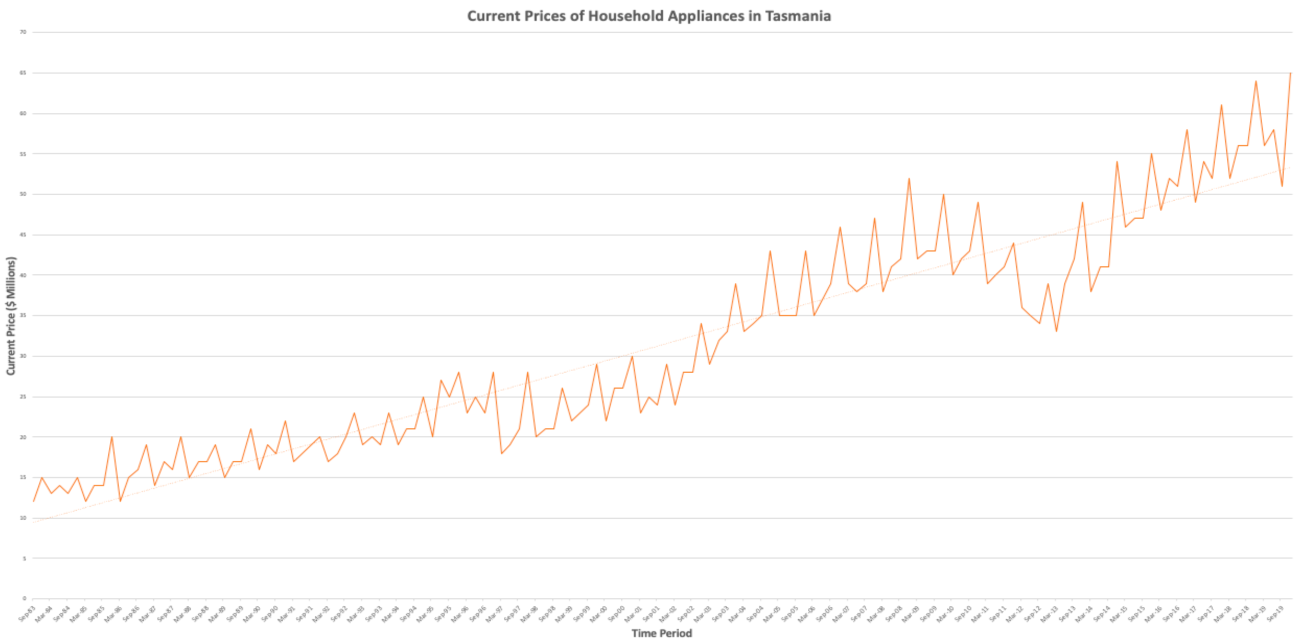
Questions 1 & 2 (1 page) – Plot and Components

This report bases itself on the data of 'Household appliances: Current prices' in Tasmania, Australia during the period of September 1983 to December 2019, reported quarterly. According to the Australian Bureau of Statistics, current prices refers to the current price estimates, which are valued at the prices of the period from which the observation is made. For instance, estimates for the last financial year are valued using the last financial year's prices. It is important that the term 'current prices' is not mistaken for chain volume measures, where prices used in the assessment denote the prices of the previous year. The time series was obtained through the Australian Bureau of Statistics website in the 'Australian National Accounts: National Income, Expenditure and Product Dec 2019' section. From there, 'Table 31. State Final Demand, Detailed Components: Tasmania' was identified, and the corresponding spreadsheet was downloaded. Two sets of data were located relating to household appliances, chain volume measures and current prices, out of which current prices was considered. The reference for the relevant time series is given below:

Australian Bureau of Statistics, 2019, *Australian National Accounts: National Income, Expenditure and Product Dec 2019*, 'Table 31. State Final Demand, Detailed Components: Tasmania', time series spreadsheet, series ID A3605894L, viewed 26 April 2020, https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/5206.0Dec%202019?OpenDocument.

