W271 Lab 3

April 17, 2016

Part 1

Load data and display some basic statistics:

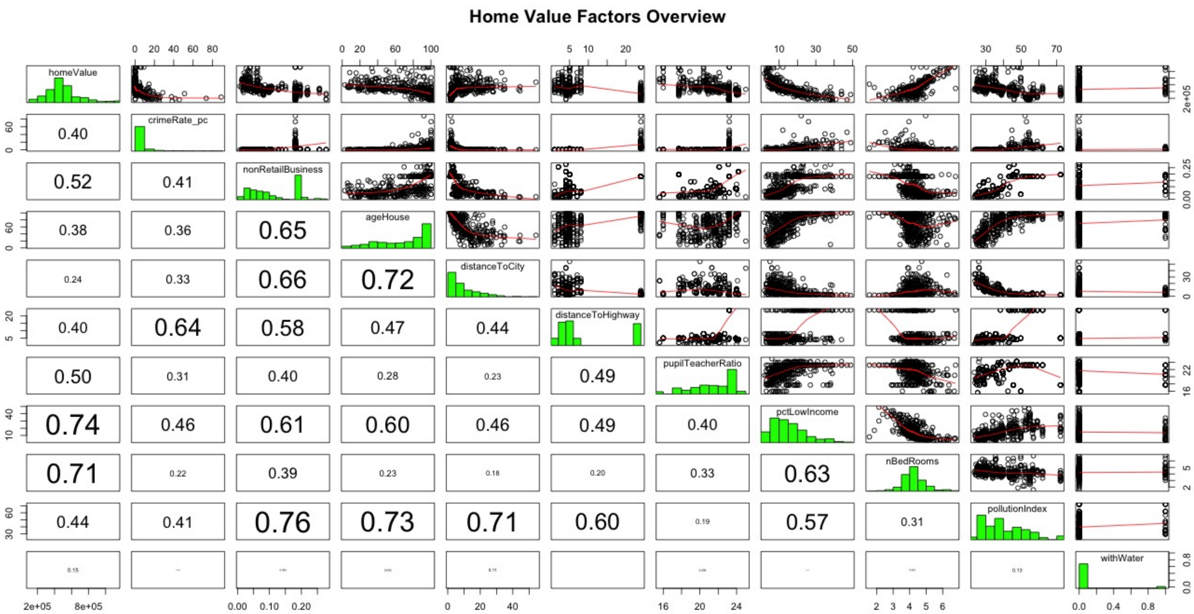
```
## Loading required package: zoo
##
## Attaching package: 'zoo'
##
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
##
## Loading required package: survival
## Loading required package: splines
##
## Please cite as:
##
##  Hlavac, Marek (2015). stargazer: Well-Formatted Regression and Summary Statistics Tables.
##  R package version 5.2. http://CRAN.R-project.org/package=stargazer
```

```
## 'data.frame':    400 obs. of  11 variables:
##  $ crimeRate_pc     : num  37.6619 0.5783 0.0429 22.5971 0.0664 ...
##  $ nonRetailBusiness: num  0.181 0.0397 0.1504 0.181 0.0405 ...
##  $ withWater        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ ageHouse         : num  78.7 67 77.3 89.5 74.4 71.3 68.2 97.3 92.2 96.2 ...
##  $ distanceToCity   : num  2.71 4.12 7.82 1.95 5.54 ...
##  $ distanceToHighway: int  24 5 4 24 5 5 5 5 3 5 ...
##  $ pupilTeacherRatio: num  23.2 16 21.2 23.2 19.6 23.9 22.2 17.7 20.8 17.7 ...
##  $ pctLowIncome     : int  18 9 13 41 8 9 12 18 5 4 ...
##  $ homeValue        : int  245250 1125000 463500 166500 672750 596250 425250 483750 852750 1125000 .
##  $ pollutionIndex   : num  52.9 42.5 31.4 55 36 37 34.9 72.1 33.8 45.5 ...
##  $ nBedRooms        : num  4.2 6.3 4.25 3 4.86 ...
```

```
##   crimeRate_pc      nonRetailBusiness   withWater         ageHouse
##  Min.   : 0.00632   Min.   :0.0074    Min.   :0.0000   Min.   :  2.90
##  1st Qu.: 0.08260   1st Qu.:0.0513    1st Qu.:0.0000   1st Qu.: 45.67
##  Median : 0.26600   Median :0.0969    Median :0.0000   Median : 77.95
##  Mean   : 3.76256   Mean   :0.1115    Mean   :0.0675   Mean   : 68.93
##  3rd Qu.: 3.67481   3rd Qu.:0.1810    3rd Qu.:0.0000   3rd Qu.: 94.15
##  Max.   :88.97620   Max.   :0.2774    Max.   :1.0000   Max.   :100.00
##  distanceToCity   distanceToHighway pupilTeacherRatio  pctLowIncome
##  Min.   : 1.228   Min.   : 1.000    Min.   :15.60     Min.   : 2.00
##  1st Qu.: 3.240   1st Qu.: 4.000    1st Qu.:19.90     1st Qu.: 8.00
##  Median : 6.115   Median : 5.000    Median :21.90     Median :14.00
##  Mean   : 9.638   Mean   : 9.582    Mean   :21.39     Mean   :15.79
##  3rd Qu.:13.628   3rd Qu.:24.000    3rd Qu.:23.20     3rd Qu.:21.00
##  Max.   :54.197   Max.   :24.000    Max.   :25.00     Max.   :49.00
##    homeValue       pollutionIndex    nBedRooms
```

```
##  Min.   : 112500   Min.   :23.50   Min.   :1.561
##  1st Qu.: 384188   1st Qu.:29.88   1st Qu.:3.883
##  Median : 477000   Median :38.80   Median :4.193
##  Mean   : 499584   Mean   :40.61   Mean   :4.266
##  3rd Qu.: 558000   3rd Qu.:47.58   3rd Qu.:4.582
##  Max.   :1125000   Max.   :72.10   Max.   :6.780
```

