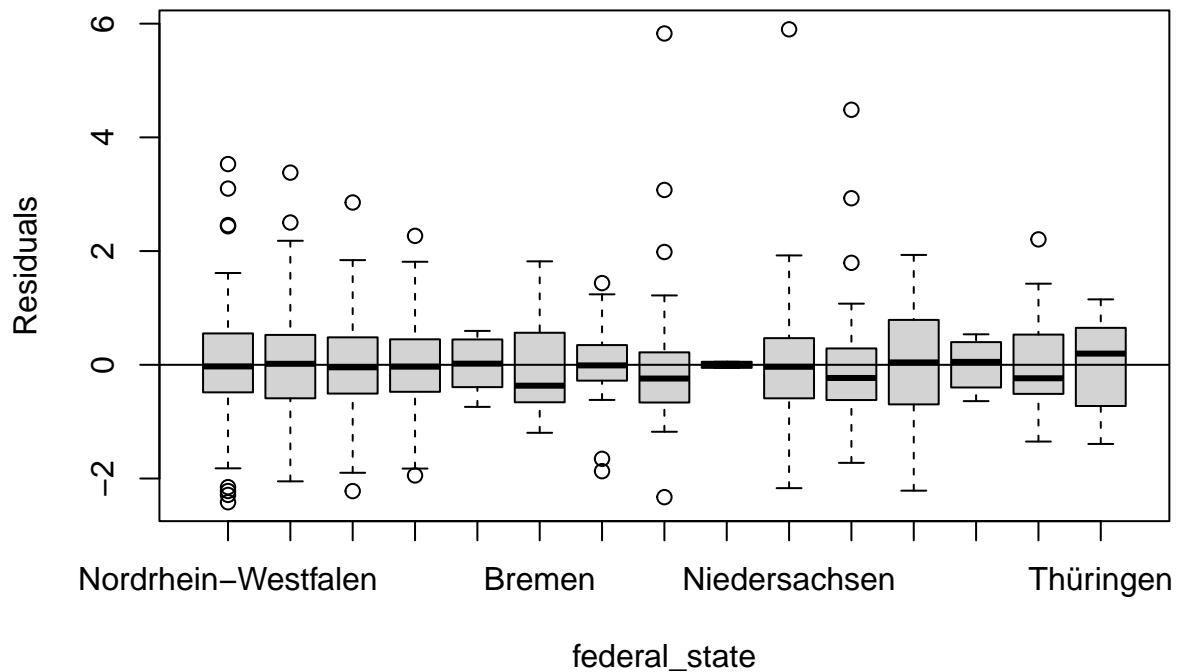
```
plot(df1$income, res1, xlab = "Income", ylab = "Residuals")  
abline(h = 0)
```



```
#plot(df1$urban_rural_class, res1, xlab = "urban_rural_class", ylab = "Residuals")
#abline(h = 0)
```

```
#plot(df1$education, res1, xlab = "education", ylab = "Residuals")
#abline(h = 0)
```

```
plot(df1$federal_state, res1, xlab = "federal_state", ylab = "Residuals")
abline(h = 0)
```



```
#plot(df1$political_party, res1, xlab = "Political Party", ylab = "Residuals")
#abline(h = 0)
```

```
# Durbin-Watson Test: Independence of the error terms
# H0 (null hypothesis): There is no correlation among the residuals
```

```
durbinWatsonTest(model1_trans)
```

```
## lag Autocorrelation D-W Statistic p-value
## 1 0.04184228 1.912674 0.3
## Alternative hypothesis: rho != 0
```

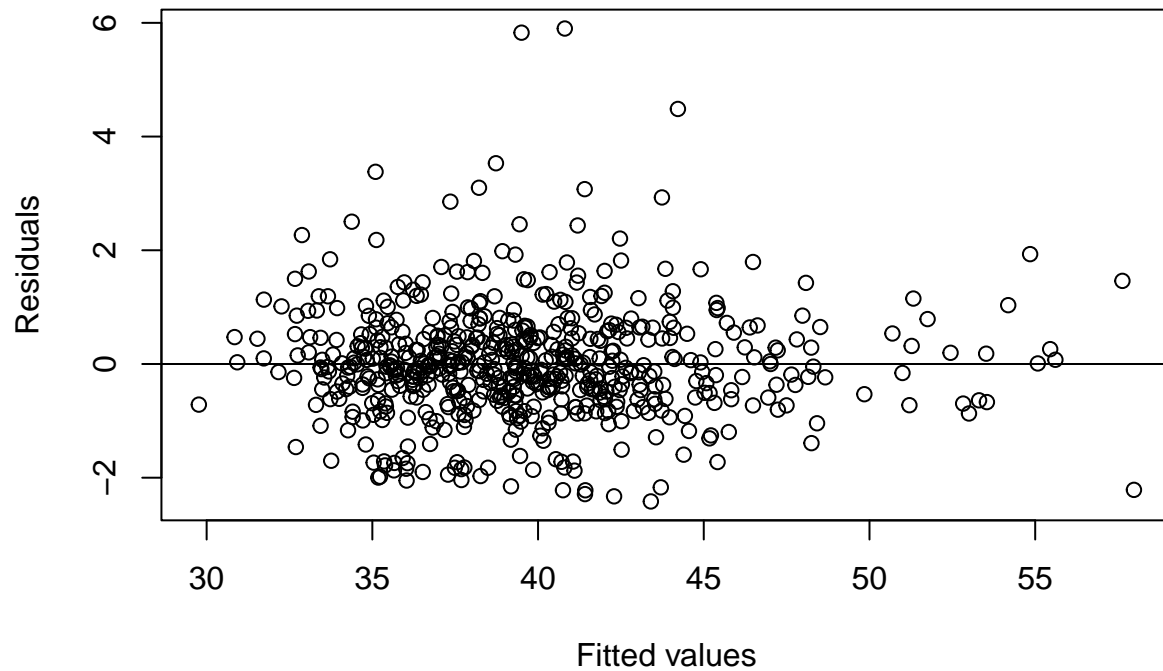
```
# Breusch-Pagan TEST: Heteroscedasticity
# H0: Homoscedasticity is present
```

```
bptest(model1_trans)
```

```
##
## studentized Breusch-Pagan test
##
## data: model1_trans
## BP = 7.5682, df = 16, p-value = 0.9607
```