Figure 1. illustrates the time series for current prices of household appliances in Tasmania from September 1983 to December 2019.



It can be reasoned that the time series contains trend, seasonal and random components. The data referring to the current prices of household appliances exhibit a positive trend, which appears reasonably constant. There is some random fluctuation around what appears to be a predominantly linear trend, as indicated by the trendline. The data is shown to increase steadily at a constant rate from 1983 to the end of 2001, where prices start to rise at an increasing rate, that is, the gradient of the time series becomes steeper until 2008 and then again from 2013 to 2019. In spite of this, it is unlikely the upward trend is non-linear and that any fluctuation is attributed to random errors. There is a structural break from this upward trend in 2011, where the data begins to present a negative trend until 2013, where prices return to following an upward trend but with a steeper ascent i.e. prices begin to rise at a greater rate. The data also indicates another systematic component, seasonality. That is, the data shows that on average, the current prices for household appliances experiences a peak in December each year, then plunges to its lowest value in March, which is then followed by a gradual increase through to June and September until it reaches its peak again in December. This pattern appears to repeat itself each year from 1983 to 2019. It is also possible that additive seasonality is evident as the magnitude of seasonal fluctuation does not vary with the level of time series, particularly in the latter half of the time series.

Questions 3 & 4 (1 page) – Corellogram and Factors

General economic factors influence the trend component of the time series. This implies an increase in disposable income, which results in the higher purchasing power of consumers, in turn leading to an increase in consumption and the demand for goods resulting in the prices of goods such as household appliances increase. The 1980s signified the beginning of Australia's economic liberalisation and deregulation through trade (Emmery, M, 1999). An open economy enables imports of higher-quality materials, hence increasing the quality of household appliances and thus, their prices. Technological advancements are also influential, encouraging companies to invest in producing higher quality products that meet the changing technological needs of consumers, this reflects an increase in prices. Tasmania's population also contributed, increasing from 435,100 in 1983 (ABS, 2008) to 535,500 in 2019 (ABS, 2020). During 1991 to 2001, Tasmania experienced net losses of interstate migrants, ensuing in an increase in interstate and overseas migration (Department of State Growth, 2015). As increased migration yields a larger circulation of funds within the economy, the demand for goods increases through consumption and results in increased prices for goods such as household appliances. Additionally, as the lowest populated state, Tasmania is subject to monopolies. With monopolies establishing their foothold in the industry by cohabiting a market with high barriers of entry and acquiring their competition, organisations like Harvey Norman can attain the roles of main seller and most importantly, price maker. Their near control of the market indicates that they can increase the prices of their products at will. The structural break in the series during 2011 – 2014 could be a result of the Global Financial Crisis. Although Australia averted a recession, the economy grew at a much slower rate, with a higher unemployment rate (RBA, n.d.) and people hesitant to consume. The overall demand for goods and services decreased, resulting in the prices of household appliances to drop. The seasonality component in the time series is likely due to weather and seasonal holidays, with the high points in December representing the Christmas and summer season. As people take vacations, consumption increases. With the demand for goods and services increasing, goods such as household appliances, are set at higher prices. The low points in March are likely to represent the end of the vacation period, with schools and places of work having recommenced. Consumption in December leads to a downward adjustment in March as people pay off accumulated debts. In an attempt to gain revenue, prices decrease so that household appliances are perceived as more attractive to consumers. Random fluctuations around this systematic component may be due to unnatural weather patterns such as floods or heatwaves.

The circumstances explained above will apply to the relevant forecasting period. It is likely the factors influencing the seasonal and trend components will not change. However, due to the development of COVID-19, it is likely these factors affecting the trend component will have an adverse reaction on the prices of household appliances, as the purchasing power of consumers drop hence driving down the demand for goods. Although it is probable, the seasonal component will remain intact in the forecasting period, it is likely the time series will illustrate a temporary structural break, portraying a negative trend similar to the one as shown from 2011 to 2014, possibly, much worse.

