STA hwk 2 (2)

2024-10-22

Problem 1) I would not hire this TA The F-value formula that TA provided seems wrong, the numerator are the difference between two means, the denominator are the addition between two groups variance. thats actually more like a t-test, not a f-test. The correct F-test formula should be F = MSB(The mean square of between groups)/MSE(The mean square of error). TA's word seems confusing to me because he mixed up SSB and SSW as he talked about in b). Moreover, the between part reflects the differences between the attitudes of engineers and administrators toward the new health plan While, the whithin part reflects the differences that exist among the 50 engineers and the 50 administrators toward the new health plan.

Problem2)

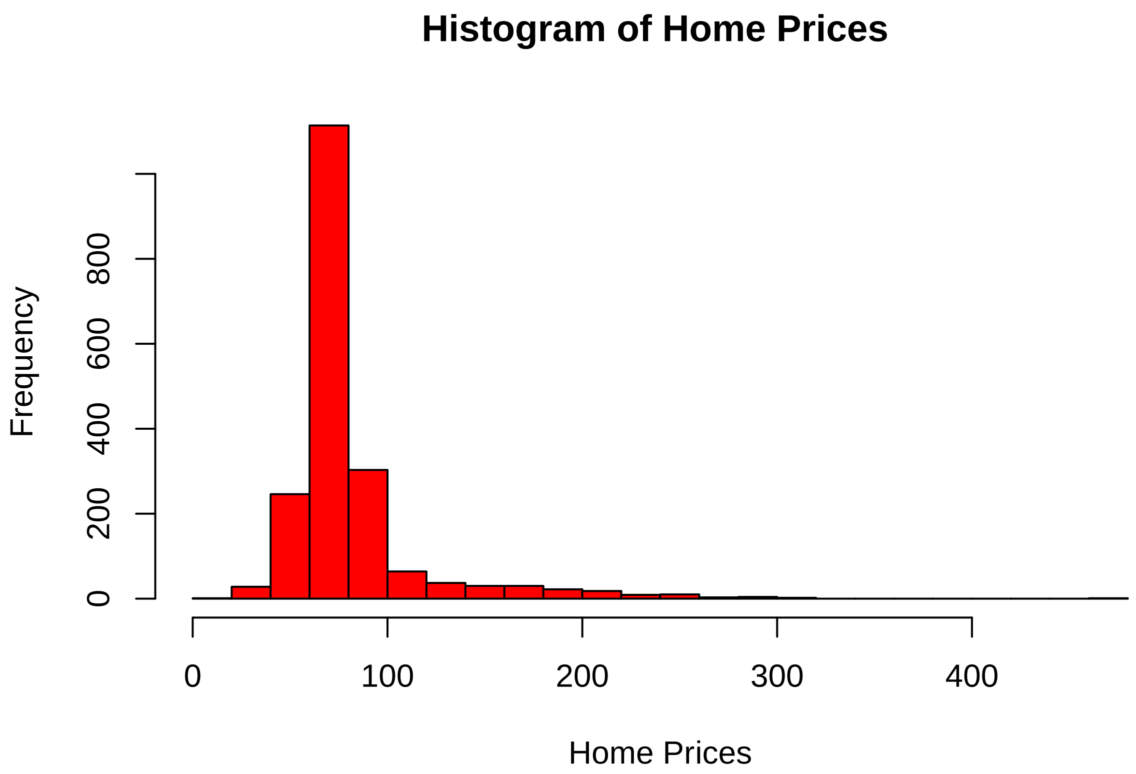
```
library(car)
```

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

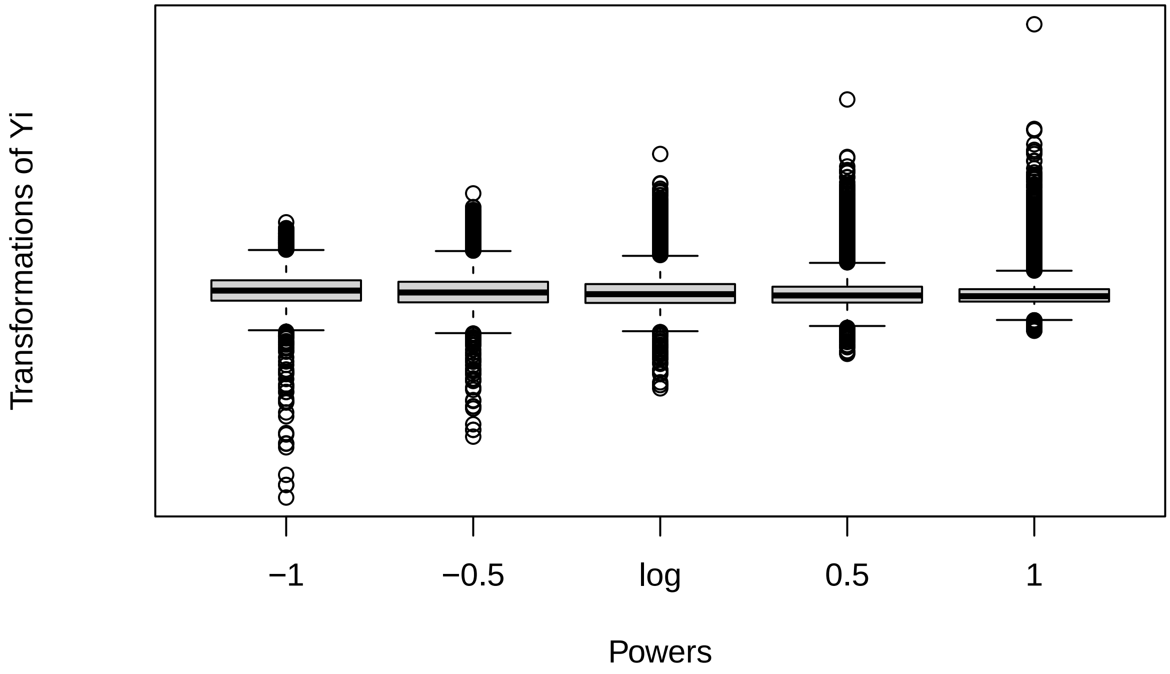
```
library(forecast)
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
library(moments)




#2a)
houstonrealesate = read.csv("/Users/shuhong/Desktop/2/houstonrealesate.csv")

hist(houstonrealesate$Yi, breaks = 30,
     main = "Histogram of Home Prices ",
     xlab = "Home Prices", col = "red")
```

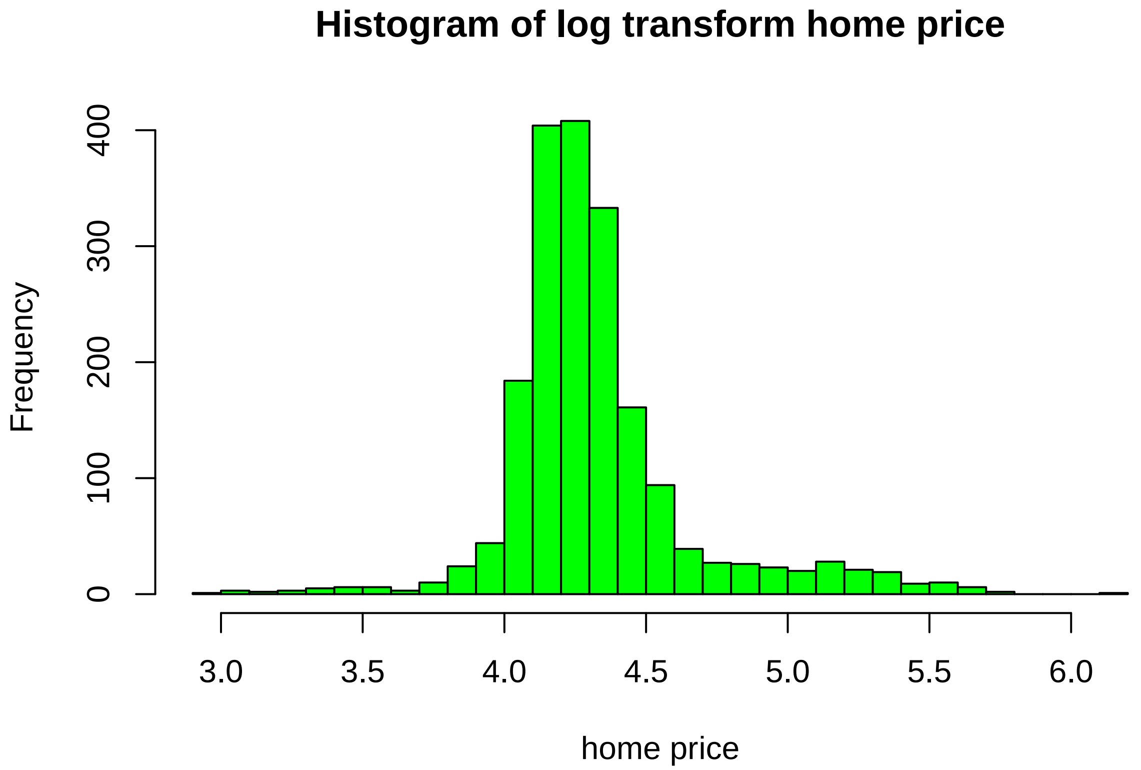


```r
#b)
symbox(~Yi,data=houstonrealesate)
```



