

# ETC2410 Assignment 2

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## Question 2 (31 Marks)

### 2(a) (4 marks)

$$\widehat{HOUSTNSA} = 92.871 - 4.592 \underset{(4.196)}{Jan} - 1.935 \underset{(5.911)}{Feb} + 26.184 \underset{(5.934)}{Mar} \\ + 41.452 \underset{(5.934)}{Apr} + 46.786 \underset{(5.934)}{May} + 46.263 \underset{(5.934)}{Jun} + 40.937 \underset{(5.934)}{Jul} \\ + 38.714 \underset{(5.934)}{Aug} + 32.252 \underset{(5.934)}{Sep} + 36.170 \underset{(5.934)}{Oct} + 15.600 \underset{(5.934)}{Nov} \quad (1)$$

The above linear regression estimates the US monthly ‘housing starts’ based on the month that is being modelled. The intercept on its own implies that estimated ‘housing starts’ for the month of December, which means the other values are relative to the ‘housing starts’ of December. The variables in the linear regression are seasonal dummies which mean they only take a binary value (0 or 1). The  $\beta$  values for the seasonal dummies are the average change in the ‘housing starts’ relative to the month December.

### 2(b) (4 marks)

#### Steps

In order to formulate the linear regression, first we need to determine the intercept: From equation 1 we can determine the values of each month because of the dummy variables.  $92.871 - 4.592 = c \rightarrow c = 88.280$ , where the LHS is the month of Jan from calculated from equation 1.

Next we need to determine the  $\beta$  values for Feb - Dec. Since we know the intercept for the

new equation, we can substitute it in.