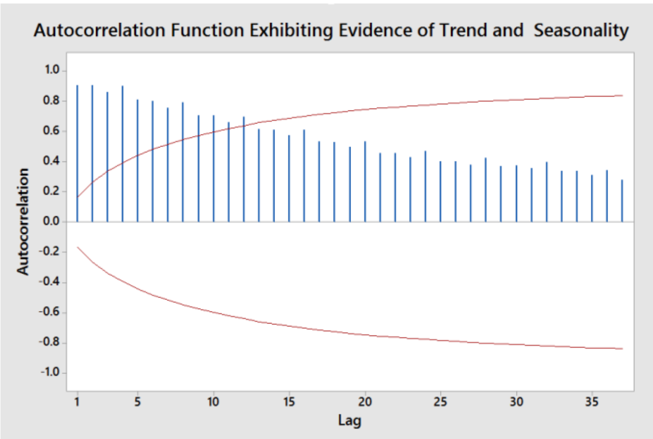


Figure 2 portrays the Autocorrelation Function (ACF) of Tasmania's household appliances' current prices from September 1983 to December 2019.

The Autocorrelation function (ACF) provides evidence of both trend and seasonality. The spikes are statistically significant at the beginning, showing evidence of autocorrelation i.e. the current prices of household appliances in Tasmania are highly correlated with each other. This implies that when current prices increase, it's likely to continue increasing. It is similar for when current prices begin to decrease. The smaller lags show ACF values that are positive and significant. Although these values continue to remain positive, they slowly decrease in size as the lags increase, validating the presence of a trend component. The ACF values are also larger for every fourth lag corresponding to the peak in current prices observed for each December quarter, confirming the data is seasonal.

Questions 5 & 6 (two pages) – WES Method

Initial values for the level, trend and seasonal component, that is, in the period December 2016, were calculated first on an excel spreadsheet. It was assumed the initial valued be calculated using the last four years of data. The initial value for the level component was calculated by taking the average of the prices corresponding to the first four quarters, from March 2016 to December 2016. The initial value for the trend component was determined by individually subtracting the first year's values, in this case, the quarterly values from 2016, from the second year's values i.e. 2017, then diving it by four as the data is reported quarterly. These values are then averaged to provide the initial trend value. The first four seasonal values were calculated by dividing the corresponding quarter's actuals by the initial trend value.

For the time periods between March 2017 to December 2019, the corresponding values for the level trend and seasonal component were calculated using the first, second and thirds equations respectively as illustrated on page 5 of this report. It is important to note that all three equations contain the smoothing parameters: α, β and γ. α signifying the coefficient for the level smoothing, β representing the coefficient for the trend smoothing and γ, the coefficient for seasonal smoothing. These variables were all initially set at 0.2, the solver function was later utilised to generate the appropriate values for α, β and γ by minimising the mean absolute error. The prediction values from March 2017 to December 2019 were determined by multiplying the previous year's corresponding seasonal value and the sum of the previous quarter's values for the level and trend component i.e. each prediction value took into account the level, trend and seasonal components for that period. Forecasts for the year of 2020 were then calculated using the fourth equation on page 5. Note that these analyses were performed only on the values observed in the last four years, that is, from March 2016 to December 2019. As such, the values preceding this period were not considered in the calculations. The results of these calculations are presented in figure 1.5. The observed values, predictions and forecasts were then plotted on a line graph as per below, with the predictions representing the 'smoothing' values and α, β and γ signifying the smoothing parameter.

