project

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2023-11-21

(1) Data cleaning

```
rm(list = ls())
gc()
```

```
##          used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 469544 25.1    1011124   54   660860 35.3
## Vcells 877636  6.7    8388608   64  1800812 13.8
```

```
set.seed(123)
############### (1) Data cleaning ########################################
library(NHANES)
df <- NHANES[NHANES$Age >= 18 & NHANES$Age < 60, ]
# colSums(is.na(df)) / nrow(df)
df <- df[, which(colSums(is.na(df)) / nrow(df) < 0.3)]
# colSums(is.na(df)) / nrow(df)
# df$BPSysAve
library(dplyr)
```

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

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
df2 <- df %>% select(
  SleepHrsNight,
  TotChol,
  DirectChol,
  Age,
  Gender,
  Race1,
  BMI,
  BPDiaAve,
  BPSysAve,
  AlcoholYear,
  Poverty,
  HomeRooms,
```

```
  SexNumPartnLife,
  SexNumPartYear,
  DaysMentHlthBad
)

Hmisc::describe(df2)
```

```
## df2
##
##  15  Variables      5642  Observations
## --------------------------------------------------------------------------------
## SleepHrsNight
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     5628       14       11     0.94    6.845    1.424        4        5
##      .25      .50      .75      .90      .95
##        6        7        8        8        9
##
## lowest :  2  3  4  5  6, highest:  8  9 10 11 12
##
## Value          2     3     4     5     6     7     8     9    10    11    12
## Frequency      7    43   245   434  1408  1631  1512   245    79    11    13
## Proportion 0.001 0.008 0.044 0.077 0.250 0.290 0.269 0.044 0.014 0.002 0.002
## --------------------------------------------------------------------------------
## TotChol
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     5349      293      231        1    5.029    1.165     3.49     3.78
##      .25      .50      .75      .90      .95
##     4.27     4.94     5.66     6.36     6.80
##
## lowest :  1.53  2.35  2.38  2.40  2.43, highest:  9.34  9.90  9.93 12.28 13.65
## --------------------------------------------------------------------------------
## DirectChol
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     5349      293      100        1     1.35    0.444     0.80     0.91
##      .25      .50      .75      .90      .95
##     1.06     1.29     1.58     1.89     2.09
##
## lowest : 0.39 0.41 0.47 0.52 0.54, highest: 3.41 3.44 3.59 3.72 3.83
## --------------------------------------------------------------------------------
## Age
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     5642        0       42    0.999    38.47    13.78       20       22
##      .25      .50      .75      .90      .95
##       28       39       49       55       57
##
## lowest : 18 19 20 21 22, highest: 55 56 57 58 59
## --------------------------------------------------------------------------------
## Gender
##        n  missing distinct
##     5642        0        2
##
## Value      female   male
## Frequency    2774   2868
## Proportion  0.492  0.508
```

```
## ---------------------------------------------------------------------------------
## Race1
##        n  missing distinct
##     5642        0        5
##
## lowest : Black    Hispanic Mexican  White    Other
## highest: Black    Hispanic Mexican  White    Other
##
## Value         Black Hispanic  Mexican    White    Other
## Frequency       672      355      577     3554      484
## Proportion    0.119    0.063    0.102    0.630    0.086
## ---------------------------------------------------------------------------------
## BMI
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     5606       36     1445        1    28.57    7.322    19.85    21.10
##      .25      .50      .75      .90      .95
##    23.74    27.40    32.13    37.36    41.00
##
## lowest : 15.02 15.80 15.90 15.97 15.98, highest: 67.83 68.63 69.00 80.60 81.25
## ---------------------------------------------------------------------------------
## BPDiaAve
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     5428      214       87    0.999    71.03    12.66       53       57
##      .25      .50      .75      .90      .95
##       64       71       78       85       89
##
## lowest :   0  20  21  22  24, highest: 108 109 110 114 116
## ---------------------------------------------------------------------------------
## BPSysAve
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     5428      214      107    0.999    117.4     15.7       97      101
##      .25      .50      .75      .90      .95
##      108      116      125      135      142
##
## lowest :  78  82  83  84  85, highest: 197 202 209 221 226
## ---------------------------------------------------------------------------------
## AlcoholYear
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     4472     1170       58    0.993    71.96    93.01        0        0
##      .25      .50      .75      .90      .95
##        4       24      104      208      300
##
## lowest :   0   1   2   3   4, highest: 260 300 312 360 364
## ---------------------------------------------------------------------------------
## Poverty
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     5224      418      418    0.986    2.878    1.932     0.39     0.66
##      .25      .50      .75      .90      .95
##     1.30     2.88     4.92     5.00     5.00
##
## lowest : 0.00 0.01 0.02 0.03 0.04, highest: 4.95 4.96 4.97 4.99 5.00
## ---------------------------------------------------------------------------------
## HomeRooms
##        n  missing distinct     Info     Mean      Gmd      .05      .10
```

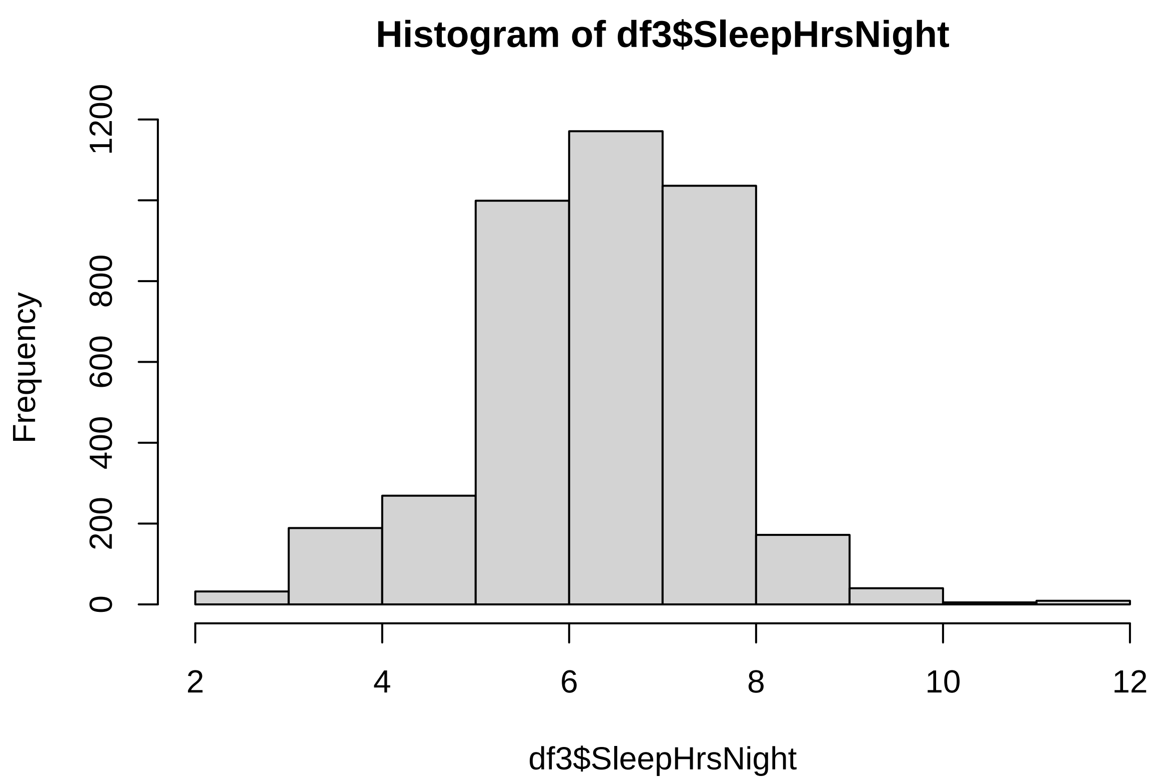
```
##     5597       45       13    0.981    6.066    2.579        3        3
##      .25      .50      .75      .90      .95
##        4        6        7        9       10
##
## lowest :  1  2  3  4  5, highest:  9 10 11 12 13
##
## Value          1     2     3     4     5     6     7     8     9    10    11
## Frequency     86    81   424   941   992   934   787   521   334   238   134
## Proportion 0.015 0.014 0.076 0.168 0.177 0.167 0.141 0.093 0.060 0.043 0.024
##
## Value         12    13
## Frequency     58    67
## Proportion 0.010 0.012
## ---------------------------------------------------------------------------
## SexNumPartnLife
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     4911      731       85    0.995    15.34    21.48        1        1
##      .25      .50      .75      .90      .95
##        3        6       12       27       48
##
## lowest :    0    1    2    3    4, highest:  700  800  999 1000 2000
## ---------------------------------------------------------------------------
## SexNumPartYear
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     4928      714       23    0.691    1.342    1.243        0        0
##      .25      .50      .75      .90      .95
##        1        1        1        2        3
##
## lowest :  0  1  2  3  4, highest: 19 20 30 50 69
## ---------------------------------------------------------------------------
## DaysMentHlthBad
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     4993      649       30    0.848    4.545    7.018        0        0
##      .25      .50      .75      .90      .95
##        0        0        5       15       30
##
## lowest :  0  1  2  3  4, highest: 26 27 28 29 30
## ---------------------------------------------------------------------------
```