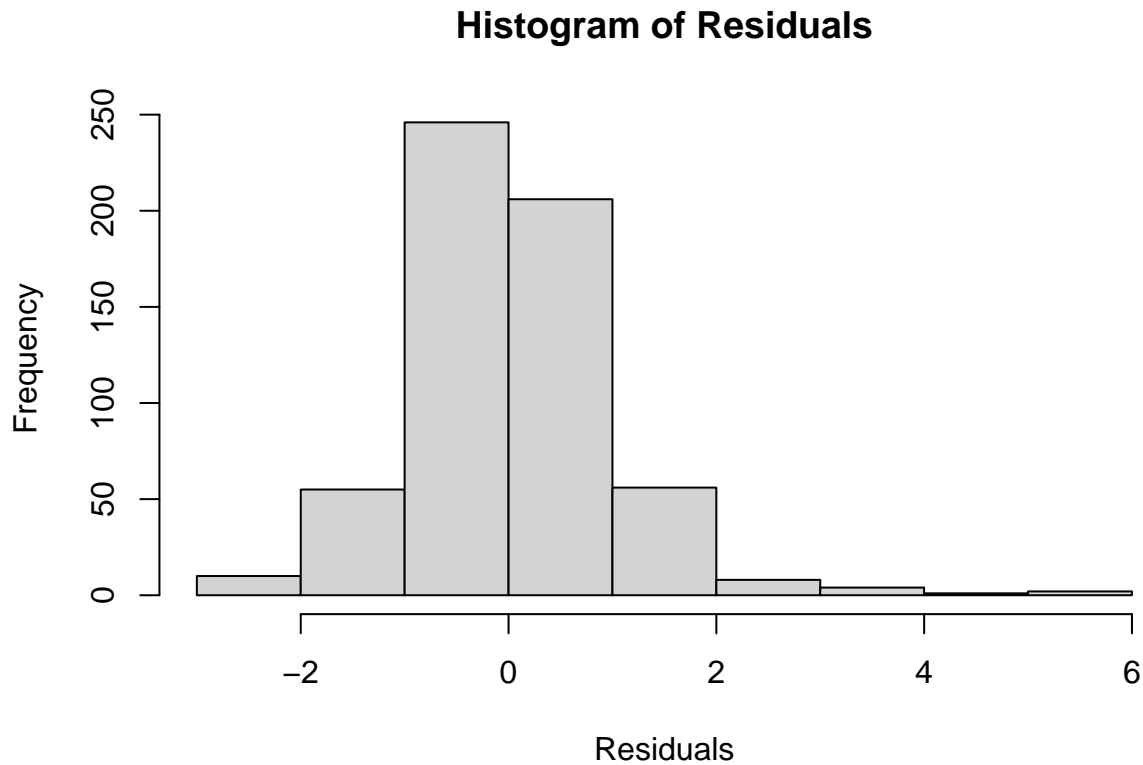
```
# Constant variance and independent error term assumption
```

```
plot(fitted(model1_trans), res1, xlab = "Fitted values", ylab = "Residuals")  
abline(h = 0)
```



```
# Normality assumption
```

```
hist(res1, xlab="Residuals", main= "Histogram of Residuals")
```

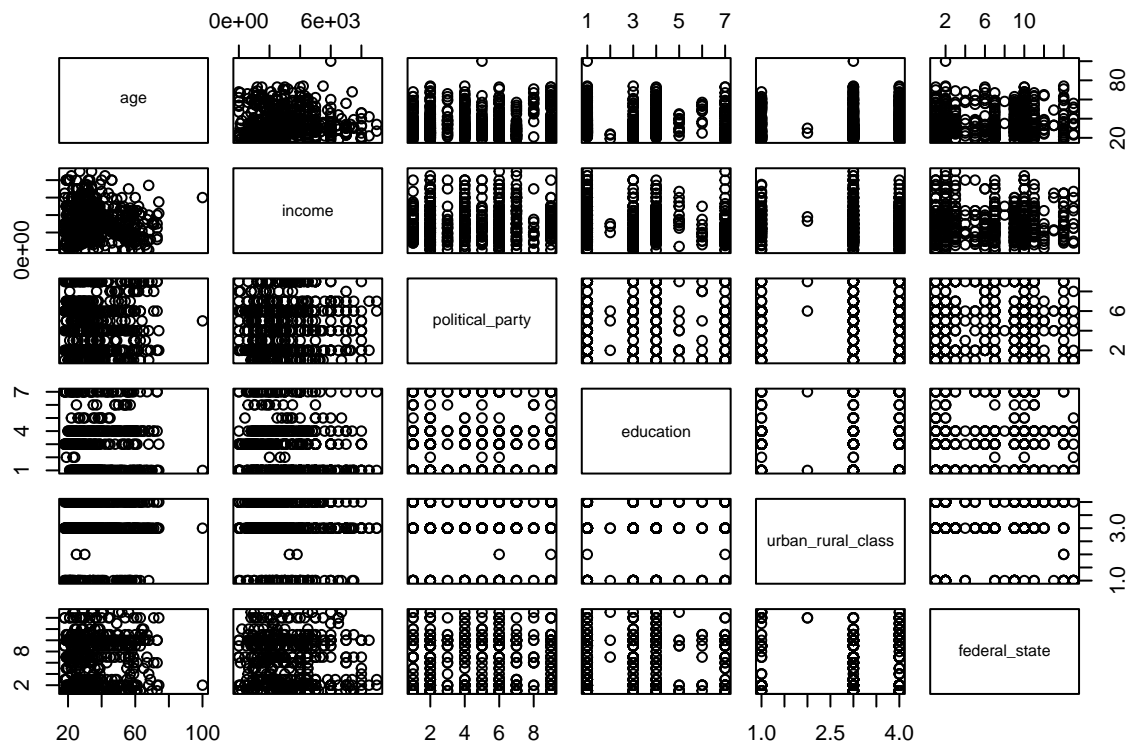
```
## normality test using shapiro-test: reject the H0  
#H0: the sample comes from a normal distribution
```

```
res1_num = res1[is.finite(res1)]  
shapiro.test(res1_num)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: res1_num  
## W = 0.94014, p-value = 1.227e-14
```

III. Multivariate Regression: belief diff housing and electricity

```
# Checking the possible correlation in the data  
plot(df2[1:6])
```



1. Modeling

```
## defining a reference level
```

```
df2$political_party <- relevel(df2$political_party, ref='Bündnis 90/Die Grünen')
df2$education <- relevel(df2$education, ref='(Fach-) Hochschulabschluss (Bachelor, Master, Magister, D
df2$urban_rural_class <- relevel(df2$urban_rural_class, ref='sehr zentral')
df2$federal_state <- relevel(df2$federal_state, ref='Nordrhein-Westfalen')
```

```
# regression model
```

```
options(scipen=-0, digits=2)
```

```
model2 = lm(belief_diff_housing_electricity ~ age + income + political_party + education + urban_rural_
```

```
summary(model2)
```

FINAL MODEL

```
##
## Call:
## lm(formula = belief_diff_housing_electricity ~ age + income +
##     political_party + education + urban_rural_class + federal_state,
##     data = df2)
```

```

##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -87.23 -23.68  -0.92  21.89 101.41
##
## Coefficients:
##                                     Estimate
## (Intercept)                        1.15e+00
## age                                -4.97e-01
## income                             1.78e-03
## political_partyAfD                 2.24e-01
## political_partyBündnis Sarah Wagenknecht -2.50e+00
## political_partyCDU/CSU              2.48e+00
## political_partyDie Linke            -5.09e-01
## political_partyEiner anderen Partei  -1.32e+00
## political_partyFDP                  -1.55e+00
## political_partyKeine Angabe         7.48e+00
## political_partySPD                  4.39e+00
## education(Noch) kein Abschluss      1.84e+01
## educationAllgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS) -2.83e+00
## educationBerufsausbildung, Lehre oder Ausbildung an einer Fachschule 2.02e+00
## educationDoktorgrad oder Habilitation -5.53e+00
## educationHauptschulabschluss (Volksschulabschluss) oder gleichwertiger Abschluss 1.35e+01
## educationRealschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss -1.45e+00
## urban_rural_classperipher           -4.17e+00
## urban_rural_classsehr peripher      1.25e+01
## urban_rural_classzentral            4.51e+00
## federal_stateBaden-Württemberg       1.24e+01
## federal_stateBayern                  7.10e+00
## federal_stateBerlin                 3.67e+00
## federal_stateBrandenburg            1.29e+01
## federal_stateBremen                 -4.49e-01
## federal_stateHamburg                6.45e-02
## federal_stateHessen                 -6.54e-01
## federal_stateMecklenburg-Vorpommern  2.08e+01
## federal_stateNiedersachsen           -7.46e-01
## federal_stateRheinland-Pfalz        -1.91e+00
## federal_stateSaarland               -1.22e+01
## federal_stateSachsen-Anhalt         -1.75e+01
## federal_stateSchleswig-Holstein      3.40e+00
## federal_stateThüringen              -1.40e+01
##                                     Std. Error
## (Intercept)                        6.45e+00
## age                                1.14e-01
## income                             7.64e-04
## political_partyAfD                 5.47e+00
## political_partyBündnis Sarah Wagenknecht 7.66e+00
## political_partyCDU/CSU              4.91e+00
## political_partyDie Linke            5.92e+00
## political_partyEiner anderen Partei  4.39e+00
## political_partyFDP                  5.69e+00
## political_partyKeine Angabe         9.85e+00
## political_partySPD                  5.00e+00
## education(Noch) kein Abschluss      2.00e+01