We first generate the matrix plot to have an overview of all variables.



Upon first galance, two things stands out: no highly-correlated pair of variables, thus collinearity won't be a concern of our analysis, in addition, the majority of the distributions are skewed and non-normal. More specifically:

- crime rate, distance to city, low income percentage, and pollution index are negatively skewed.
- age of house, pupil teacher ratio are positively skewed
- non retail business, and distance to highway have bi-modal distribution
- home value, number of bedroom are approximately normal

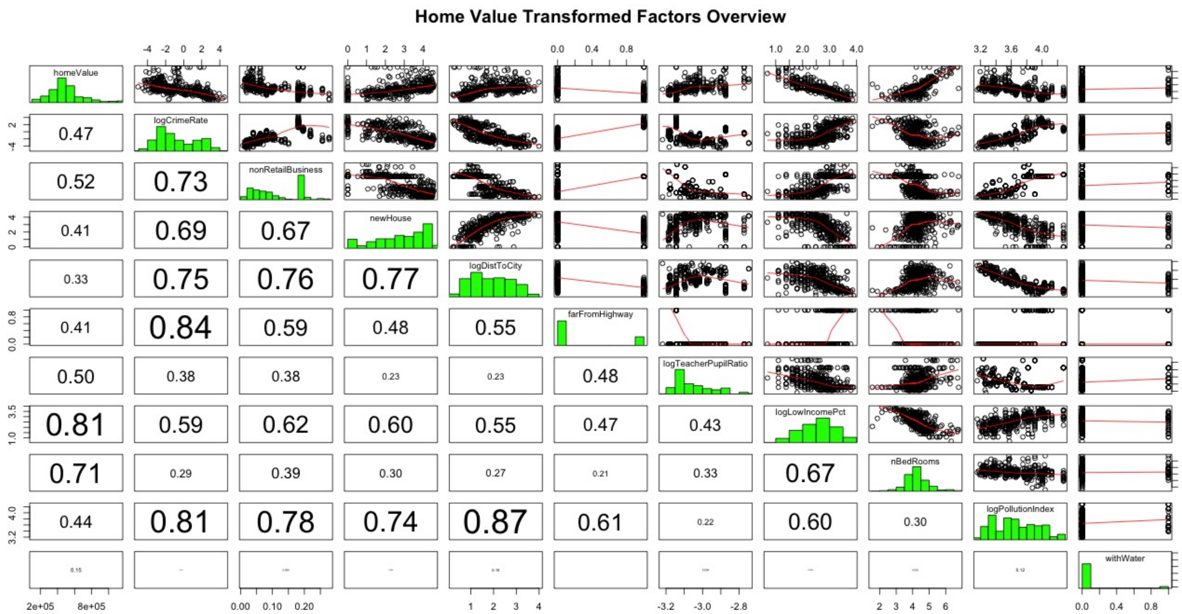
we then do some transformation on the variables:

- take log of the negatively skewed variables
- convert distance to highway to a binary variable, **farFromHighway**, if it's bigger than 10
- for positive skewness, we "reverse" the variable first then take log, and the interpretation of coefficients in the model need to adjust accordingly. Specifically:

a. take the reciprocal of pupilTeacherRatio, it becomes teacherPupilRatio

b. take 100 - ageHouse, it becomes proportion of house built **after** 1950

Let's evaluate matrix plot again with the transformed variables:



Based on correlation coefficients, we propose a hypothesis of house value:

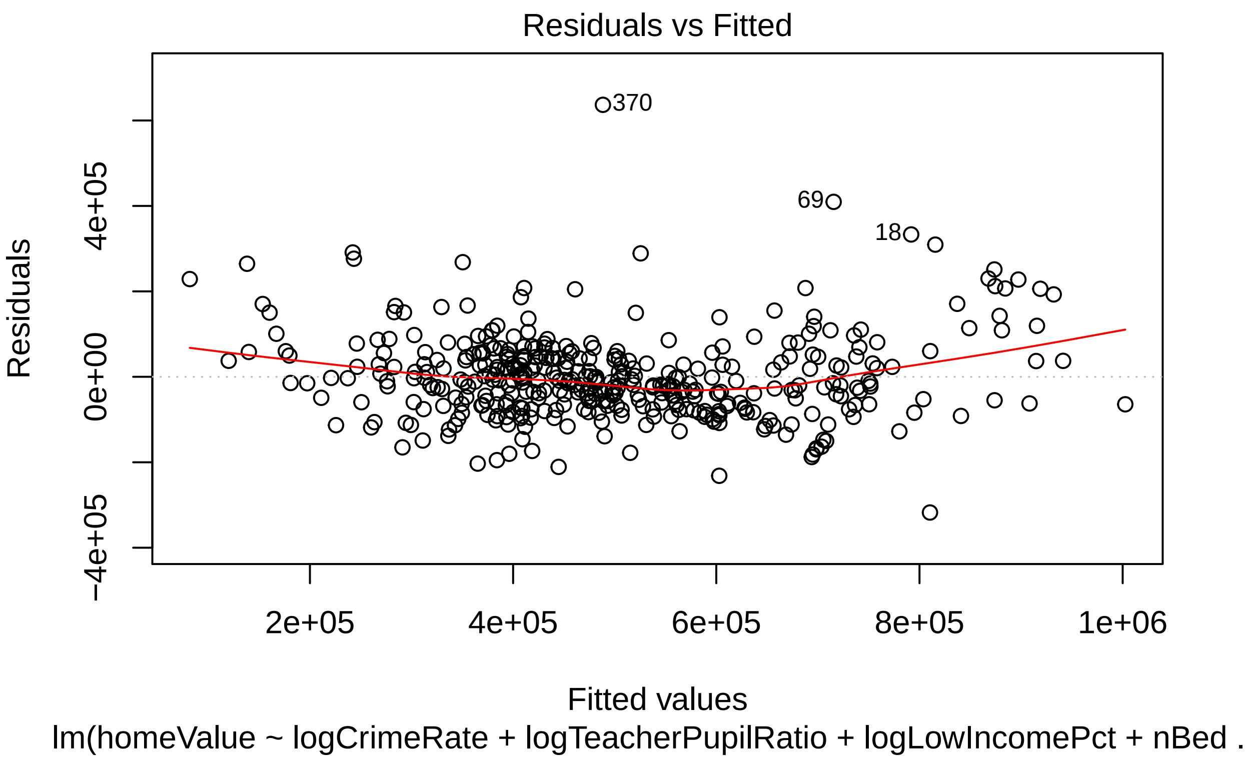
House value is significantly affected by factors from crime rate, education quality (represented by teacher pupil ratio), low income percentage, bedroom nuber, and pollution index.

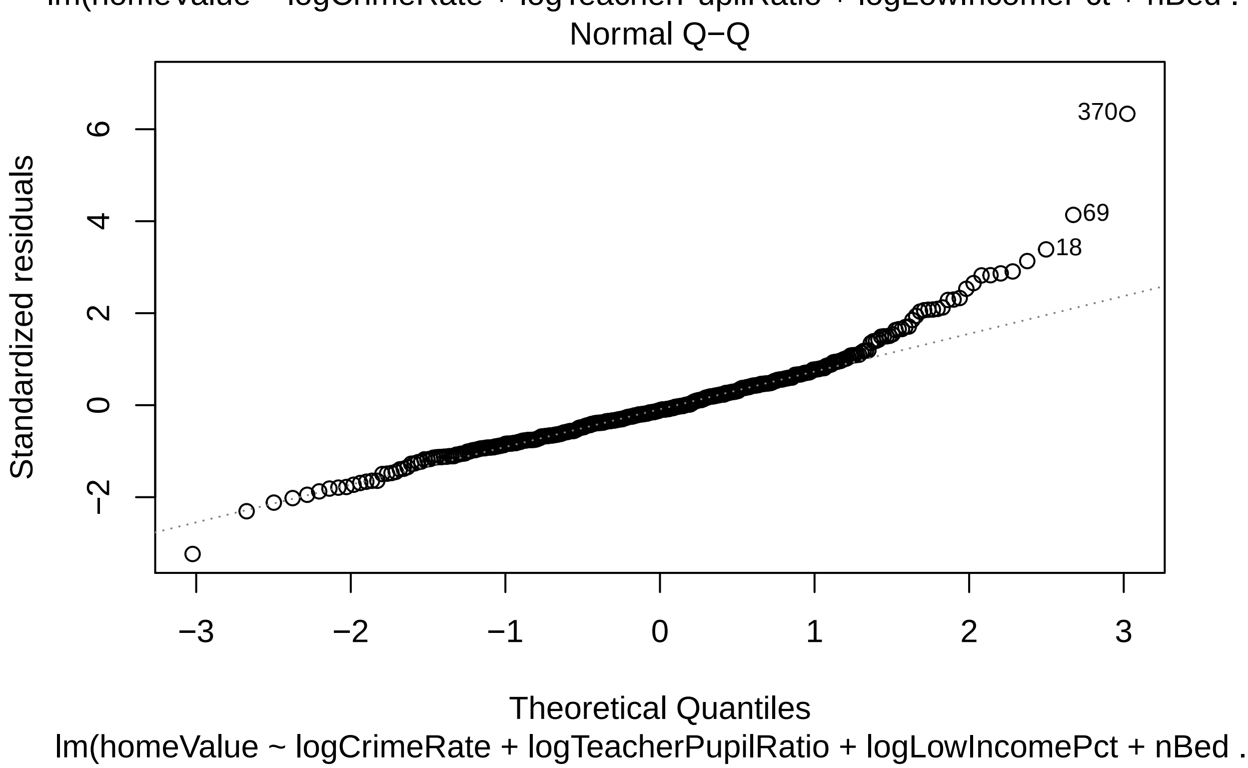
We build a linear model first with those variables:

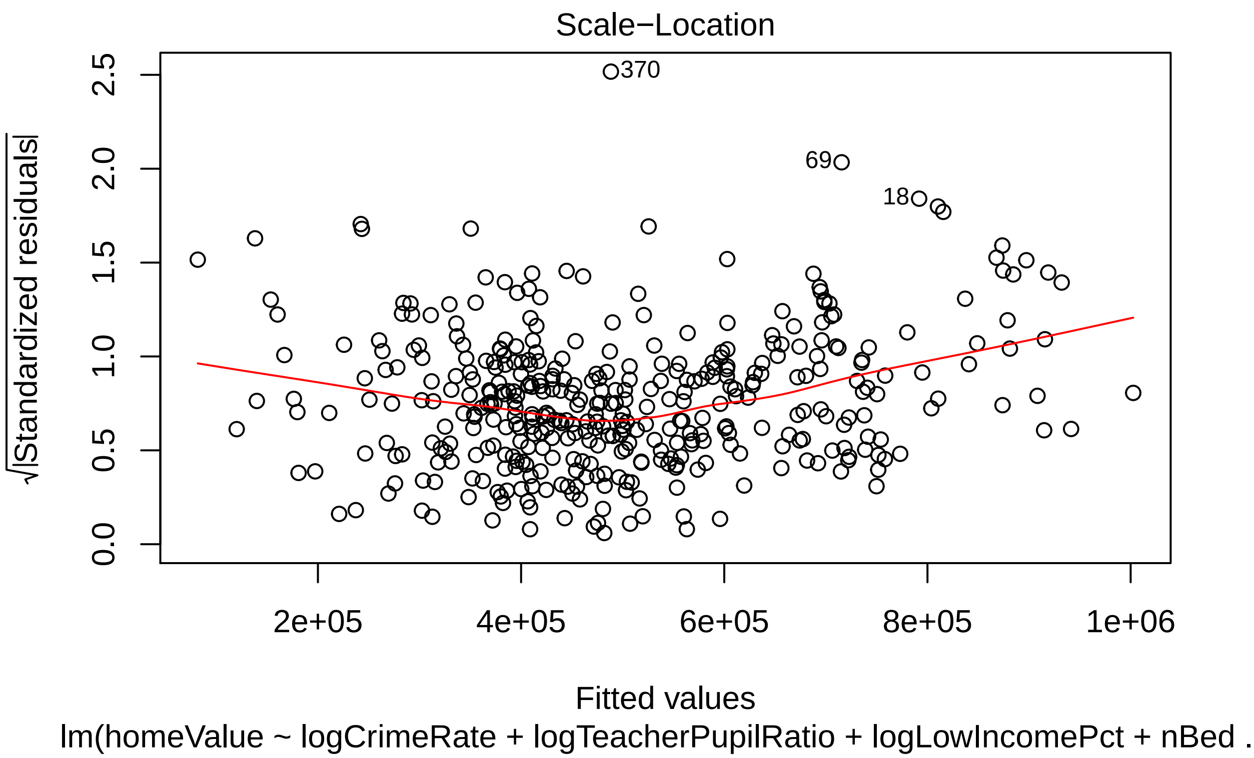
```
##
## Call:
## lm(formula = homeValue ~ logCrimeRate + logTeacherPupilRatio +
##     logLowIncomePct + nBedRooms + logPollutionIndex, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -317589  -64311  -10894   46801  636599
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          1554893.2   234001.9   6.645 1.01e-10 ***
## logCrimeRate             961.9     4320.6   0.223    0.824
## logTeacherPupilRatio  314867.8    55323.6   5.691 2.46e-08 ***
## logLowIncomePct      -173745.0    13708.0 -12.675  < 2e-16 ***
## nBedRooms              78593.6     9713.1   8.092 7.38e-15 ***
## logPollutionIndex       5615.7    32473.7   0.173    0.863
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 101100 on 394 degrees of freedom
## Multiple R-squared:  0.7374, Adjusted R-squared:  0.7341
## F-statistic: 221.3 on 5 and 394 DF,  p-value: < 2.2e-16
```