```
df3 <- na.omit(df2)
#df3$SleepHrsNight <- df3$SleepHrsNight * 60
#df3 <- df3[, -which(names(df3) %in% "SleepHrsNight")]
# cor(df3$BPSysAve,df3$BPDiaAve)
psych::describe(df3)
```

```
##                 vars    n   mean    sd median trimmed   mad   min    max
## SleepHrsNight      1 3922   6.83  1.30   7.00    6.90  1.48  2.00  12.00
## TotChol            2 3922   5.08  1.06   5.02    5.03  1.04  1.53  13.65
## DirectChol         3 3922   1.35  0.42   1.29    1.31  0.39  0.39   3.83
## Age                4 3922  39.34 11.63  40.00   39.41 14.83 18.00  59.00
## Gender*            5 3922   1.54  0.50   2.00    1.55  0.00  1.00   2.00
## Race1*             6 3922   3.57  1.04   4.00    3.76  0.00  1.00   5.00
## BMI                7 3922  28.64  6.59  27.50   28.05  6.08 15.02  69.00
## BPDiaAve           8 3922  71.51 11.40  72.00   71.62 10.38  0.00 116.00
## BPSysAve           9 3922 117.72 14.28 116.00  116.85 13.34 78.00 226.00
```

```
## AlcoholYear        10 3922  71.91 95.14  24.00   52.26 35.58  0.00  364.00
## Poverty            11 3922   3.01  1.66   3.15    3.08  2.65  0.00    5.00
## HomeRooms          12 3922   6.14  2.29   6.00    6.02  1.48  1.00   13.00
## SexNumPartnLife    13 3922  16.21 61.34   6.00    8.64  5.93  0.00 2000.00
## SexNumPartYear     14 3922   1.38  3.04   1.00    0.99  0.00  0.00   69.00
## DaysMentHlthBad    15 3922   4.41  7.99   0.00    2.34  0.00  0.00   30.00
##                    range  skew kurtosis   se
## SleepHrsNight      10.00 -0.25     0.72 0.02
## TotChol            12.12  0.76     2.22 0.02
## DirectChol          3.44  1.15     2.49 0.01
## Age                41.00 -0.06    -1.18 0.19
## Gender*             1.00 -0.17    -1.97 0.01
## Race1*              4.00 -1.48     1.25 0.02
## BMI                53.98  1.10     2.20 0.11
## BPDiaAve          116.00 -0.30     2.51 0.18
## BPSysAve          148.00  1.08     3.90 0.23
## AlcoholYear       364.00  1.62     1.82 1.52
## Poverty             5.00 -0.15    -1.43 0.03
## HomeRooms          12.00  0.53     0.27 0.04
## SexNumPartnLife  2000.00 17.33   399.45 0.98
## SexNumPartYear     69.00 12.99   222.05 0.05
## DaysMentHlthBad    30.00  2.19     3.89 0.13
```

```r
# psych::pairs.panels(df3)
hist(df3$SleepHrsNight)
```



```r
# colSums(is.na(df2)) / nrow(df2)
fit0 <-
  lm(SleepHrsNight ~ .,
     data = df3)
#data type
df3$Gender <- ifelse(df3$Gender == "male", 0, 1)
df3 <- df3 %>%
  mutate(
    Race1 = case_when(
      Race1 == 'Black' ~ 1,
      Race1 == 'Hispanic' ~ 2,
      Race1 == 'Mexican' ~ 3,
      Race1 == 'White' ~ 4,
      Race1 == 'Other' ~ 5,
      TRUE ~ NA_integer_  # Default value if none of the conditions are met
    )
  )
```

(2) Baseline characteristics

(3) linear regression model

```r
##simple linear regression##
model1 = lm(df3$SleepHrsNight ~ df3$TotChol, data = df3)
summary(model1)
```

```
##
## Call:
## lm(formula = df3$SleepHrsNight ~ df3$TotChol, data = df3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.8542 -0.8298  0.1652  1.1616  5.1725
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.89986    0.10145  68.014   <2e-16 ***
## df3$TotChol -0.01391    0.01954  -0.712    0.477
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.296 on 3920 degrees of freedom
## Multiple R-squared:  0.0001292,  Adjusted R-squared:  -0.0001258
## F-statistic: 0.5066 on 1 and 3920 DF,  p-value: 0.4766
```

```r
## multiple linear regression##
m_initial = lm(SleepHrsNight ~ TotChol + Age + Gender + factor(Race1), df3)
summary(m_initial)
```

```
##
## Call:
## lm(formula = SleepHrsNight ~ TotChol + Age + Gender + factor(Race1),
```

```
##     data = df3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.9588 -0.8155  0.1140  1.0490  5.3532
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)     6.705872   0.124437  53.890  < 2e-16 ***
## TotChol         0.002877   0.020350   0.141 0.887570
## Age            -0.008276   0.001874  -4.416 1.03e-05 ***
## Gender          0.200836   0.041361   4.856 1.25e-06 ***
## factor(Race1)2  0.191060   0.109405   1.746 0.080829 .
## factor(Race1)3  0.420208   0.095508   4.400 1.11e-05 ***
## factor(Race1)4  0.389393   0.070200   5.547 3.10e-08 ***
## factor(Race1)5  0.381915   0.102533   3.725 0.000198 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.285 on 3914 degrees of freedom
## Multiple R-squared:  0.01889,    Adjusted R-squared:  0.01713
## F-statistic: 10.76 on 7 and 3914 DF,  p-value: 1.664e-13
```

```r
m_knrisk = lm(
  SleepHrsNight ~ TotChol + Age + Gender + factor(Race1) + BMI + BPDiaAve +
    BPSysAve + AlcoholYear + DaysMentHlthBad,
  df3
)
summary(m_knrisk)
```

```
##
## Call:
## lm(formula = SleepHrsNight ~ TotChol + Age + Gender + factor(Race1) +
##     BMI + BPDiaAve + BPSysAve + AlcoholYear + DaysMentHlthBad,
##     data = df3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.0151 -0.8371  0.0538  0.9651  5.3364
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      7.1462829  0.2154155  33.174  < 2e-16 ***
## TotChol          0.0027643  0.0202261   0.137 0.891300
## Age             -0.0087863  0.0019017  -4.620 3.96e-06 ***
## Gender           0.2421933  0.0423999   5.712 1.20e-08 ***
## factor(Race1)2   0.1615075  0.1080191   1.495 0.134949
## factor(Race1)3   0.3670216  0.0943591   3.890 0.000102 ***
## factor(Race1)4   0.3361684  0.0697583   4.819 1.50e-06 ***
## factor(Race1)5   0.3107938  0.1019396   3.049 0.002313 **
## BMI             -0.0032441  0.0032012  -1.013 0.310923
## BPDiaAve         0.0020128  0.0021165   0.951 0.341646
## BPSysAve        -0.0030312  0.0017413  -1.741 0.081793 .
## AlcoholYear      0.0006543  0.0002219   2.949 0.003209 **
## DaysMentHlthBad -0.0299239  0.0025406 -11.778  < 2e-16 ***
```

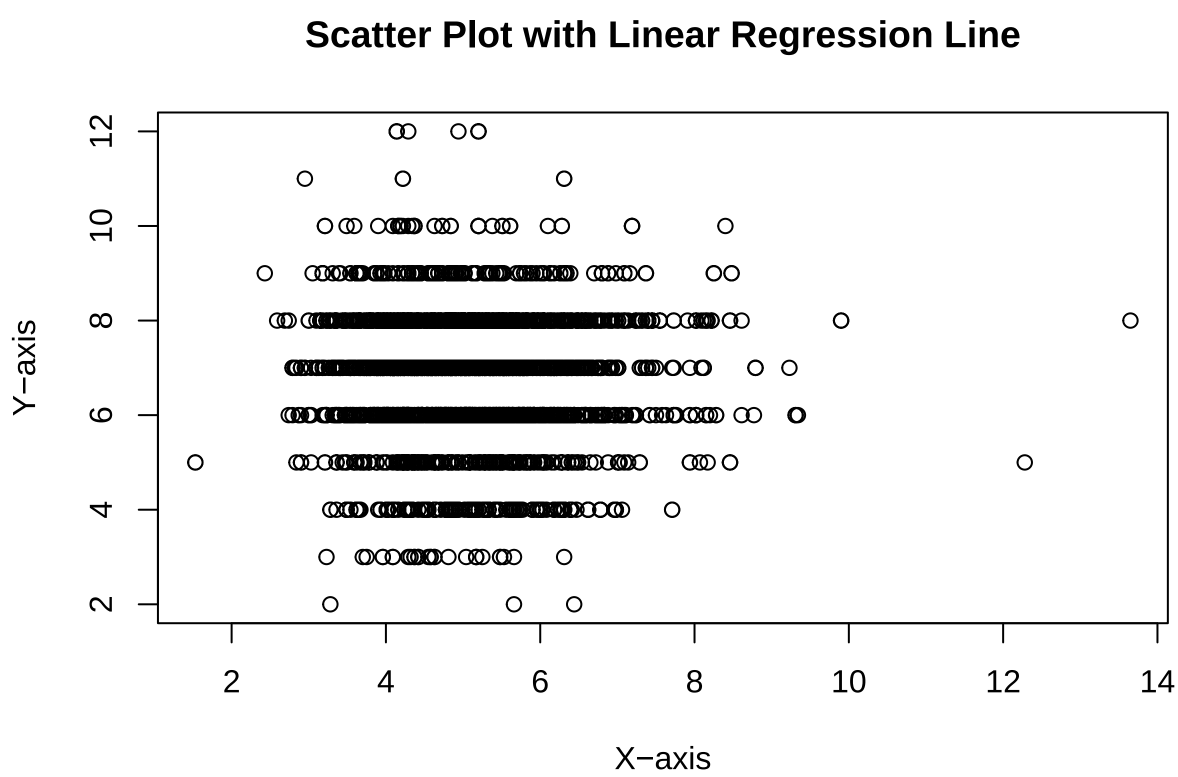
```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.262 on 3909 degrees of freedom
## Multiple R-squared:  0.05591,    Adjusted R-squared:  0.05302
## F-statistic: 19.29 on 12 and 3909 DF,  p-value: < 2.2e-16
```

