

Indy Regression

2023-04-23

```
#Load Libraries  
library(tidyverse)
```

```
## — Attaching core tidyverse packages ————— tidyverse 2.0.0 —  
## ✓ dplyr    1.1.0    ✓ readr    2.1.4  
## ✓ forcats  1.0.0    ✓ stringr  1.5.0  
## ✓ ggplot2   3.4.1    ✓ tibble   3.1.8  
## ✓ lubridate 1.9.2    ✓ tidyrr   1.3.0  
## ✓ purrr    1.0.1  
## — Conflicts ————— tidyverse_conflicts() —  
## ✘ dplyr::filter() masks stats::filter()  
## ✘ dplyr::lag()   masks stats::lag()  
## i Use the http://conflicted.r-lib.org/ package to force all conflicts to become errors
```

```
library(dplyr)  
library(ggplot2)  
library(stringr)  
library(ggfortify)
```

```
## Warning: package 'ggfortify' was built under R version 4.2.3
```

```

## Loading data.
income<- read.csv("C:/Users/ureka/OneDrive/Documents/Stata 2022/Danicia_stats/COMPLETE_income50_75k.csv", header = TRUE)
poverty<- read.csv("C:/Users/ureka/OneDrive/Documents/Stata 2022/Danicia_stats/COMPLETE_povertytable.csv", header = TRUE)
homeown<- read.csv("C:/Users/ureka/OneDrive/Documents/Stata 2022/Danicia_stats/COMPLETE_homeowner_occupied.csv", header = TRUE)
foodstamps<- read.csv("C:/Users/ureka/OneDrive/Documents/Stata 2022/Danicia_stats/COMPLETE_perce ntfoodstamps.csv", header = TRUE)
mobility<- read.csv("C:/Users/ureka/OneDrive/Documents/Stata 2022/Danicia_stats/mobility.csv", header = TRUE)
insurance<- read.csv("C:/Users/ureka/OneDrive/Documents/Stata 2022/Danicia_stats/healthinsurance.csv", header = TRUE)
crimes<- read.csv("C:/Users/ureka/OneDrive/Documents/Stata 2022/Danicia_stats/crimestable.csv", header = TRUE)
artcount<- read.csv("C:/Users/ureka/OneDrive/Documents/Stata 2022/Danicia_stats/Indyarts_censusc ount.csv", header = TRUE)
walk<- read.csv("C:/Users/ureka/OneDrive/Documents/Stata 2022/Danicia_stats/walk.csv", header = TRUE)

# Aggregate by GEO_ID and calculate the mean of walkability
walk <- aggregate(walkability ~ GEO_ID, data = walk, mean)

load("C:/Users/ureka/OneDrive/Documents/Stata 2022/Danicia_stats/ICPSR_38586-V1/ICPSR_38586/DS00 01/38586-0001-Data.rda")
parks<- da38586.0001
parks$TRACT_FIPS10 <- paste0("1400000US", as.character(parks$TRACT_FIPS10))
parks$GEO_ID <- parks$TRACT_FIPS10

```

```

## Merge each table one at a time. Each iteration only keeps observations that exist in BOTH tab les,
## while excluding those that only exist in one.
merged_table <- merge(income, poverty, by = "GEO_ID")
merged_table <- merge(merged_table, homeown, by = "GEO_ID")
merged_table <- merge(merged_table, foodstamps, by = "GEO_ID")
merged_table <- merge(merged_table, mobility, by = "GEO_ID")
merged_table <- merge(merged_table, insurance, by = "GEO_ID")
merged_table <- merge(merged_table, artcount, by = "GEO_ID")
merged_table <- merge(merged_table, parks, by = "GEO_ID")
merged_table <- merge(merged_table, walk, by = "GEO_ID")
merged_table <- merge(merged_table, crimes, by = "GEO_ID")

wbindex <- merged_table

wbindex$percentPoverty <- as.numeric(wbindex$percentPoverty)
wbindex$income <- as.numeric(wbindex$income)
wbindex$owneroccupied <- as.numeric(wbindex$owneroccupied)
wbindex$foodstamps <- as.numeric(wbindex$foodstamps)
wbindex$mobility <- as.numeric(wbindex$mobility)
wbindex$healthinsurance <- as.numeric(wbindex$healthinsurance)

```

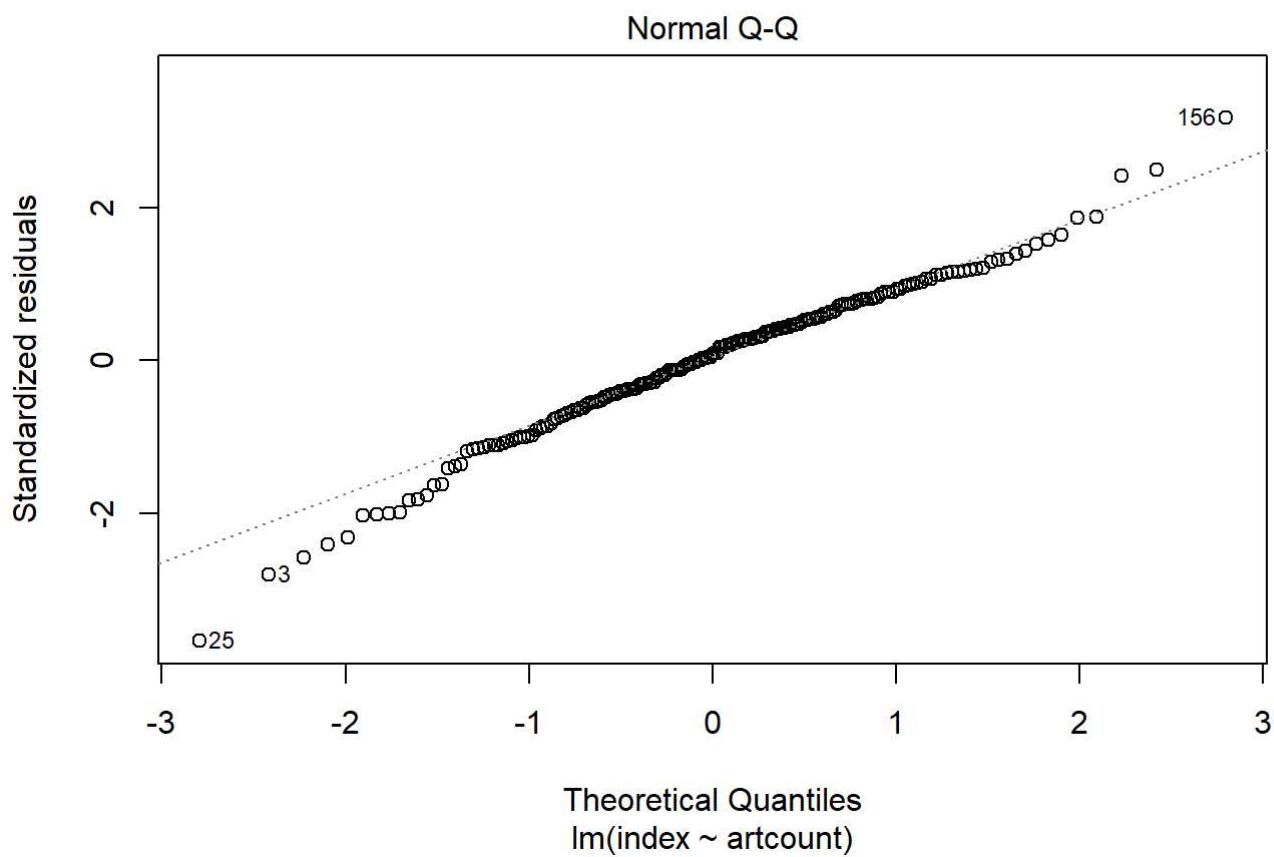
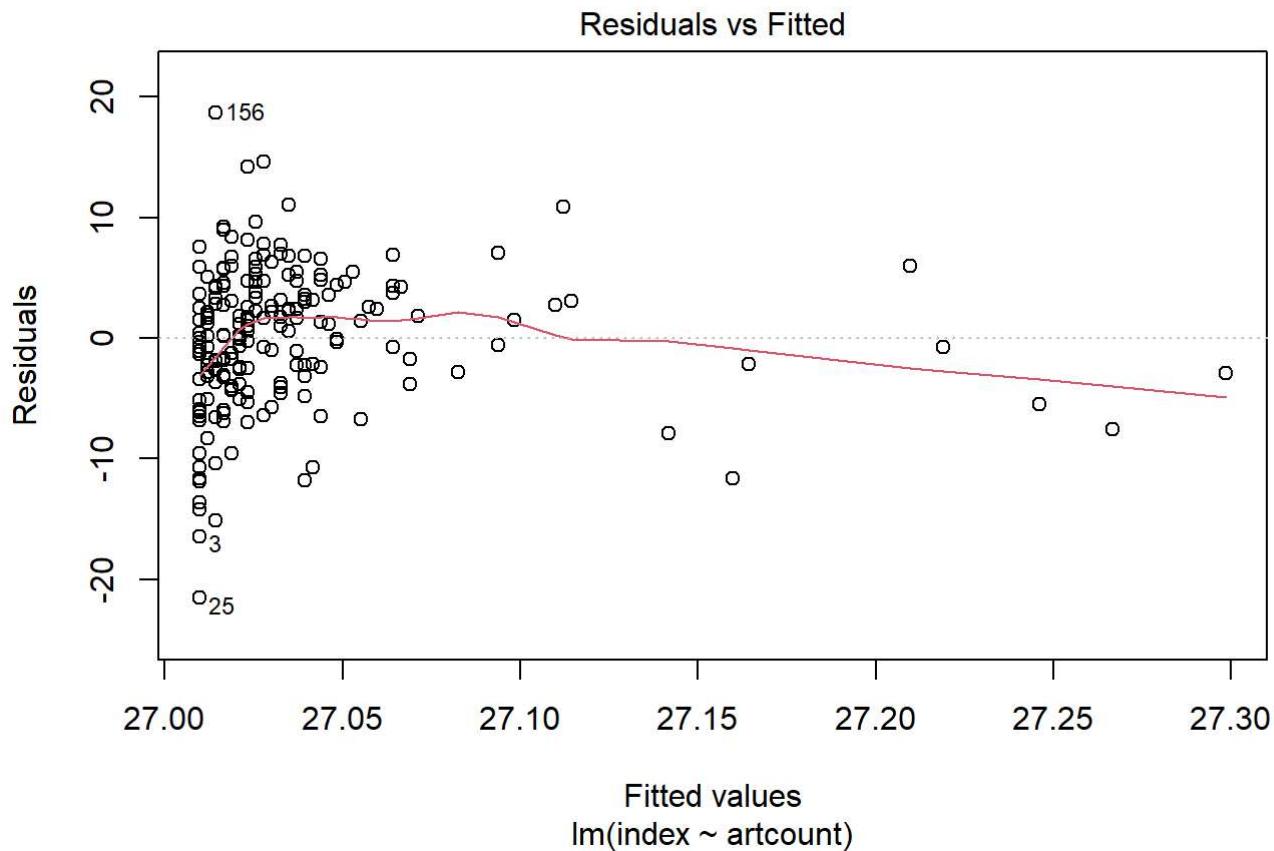
```
## Creating outcome variable
wbindex$index <- ((wbindex$income) + (wbindex$percentPoverty) + (wbindex$owneroccupied) + (wbindex$foodstamps))/ 4

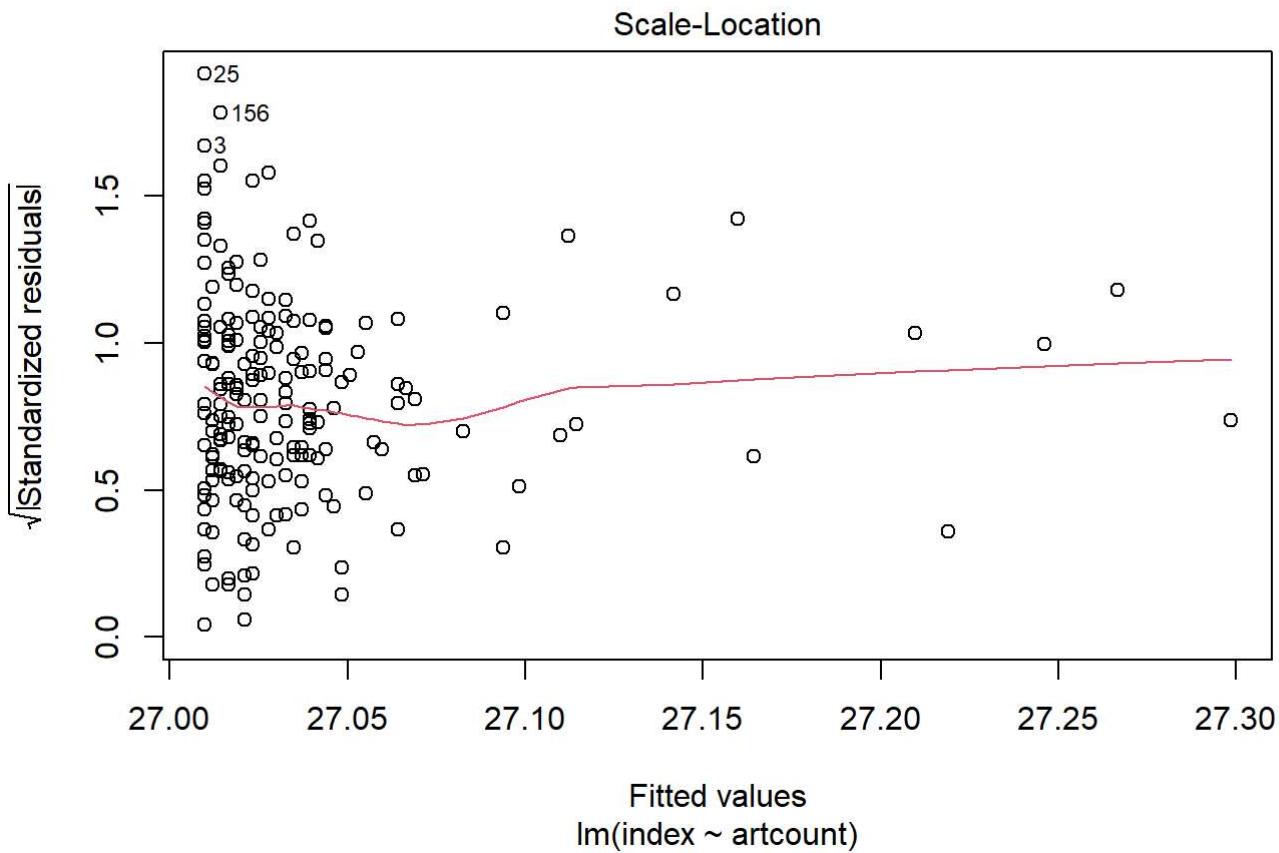
wbindex <- wbindex[, c("GEO_ID", "index", "income", "percentPoverty",
                      "owneroccupied", "foodstamps", "healthinsurance",
                      "artcount", "mobility", "crimes", "walkability", "TOT_PARK_AREA_SQMILE
S")]
colnames(wbindex)
```

```
## [1] "GEO_ID"                 "index"                  "income"
## [4] "percentPoverty"          "owneroccupied"          "foodstamps"
## [7] "healthinsurance"          "artcount"                "mobility"
## [10] "crimes"                  "walkability"            "TOT_PARK_AREA_SQMILES"
```

```
model <- lm(index ~ artcount, data = wbindex)

plot(model)
```

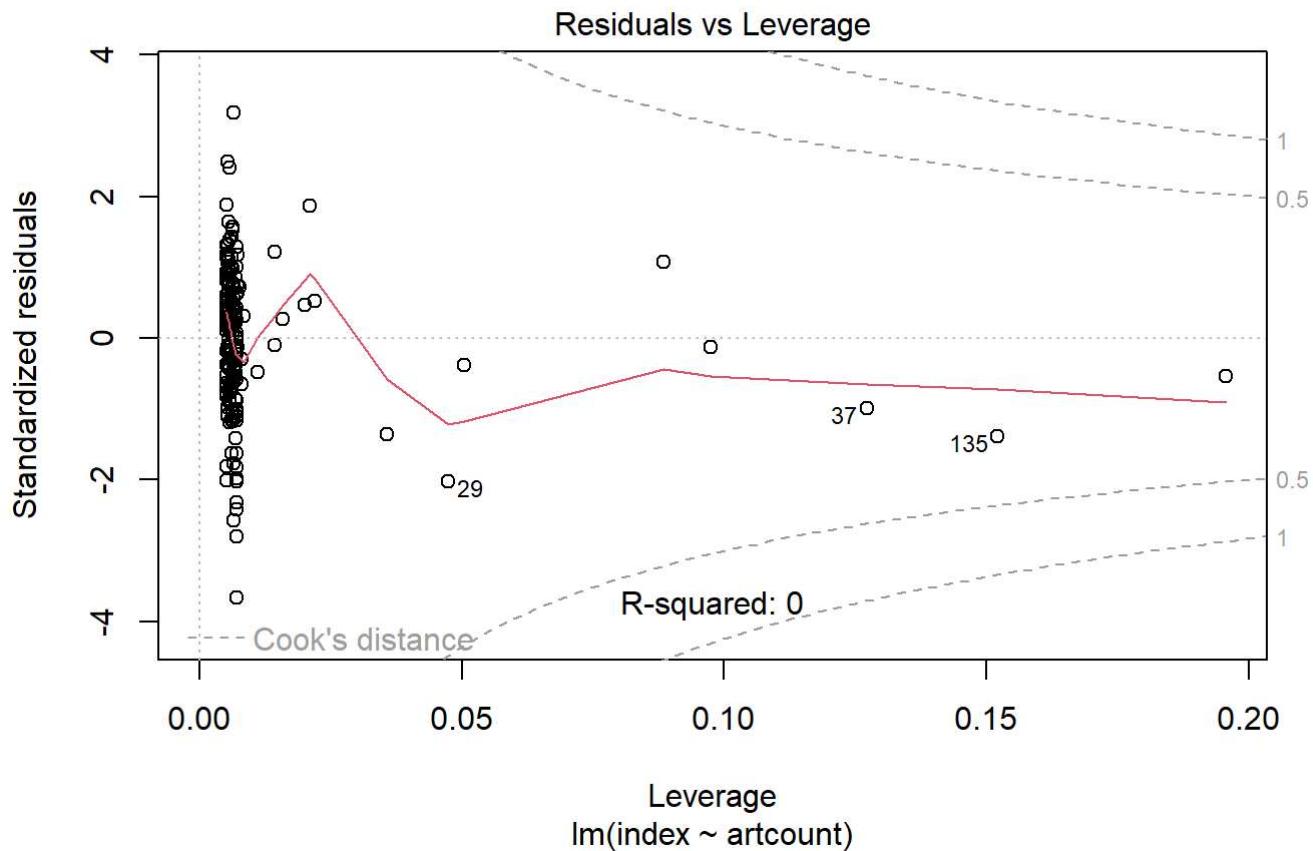




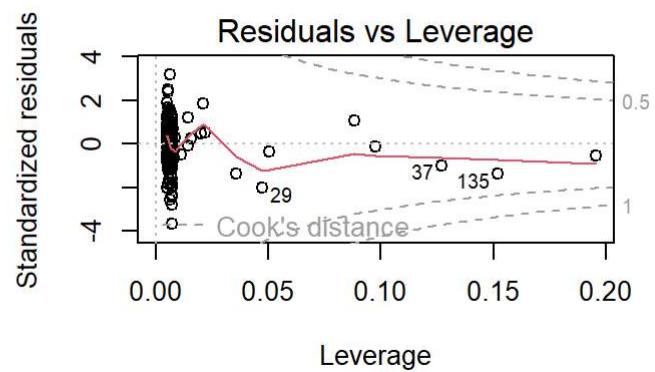
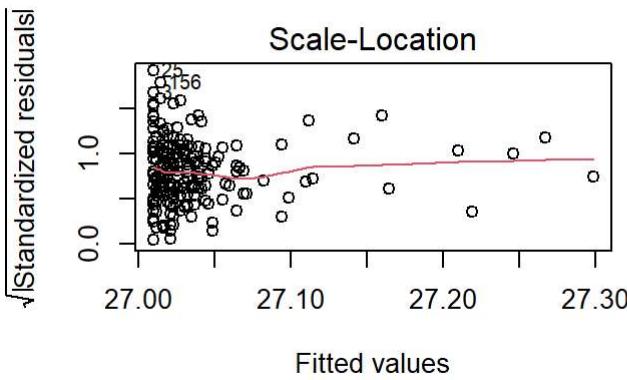
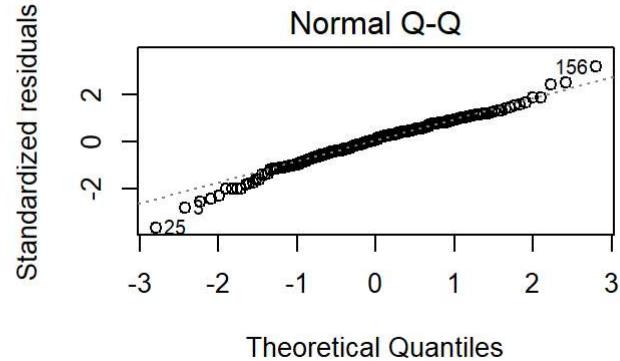
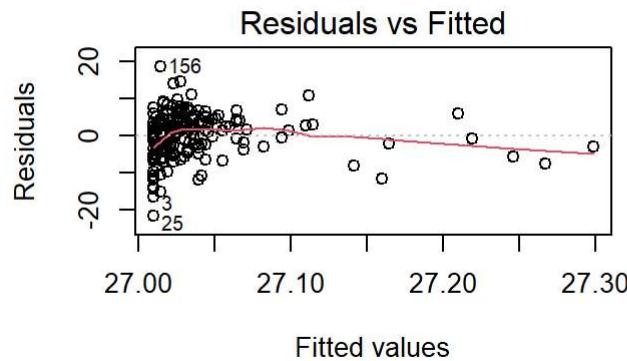
```
# View summary of the model with R-squared value included
rsq <- summary(model)$r.squared
summary_text <- paste0("R-squared: ", round(rsq, 2))
summary(model)
```

```
##
## Call:
## lm(formula = index ~ artcount, data = wbindex)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -21.5347  -3.2666   0.4403   3.8244  18.6607
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 27.009731  0.498794 54.150 <2e-16 ***
## artcount     0.002273  0.022302  0.102    0.919
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.889 on 191 degrees of freedom
## Multiple R-squared:  5.44e-05, Adjusted R-squared:  -0.005181
## F-statistic: 0.01039 on 1 and 191 DF,  p-value: 0.9189
```

