Obaid Masih

Assignment 10 - Time Series

Please complete the following questions found in your textbook.

Question 9.2 (p.382-383)

$$\widehat{SALES}_t = 25.34 + 1.842\ ADV_t + 3.802\ ADV_{t-1} + 2.265\ ADV_{t-2}$$

a) It is a distributed lag model with 2 lags.
Increasing 1 million in ADV will have a sustained effect of (1.842 + 3.802 + 2.265) $7.9MM.
Impact is greatest at the 2nd week which is $3.802 MM.

adv is impact multiplier = 1.842
adv + advt-1 is interim multiplier for 1 period = 5.644
adv + advt-1 + advt-2 is the interim multiplier for 2 periods = 7.909
adv + advt-1 + advt-2 is total multiplier for all period = 7.909

b)

				5% level	10 % level
	Estimate	var	T value	Tc (0.95,101)	Tc(0.9,101)
adv	1.842	1.3946	1.559785201	1.645	1.282
adv(t-1)	3.802	2.1606	2.586574112	1.645	1.282
adv(t-2)	2.265	1.4214	1.899809481	1.645	1.282

Adv is significant at 10% level but not at 5% level
Adv(t-1) is significant at both 5% & 10% level
Adv (t-2) is significant at both 5% level and 10% level

c)

95% interval for impact multiplier
tc = 1.96

se = sqrt(1.3946)
beta = 1.842
Lo = beta-(1.96*se) = -0.472
Hi= beta+ (1.96*se) = 4.15

[-0.472 , 4.15]
95% interval for one period interim multiplier
tc = 1.96

se = sqrt(1.3946 + 2.1606 + 2 *(-1.0406))
beta = 1.842 + 3.802
Lo = beta-(1.96*se) = 3.263
Hi= beta+ (1.96*se) = 8.02

[3.262 , 8.02]

95% interval for two period interim multiplier
tc = 1.96
se = SQRT(var_ADV + var_ADV t-1 + var_ ADVT-2+ 2 cov(ADV, ADV t-1) + 2cov(ADV t-1, ADV t-2) + 2(ADV t-2, ADV)
se = sqrt(1.3946 + 2.1606 + 1.414 + 2 *(-1.0406) + 2*(-1.0367) + 2*(0.098))
beta = 1.842 + 3.802 + 2.265
Lo = beta-(1.96*se) # 5.9386
Hi= beta+ (1.96*se) # 9.8793

[5.938 , 9.879]

<u>Question 9.4 (p.383) - for part 9.4(b) please refer to equation 9.17 page 349</u>

a)

t	1	2	3	4	5	6	7	8	9	10
e	0.28	-0.31	-0.09	0.03	-0.37	-0.17	-0.39	-0.03	0.03	1.02
e^2	0.0784	0.0961	0.0081	0.0009	0.1369	0.0289	0.1521	0.0009	0.0009	1.0404
et * t-1		-0.0868	0.0279	-0.0027	-0.0111	0.0629	0.0663	0.0117	-0.0009	0.0306
et*t-2			-0.0252	-0.0093	0.0333	-0.0051	0.1443	0.0051	-0.0117	-0.0306

r1	0.063423
r2	0.065302

b)

$$Z = \frac{r_k - 0}{\sqrt{1/T}} = \sqrt{T} r_k \sim N(0,1) \qquad (9.17)$$

Test significance thru T test at 5% level
H0: r1 =0
r1 is not equal to 0

T = 10 and Z for r1 = 0.200
Critical value for z = 1.9 (from the table)

Since 1.9 >> 0.2 so we CANNOT reject the null

Test significance thru T test at 5% level
H0: r2 =0
R2 is not equal to 0

T = 10 and Z for r2 = 0.206
Critical value for z = 1.9 (from the table)

Since 1.9 >> 0.206 so we CANNOT reject the null

Question 9.6 (p. 384) Note: in part (b) use only the correlogram

$$\widehat{DHOMES_t} = -2.077 - 53.51 DIRATE_{t-1} \qquad \text{obs} = 218$$
$$(\text{se}) \qquad (3.498) \quad (16.98)$$

(part a)

1 % change in Interest rate that happened in previous month is estimated to decrease Home sale numbers by 53,510 homes in the current month.