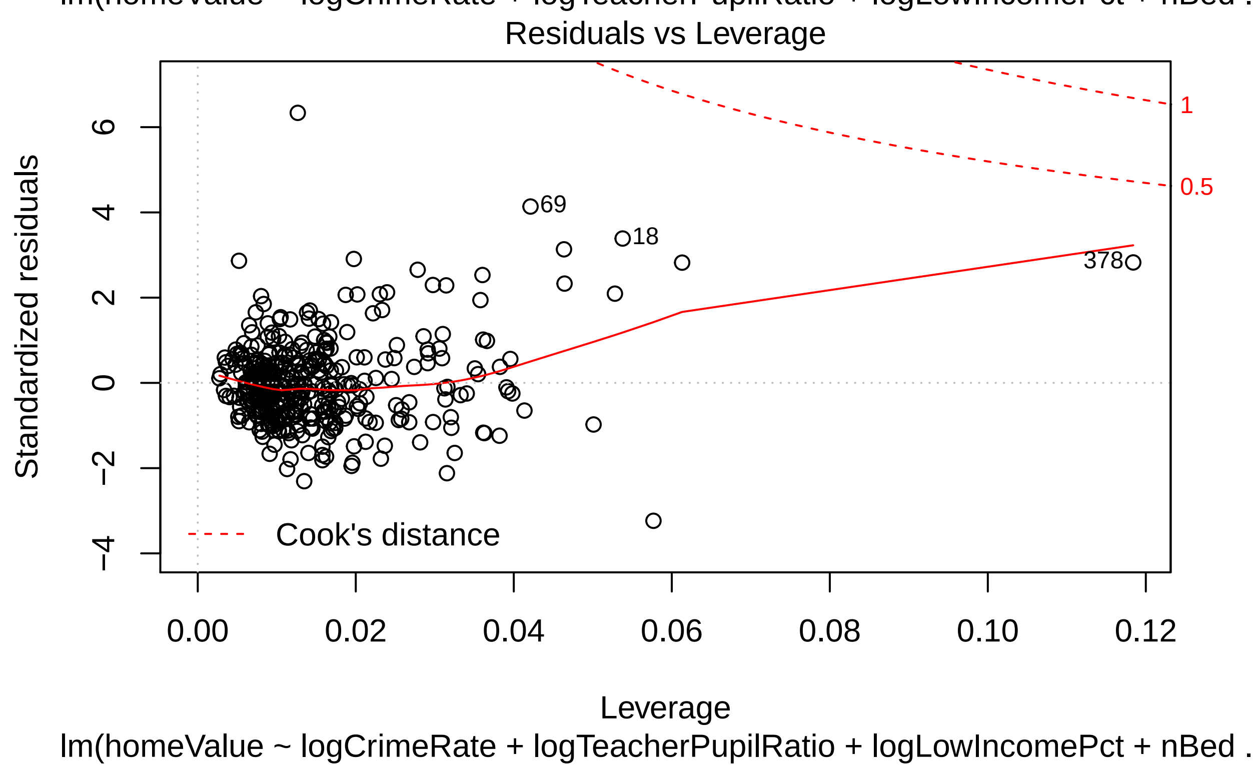
We can see that education quality, low income percentage, and number of bedrooms have significant impact on house value. On average, one more bedroom will increase the value by $78.6k, one percent increase in the low income percentage will reduce house value by $173.7k, and one percent increase in teacher pupil ratio will increase house value by $314.9k. Surprisingly here crime rate is not a significant factor.

Next, we do model diagnostics:









From the chart we can see, the model doesn't violate homoscedasticity assumption, and there is no concern of outliers in the data. However, the normality and zero-conditional mean assumptions are questionable towards the high value house.

We now add the omitted variables to our model and compare the results:

We can see that in model 3 pollution index becomes significant. In addition, distance to city and water