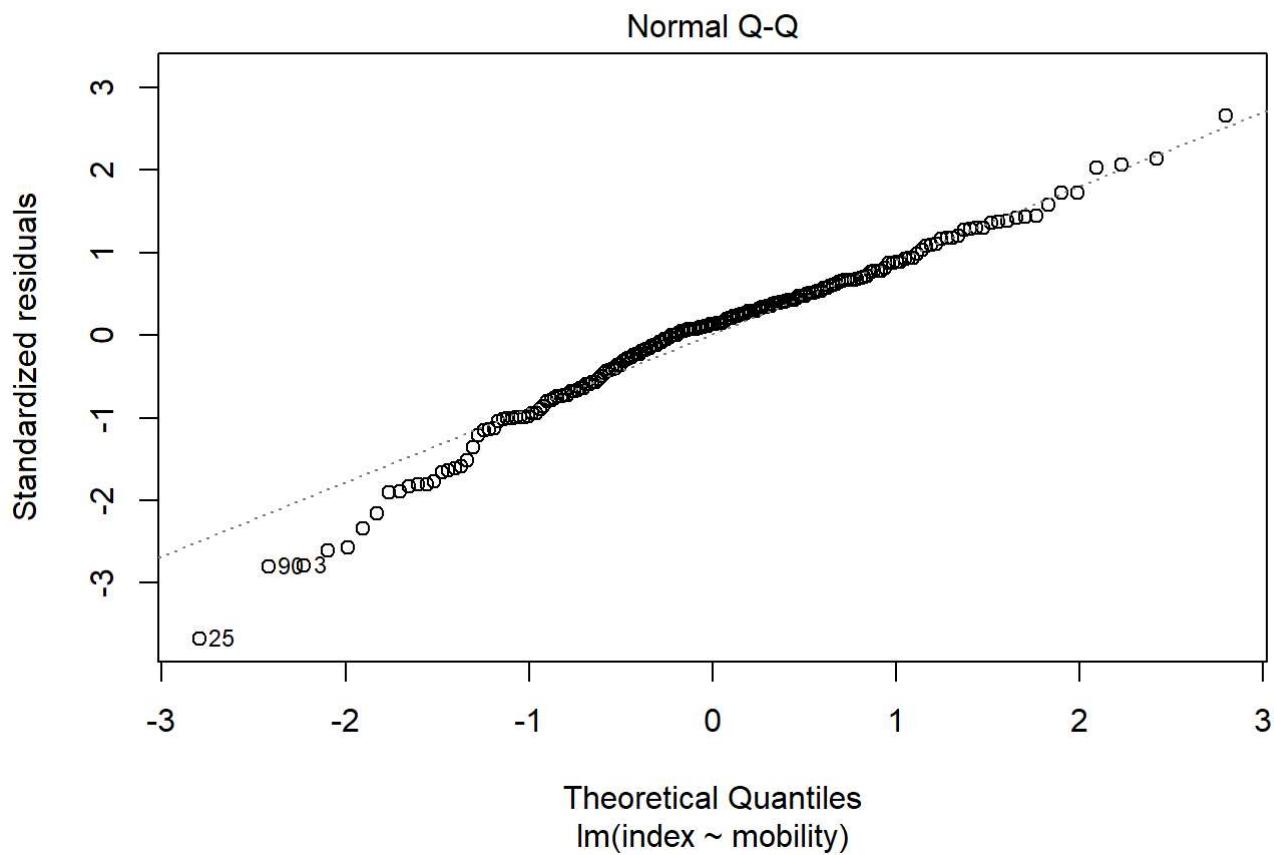
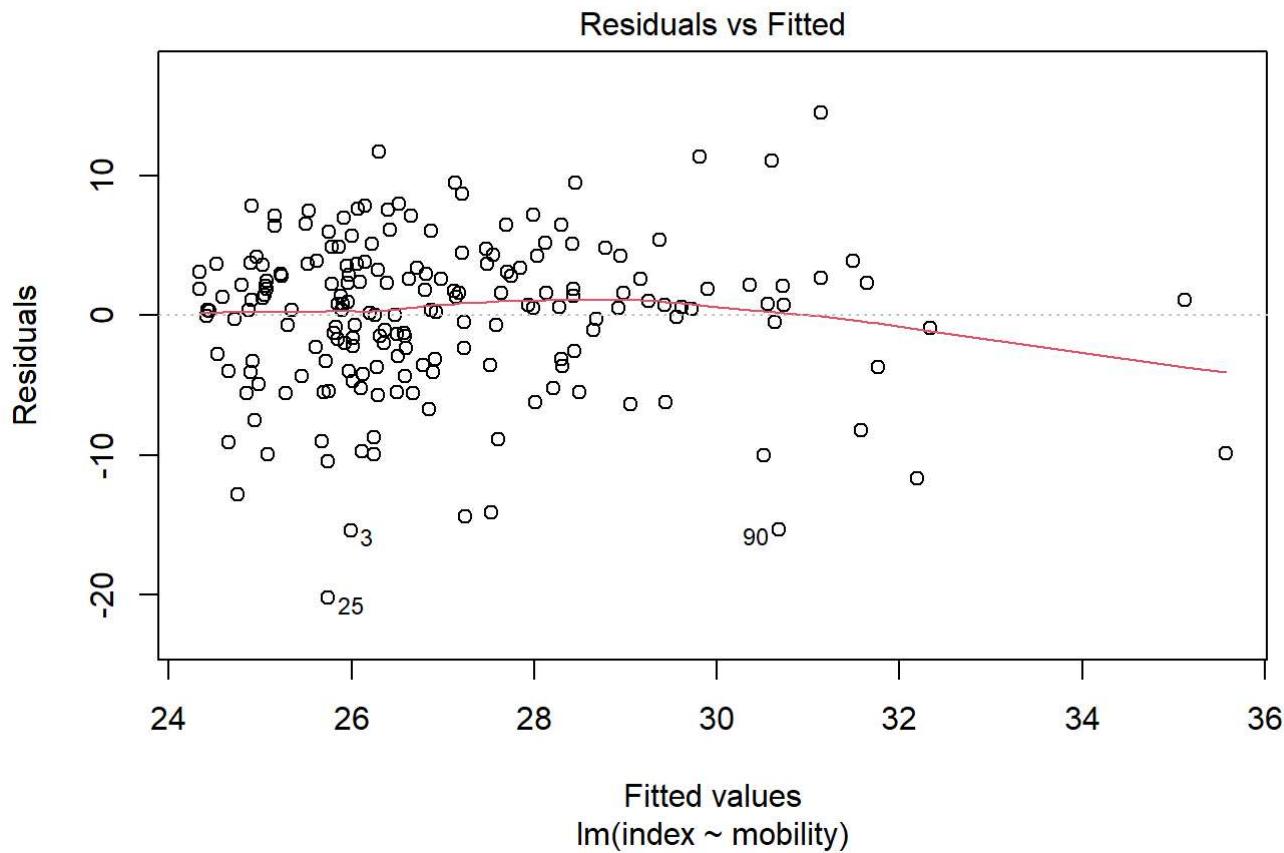
```
mtext(summary_text, side = 1, line = -2)
```

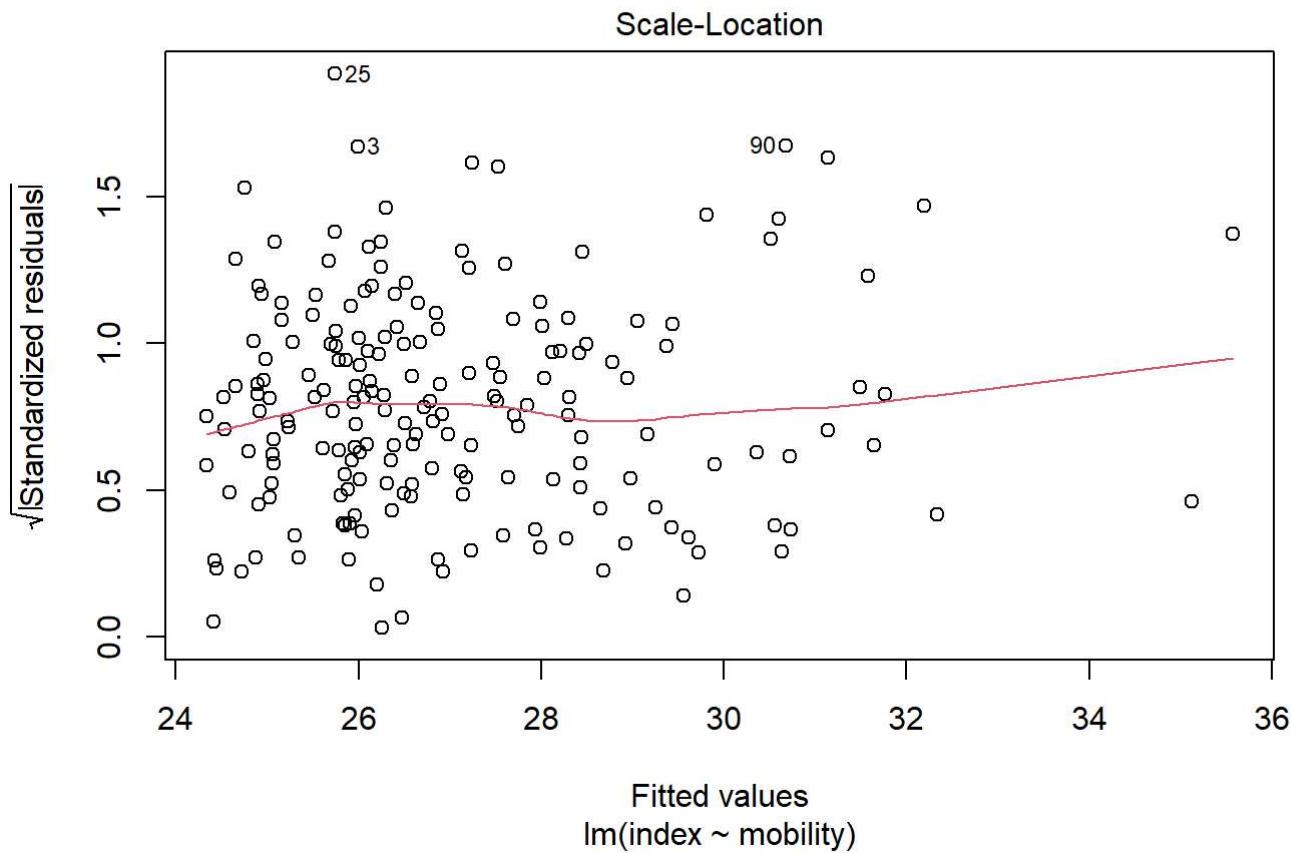


```
# Check model assumptions and residuals in a grid of plots
par(mfrow = c(2, 2))
plot(model)
```



```
model <- lm(index ~ mobility, data = wbindex)
plot(model)
```

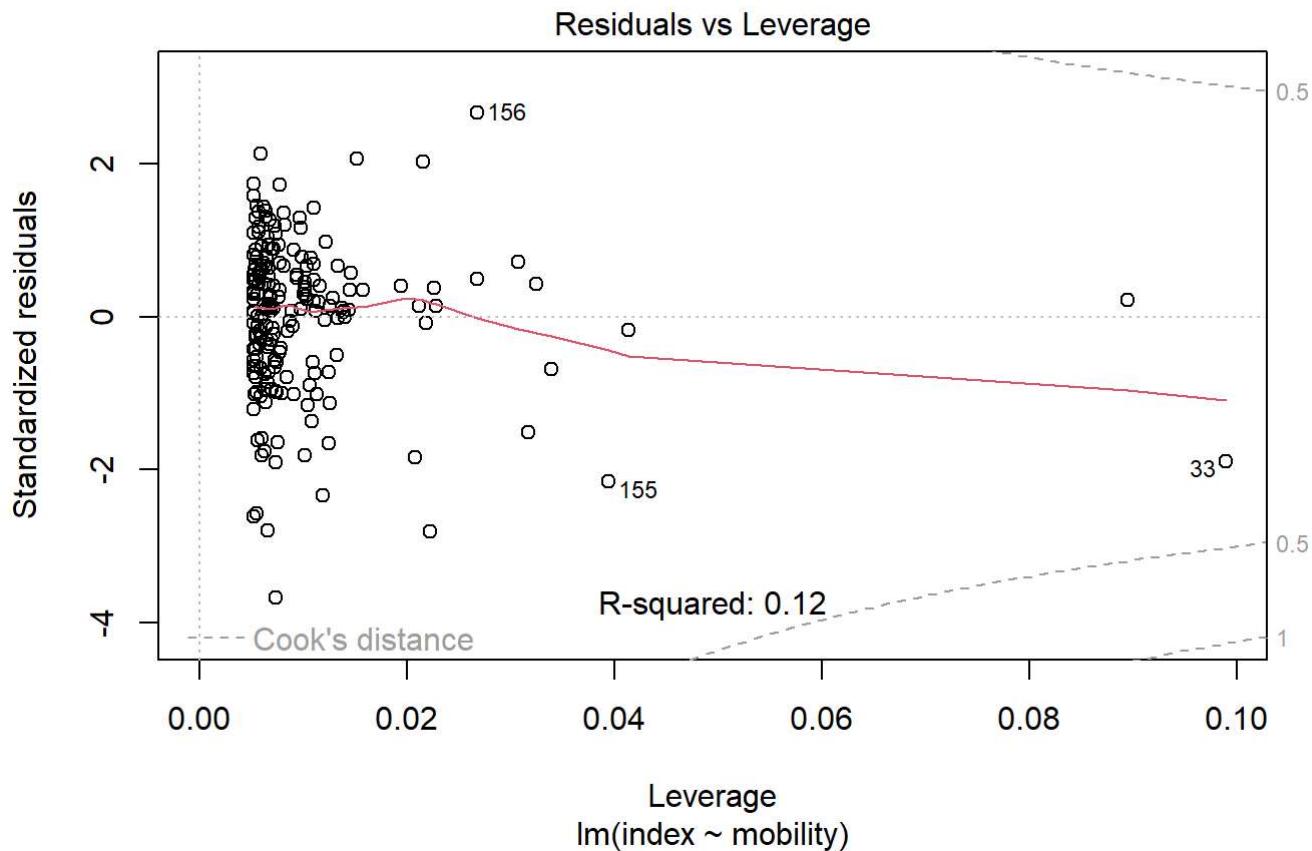




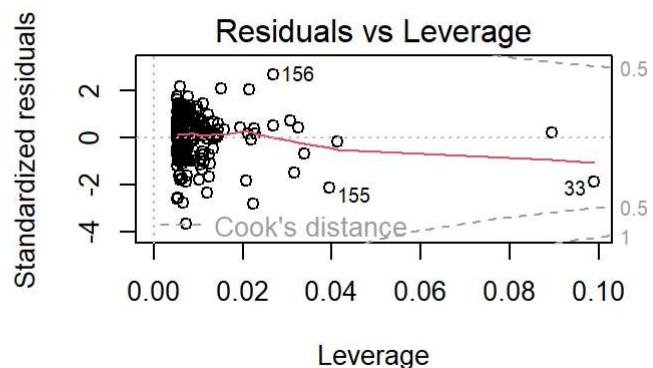
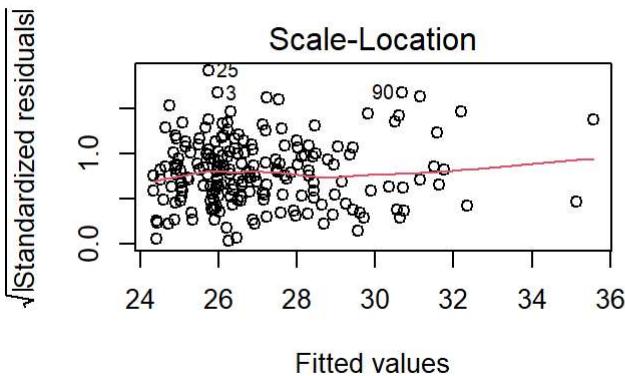
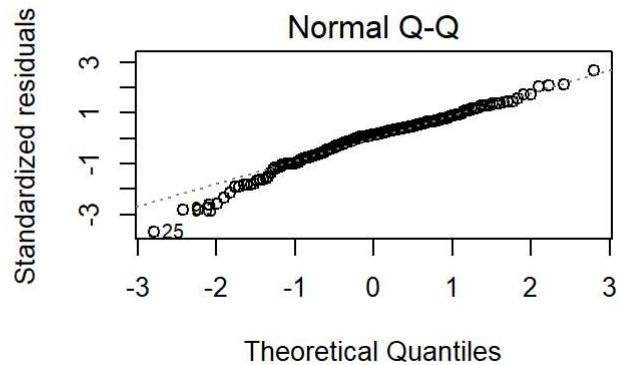
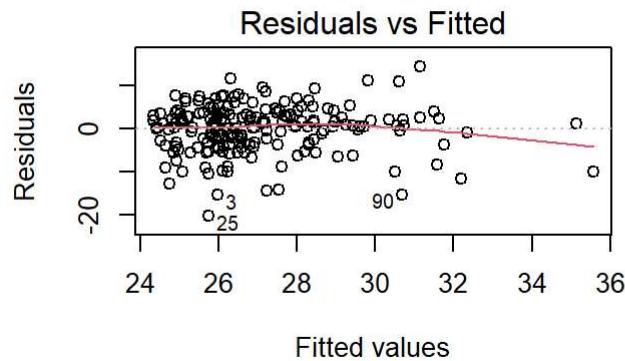
```
# View summary of the model with R-squared value included
rsq <- summary(model)$r.squared
summary_text <- paste0("R-squared: ", round(rsq, 2))
summary(model)
```

```
##
## Call:
## lm(formula = index ~ mobility, data = wbindex)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -20.2714  -3.2433   0.7404   3.4237  14.5390
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 2.418e+01  6.924e-01  34.928 < 2e-16 ***
## mobility    4.626e-03  9.181e-04   5.039 1.08e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.533 on 191 degrees of freedom
## Multiple R-squared:  0.1173, Adjusted R-squared:  0.1127
## F-statistic: 25.39 on 1 and 191 DF,  p-value: 1.081e-06
```

```
mtext(summary_text, side = 1, line = -2)
```

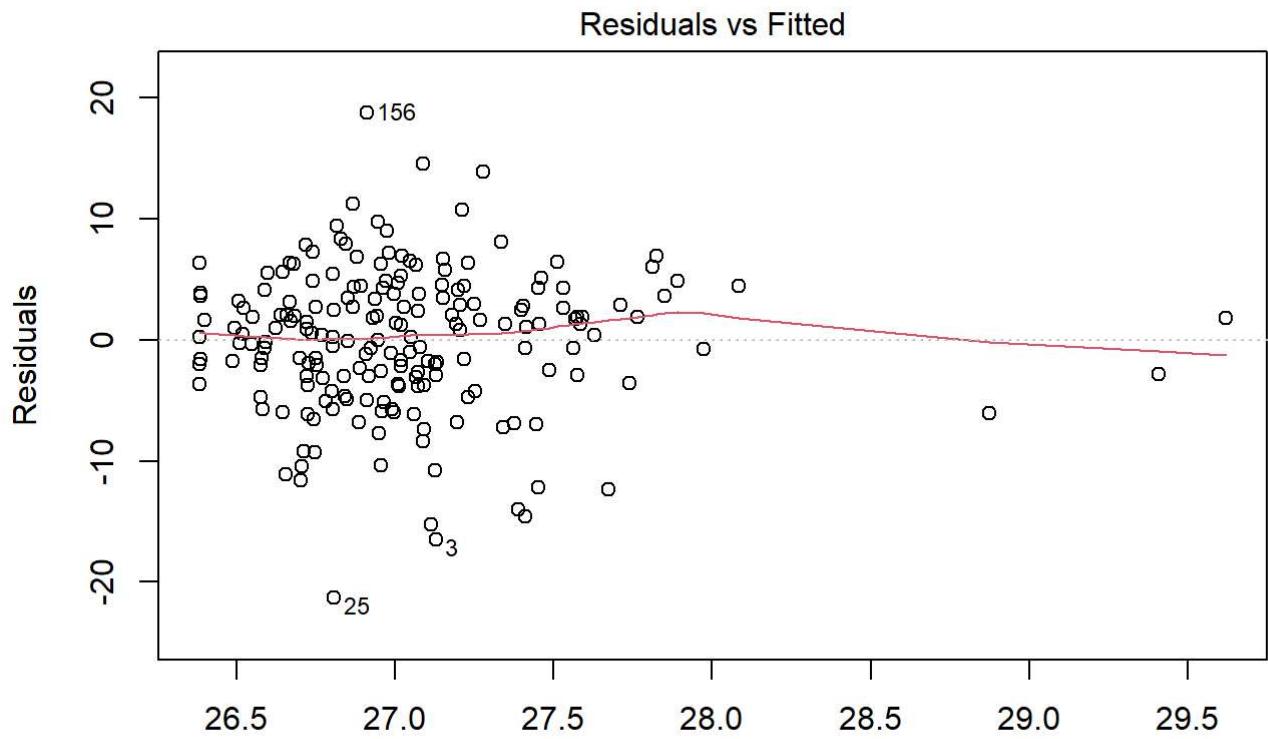


```
# Check model assumptions and residuals in a grid of plots
par(mfrow = c(2, 2))
plot(model)
```

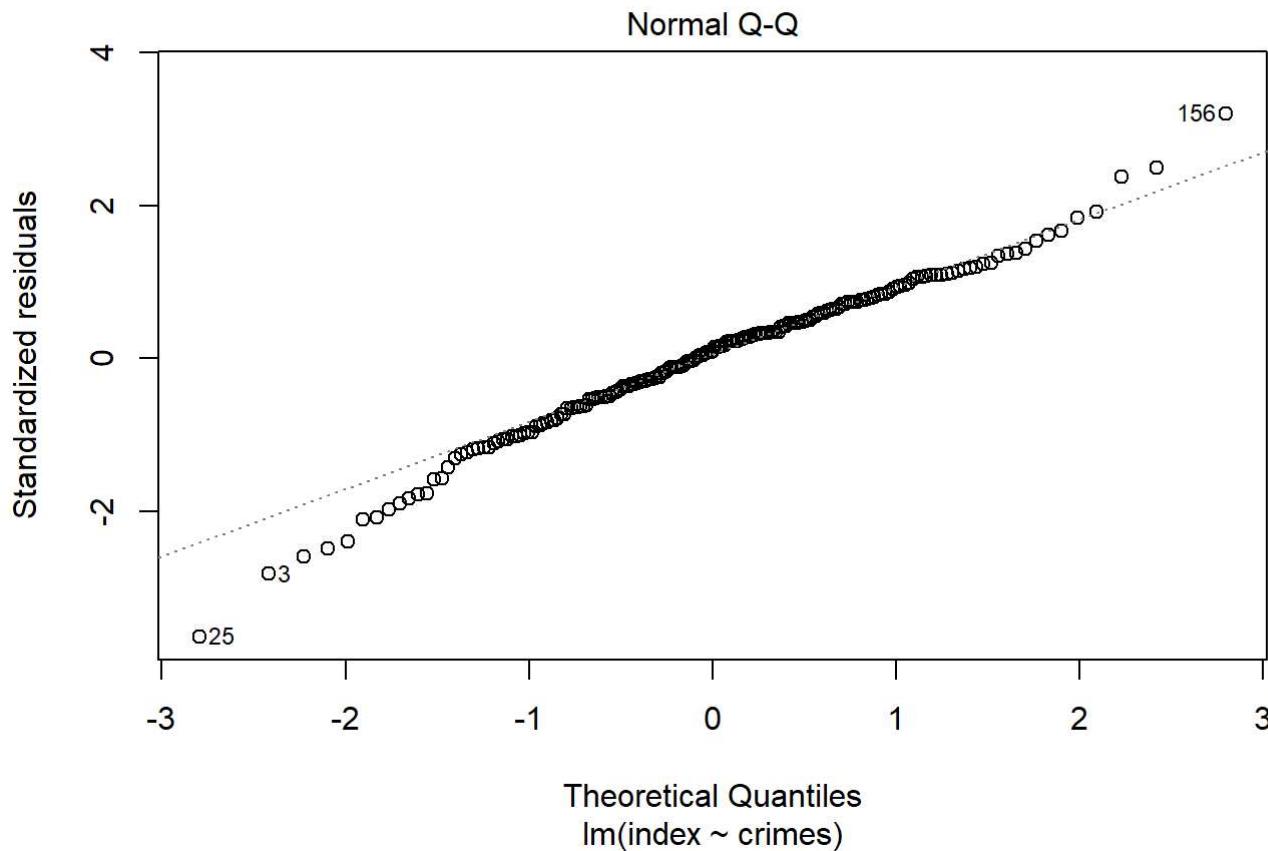


```
## Linear regression
model <- lm(index ~ crimes, data = wbindex)

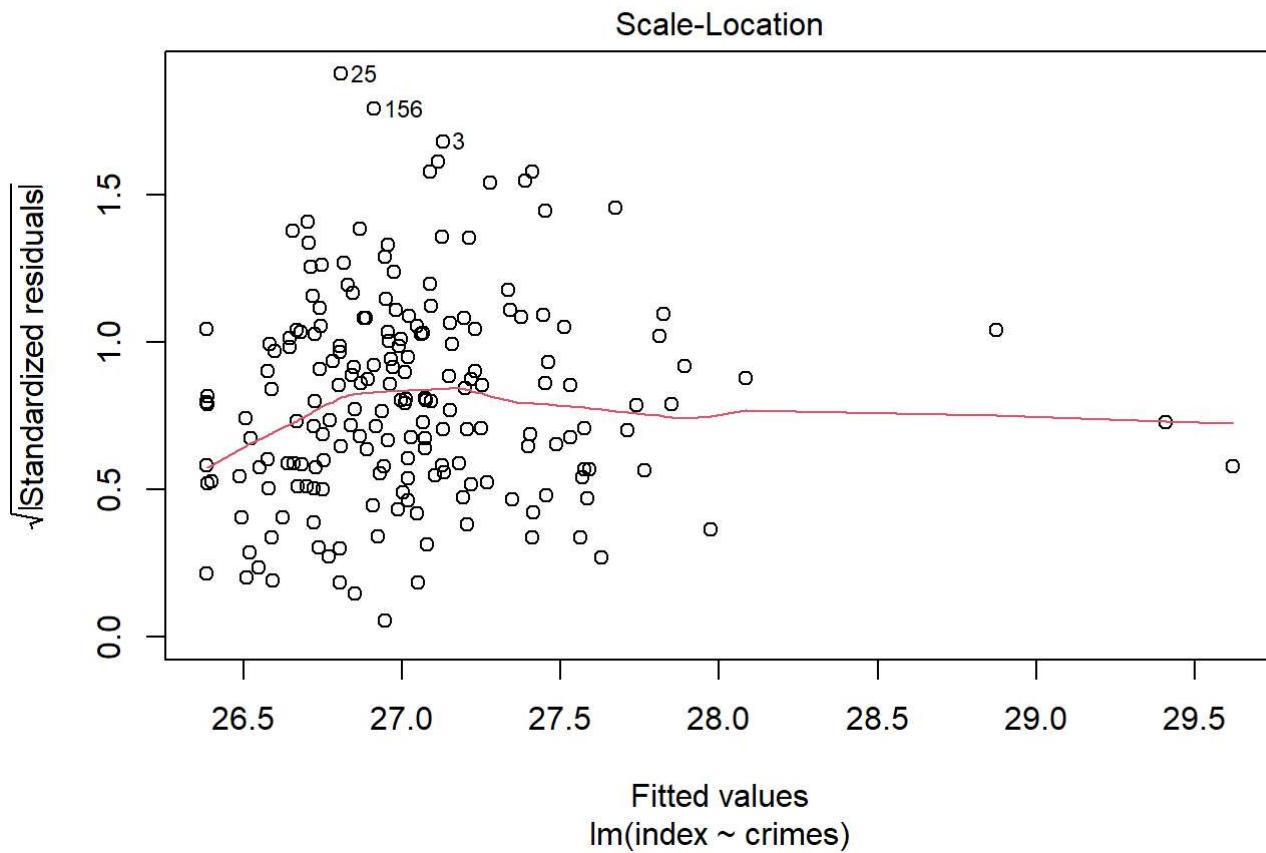
plot(model)
```