```

| | |
|--|----------|
| ## educationAllgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS) | 3.89e+00 |
| ## educationBerufsausbildung, Lehre oder Ausbildung an einer Fachschule | 3.97e+00 |
| ## educationDoktorgrad oder Habilitation | 9.70e+00 |
| ## educationHauptschulabschluss (Volksschulabschluss) oder gleichwertiger Abschluss | 1.11e+01 |
| ## educationRealschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss | 5.05e+00 |
| ## urban_rural_classperipher | 5.08e+00 |
| ## urban_rural_classsehr peripher | 2.52e+01 |
| ## urban_rural_classzentral | 3.73e+00 |
| ## federal_stateBaden-Württemberg | 4.84e+00 |
| ## federal_stateBayern | 4.97e+00 |
| ## federal_stateBerlin | 6.04e+00 |
| ## federal_stateBrandenburg | 1.27e+01 |
| ## federal_stateBremen | 9.25e+00 |
| ## federal_stateHamburg | 7.53e+00 |
| ## federal_stateHessen | 5.78e+00 |
| ## federal_stateMecklenburg-Vorpommern | 2.42e+01 |
| ## federal_stateNiedersachsen | 5.88e+00 |
| ## federal_stateRheinland-Pfalz | 7.25e+00 |
| ## federal_stateSaarland | 1.14e+01 |
| ## federal_stateSachsen-Anhalt | 1.75e+01 |
| ## federal_stateSchleswig-Holstein | 8.48e+00 |
| ## federal_stateThüringen | 1.29e+01 |
| ## | t value |
| ## (Intercept) | 0.18 |
| ## age | -4.35 |
| ## income | 2.34 |
| ## political_partyAfD | 0.04 |
| ## political_partyBündnis Sarah Wagenknecht | -0.33 |
| ## political_partyCDU/CSU | 0.50 |
| ## political_partyDie Linke | -0.09 |
| ## political_partyEiner anderen Partei | -0.30 |
| ## political_partyFDP | -0.27 |
| ## political_partyKeine Angabe | 0.76 |
| ## political_partySPD | 0.88 |
| ## education(Noch) kein Abschluss | 0.92 |
| ## educationAllgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS) | -0.73 |
| ## educationBerufsausbildung, Lehre oder Ausbildung an einer Fachschule | 0.51 |
| ## educationDoktorgrad oder Habilitation | -0.57 |
| ## educationHauptschulabschluss (Volksschulabschluss) oder gleichwertiger Abschluss | 1.22 |
| ## educationRealschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss | -0.29 |
| ## urban_rural_classperipher | -0.82 |
| ## urban_rural_classsehr peripher | 0.49 |
| ## urban_rural_classzentral | 1.21 |
| ## federal_stateBaden-Württemberg | 2.57 |
| ## federal_stateBayern | 1.43 |
| ## federal_stateBerlin | 0.61 |
| ## federal_stateBrandenburg | 1.02 |
| ## federal_stateBremen | -0.05 |
| ## federal_stateHamburg | 0.01 |
| ## federal_stateHessen | -0.11 |
| ## federal_stateMecklenburg-Vorpommern | 0.86 |
| ## federal_stateNiedersachsen | -0.13 |
| ## federal_stateRheinland-Pfalz | -0.26 |
| ## federal_stateSaarland | -1.07 |

```

## federal_stateSachsen-Anhalt -1.00
## federal_stateSchleswig-Holstein 0.40
## federal_stateThüringen -1.09
## Pr(>|t|)
## (Intercept) 0.859
## age 1.6e-05
## income 0.020
## political_partyAfD 0.967
## political_partyBündnis Sarah Wagenknecht 0.744
## political_partyCDU/CSU 0.614
## political_partyDie Linke 0.932
## political_partyEiner anderen Partei 0.764
## political_partyFDP 0.785
## political_partyKeine Angabe 0.448
## political_partySPD 0.380
## education(Noch) kein Abschluss 0.358
## educationAllgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS) 0.467
## educationBerufsausbildung, Lehre oder Ausbildung an einer Fachschule 0.610
## educationDoktorgrad oder Habilitation 0.569
## educationHauptschulabschluss (Volksschulabschluss) oder gleichwertiger Abschluss 0.224
## educationRealschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss 0.775
## urban_rural_classperipher 0.413
## urban_rural_classsehr peripher 0.621
## urban_rural_classzentral 0.226
## federal_stateBaden-Württemberg 0.011
## federal_stateBayern 0.154
## federal_stateBerlin 0.544
## federal_stateBrandenburg 0.309
## federal_stateBremen 0.961
## federal_stateHamburg 0.993
## federal_stateHessen 0.910
## federal_stateMecklenburg-Vorpommern 0.391
## federal_stateNiedersachsen 0.899
## federal_stateRheinland-Pfalz 0.792
## federal_stateSaarland 0.284
## federal_stateSachsen-Anhalt 0.318
## federal_stateSchleswig-Holstein 0.688
## federal_stateThüringen 0.276
##
## (Intercept)
## age ***
## income *
## political_partyAfD
## political_partyBündnis Sarah Wagenknecht
## political_partyCDU/CSU
## political_partyDie Linke
## political_partyEiner anderen Partei
## political_partyFDP
## political_partyKeine Angabe
## political_partySPD
## education(Noch) kein Abschluss
## educationAllgemeine oder fachgebundene Hochschulreife/Abitur (Gymnasium bzw. EOS)
## educationBerufsausbildung, Lehre oder Ausbildung an einer Fachschule
## educationDoktorgrad oder Habilitation

```

```
## educationHauptschulabschluss (Volksschulabschluss) oder gleichwertiger Abschluss
## educationRealschulabschluss (Mittlere Reife) oder gleichwertiger Abschluss
## urban_rural_classperipher
## urban_rural_classsehr peripher
## urban_rural_classzentral
## federal_stateBaden-Württemberg *
## federal_stateBayern
## federal_stateBerlin
## federal_stateBrandenburg
## federal_stateBremen
## federal_stateHamburg
## federal_stateHessen
## federal_stateMecklenburg-Vorpommern
## federal_stateNiedersachsen
## federal_stateRheinland-Pfalz
## federal_stateSaarland
## federal_stateSachsen-Anhalt
## federal_stateSchleswig-Holstein
## federal_stateThüringen
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 33 on 554 degrees of freedom
## Multiple R-squared:  0.0898, Adjusted R-squared:  0.0355
## F-statistic: 1.66 on 33 and 554 DF,  p-value: 0.0133
```

```
# Checking the VIFs for multicollinearity
```

```
vif(model2)
```

```
##              GVIF Df GVIF^(1/(2*Df))
## age           1.3  1             1.1
## income        1.1  1             1.0
## political_party 1.8  8             1.0
## education     1.8  6             1.1
## urban_rural_class 2.1  3             1.1
## federal_state  3.0 14             1.0
```

```
# threshold for multicollinearity
```

