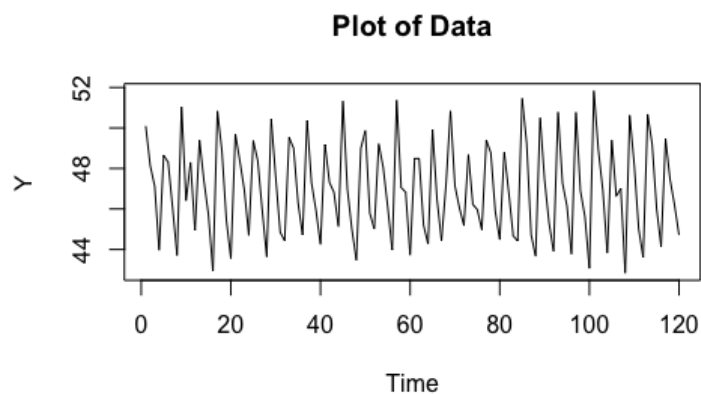


Question 3

First, we plot the data to see the general pattern:



We notice that there is a seasonal component in the data, so the assumed simple causal model is applicable:

$$Y_t = \beta_0 + \sum_{k=1}^3 \beta_k X_{t,k} + \epsilon_t$$

We fit the model and the following estimates:

Residual Standard Error=0.9076

R-Square=0.855

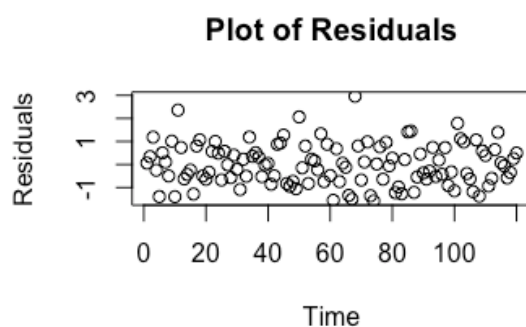
F-statistic (df=3, 116)=228.0701

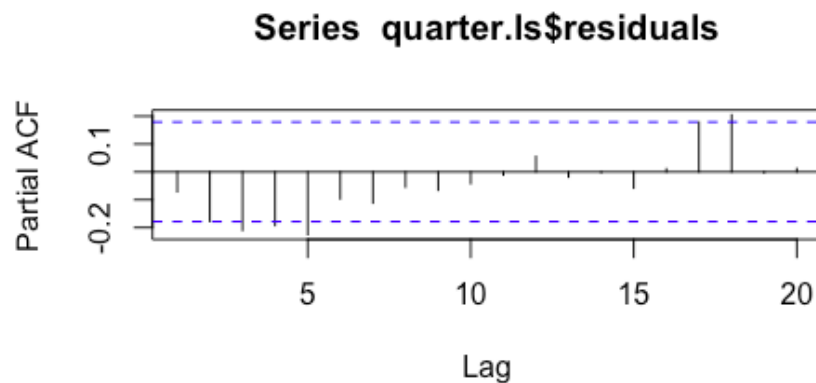
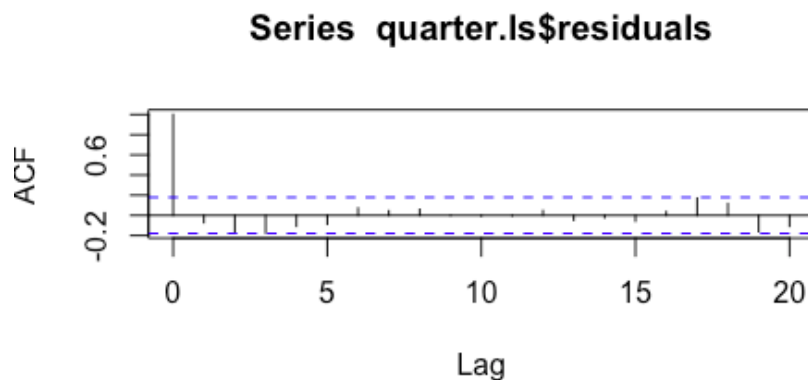
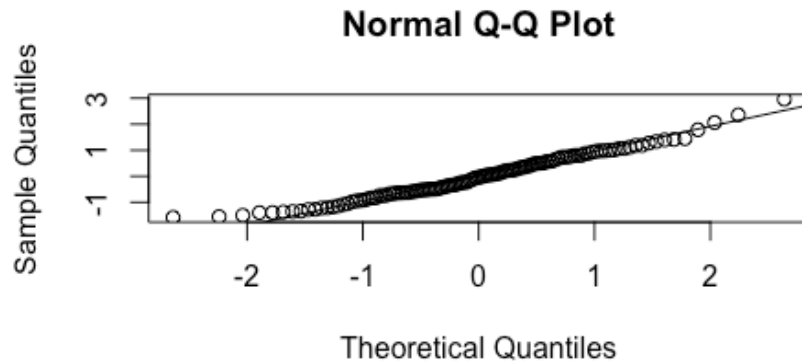
p-value=0