Fitted values
 $\text{lm}(\text{index} \sim \text{crimes})$



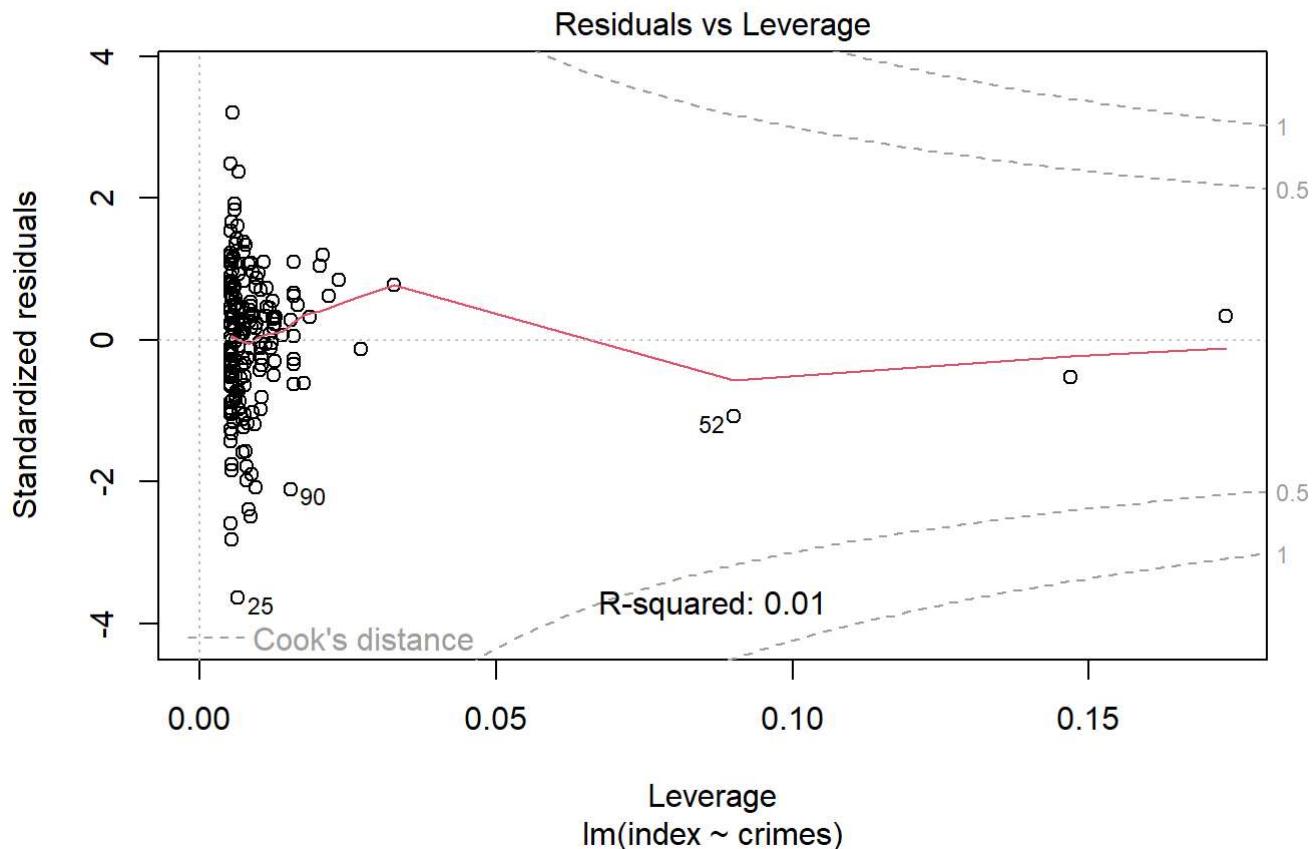
Theoretical Quantiles
 $\text{lm}(\text{index} \sim \text{crimes})$



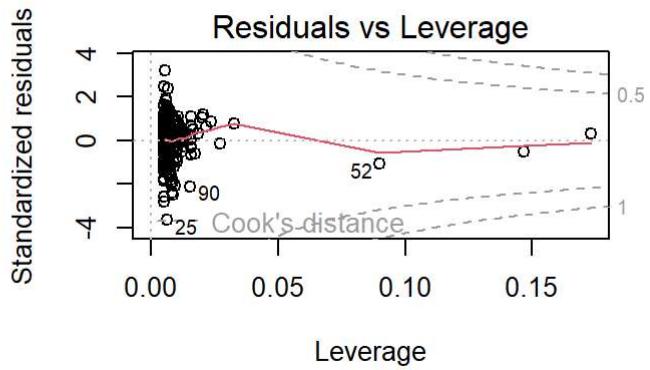
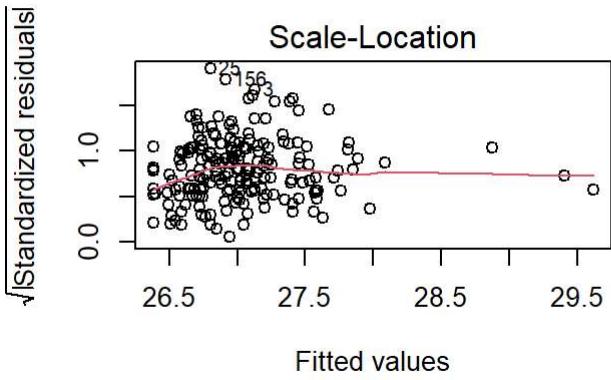
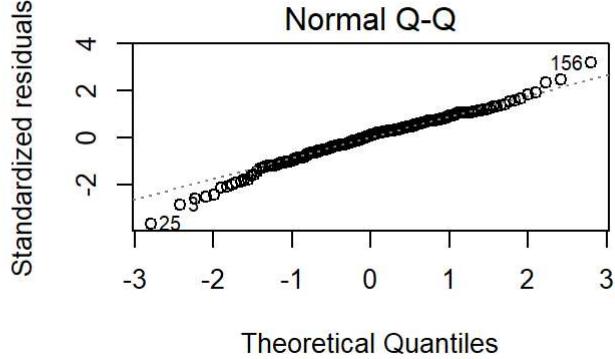
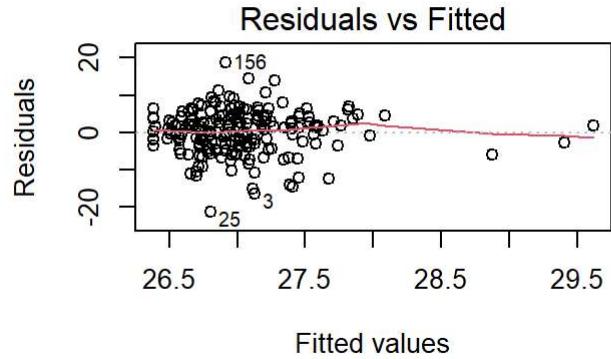
```
# View summary of the model with R-squared value included
rsq <- summary(model)$r.squared
summary_text <- paste0("R-squared: ", round(rsq, 2))
summary(model)
```

```
##
## Call:
## lm(formula = index ~ crimes, data = wbindex)
##
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -21.331   -3.171    0.539   3.779   18.764 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 26.381950  0.741558 35.576 <2e-16 ***
## crimes       0.002926  0.002724  1.074    0.284    
## ---      
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 5.871 on 191 degrees of freedom
## Multiple R-squared:  0.006006, Adjusted R-squared:  0.0008014 
## F-statistic: 1.154 on 1 and 191 DF,  p-value: 0.2841
```

```
mtext(summary_text, side = 1, line = -2)
```

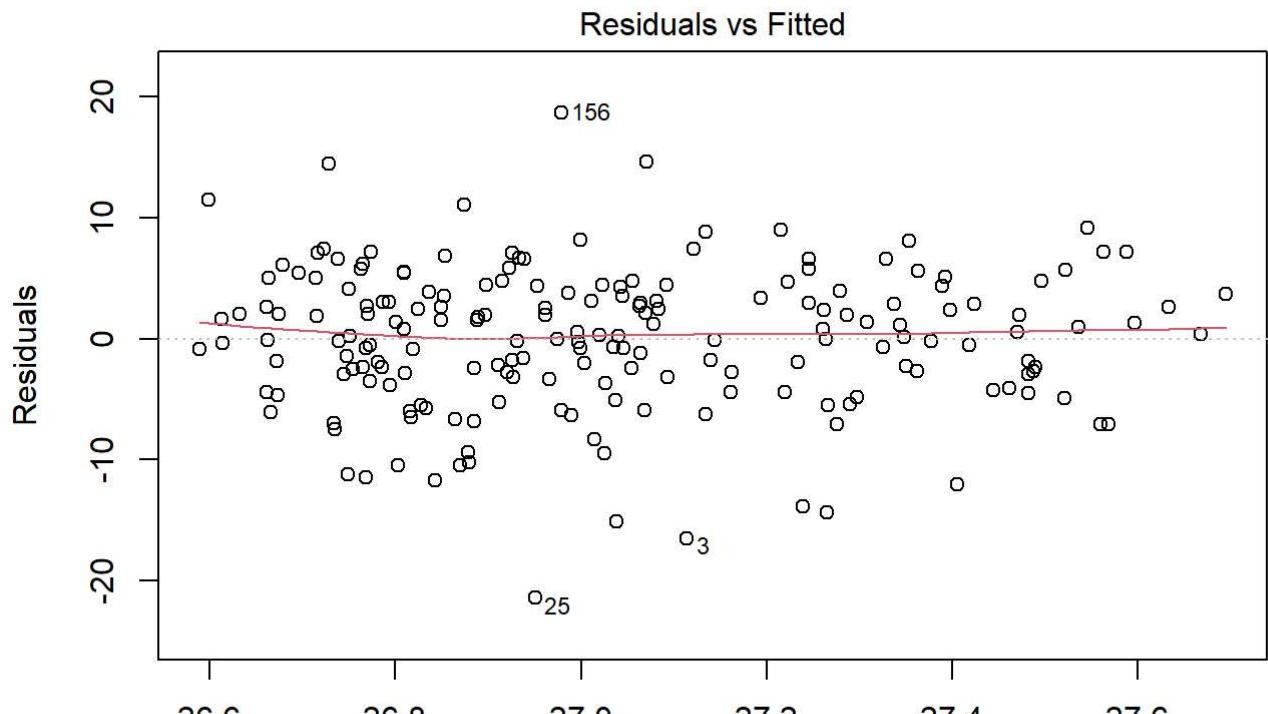


```
# Check model assumptions and residuals in a grid of plots
par(mfrow = c(2, 2))
plot(model)
```

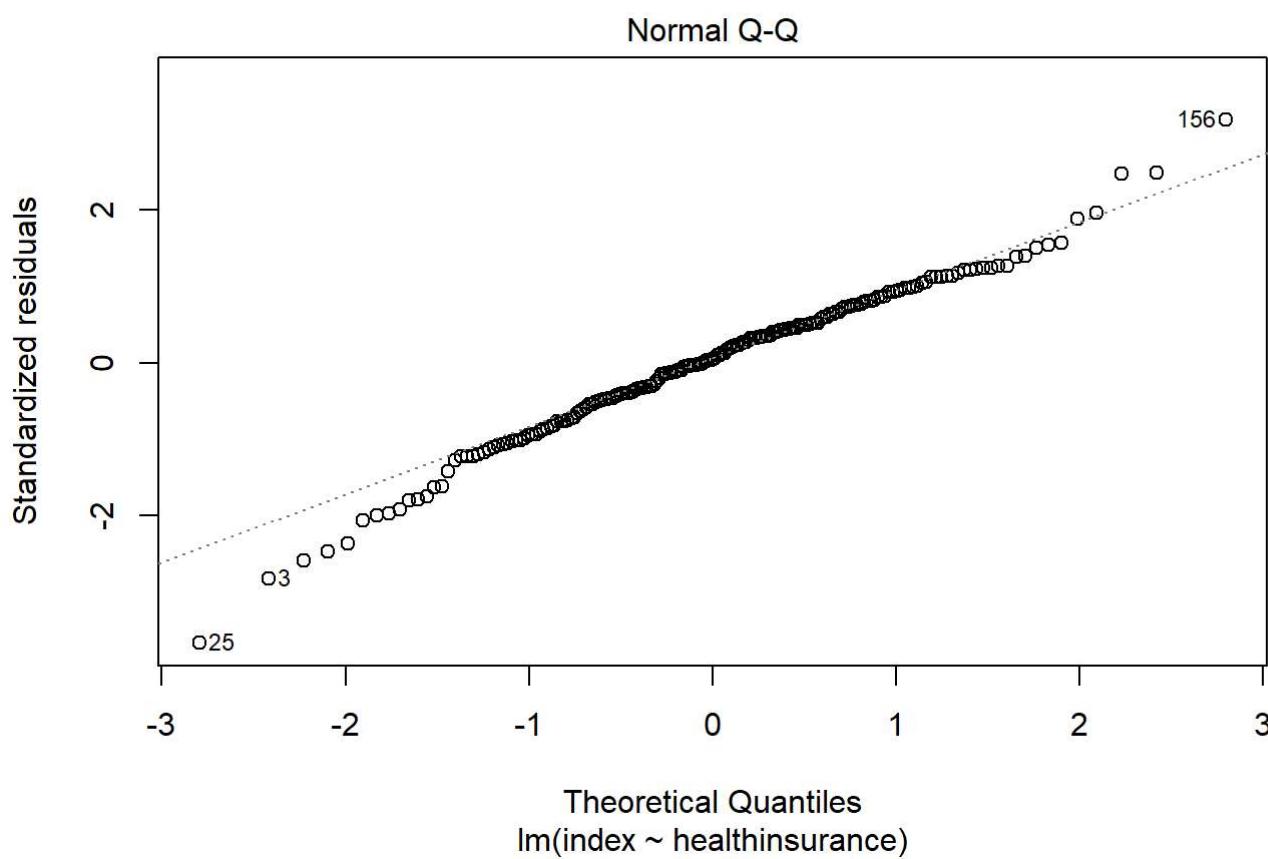


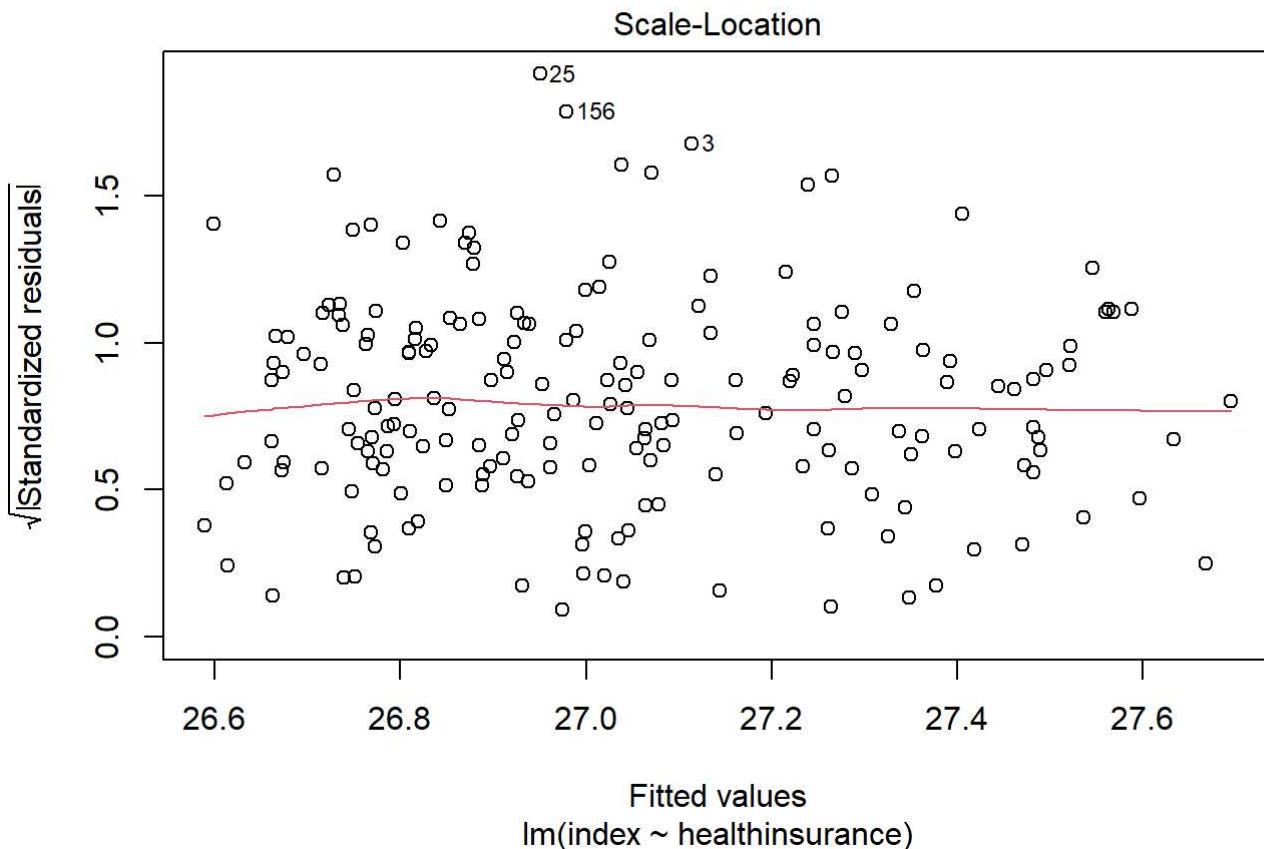
```
## Linear regression
model <- lm(index ~ healthinsurance, data = wbindex)

plot(model)
```



Fitted values
lm(index ~ healthinsurance)

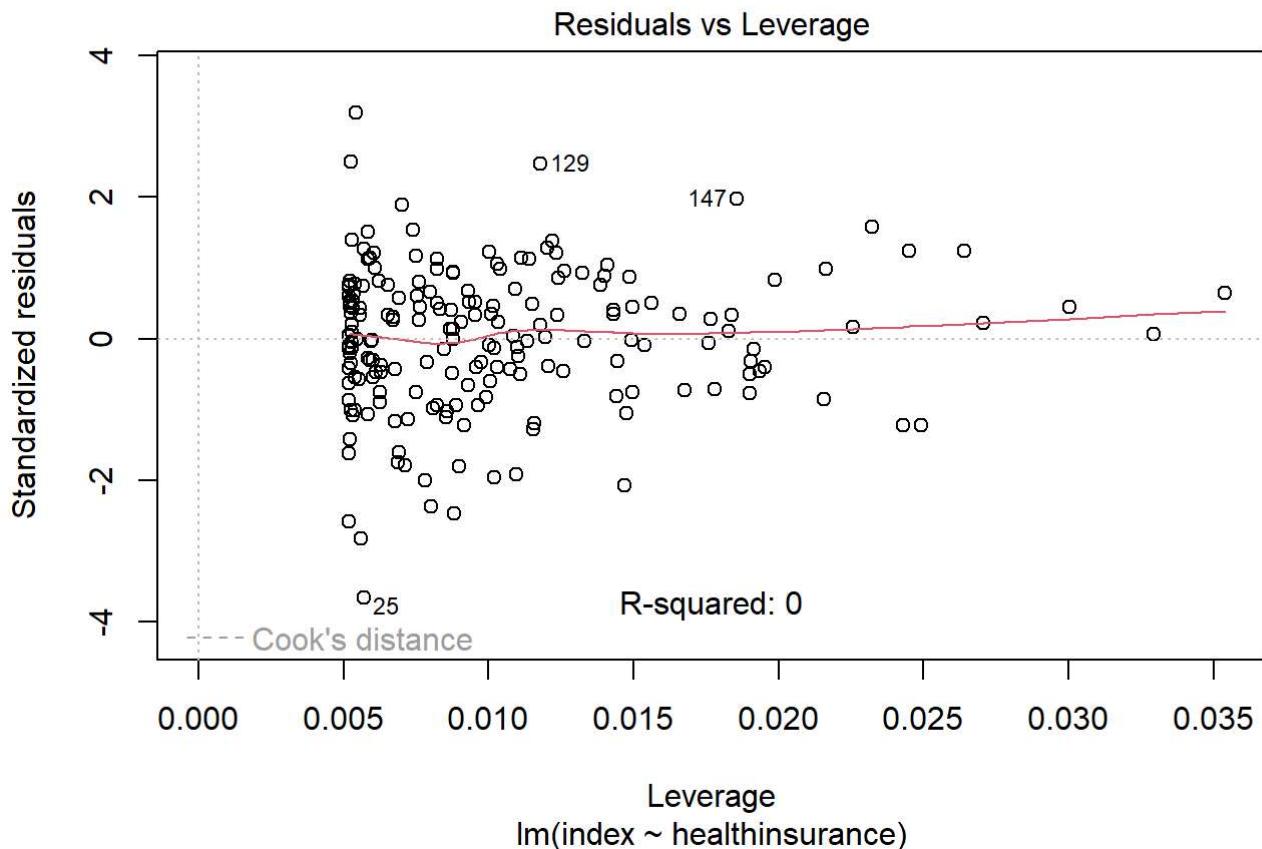




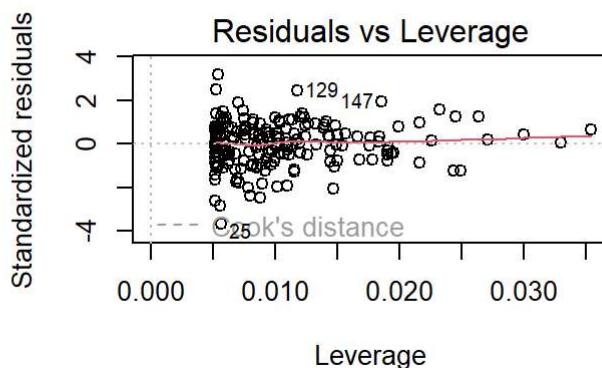
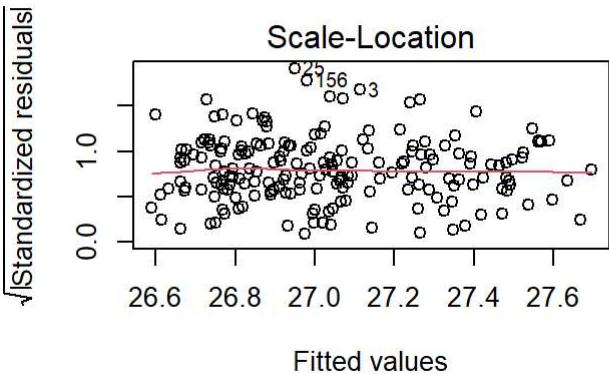
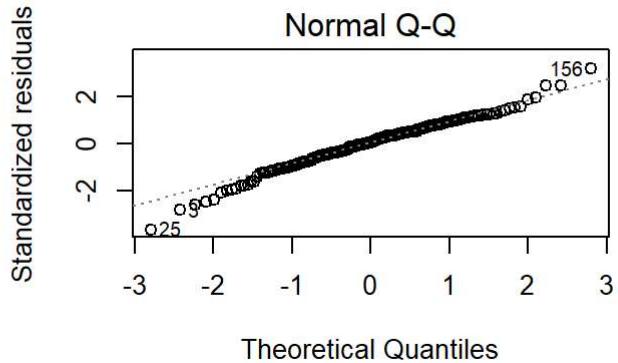
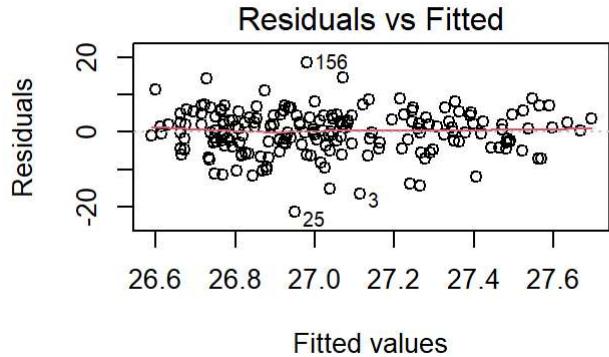
```
# View summary of the model with R-squared value included
rsq <- summary(model)$r.squared
summary_text <- paste0("R-squared: ", round(rsq, 2))
summary(model)
```

```
##
## Call:
## lm(formula = index ~ healthinsurance, data = wbindex)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -21.4756  -3.1773   0.2552   3.8634  18.6962
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 2.639e+01 1.086e+00 24.301 <2e-16 ***
## healthinsurance 1.752e-04 2.722e-04   0.644    0.521
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.883 on 191 degrees of freedom
## Multiple R-squared:  0.002164, Adjusted R-squared: -0.003061
## F-statistic: 0.4142 on 1 and 191 DF, p-value: 0.5206
```

```
mtext(summary_text, side = 1, line = -2)
```