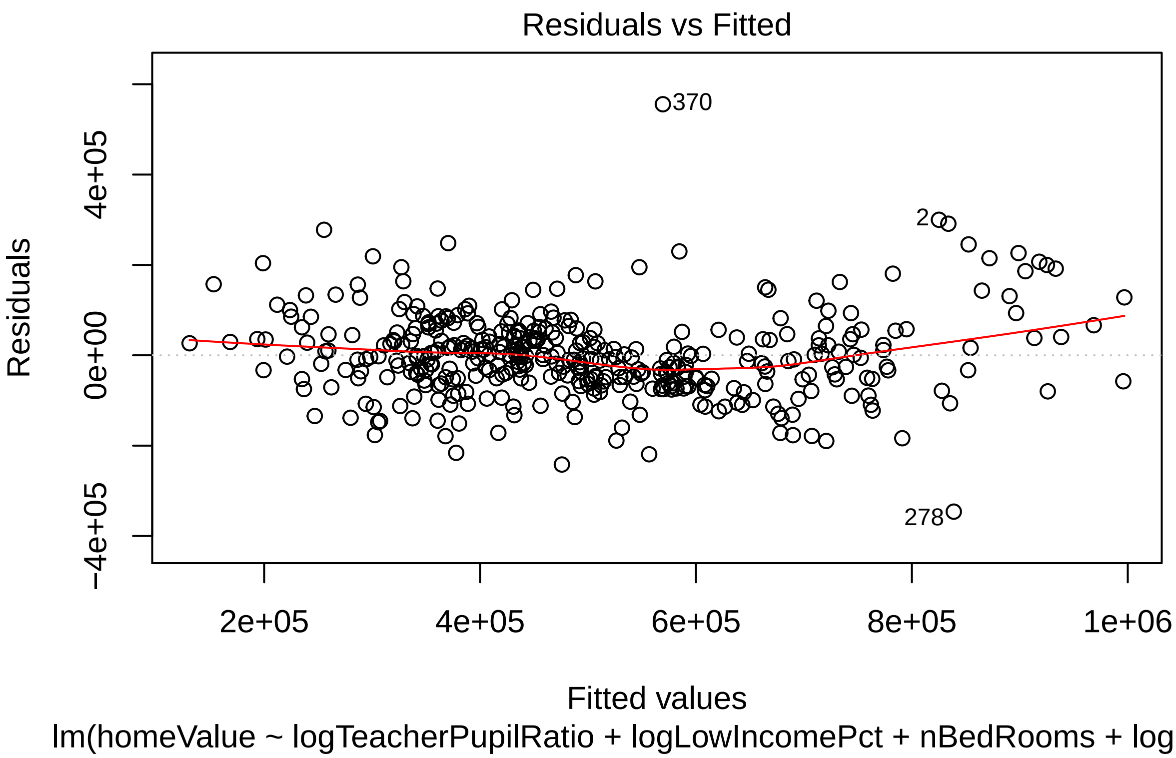
Table 1: House Value Model Summary

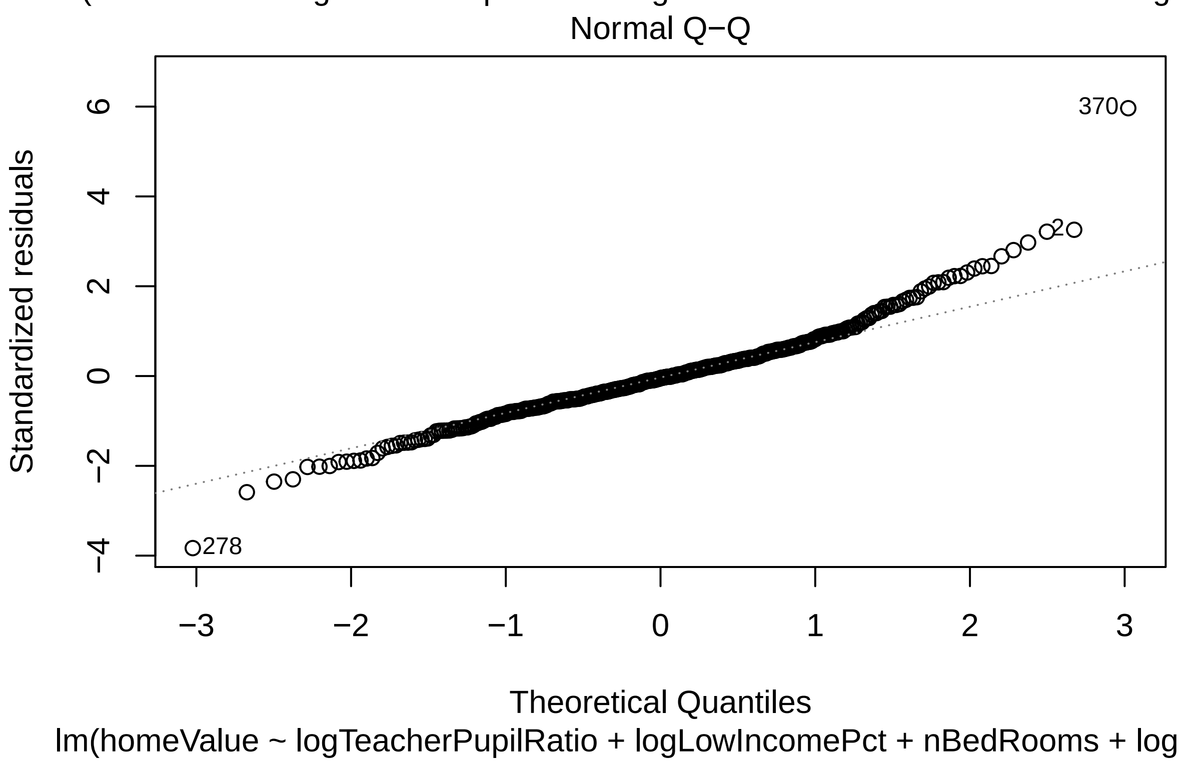
	Dependent variable:		
	House Value		
	(1)	(2)	(3)
logCrimeRate	961.901	8,156.263	1,666.250
	(−7,506.387, 9,430.188)	(−3,607.645, 19,920.170)	(−9,613.651, 12,946.150)
logTeacherPupilRatio	314,867.800***	276,554.600***	274,726.300***
	(206,435.600, 423,300.000)	(163,014.900, 390,094.300)	(165,000.700, 384,451.900)
logLowIncomePct	−173,745.000***	−172,090.700***	−181,403.400***
	(−200,612.200, −146,877.800)	(−198,877.200, −145,304.200)	(−208,434.500, −154,372.300)
nBedRooms	78,593.580***	78,980.880***	69,215.170***
	(59,556.310, 97,630.850)	(60,093.840, 97,867.920)	(50,660.260, 87,770.080)
logPollutionIndex	5,615.722	−14,073.550	−182,025.200***
	(−58,031.470, 69,262.920)	(−78,298.340, 50,151.240)	(−264,518.800, −99,531.650)
farFromHighway		−37,459.410	−14,017.560
		(−82,239.580, 7,320.766)	(−57,147.040, 29,111.930)
withWater		53,643.820***	54,161.730***
		(13,550.510, 93,737.120)	(16,438.880, 91,884.590)
nonRetailBusiness			−297,234.800**
			(−540,375.300, −54,094.240)
ageHouse			393.526
			(−237.781, 1,024.833)
logDistToCity			−81,172.700***
			(−105,548.500, −56,796.860)
Constant	1,554,893.000***	1,515,577.000***	2,339,513.000***
	(1,096,258.000, 2,013,528.000)	(1,056,843.000, 1,974,311.000)	(1,827,152.000, 2,851,874.000)
Observations	400	400	400
R^2	0.737	0.744	0.777
Adjusted R^2	0.734	0.739	0.771
Residual Std. Error	101,125.200	100,125.200	93,770.050
F Statistic	221.330***	162.682***	135.630***
Note:			*p<0.1; **p<0.05; ***p<0.01