The Winters' Exponential Smoothing (WES) method appears to better represent the data and attempts to reduce forecasting errors, by more visibly presenting further proof of seasonality and trend. As illustrated in figure 1.2, positive errors are mostly present until May 2019, after which negative errors becoming prevalent. Positive errors indicate that the predicted value is less than the corresponding observed value while negative errors indicate that the predicted value exceeds the observed value. This is evident in the graph below, particularly during September 2019, where the error value drops considerably below. As the smoothing method assumes that extreme fluctuations represent randomness, the smoothing method does a reasonably good job at minimising potential random errors as the prediction displays a higher value for 2019, while still accounting for the 'dip', thus reducing randomness. While the predictions do counteract the random fluctuations evident in the observations, it maintains the trend component and seasonal structure, including the peaks and troughs. It also does not deviate significantly from the actuals, evidencing minimal error. As the mean absolute error, the root of mean squared error and the mean absolute percentage error are also all low in value, it is apparent that exponential smoothing represents the data well.

The forecast also appears feasible as it is evident more weight is given to the most recent observations. As illustrated in the graph below, it seems to be affected by the sizeable drop in current prices recorded in Sept 2019, as the quarterly forecasts appear to not share the same steepness as the results of its prior counterparts.

Questions 5 & 6 (continued) – WES Method

Figure 3 illustrates the original time series graphed the smoothed values using Winters' Exponential Smoothing (multiplicative)as well as the forecasts for 2020.

Questions 7 & 8 (one page) – Tests and Notation

The appropriate tests were conducted to calculate the mean absolute error, the mean squared error, the root of mean squared error and the mean absolute percentage error. Errors for the data were calculated by individually subtracting the prediction values from their corresponding actuals. The absolute value was taken for the errors and was then averaged to determine the *mean absolute error* (MAE). The *mean squared error* (MSE) was calculated by averaging the squared values taken for the errors. Taking the root of this value results in the *root of mean squared error* (RMSE). The *mean absolute percentage error* (MAPE) was calculated by individually finding the percentage of absolute errors in the equivalent actuals. The mean absolute error and the root of mean squared error are indicators of the average size of prediction error, while the mean absolute percentage error is a more suitable indicator for the 'typical' error. Referring to figure 1.1, the mean absolute error and the root of mean squared error indicates that the average size of the error is relatively low: 1.34 and 2.33 respectively. While the mean absolute percentage error suggests that the typical prediction error is approximately 2.55% (figure 1.1) for the Winters Exponential Smoothing Method (α = 0.21, β = 0.25, γ = 0.64) in this time series, which proves to be quite low.

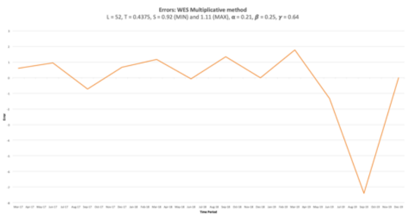


Figure 1.2: Errors vs time period – see appendix

Figure 1.2 indicates that there are mostly positive errors for most of the period observed i.e. from Mar 16 to May 19, followed by a significant drop in the error value, which remains negative for the rest of 2019. It is probable that for the most part the negative values counteract the positive values, but not fully, as the errors produce a mean about zero (-0.25). Despite this, it is possible that the errors may follow a pattern and are therefore, systematic and not random.

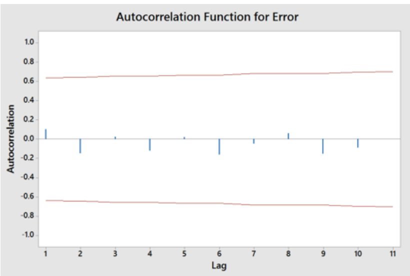


Figure 1.3: ACF for errors – see appendix

An additional test that proves this is the Autocorrelation Function on the errors calculated. Figure 1.3 reveals that the none of the errors are significant, affirming the accuracy of the WES Method. 60% of the ACF values are also negative, indicating mostly negative correlation. There is also no observable increase or decrease in the values, suggesting the errors do not follow a trend. Although there is no evidence of trend, the ACF values are larger and negative at almost each multiple of two i.e. at lags, 2, 4, 6, 9 and 10, while lags 1, 3, 5 and 8 display insignificant and positively correlated ACF values, suggesting that the errors may have a systematic pattern and that it is likely they are not random.