```
m_full = lm(
  SleepHrsNight ~ TotChol + Age + Gender + factor(Race1) + BMI + BPDiaAve +
    BPSysAve + AlcoholYear + DaysMentHlthBad + HomeRooms + SexNumPartnLife +
    SexNumPartYear + Poverty,
  df3
)
summary(m_full)
```

```
##
## Call:
## lm(formula = SleepHrsNight ~ TotChol + Age + Gender + factor(Race1) +
##     BMI + BPDiaAve + BPSysAve + AlcoholYear + DaysMentHlthBad +
##     HomeRooms + SexNumPartnLife + SexNumPartYear + Poverty, data = df3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.8534 -0.8280  0.0354  0.9312  5.4440
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      6.8271794  0.2226486  30.663  < 2e-16 ***
## TotChol          0.0047184  0.0201452   0.234 0.814828
## Age             -0.0107341  0.0019748  -5.435 5.80e-08 ***
## Gender           0.2300247  0.0423898   5.426 6.10e-08 ***
## factor(Race1)2   0.1634606  0.1075484   1.520 0.128622
## factor(Race1)3   0.3982799  0.0942020   4.228 2.41e-05 ***
## factor(Race1)4   0.2862593  0.0702207   4.077 4.66e-05 ***
## factor(Race1)5   0.2854605  0.1016592   2.808 0.005010 **
## BMI             -0.0026447  0.0031871  -0.830 0.406694
## BPDiaAve         0.0018866  0.0021093   0.894 0.371149
## BPSysAve        -0.0022470  0.0017400  -1.291 0.196654
## AlcoholYear      0.0005280  0.0002223   2.375 0.017598 *
## DaysMentHlthBad -0.0280171  0.0025566 -10.959  < 2e-16 ***
## HomeRooms        0.0260173  0.0095185   2.733 0.006298 **
## SexNumPartnLife -0.0011068  0.0003339  -3.315 0.000925 ***
## SexNumPartYear   0.0187508  0.0067967   2.759 0.005828 **
## Poverty          0.0522337  0.0137235   3.806 0.000143 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.255 on 3905 degrees of freedom
## Multiple R-squared:  0.06694,    Adjusted R-squared:  0.06312
## F-statistic: 17.51 on 16 and 3905 DF,  p-value: < 2.2e-16
```

```
plot(
  df3$TotChol,
  df3$SleepHrsNight,
  main = "Scatter Plot with Linear Regression Line",
```

```r
  xlab = "X-axis",
  ylab = "Y-axis"
)
```




```r
#log outcome
df3$logSleepHrsNight = log(df3$SleepHrsNight + 1)
m_logfull_1 = lm(
  logSleepHrsNight ~ TotChol + Age + Gender + factor(Race1) + BMI + BPDiaAve +
    BPSysAve + AlcoholYear + DaysMentHlthBad + HomeRooms + SexNumPartnLife +
    SexNumPartYear + Poverty,
  df3
)
summary(m_logfull_1)
```

```
##
## Call:
## lm(formula = logSleepHrsNight ~ TotChol + Age + Gender + factor(Race1) +
##     BMI + BPDiaAve + BPSysAve + AlcoholYear + DaysMentHlthBad +
##     HomeRooms + SexNumPartnLife + SexNumPartYear + Poverty, data = df3)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.94458 -0.09816  0.01636  0.12163  0.56510
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)      2.033e+00  3.033e-02  67.026  < 2e-16 ***
## TotChol          4.578e-04  2.744e-03   0.167 0.867504
## Age             -1.485e-03  2.690e-04  -5.520 3.60e-08 ***
## Gender           2.838e-02  5.774e-03   4.915 9.26e-07 ***
## factor(Race1)2   2.478e-02  1.465e-02   1.691 0.090882 .
## factor(Race1)3   5.693e-02  1.283e-02   4.437 9.38e-06 ***
## factor(Race1)4   4.259e-02  9.566e-03   4.453 8.72e-06 ***
## factor(Race1)5   4.232e-02  1.385e-02   3.056 0.002260 **
## BMI             -4.730e-04  4.342e-04  -1.090 0.275981
## BPDiaAve         3.782e-04  2.873e-04   1.316 0.188144
## BPSysAve        -2.977e-04  2.370e-04  -1.256 0.209220
## AlcoholYear      8.234e-05  3.028e-05   2.719 0.006578 **
## DaysMentHlthBad -4.145e-03  3.483e-04 -11.903  < 2e-16 ***
## HomeRooms        3.765e-03  1.297e-03   2.904 0.003705 **
## SexNumPartnLife -1.623e-04  4.548e-05  -3.569 0.000362 ***
## SexNumPartYear   2.441e-03  9.258e-04   2.637 0.008400 **
## Poverty          8.175e-03  1.869e-03   4.373 1.26e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1709 on 3905 degrees of freedom
## Multiple R-squared:  0.07513,    Adjusted R-squared:  0.07134
## F-statistic: 19.83 on 16 and 3905 DF,  p-value: < 2.2e-16
```

```r
#log x
df3$logTotChol = log(df3$TotChol + 1)
m_logfull_2 = lm(
  SleepHrsNight ~ logTotChol + Age + Gender + factor(Race1) + BMI + BPDiaAve +
    BPSysAve + AlcoholYear + DaysMentHlthBad + HomeRooms + SexNumPartnLife +
    SexNumPartYear + Poverty,
  df3
)
summary(m_logfull_2)
```

```
##
## Call:
## lm(formula = SleepHrsNight ~ logTotChol + Age + Gender + factor(Race1) +
##     BMI + BPDiaAve + BPSysAve + AlcoholYear + DaysMentHlthBad +
##     HomeRooms + SexNumPartnLife + SexNumPartYear + Poverty, data = df3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.8497 -0.8276  0.0368  0.9335  5.4407
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      6.8300088  0.2782326  24.548  < 2e-16 ***
## logTotChol       0.0071259  0.1247304   0.057 0.954444
## Age             -0.0106525  0.0019745  -5.395 7.26e-08 ***
## Gender           0.2305375  0.0423961   5.438 5.73e-08 ***
## factor(Race1)2   0.1640112  0.1075538   1.525 0.127360
## factor(Race1)3   0.3990122  0.0942051   4.236 2.33e-05 ***
## factor(Race1)4   0.2869727  0.0702076   4.087 4.45e-05 ***
## factor(Race1)5   0.2857811  0.1016579   2.811 0.004960 **
## BMI             -0.0026393  0.0031873  -0.828 0.407686
```

```
## BPDiaAve         0.0019209  0.0021091   0.911 0.362487    
## BPSysAve        -0.0022300  0.0017399  -1.282 0.200043    
## AlcoholYear      0.0005299  0.0002224   2.383 0.017226 *  
## DaysMentHlthBad -0.0280195  0.0025566 -10.960  < 2e-16 ***
## HomeRooms        0.0259722  0.0095189   2.728 0.006391 ** 
## SexNumPartnLife -0.0011085  0.0003339  -3.320 0.000909 ***
## SexNumPartYear   0.0187184  0.0067976   2.754 0.005920 ** 
## Poverty          0.0522189  0.0137235   3.805 0.000144 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 1.255 on 3905 degrees of freedom
## Multiple R-squared:  0.06693,    Adjusted R-squared:  0.06311 
## F-statistic: 17.51 on 16 and 3905 DF,  p-value: < 2.2e-16
```