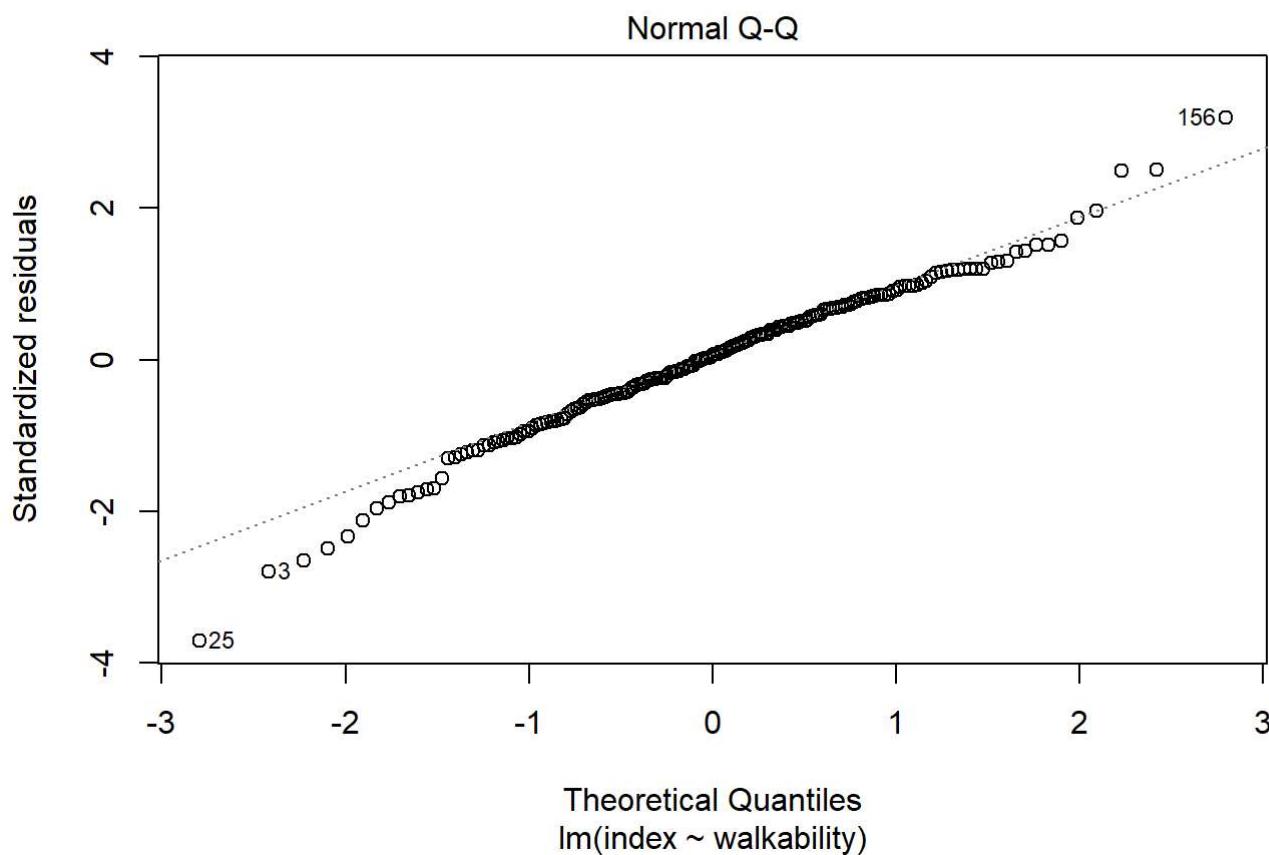
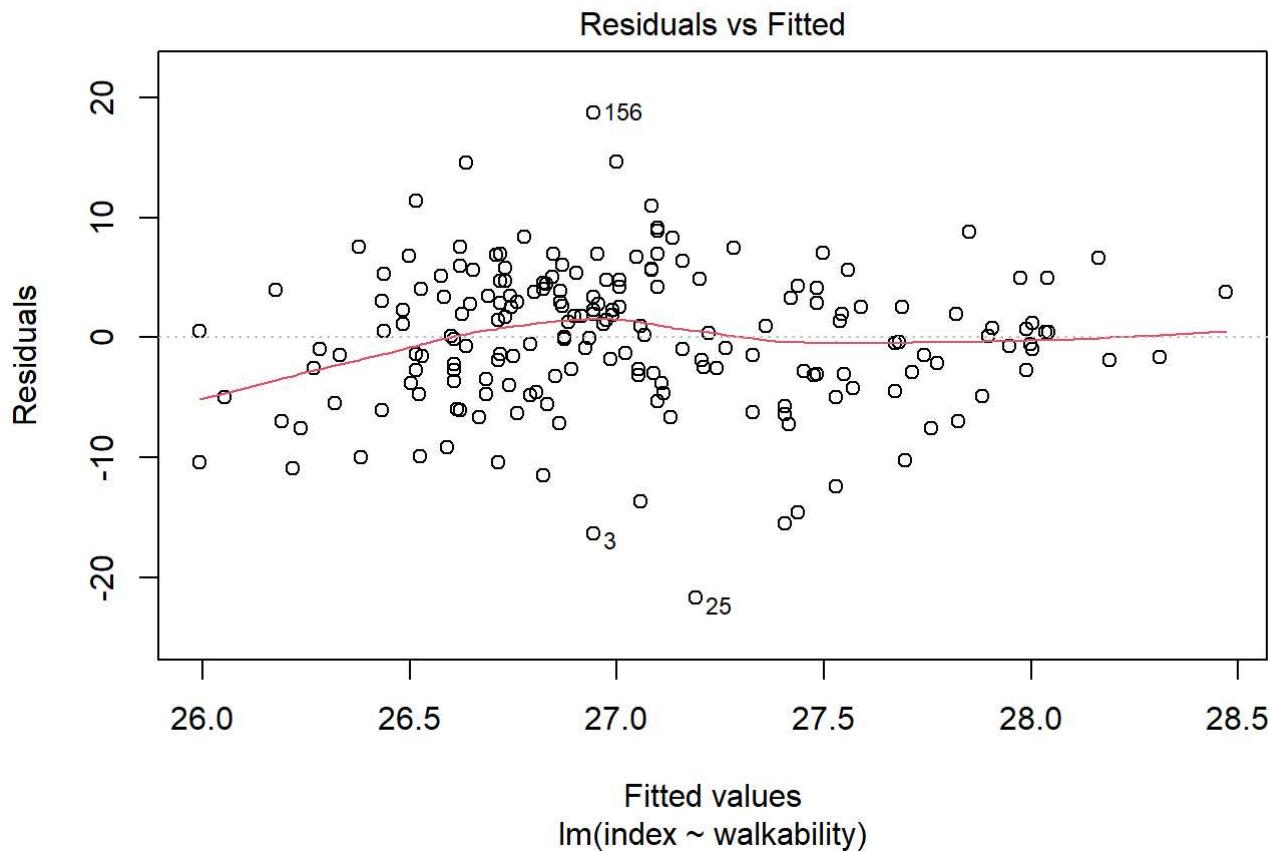


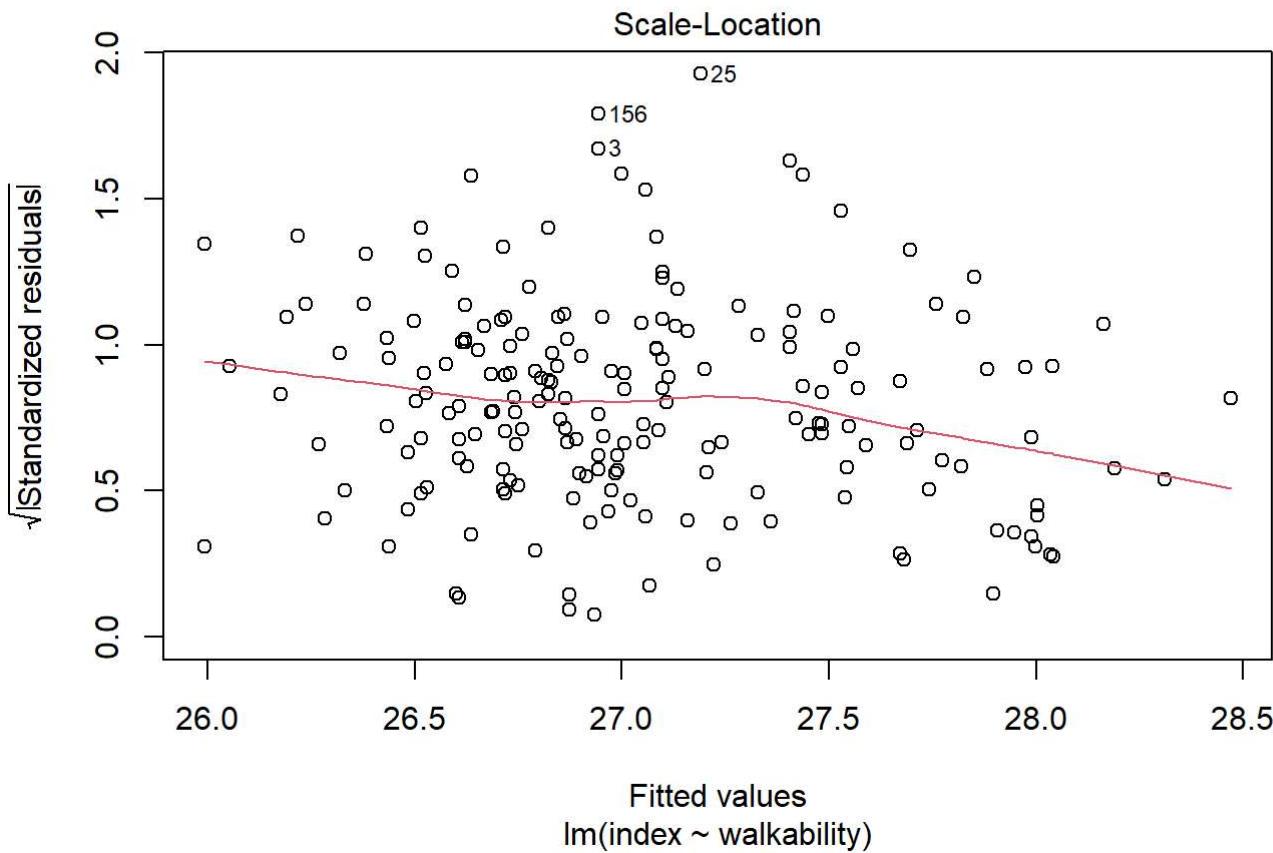
```
# Check model assumptions and residuals in a grid of plots
par(mfrow = c(2, 2))
plot(model)
```



```
## Linear regression
model <- lm(index ~ walkability, data = wbindex)

plot(model)
```

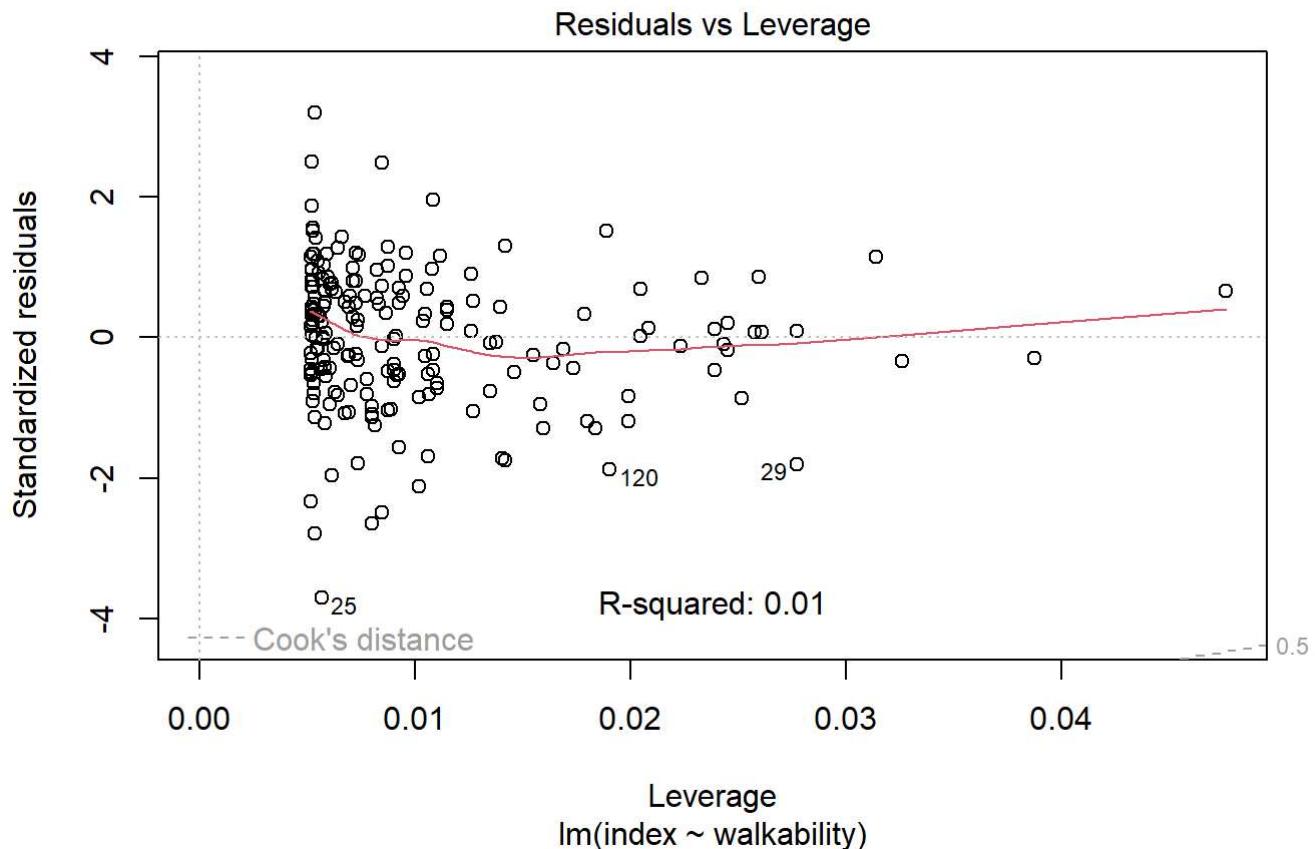




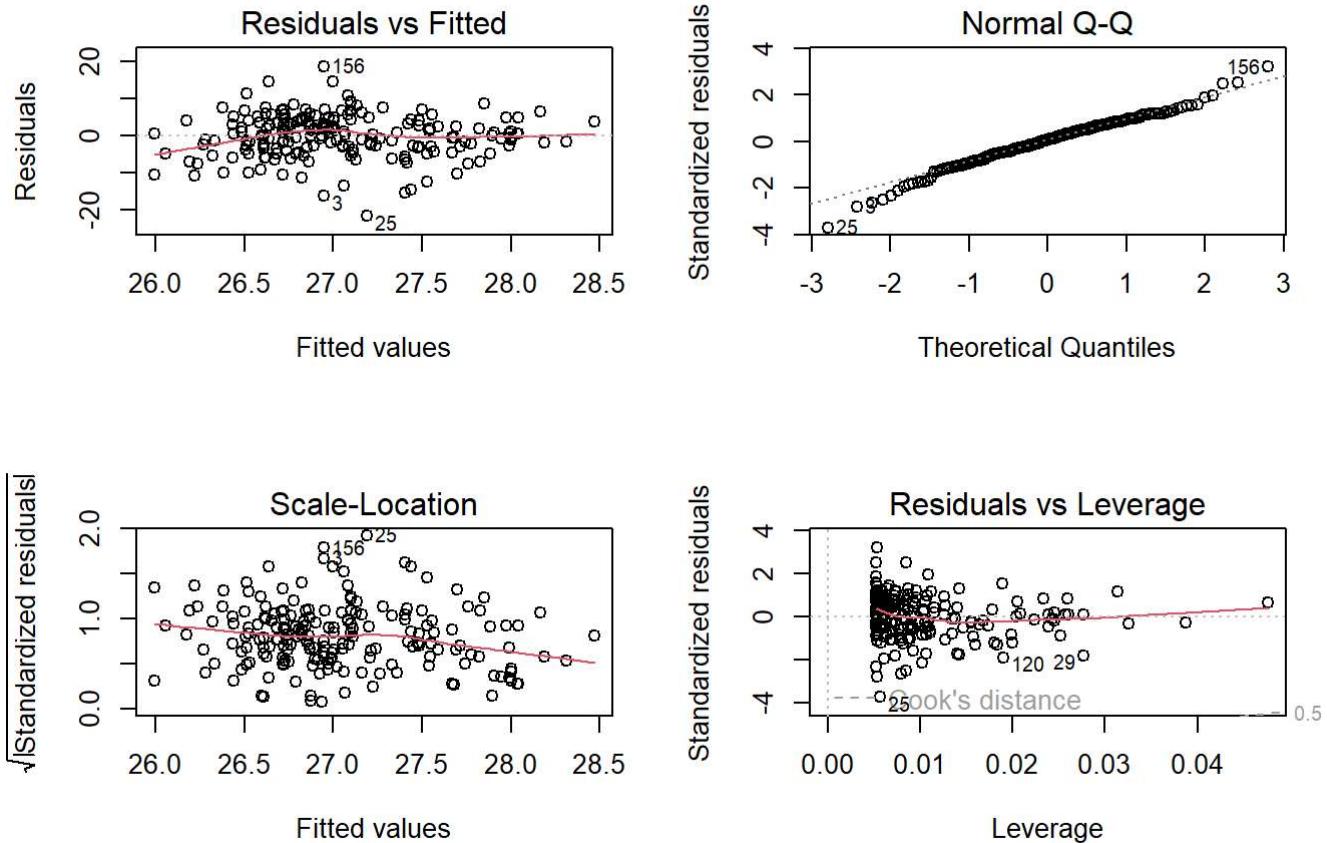
```
# View summary of the model with R-squared value included
rsq <- summary(model)$r.squared
summary_text <- paste0("R-squared: ", round(rsq, 2))
summary(model)
```

```
##
## Call:
## lm(formula = index ~ walkability, data = wbindex)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -21.7149  -3.1266   0.3543   4.0286  18.7308
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 29.2172    1.8872  15.482 <2e-16 ***
## walkability -0.1843    0.1554  -1.186    0.237
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.867 on 191 degrees of freedom
## Multiple R-squared:  0.007305, Adjusted R-squared:  0.002108
## F-statistic: 1.406 on 1 and 191 DF,  p-value: 0.2373
```

```
mtext(summary_text, side = 1, line = -2)
```

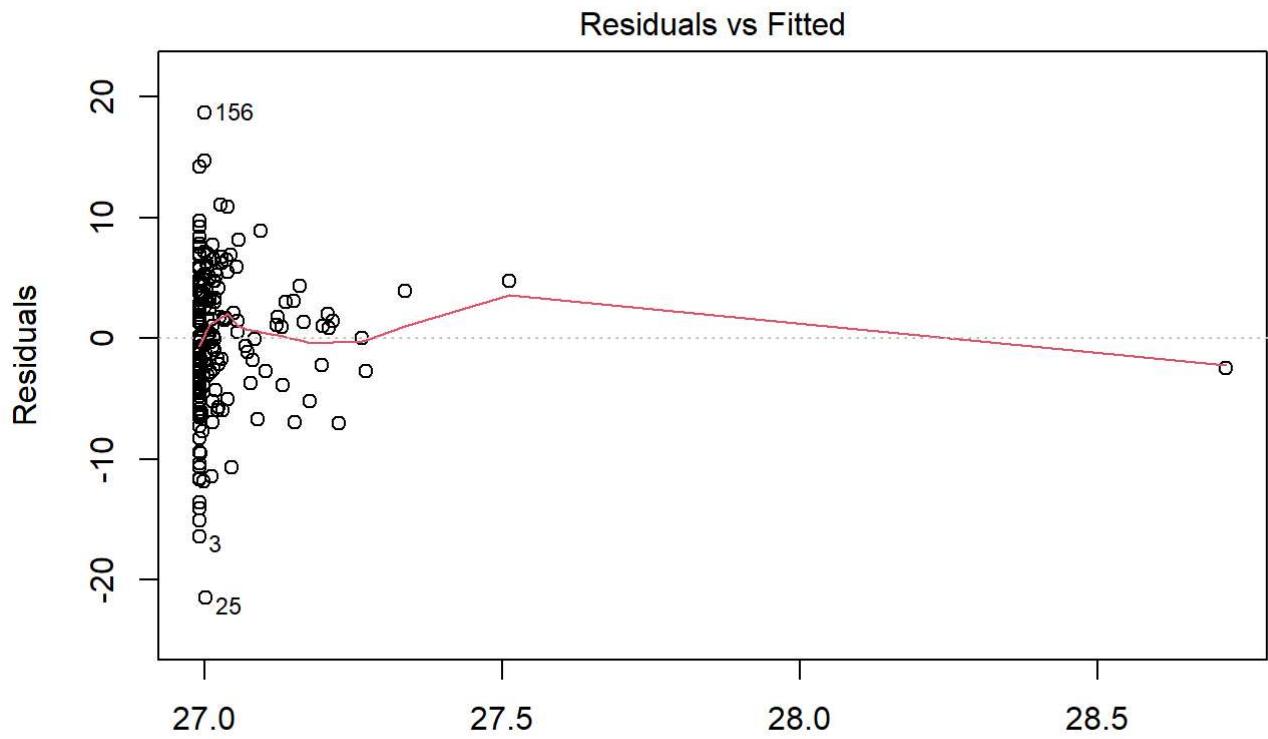


```
# Check model assumptions and residuals in a grid of plots
par(mfrow = c(2, 2))
plot(model)
```

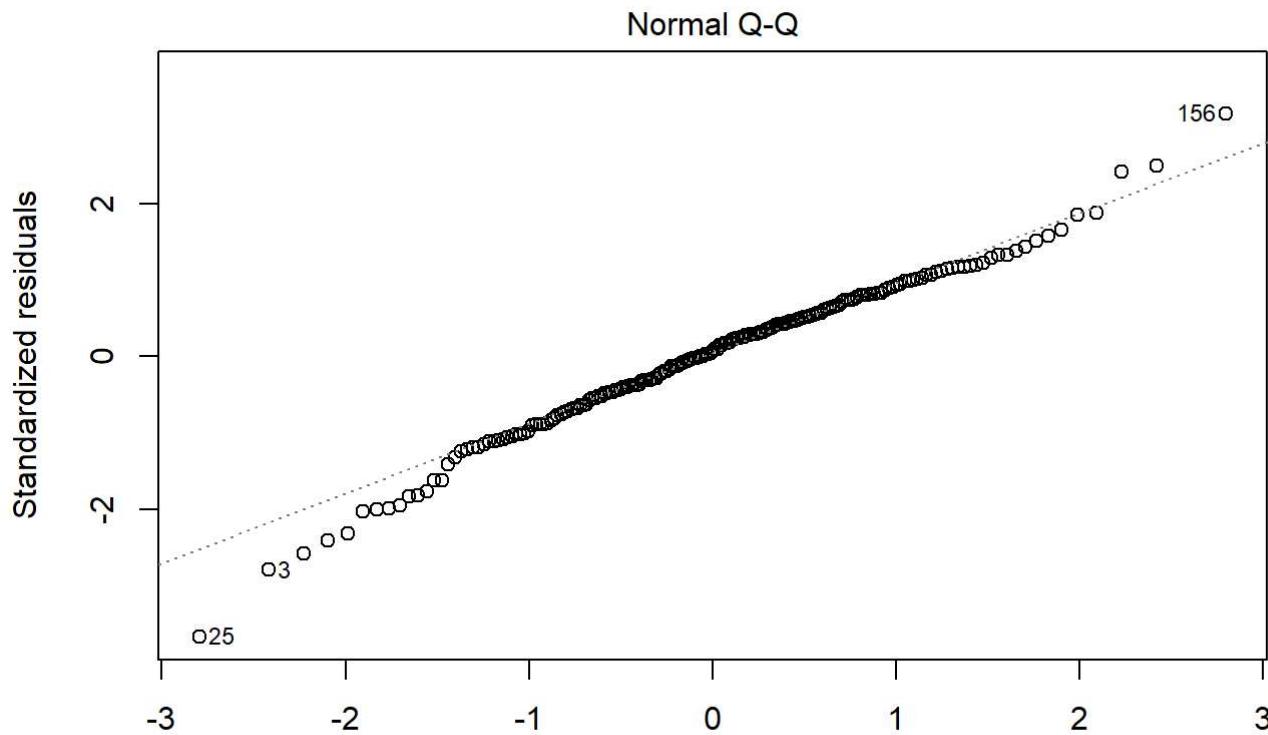


```
## Linear regression
model <- lm(index ~ TOT_PARK_AREA_SQMILES, data = wbindex)

plot(model)
```

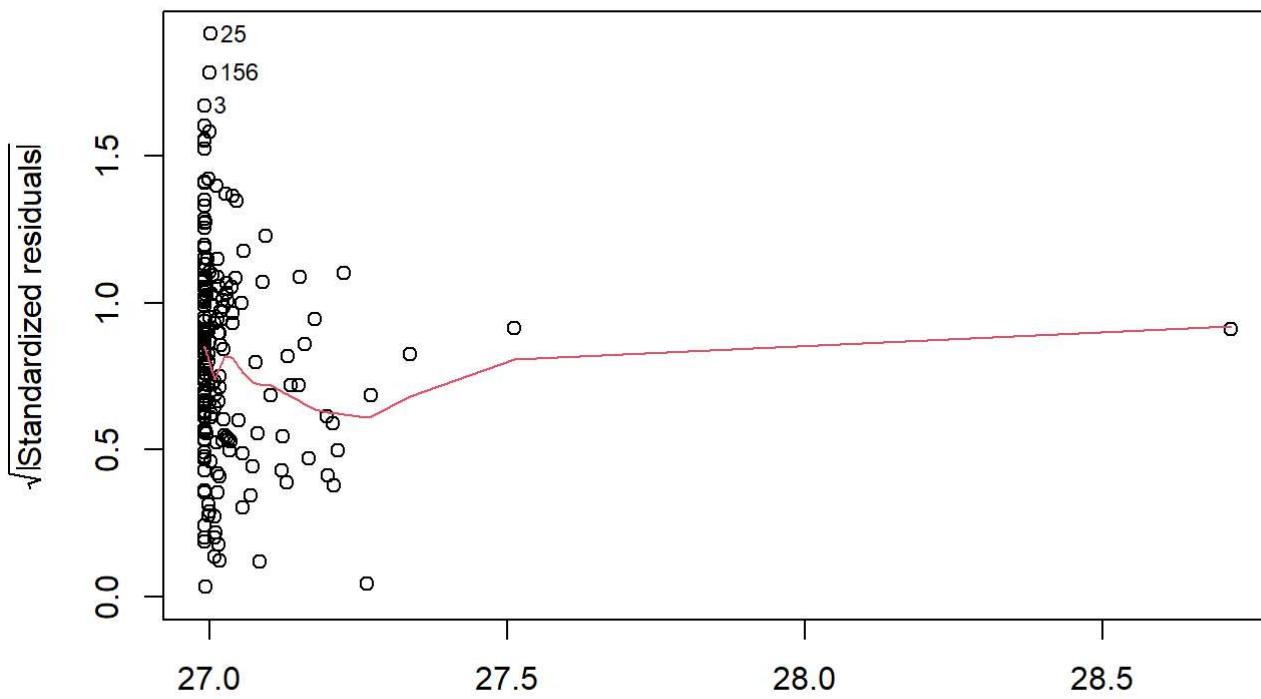


Fitted values
 $\text{lm}(\text{index} \sim \text{TOT_PARK_AREA_SQMILES})$



Theoretical Quantiles
 $\text{lm}(\text{index} \sim \text{TOT_PARK_AREA_SQMILES})$

