/02 Modelling And Forecasting Trend

Modelling And Forecasting Trend

成蹊风险研究资料

MEAN SQUARED ERROR:

- **Mean squared error** (MSE) is a statistical measure computed as the sum of squared residuals divided by the total number of observations in the sample.

$$\mathrm{MSE} = \frac{\sum_{t=1}^{T} e_t^2}{T}$$

Where :

$e_t = y_t - \hat{y}_t$ (difference between observed & expected observations)

$y_t = \hat{\beta}_0 - \hat{\beta}_1 \mathrm{Time}_t$ (a regression model)

- The MSE is based on in-sample data.
- The residuals are calculated as the difference between the actual value observed and the predicated valued based on the regression model.
- The coefficient f determination $R^2 = 1 - \frac{\sum_{t=1}^{T} e_t^2}{\sum_{t=1}^{T} (y_t - \bar{y})^2}$
- The methodology to select the best forecasting model is to find the model with the smallest out-of-sample one-step-ahead MSE.

Modelling And Forecasting Trend

MEAN SQUARED ERROR:

Reducing MSE Bias

- To reduce the bias associated with MSE is to impose a penalty on the degrees of freedom, k.
- The s^2 measure is an unbiased estimator of the MSE because it corrects degrees of freedom as follows:

$$s^2 = \frac{\sum_{t=1}^{T} e_t^2}{T - k}$$

- As more variables are included in a regression equation the model is at greater risk of over-fitting the in-sample data.
- This problem is also often referred to as data mining, which causes poor forecasting of out-of-sample data.
- As more parameters are introduced to a regression model, it will explain the data better, but may be worse at forecasting out-of-sample data.
- Therefore, it is important to adjust for the number of variables or parameters used in a regression model.
- The best model is selected based on the smallest unbiased MSE, or s^2.
- Adjusted R^2 estimates can be computed as follows:

$$\bar{R}^2 = 1 - \frac{s^2}{\sum_{t=1}^{T} \frac{(y_t - \bar{y})^2}{T - 1}}$$

Modelling And Forecasting Trend

MODEL SELECTION CRITERIA:

- The selection criteria are often compared based on a penalty factor.

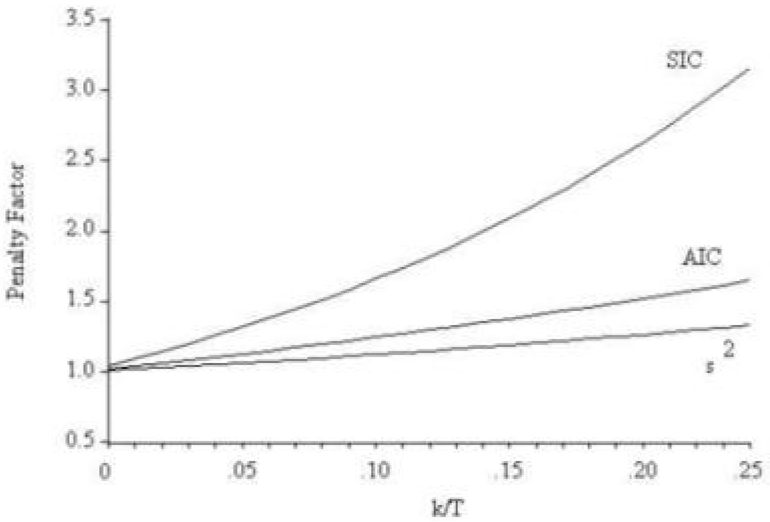
$$s^2 = \left(\frac{T}{T-k}\right)\frac{\sum_{t=1}^{T} e_t^2}{T}$$

- The Akaike information criterion (AIC)

$$AIC = e^{\left(\frac{2k}{T}\right)}\frac{\sum_{t=1}^{T} e_t^2}{T}$$

- Schwarz information criterion (SIC)

$$SIC = T^{\left(\frac{k}{T}\right)}\frac{\sum_{t=1}^{T} e_t^2}{T}$$



- As shown in Figure, when the degree of freedom, K rises to one-fourth of the total observations (T) i.e. k/T = 0.25 then the SIC penalty increases rapidly at 3 whereas the S2 penalty remains the lowest at marginally over 1. The AIC penalty also moves at a slower rate (a little faster than S2) as compared to fast rated movement of SIC penalty. Thus, with the increase in degree of freedom the penalty factor increases the most for SIC followed by AIC & S2.

Modelling And Forcasting Trend

- **EVALUATING CONSISTENCY:**
  - Two conditions are required for a model selection criteria to be consistent.
    - ✓When the true model or data-generating process (DGP) is one of the defined regression models, then the probability of selecting the true model approaches one as the sample size increases.
    - ✓When the true model is not one of the defined regression models being considered, then he probability of selecting the best approximation model approaches one as the sample size increases.
  - Asymptotic efficiency is the property that chooses a regression model with one-step-ahead forecast error variances closest to the variance of the true model.
  - The AIC is asymptotically efficient and the SIC is not asymptotically efficient.

Thanks
Leading Derivative & Risk Advisors

成蹊风险研究

riskmacro.com