	Estimate	Std.Err	t-value	Pr(> t)
Intercept	44.2095	0.1657	266.8058	0
X1	5.8279	0.2343	24.8700	0
X2	3.5992	0.2343	15.3595	0
X3	1.7326	0.2343	7.3938	0

Here, $\widehat{\beta}_0 = 44.2095$, $\widehat{\beta}_1 = 5.8279$, $\widehat{\beta}_2 = 3.5992$, $\widehat{\beta}_3 = 1.7326$

Then we perform Residual Analysis:





- From the first plot, we see no particular evidence against stationarity i.e. no changing mean or variance.
- The q-q plot doesn't show any evidence against normality, it fits the line perfectly in the middle part of the graph.
- Sample ACF plot shows no significant spikes, hence, correlation is 0 (no exponential decay)
- Sample PACF plot shows spikes at lags 3,4,5,18, which suggest that there may be some correlation.
- Since there is still some correlation left and there is spikes only in SPACF graph let's use MA (2) and ARMA (1,1) models i.e.

$$Y_t = \beta_0 + \sum_{k=1}^3 \beta_k X_{t,k} + \epsilon_t$$

$$\epsilon_t \sim MA(2) \text{ or } ARMA(1,1)$$

MA (2):

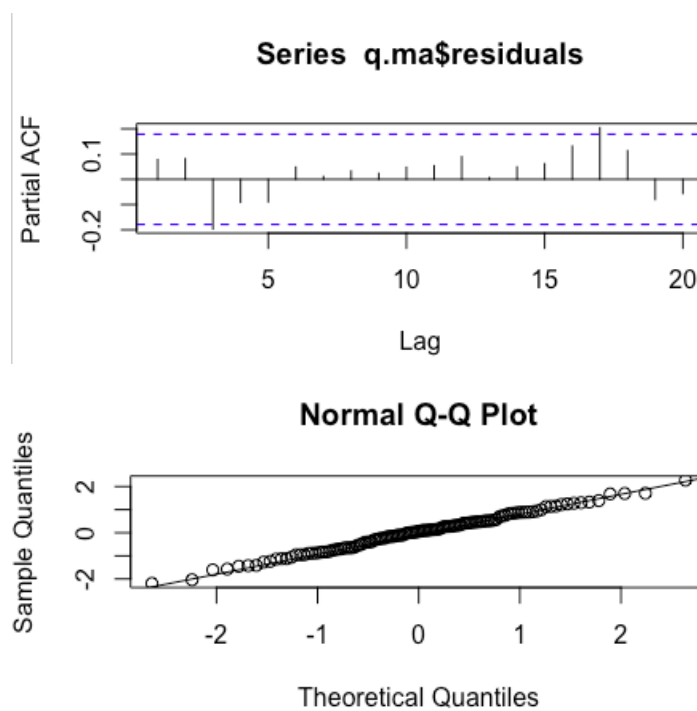
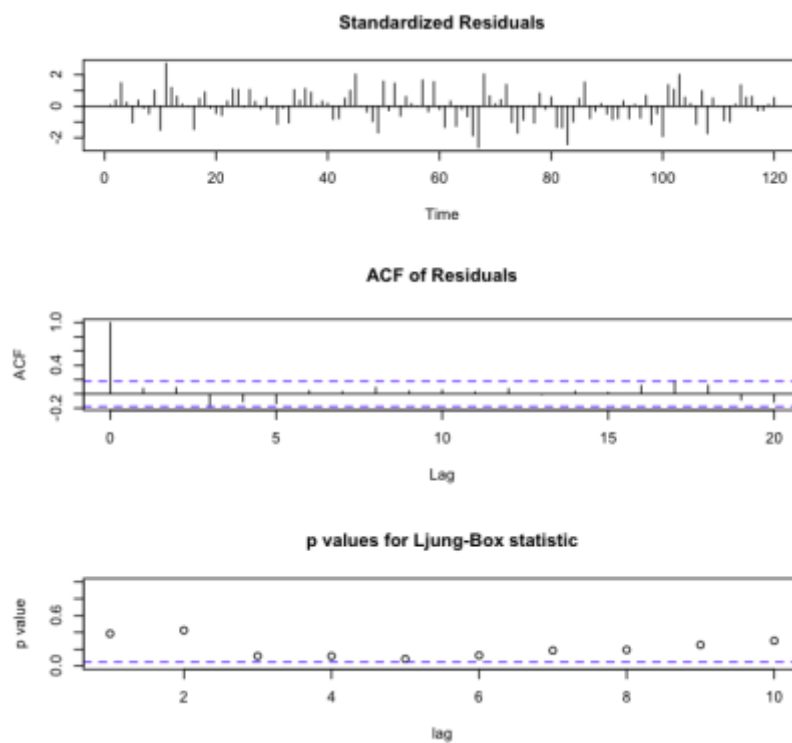
Call:

```
arima(x = quarter.y, order = c(0, 0, 2), xreg = x, method = "ML")
```

