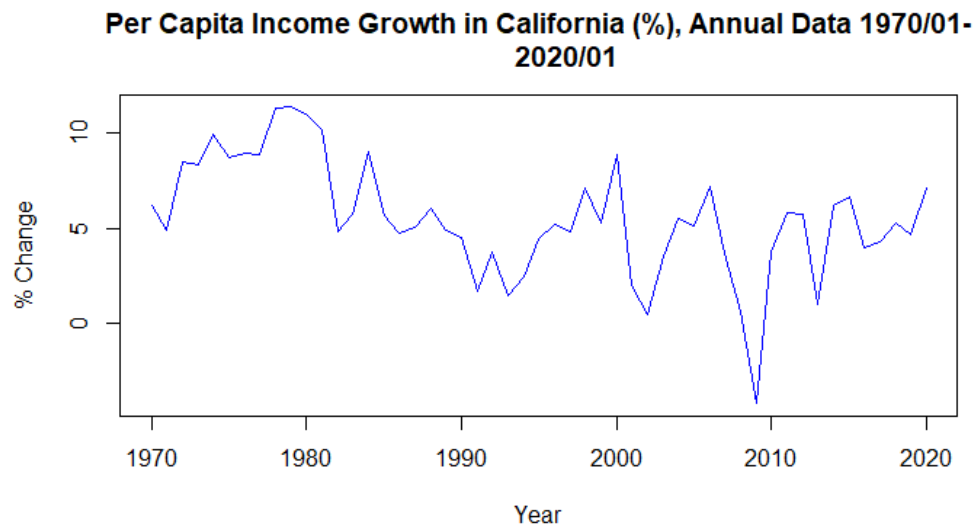


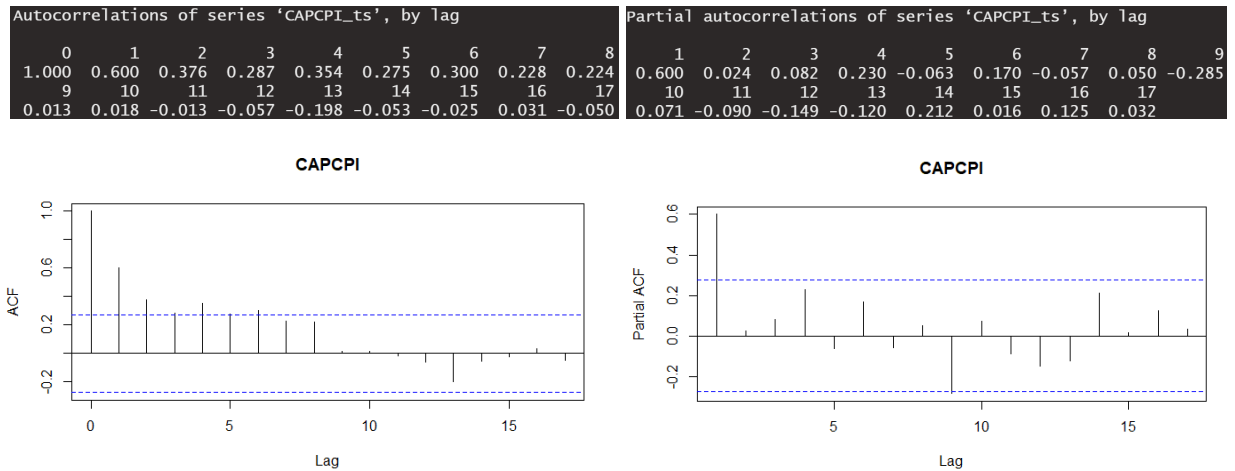
1.

a.

Time series plotted:

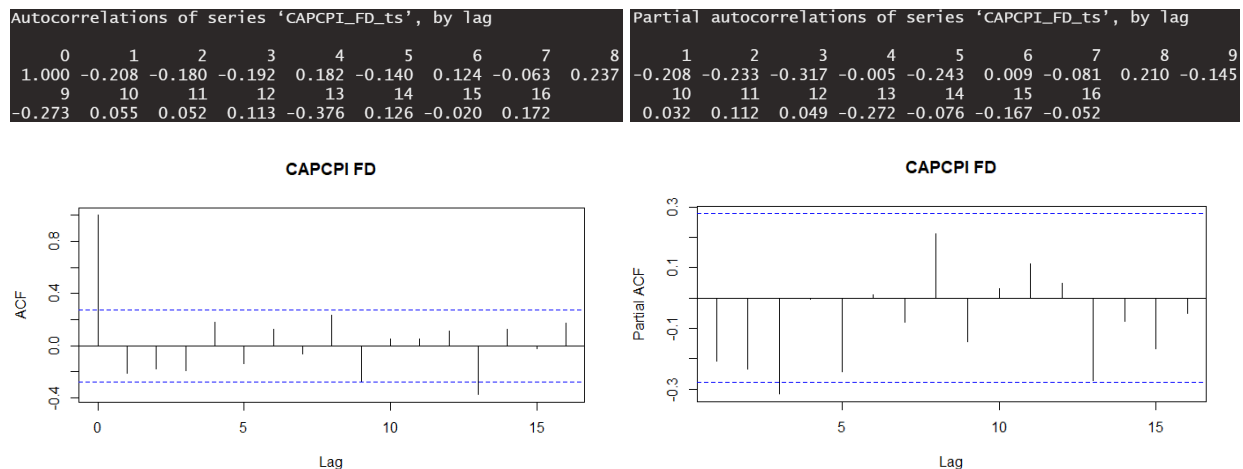


b.



After computing the ACF of the time series, we deduce that the data is not stationary since the ACF should die down much quicker or cut off within the first few lags. Thus, we compute the first difference to yield a stationary series.

The ACF and PACF from first differencing are as follows.



c.

From the ACF and PACF of the first difference model, the time series model I would consider for this series is the ARMA(1, 1) model since both the ACF and PACF die down quickly. Furthermore, observing the PACF also depicts it being inside the confidence interval at lag 1 which further emphasises the characteristic of the ARMA model I chose. Additionally, I also considered other time series models such as AR(1) and MA(1) models since they both cutoff at order 1 equally abruptly. However, the AIC value of the ARMA(1, 1) model is still the lowest amongst all the other models thus, I picked the ARMA(1, 1) model.

d.

The model estimated can be computed from R:

```
Call:
arima(x = CAPCPI_ts, order = c(1, 1, 1))

Coefficients:
          ar1          ma1
      0.4350    -0.8665
s.e.  0.1932    0.1160

sigma^2 estimated as 5.952:  log likelihood = -115.87,  aic = 237.73
```

Thus, the estimated model is as follows:

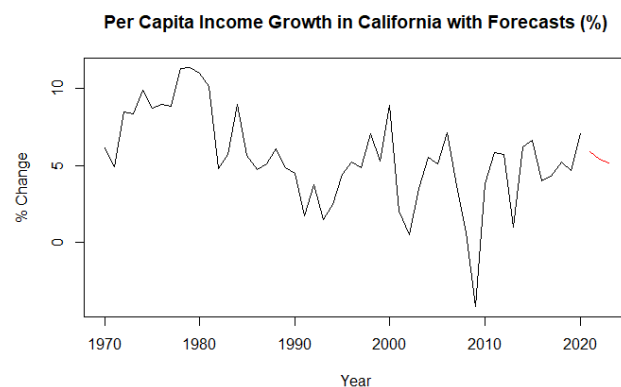
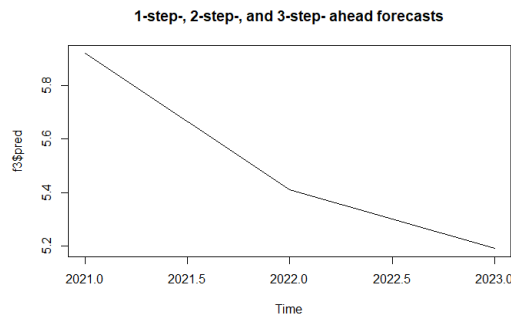
$$y_t = 0.4350 y_{t-1} - 0.8665 \varepsilon_{t-1} + \varepsilon_t$$

(0.1932)      (0.1160)

The 1-step-, 2-step-, and 3-step- ahead forecasts are as follows:

```
$pred
Time Series:
Start = 2021
End = 2023
Frequency = 1
[1] 5.921143 5.410933 5.189015

$se
Time Series:
Start = 2021
End = 2023
Frequency = 1
[1] 2.439608 2.806231 2.955972
```



Therefore, the forecasts are as follows (standard error in brackets):

1-step forecast = 5.921143 (2.439608)

2-step forecast = 5.410933 (2.806231)

3-step forecast = 5.189015 (2.955972)