ASSIGNMENT 2

Applied Econometrics and Time Series Analysis

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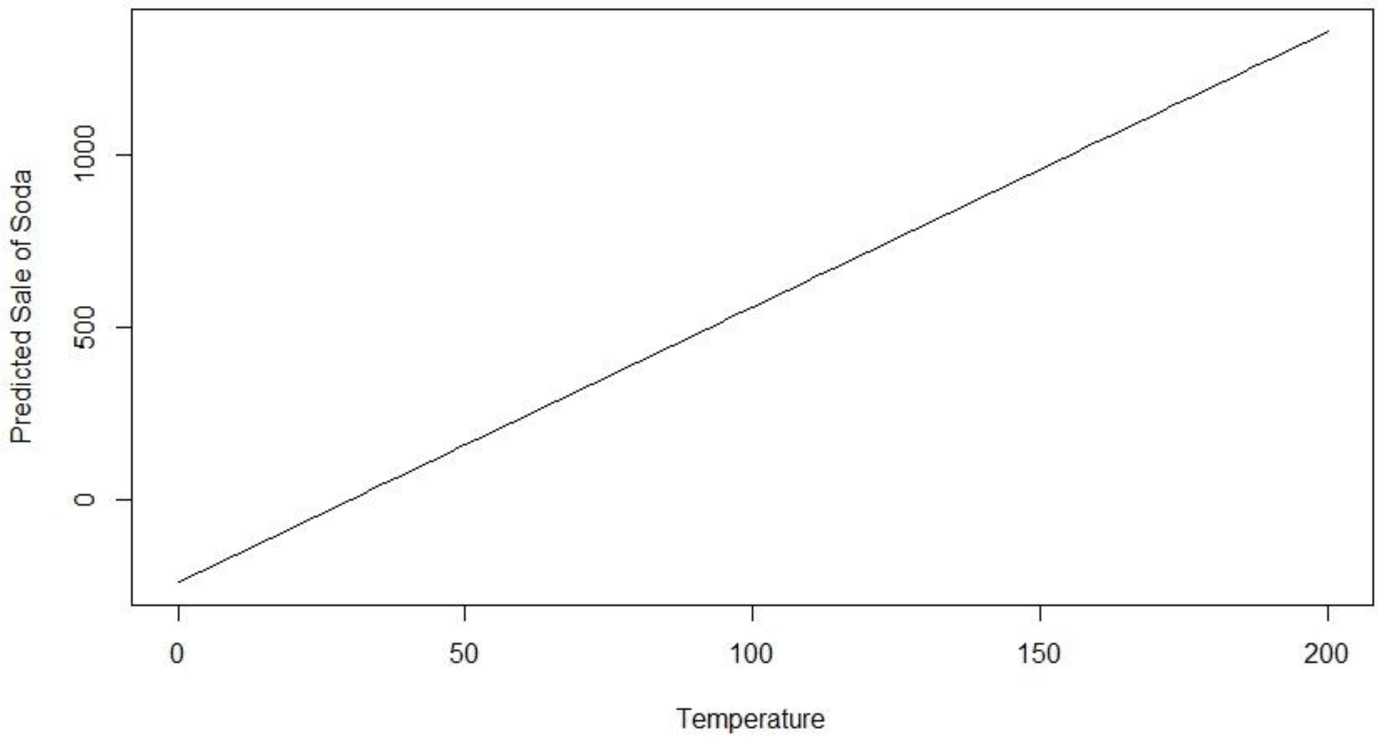
Q 2.6 d