Coefficients:

	ma1	ma2	intercept	x1	x2	x3
	-0.3147	-0.3656	44.1987	5.8326	3.6044	1.7375
s.e.	0.0778	0.0718	0.1691	0.2572	0.3013	0.2583

sigma^2 estimated as 0.6997: log likelihood = -149.13, aic = 312.27



ARMA (1, 1):

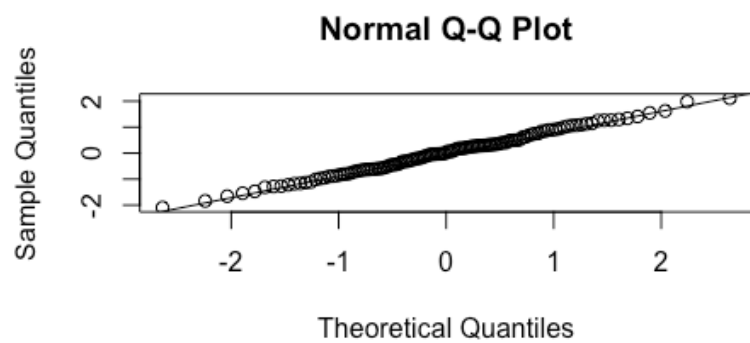
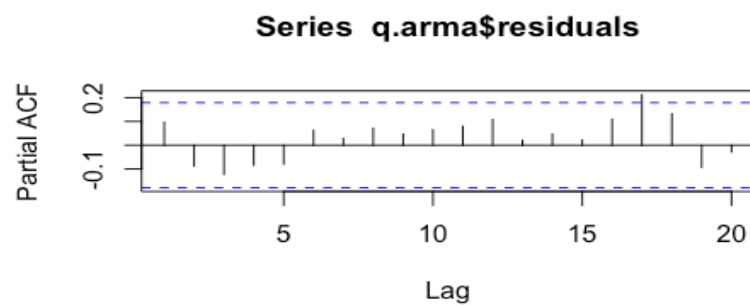
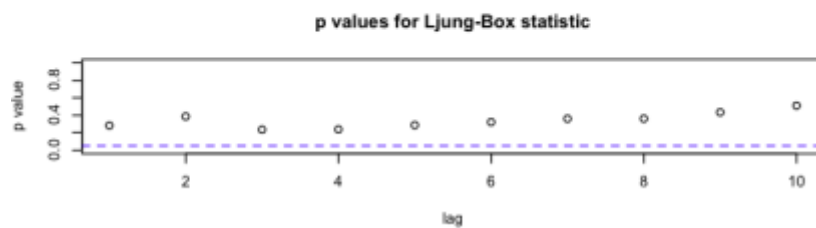
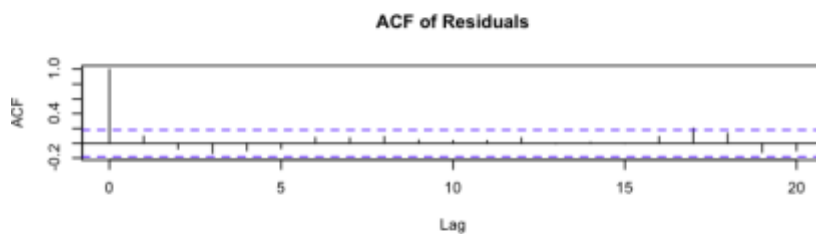
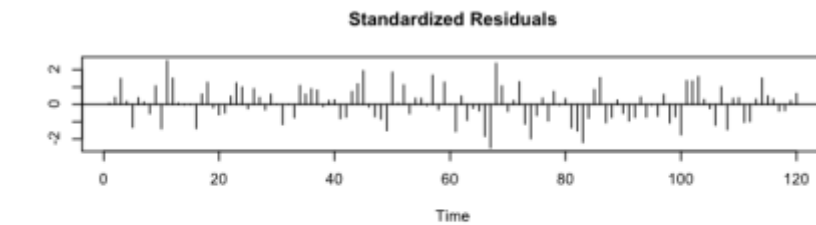
Call:

```
arma(x = quarter.y, order = c(1, 0, 1), xreg = x, method = "ML")
```

