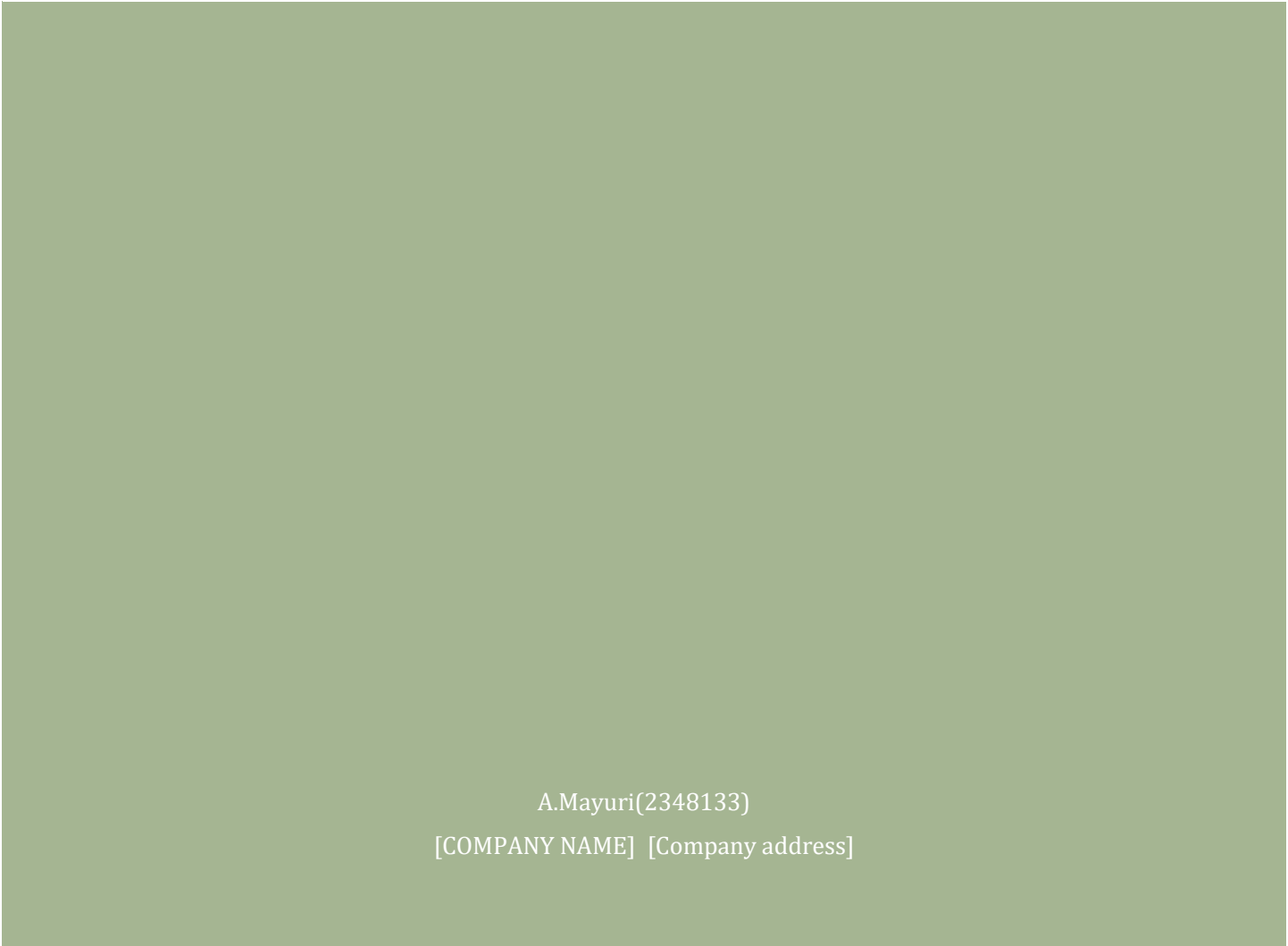




CLATHERATE FORMATION DATA LAB 5



A.Mayuri(2348133)
[COMPANY NAME] [Company address]