$$92.871 + 1.935 = 88.280 + \beta_2 \text{ } Feb$$

$$\rightarrow \beta_2 = 2.656$$

$$92.871 + 26.184 = 88.280 + \beta_3 \text{ } Mar$$

$$\rightarrow \beta_3 = 30.776$$

$$92.871 + 41.452 = 88.280 + \beta_4 \text{ } Apr$$

$$\rightarrow \beta_4 = 46.044$$

$$92.871 + 46.786 = 88.280 + \beta_5 \text{ } May$$

$$\rightarrow \beta_5 = 51.377$$

$$92.871 + 46.263 = 88.280 + \beta_6 \text{ } Jun$$

$$\rightarrow \beta_6 = 50.855$$

$$92.871 + 40.937 = 88.280 + \beta_7 \text{ } Jul$$

$$\rightarrow \beta_7 = 45.528$$

$$92.871 + 38.714 = 88.280 + \beta_8 \text{ } Aug$$

$$\rightarrow \beta_8 = 43.306$$

$$92.871 + 32.252 = 88.280 + \beta_9 \text{ } Sep$$

$$\rightarrow \beta_9 = 36.844$$

$$92.871 + 36.170 = 88.280 + \beta_{10} \text{ } Oct$$

$$\rightarrow \beta_{10} = 40.762$$

$$92.871 + 15.600 = 88.280 + \beta_{11} \text{ } Nov$$

$$\rightarrow \beta_{11} = 20.192$$

$$92.871 = 88.280 + \beta_{12} \text{ } Dec$$

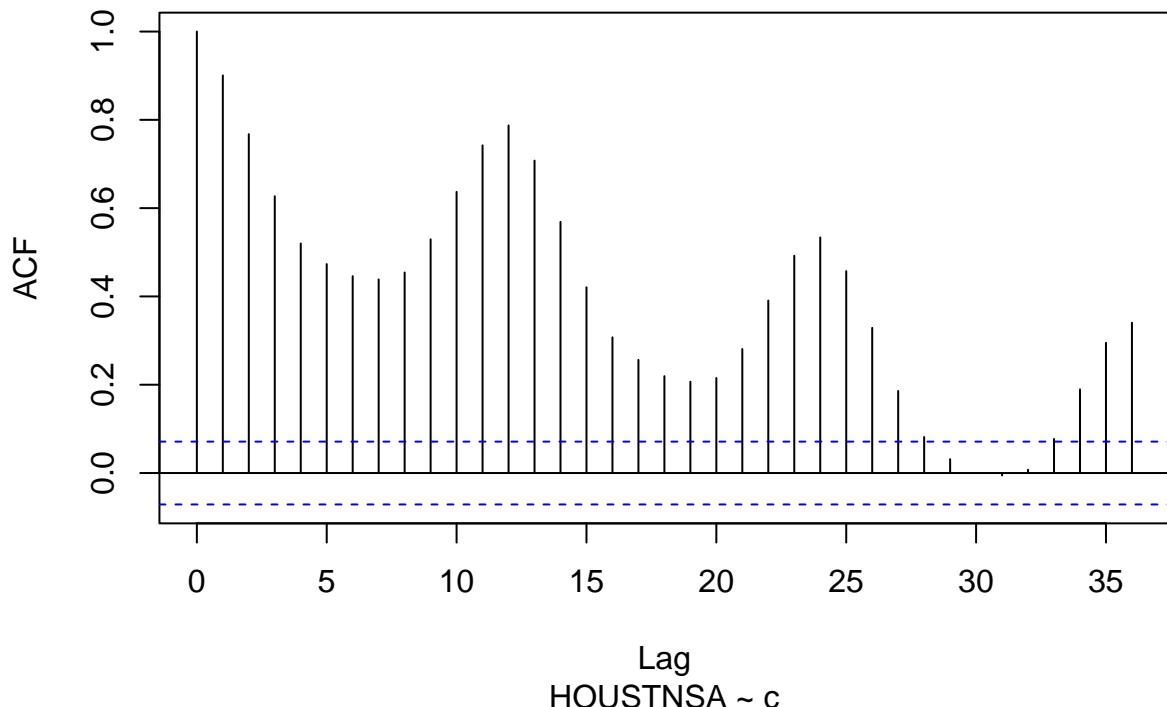
$$\rightarrow \beta_{12} = 4.592$$

$$\widehat{HOUSTNSA} = 88.280 + 2.656 \text{ Feb} + 30.776 \text{ Mar} + 46.044 \text{ Apr} \\ + 51.377 \text{ May} + 50.855 \text{ Jun} + 45.528 \text{ Jul} + 43.306 \text{ Aug} \\ + 36.844 \text{ Sep} + 40.762 \text{ Oct} + 20.192 \text{ Nov} + 4.592 \text{ Dec} \quad (2)$$

2(c) (6 marks)

$$\widehat{HOUSTNSA} = 119.3_{(1.377)} \quad (3)$$

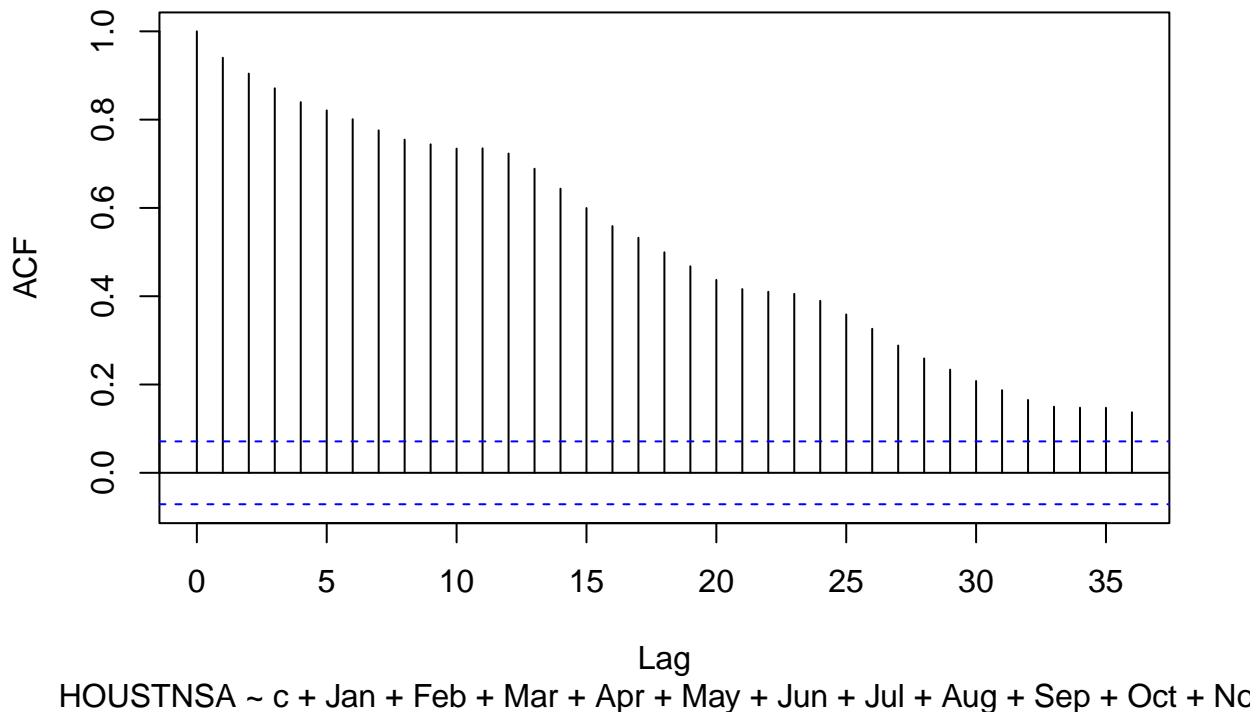
**Residuals ACF plot**



Lag  
HOUSTNSA ~ c

The residual ACF plot for the linear model  $HOUSTNSA \sim 1$  shows a few things. Firstly, each non seasonal lag ( $lag \neq \{12, 24, 36\}$ ) have a large positive spike which is the tell tail sign of the existance of a trend. Secondly, the seasonal lags have large positive spikes which indicates that there is also seasonality in the data. So we can attribute the gradual decrease in the lag values is because of trend while the scallop pattern is due to the seasonality.

### Residuals ACF plot



The residual ACF plot for the linear model  $\text{HOUSTNSA} \sim c + \text{Jan} + \text{Feb} + \text{Mar} + \text{Apr} + \text{May} + \text{Jun} + \text{Jul} + \text{Aug} + \text{Sep} + \text{Oct} + \text{Nc}$ , shows a significant difference compared to the residual ACF plot for the linear model  $\text{HOUSTNSA} \sim 1$ . The linear model  $\text{HOUSTNSA} \sim c + \text{Jan} + \text{Feb} + \text{Mar} + \text{Apr} + \text{May} + \text{Jun} + \text{Jul} + \text{Aug} + \text{Sep} + \text{Oct} + \text{Nc}$ , has no seasonality in the residual acf plot since the linear model has already captured it. What is remaining is the trend as depicted by decreasing values as the lags increase. Thus showing that the seasonal dummy variables have improved the model.

**2(d) (9 marks)**

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## [1] TRUE
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**2(e) (8 marks)**