Q 10 b

```
R version 3.2.5 (2016-04-14) -- "Very, Very Secure Dishes"
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Platform: x86_64-w64-mingw32/x64 (64-bit)

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Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> library(haven)
> capm4 <- read_dta("D:/Class Notes/Fall 17 Classes/ECON/Data_sets/capm4.dta")
> View(capm4)
> nrow(capm4)
[1] 132
> capm4$Disney_Y=capm4$dis - capm4$riskfree
> capm4$GE_Y=capm4$ge - capm4$riskfree
> capm4$GM_Y=capm4$gm - capm4$riskfree
> capm4$IBM_Y=capm4$ibm - capm4$riskfree
> capm4$MICROSOFT_Y=capm4$msft - capm4$riskfree
> capm4$EXXON_Y=capm4$xom - capm4$riskfree
> capm4$Risk_X=capm4$mkt - capm4$riskfree
> regDisney <- lm(Disney_Y ~ Risk_X)
```

```
Error in eval(expr, envir, enclos) : object 'Disney_Y' not found
> regDisney <- lm(Disney_Y ~ Risk_X, data = capm4)
> summary(regDisney)

Call:
lm(formula = Disney_Y ~ Risk_X, data = capm4)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.182443 -0.028738 -0.007054  0.027853  0.276871 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.00366    0.00694  -0.527    0.599    
Risk_X       0.91460    0.12015   7.612 4.87e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.06848 on 130 degrees of freedom
Multiple R-squared:  0.3083,	Adjusted R-squared:  0.303 
F-statistic: 57.94 on 1 and 130 DF,  p-value: 4.866e-12

> regGE <- lm(GE_Y ~ Risk_X, data = capm4)
> summary(regGE)

Call:
lm(formula = GE_Y ~ Risk_X, data = capm4)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.156837 -0.036767 -0.004774  0.034106  0.181055 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.005324   0.005518  -0.965    0.336    
Risk_X       0.858974   0.095525   8.992 2.48e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05444 on 130 degrees of freedom
Multiple R-squared:  0.3835,	Adjusted R-squared:  0.3787 
F-statistic: 80.86 on 1 and 130 DF,  p-value: 2.477e-15

> regGM <- lm(GM_Y ~ Risk_X, data = capm4)
> summary(regGM)

Call:
lm(formula = GM_Y ~ Risk_X, data = capm4)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.40666 -0.06120 -0.00273  0.06278  0.29125 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.007248   0.011393  -0.636    0.526    
Risk_X       1.146838   0.197242   5.814 4.46e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1124 on 130 degrees of freedom
Multiple R-squared:  0.2064,	Adjusted R-squared:  0.2003 
F-statistic: 33.81 on 1 and 130 DF,  p-value: 4.464e-08
```

```
> regIBM <- lm(IBM_Y ~ Risk_X, data = capm4)
> summary(regIBM)

Call:
lm(formula = IBM_Y ~ Risk_X, data = capm4)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.262998 -0.039921 -0.002788  0.038935  0.269202 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.010207   0.007114   1.435    0.154    
Risk_X      1.148245   0.123152   9.324 3.83e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.07019 on 130 degrees of freedom
Multiple R-squared:  0.4007,	Adjusted R-squared:  0.3961 
F-statistic: 86.93 on 1 and 130 DF,  p-value: 3.829e-16

> regMicrosoft <- lm(MICROSOFT_Y ~ Risk_X, data = capm4)
> summary(regMicrosoft)

Call:
lm(formula = MICROSOFT_Y ~ Risk_X, data = capm4)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.26864 -0.05569 -0.00845  0.04261  0.35678 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.013737   0.009061   1.516    0.132    
Risk_X      1.259919   0.156861   8.032 5.03e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0894 on 130 degrees of freedom
Multiple R-squared:  0.3317,	Adjusted R-squared:  0.3265 
F-statistic: 64.51 on 1 and 130 DF,  p-value: 5.034e-13

> regExxon <- lm(EXXON_Y ~ Risk_X, data = capm4)
> summary(regExxon)

Call:
lm(formula = EXXON_Y ~ Risk_X, data = capm4)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.127422 -0.032706 -0.002982  0.027316  0.216216 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.007966   0.005118  -1.556    0.122    
Risk_X       0.461258   0.088607   5.206 7.35e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0505 on 130 degrees of freedom
Multiple R-squared:  0.1725,	Adjusted R-squared:  0.1661 
F-statistic:  27.1 on 1 and 130 DF,  p-value: 7.349e-07
```