c) i will choose log transformed

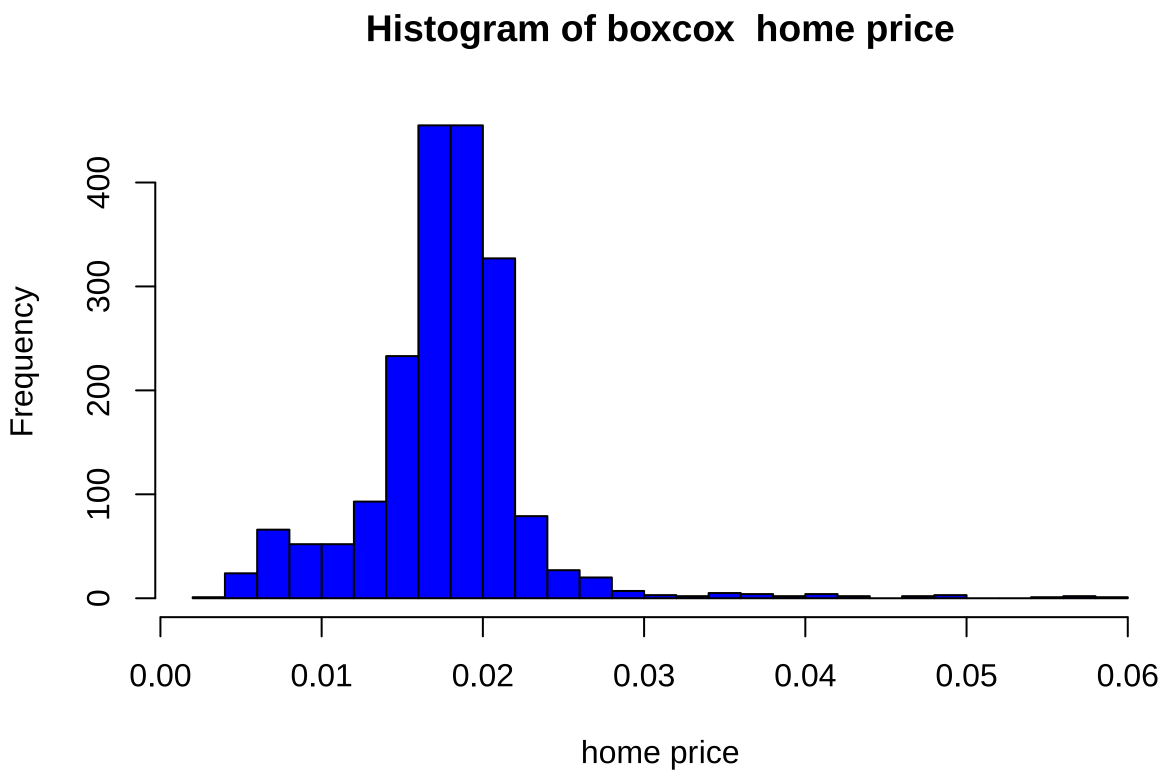
```r
log.Yi = log(houstonrealesate$Yi)

hist(log.Yi, breaks = 30, main = "Histogram of log transform home price",
     xlab = "home price", col = "green")
```



```
#d)
library(forecast)
lambda=BoxCox.lambda(houstonrealesate$Yi)
lambda
```

```
## [1] -0.9423097
```

```
boxcox.Yi=houstonrealesate$Yi^-0.9423097
boxcox.Yi=houstonrealesate$Yi^-0.9423097
hist(boxcox.Yi, breaks = 30, main = "Histogram of boxcox  home price",
     xlab = "home price", col = "blue")
```