95% confidence interval for DIRATE

Beta +/- se*tc tc =1.96

-53.51 + 16.98(1.96) = -20.22
-53.51 – 16.98(1.96) =- 86.79

[-86.79, -20.22]

B)

Use t test to see whether there is serial correlation present or not

Ho: B0 = 0 --- there is no serial correlation present
H1 B0 is not equal to 0 --- there is serial correlation present

Critical value of t = 1.96

t = b3/se(b3)

T value for B3 = (-0.3306)/0.0649
T value for B3 = -5.093

Since, |t| >> |tc|, the coefficient is significantly different from zero

We reject the null hypothesis and there could be serial correlation present in the model

(c) The model with AR(1) errors was estimated as

$$\widehat{DHOMES_t} = -2.124 - 58.61 DIRATE_{t-1} \qquad e_t = -0.3314 e_{t-1} + \hat{v}_t$$
$$(\text{se}) \qquad (2.497) \quad (14.10) \qquad\qquad (0.0649)$$
$$\text{obs} = 217$$

95% confidence interval

Beta +/- se*tc tc =1.96
-58.61 + 14.10(1.96) = -30.974
-58.61 – 14.10(1.96) = -86.246

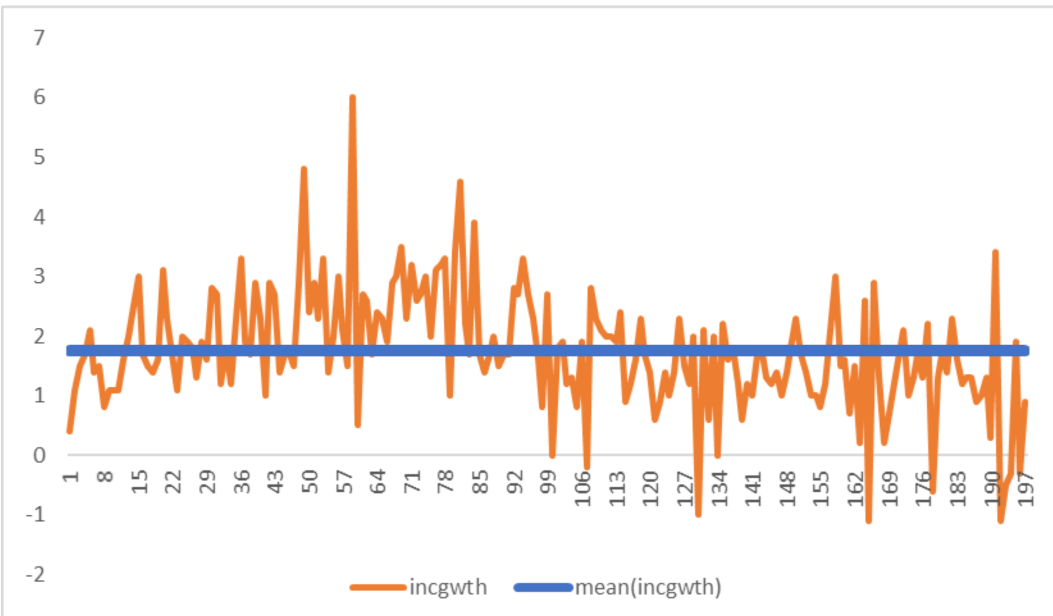
[-86.24 , -30.97]

After removing the autocorrelation error the confidence interval becomes smaller and more precise