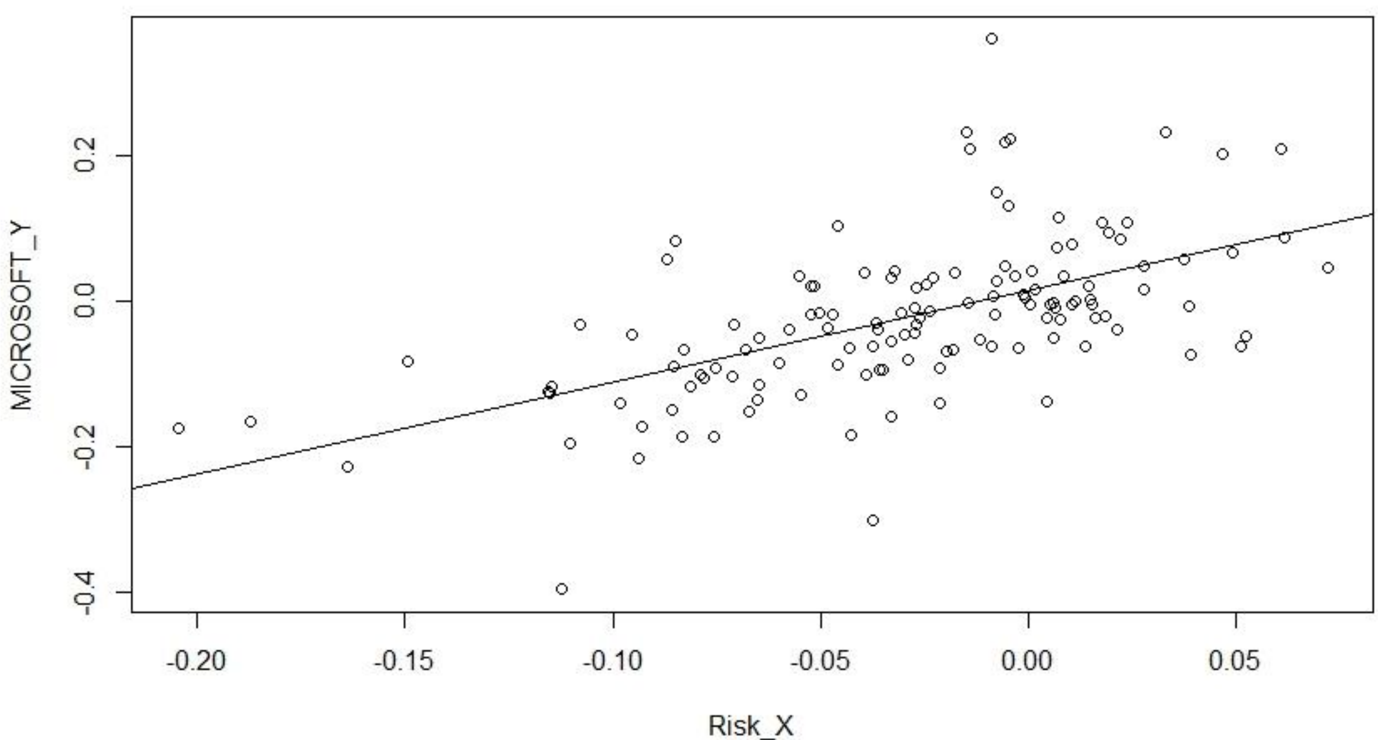
Microsoft appears to be most aggressive with Beta 2 of 1.2599 and Exxon appears to be most defensive with Beta 2 of 0.4612.

Q 10. C

Company	Alpha
Disney	-0.0036
GE	-0.0053
GM	-0.0072
IBM	0.0102
Microsoft	0.0137
Exxon	-0.0079

As all the alpha values are almost equal to zero, we can say that it is consistent with Finance Theory.

```
plot (MICROSOFT_Y ~ Risk_X, data = capm4)
> abline(regMicrosoft)
```