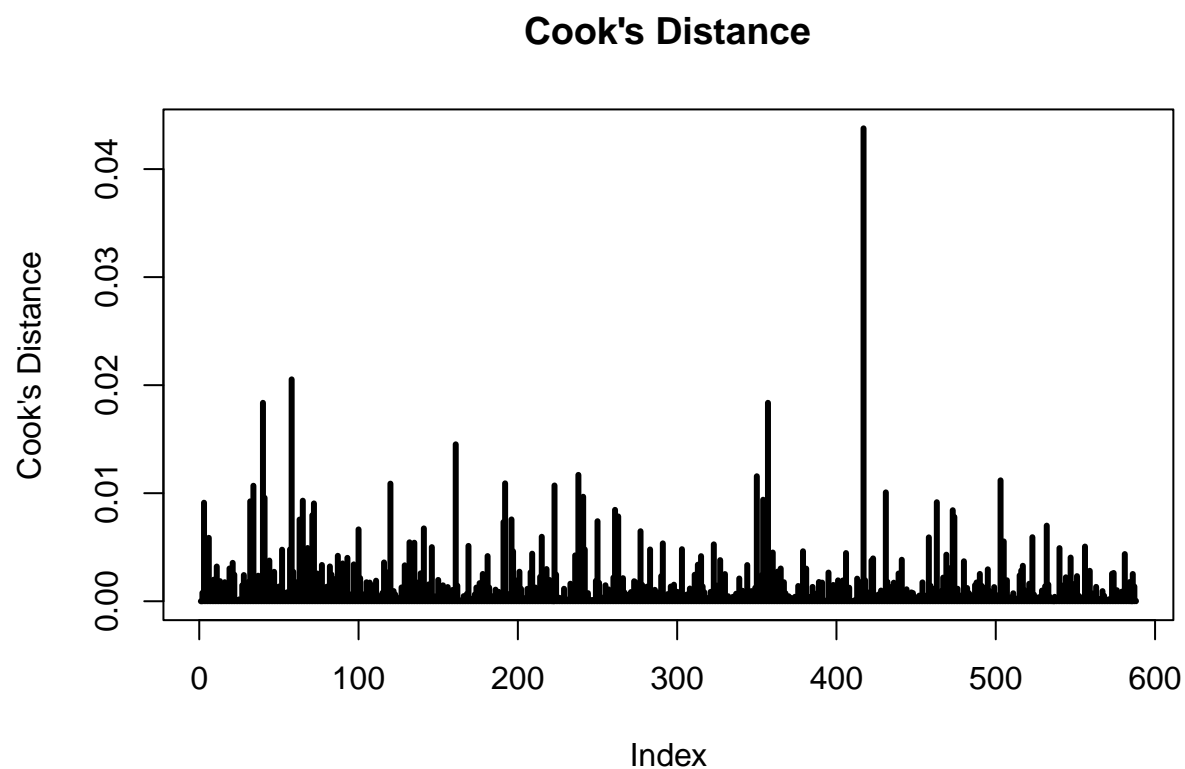
```
# Calculating the threshold
```

```
max(10, 1/(1-summary(model2)$r.square))
```

```
## [1] 10
```

```
# Checking outliers
```

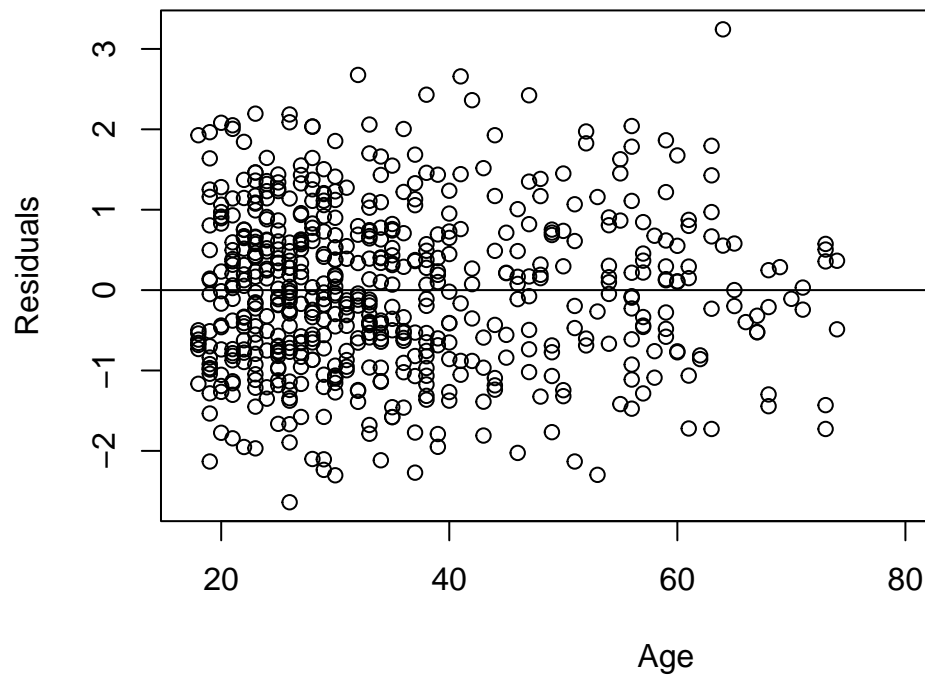
```
cook = cooks.distance(model2)
plot(cook,
     type="h",
     lwd=3,
     ylab = "Cook's Distance",
     main="Cook's Distance")
abline(h = 1)
```



```
res2 = stdres(model2) ## (Standardized) Residuals

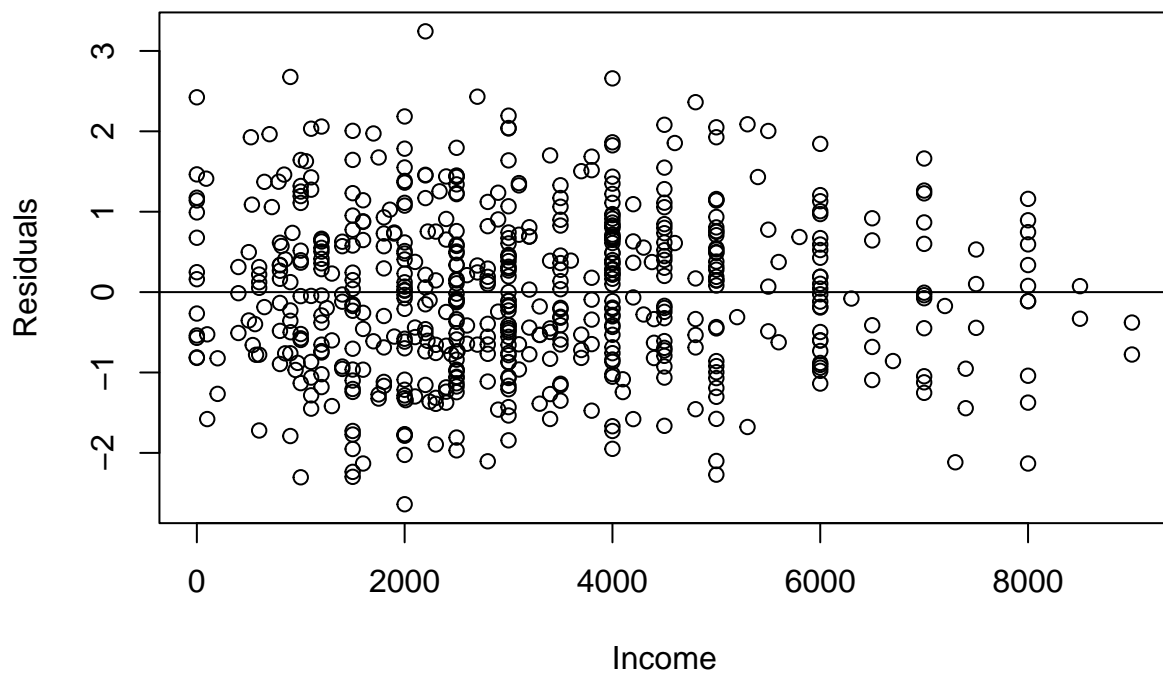
# Linearity assumption/Mean zero assumption

plot(df2$age, res2, xlab = "Age", ylab = "Residuals")
abline(h = 0)
```