```
# x^2
df3$sqTotChol = (df3$TotChol - mean(df3$TotChol)) ^ 2
m_sqfull_1 = lm(
  SleepHrsNight ~ TotChol + sqTotChol + Age + Gender + factor(Race1) + BMI +
    BPDiaAve + BPSysAve + AlcoholYear + DaysMentHlthBad + HomeRooms + SexNumPartnLife +
    SexNumPartYear + Poverty,
  df3
)
summary(m_sqfull_1)
```

```
## 
## Call:
## lm(formula = SleepHrsNight ~ TotChol + sqTotChol + Age + Gender + 
##     factor(Race1) + BMI + BPDiaAve + BPSysAve + AlcoholYear + 
##     DaysMentHlthBad + HomeRooms + SexNumPartnLife + SexNumPartYear + 
##     Poverty, data = df3)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -4.8478 -0.8260  0.0405  0.9374  5.4429 
## 
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)    
## (Intercept)      6.8577303  0.2238478  30.636  < 2e-16 ***
## TotChol         -0.0056651  0.0216483  -0.262 0.793577    
## sqTotChol        0.0123034  0.0093972   1.309 0.190524    
## Age             -0.0106509  0.0019757  -5.391 7.42e-08 ***
## Gender           0.2311086  0.0423940   5.451 5.31e-08 ***
## factor(Race1)2   0.1650502  0.1075454   1.535 0.124938    
## factor(Race1)3   0.3997089  0.0941997   4.243 2.25e-05 ***
## factor(Race1)4   0.2850197  0.0702207   4.059 5.03e-05 ***
## factor(Race1)5   0.2847735  0.1016512   2.801 0.005112 ** 
## BMI             -0.0024955  0.0031888  -0.783 0.433929    
## BPDiaAve         0.0018701  0.0021091   0.887 0.375317    
## BPSysAve        -0.0022354  0.0017399  -1.285 0.198941    
## AlcoholYear      0.0005359  0.0002224   2.410 0.016001 *  
## DaysMentHlthBad -0.0279488  0.0025569 -10.931  < 2e-16 ***
## HomeRooms        0.0257677  0.0095196   2.707 0.006823 ** 
## SexNumPartnLife -0.0011115  0.0003339  -3.329 0.000879 ***
## SexNumPartYear   0.0185336  0.0067981   2.726 0.006434 ** 
```

```
## Poverty          0.0528694  0.0137308   3.850 0.000120 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.255 on 3904 degrees of freedom
## Multiple R-squared:  0.06735,    Adjusted R-squared:  0.06329
## F-statistic: 16.58 on 17 and 3904 DF,  p-value: < 2.2e-16
```

(4) Diagnosis: 10-fold CV

```
library(caret)
```

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

```
## Loading required package: lattice
```

```
splitIndex <-
  createDataPartition(df3$SleepHrsNight, p = 0.7, list = FALSE)
trainData <- df3[splitIndex,]
testData <- df3[-splitIndex,]
predictions <- predict(m_sqfull_1, newdata = testData)
mse <- mean((testData$SleepHrsNight - predictions) ^ 2)
control <-
  trainControl(method = "cv", number = 10)  # 10-fold cross-validation
cv_model <-
  train(
    SleepHrsNight ~ .,
    data = df3,
    method = "lm",
    trControl = control
  )
cv_model
```

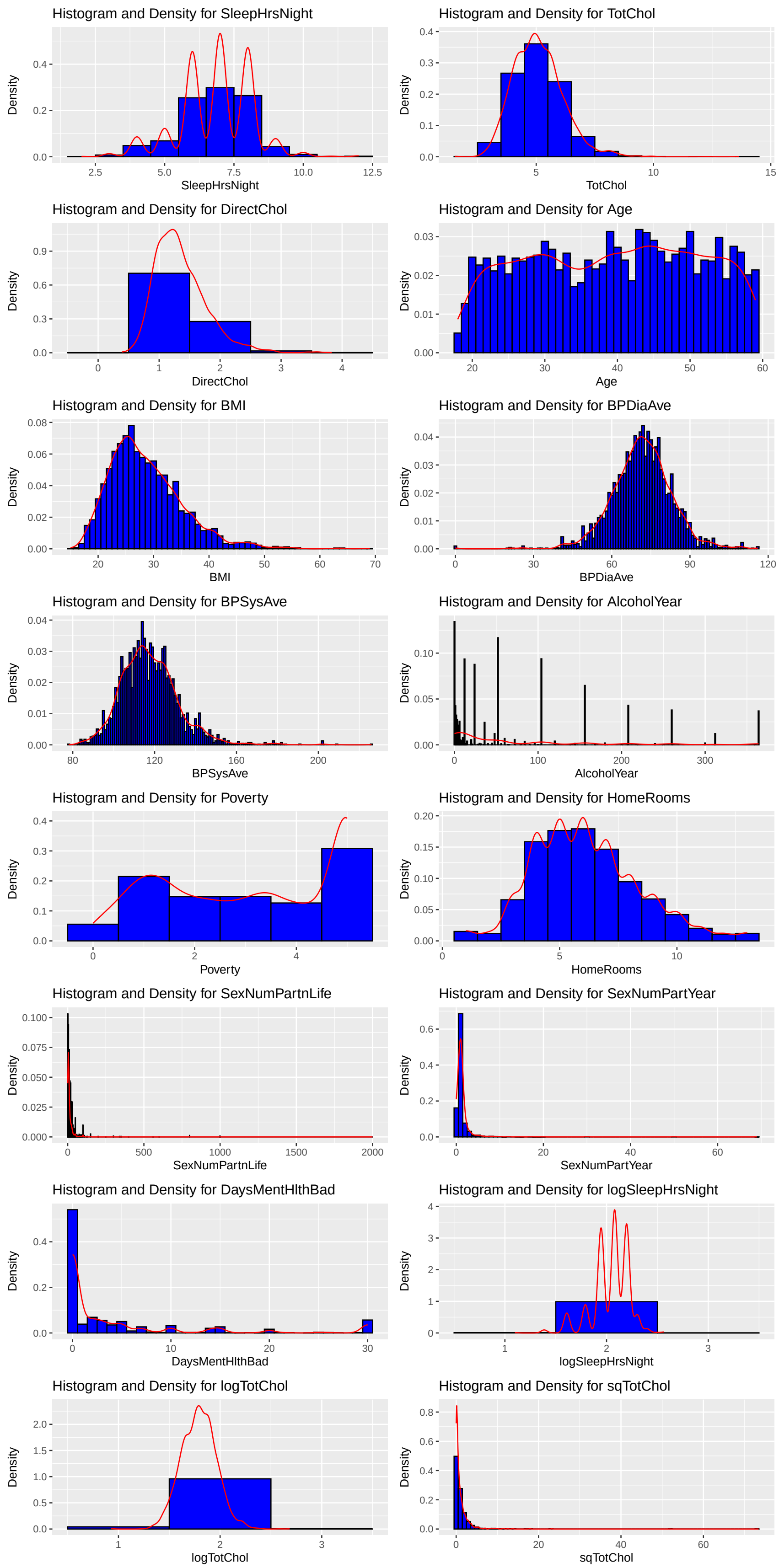
```
## Linear Regression
##
## 3922 samples
##   17 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 3529, 3529, 3529, 3530, 3530, 3530, ...
## Resampling results:
##
##   RMSE       Rsquared   MAE
##   0.1819272  0.9804423  0.1196029
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```
(cv_results <- cv_model$results)
```

```
##   intercept      RMSE  Rsquared       MAE     RMSESD  RsquaredSD       MAESD
## 1      TRUE 0.1819272 0.9804423 0.1196029 0.03027278 0.005037844 0.007475503
```

(4) Diagnosis: Normality Assumption

```r
library(ggplot2)
library(patchwork)
# Initializes an empty patchwork object
plot_list <- list()

# Draw a histogram for each numeric variable (except Race1 and Gender) and add it to the list
for (var in names(df3)) {
  if (is.numeric(df3[[var]]) && !(var %in% c("Race1", "Gender"))) {
    p <- ggplot(df3, aes(x = .data[[var]])) +
      geom_histogram(
        aes(y = after_stat(density)),
        binwidth = 1,
        fill = "blue",
        color = "black"
      ) +
      geom_density(col = "red") +
      ggtitle(paste("Histogram and Density for", var)) +
      xlab(var) +
      ylab("Density")
    plot_list[[length(plot_list) + 1]] <- p
  }
}