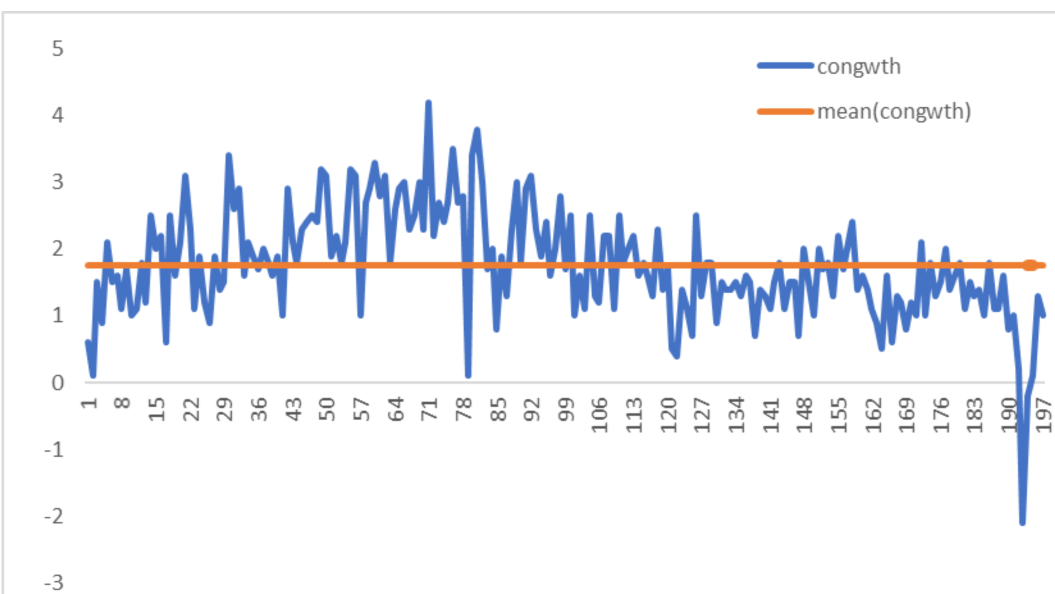
<u>Question 9.22 (p.391-392) Note: in part (b) use only the correlogram</u>

(part a)

INCGWTH VS Time(quarters)



CONGWTH VS Time(Quarters)



It is evident that both graphs are stationary as Mean mostly passes thru all quarters.

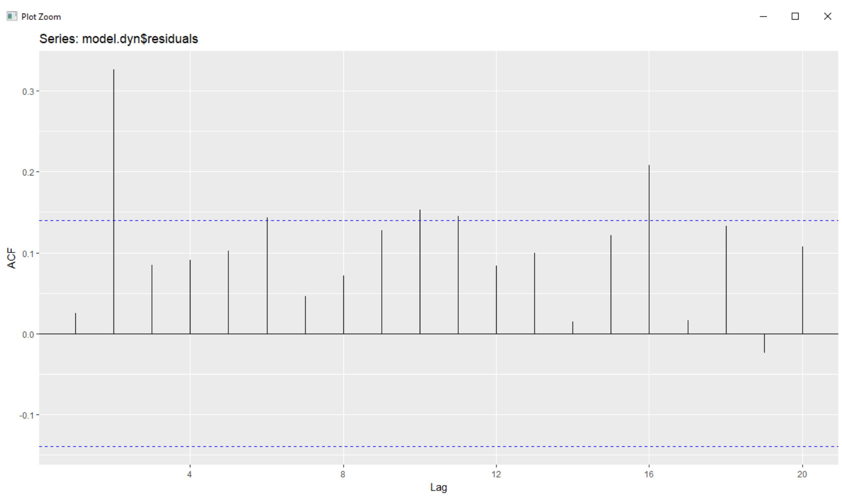
(part b)

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    0.97384    0.09961   9.776   <2e-16 ***
L(incgwth, 0)  0.44958    0.04967   9.052   <2e-16 ***
```