The relevant equations representing systematic components used in the Multiplicative Winters Exponential Smoothing include:

The first equation signifies the level component, which adjusts the actual value of the time series by a seasonal estimate:

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1})$$

The second equation signifies the trend component:

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

The third equation represents the seasonality component, providing an updated estimate of the seasonal estimate at each time period:

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s}$$

The fourth equation, is the forecasting equation, allowing for 'm' periods of data into the future to be predicted. $(L_t + T_t p)$ is a trend projection 'm' periods ahead. The result is adjusted by an estimate of seasonality for that specific season (S_{t+p-s}). Note that α, β and γ lies between 0 and 1.

$$\hat{Y}_t = (L_t + T_t p) * S_{t+p-s}$$

Questions 9 & 10 (two pages) – Critique and Forecasts

Winters' Exponential Smoothing relies on past values to convey information about what will happen in the future. Smoothing is utilised as past values not only contain an underlying systematic pattern, in this case trend and seasonal components, but also random fluctuations as well. The model provides accurate forecasts, accounting for the level, trend and seasonal components and gives more weight to recent observations. It is important to note that Exponential Smoothing is a prevalent method, commonly used for short-term forecasting, due to its low cost and simplicity. Hence, the Winters' Exponential Smoothing method is suitable for forecasting this time series as only the subsequent four quarters if forecasted. However, this is only a suitable method with the given values for the smoothing parameters (α = 0.21, β = 0.25, γ = 0.64), as these three values are calculated in such a way as to yield the lowest error criteria. Despite this, note that the multiplicative model was used, it is possible that the additive model may be better suited to this data, as according to the graph on page 4, the degree of seasonality does not seem to change, and the errors do not increase with time. Assuming the absence of any other information and that future patterns will mirror current patterns; the Winters' Exponential Smoothing method would be the best smoothing and forecasting method and no re-evaluation of the model would be necessary.

However, considering the emergence of COVID-19, it is likely the model would need to be reassessed as new factors will contribute considerably to the forecasts generated for the second or third year. The most influential factor will be the loss of disposable income caused by higher unemployment and termination, as many people lose their main stream of income. The change in consumer behaviour is also likely to shoulder an influential role, as consumers are more likely to save their funds following an economic contraction due to the fear and uncertainty it has caused, thus allocating less funds for personal expenditure. It is probably that the fall in consumption will lead to a fall in the demand for goods and as a result, prices will drop so that household appliances are perceived as more attractive to consumers.

Business confidence is also likely to decrease, as the effects of COVID-19 make it problematic to gain revenue and maintain cash flow. Subsequently, investment in the household appliances' industry decreases, diminishing supply and compromising the quality of products and services.

Following the results of COVID-19, government expenditure is likely to increase in an attempt to stimulate the economy by increasing investment and consumption. This will cause public investment to rise and personal and company tax to decrease. The Australian Government has since announced three stimulus packages: $17.6 billion on 12 March 2020, $66 billion on 22 March 2020 and $130 billion on 30 March 2020. (The Treasury, May 2020). The financial subsidies, tax reliefs and JobKeeper payments to both companies and employees will have a positive effect on the current prices, however it is uncertain whether it will be enough to offset the adverse effect caused by COVID-19.

Considering the factors mentioned above, it is likely the forecasts made for current prices for household appliances in Tasmania won't necessarily reflect the movement observed in the previous years. Although Winters' Exponential Smoothing has proved to be a suitable model thus far, it is not an appropriate model for forecasting the next few years, as it is limited by the notion that its forecasts lag behind the underlying pattern. Hence, it fails to take into account one-off events that are capable of drastically changing current prices of household appliances and has thus failed in forecasting realistically the prices for the period of March 2020 to December 2020. It is instead probable that the current prices for 2021 and 2022 will either slightly increase at a much slower rate, i.e. have a lower gradient, or even drop in value, much more substantial than the one observed in 2011 to 2014.