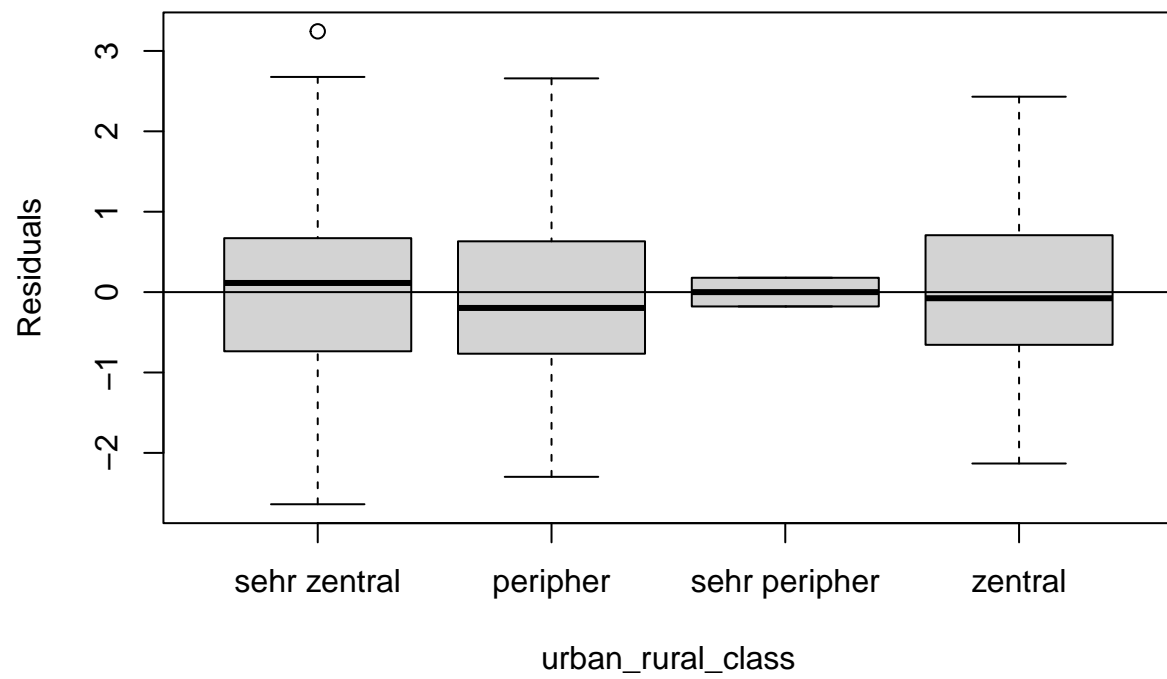


2. Assumptions check in the residuals

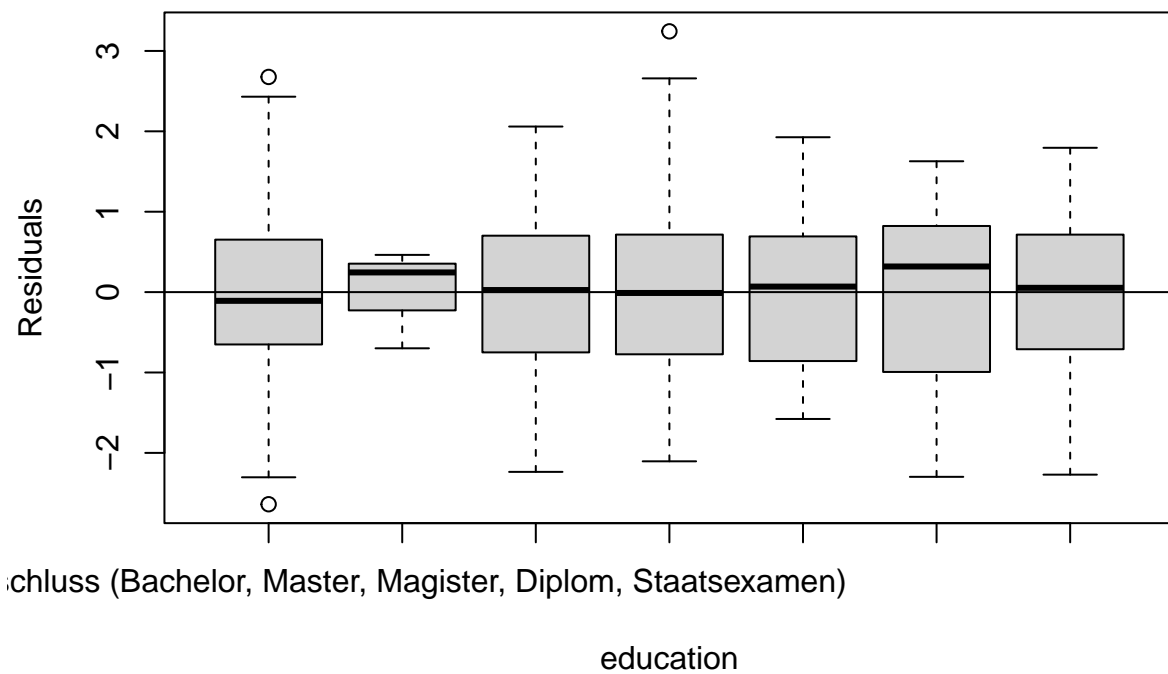
```
plot(df2$income, res2, xlab = "Income", ylab = "Residuals")  
abline(h = 0)
```

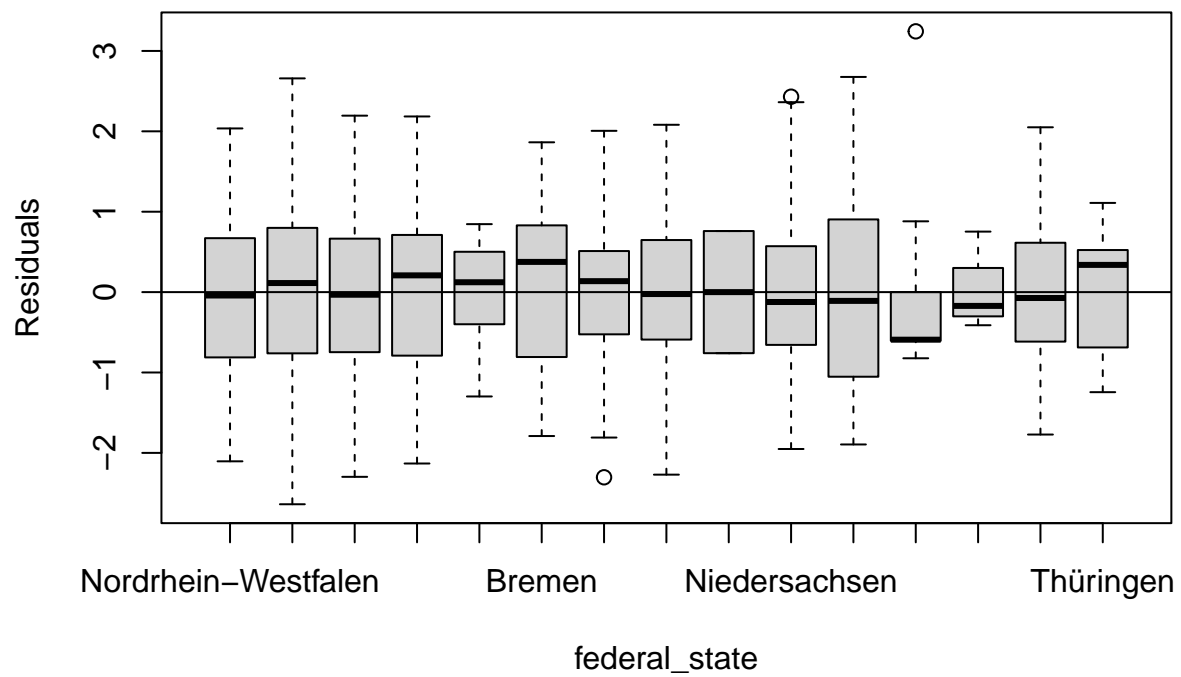
```
plot(df2$urban_rural_class, res2, xlab = "urban_rural_class", ylab = "Residuals")  
abline(h = 0)
```