Scale-Location

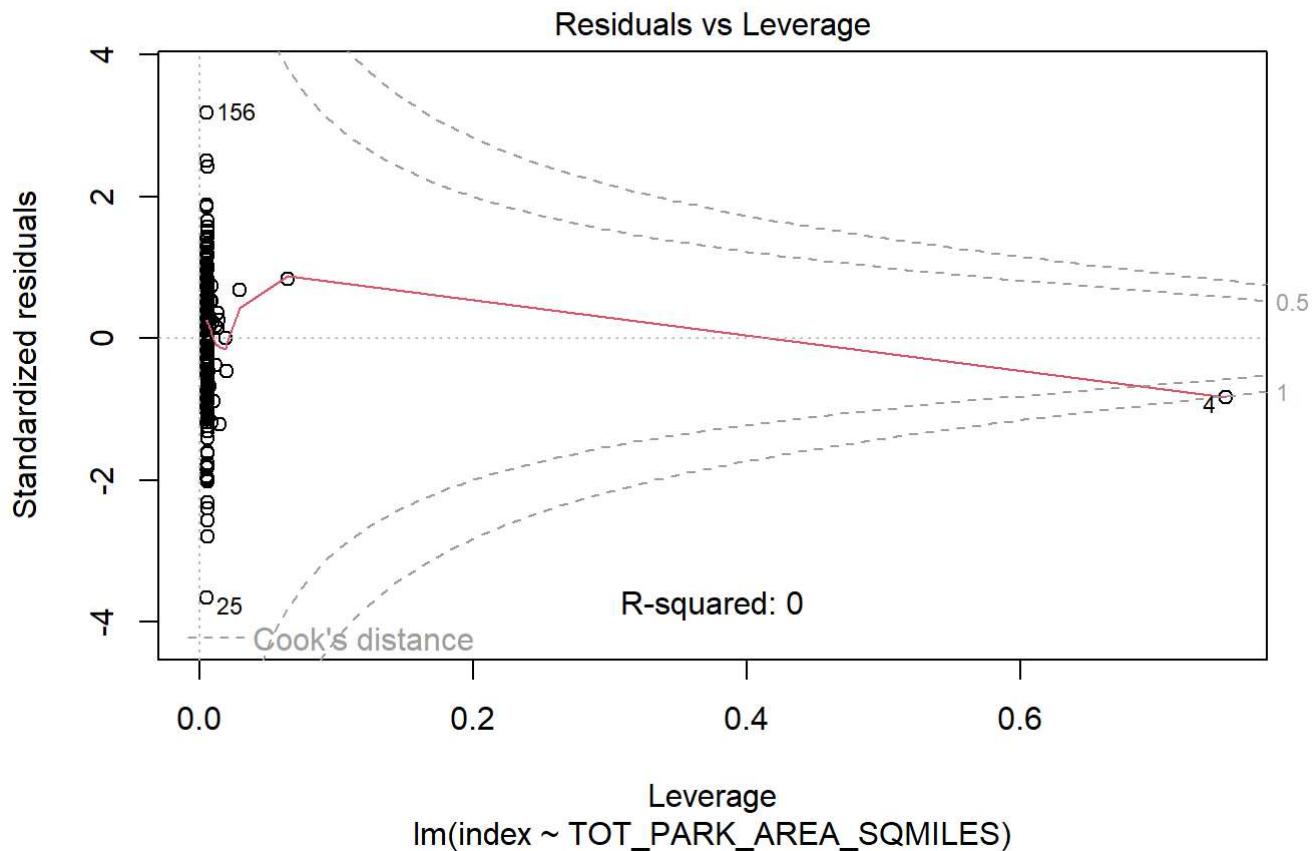


Fitted values
 $\text{lm}(\text{index} \sim \text{TOT_PARK_AREA_SQMILES})$

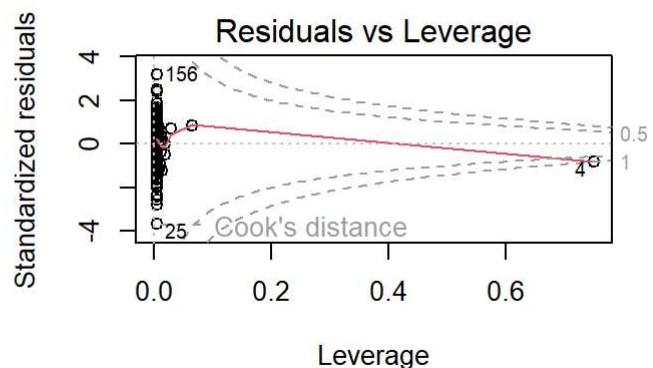
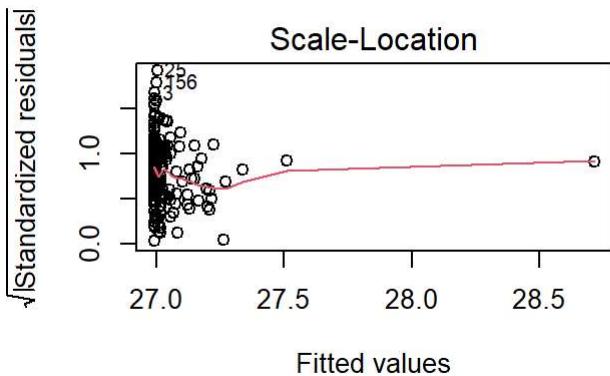
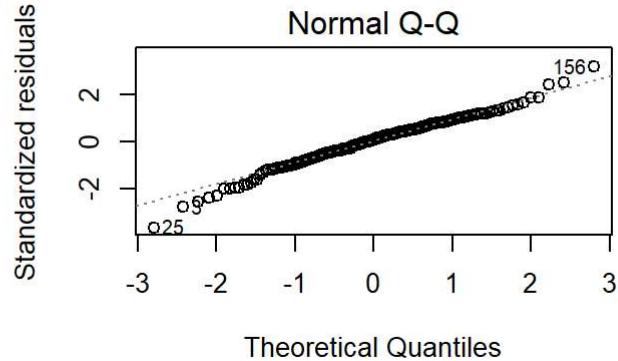
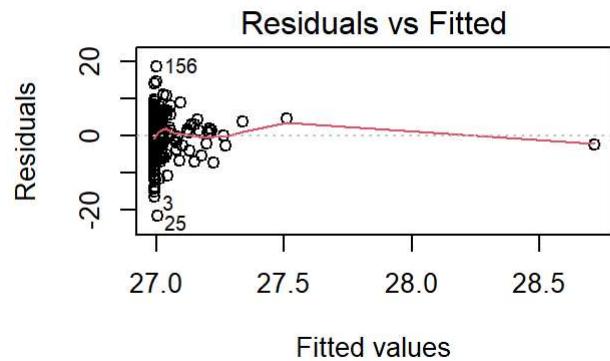
```
# View summary of the model with R-squared value included
rsq <- summary(model)$r.squared
summary_text <- paste0("R-squared: ", round(rsq, 2))
summary(model)
```

```
##
## Call:
## lm(formula = index ~ TOT_PARK_AREA_SQMILES, data = wbindex)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -21.5274  -3.2415   0.4416   3.8568  18.6745
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 26.9915    0.4452   60.63   <2e-16 ***
## TOT_PARK_AREA_SQMILES 1.0810     3.2725    0.33    0.742
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.887 on 191 degrees of freedom
## Multiple R-squared:  0.000571,   Adjusted R-squared:  -0.004662
## F-statistic: 0.1091 on 1 and 191 DF,  p-value: 0.7415
```

```
mtext(summary_text, side = 1, line = -2)
```

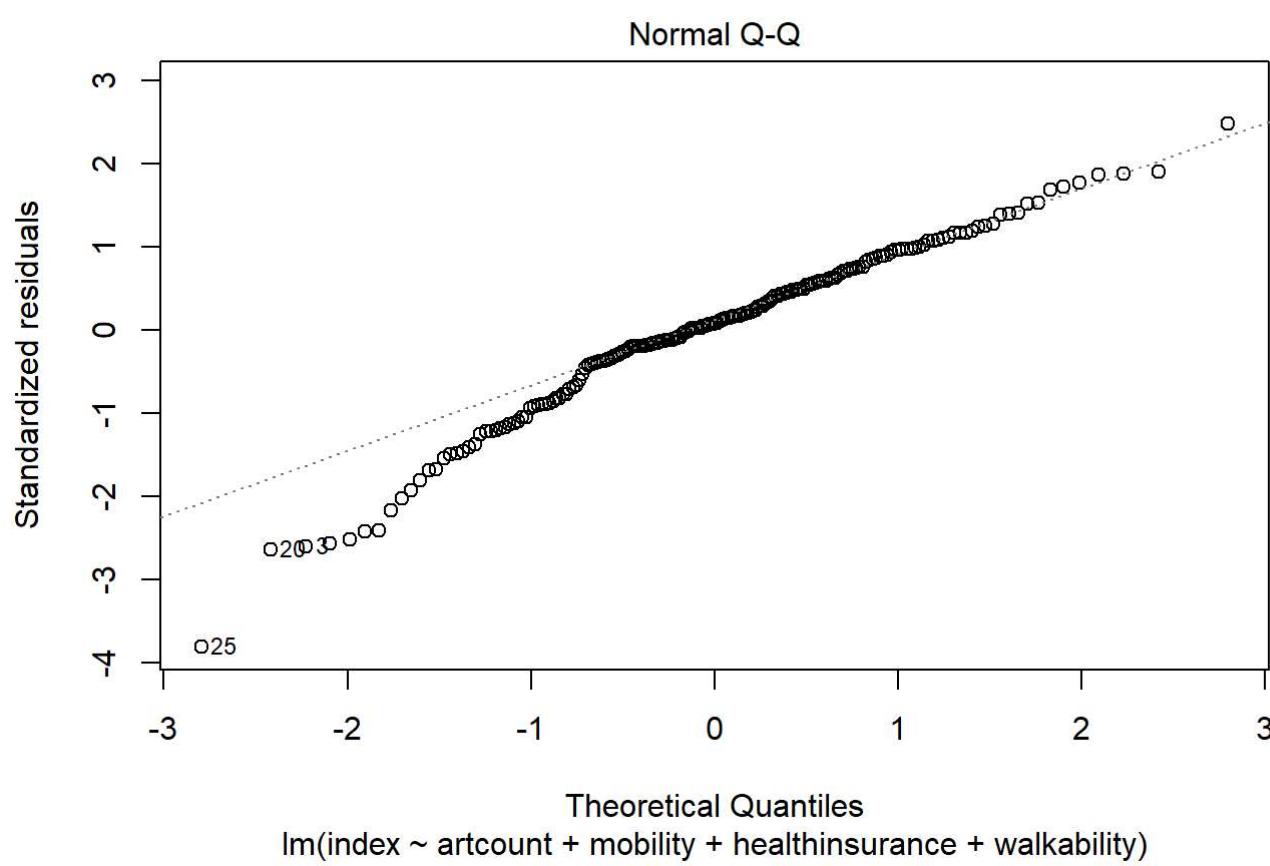
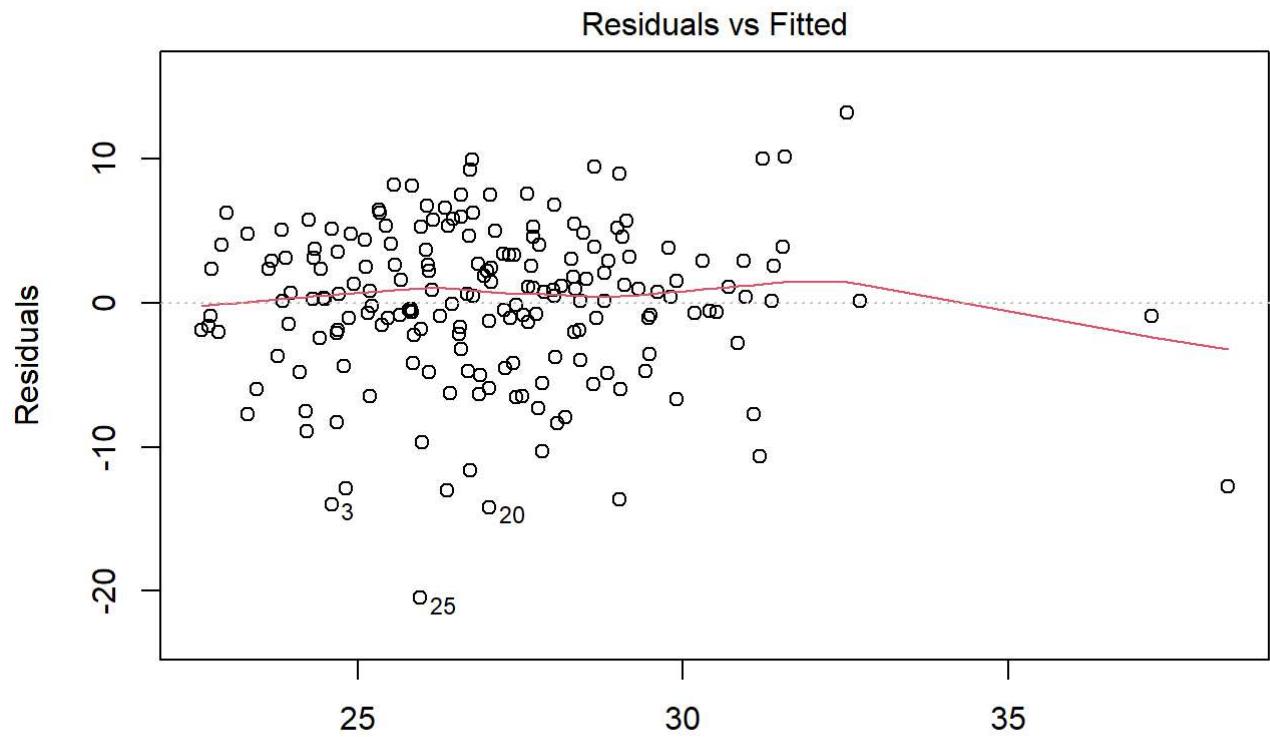


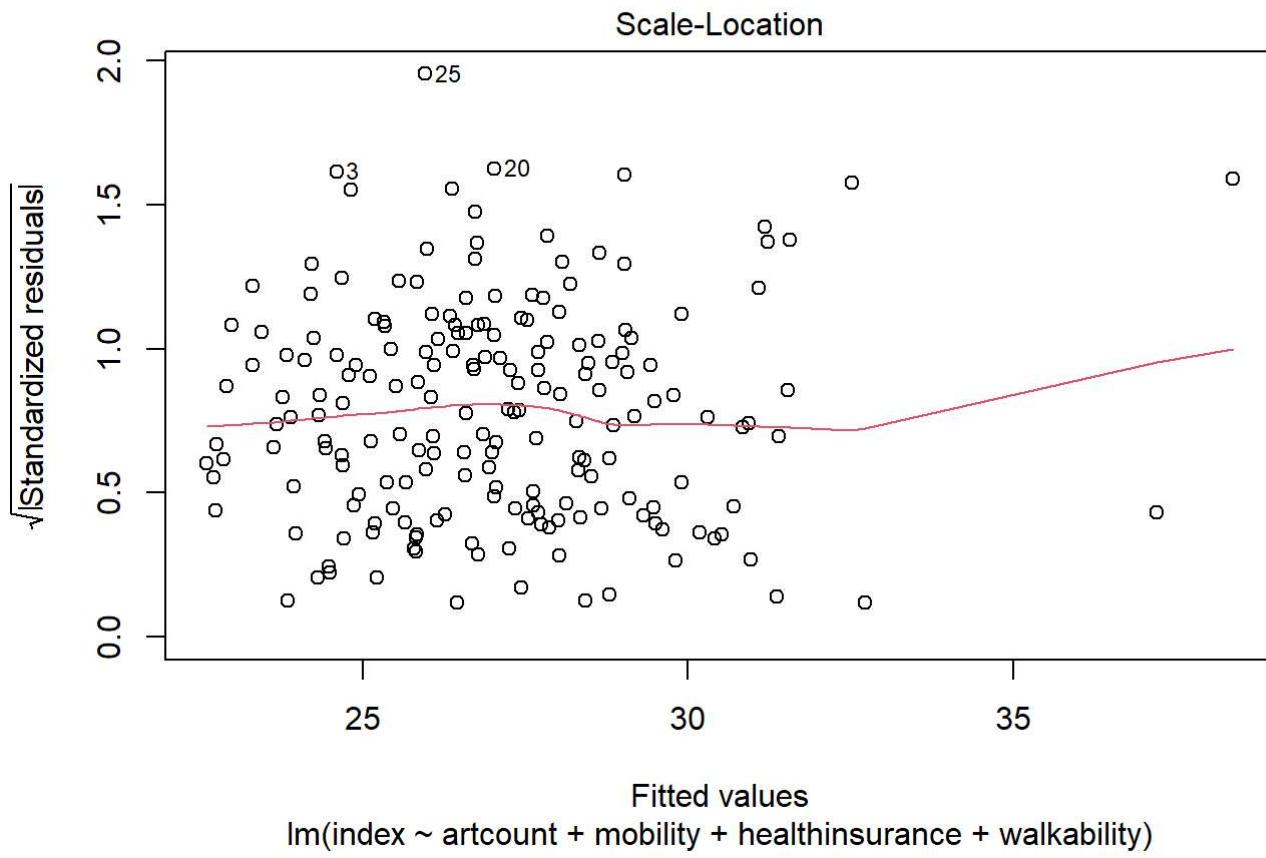
```
# Check model assumptions and residuals in a grid of plots
par(mfrow = c(2, 2))
plot(model)
```



```
## Linear regression
model <- lm(index ~ artcount + mobility + healthinsurance + walkability, data = wbindex)

plot(model)
```





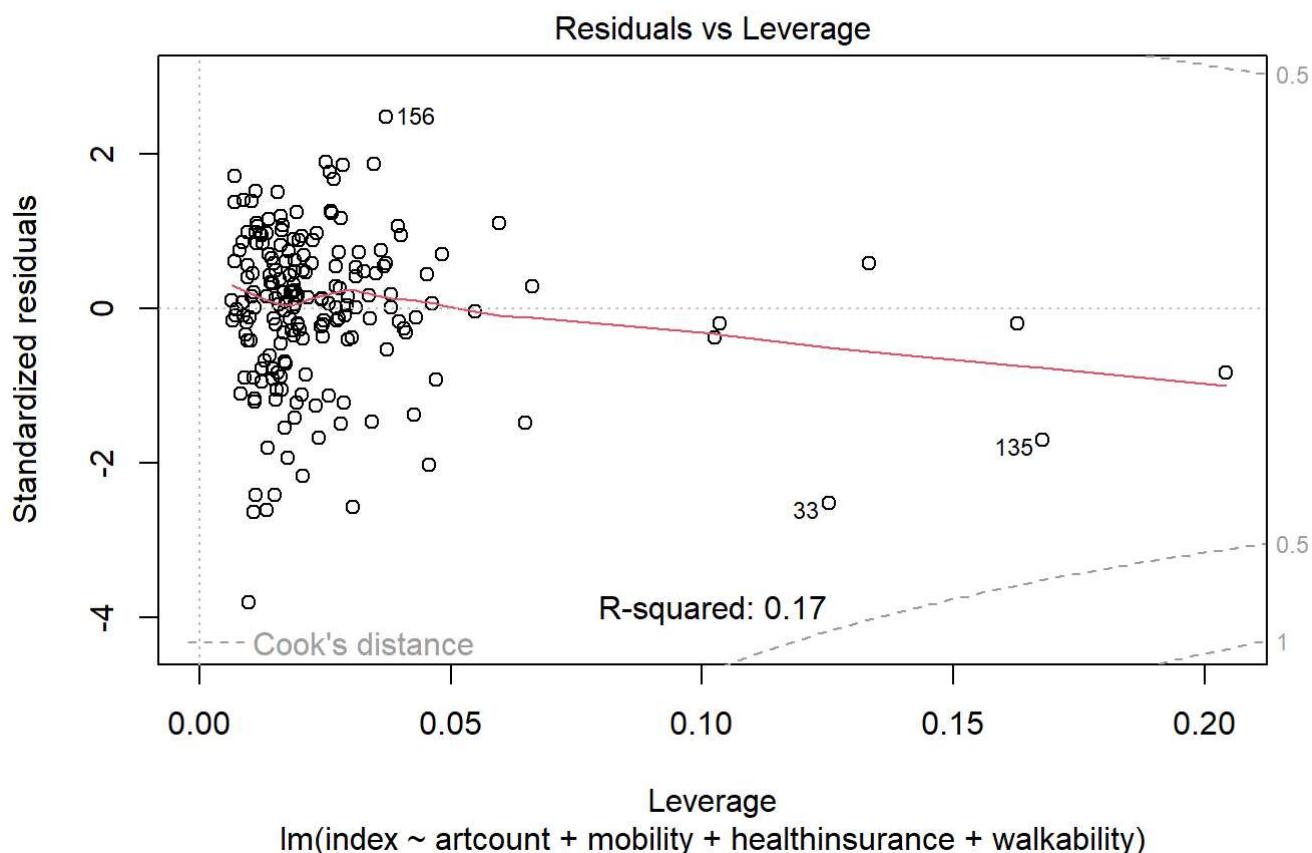
```
# View summary of the model with R-squared value included
rsq <- summary(model)$r.squared
summary_text <- paste0("R-squared: ", round(rsq, 2))
summary(model)
```

```

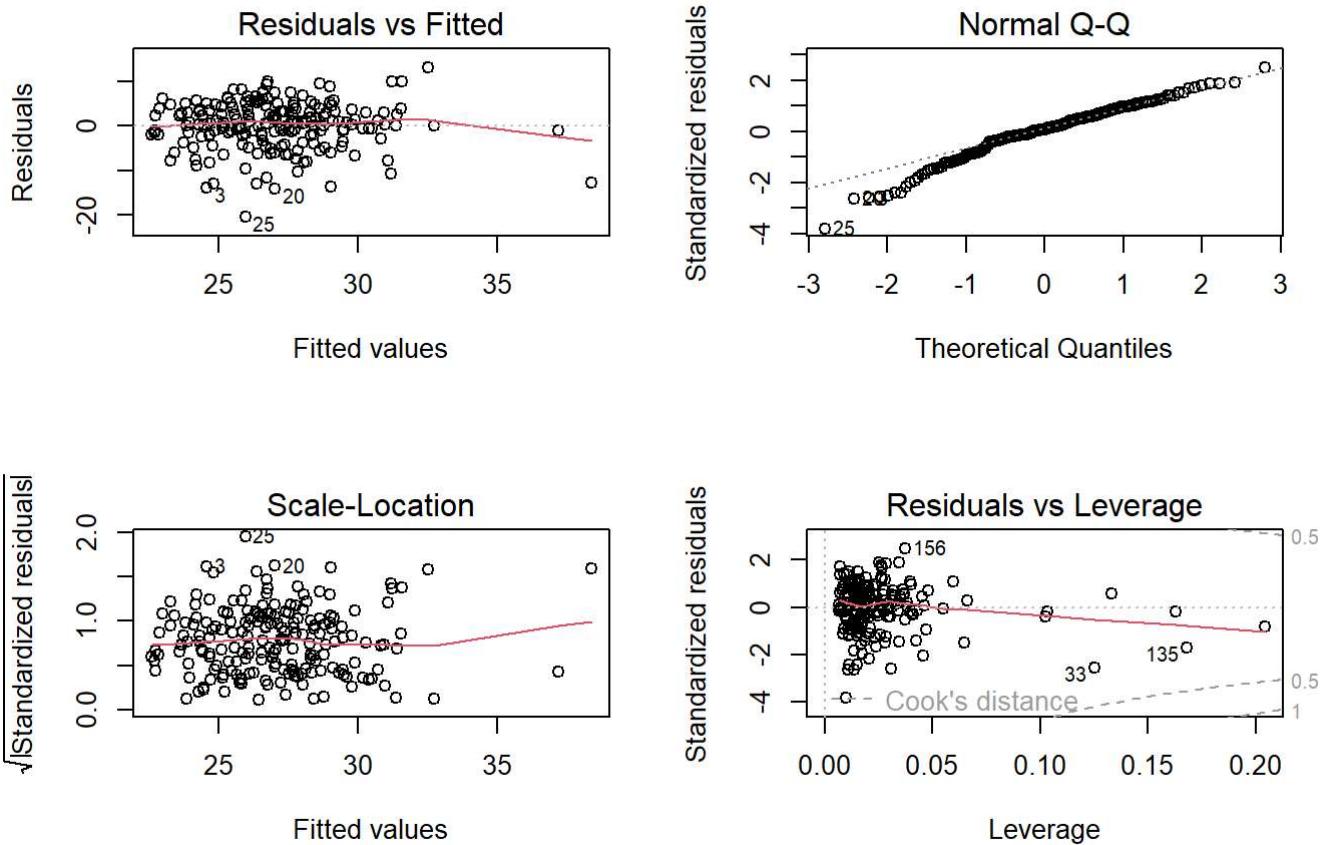
## 
## Call:
## lm(formula = index ~ artcount + mobility + healthinsurance +
##     walkability, data = wbindex)
##
## Residuals:
##    Min      1Q  Median      3Q     Max 
## -20.485 -2.200   0.427   3.512  13.157 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 33.4019345  2.7296378 12.237 < 2e-16 ***
## artcount      0.0227235  0.0216027  1.052  0.29420  
## mobility       0.0063978  0.0010439  6.129 5.09e-09 ***
## healthinsurance -0.0009948  0.0003298 -3.016  0.00291 ** 
## walkability     -0.5852024  0.1806658 -3.239  0.00142 ** 
## --- 
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 5.396 on 188 degrees of freedom
## Multiple R-squared:  0.1737, Adjusted R-squared:  0.1561 
## F-statistic: 9.882 on 4 and 188 DF,  p-value: 2.808e-07