Questions 9 & 10 (continued) – Critique and Forecasts

Below are the quarterly forecasts for expenditure on household appliances in Tasmania for the year 2020:

Let $\alpha = 0.2098$, $\beta = 0.2469$, $\gamma = 0.6364$ (VALUES FROM SOLVER)

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$L_{DEC19} = 0.2098\left(\frac{65}{1.1163}\right) + (1-0.2098)(57.9417 + 0.2868)$$

$$= 58.2284$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

$$T_{DEC19} = 0.2469(58.2284 - 57.9417) + (1-0.2469)(0.2868)$$

$$= 0.2868$$

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma) S_{t-s}$$

$$= 0.6 \; S_{MAR19} = 0.6364\left(\frac{56}{58.3809}\right) + (1 - 0.6364)(0.9350)$$

$$= 0.9504$$

$$S_{JUN19} = 0.6364\left(\frac{58}{58.8473}\right) + (1 - 0.6364)(1.0036)$$

$$= 0.9921$$

$$S_{SEP19} = 0.6364\left(\frac{51}{57.9417}\right) + (1 - 0.6364)(0.9812)$$

$$= 0.9169$$

$$S_{DEC19} = 0.6364\left(\frac{65}{58.2285}\right) + (1 - 0.6364)(1.1163)$$

$$= 1.1163$$

$$\hat{Y}_t = (L_t + T_t \times p) S_{t+p-s}$$

$$\rightarrow \hat{Y}_{MAR20} = (58.2284 + 0.2868 \times 1)(0.9504)$$

$$= 55.6128$$

$$\rightarrow \hat{Y}_{JUN20} = (58.2284 + 0.2868 \times 2)(0.9921)$$

$$= 58.3375$$

$$\rightarrow \hat{Y}_{SEP20} = (58.2284 + 0.2868 \times 3)(0.9169)$$

$$= 54.1785$$

$$\rightarrow \hat{Y}_{DEC20} = (58.2284 + 0.2868 \times 4)(1.1163)$$

$$= 66.2810$$

NOTE: ALL VALUES LISTED ABOVE ARE ROUNDED TO 4 DECIMAL PLACES WHERE POSSIBLE, THEREFORE EXPECT SLIGHT ERRORS IN ANSWERS.

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Appendices

Period	Prices	Error	Abs Error	Sq Error	Abs % Error
Mar-16	48				
Jun-16	52				
Sep-16	51				
Dec-16	58				
Mar-17	49	0.598086124	0.5980861	0.357707	1.2205839
Jun-17	54	0.959683577	0.9596836	0.9209926	1.7771918
Sep-17	52	-0.72649151	0.7264915	0.5277899	1.3970991
Dec-17	61	0.674160201	0.6741602	0.454492	1.1051807
Mar-18	52	1.172796302	1.1727963	1.3754512	2.2553775
Jun-18	56	-0.069239223	0.0692392	0.0047941	0.1236415
Sep-18	56	1.337121882	1.3371219	1.7878949	2.3877176
Dec-18	64	0.002385526	0.0023855	5.691E-06	0.0037274
Mar-19	56	1.78730146	1.7873015	3.1944465	3.1916098
Jun-19	58	-1.341246113	1.3412461	1.7989411	2.3124933
Sep-19	51	-7.403158693	7.4031587	54.806759	14.515997
Dec-19	65	-3.29828E-06	3.298E-06	1.088E-11	5.074E-06
Mar-20					
Jun-20			**MAE**	**MSE**	**MAPE**
Sep-20			1.3393062	5.4357728	2.5242188
Dec-20				**RMSE**	
				2.3314744	