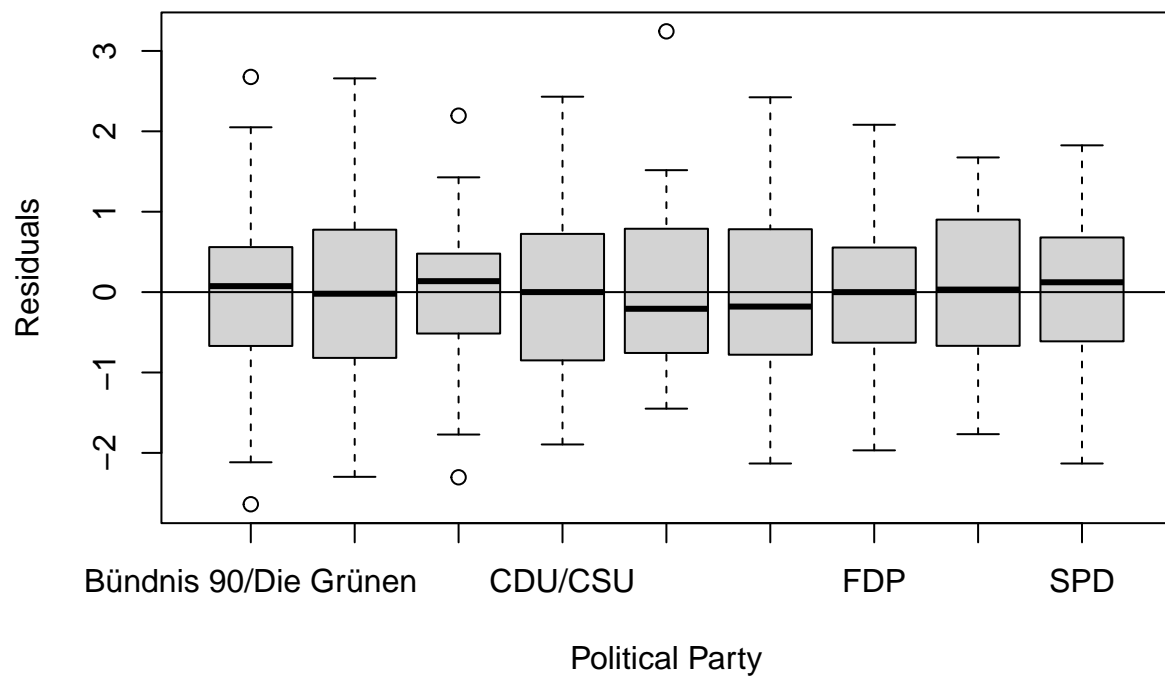
```
plot(df2$education, res2, xlab = "education", ylab = "Residuals")  
abline(h = 0)
```



```
plot(df2$federal_state, res2, xlab = "federal_state", ylab = "Residuals")
abline(h = 0)
```

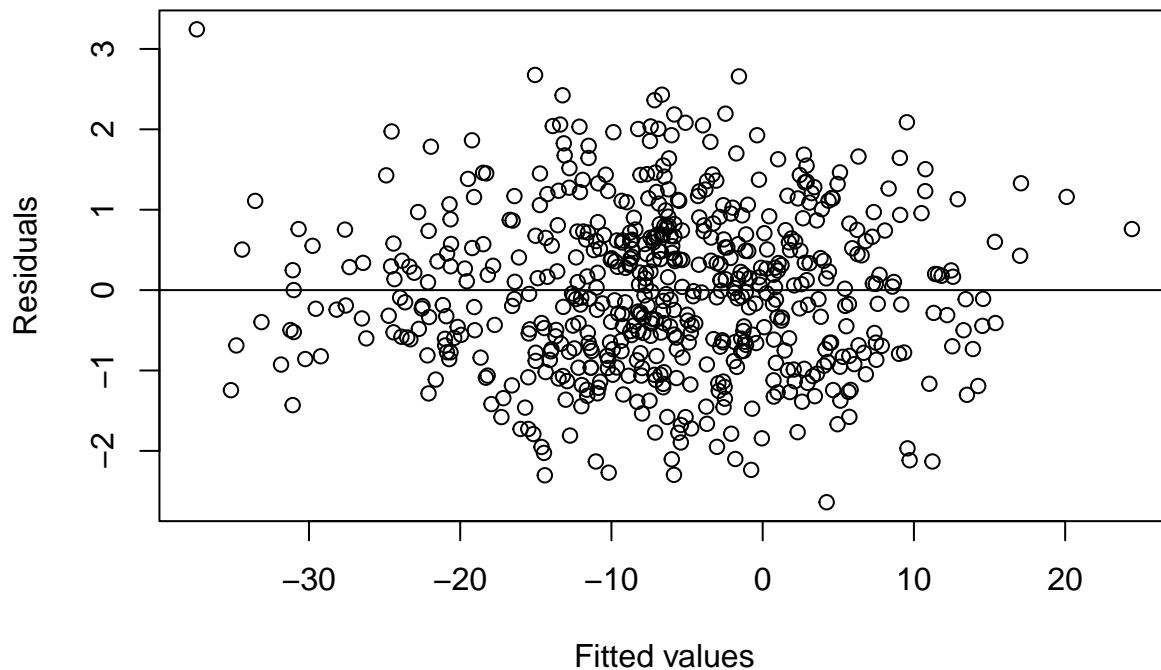


```
plot(df2$political_party, res2, xlab = "Political Party", ylab = "Residuals")
abline(h = 0)
```



Constant variance and independent error term assumption

```
plot(fitted(model2), res2, xlab = "Fitted values", ylab = "Residuals")  
abline(h = 0)
```



```
# Durbin-Watson Test: Independence of the error terms
# H0 (null hypothesis): There is no correlation among the residuals
```

```
durbinWatsonTest(model2)
```

```
## lag Autocorrelation D-W Statistic p-value
## 1 -0.071 2.1 0.096
## Alternative hypothesis: rho != 0
```

```
# Breusch-Pagan Test: Heteroscedasticity
# H0: Homoscedasticity is present
```

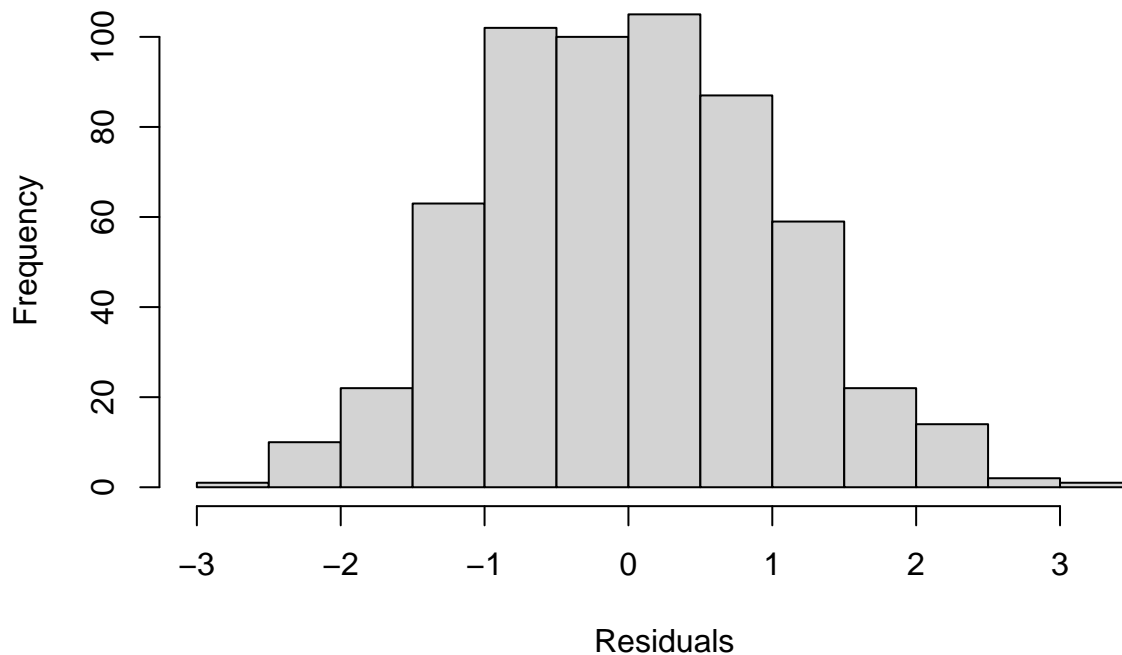
```
bptest(model2)
```

```
##
## studentized Breusch-Pagan test
##
## data: model2
## BP = 39, df = 33, p-value = 0.2
```

```
# Normality assumption
```

```
hist(res2, xlab="Residuals", main= "Histogram of Residuals")
```