Coefficients:

	ar1	ma1	intercept	x1	x2	x3
	0.5496	-0.8642	44.1980	5.8312	3.6041	1.7364
s.e.	0.1021	0.0522	0.1564	0.2535	0.2492	0.2544

sigma^2 estimated as 0.6965: log likelihood = -148.8, aic = 311.59



- The estimated variance for MA (2) model of WN process is 0.6997 which is lower than the variance of the original residuals 0.9076.
- The estimated variance for ARMA (1,1) model of WN process is 0.6965 which is lower than the variance of the original residuals 0.9076 and the variance of MA (2).
- Also, AIC for MA (2) is 312.27 and is higher than AIC for ARMA (1,1) 311.59.
- So, we can conclude that ARMA (1,1) is a better model based on AIC statistic and rule of parsimony.
- For MA (2) Model:
- We see no obvious patterns of violation of stationarity and symmetry from the first plot.
- From ACF plot there are no spikes. So, we have no evidence against WN.
- From third plot, we see that at lag 5 dot is a bit below the blue dashed line, which suggests that we should reject H_0 : all correlations are zero.
- We notice spikes at lags 3, 17 in the PACF plot. From plot 5 we see no evidence against normality since the plot fits the line in the middle. However, spikes in PACF plot and rejection of H_0 in Ljung-Box test suggests that the process Z_t is not WN and MA (2) is not a good model.
- For ARMA (1,1):
- We see no obvious patterns of violation of stationarity and symmetry from the first plot.
- From ACF plot there are no spikes.
- From third plot, we see that all dots are above blue dashed line, which suggests that there is no evidence to reject H_0 : all correlations are zero. So, we have no evidence against WN.
- We notice spike at lag 17 in the PACF plot too, however, behavior of Ljung-Box statistic suggests that spike at lag 17 is not significant.
- From plot 5 we see no evidence against normality since the plot fits the line in the middle.
- Hence, there are no evidences against normality or WN of Z_t . Moreover, we can use ARMA (1,1) model to test regression parameters and to construct CI and PI.

Forecasting and PI:

Forecasted values for Y_{121}, \dots, Y_{123} correspondingly:

49.85434

47.70594

45.88161

PI's for Y_{121}, \dots, Y_{123} correspondingly:

(48.18518, 51.52350)

(45.95615, 49.45573)

(44.10818, 47.65504)

We could consider the ARMA (2,2) model which has more parameters, but fits perfectly.

Call:

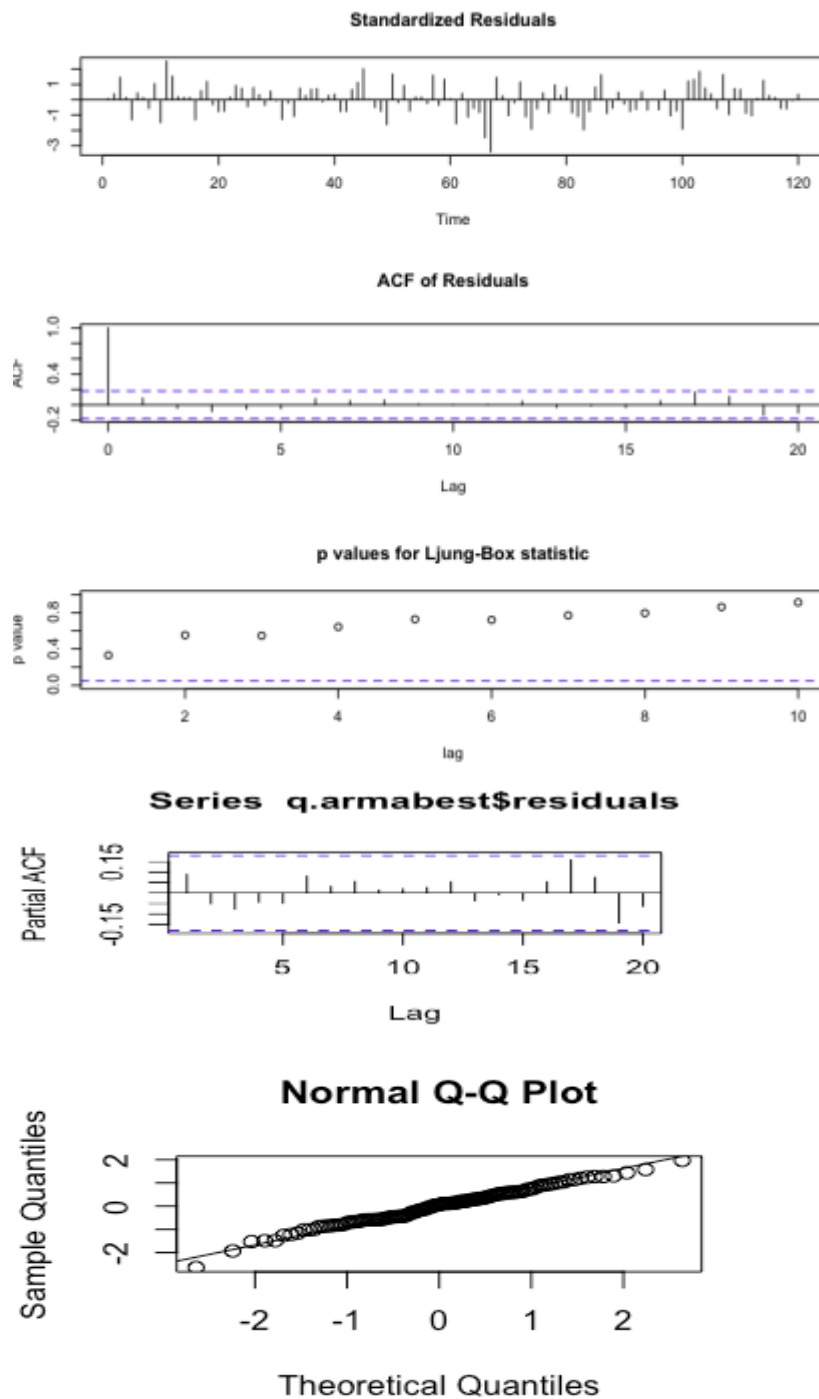
```
arima(x = quarter.y, order = c(2, 0, 2), xreg = x, method = "ML")
```

Coefficients:

	ar1	ar2	ma1	ma2	intercept	x1	x2	x3
	1.5230	-0.6104	-1.9618	0.9999	44.2078	5.8358	3.6058	1.7367
s.e.	0.0739	0.0791	0.0575	0.0581	0.1562	0.2503	0.2493	0.2513

sigma^2 estimated as 0.6012: log likelihood = -142.42, aic = 302.85

As we see both AIC and variance of the ARMA (2,2) is lower than the ones of the models indicated above. Now, let's take a look at the plots:



From the plots:

- We see no obvious patterns of violation of stationarity and symmetry from the first plot.
- From ACF plot there are no spikes. So, we have no evidence against WN.
- From third plot, we see that all dots are above blue dashed line, which suggests that there is no evidence to reject H_0 : all correlations are zero. So, we have no evidence against WN.
- We notice no spikes in the PACF plot. So, we have no evidence against WN.
- From plot 5 we see no evidence against normality since the plot fits the line in the middle.
- Hence, there are no evidences against normality or WN of Z_t . Moreover, we can use ARMA (2,2) model to test regression parameters and to construct CI and PI.

Forecasting and PI:

Forecasted values for Y_{121}, \dots, Y_{123} correspondingly:

50.06729

47.81915

45.93855

PI's for Y_{121}, \dots, Y_{123} correspondingly:

(48.50486, 51.62972)

(46.12214, 49.51616)

(44.18941, 47.68769)

We see that there is no big difference between forecasted values and PI's of ARMA (1,1) and ARMA (2,2) models. Since, there are less parameters in ARMA(1,1) by rule of parsimony I chose ARMA(1,1) Model.

Question 3

Residual Analysis

Arima

Forecasting and PI

```
new.x <- b1
q.pr <- predict(q.arma,n.ahead=3,newxreg=new.x,se.fit=TRUE)
## Predicted value
y.pred <- q.pr$pred
y.sd <- q.pr$se
## Upper bounds of PIs
U <- y.pred + 2*y.sd
## Lower bounds of PIs
L <- y.pred - 2*y.sd
```