Figure 1.1

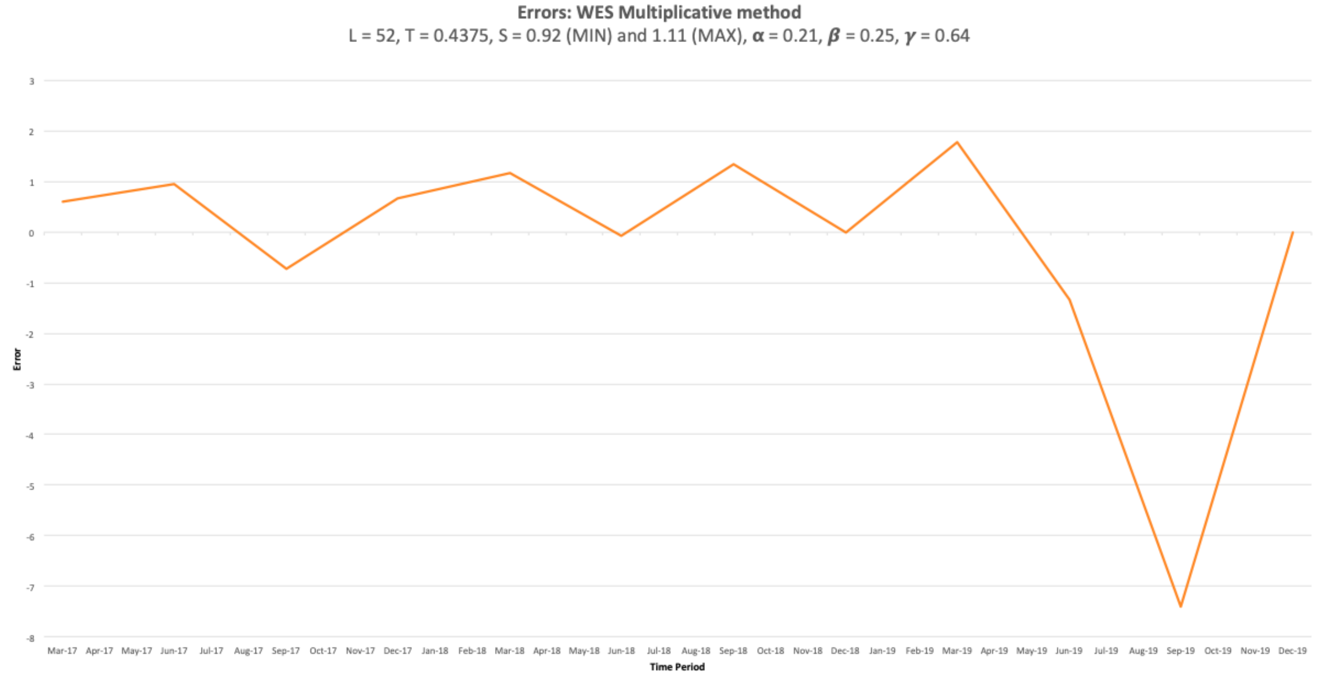

Figure 1.2

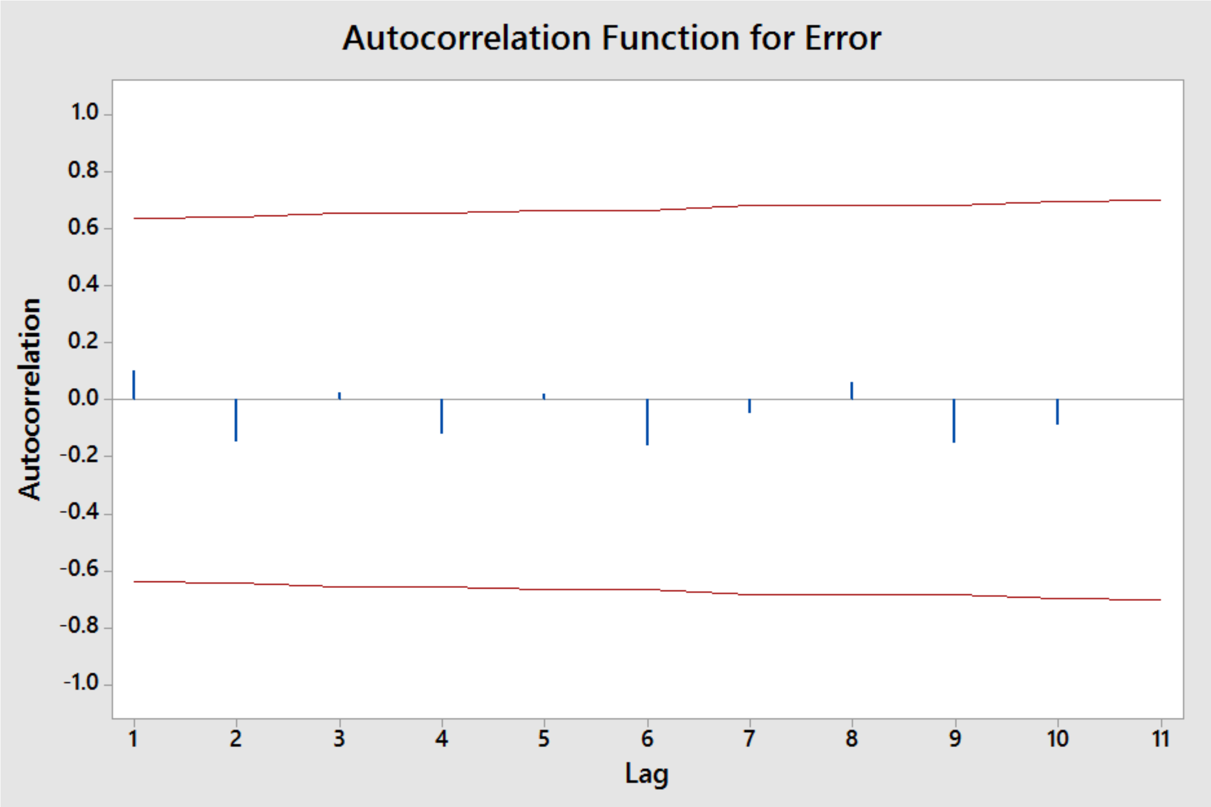

Figure 1.3

Period	Prices	Level	Trend	Seasonal	Predictions	m	Forecasts	alpha	0.20981251					
Mar-16	48			0.91866029				beta	0.24686734		Initial trend calculation			
Jun-16	52			0.99521531				gamma	0.63635131		Year 1	Year 2	Y2-Y1	(Y2-Y1)/4
Sep-16	51			0.97607656							48	49	1	0.25
Dec-16	58	52	0.4375	1.11004785							52	54	2	0.5
Mar-17	49	52.82409668	0.47122126	0.92435352	48.4019139						51	52	1	0.25
Jun-17	54	53.49763961	0.52116787	1.0042356	53.0403164						58	61	3	0.75
Sep-17	52	53.86264452	0.48261634	0.96929436	52.7264915								Initial trend:	0.4375
Dec-17	61	54.47268531	0.51407327	1.11627101	60.325840									
Mar-18	52	55.25296337	0.57979054	0.9350267	50.8272037									
Jun-18	56	55.81828793	0.57621936	1.00361186	56.0692392									
Sep-18	56	56.68393938	0.64767069	0.98115582	54.6628781									
Dec-18	64	57.33205845	0.64778138	1.11629194	63.9976145									
Mar-19	56	58.38089597	0.74678904	0.9504208	54.2126985									
Jun-19	58	58.84728756	0.67756807	0.99215122	59.3412461									
Sep-19	51	57.94174799	0.2867505	0.91690887	58.4031587									
Dec-19	65	58.22849786	0.28675034	1.11629191	65.0000033									
Mar-20						1	55.6141089							
Jun-20						2	58.3404744							
Sep-20						3	54.1789977							
Dec-20						4	66.2803893							

Figure 1.4