Histogram of Residuals



```
## normality test using shapiro-test: reject the H0  
##H0: the sample comes from a normal distribution
```

```
res2_num = res2[is.finite(res2)]  
shapiro.test(res2_num)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: res2_num  
## W = 1, p-value = 0.2
```

```
step_model2 <- stepAIC(model2, trace=TRUE, direction= "backward")
```

3. Variable selection

```
## Start: AIC=4159  
## belief_diff_housing_electricity ~ age + income + political_party +  
## education + urban_rural_class + federal_state  
##  
##           Df Sum of Sq  RSS  AIC  
## - political_party    8    2667 620827 4146
```

```

## - federal_state      14      20721 638881 4151
## - education          6       4391 622551 4151
## - urban_rural_class  3       3975 622134 4157
## <none>                618160 4159
## - income             1       6099 624258 4163
## - age                1      21088 639248 4177
##
## Step: AIC=4146
## belief_diff_housing_electricity ~ age + income + education +
##   urban_rural_class + federal_state
##
##           Df Sum of Sq    RSS   AIC
## - federal_state      14      20890 641717 4137
## - education          6       4616 625443 4138
## - urban_rural_class  3       4553 625379 4144
## <none>                620827 4146
## - income             1       6206 627033 4150
## - age                1      19367 640194 4162
##
## Step: AIC=4137
## belief_diff_housing_electricity ~ age + income + education +
##   urban_rural_class
##
##           Df Sum of Sq    RSS   AIC
## - education          6       4247 645964 4129
## - urban_rural_class  3       5431 647147 4136
## <none>                641717 4137
## - income             1       7070 648787 4142
## - age                1      21764 663481 4155
##
## Step: AIC=4129
## belief_diff_housing_electricity ~ age + income + urban_rural_class
##
##           Df Sum of Sq    RSS   AIC
## - urban_rural_class  3       4824 650788 4127
## <none>                645964 4129
## - income             1       7280 653244 4134
## - age                1      20681 666645 4146
##
## Step: AIC=4127
## belief_diff_housing_electricity ~ age + income
##
##           Df Sum of Sq    RSS   AIC
## <none>                650788 4127
## - income      1       6842 657630 4132
## - age         1      20818 671607 4144

```

```
summary(step_model2)
```

```

##
## Call:
## lm(formula = belief_diff_housing_electricity ~ age + income,
##     data = df2)
##

```

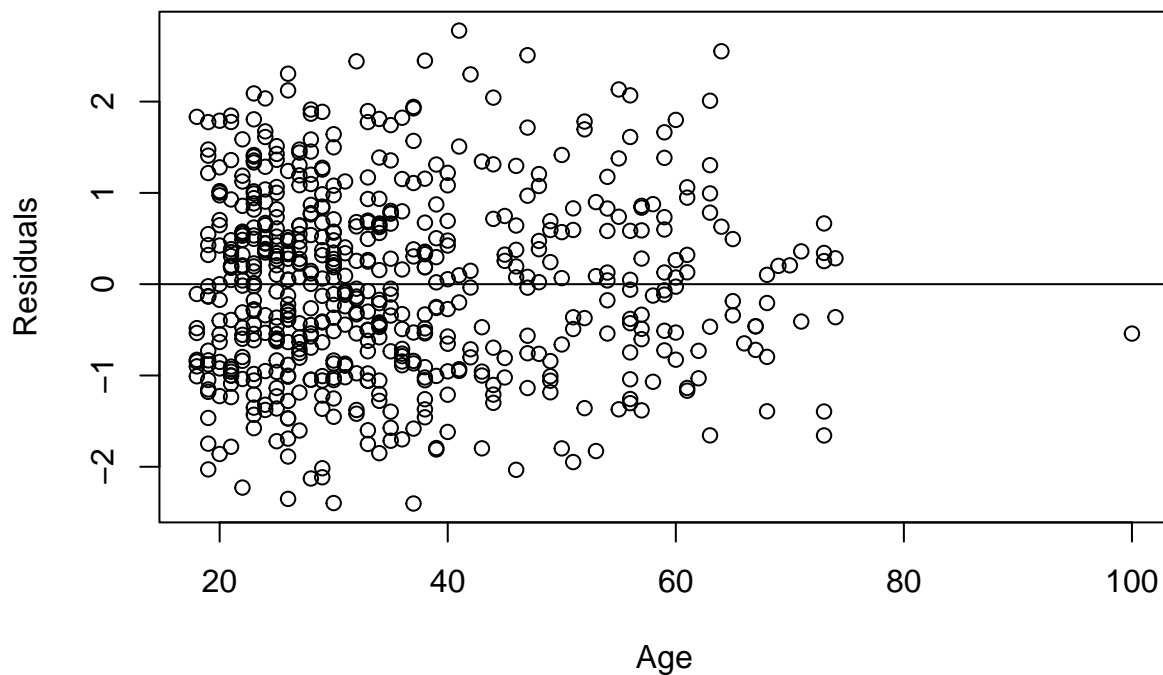


```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -79.99 -25.35   0.52  22.19  92.53
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.915498   4.477743   0.65   0.515
## age         -0.430873   0.099602  -4.33 1.8e-05 ***
## income        0.001804   0.000727   2.48  0.013 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 33 on 585 degrees of freedom
## Multiple R-squared:  0.0417, Adjusted R-squared:  0.0384
## F-statistic: 12.7 on 2 and 585 DF,  p-value: 3.87e-06
```