e) I would say log-transform a bit better the best since it looks more symmetric and the tails looks better than the box-cox one. But both of them were not good plot ideally.

```
#f)



skewness.log = skewness(log.Yi)
skewness.boxcox = skewness(boxcox.Yi)

skewness.log
```

```
## [1] 1.274064
```

```
skewness.boxcox
```

```
## [1] 1.608676
```

since the skewness index of log is smaller than boxcox, log transformed histogram is better.

```
#g)
shapiro.test(houstonrealesate$Yi)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  houstonrealesate$Yi
## W = 0.64268, p-value < 2.2e-16
```

```
shapiro.test(log.Yi)
```

```
##
##  Shapiro-Wilk normality test
##
```

```
## data:  log.Yi
## W = 0.85284, p-value < 2.2e-16
```

```
shapiro.test(boxcox.Yi)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  boxcox.Yi
## W = 0.84442, p-value < 2.2e-16
```

we reject the null hypothesis for all of them and say none of them follow a normal distribution

```
#h)
model.Yi = lm(Yi ~ x1i + x2i, data = houstonrealesate)
summary(model.Yi)
```

```
##
## Call:
## lm(formula = Yi ~ x1i + x2i, data = houstonrealesate)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -59.54 -16.64  -9.02   1.94 385.75
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   89.469      1.138  78.603   <2e-16 ***
## x1i            5.867      3.023   1.941   0.0524 .
## x2i          -90.896      5.915 -15.368   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 34.27 on 1919 degrees of freedom
## Multiple R-squared:  0.1209, Adjusted R-squared:   0.12
## F-statistic:   132 on 2 and 1919 DF,  p-value: < 2.2e-16
```

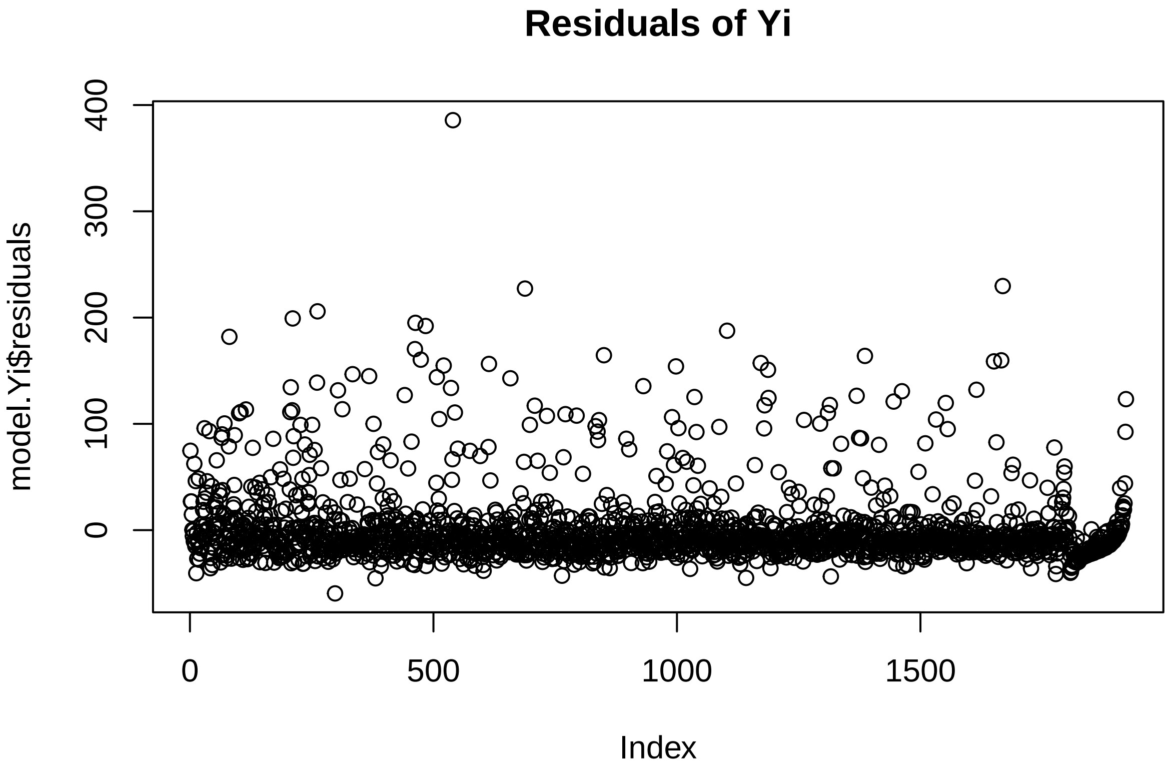
```
model.logYi = lm(log.Yi ~ x1i + x2i, data = houstonrealesate)
summary(model.logYi)
```

```
##
## Call:
## lm(formula = log.Yi ~ x1i + x2i, data = houstonrealesate)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.03501 -0.16497 -0.06736  0.07206  1.72991
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.433868   0.009705 456.851  < 2e-16 ***
## x1i          0.081786   0.025773   3.173  0.00153 **
## x2i         -1.136640   0.050433 -22.538  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2922 on 1919 degrees of freedom
## Multiple R-squared:   0.23,  Adjusted R-squared:  0.2292
## F-statistic: 286.5 on 2 and 1919 DF,  p-value: < 2.2e-16
```