```
Estimate is significantly different from 0 for L(incgwth, 0)
```

```
> AIC(model.dyn)
[1] 415.6031
> BIC(model.dyn)
[1] 425.4527
```

```
Increase of 1 unit in income growth is estimated to increases the consumption
growth by 0.44 for the current month
```



At lag 2 there is significant serial correlation. There is also significant serial correlation at lag 16.

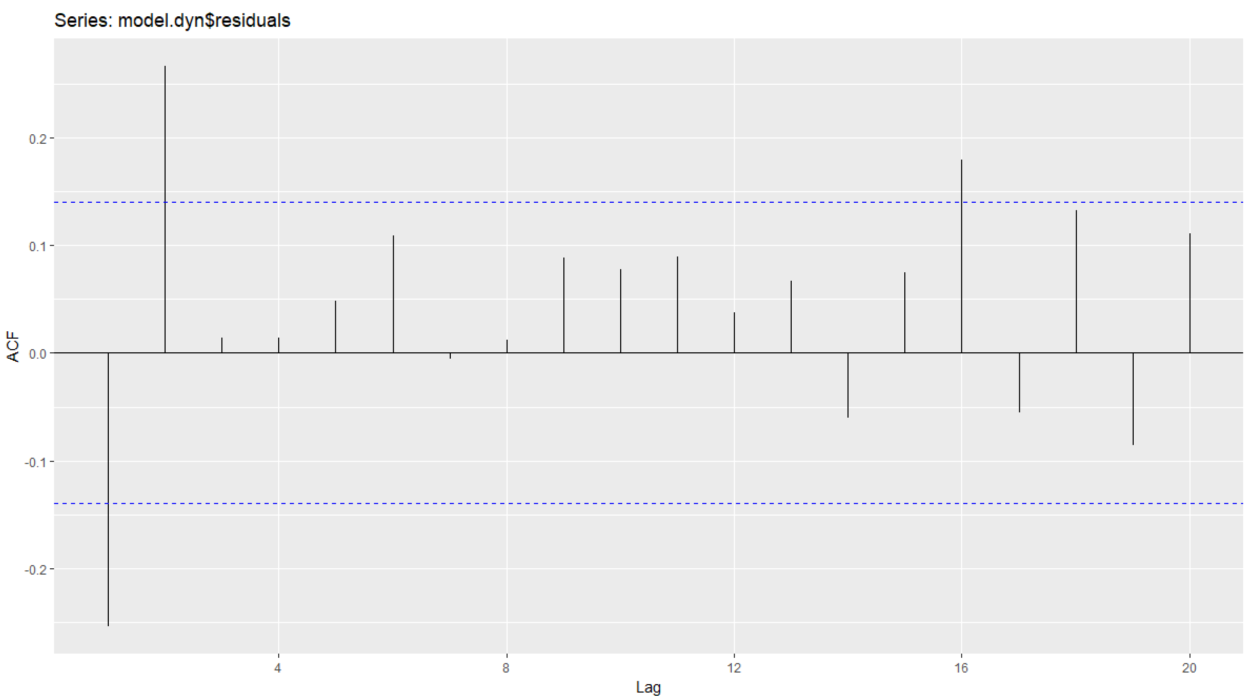
(part c)

```
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.67820    0.12083   5.613 6.84e-08 ***
L(congwth, 1)    0.26882    0.06413   4.192 4.22e-05 ***
L(incgwth, 0)    0.34953    0.05314   6.577 4.39e-10 ***
```

```
Estimate is significantly different from 0 for L(incgwth, 0)  and L(congwth, 1)
```

```
> AIC(model.dyn)
[1] 398.7832
> BIC(model.dyn)
[1] 411.8957
```

AIC and BIC have decreased significantly indicating that this is better model



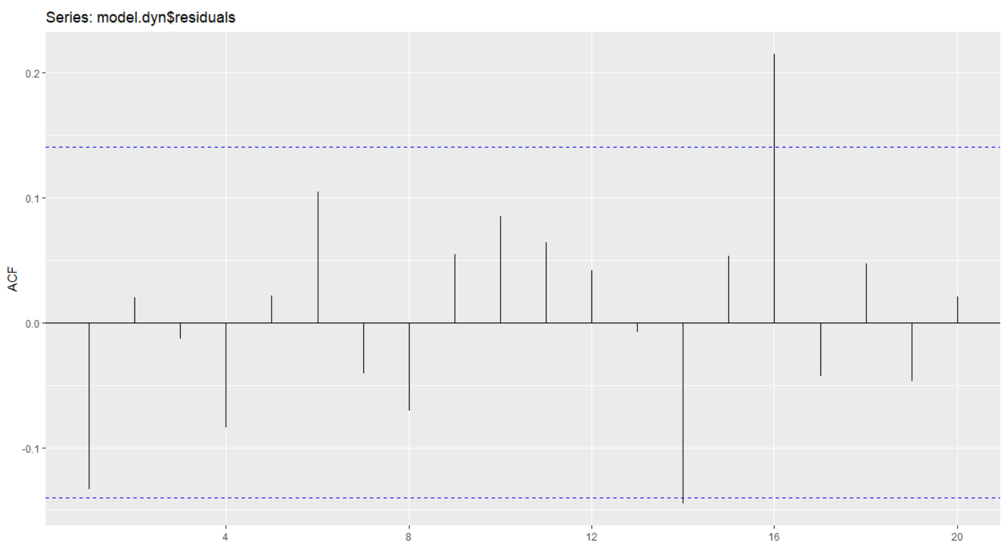
There is significant serial correlation at lag 1 ad lag 2. Even though AIC and BIC have decreased but this model has significant serial correlation

(part d)