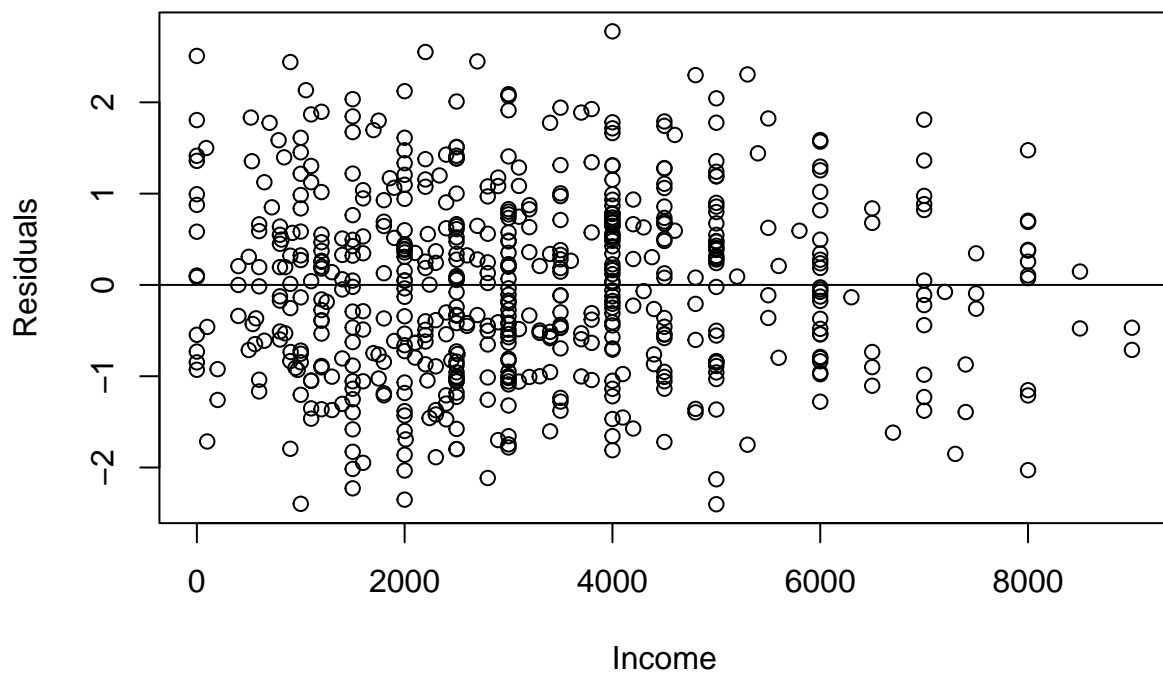
```
res2 = stdres(step_model2) ## (Standardized) Residuals
```

```
# Linearity assumption/Mean zero assumption
```

```
plot(df2$age, res2, xlab = "Age", ylab = "Residuals")
abline(h = 0)
```

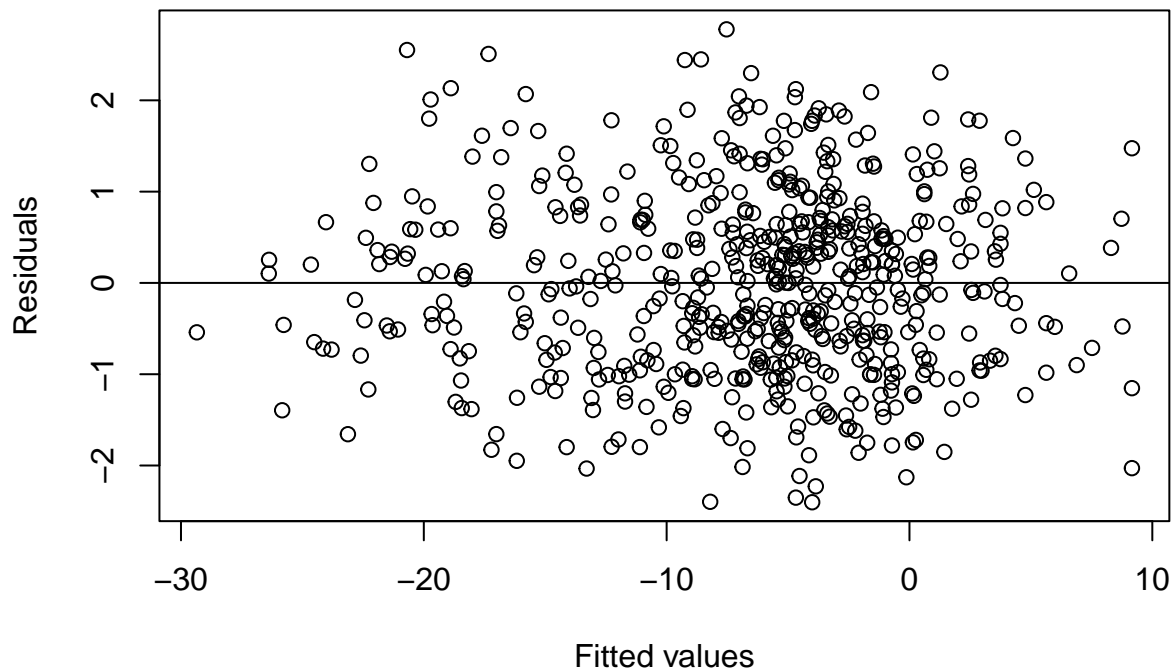


```
plot(df2$income, res2, xlab = "Income", ylab = "Residuals")
abline(h = 0)
```



```
# Constant variance and independent error term assumption
```

```
plot(fitted(step_model2), res2, xlab = "Fitted values", ylab = "Residuals")  
abline(h = 0)
```



```
# Durbin-Watson Test: Independence of the error terms
# H0 (null hypothesis): There is no correlation among the residuals
```

```
durbinWatsonTest(step_model2)
```

```
## lag Autocorrelation D-W Statistic p-value
## 1 -0.04 2.1 0.34
## Alternative hypothesis: rho != 0
```

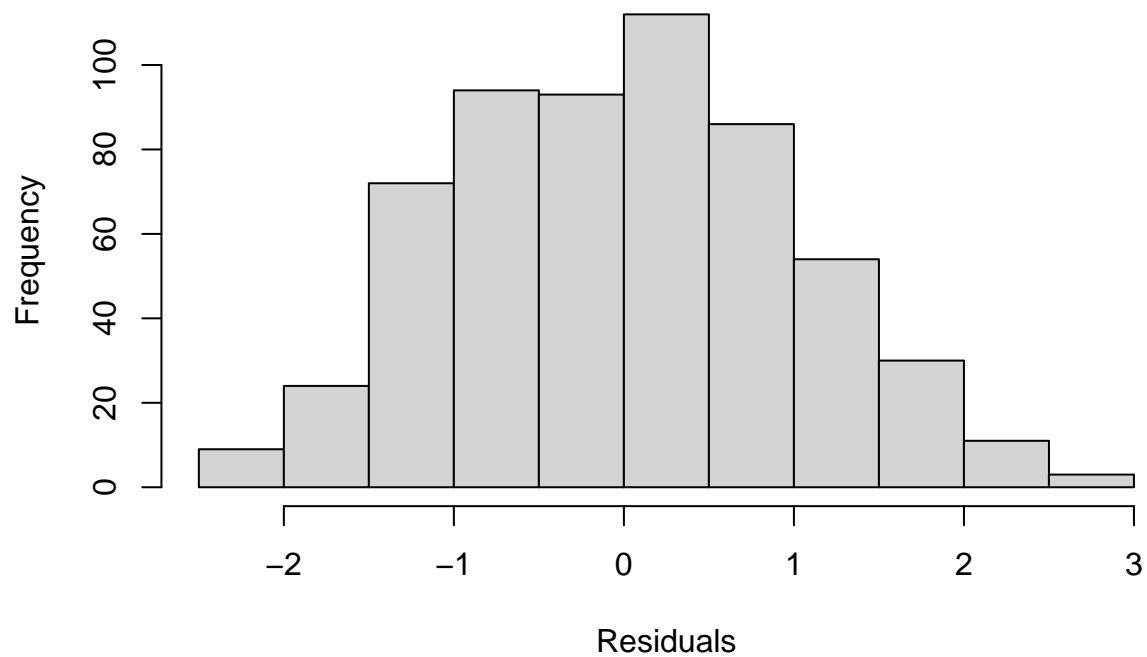
```
# Breusch-Pagan TEST: Heteroscedasticity
# H0: Homoscedasticity is present
```

```
bptest(step_model2)
```

```
##
## studentized Breusch-Pagan test
##
## data: step_model2
## BP = 2, df = 2, p-value = 0.4
```

```
hist(res2, xlab="Residuals", main= "Histogram of Residuals")
```

Histogram of Residuals



```
## normality test using shapiro-test: reject the H0  
#H0: the sample comes from a normal distribution
```

```
res2_num = res2[is.finite(res2)]  
shapiro.test(res2_num)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: res2_num  
## W = 1, p-value = 0.01
```