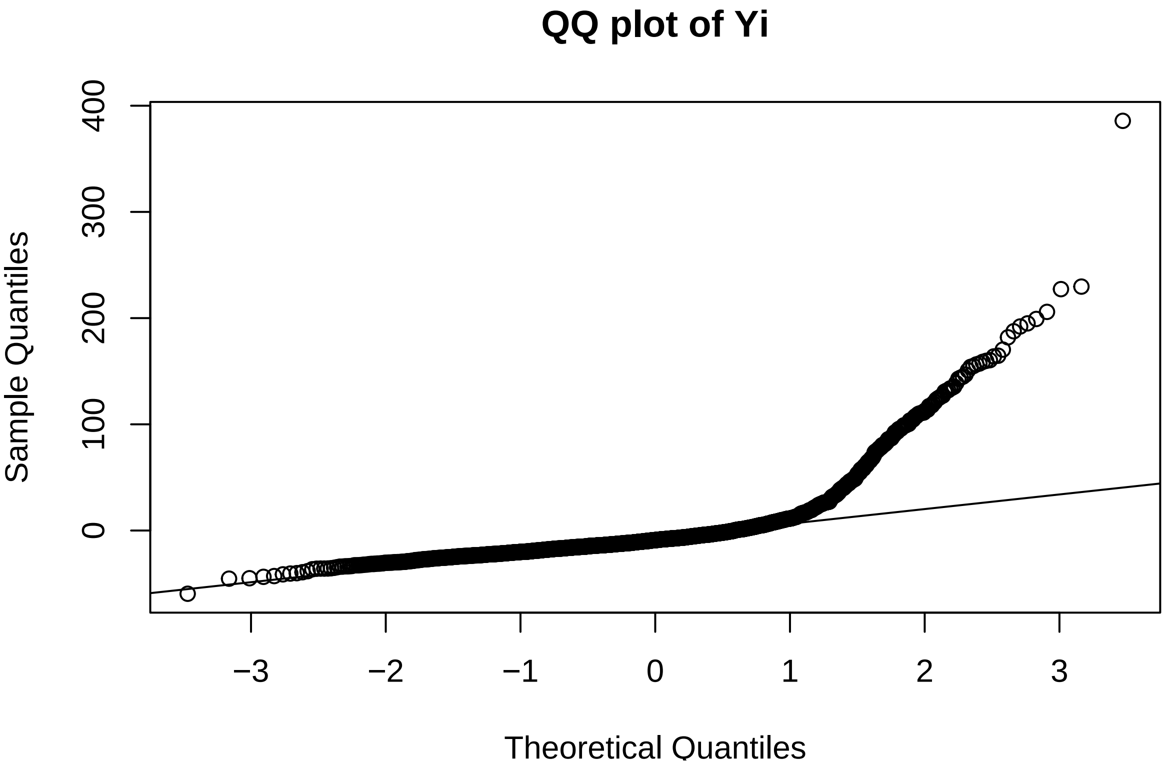
```
model.boxcoxYi = lm(boxcox.Yi ~ x1i + x2i, data = houstonrealesate)
summary(model.boxcoxYi)
```

```
##
## Call:
## lm(formula = boxcox.Yi ~ x1i + x2i, data = houstonrealesate)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0133721 -0.0018268  0.0004361  0.0022037  0.0287460
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.0156602  0.0001397 112.089  < 2e-16 ***
## x1i         -0.0012192  0.0003710  -3.286  0.00103 **
## x2i          0.0213607  0.0007260  29.422  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.004207 on 1919 degrees of freedom
## Multiple R-squared:  0.3332, Adjusted R-squared:  0.3325
## F-statistic: 479.5 on 2 and 1919 DF,  p-value: < 2.2e-16
```