Q 10. D

```
> regDisney <- lm(Disney_Y ~ Risk_X -1, data = capm4)
> summary(regDisney)

Call:
lm(formula = Disney_Y ~ Risk_X - 1, data = capm4)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.18236 -0.03291 -0.01024  0.02550  0.27625 

Coefficients:
       Estimate Std. Error t value Pr(>|t|)    
Risk_X   0.9471     0.1029   9.204 7.15e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.06829 on 131 degrees of freedom
Multiple R-squared:  0.3927,	Adjusted R-squared:  0.3881 
F-statistic:  84.7 on 1 and 131 DF,  p-value: 7.145e-16

> regGE <- lm(GE_Y ~ Risk_X -1, data = capm4)
> summary(regGE)

Call:
lm(formula = GE_Y ~ Risk_X - 1, data = capm4)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.163981 -0.042103 -0.008105  0.029787  0.180365 

Coefficients:
       Estimate Std. Error t value Pr(>|t|)    
Risk_X  0.90619    0.08202   11.05   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05443 on 131 degrees of freedom
Multiple R-squared:  0.4824,	Adjusted R-squared:  0.4784 
F-statistic: 122.1 on 1 and 131 DF,  p-value: < 2.2e-16

> regGM <- lm(GM_Y ~ Risk_X -1, data = capm4)
> summary(regGM)

Call:
lm(formula = GM_Y ~ Risk_X - 1, data = capm4)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.41527 -0.06368 -0.00793  0.05847  0.28786 

Coefficients:
       Estimate Std. Error t value Pr(>|t|)    
Risk_X    1.211      0.169   7.166 5.03e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1122 on 131 degrees of freedom
Multiple R-squared:  0.2816,	Adjusted R-squared:  0.2761 
F-statistic: 51.35 on 1 and 131 DF,  p-value: 5.026e-11

> regIBM <- lm(IBM_Y ~ Risk_X - 1, data = capm4)