# Use patchwork to put all the charts together
combined_plot <- wrap_plots(plot_list, ncol = 2)
print(combined_plot)
```


Histogram and Density for SleepHrsNight
SleepHrsNight
Histogram and Density for TotChol
TotChol
Histogram and Density for DirectChol
DirectChol
Histogram and Density for Age
Age
Histogram and Density for BMI
BMI
Histogram and Density for BPDiaAve
BPDiaAve
Histogram and Density for BPSysAve
BPSysAve
Histogram and Density for AlcoholYear
AlcoholYear
Histogram and Density for Poverty
Poverty
Histogram and Density for HomeRooms
HomeRooms
Histogram and Density for SexNumPartnLife
SexNumPartnLife
Histogram and Density for SexNumPartYear
SexNumPartYear
Histogram and Density for DaysMentHlthBad
DaysMentHlthBad
Histogram and Density for logSleepHrsNight
logSleepHrsNight
Histogram and Density for logTotChol
logTotChol
Histogram and Density for sqTotChol
sqTotChol
Density

```r
df3 <- data.frame(df3)
library(dplyr)
# Shapiro-Wilk normality test is performed for each numerical variable in df3
results <- sapply(df3, function(x) {
  if (is.numeric(x)) {
    shapiro_test <- shapiro.test(x)
    return(c(shapiro_test$statistic, shapiro_test$p.value))
  } else {
    return(c(NA, NA))
  }
})
# Convert the result to a data box and name the column
results_df <- as.data.frame(t(results))
names(results_df) <- c("W", "p.value")
# Add a variable name as a new column
results_df$Variable <- rownames(results_df)
# Rearrange the order of columns
results_df <- results_df[, c("Variable", "W", "p.value")]
# Calculate the corrected P-value (for example, using Bonferroni correction)
results_df$p.adjusted <-
  p.adjust(results_df$p.value, method = "bonferroni")
print(results_df)
```

```
##                         Variable         W      p.value   p.adjusted
## SleepHrsNight      SleepHrsNight 0.9324408 6.174763e-39 1.111457e-37
## TotChol                  TotChol 0.9724090 7.211614e-27 1.298090e-25
## DirectChol            DirectChol 0.9389239 1.850577e-37 3.331039e-36
## Age                          Age 0.9565820 1.100461e-32 1.980830e-31
## Gender                    Gender 0.6340133 4.238105e-68 7.628589e-67
## Race1                      Race1 0.6732812 7.054979e-66 1.269896e-64
## BMI                          BMI 0.9420252 1.043365e-36 1.878057e-35
## BPDiaAve                BPDiaAve 0.9787402 8.519951e-24 1.533591e-22
## BPSysAve                BPSysAve 0.9505758 1.857649e-34 3.343769e-33
## AlcoholYear          AlcoholYear 0.7494486 7.869506e-61 1.416511e-59
## Poverty                  Poverty 0.8916507 3.020524e-46 5.436943e-45
## HomeRooms              HomeRooms 0.9631989 1.707583e-30 3.073650e-29
## SexNumPartnLife   SexNumPartnLife 0.1633647 2.016343e-85 3.629418e-84
## SexNumPartYear     SexNumPartYear 0.2272038 1.134070e-83 2.041325e-82
## DaysMentHlthBad   DaysMentHlthBad 0.6061789 1.487607e-69 2.677692e-68
## logSleepHrsNight logSleepHrsNight 0.8994157 4.724481e-45 8.504065e-44
## logTotChol            logTotChol 0.9966458 1.103791e-07 1.986823e-06
## sqTotChol              sqTotChol 0.4074052 5.946496e-78 1.070369e-76
```

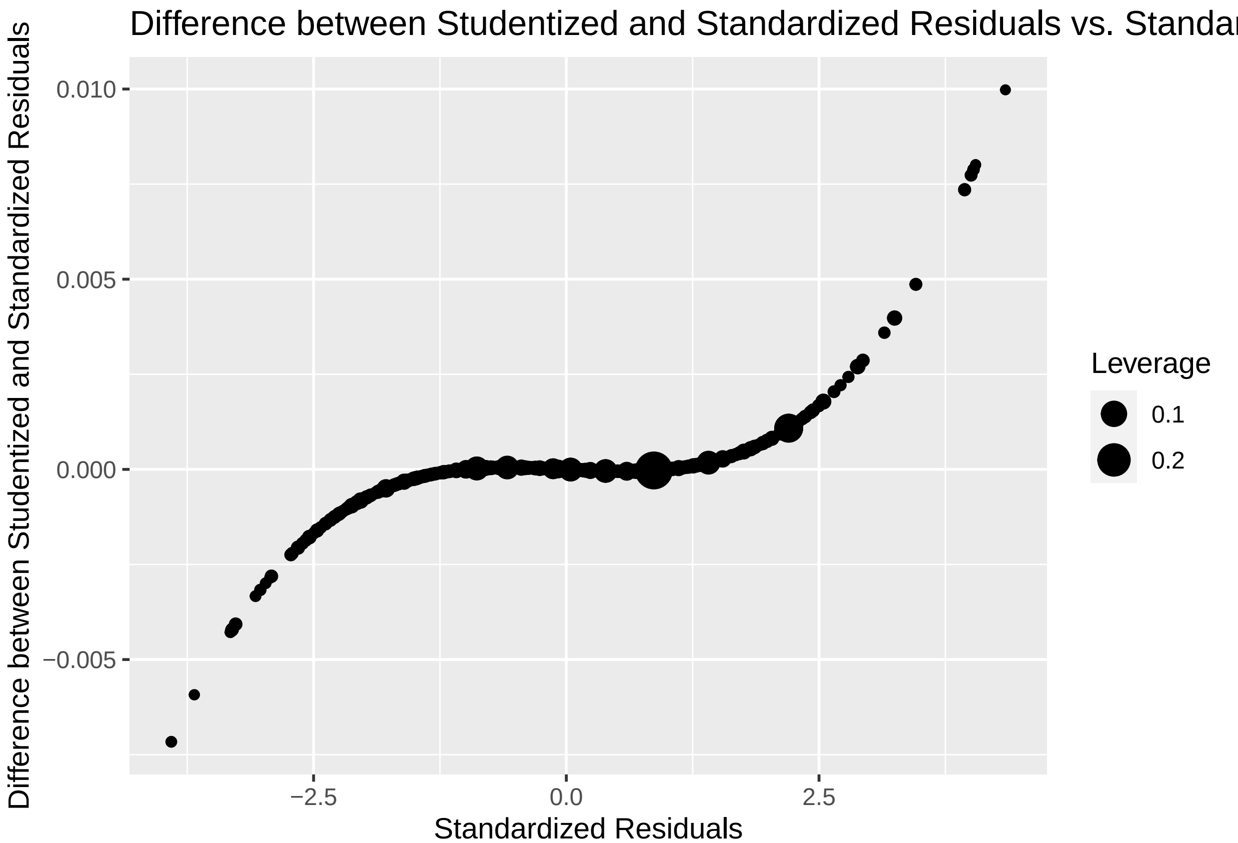
Standardized residuals, Studentized residuals

```r
# Regular residuals
residual_1 <- fit0$residuals

# Standardized residuals
residual_2 <- rstandard(fit0)

# Studentized residuals
```

```r
residual_3 <- rstudent(fit0)

# Externally studentized residuals
# Note: Externally studentized residuals are the same as studentized residuals in most cases
residual_4 <- rstudent(fit0)

# Creating a data frame to summarize these residuals
residual_summary <- data.frame(
  Residuals = c("Regular", "Standardized", "Studentized", "Externally Studentized"),
  Mean = c(mean(residual_1), mean(residual_2), mean(residual_3), mean(residual_4)),
  SD = c(sd(residual_1), sd(residual_2), sd(residual_3), sd(residual_4)),
  Min = c(min(residual_1), min(residual_2), min(residual_3), min(residual_4)),
  Max = c(max(residual_1), max(residual_2), max(residual_3), max(residual_4))
)

# Display the summary
print(residual_summary)
```

```
##                Residuals          Mean       SD       Min      Max
## 1                Regular -1.149380e-16 1.251851 -4.894975 5.444620
## 2           Standardized  9.976361e-05 1.000389 -3.907567 4.343986
## 3            Studentized  8.874780e-05 1.000738 -3.914730 4.353965
## 4 Externally Studentized  8.874780e-05 1.000738 -3.914730 4.353965
```

```r
# Load necessary library
library(ggplot2)

# Assuming fit0 is your linear model
# fit0 <- lm(SleepMinNight ~ ., data = df3)

# Calculate standardized and studentized residuals
residual_2 <- rstandard(fit0)
residual_3 <- rstudent(fit0)

# Calculate leverage values
leverage_values <- hatvalues(fit0)

# Create a data frame for plotting
plot_data <- data.frame(
  Standardized_Residuals = residual_2,
  Difference = residual_3 - residual_2,
  Leverage = leverage_values
)