Clathrate Formation Data

Lab 5

A.Mayuri(2348133)

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Problem Statement:

1. Fit a suitable linear regression model.
2. Construct a normal probability plot of the residuals. Does there seem to be any problem with the normality and constant variance assumption? If yes, what remedial measure will u perform?
3. Construct and interpret a plot of the residuals.
4. Are the residuals correlated?
5. Is multicollinearity a potential problem in your model? If it is a problem, what is your remedy?
6. Are there any outliers in the data? If it exists, how will you treat it?

Import Dataset

```
library(readxl)
Chem <- read_excel("C:/Users/mayur/Desktop/Mstat/Semesters/Tri-sem2/Regression/Dataset/Chem.xlsx")
View(Chem)
attach(Chem)
```

1) Understanding the Variables Using correlation

```
cor(Chem)

##           x1           x2           y
## x1  1.0000000 -0.1275387  0.5192537
## x2 -0.1275387  1.0000000  0.6838246
## y   0.5192537  0.6838246  1.0000000
```

We observe that there is a positive linear relation between the independent and dependent variable ie, (X1,Y) AND (X2,Y). Also there is a very low correlation between (X1,X2). Hence they are independent to each other.

2) Fitting a Linear Regression Model

```
model1=lm(Chem$y~.,data = Chem)
model1

##
## Call:
## lm(formula = Chem$y ~ ., data = Chem)
##
## Coefficients:
```

```
## (Intercept)          x1          x2
##      11.0870      350.1192      0.1089

summary(model1)

##
## Call:
## lm(formula = Chem$y ~ ., data = Chem)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -9.7716 -4.1656  0.0802  3.8323  8.3349
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.109e+01  1.669e+00   6.642 1.48e-07 ***
## x1           3.501e+02  3.968e+01   8.823 3.38e-10 ***
## x2           1.089e-01  9.983e-03  10.912 1.74e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.782 on 33 degrees of freedom
## Multiple R-squared:  0.8415, Adjusted R-squared:  0.8319
## F-statistic: 87.6 on 2 and 33 DF,  p-value: 6.316e-14
```

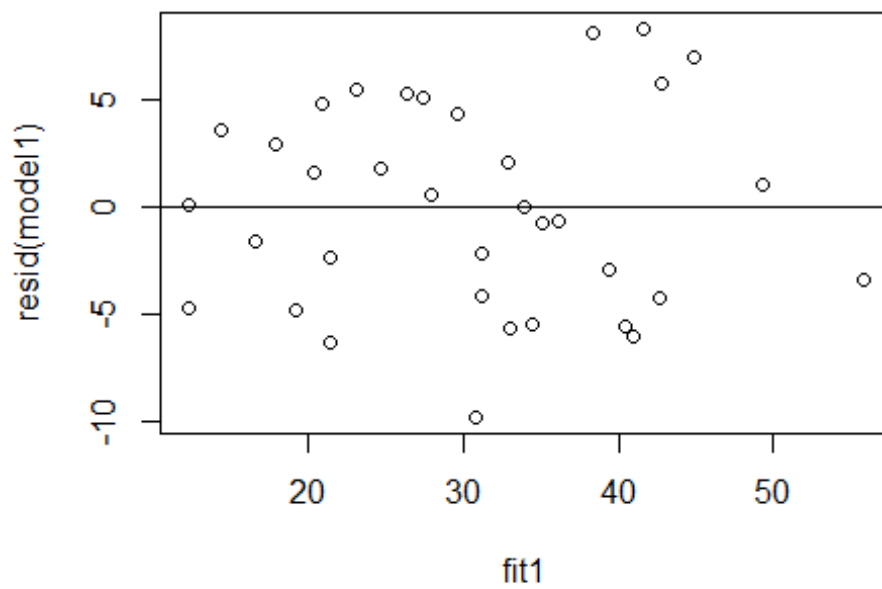
Interpretation: We observe that both the independent variables have a significant linear relationship. since the values of both the independent variables are ≤ 0.05 we reject null hypothesis and accept alternative hypothesis. ie, there exist a linear relationship between parameter and dependent variable.