```

```
mtext(summary_text, side = 1, line = -2)
```

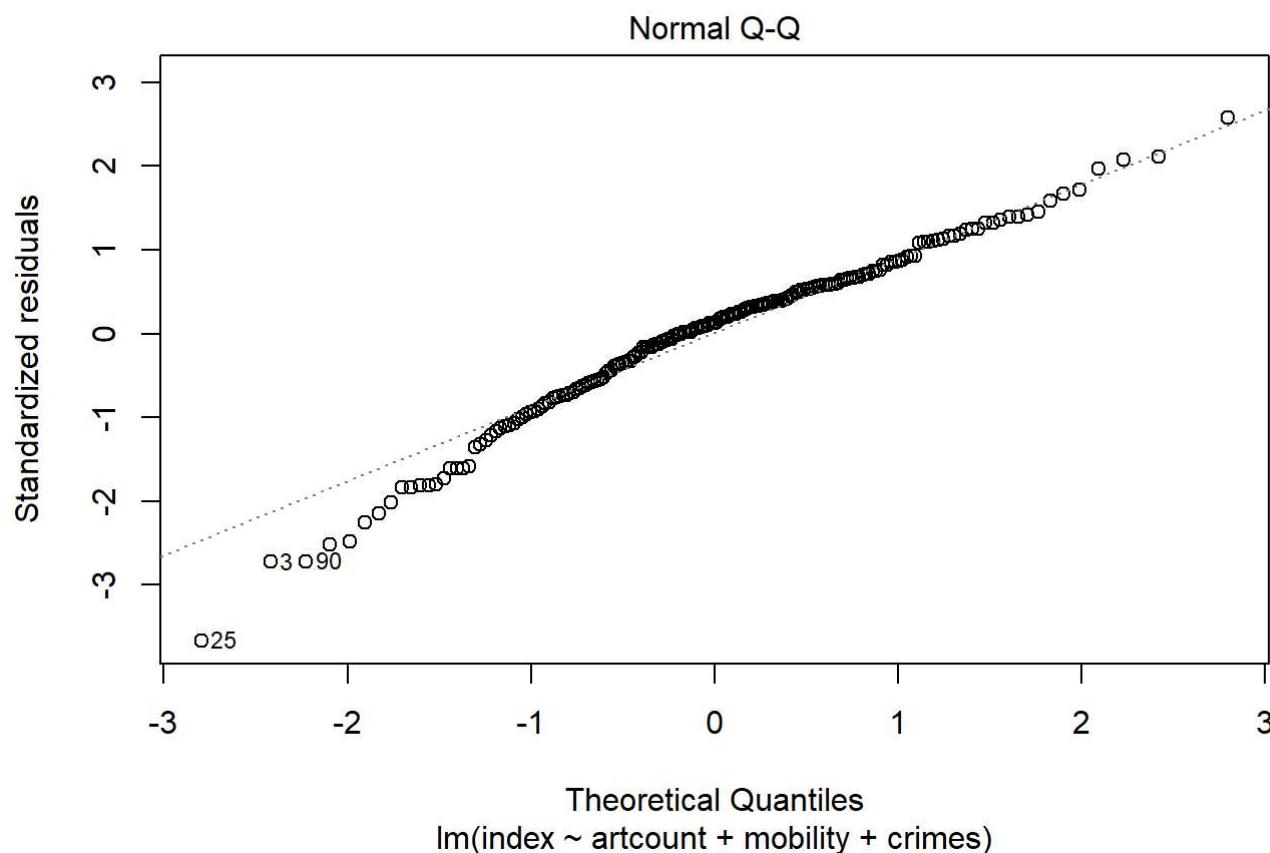
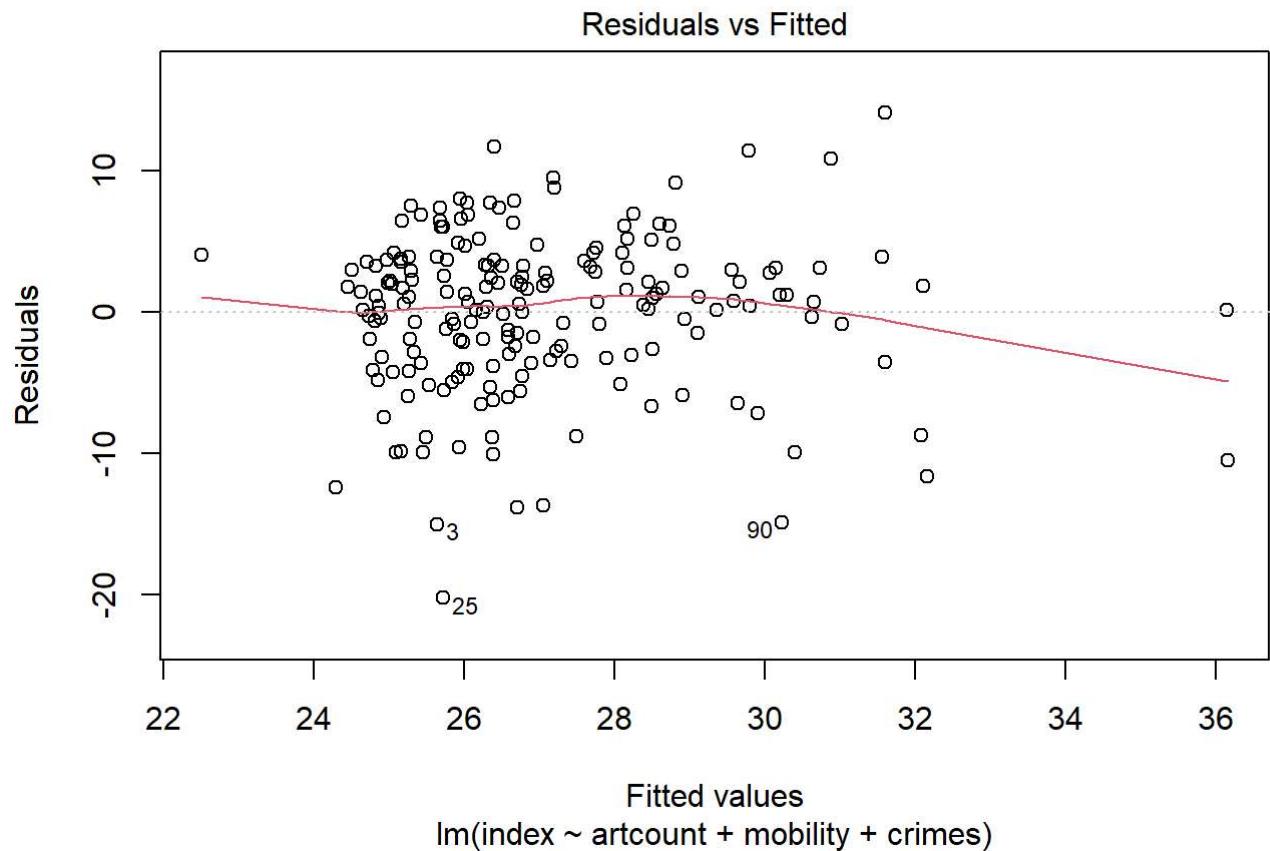


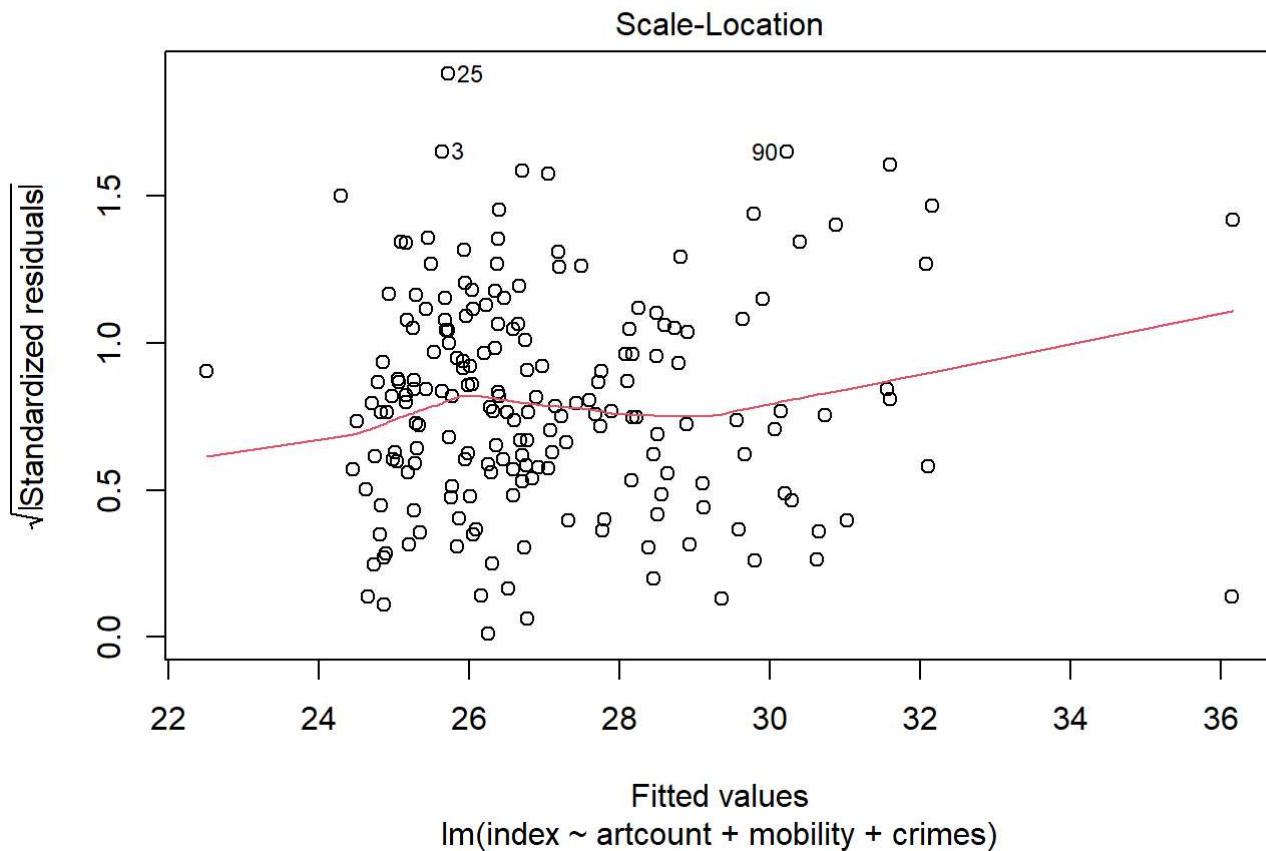
```
# Check model assumptions and residuals in a grid of plots
par(mfrow = c(2, 2))
plot(model)
```



```
## Linear regression
model <- lm(index ~ artcount + mobility + crimes, data = wbindex)

plot(model)
```





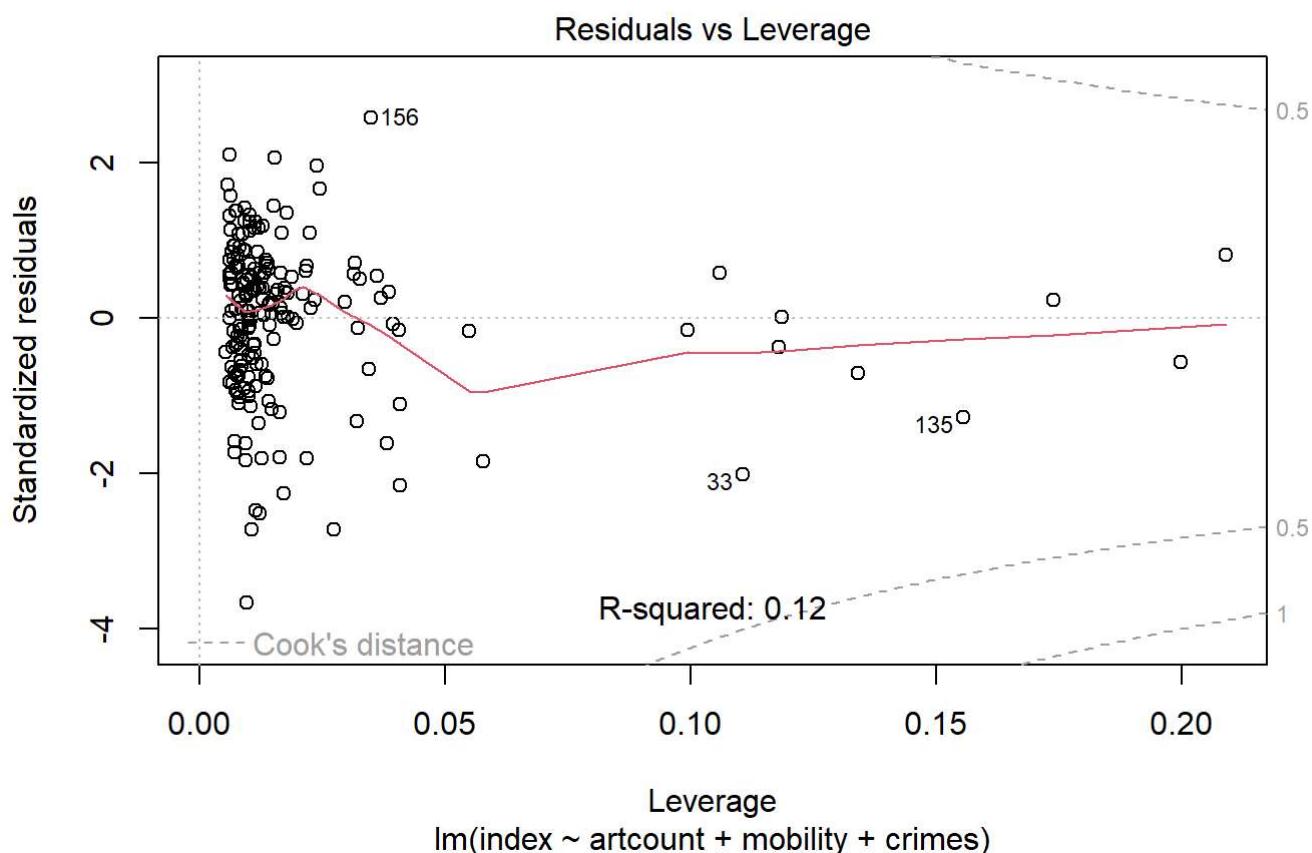
```
# View summary of the model with R-squared value included
rsq <- summary(model)$r.squared
summary_text <- paste0("R-squared: ", round(rsq, 2))
summary(model)
```

```

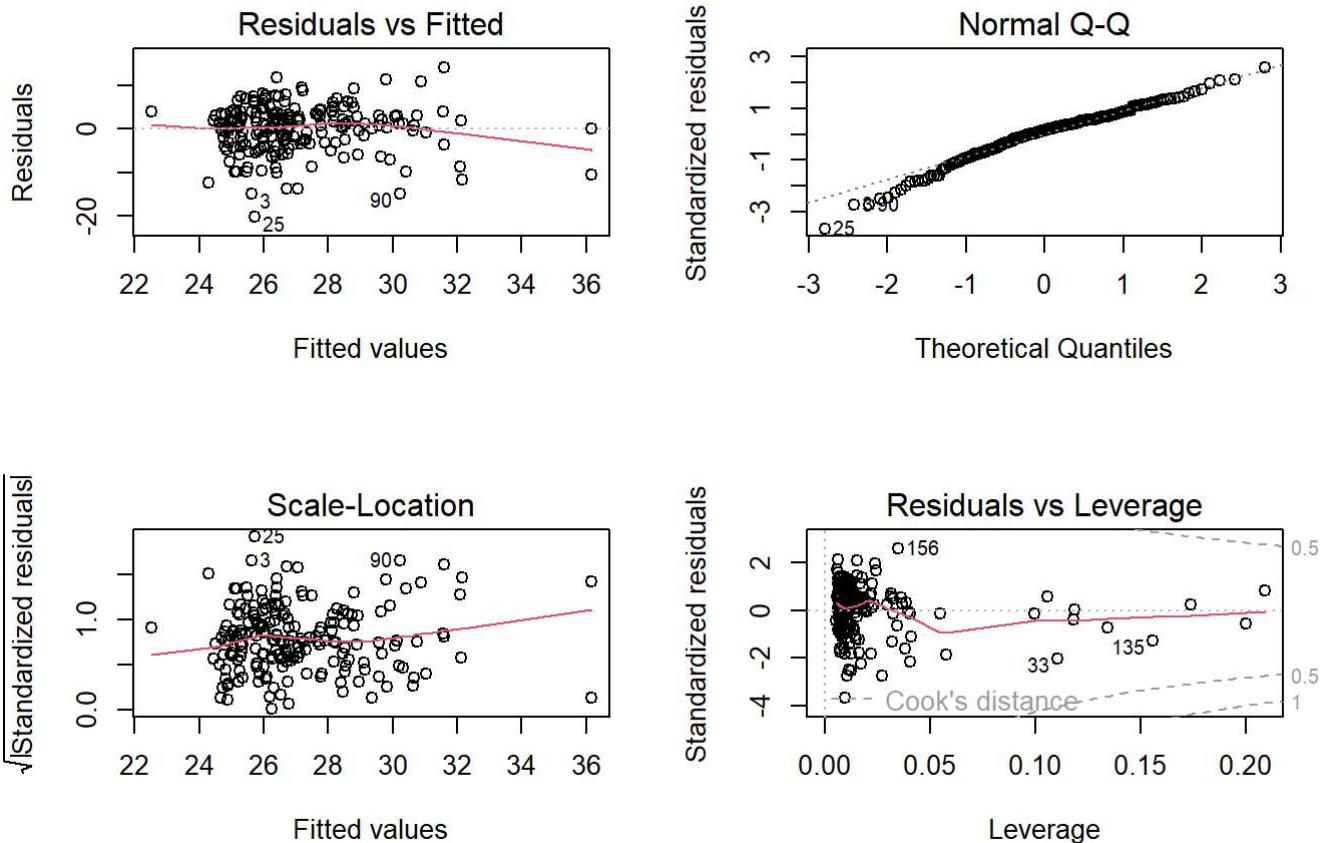
## 
## Call:
## lm(formula = index ~ artcount + mobility + crimes, data = wbindex)
##
## Residuals:
##    Min      1Q  Median      3Q     Max 
## -20.2458 -3.2280  0.7237  3.3423 14.0705 
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 24.456533   0.814188 30.038 < 2e-16 ***
## artcount     0.011876   0.021417   0.555   0.580    
## mobility     0.005130   0.001018   5.039 1.09e-06 *** 
## crimes      -0.003239   0.002879  -1.125   0.262    
## --- 
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.542 on 189 degrees of freedom
## Multiple R-squared:  0.1238, Adjusted R-squared:  0.1098 
## F-statistic: 8.898 on 3 and 189 DF,  p-value: 1.519e-05

```

```
mtext(summary_text, side = 1, line = -2)
```

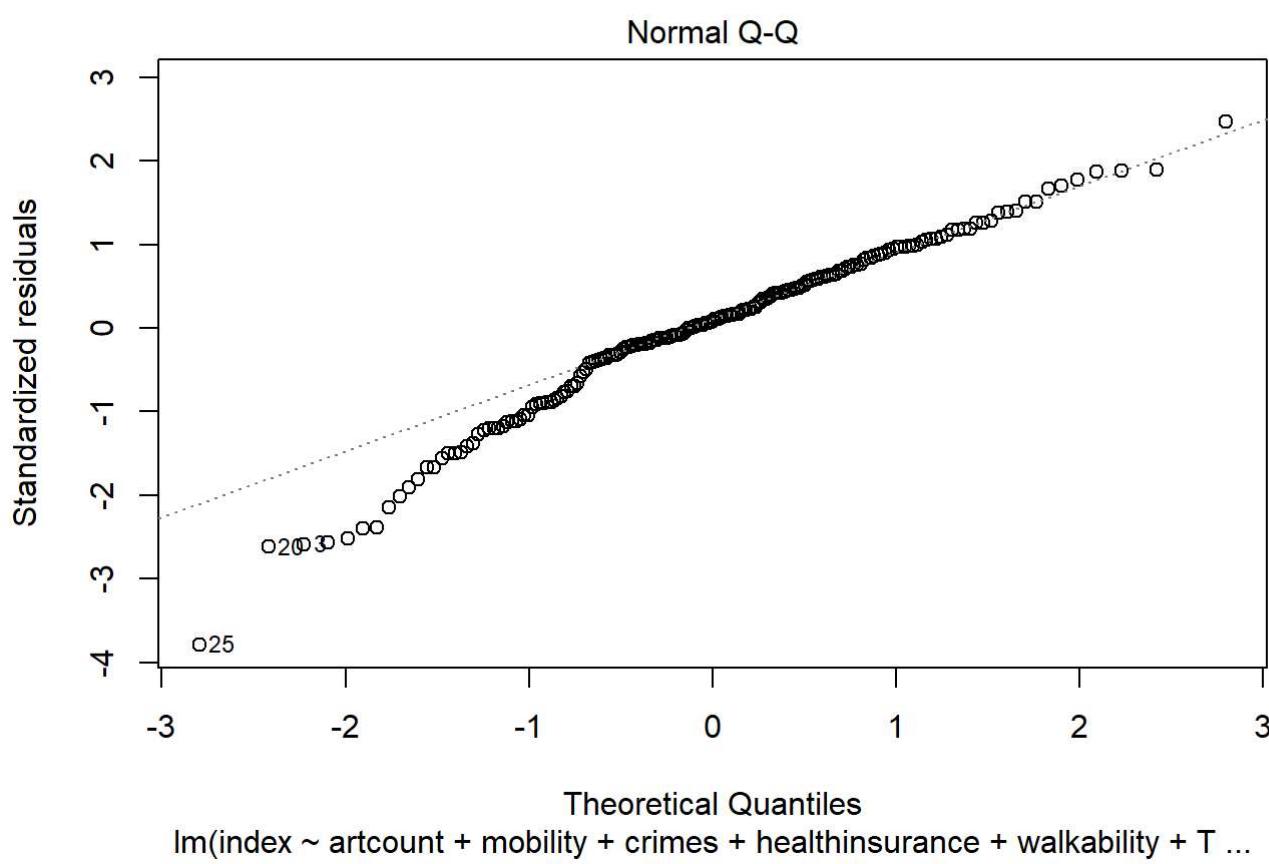
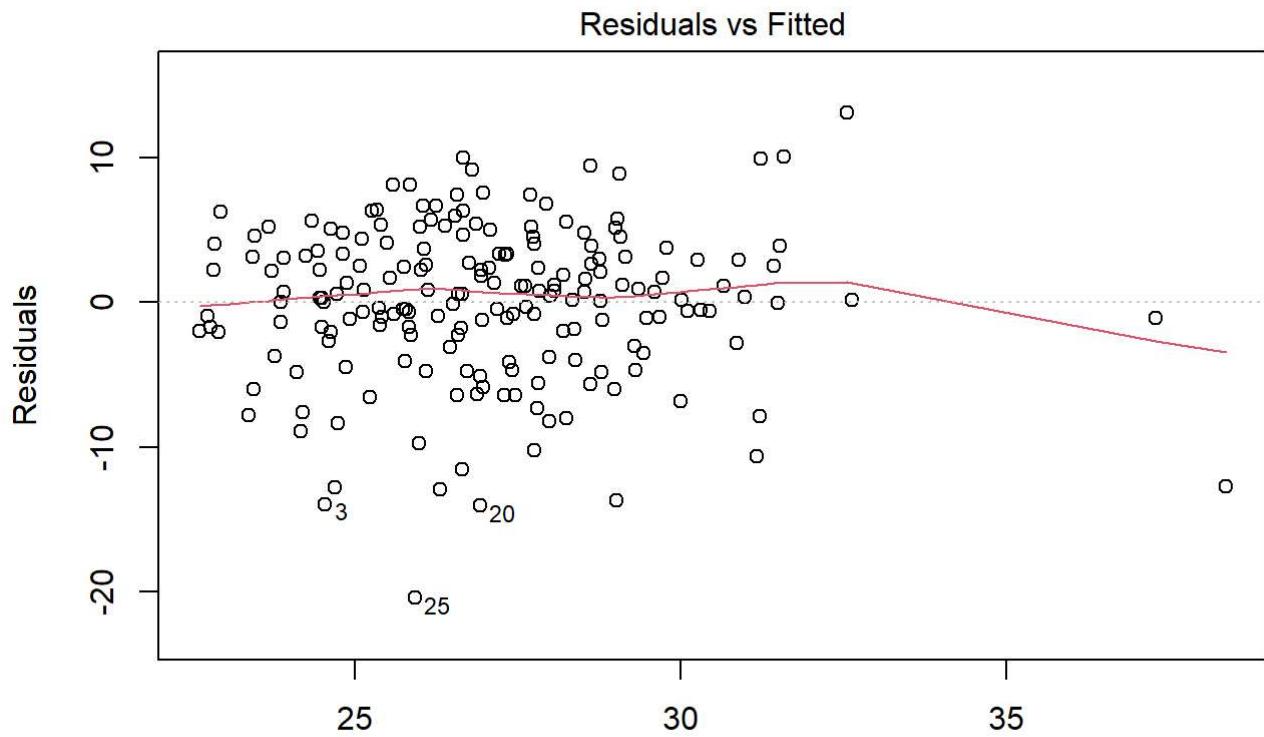