# Create the plot
ggplot(plot_data, aes(x = Standardized_Residuals, y = Difference)) +
  geom_point(aes(size = Leverage)) +
  ggtitle("Difference between Studentized and Standardized Residuals vs. Standardized Residuals") +
  xlab("Standardized Residuals") +
  ylab("Difference between Studentized and Standardized Residuals")
```

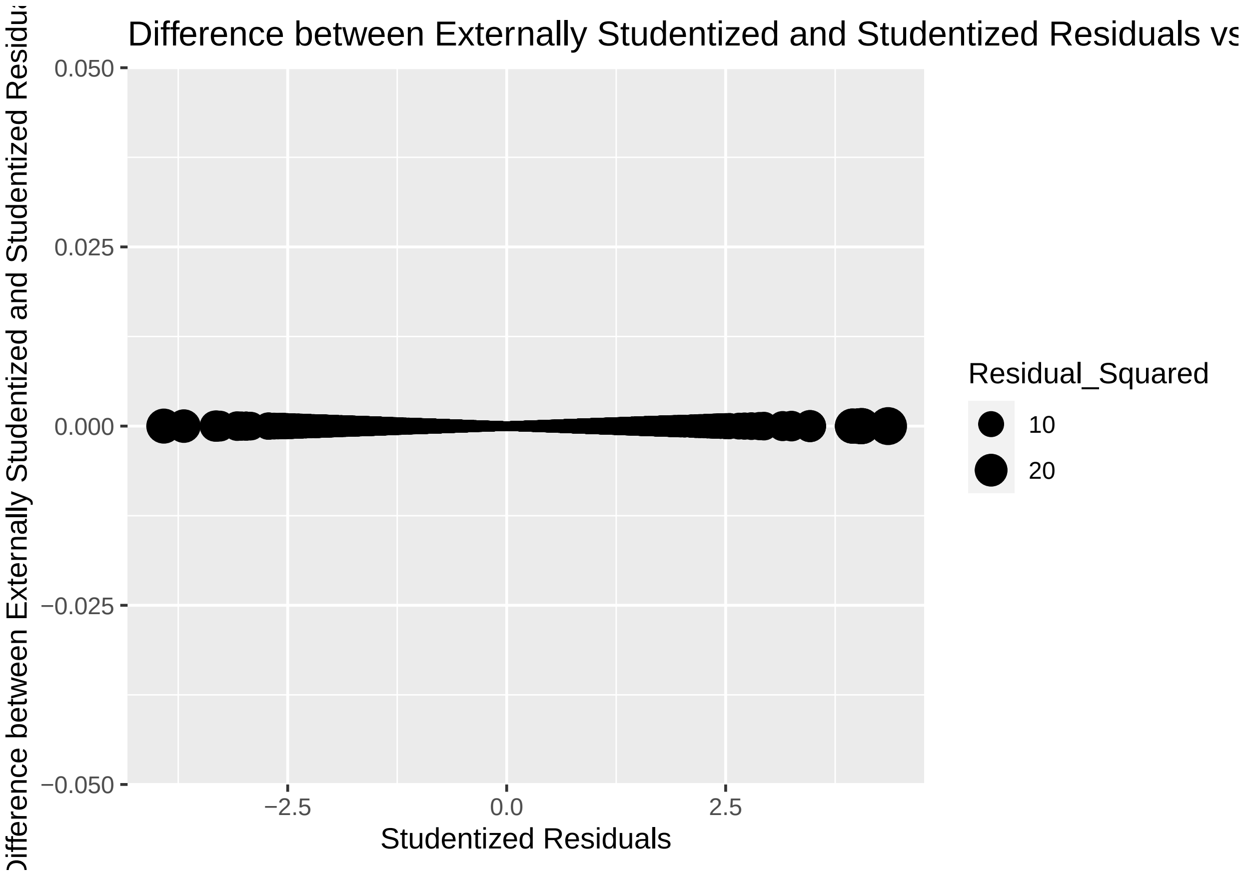



```
# Display the plot
print(ggplot)
```

```
## function (data = NULL, mapping = aes(), ..., environment = parent.frame())
## {
##     UseMethod("ggplot")
## }
## <bytecode: 0x6102cc0>
## <environment: namespace:ggplot2>
```

```
# Load necessary library
library(ggplot2)

# Assuming fit0 is your linear model
# fit0 <- lm(SleepMinNight ~ ., data = df3)

# Calculate studentized and externally studentized residuals
residual_3 <- rstudent(fit0)
residual_4 <- rstudent(fit0)  # Externally studentized residuals are typically the same as studentized

# Regular residuals
residual_1 <- fit0$residuals

# Create a data frame for plotting
plot_data <- data.frame(
  Studentized_Residuals = residual_3,
  Difference = residual_4 - residual_3,
```

```r
  Residual_Squared = residual_1^2
)

# Create the plot
ggplot(plot_data, aes(x = Studentized_Residuals, y = Difference)) +
  geom_point(aes(size = Residual_Squared)) +
  ggtitle("Difference between Externally Studentized and Studentized Residuals vs. Studentized Residuals
  xlab("Studentized Residuals") +
  ylab("Difference between Externally Studentized and Studentized Residuals")
```

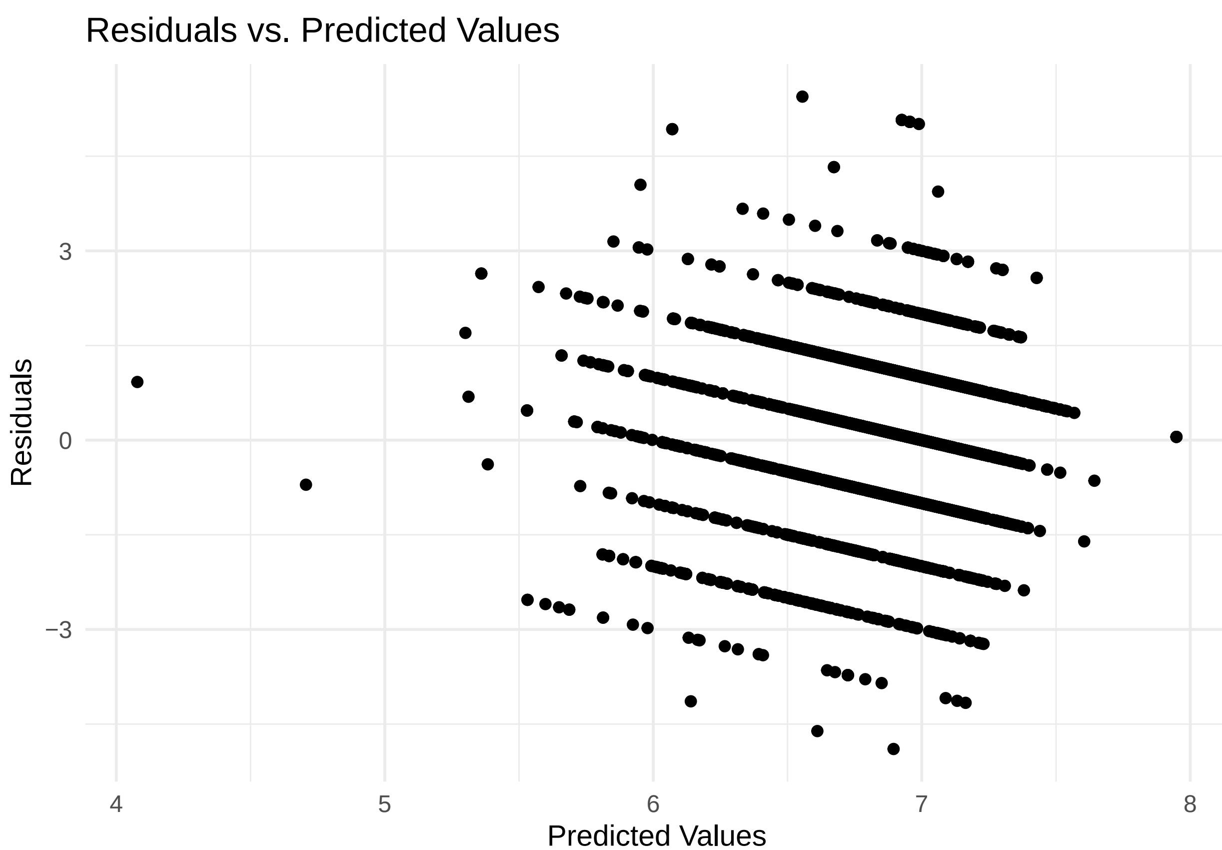



```r
# Display the plot
print(ggplot)
```

```
## function (data = NULL, mapping = aes(), ..., environment = parent.frame())
## {
##     UseMethod("ggplot")
## }
## <bytecode: 0x6102cc0>
## <environment: namespace:ggplot2>
```