```
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.46074    0.12776   3.606 0.000397 ***
L(congwth, 1)    0.14905    0.06600   2.258 0.025056 *
L(congwth, 2)    0.27521    0.06212   4.430 1.58e-05 ***
L(incgwth, 0)    0.32065    0.05089   6.301 2.00e-09 ***
```

All estimates are significantly different from 0

```
> AIC(model.dyn)
[1] 377.7218
> BIC(model.dyn)
[1] 394.0868
```



There is no serial correlation in the early lags. There is SC present at lag 14 and 16 but it is irrelevant to this model.

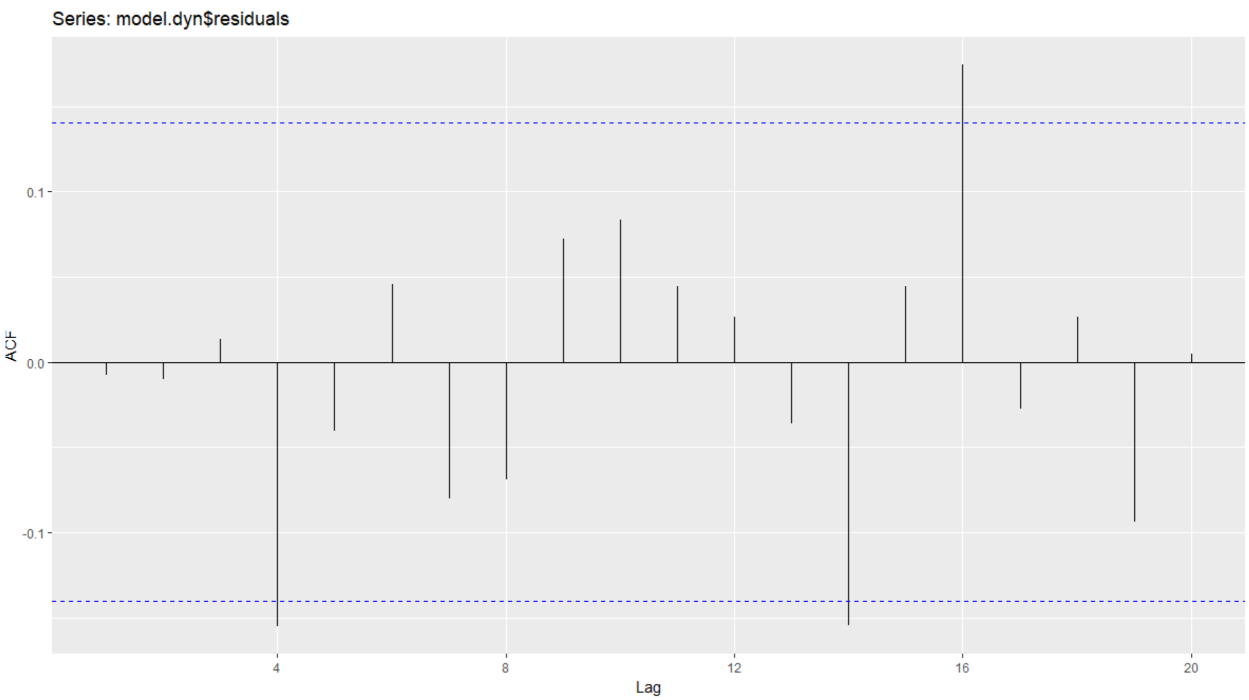
This is a much better model because AIC and BIC values are lower and there is no serial correlation present in the lags that we are using.

(part e)

```
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.36501    0.12438   2.935  0.00375 **
L(congwth, 1)    0.01609    0.07044   0.228  0.81953
L(congwth, 2)    0.20535    0.06169   3.329  0.00105 **
L(incgwth, 0)    0.34831    0.04916   7.085 2.64e-11 ***
L(incgwth, 1)    0.23080    0.05398   4.276 3.01e-05 ***
```

All estimates are significantly different from o