> summary(regIBM)

Call:
lm(formula = IBM_Y ~ Risk_X - 1, data = capm4)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.251126 -0.030083  0.003168  0.046038  0.278618 

Coefficients:
```

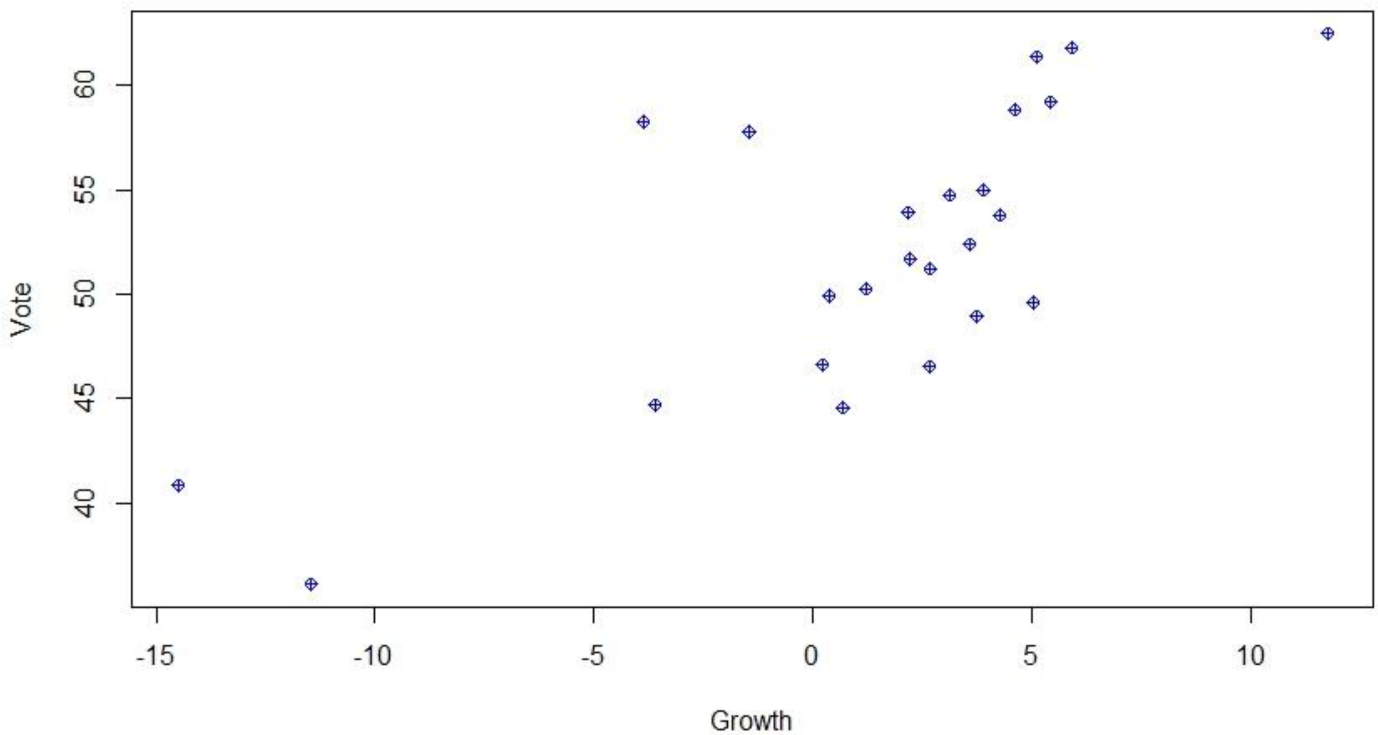
```
       Estimate Std. Error t value Pr(>|t|)
Risk_X   1.0577     0.1062   9.961   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.07047 on 131 degrees of freedom
Multiple R-squared:  0.431,    Adjusted R-squared:  0.4266
F-statistic: 99.21 on 1 and 131 DF,  p-value: < 2.2e-16

> regMicrosoft <- lm(MICROSOFT_Y ~ Risk_X -1, data = capm4)
> summary(regMicrosoft)

Call:
lm(formula = MICROSOFT_Y ~ Risk_X - 1, data = capm4)

Residuals:
     Min       1Q   Median       3Q      Max
-0.26857 -0.04153  0.00489  0.05142  0.36945

Coefficients:
       Estimate Std. Error t value Pr(>|t|)
Risk_X   1.1381     0.1354   8.407 6.18e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.08984 on 131 degrees of freedom
Multiple R-squared:  0.3504,   Adjusted R-squared:  0.3455
F-statistic: 70.67 on 1 and 131 DF,  p-value: 6.184e-14

> regExxon <- lm(EXXON_Y ~ Risk_X - 1, data = capm4)
> summary(regExxon)

Call:
lm(formula = EXXON_Y ~ Risk_X - 1, data = capm4)

Residuals:
      Min        1Q    Median        3Q       Max
-0.133878 -0.040743 -0.006133  0.019296  0.208411

Coefficients:
       Estimate Std. Error t value Pr(>|t|)
Risk_X  0.53191    0.07651   6.952 1.53e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05077 on 131 degrees of freedom
Multiple R-squared:  0.2695,   Adjusted R-squared:  0.2639
F-statistic: 48.33 on 1 and 131 DF,  p-value: 1.531e-10
```