```r
# Load necessary library
library(ggplot2)

# Assuming fit0 is your linear model
# fit0 <- lm(SleepMinNight ~ ., data = df3)

# Calculate regular residuals
```

```r
residual_1 <- fit0$residuals

# Get predicted values from the model
predicted_values <- predict(fit0)

# Create the plot
ggplot() +
  geom_point(aes(x = predicted_values, y = residual_1)) +
  ggtitle("Residuals vs. Predicted Values") +
  xlab("Predicted Values") +
  ylab("Residuals") +
  theme_minimal()
```

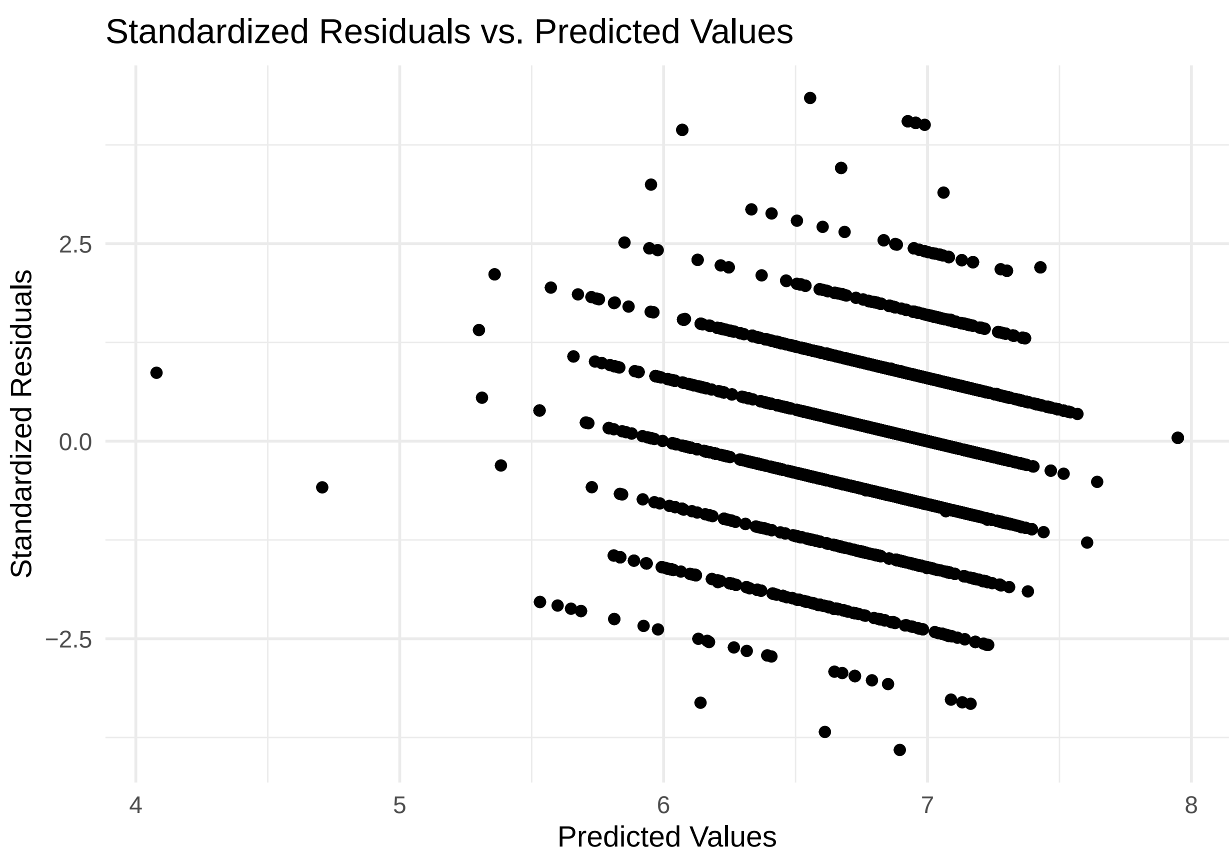



```r
# Display the plot
print(ggplot)
```

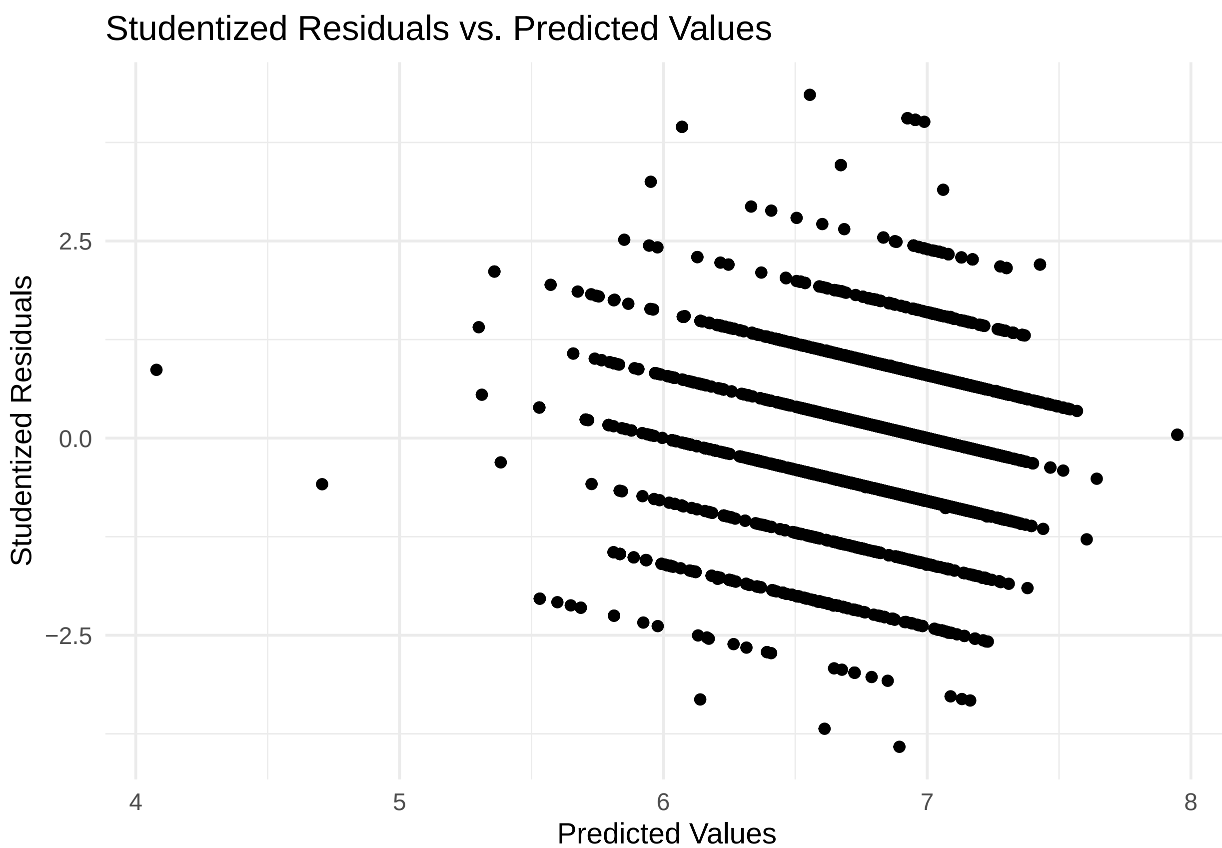
```
## function (data = NULL, mapping = aes(), ..., environment = parent.frame())
## {
##     UseMethod("ggplot")
## }
## <bytecode: 0x6102cc0>
## <environment: namespace:ggplot2>
```

```r
# Load necessary library
library(ggplot2)