3) Residual Analysis (Question3)

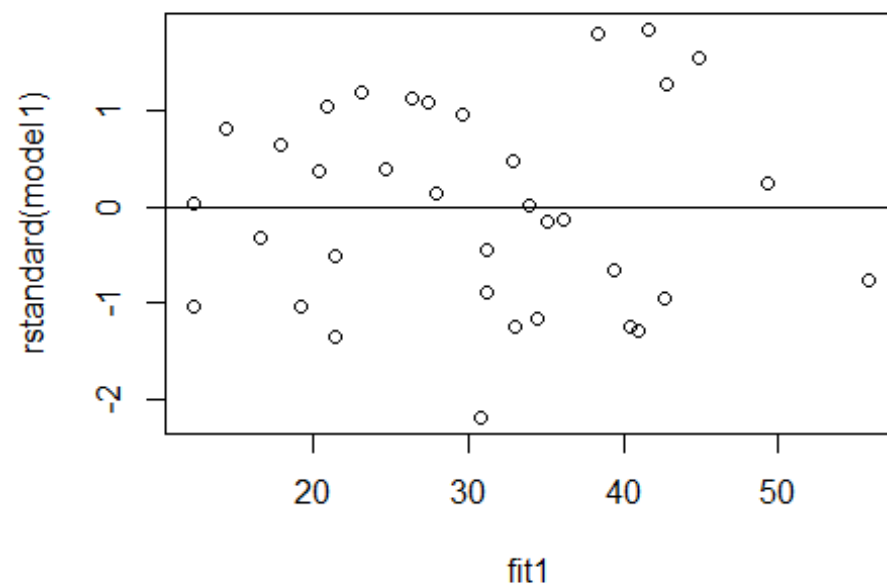
```
fit1=fitted.values(model1)
fit1
```

##	1	2	3	4	5	6	7	8
##	12.17632	16.53370	20.34641	23.06977	26.33780	29.60583	32.87386	36.14190
##	9	10	11	12	13	14	15	16
##	39.40993	42.67796	12.17632	14.35501	17.84091	20.89108	27.42714	33.96321
##	17	18	19	20	21	22	23	24
##	40.49927	19.17871	21.35740	24.62543	27.89346	31.16150	40.96559	21.35740
##	25	26	27	28	29	30	31	32
##	24.62543	31.16150	34.42953	30.77163	32.95032	42.75442	49.29048	55.82655
##	33	34	35	36				
##	35.12901	38.39704	41.66507	44.93311				

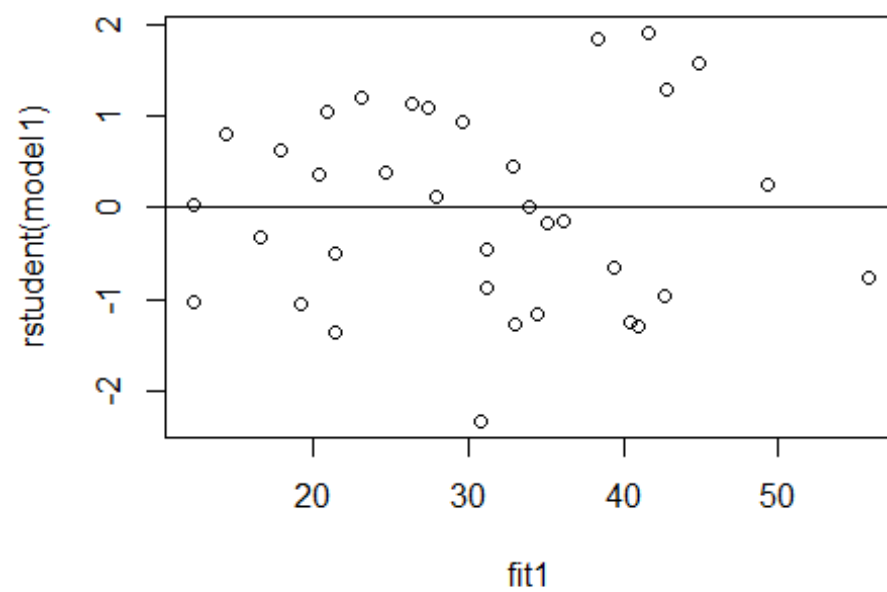
```
# Residual analysis  
plot(fit1,resid(model1))  
abline(0,0)
```



```
plot(fit1,rstandard(model1))#standardized residual model  
abline(0,0)
```



```
plot(fit1,rstudent(model1))# studentized residual model  
abline(0,0)
```