Company	**Alpha != 0**	**Alpha = 0**
Disney	0.91460	0.9471
GE	0.858974	0.90619
GM	1.146838	1.211
IBM	1.148245	1.0577
Microsoft	1.259919	1.1381
Exxon	0.461258	0.53191

As we can see, there is not much difference between the beta values. Exxon still remains the most defensive and GM goes to most aggressive instead of Microsoft.

Q14. A

There appear to be a positive relation between vote and growth.

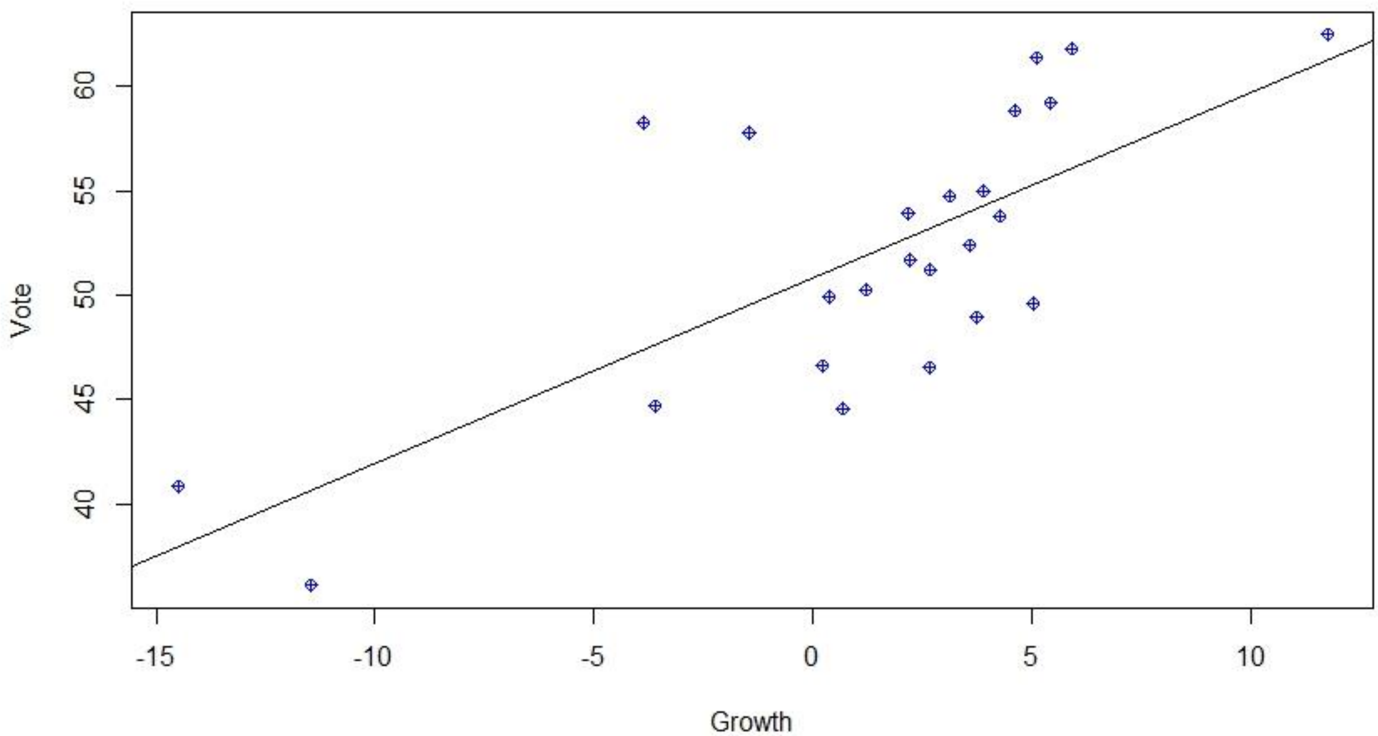


Q14. b

```
> fit <- lm(vote ~ growth, data = fair4, fair4$year>1915)
> summary(fit)

Call:
lm(formula = vote ~ growth, data = fair4, subset = fair4$year >
    1915)

Residuals:
   Min     1Q Median     3Q    Max
-6.866 -3.334 -1.003  3.004 10.826

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  50.8484     1.0125  50.218  < 2e-16 ***
growth        0.8859     0.1819   4.871  7.2e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.798 on 22 degrees of freedom
Multiple R-squared:  0.5189,	Adjusted R-squared:  0.497
F-statistic: 23.73 on 1 and 22 DF,  p-value: 7.199e-05
```

Estimated Vote = 50.8484 + 0.8859* Growth

The model can be interpreted as, when everything else is kept constant, every one percent additional increase in growth (GDP) will increase the vote share by 0.8859 of the incumbent party.



Q14 C

```
> fit <- lm(vote ~ growth, data = fair4, fair4$year>1915 & fair4$year<2008)
> summary(fit)

Call:
lm(formula = vote ~ growth, data = fair4, subset = fair4$year >
    1915 & fair4$year < 2008)

Residuals:
   Min     1Q Median     3Q    Max
-7.065 -2.690 -1.036  2.929 10.590

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  51.0533     1.0379  49.187  < 2e-16 ***
growth        0.8780     0.1825   4.811 9.39e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4.81 on 21 degrees of freedom
Multiple R-squared:  0.5243,   Adjusted R-squared:  0.5016
F-statistic: 23.14 on 1 and 21 DF,  p-value: 9.387e-05


> fair4[fair4$year>2007, ]
```

```
# A tibble: 1 × 9
   year  vote party person duration   war growth inflation goodnews
  <dbl> <dbl> <dbl>  <dbl>    <dbl> <dbl>  <dbl>     <dbl>    <dbl>
1  2008  46.6    -1      0        1     0   0.22      2.88        3
```