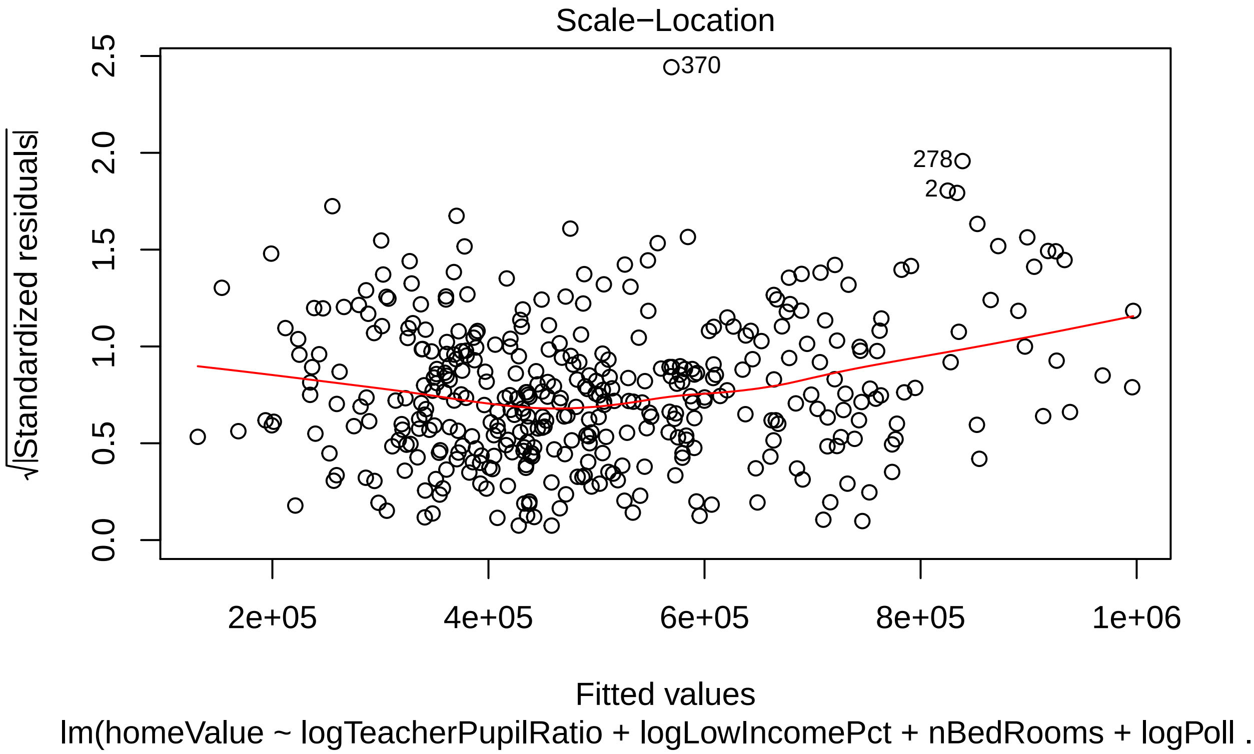
proximity are also significantly affecting house value. Finally, we build the linear model with the significant predictors identified above:

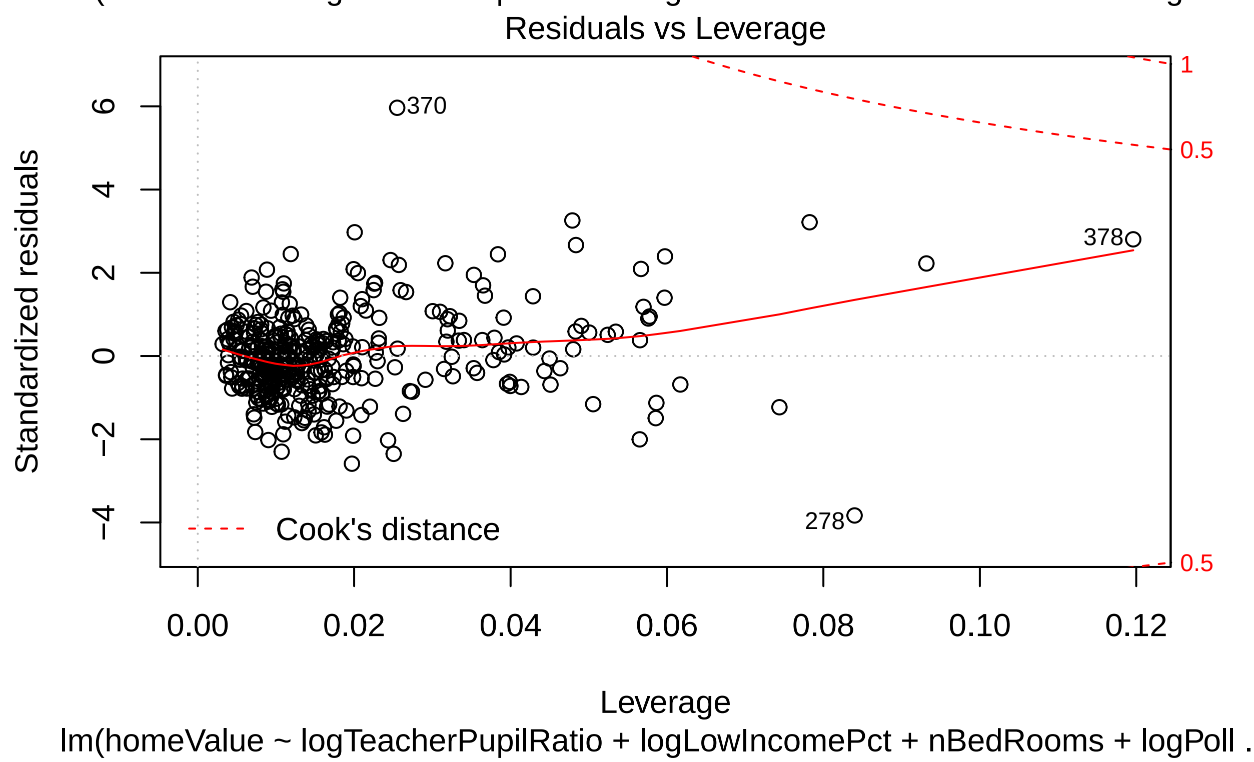
```
##
## Call:
## lm(formula = homeValue ~ logTeacherPupilRatio + logLowIncomePct +
##     nBedRooms + logPollutionIndex + withWater + logDistToCity,
##     data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -346067  -53036   -4417   46708  555679
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)           2517544     216732  11.616  < 2e-16 ***
## logTeacherPupilRatio   318860      49288   6.469 2.93e-10 ***
## logLowIncomePct       -178453      12737 -14.011  < 2e-16 ***
## nBedRooms               73823       9028   8.177 4.06e-15 ***
## logPollutionIndex     -204869      35696  -5.739 1.90e-08 ***
## withWater               52940      19262   2.749  0.00626 **
## logDistToCity          -79854      11138  -7.169 3.77e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 94370 on 393 degrees of freedom
## Multiple R-squared:  0.7719, Adjusted R-squared:  0.7685
## F-statistic: 221.7 on 6 and 393 DF,  p-value: < 2.2e-16
```

we see that being further away from city will reduce house value, while having a body of water closeby will increase the value. Finally we diagnose this model


Residuals vs Fitted
Residuals
4e+05
0e+00
−4e+05
370
2
278
2e+05
4e+05
6e+05
8e+05
1e+06
Fitted values
lm(homeValue ~ logTeacherPupilRatio + logLowIncomePct + nBedRooms + logPoll .


Normal Q−Q
Standardized residuals
6
4
2
0
−2
−4
370
2
278
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(homeValue ~ logTeacherPupilRatio + logLowIncomePct + nBedRooms + logPoll .





Similarly, the normality and zero-conditional mean assumption are questionable as price increases. Therefore we will use robust error to compensate:

```
##
## Call:
## lm(formula = homeValue ~ logTeacherPupilRatio + logLowIncomePct +
```

```
##     nBedRooms + logPollutionIndex + withWater + logDistToCity,
##     data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -346067  -53036   -4417   46708  555679
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)           2517544     216732  11.616  < 2e-16 ***
## logTeacherPupilRatio   318860      49288   6.469 2.93e-10 ***
## logLowIncomePct       -178453      12737 -14.011  < 2e-16 ***
## nBedRooms               73823       9028   8.177 4.06e-15 ***
## logPollutionIndex     -204869      35696  -5.739 1.90e-08 ***
## withWater               52940      19262   2.749  0.00626 **
## logDistToCity          -79854      11138  -7.169 3.77e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 94370 on 393 degrees of freedom
## Multiple R-squared:  0.7719, Adjusted R-squared:  0.7685
## F-statistic: 221.7 on 6 and 393 DF,  p-value: < 2.2e-16

## [1] "Robust Standard Errors"

##          (Intercept) logTeacherPupilRatio      logLowIncomePct
##            231450.28             55184.01             18941.97
##            nBedRooms    logPollutionIndex            withWater
##             15365.45             36594.87             23188.05
##        logDistToCity
##             14596.04
```