Residual values

```
residual=resid(model1)
```

residual

##	1	2	3	4	5	6
##	-4.67632456	-1.53370131	1.65359404	5.53023358	5.26220102	4.39416846
##	7	8	9	10	11	12
##	2.12613590	-0.64189666	-2.90992922	-4.17796177	0.12367544	3.64498707
##	13	14	15	16	17	18
##	2.95908567	4.80892195	5.07285683	0.03679172	-5.49927340	-4.77870947
##	19	20	21	22	23	24
##	-2.35739785	1.77456959	0.60653704	-2.16149552	-5.96559320	-6.25739785
##	25	26	27	28	29	30
##	1.77456959	-4.16149552	-5.42952808	-9.77163103	-5.65031940	5.74558292
##	31	32	33	34	35	36
##	1.10951780	-3.32654731	-0.72900778	8.10295966	8.33492711	6.96689455

Interpretation: Using standard and studentized residual plot we observe that there is no pattern hence we cannot comment about both the assumption . we will further check it by using the test.

4a)Normality (Question2) and Variance

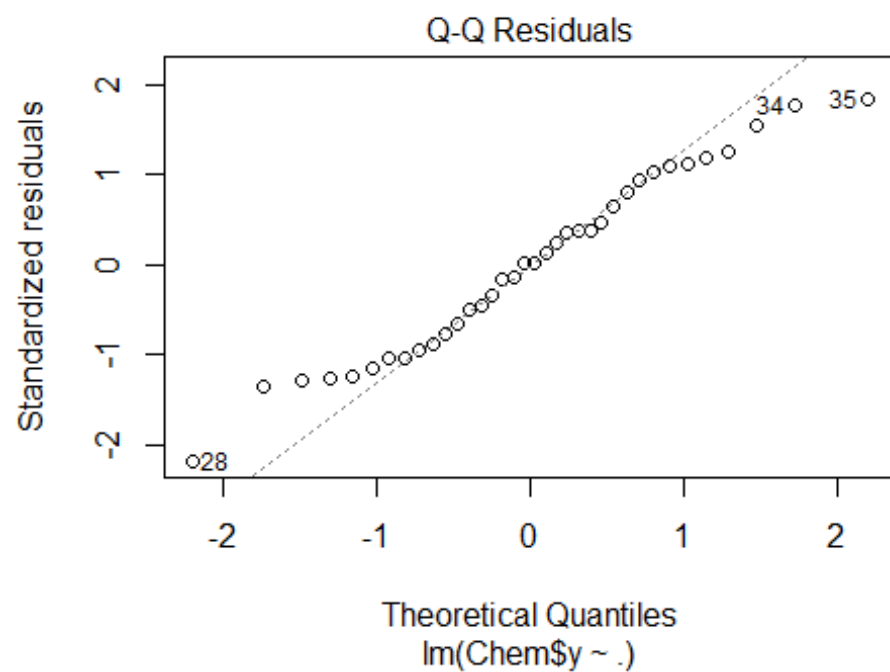
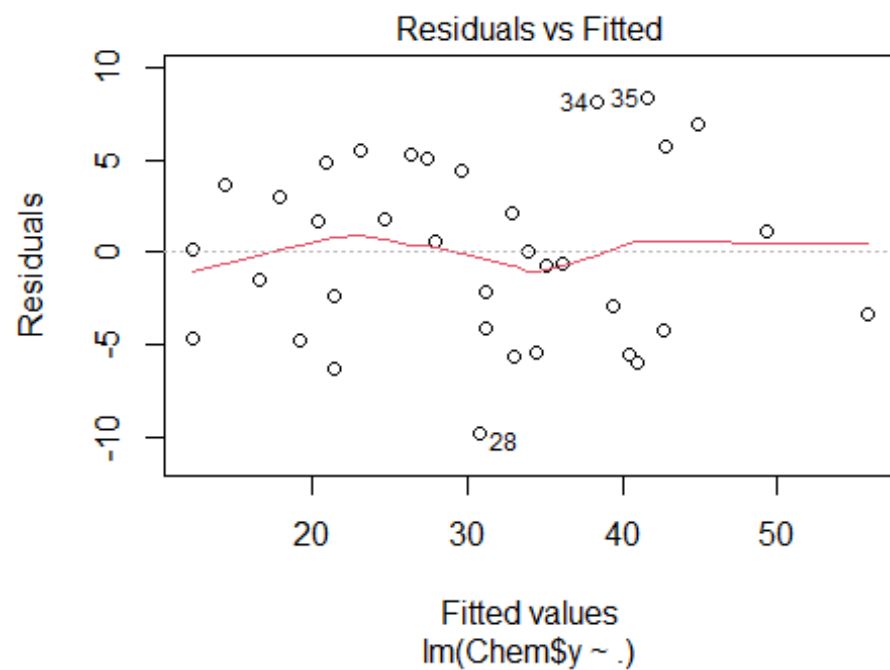
to check for res vales (Normality check)