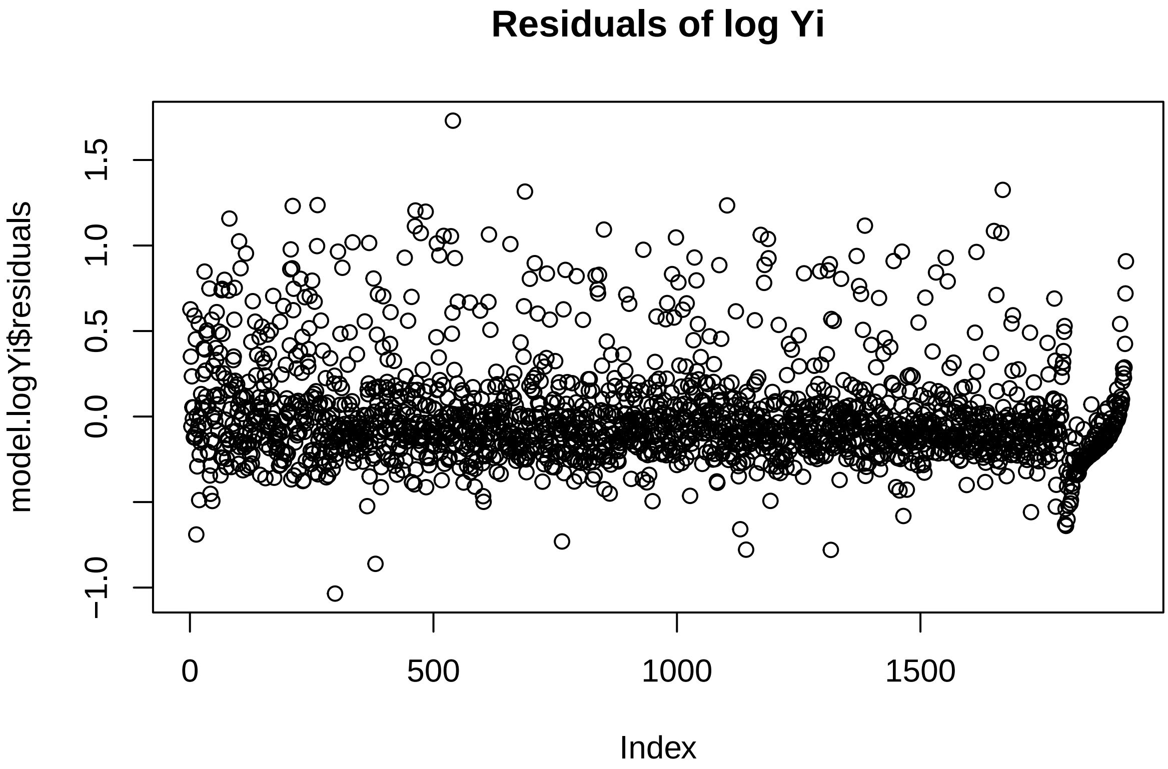
```
plot(model.Yi$residuals, main = "Residuals of Yi")
```