```
> AIC(model.dyn)
[1] 361.8067
> BIC(model.dyn)
[1] 381.4447
```



No serial correlation present. This is a better model because AIC & BIC have gone further down.

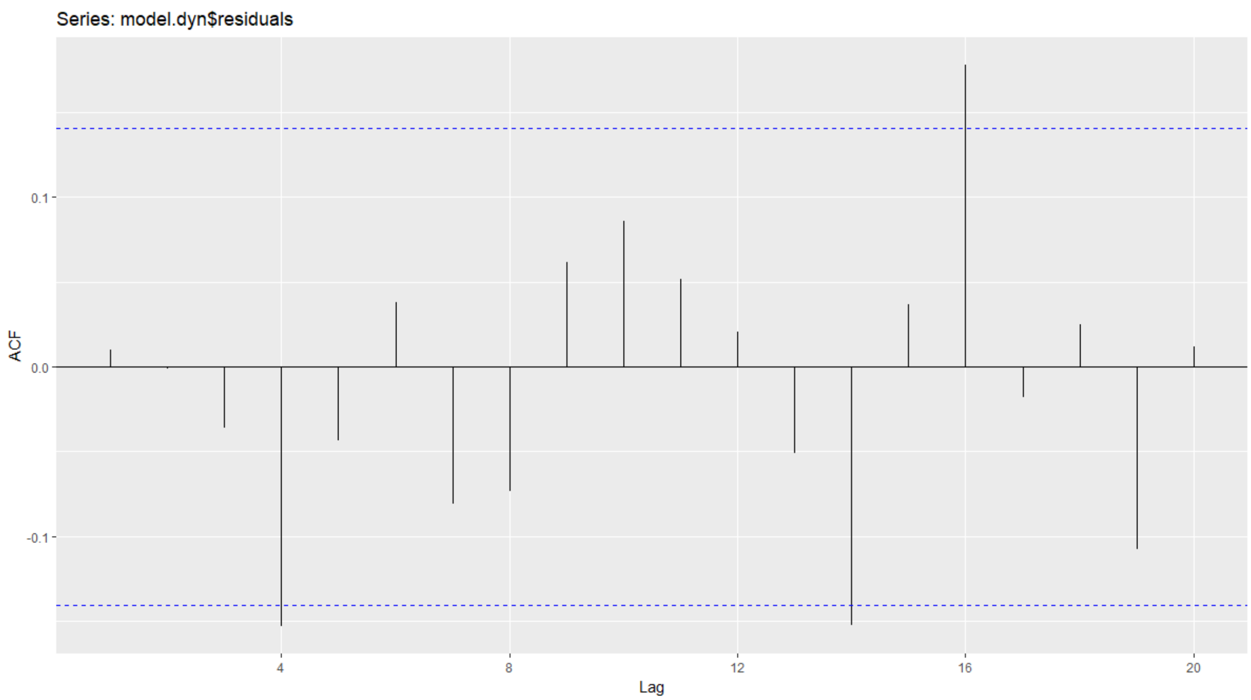
More importantly serial correlation has decreased significantly in first 3 lags.

(part f)

Add congwth(t-3) that is the 3rd lag

```
               Estimate Std. Error t value Pr(>|t|)
(Intercept)    0.331289   0.130596   2.537  0.01200 *
L(congwth, 1) 0.007871   0.073013   0.108  0.91426
L(congwth, 2) 0.192861   0.064534   2.989  0.00318 **
L(congwth, 3) 0.050735   0.064904   0.782  0.43538
L(incgwth, 0) 0.338155   0.050725   6.666 2.83e-10 ***
L(incgwth, 1) 0.229157   0.054245   4.224 3.73e-05 ***
```