Growth in 2008 = 0.22

Estimating the model

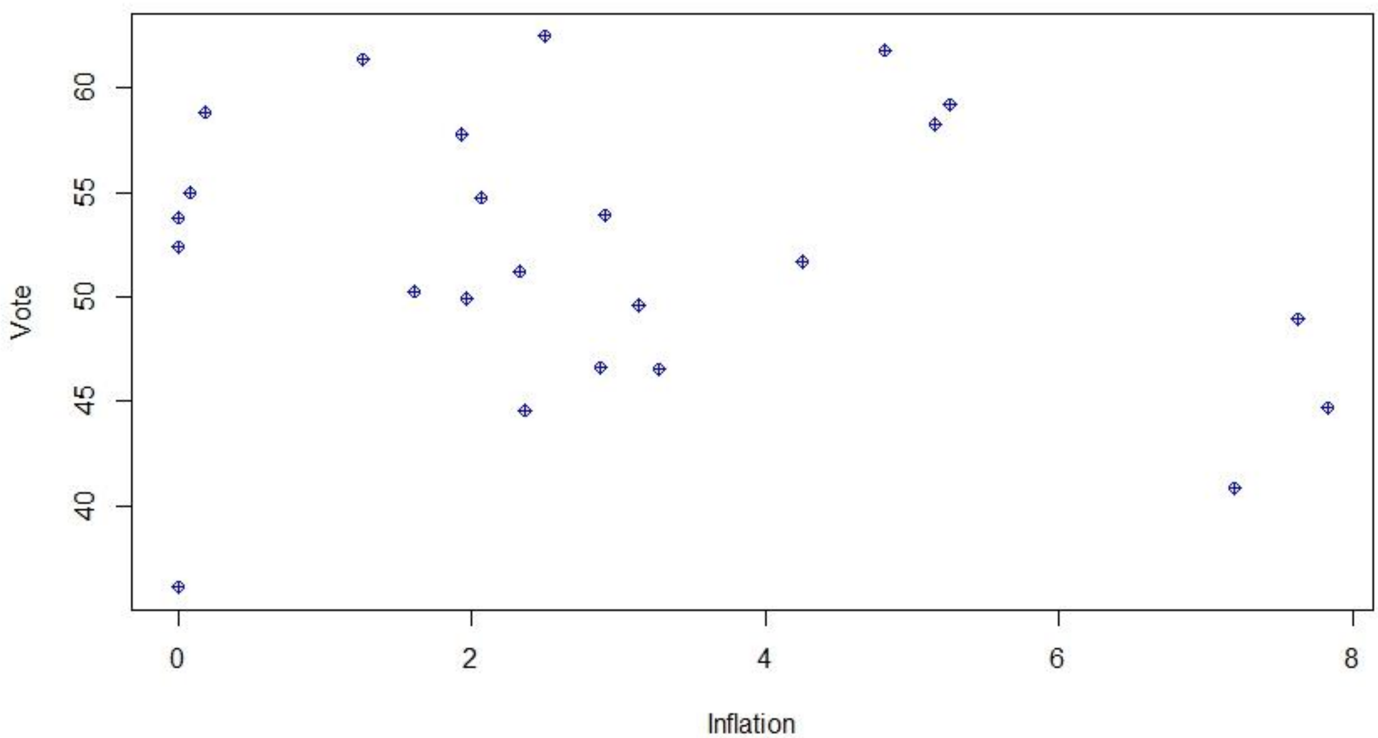
Predicted Vote Share = 51.0533 + 0.8780*Growth

Predicted Vote Share = 51.2464

Actual Vote Share = 46.6

As we can see there is a significant difference in predicted vote share and actual vote share. We can say that our model did not predict the vote share correctly.

Q14 D




```
> fit <- lm(vote ~ inflation, data = fair4, fair4$year>1915)
> summary(fit)

Call:
lm(formula = vote ~ inflation, data = fair4, subset = fair4$year >
    1915)
```

```
Residuals:
     Min       1Q   Median       3Q      Max
-17.2887  -3.2734  -0.4371   5.2854  10.5206

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  53.4077     2.2500  23.737   <2e-16 ***
inflation    -0.4443     0.5999  -0.741    0.467
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.833 on 22 degrees of freedom
Multiple R-squared:  0.02433, Adjusted R-squared:  -0.02002
F-statistic: 0.5485 on 1 and 22 DF,  p-value: 0.4668
```

Predicted vote share = 53.4077 – 0.4443*inflation

We can say that there is a negative correlation in inflation and vote share.

The model can be interpreted as, when everything else is constant, for every 1 percent increase in inflation during administration’s first 15 quarters the vote share will decrees by 0.4443%.

We can say that lower the inflation, there is a larger possibility of the party winning the election.