# Assuming fit0 is your linear model
```

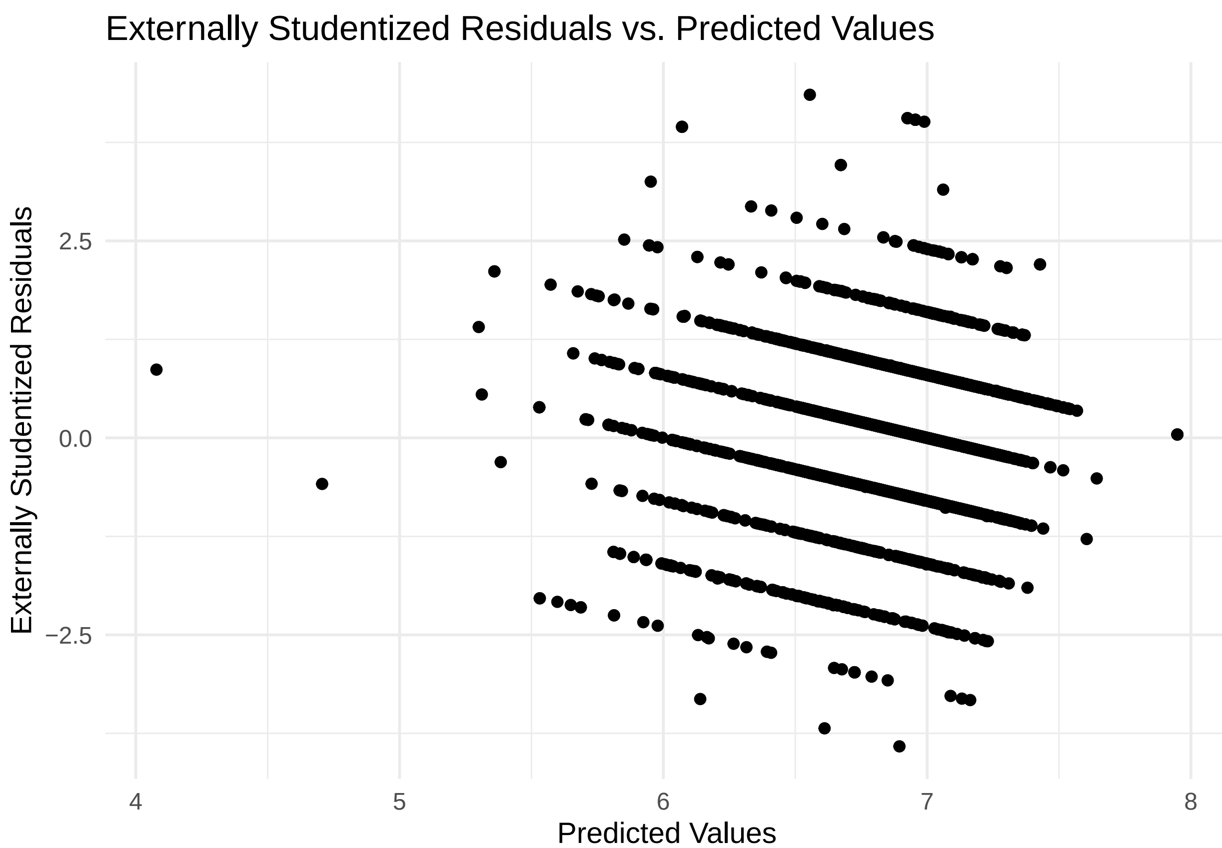
```r
# fit0 <- lm(SleepMinNight ~ ., data = df3)

# Calculate different types of residuals
residual_2 <- rstandard(fit0)
residual_3 <- rstudent(fit0)
residual_4 <- rstudent(fit0)  # Externally studentized residuals

# Get predicted values from the model
predicted_values <- predict(fit0)

# Plot for Standardized Residuals
ggplot() +
  geom_point(aes(x = predicted_values, y = residual_2)) +
  ggtitle("Standardized Residuals vs. Predicted Values") +
  xlab("Predicted Values") +
  ylab("Standardized Residuals") +
  theme_minimal()
```




```r
# Plot for Studentized Residuals
ggplot() +
  geom_point(aes(x = predicted_values, y = residual_3)) +
  ggtitle("Studentized Residuals vs. Predicted Values") +
  xlab("Predicted Values") +
  ylab("Studentized Residuals") +
  theme_minimal()
```




```r
# Plot for Externally Studentized Residuals
ggplot() +
  geom_point(aes(x = predicted_values, y = residual_4)) +
  ggtitle("Externally Studentized Residuals vs. Predicted Values") +
  xlab("Predicted Values") +
  ylab("Externally Studentized Residuals") +
  theme_minimal()
```



(5) Model Selection

```
step(fit0)
```

```
## Start:  AIC=1796.94
## SleepHrsNight ~ TotChol + DirectChol + Age + Gender + Race1 +
##     BMI + BPDiaAve + BPSysAve + AlcoholYear + Poverty + HomeRooms +
##     SexNumPartnLife + SexNumPartYear + DaysMentHlthBad
##
##                   Df Sum of Sq    RSS    AIC
## - TotChol          1     0.387 6145.1 1795.2
## - BPDiaAve         1     1.147 6145.9 1795.7
## - BPSysAve         1     2.270 6147.0 1796.4
## - BMI              1     2.872 6147.6 1796.8
## <none>                         6144.7 1796.9
## - DirectChol       1     3.700 6148.4 1797.3
## - AlcoholYear      1    11.211 6155.9 1802.1
## - SexNumPartYear   1    12.425 6157.1 1802.9
## - HomeRooms        1    12.586 6157.3 1803.0
## - SexNumPartnLife  1    17.677 6162.4 1806.2
## - Poverty          1    24.042 6168.8 1810.3
## - Race1            4    33.645 6178.4 1810.4
## - Age              1    46.071 6190.8 1824.2
## - Gender           1    49.306 6194.0 1826.3
```

```
## - DaysMentHlthBad  1   187.449 6332.2 1912.8
##
## Step:  AIC=1798.4
## SleepHrsNight ~ DirectChol + Age + Gender + Race1 + BMI + BPDiaAve +
##     BPSysAve + AlcoholYear + Poverty + HomeRooms + SexNumPartnLife +
##     SexNumPartYear + DaysMentHlthBad

##
## Call:
## lm(formula = SleepHrsNight ~ DirectChol + Age + Gender + Race1 +
##     BMI + BPDiaAve + BPSysAve + AlcoholYear + Poverty + HomeRooms +
##     SexNumPartnLife + SexNumPartYear + DaysMentHlthBad, data = df3)
##
## Coefficients:
##     (Intercept)       DirectChol              Age           Gender
##       7.0066602       -0.0868565       -0.0103630        0.2492065
##           Race1              BMI         BPDiaAve         BPSysAve
##       0.0709518       -0.0045456        0.0017997       -0.0021224
##     AlcoholYear          Poverty        HomeRooms  SexNumPartnLife
##       0.0005835        0.0485063        0.0262798       -0.0011571
##  SexNumPartYear  DaysMentHlthBad
##       0.0185115       -0.0283090
```

```
library(olsrr)
```

```
##
## Attaching package: 'olsrr'

## The following object is masked from 'package:datasets':
##
##     rivers
```

```
ols_step_forward_p(fit0,penter=0.1,details=F)
```

```
##
##                                   Selection Summary
## ----------------------------------------------------------------------------------
##        Variable                        Adj.
## Step       Entered        R-Square    R-Square      C(p)          AIC         RMSE
## ----------------------------------------------------------------------------------
##    1    DaysMentHlthBad      0.0319      0.0316    135.1234    13044.1166    1.2757
##    2    Gender               0.0401      0.0396    102.7354    13012.6991    1.2704
##    3    Race1                0.0454      0.0446     82.6655    12993.1011    1.2671
##    4    Age                  0.0512      0.0502     60.3184    12971.1357    1.2634
##    5    Poverty              0.0570      0.0558     38.1552    12949.2058    1.2597
##    6    SexNumPartnLife      0.0591      0.0577     31.1607    12942.2607    1.2584
##    7    SexNumPartYear       0.0610      0.0593     25.1899    12936.3166    1.2573
##    8    HomeRooms            0.0628      0.0609     19.7213    12930.8583    1.2563
##    9    AlcoholYear          0.0641      0.0619     16.4559    12927.5917    1.2556
## ----------------------------------------------------------------------------------
```

```
ols_step_forward_p(fit0,penter=0.05,details=F)
```

```
##
##                                   Selection Summary
## ----------------------------------------------------------------------------------
##        Variable                        Adj.
```

```
## Step         Entered         R-Square     R-Square       C(p)          AIC          RMSE
## --------------------------------------------------------------------------------------
##    1     DaysMentHlthBad       0.0319       0.0316     135.1234     13044.1166    1.2757
##    2     Gender                0.0401       0.0396     102.7354     13012.6991    1.2704
##    3     Race1                 0.0454       0.0446      82.6655     12993.1011    1.2671
##    4     Age                   0.0512       0.0502      60.3184     12971.1357    1.2634
##    5     Poverty               0.0570       0.0558      38.1552     12949.2058    1.2597
##    6     SexNumPartnLife       0.0591       0.0577      31.1607     12942.2607    1.2584
##    7     SexNumPartYear        0.0610       0.0593      25.1899     12936.3166    1.2573
##    8     HomeRooms             0.0628       0.0609      19.7213     12930.8583    1.2563
##    9     AlcoholYear           0.0641       0.0619      16.4559     12927.5917    1.2556
## --------------------------------------------------------------------------------------
```

```
ols_mallows_cp(model =m_logfull_1, fullmodel =m_full)  # Mallows' Cp
```

```
## [1] -3821.538
```

```
ols_mallows_cp(model =m_logfull_2, fullmodel =m_full)  # Mallows' Cp
```

```
## [1] 11.05159
```

```
ols_mallows_cp(model =m_sqfull_1, fullmodel =m_full)  # Mallows' Cp
```

```
## [1] 11.28616
```