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Homework #3

Q1. Linear Consumption Model Trend: $y_t = \beta_0 + \beta_1 TIME_t + \varepsilon_t$
where $\varepsilon_t \sim N(0, \sigma^2)$

Point Forecast: 2010Q1

$t = 1990; 2010$

$= 2010 - 1990$

$= 20$

$y_t = 0.51 + 2.3(20)(4)$

$= .51 + 184$

$y_t = \boxed{184.51}$ Singapore Dollars for 2010Q1

Interval Forecast: 2010Q1

$\hat{y}_{t+h} \pm 1.96\hat{\sigma} \rightarrow \sqrt{\sigma^2} = \sqrt{16} = 4$

$184.51 \pm (1.96)(4)$

$= 184.5 \pm 7.84$

$\hat{y}_t = \boxed{(176.67, 192.35)}$

Density Forecast: 2010Q1

$N(\hat{y}_{t+h}, \hat{\sigma}^2) \rightarrow \boxed{N(184.51, 16)}$

Q2. If you are to utilize a trend forecast on the sum of squared residuals (MSE), it is best to pick the model with the least MSE output. Out of the 3 models presented, the exponential trend model has the least MSE output @ 2,749. This makes it the best model and why I would select it for my forecast.

Q3.

1. When accounting for OLS and least square estimates, outlier data points can drastically affect the model and slope of the regression line. Outliers can pose significant challenges to models trying to emphasize the effects one variable has on another.

2. These other data points may be affected because they may be susceptible to that same measurement error posed in the data set. This would cause significant inaccuracies in the models and drastically affect regression outputs. It is always best practice to remove errors within data sets and assess the practicality of the model w/ those errors removed.

3. as a forecaster w/ outliers in my data set, I would assess the practicality of the outlier. Is the outlier redundant throughout the data set? Does it seem to be a one-off measurement error? Questions like these are all factors I must work to assess in the data set. From there, I would be able to think of including the outlier in my model(s) or not.

Q4.

1. We might be interested in examining data at the log-level rather than level of the $/FT exchange rate for numerous reasons. The advantage of using the natural log on data is that the interpretation of reg coefficients is straightforward. The reg. coefficients in a log-log model represent the elasticity of your y variable w/ respect to your x variable. Log transformations can also be used to make highly skewed distributions less skewed.

2. after taking the logs of ftusdrate data, we produced a time series plot showing FT/USD Exchange rates over the last 502 days, this is a log-log model, where the data is transformed to represent elasticity between the y-var and x-var. With this, over 502 days, we find the highest exchange rate between the 2 currencies was around days 10-20, while the lowest exchange rates were around day 175.

3. After running logs and producing a time series plot for log $/Ft exchange rate, the data appears to be normally distributed. There is little to no skewness in the histogram. There does not seem to be any deviation from normality in both the log-log model or the histogram of Y1change.

Q5.

1. After producing a time-series plot for Liquor Sales in the U.S. from 1988-2016, we see that liquor sales reached a peak in between years 2010-2011, and had a low in between years 1990-1991. This significant increase of liquor sales from 1988-2016 could be for a variety of reasons - population growing and getting older, easier and more access to alcohol, and/or people are drinking more.

2. Log-Linear model: When creating the log-linear model, we find significant increases to liquor sales over time. The regression has an upwards trend along w/ a high MSE (.8433). The DW stat is not as close to 2 as would be desirable - meaning this model may not fit the data as much as is warranted w/ the DW-Test.
Log-Quadratic model: When creating the log-quadratic model on liquor sales, we find also find a significant increase in liquor sales from 1988-2016. We also find that this model fits better w/ the regression trend, as the DW-test stat is closer to 2 (1.7544). It also registers a higher MSE score of 0.9037.

3. AIC and BIC are used for model selection. When calculating and comparing the AIC & BIC scores of several models, a lower score means a model is a better fit. Out of the 2 models examined, the Log-quadratic is a better fit for the data being examined. This model's AIC/BIC scores registered

at AIC: -436.5158 and BIC: -421.2473. This model fits the data and scores better than the log-linear model. This model also has a higher DW-test score. In turn, it is a better model and fit for the data at hand.

4. Log-Quadratic Model for 95% CI @ 2015.01

Point Forecast: $\boxed{7.515064}$

Interval Forecast: $\boxed{(\underbrace{7.474438}_{lwr}, \underbrace{7.555690}_{upr})}$