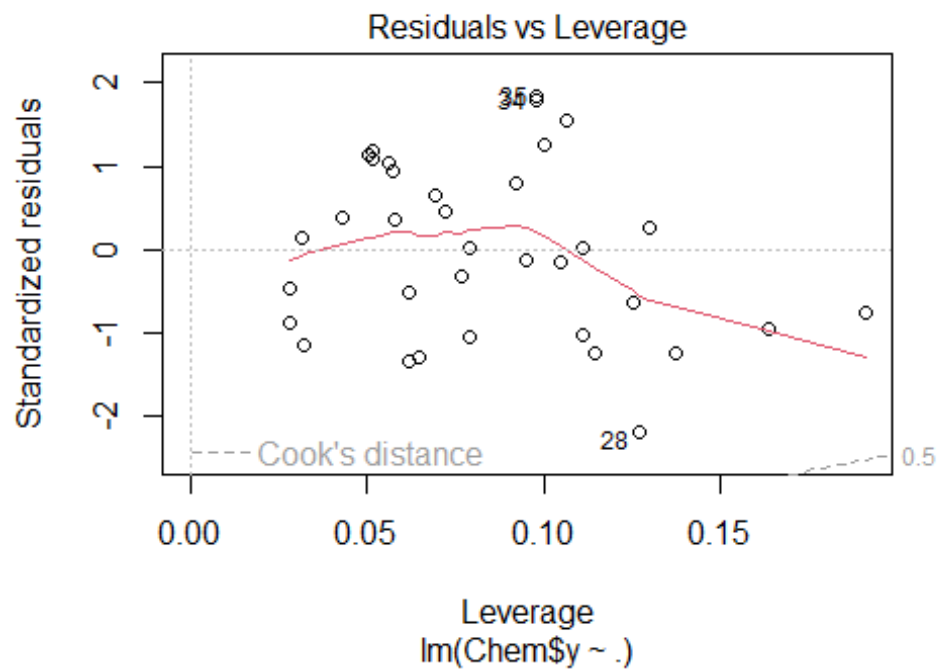
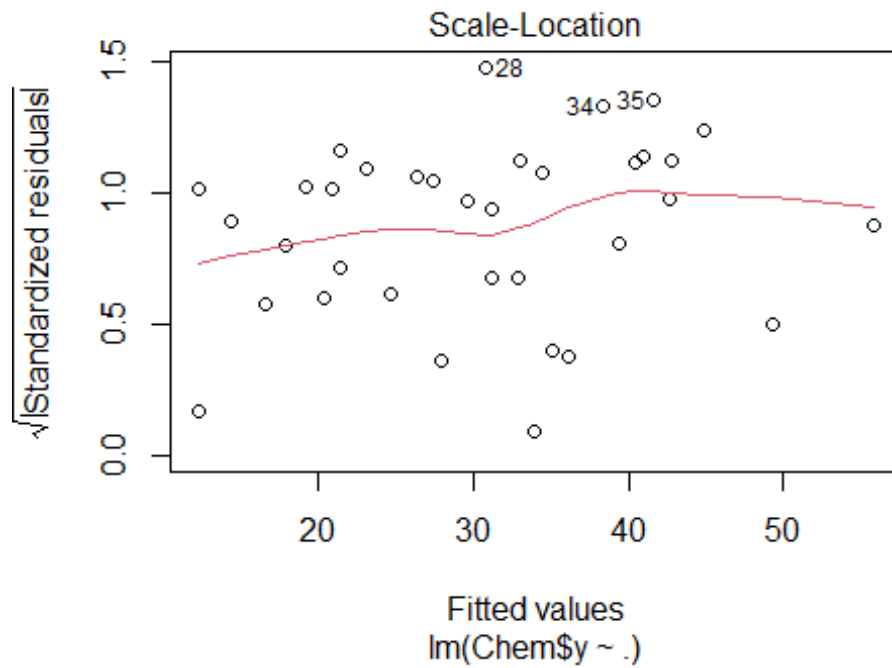
```
re1=rstandard(model1)
```