```
> AIC(model.dyn)
[1] 362.2206
> BIC(model.dyn)
[1] 385.0956
```



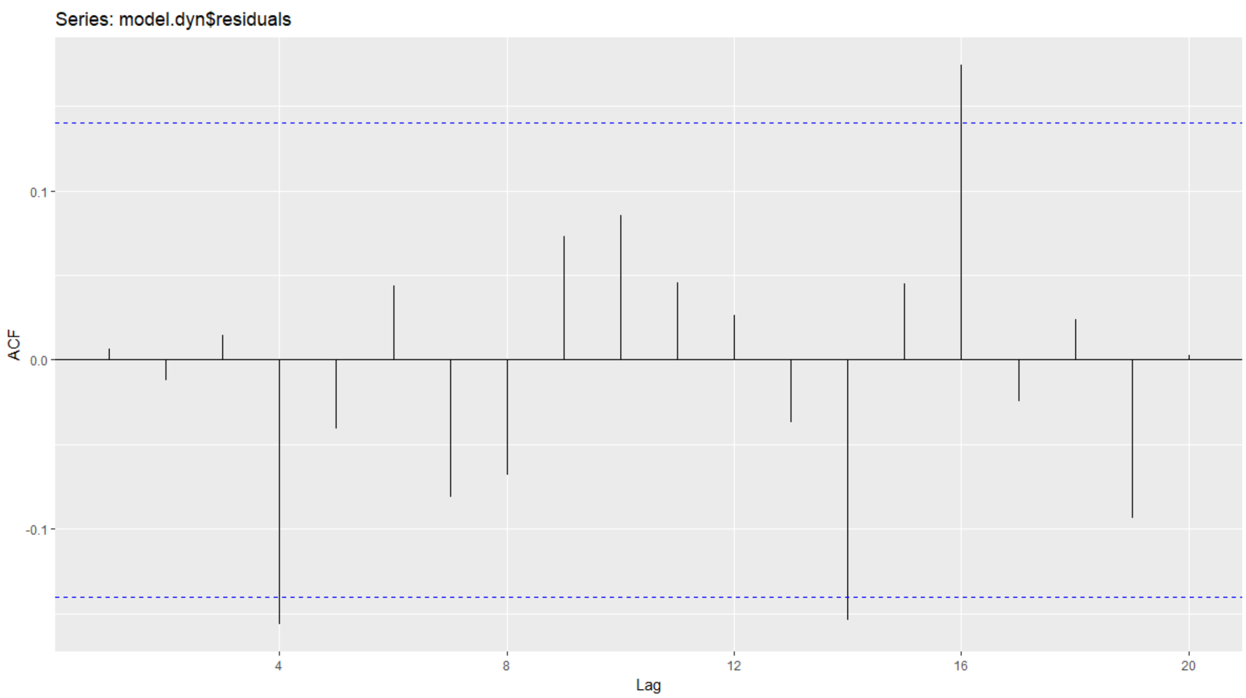
Adding 3rd lag of congwth increases AIC and BIC. Also serial correlation has increased at lag 3 but it's still within bounds.

Based on aforementioned analysis it is better to not add congwth(t-3) and leave model as in part (e)

(part g)

```
Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)     0.37149    0.12080   3.075 0.002411 ** 
L(congwth, 2)  0.20828    0.06019   3.460 0.000666 ***
L(incgwth, 0)  0.35244    0.04562   7.726 6.13e-13 ***
L(incgwth, 1)  0.23624    0.04831   4.890 2.13e-06 ***
```

```
> AIC(model.dyn)
[1] 359.8602
> BIC(model.dyn)
[1] 376.2252
```



AIC and BIC values are at their lowest. There is no sign of serial correlation in first 3 lags. However there is evidence of serial correlation at lag 4.

******************R STUDIO CODE FOR ABOVE QUESTIONS******************************

```
### QUESTION 9.2

rm(list=ls(all=TRUE))


library(multcomp)
library(data.table)
library(dplyr)
library(lmtest)
library(tseries)
library(dynlm)

context = fread('ex9.csv')


#table <- read.dta13("okun.dta")
#check.ts <- is.ts(table) # "is structured as time series?"
#okun.ts <- ts(table, start=c(1985,2), end=c(2009,3),frequency=4)
#okunL3.dyn <- dynlm(d(u)~L(g, 0:3), data=okun.ts)  # g is explanotary variable and u is teh column we
tryin to preict
#summary(okunL3.dyn)

table <- context
check.ts <- is.ts(table) # "is structured as time series?"
table.ts <- ts(table, start=c(2008,1),frequency=7)
check.ts <- is.ts(table.ts)
```

```
model.dyn <- dynlm(sales~L(adv, 0:2), data=table.ts)  # g is explanotary variable and u is teh column we tryin to preict

summary(model.dyn)

apply(table.ts, MARGIN = 2, class)