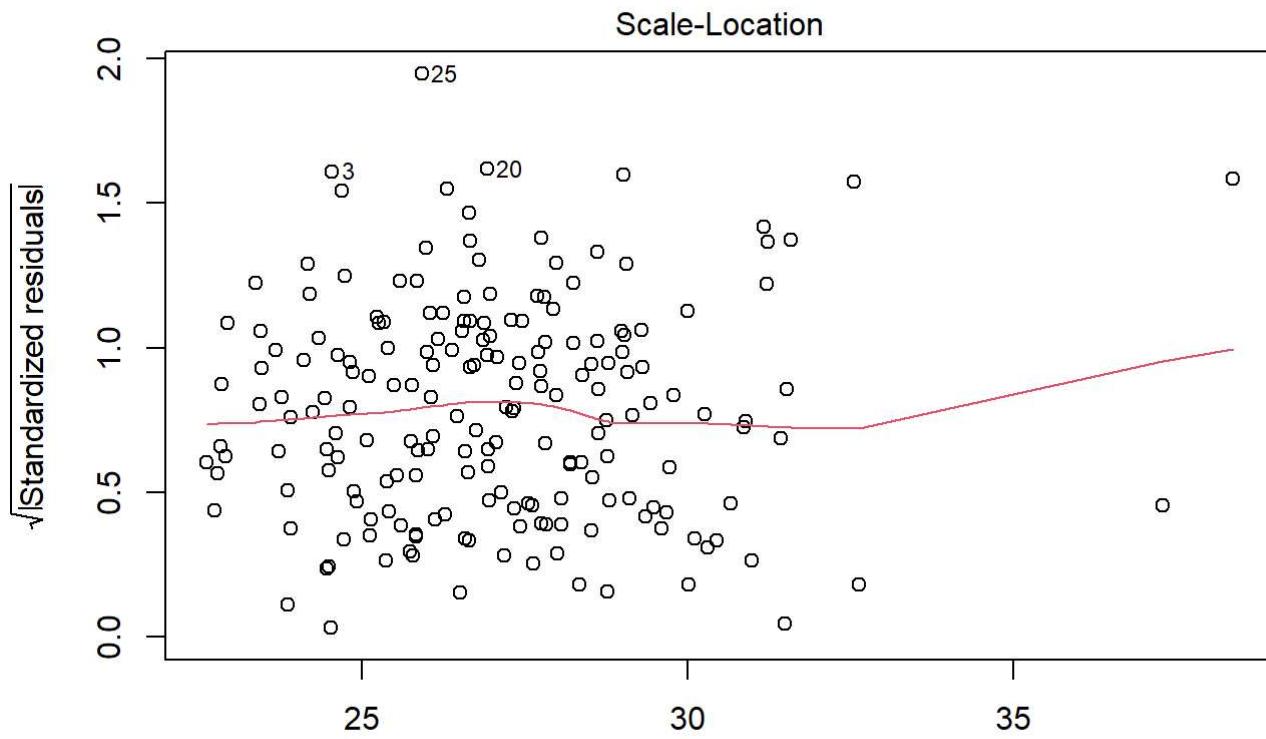
```
# Check model assumptions and residuals in a grid of plots
par(mfrow = c(2, 2))
plot(model)
```



```
## Linear regression
model <- lm(index ~ artcount + mobility + crimes + healthinsurance + walkability + TOT_PARK_AREA
           _SQMILES, data = wbindex)

plot(model)
```



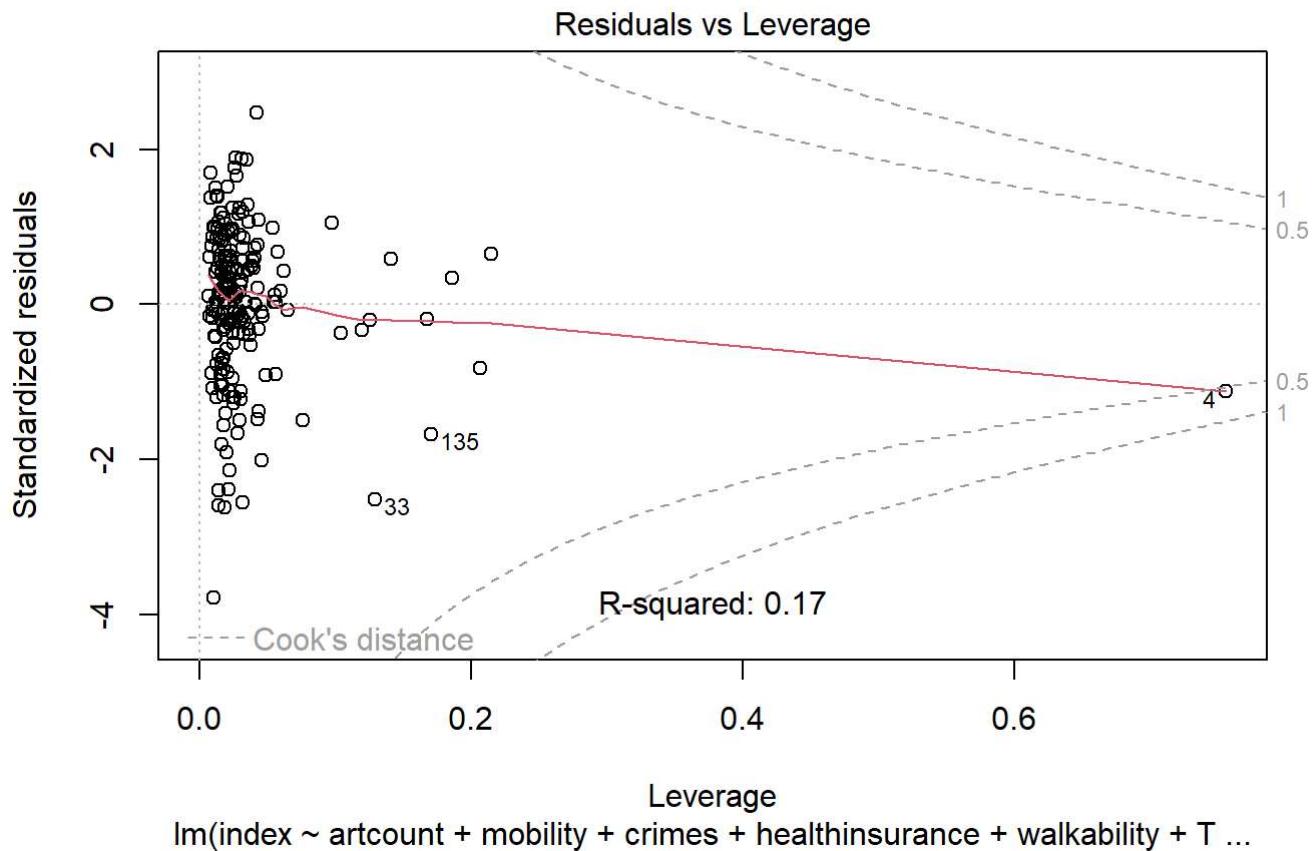


Fitted values
lm(index ~ artcount + mobility + crimes + healthinsurance + walkability + T ...)

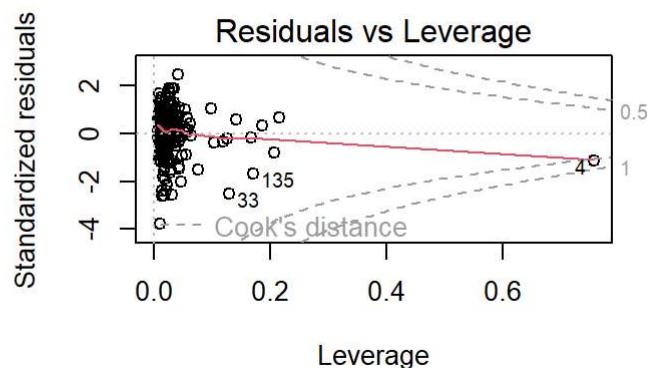
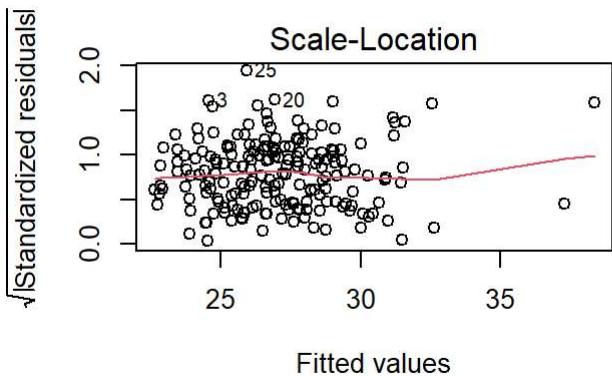
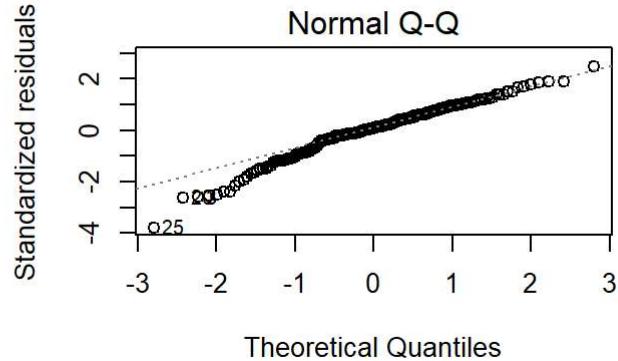
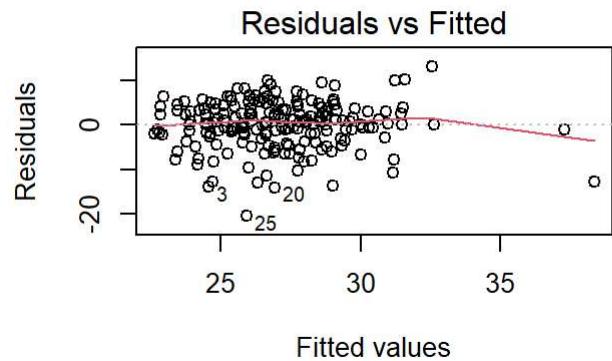
```
# View summary of the model with R-squared value included
rsq <- summary(model)$r.squared
summary_text <- paste0("R-squared: ", round(rsq, 2))
summary(model)
```

```
##  
## Call:  
## lm(formula = index ~ artcount + mobility + crimes + healthinsurance +  
##      walkability + TOT_PARK_AREA_SQMILES, data = wbindex)  
##  
## Residuals:  
##       Min     1Q   Median     3Q    Max  
## -20.4391 -2.2498  0.4523  3.3850 13.1212  
##  
## Coefficients:  
##                               Estimate Std. Error t value Pr(>|t|)  
## (Intercept)            33.1073132  2.8641083 11.559 < 2e-16 ***  
## artcount                 0.0224592  0.0218787  1.027  0.30597  
## mobility                  0.0064542  0.0010980  5.878 1.89e-08 ***  
## crimes                  -0.0003304  0.0029667 -0.111  0.91144  
## healthinsurance          -0.0009839  0.0003381 -2.910  0.00405 **  
## walkability                -0.5641508  0.1950582 -2.892  0.00428 **  
## TOT_PARK_AREA_SQMILES  1.1367998  3.1170593  0.365  0.71575  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 5.422 on 186 degrees of freedom  
## Multiple R-squared:  0.1744, Adjusted R-squared:  0.1477  
## F-statistic: 6.547 on 6 and 186 DF,  p-value: 2.736e-06
```

```
mtext(summary_text, side = 1, line = -2)
```



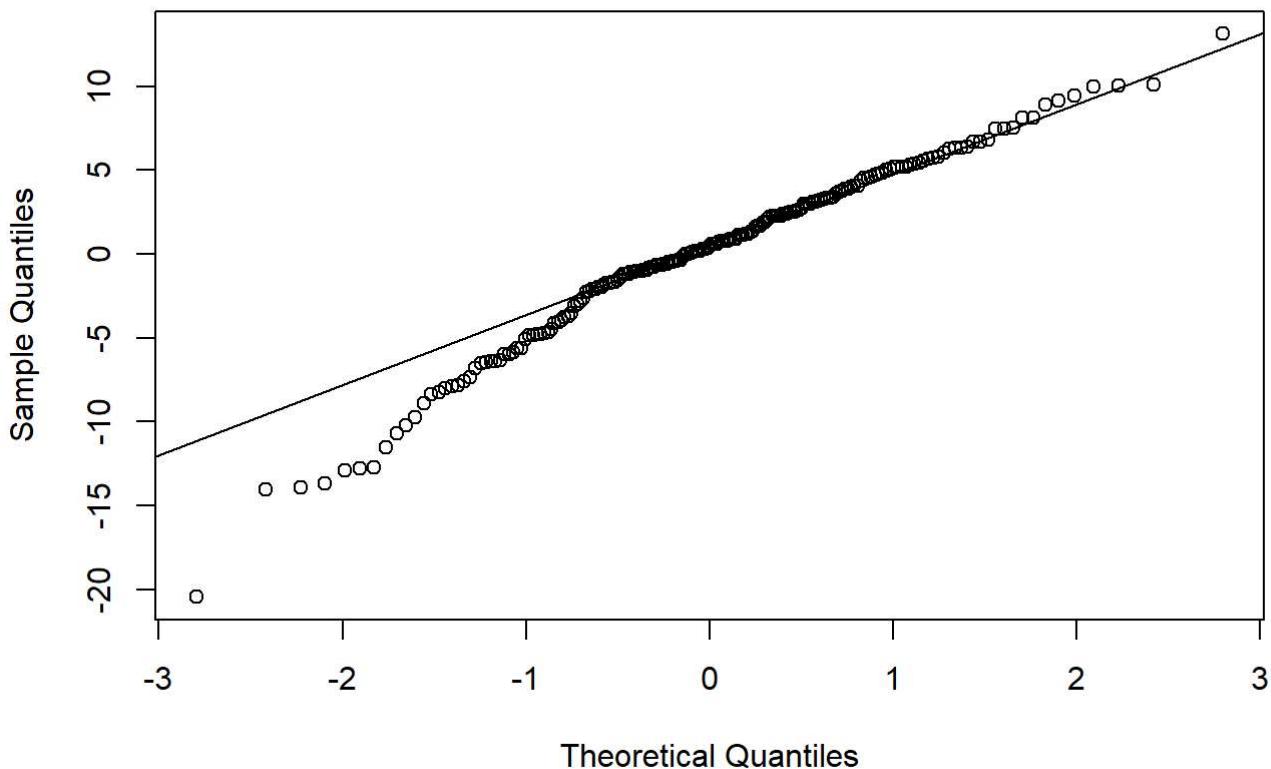
```
# Check model assumptions and residuals in a grid of plots
par(mfrow = c(2, 2))
plot(model)
```



```
# Check model assumptions

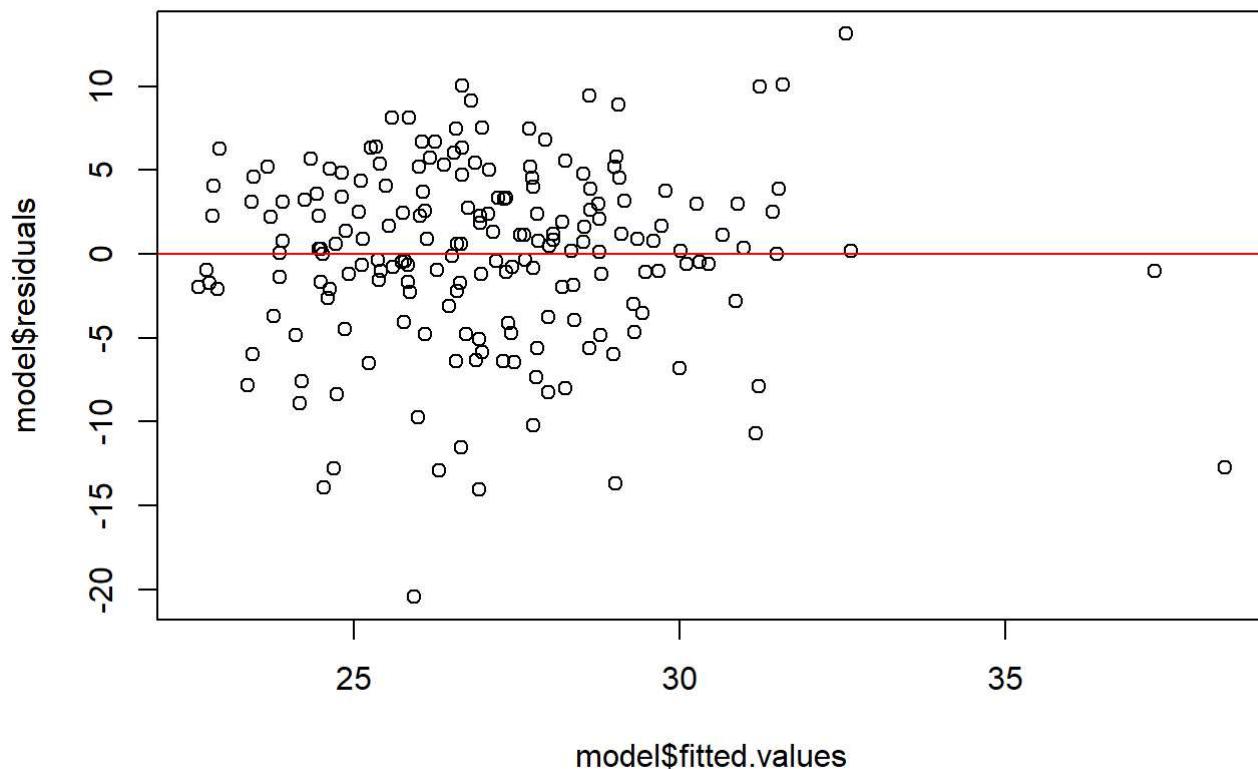
# Check for normality of residuals
qqnorm(model$residuals, main = "Normal Q-Q Plot")
qqline(model$residuals)
```

Normal Q-Q Plot



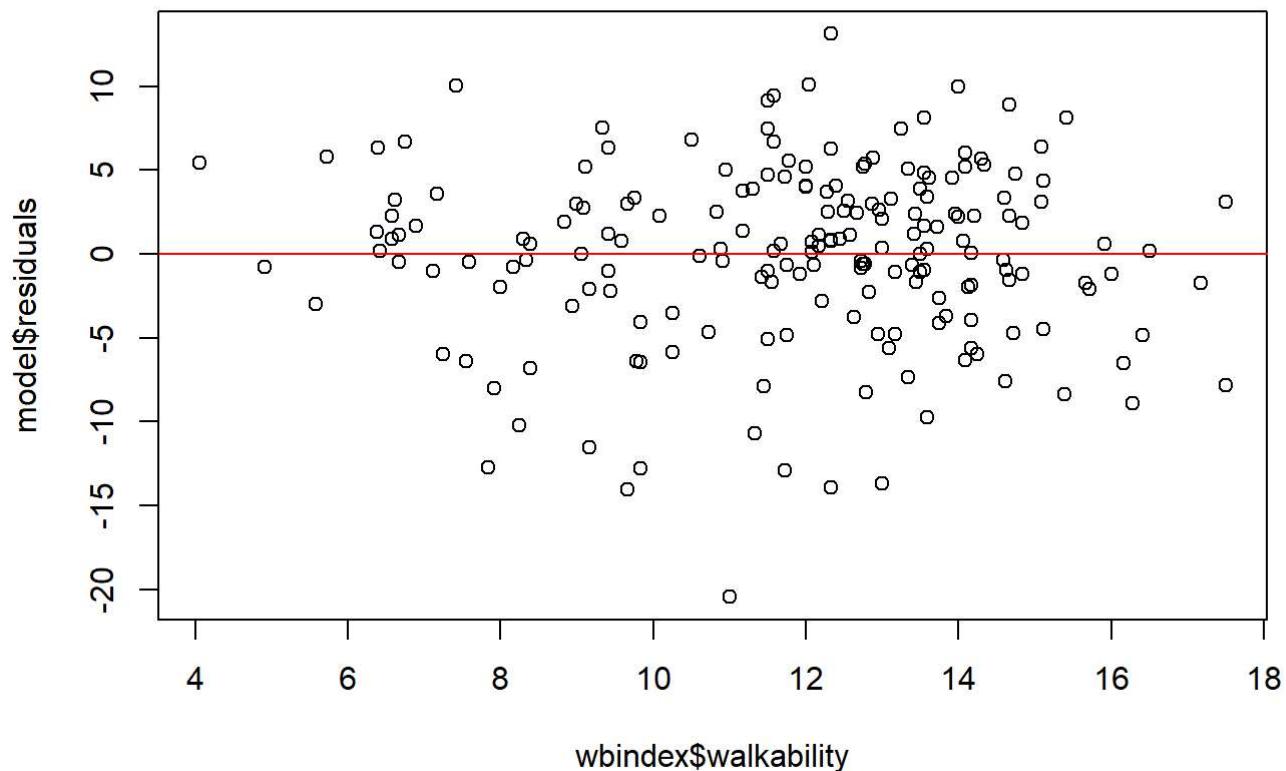
```
# Check for homoscedasticity (equal variance)
plot(model$fitted.values, model$residuals, main = "Residuals vs. Fitted Values")
abline(h = 0, col = "red")
```

Residuals vs. Fitted Values

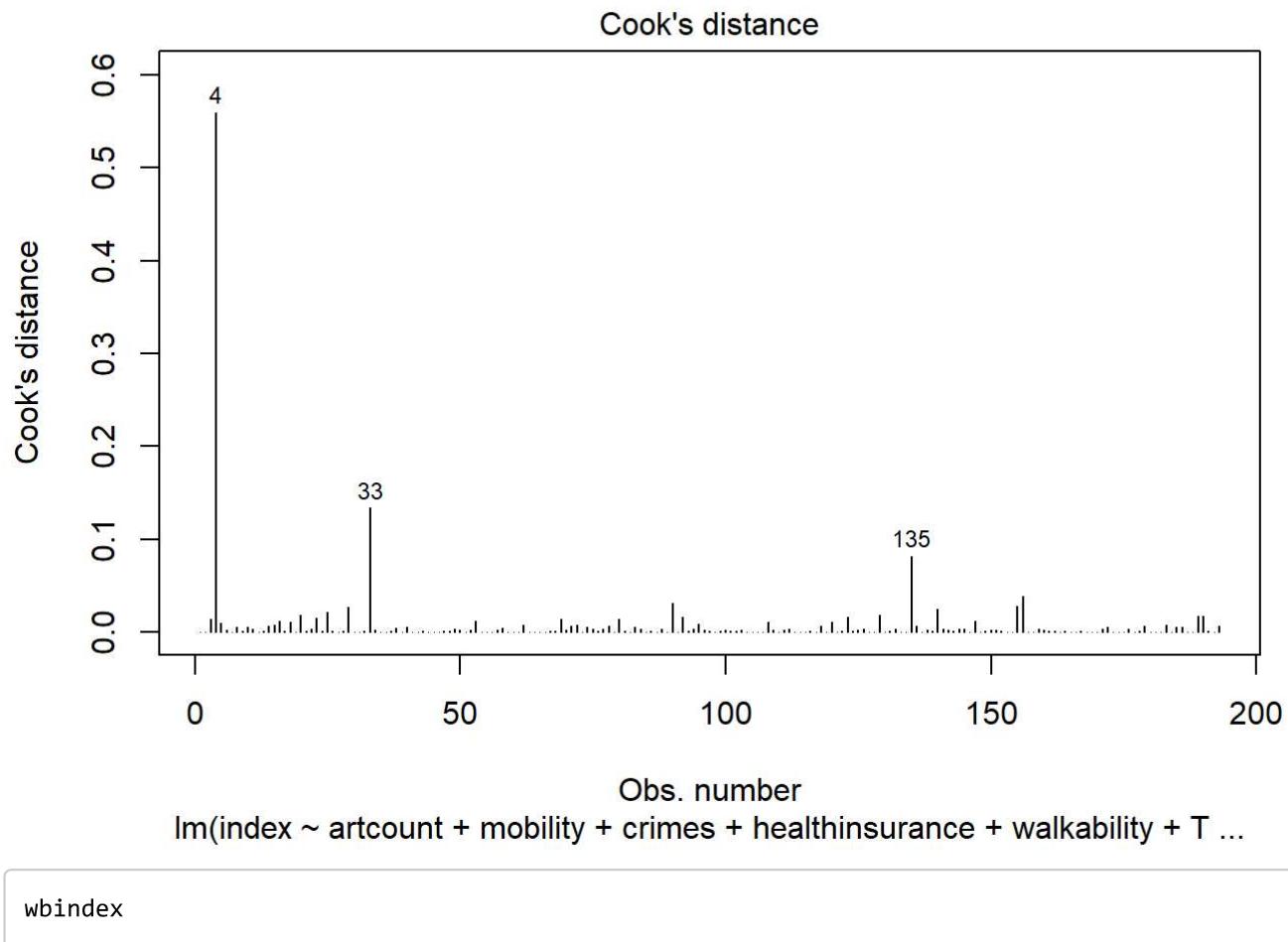


```
# Check for linearity
plot(wbindex$walkability, model$residuals, main = "Residuals vs. Walkability")
abline(h = 0, col = "red")
```

Residuals vs. Walkability



```
# Check for influential observations  
plot(model, which = 4)
```