re1

##	1	2	3	4	5	6
##	-1.037115175	-0.333758043	0.356275584	1.187266673	1.129176925	0.946369325
##	7	8	9	10	11	12
##	0.461534357	-0.141070312	-0.650555446	-0.955185630	0.027428737	0.799919557
##	13	14	15	16	17	18
##	0.641316052	1.035126037	1.089371414	0.008015465	-1.237884530	-1.041331230
##	19	20	21	22	23	24
##	-0.508984388	0.379286883	0.128876651	-0.458446375	-1.289781318	-1.351031103
##	25	26	27	28	29	30
##	0.379286883	-0.882640059	-1.154169443	-2.186886007	-1.255401518	1.266420897

```
##          31          32          33          34          35
36
##  0.248696768 -0.773278110 -0.161131924  1.783666308  1.835215764  1.541125
067
plot(model1)
```





```
shapiro.test(re1)
```

```
##
```

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

```
##  
## data:  re1  
## W = 0.97171, p-value = 0.474
```

Interpretation: For Normality assumption using Shapiro Wilk Test at 0.05 level of significance the p value ≥ 0.05 thus we fail to reject null thus the residual follow normal distribution hence the assumption of errors. This is also confirmed using the QQ residual plot

4b) Hypothesis testing for constant variance using BP test :

test for errors have constant variance through errors. use the fitted model.