## 95% interval for impact multiplier

# tc = 1.96

# sqrt of  var(adv t) + var( adv t-1) + 2cov(advt , advt-1)


se = sqrt(1.3946)

beta = 1.842

Lo = beta-(1.96*se) # -0.472

Hi= beta+ (1.96*se) # 4.15



## 95% interval for one period interim multiplier

# tc = 1.96



se = sqrt(1.3946 + 2.1606 + 2 *(-1.0406)  )

beta = 1.842 + 3.802

Lo = beta-(1.96*se)  #  3.263

Hi= beta+ (1.96*se)   # 8.02


## 95% interval for two period interim multiplier

# tc = 1.96

#     = a2 + b2 + c2 + 2ab + 2bc + 2ca

#     var. a + var b + var c + 2cov(a,b) + 2cov(b,c)+ 2 cov(c,a)

se = sqrt(1.3946 + 2.1606 + 1.414 +  2 *(-1.0406) + 2*(-1.0367) + 2*(0.098) )
```

```
beta = 1.842 + 3.802 + 2.265

Lo = beta-(1.96*se)  #  5.9386

Hi= beta+ (1.96*se)   # 9.8793



### QUESTION 9.22


rm(list=ls(all=TRUE))



library(multcomp)

library(data.table)

library(dplyr)

library(lmtest)

library(tseries)

library(dynlm)

library(forecast)


context = fread('consumption.csv')

# income growth

# consumption growth


context = context[ 4:200, c("incgwth","congwth")]


table <- context

check.ts <- is.ts(table) # "is structured as time series?"

table.ts <- ts(table, start=c(1960,4),frequency=4)

check.ts <- is.ts(table.ts)

model.dyn <- dynlm(congwth~L(incgwth, 0), data=table.ts)
```

```
summary(model.dyn)

plot <- ggAcf(model.dyn$residuals,lag.max = 20)

plot

AIC(model.dyn)

BIC(model.dyn)

# part c


table <- context

check.ts <- is.ts(table) # "is structured as time series?"

table.ts <- ts(table, start=c(1960,4),frequency=4)

check.ts <- is.ts(table.ts)

model.dyn <- dynlm(congwth~L(congwth, 1) + L(incgwth, 0), data=table.ts)

summary(model.dyn)

plot <- ggAcf(model.dyn$residuals,lag.max = 20)

plot

AIC(model.dyn)

BIC(model.dyn)


# part d


table <- context

check.ts <- is.ts(table) # "is structured as time series?"

table.ts <- ts(table, start=c(1960,4),frequency=4)

check.ts <- is.ts(table.ts)

model.dyn <- dynlm(congwth~L(congwth, 1)+L(congwth, 2) + L(incgwth, 0), data=table.ts)

summary(model.dyn)

plot <- ggAcf(model.dyn$residuals,lag.max = 20)

plot

AIC(model.dyn)
```

```
BIC(model.dyn)


# part e


table <- context

check.ts <- is.ts(table) # "is structured as time series?"

table.ts <- ts(table, start=c(1960,4),frequency=4)

check.ts <- is.ts(table.ts)

model.dyn <- dynlm(congwth~L(congwth, 1)+L(congwth, 2) + L(incgwth, 0) + L(incgwth, 1)  ,
data=table.ts)

summary(model.dyn)

plot <- ggAcf(model.dyn$residuals,lag.max = 20)

plot

AIC(model.dyn)

BIC(model.dyn)


# part f  add congwth at lag 3


table <- context

check.ts <- is.ts(table) # "is structured as time series?"

table.ts <- ts(table, start=c(1960,4),frequency=4)

check.ts <- is.ts(table.ts)

model.dyn <- dynlm(congwth~L(congwth, 1)+L(congwth, 2) + L(congwth, 3) +  L(incgwth, 0) + L(incgwth,
1)  , data=table.ts)

summary(model.dyn)

plot <- ggAcf(model.dyn$residuals,lag.max = 20)

plot

AIC(model.dyn)

BIC(model.dyn)
```

```
# part g drop congwth t-1 from part e

table <- context
check.ts <- is.ts(table) # "is structured as time series?"
table.ts <- ts(table, start=c(1960,4),frequency=4)
check.ts <- is.ts(table.ts)
model.dyn <- dynlm(congwth~ L(congwth, 2) + L(incgwth, 0) + L(incgwth, 1)  , data=table.ts)
summary(model.dyn)
plot <- ggAcf(model.dyn$residuals,lag.max = 20)
plot
AIC(model.dyn)
BIC(model.dyn)
```