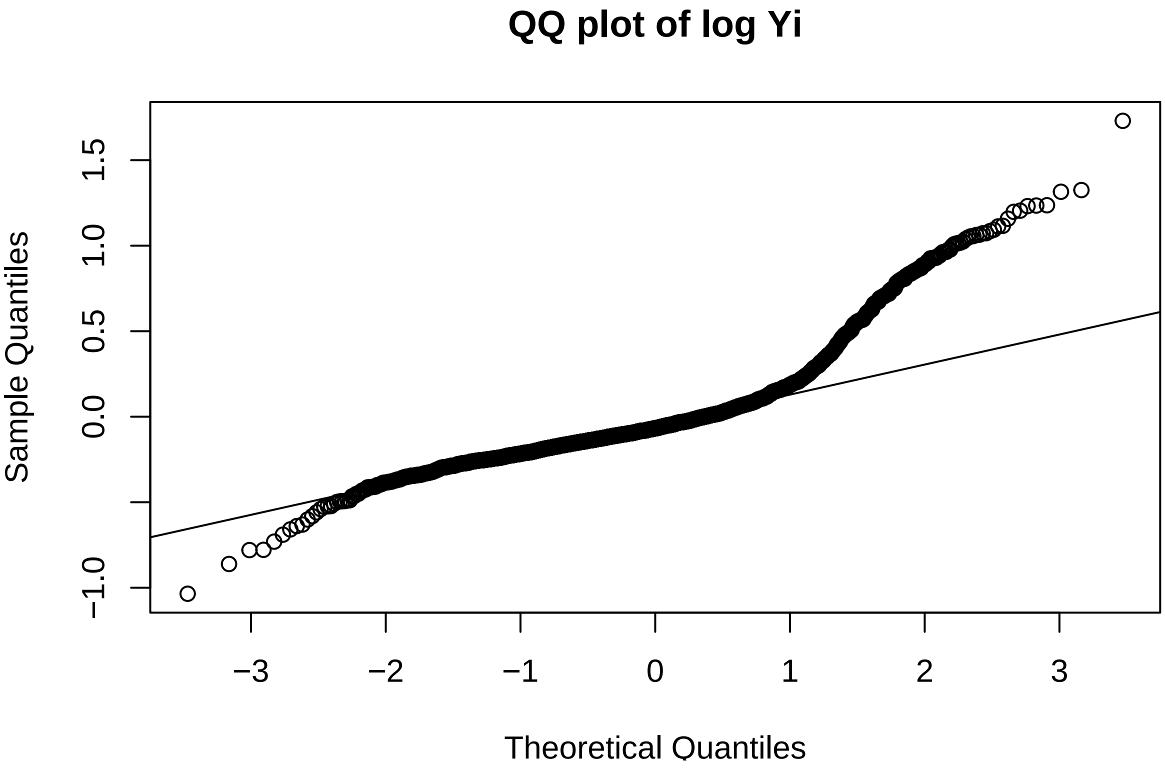
```
qqnorm(model.Yi$residuals, main = "QQ plot of Yi")
qqline(model.Yi$residuals)
```



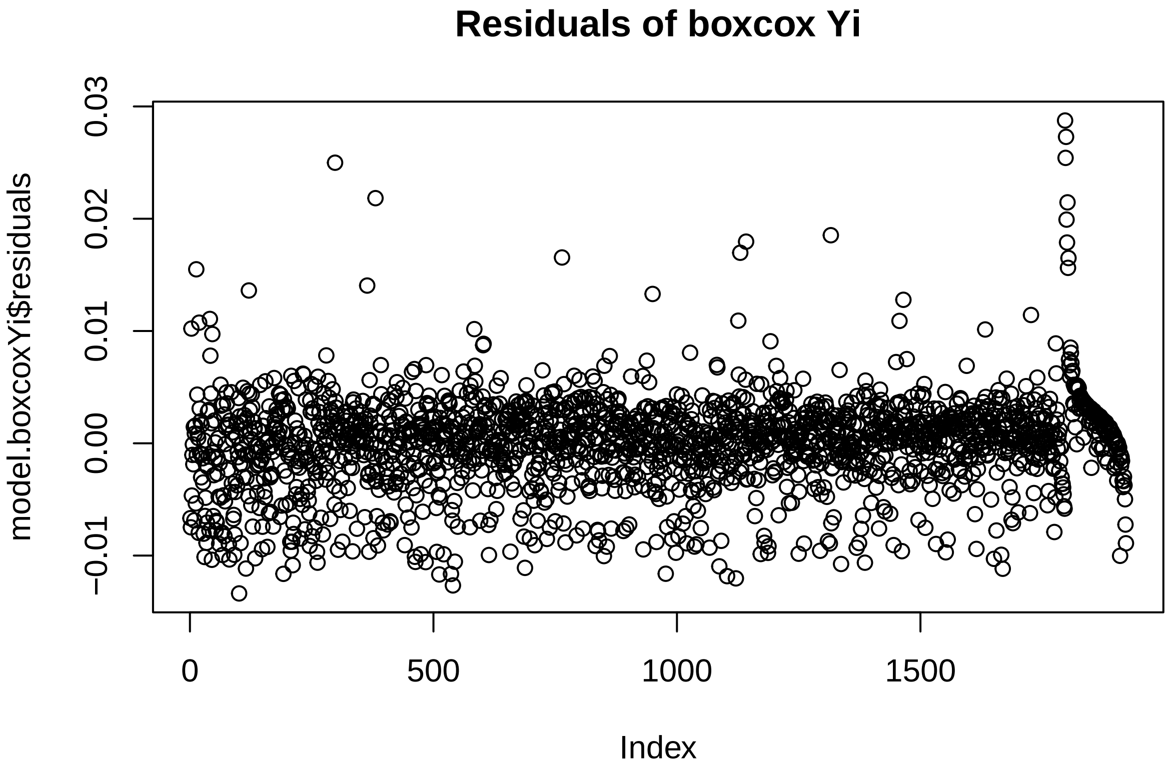
```r
plot(model.logYi$residuals, main = "Residuals of log Yi")
```