H_0 : error have const variance H_1 : error have not const variance

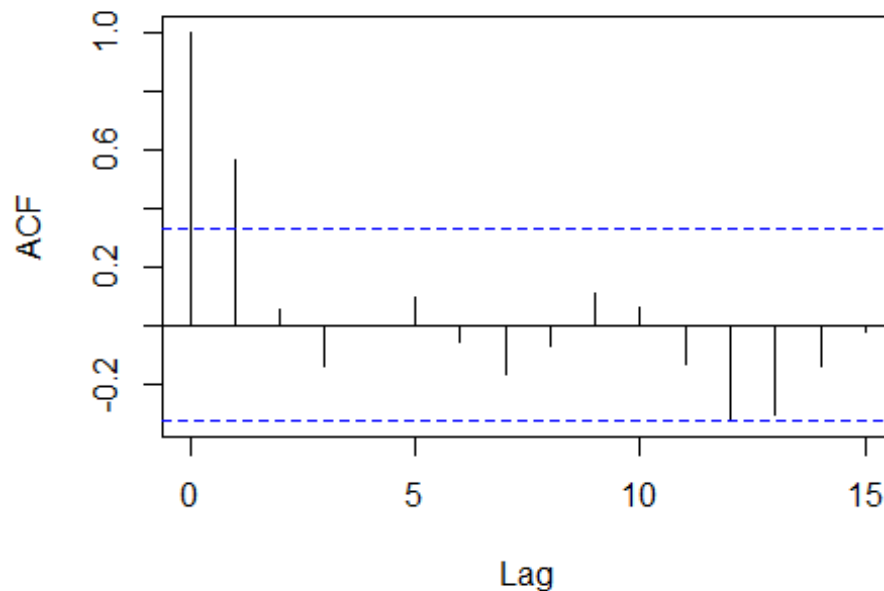
```
library(lmtest)  
## Loading required package: zoo  
##  
## Attaching package: 'zoo'  
## The following objects are masked from 'package:base':  
##  
##      as.Date, as.Date.numeric  
bptest(model1)  
##  
## studentized Breusch-Pagan test  
##  
## data:  model1  
## BP = 8.0945, df = 2, p-value = 0.01747
```

Interpretation: since p-value is ≤ 0.05 we reject H_0 , thus there is no constant variance . hence the assumption of constant variance is not validated . we can perform a log transformation to the dependent variable and try to redefine the model.

5a) Autocorrelation (question4)

```
acf(residual)
```

Series residual



Interpretation: ACF at 0 is always 1. and all acf points are not within the threshold lines from lag 1 it indicates that there is a significant autocorrelation among the residual series. However we can also confirm the same with durbin watson test procedure.

b) Durbin watson for ACF

$H_0: \rho=0$ there is no autocorrelation $H_1: \rho \neq 0$ there is autocorrelation

```
dwtest(model1)

##
##  Durbin-Watson test
##
## data:  model1
## DW = 0.77943, p-value = 6.004e-06
## alternative hypothesis: true autocorrelation is greater than 0
```

Interpretation: at 5 % level of significance, the p value ($6.004e-06$) < 0.05 , we reject the null hypothesis that there is a significant auto-correlation. ie, $\rho \neq 0$.

6) Multi-collinearity (Question5):

We observe that there could be no multi-collinearity between independent variable since the correlation between them is $(-0.12) < 0.7$. hence their VIF would be less than 5.

For confirmation,

```
library(car)

## Loading required package: carData

vif(model1)

##          x1          x2
## 1.016535 1.016535
```

Interpretation: As stated the $VIF \leq 5$ thus there is no multi-collinearity.

7) Outliers (Question 6)

```
rstandard(model1)
```

##	1	2	3	4	5
6					
##	-1.037115175	-0.333758043	0.356275584	1.187266673	1.129176925
325					
##	7	8	9	10	11
12					
##	0.461534357	-0.141070312	-0.650555446	-0.955185630	0.027428737
557					
##	13	14	15	16	17
18					
##	0.641316052	1.035126037	1.089371414	0.008015465	-1.237884530
230					
##	19	20	21	22	23
24					
##	-0.508984388	0.379286883	0.128876651	-0.458446375	-1.289781318
103					
##	25	26	27	28	29
30					
##	0.379286883	-0.882640059	-1.154169443	-2.186886007	-1.255401518
897					
##	31	32	33	34	35
36					
##	0.248696768	-0.773278110	-0.161131924	1.783666308	1.835215764
067					

Interpretation: Here we observe that there is no observation below -3 and above 3. hence there are no outliers.