##	GEO_ID	index	income	percentPoverty	owneroccupied	foodstamps
## 1	1400000US18097310104	24.150	18.8	11.9	55.9	10.0
## 2	1400000US18097310105	28.275	30.6	10.1	56.2	16.2
## 3	1400000US18097310106	10.600	5.7	9.5	20.9	6.3
## 4	1400000US18097310108	26.275	12.2	4.9	86.2	1.8
## 5	1400000US18097310110	20.225	19.3	12.2	44.3	5.1
## 6	1400000US18097310111	21.025	17.0	15.4	42.5	9.2
## 7	1400000US18097310201	25.350	21.7	11.1	61.6	7.0
## 8	1400000US18097310203	29.200	41.6	5.7	63.5	6.0
## 9	1400000US18097310204	29.725	12.5	16.2	70.5	19.7
## 10	1400000US18097310305	20.150	16.5	11.5	38.8	13.8
## 11	1400000US18097310306	31.400	29.5	24.2	40.8	31.1
## 12	1400000US18097310308	29.500	20.8	9.6	79.6	8.0
## 13	1400000US18097310309	21.950	26.2	11.5	28.9	21.2
## 14	1400000US18097310310	32.925	30.8	7.0	86.7	7.2
## 15	1400000US18097310311	34.800	29.8	13.1	87.6	8.7
## 16	1400000US18097310312	20.475	12.2	21.8	43.9	4.0
## 17	1400000US18097320105	21.100	18.3	14.4	43.4	8.3
## 18	1400000US18097320106	17.500	5.2	12.3	50.3	2.2
## 19	1400000US18097320107	26.225	11.9	1.6	91.0	0.4
## 20	1400000US18097320108	12.850	8.7	13.9	13.7	15.1
## 21	1400000US18097320109	30.700	10.2	13.7	87.1	11.8
## 22	1400000US18097320202	28.050	23.9	4.6	83.7	0.0
## 23	1400000US18097320203	15.125	28.8	7.6	17.9	6.2
## 24	1400000US18097320301	23.350	10.5	8.5	74.4	0.0
## 25	1400000US18097320303	5.475	8.9	10.5	0.3	2.2
## 26	1400000US18097320400	21.675	28.7	5.4	51.1	1.5
## 27	1400000US18097320500	23.600	11.8	15.7	58.7	8.2
## 28	1400000US18097320600	28.200	30.6	9.6	67.4	5.2
## 29	1400000US18097320700	15.550	0.0	5.0	57.2	0.0
## 30	1400000US18097320800	24.750	3.2	2.0	93.8	0.0
## 31	1400000US18097320901	22.550	14.7	7.1	64.5	3.9
## 32	1400000US18097320902	25.900	18.5	24.1	43.7	17.3
## 33	1400000US18097320903	25.650	14.2	41.0	36.5	10.9
## 34	1400000US18097321001	34.025	31.4	14.0	83.0	7.7
## 35	1400000US18097321002	28.675	19.2	17.1	74.7	3.7
## 36	1400000US18097321100	27.275	19.6	10.3	71.5	7.7
## 37	1400000US18097321200	21.775	9.4	1.5	75.4	0.8
## 38	1400000US18097321300	17.450	4.2	5.9	59.7	0.0
## 39	1400000US18097321400	22.475	22.0	6.4	60.4	1.1
## 40	1400000US18097321600	23.200	11.9	18.9	54.8	7.2
## 41	1400000US18097321700	23.925	20.5	9.4	65.8	0.0
## 42	1400000US18097321800	20.650	2.0	3.0	76.4	1.2
## 43	1400000US18097321900	25.100	9.2	15.2	75.0	1.0
## 44	1400000US18097322000	26.925	19.2	22.9	51.7	13.9
## 45	1400000US18097322100	25.175	20.8	16.5	60.5	2.9
## 46	1400000US18097322200	24.450	20.0	5.2	71.5	1.1
## 47	1400000US18097322300	20.825	20.0	6.4	55.2	1.7
## 48	1400000US18097322400	20.050	21.0	6.2	50.5	2.5
## 49	1400000US18097322500	20.550	10.0	29.2	30.2	12.8
## 50	1400000US18097322700	32.100	17.8	16.8	77.8	16.0
## 51	1400000US18097330103	24.350	21.4	10.7	64.3	1.0

## 52	1400000US18097330105	22.800	30.5	12.5	36.9	11.3
## 53	1400000US18097330106	13.375	13.2	17.9	18.6	3.8
## 54	1400000US18097330107	28.475	11.2	7.6	94.6	0.5
## 55	1400000US18097330108	27.000	9.2	3.1	94.7	1.0
## 56	1400000US18097330109	27.200	11.9	3.8	93.1	0.0
## 57	1400000US18097330203	27.450	13.4	0.6	94.7	1.1
## 58	1400000US18097330204	28.025	10.7	4.8	95.5	1.1
## 59	1400000US18097330206	26.650	10.1	6.8	88.5	1.2
## 60	1400000US18097330208	24.400	9.4	1.8	85.1	1.3
## 61	1400000US18097330401	24.525	10.2	5.7	77.8	4.4
## 62	1400000US18097330500	33.225	32.6	16.0	70.8	13.5
## 63	1400000US18097330600	30.250	18.6	16.6	58.8	27.0
## 64	1400000US18097330803	31.350	14.7	39.7	26.0	45.0
## 65	1400000US18097330804	28.900	22.4	28.9	30.7	33.6
## 66	1400000US18097330805	24.875	17.9	29.8	27.6	24.2
## 67	1400000US18097330806	36.250	18.7	51.9	41.1	33.3
## 68	1400000US18097330900	28.050	10.8	26.6	42.9	31.9
## 69	1400000US18097331000	41.675	26.2	36.0	78.0	26.5
## 70	1400000US18097340101	31.200	12.5	14.4	88.6	9.3
## 71	1400000US18097340102	18.700	27.1	21.9	15.1	10.7
## 72	1400000US18097340108	16.275	17.8	19.1	21.1	7.1
## 73	1400000US18097340111	28.675	26.5	5.5	81.6	1.1
## 74	1400000US18097340112	20.875	29.7	9.8	33.0	11.0
## 75	1400000US18097340113	34.525	29.7	12.2	79.1	17.1
## 76	1400000US18097340114	29.175	20.3	4.3	89.9	2.2
## 77	1400000US18097340201	35.175	22.9	23.8	78.2	15.8
## 78	1400000US18097340202	22.700	15.6	26.2	39.9	9.1
## 79	1400000US18097340400	30.600	24.2	20.7	56.2	21.3
## 80	1400000US18097340500	23.325	22.0	30.4	24.2	16.7
## 81	1400000US18097340600	30.200	27.2	22.1	58.0	13.5
## 82	1400000US18097340700	30.175	24.4	25.4	48.7	22.2
## 83	1400000US18097340800	32.750	16.7	9.6	90.6	14.1
## 84	1400000US18097340901	31.575	22.4	5.9	93.5	4.5
## 85	1400000US18097341000	24.800	12.0	3.7	78.4	5.1
## 86	1400000US18097341100	29.475	28.1	17.7	55.2	16.9
## 87	1400000US18097341200	30.350	9.0	35.9	54.9	21.6
## 88	1400000US18097341600	34.175	17.4	40.3	52.3	26.7
## 89	1400000US18097341902	29.575	29.0	12.9	74.7	1.7
## 90	1400000US18097341903	15.350	14.1	24.8	12.0	10.5
## 91	1400000US18097341904	23.825	11.4	20.0	48.1	15.8
## 92	1400000US18097342000	36.675	36.9	9.7	96.6	3.5
## 93	1400000US18097342101	31.775	27.1	19.4	65.8	14.8
## 94	1400000US18097342200	32.525	28.0	23.7	59.5	18.9
## 95	1400000US18097342300	34.775	38.7	17.3	60.4	22.7
## 96	1400000US18097342400	31.725	27.9	26.2	56.9	15.9
## 97	1400000US18097342500	30.575	13.1	23.5	65.4	20.3
## 98	1400000US18097342600	31.800	24.1	32.8	50.9	19.4
## 99	1400000US18097350100	28.200	14.6	5.9	69.3	23.0
## 100	1400000US18097350300	22.975	7.0	39.1	15.4	30.4
## 101	1400000US18097350400	21.300	24.6	15.9	39.1	5.6
## 102	1400000US18097350500	32.300	14.3	35.6	54.2	25.1
## 103	1400000US18097350600	35.425	22.3	28.8	70.1	20.5

## 104 1400000US18097350700	29.250	8.8	35.0	53.1	20.1
## 105 1400000US18097350800	28.725	18.3	31.9	35.4	29.3
## 106 1400000US18097350900	28.675	12.1	13.4	66.5	22.7
## 107 1400000US18097351000	28.400	16.6	37.7	38.9	20.4
## 108 1400000US18097351200	37.950	36.1	36.2	44.8	34.7
## 109 1400000US18097351500	21.950	21.5	24.4	33.1	8.8
## 110 1400000US18097351600	21.075	15.1	10.8	54.2	4.2
## 111 1400000US18097351700	20.350	9.6	14.0	50.0	7.8
## 112 1400000US18097351900	33.725	31.2	15.7	65.8	22.2
## 113 1400000US18097352100	30.850	19.3	37.4	40.8	25.9
## 114 1400000US18097352300	25.750	11.9	22.8	51.2	17.1
## 115 1400000US18097352400	28.875	13.3	22.3	55.0	24.9
## 116 1400000US18097352500	31.675	12.2	23.1	71.6	19.8
## 117 1400000US18097352600	31.475	23.8	40.1	39.4	22.6
## 118 1400000US18097352700	33.950	33.1	22.3	49.9	30.5
## 119 1400000US18097352800	26.275	5.7	29.3	42.7	27.4
## 120 1400000US18097353300	15.275	23.8	15.8	15.3	6.2
## 121 1400000US18097353500	27.600	37.9	40.8	20.0	11.7
## 122 1400000US18097353600	31.275	30.8	25.5	49.1	19.7
## 123 1400000US18097354400	26.550	30.6	12.4	43.5	19.7
## 124 1400000US18097354500	23.225	11.0	26.2	35.9	19.8
## 125 1400000US18097354700	22.225	14.3	33.9	27.0	13.7
## 126 1400000US18097354800	33.800	28.7	29.1	40.4	37.0
## 127 1400000US18097354900	29.475	9.6	41.5	40.9	25.9
## 128 1400000US18097355000	29.850	6.3	41.9	38.2	33.0
## 129 1400000US18097355100	41.175	11.7	64.3	34.1	54.6
## 130 1400000US18097355300	29.275	13.0	32.4	57.8	13.9
## 131 1400000US18097355400	33.600	31.6	32.2	46.8	23.8
## 132 1400000US18097355500	35.950	29.7	15.5	78.6	20.0
## 133 1400000US18097355600	28.800	16.0	30.4	34.3	34.5
## 134 1400000US18097355700	28.625	17.5	31.9	41.1	24.0
## 135 1400000US18097355900	19.725	11.4	12.2	45.8	9.5
## 136 1400000US18097356200	19.250	11.2	7.4	55.0	3.4
## 137 1400000US18097356400	30.175	16.1	36.3	44.3	24.0
## 138 1400000US18097356900	26.500	10.9	25.9	44.1	25.1
## 139 1400000US18097357000	24.225	3.1	25.5	52.1	16.2
## 140 1400000US18097357100	24.425	21.4	19.1	45.6	11.6
## 141 1400000US18097357200	32.550	18.0	22.9	56.1	33.2
## 142 1400000US18097357300	33.300	13.6	43.7	47.3	28.6
## 143 1400000US18097357400	33.950	7.8	31.9	56.0	40.1
## 144 1400000US18097357500	29.725	26.8	11.1	67.5	13.5
## 145 1400000US18097357800	31.725	13.5	20.1	63.4	29.9
## 146 1400000US18097357900	25.000	19.5	10.4	50.3	19.8
## 147 1400000US18097358000	38.075	16.7	39.6	62.2	33.8
## 148 1400000US18097358100	28.450	13.6	23.2	51.1	25.9
## 149 1400000US18097360101	23.950	5.6	30.2	37.1	22.9
## 150 1400000US18097360102	32.925	19.1	27.3	49.9	35.4
## 151 1400000US18097360201	24.650	9.7	23.6	43.7	21.6
## 152 1400000US18097360202	33.550	19.1	29.3	70.4	15.4
## 153 1400000US18097360301	30.100	24.2	15.6	69.0	11.6
## 154 1400000US18097360302	32.800	19.2	47.3	34.6	30.1
## 155 1400000US18097360401	20.500	8.9	27.5	25.3	20.3

## 156	1400000US18097360402	45.675	9.7	46.1	83.1	43.8
## 157	1400000US18097360405	28.500	26.7	12.9	61.2	13.2
## 158	1400000US18097360501	24.800	15.5	7.6	67.7	8.4
## 159	1400000US18097360502	29.625	21.7	12.2	72.7	11.9
## 160	1400000US18097360601	31.875	22.9	15.4	87.9	1.3
## 161	1400000US18097360602	29.450	15.5	19.0	63.2	20.1
## 162	1400000US18097360700	27.000	16.9	9.4	78.4	3.3
## 163	1400000US18097360800	25.325	28.5	20.1	36.9	15.8
## 164	1400000US18097360900	33.850	3.8	31.4	68.6	31.6
## 165	1400000US18097361000	25.925	13.2	3.6	85.2	1.7
## 166	1400000US18097361100	26.725	23.4	10.8	61.4	11.3
## 167	1400000US18097361200	30.775	25.6	10.7	71.2	15.6
## 168	1400000US18097361300	26.025	12.1	7.3	77.8	6.9
## 169	1400000US18097370201	26.250	30.0	13.2	48.7	13.1
## 170	1400000US18097380200	26.750	20.2	22.9	43.4	20.5
## 171	1400000US18097380402	21.825	21.1	16.3	26.3	23.6
## 172	1400000US18097380403	30.000	24.4	11.5	73.9	10.2
## 173	1400000US18097380404	26.375	11.9	12.0	70.8	10.8
## 174	1400000US18097380501	29.800	19.1	25.3	64.2	10.6
## 175	1400000US18097380502	27.250	41.6	18.2	34.8	14.4
## 176	1400000US18097380600	26.900	45.2	7.8	46.9	7.7
## 177	1400000US18097380700	25.150	27.5	14.2	48.6	10.3
## 178	1400000US18097380800	31.350	19.5	15.3	81.5	9.1
## 179	1400000US18097380901	33.000	27.2	6.0	94.3	4.5
## 180	1400000US18097380902	27.200	20.6	10.5	76.8	0.9
## 181	1400000US18097381002	27.575	14.4	5.6	88.1	2.2
## 182	1400000US18097381101	24.650	18.6	4.4	73.6	2.0
## 183	1400000US18097381102	28.875	29.4	5.6	74.5	6.0
## 184	1400000US18097381203	23.750	19.5	19.4	28.1	28.0
## 185	1400000US18097381204	16.625	19.6	12.8	20.6	13.5
## 186	1400000US18097381205	23.000	18.8	16.1	50.6	6.5
## 187	1400000US18097390102	30.325	29.5	21.0	54.5	16.3
## 188	1400000US18097390200	25.275	12.2	3.2	77.4	8.3
## 189	1400000US18097390300	32.275	25.6	3.3	96.2	4.0
## 190	1400000US18097390405	11.900	10.8	3.3	32.0	1.5
## 191	1400000US18097390500	32.275	25.1	29.9	42.8	31.3
## 192	1400000US18097390700	25.300	22.5	16.6	43.6	18.5
## 193	1400000US18097390900	16.375	5.1	15.3	37.3	7.8
##	healthinsurance	artcount	mobility	crimes	walkability	TOT_PARK_AREA_SQMILES
## 1		3013	1	360	464	11.555556
## 2		3911	1	385	217	10.083333
## 3		4117	0	391	255	12.333333
## 4		3725	1	182	43	5.583333
## 5		2694	0	328	123	7.916667
## 6		3348	0	501	210	9.833333
## 7		4261	1	472	247	10.916667
## 8		5104	1	289	272	12.333333
## 9		5739	3	855	221	12.277778
## 10		5040	3	576	328	9.777778
## 11		7431	24	1763	1107	13.555556
## 12		3244	0	310	126	9.083333
## 13		3681	1	420	181	13.750000

## 14	5540	0	375	102	6.750000	0.0000538196
## 15	6823	8	889	158	5.722222	0.0000000000
## 16	6664	2	1369	340	13.333333	0.0000000000
## 17	3855	0	538	144	10.250000	0.0000000000
## 18	3613	0	446	113	8.250000	0.0000000000
## 19	2169	0	34	56	11.166667	0.0000000000
## 20	4976	0	661	351	9.666667	0.0000000000
## 21	2533	0	347	70	9.750000	0.0000000000
## 22	4951	10	227	281	11.722222	0.2009212391
## 23	2569	0	194	109	9.166667	0.0059987419
## 24	3618	2	309	242	8.944444	0.0000000000
## 25	3184	0	338	145	11.000000	0.0100811379
## 26	2965	6	159	136	9.833333	0.0000000000
## 27	3273	0	503	133	12.833333	0.0000000000
## 28	2330	5	225	116	13.583333	0.1204385723
## 29	2032	66	102	93	17.500000	0.0185203867
## 30	2957	1	58	36	10.888889	0.0108237118
## 31	6442	6	454	143	9.166667	0.0000000000
## 32	3835	0	921	207	10.250000	0.0000000000
## 33	6220	0	2462	286	7.833333	0.0000000000
## 34	3041	10	424	122	11.500000	0.0124435899
## 35	5224	12	811	94	7.111111	0.2072593693
## 36	3579	5	368	121	8.333333	0.2519754962
## 37	4987	104	75	199	14.625000	0.0205556826
## 38	2770	4	163	124	14.250000	0.0012090829
## 39	5165	10	332	290	11.416667	0.0000642133
## 40	5999	5	1136	215	8.388889	0.1287690636
## 41	4001	13	377	183	14.166667	0.0124563002
## 42	3406	8	103	90	14.125000	0.0026173057
## 43	5466	2	519	67	14.666667	0.0013630775
## 44	3322	17	735	192	12.722222	0.0227910535
## 45	3045	3	501	108	13.388889	0.0029266005
## 46	2244	5	116	66	11.750000	0.0019844821
## 47	2417	3	154	68	15.722222	0.0026466996
## 48	2809	6	173	172	13.833333	0.0210823644
## 49	1559	15	456	117	14.083333	0.0028417068
## 50	1733	1	284	74	10.944444	0.0159292328
## 51	4394	2	469	196	9.444444	0.1035814118
## 52	4718	4	587	852	13.444444	0.0000000000
## 53	4828	0	724	344	11.722222	0.0000000000
## 54	5430	6	413	57	6.375000	0.1624401144
## 55	4286	0	133	47	6.583333	0.0850437905
## 56	4970	1	190	132	6.888889	0.0000000000
## 57	5452	0	33	38	6.611111	0.0156175623
## 58	7276	6	347	5	7.166667	0.1284556648
## 59	5324	0	361	0	4.916667	0.0000000000
## 60	2807	2	50	0	9.416667	0.0000000000
## 61	6216	6	351	173	9.055556	0.2581984027
## 62	6447	88	1029	196	9.000000	0.0116728667
## 63	7081	13	1174	1	8.291667	0.0099947898
## 64	3711	2	1379	279	13.000000	0.0000000000
## 65	3247	1	885	191	12.083333	0.0000000000

## 66	2215	14	659	217	15.666667	0.0295964196
## 67	4693	3	2366	148	11.500000	0.0000000000
## 68	6149	10	1638	426	12.208333	0.0204347614
## 69	3867	8	1387	241	12.033333	0.0077970609
## 70	5059	2	715	167	12.000000	0.0291902884
## 71	3546	1	741	241	16.166667	0.0000000000
## 72	2341	0	446	110	13.583333	0.0000000000
## 73	2834	1	155	88	6.666667	0.0000000000
## 74	4230	0	415	231	7.555556	0.0000000000
## 75	4162	0	505	115	9.333333	0.0000000000
## 76	3863	9	168	48	6.583333	0.0538265381
## 77	3461	6	823	153	13.250000	0.0601487626
## 78	4386	4	1054	0	14.722222	0.0252074224
## 79	3720	16	771	263	13.111111	0.0018248185
## 80	6103	10	1598	214	11.444444	0.0801979890
## 81	5394	10	1135	393	13.433333	0.1462422781
## 82	4865	14	1197	296	13.722222	0.0155048914
## 83	1633	3	156	0	11.583333	0.0000000000
## 84	3991	3	210	122	9.416667	0.0000000000
## 85	1595	12	53	1	13.583333	0.0000000000
## 86	2151	11	381	236	15.111111	0.0000000000
## 87	2627	7	919	189	12.333333	0.0037882738
## 88	1884	37	760	204	14.083333	0.0084108321
## 89	3942	6	455	166	12.000000	0.0077608955
## 90	5781	0	1404	441	13.000000	0.0000000000
## 91	2011	1	395	156	14.666667	0.0000000000
## 92	6579	7	637	193	7.416667	0.0000000000
## 93	5688	8	1076	365	12.000000	0.0000000000
## 94	5703	12	1335	582	13.500000	0.0437994560
## 95	6678	10	1121	493	10.500000	0.0200296814
## 96	1546	6	393	262	9.666667	0.0232151290
## 97	4574	13	1036	454	14.600000	0.0036947880
## 98	3780	12	1237	392	12.166667	0.0066243357
## 99	1259	16	74	99	12.666667	0.1919936841
## 100	2290	10	870	297	14.166667	0.0000000000
## 101	2481	9	395	208	12.944444	0.0296475576
## 102	2379	7	832	217	12.555556	0.0078928404
## 103	5484	4	1581	325	11.300000	0.0000000000
## 104	1536	7	528	145	12.083333	0.2002299129
## 105	1608	6	476	187	12.583333	0.0372449562
## 106	1366	8	183	103	12.500000	0.0401814380
## 107	2609	15	973	212	13.500000	0.0000000000
## 108	2746	45	923	283	14.666667	0.0435209843
## 109	1599	5	387	159	13.166667	0.0441565848
## 110	2512	3	276	197	17.166667	0.0364444501
## 111	2419	20	339	278	15.111111	0.0901506114
## 112	2630	4	408	170	13.555556	0.0351481162
## 113	2036	7	761	237	13.000000	0.0015714673
## 114	1120	4	251	180	11.916667	0.0087215772
## 115	2877	27	635	303	12.333333	0.1217818877
## 116	2982	7	654	285	14.333333	0.0000000000
## 117	3601	17	1417	502	13.500000	0.1555046165

## 118	2172	24	480	386	15.416667	0.0485050765
## 119	1265	24	369	144	13.166667	0.0209340047
## 120	2143	13	338	366	16.277778	0.0000000000
## 121	2379	6	965	116	14.833333	0.0597479590
## 122	3200	25	793	198	12.958333	0.3197624567
## 123	1540	37	188	1035	17.500000	0.0063324525
## 124	2167	26	563	236	13.750000	0.0060503618
## 125	1535	13	520	157	13.083333	0.0003862841
## 126	1847	11	533	263	11.777778	0.0000000000
## 127	2604	12	1024	413	12.750000	0.0000000000
## 128	2283	44	917	347	12.777778	0.0000000000
## 129	1917	6	1218	306	14.000000	0.0000000000
## 130	2462	11	747	406	13.416667	0.0000000000
## 131	3088	15	994	290	13.611111	0.0223878448
## 132	4236	3	655	202	11.500000	0.0956483857
## 133	2158	10	647	367	14.833333	0.0311014934
## 134	1839	39	567	330	14.055556	0.0188785582
## 135	1946	113	238	242	12.791667	0.0006783059
## 136	1950	58	144	194	16.416667	0.0041961824
## 137	3933	46	1395	349	16.500000	0.1341773870
## 138	1976	92	496	238	14.166667	0.0074425242
## 139	2063	32	522	255	12.625000	0.0172013526
## 140	2127	127	396	236	14.166667	0.0213506430
## 141	2110	19	483	369	14.083333	0.0249241531
## 142	1971	9	852	234	14.750000	0.0344544475
## 143	5340	8	1612	218	12.291667	0.0008154198
## 144	3829	9	406	42	13.333333	0.0000000000
## 145	1837	18	339	214	15.083333	0.0220034477
## 146	3490	68	356	377	14.583333	0.1896998784
## 147	1174	11	458	165	11.583333	0.0328520040
## 148	2829	20	641	352	12.166667	0.0593337875
## 149	2385	3	721	234	11.750000	0.0056625418
## 150	2126	7	581	265	12.750000	0.0574833177
## 151	3777	15	893	408	10.722222	0.0000000000
## 152	3118	7	915	227	11.166667	0.0420660051
## 153	3533	4	548	281	8.833333	0.0123573308
## 154	3024	3	1413	516	11.583333	0.0120688974
## 155	6712	0	1732	363	11.333333	0.0000000000
## 156	3345	2	1503	181	12.333333	0.0083497751
## 157	6525	0	822	277	6.416667	0.0391610569
## 158	6248	13	460	118	8.166667	0.0094326862
## 159	4958	21	606	473	13.555556	0.0000000000
## 160	4741	15	729	201	12.875000	0.0000000000
## 161	6159	22	1162	408	13.958333	0.0160235382
## 162	2044	5	193	144	15.083333	0.0016527604
## 163	2024	3	401	217	15.916667	0.0000000000
## 164	4870	13	1503	489	12.866667	0.0000000000
## 165	2436	12	88	70	14.000000	0.0755758100
## 166	3451	17	373	160	14.208333	0.0168832124
## 167	3387	24	364	210	12.777778	0.0059899902
## 168	2145	9	156	227	12.444444	0.0228734641
## 169	3463	8	448	185	8.000000	0.0000000000

Indy Regression

## 170	3072	6	659	351	12.722222	0.0000000000
## 171	5121	0	829	66	11.500000	0.0000000000
## 172	3833	13	424	1	14.291667	0.0230187727
## 173	3665	5	436	71	10.611111	0.0713629286
## 174	2247	2	569	97	7.583333	0.0000000000
## 175	3699	3	581	228	11.666667	0.0154129357
## 176	5856	5	385	403	12.388889	0.0162401053
## 177	6262	2	890	254	12.111111	0.0000000000
## 178	2881	3	442	174	11.500000	0.0000000000
## 179	4865	4	291	97	6.388889	0.0000000000
## 180	5621	3	593	544	8.388889	0.0219407642
## 181	3444	11	192	82	10.833333	0.0061729338
## 182	5533	5	243	127	9.583333	0.0000000000
## 183	6872	5	386	411	9.111111	0.0000000000
## 184	3051	3	591	116	16.000000	0.0000000000
## 185	2779	2	322	196	14.611111	0.0000000000
## 186	6215	4	933	117	7.250000	0.0058639608
## 187	5883	2	1096	160	9.416667	0.0231618070
## 188	4798	4	150	125	6.666667	0.0821606269
## 189	6295	15	212	90	4.055556	0.4808332077
## 190	3684	2	123	250	9.833333	0.0000000000
## 191	2377	11	711	144	13.916667	0.0263445329
## 192	3114	26	516	256	13.555556	0.0347176632
## 193	2724	14	417	254	15.388889	0.0496505874