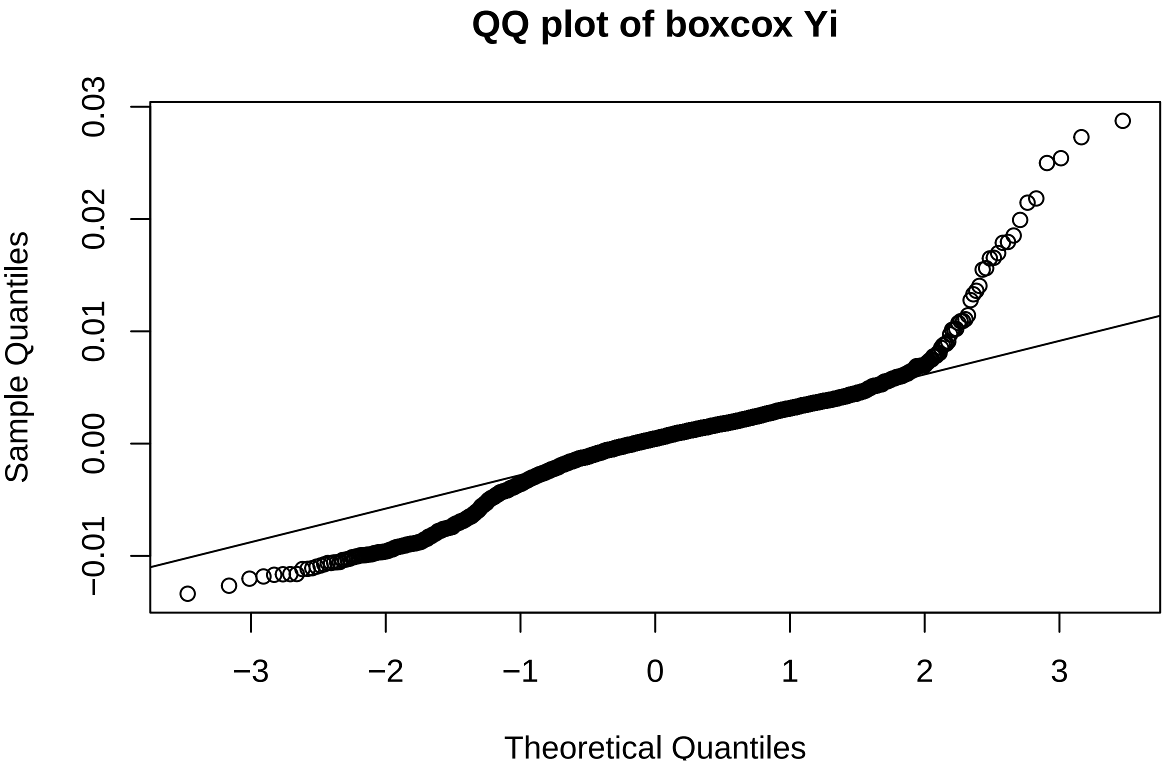
```r
qqnorm(model.logYi$residuals, main = "QQ plot of log Yi")
qqline(model.logYi$residuals)
```



```
plot(model.boxcoxYi$residuals, main = "Residuals of boxcox Yi")
```



```
qqnorm(model.boxcoxYi$residuals, main = "QQ plot of boxcox Yi")
qqline(model.boxcoxYi$residuals)
```



I think log transformed model's plots (both residual and QQ plots) are likely to be the best.Because lower tail looks much better than other two models. However, none of them solved the problem very well as the qqplot of each is not a well fit straight.