Exercise for March 15 2023

The goal of this tutorial meeting is to practice, to implement and to interpret unit root tests such that you should be able to correctly detrend/transform nonstationary time series. We start with the commodity prices of case 3. They are easier to interpret (e.g. no seasonality, not too many lags) before implementing unit root tests on your own series.

I would like that at the end of the meeting you all know about what trend you have got on your data (stochastic or deterministic).

In items 1 to 4 we do the unit root tests steps by steps by OLS. Once you get it, one can use the drop down EViews menu in a more systematic manner.

1. Take the commodity series, say call it Y_t. Plot that series and, from the graph, decide (intuitively) whether you would favor Y_t or $\ln Y_t$. Is there visually a trend? Note that you do not have seasonality, these are annual data.

2. Compute manually (namely using an OLS regression in EViews) the null hypothesis of a unit root (Dickey-Fuller test) against the alternative of a deterministic trend. Namely, run the equation (I assume that taking the logs makes sense but I might be wrong on your series). Hint: log(y) c @trend log(y(-1))

$$\ln Y_t = \alpha + \beta trend + \rho \ln Y_{t-1} + \varepsilon_t \tag{1}$$

   and test

$$H_0 : \rho = 1 \quad vs. \quad H_A : \rho < 1$$

   For that you have to run (1) by OLS, obtain the coefficient $\hat{\rho}$ in front of log(y(-1)), and compute manually the $t - test$

$$t - test : \frac{\hat{\rho} - 1}{se_{\hat{\rho}}}$$

   In order to save time, transform (ONLY) the dependent variable in first differences (or directly in the EViews regression box using Dlog(y) or D(y)) and run

$$\begin{aligned} (\ln Y_t - \ln Y_{t-1}) &= \alpha + \beta trend + \rho \ln Y_{t-1} - \ln Y_{t-1} + \varepsilon_t \\ \Delta \ln Y_t &= \alpha + \beta trend + \pi \ln Y_{t-1} + \varepsilon_t \qquad (2) \end{aligned}$$

Hint: Dlog(y) c @trend log(y(-1)) in EViews. From (2) you can now read directly in EViews output $H_0 : \pi = \rho - 1 = 0$, i.e. you have directly the t-test of the coefficient in front of log(y)

$$t - test : \frac{\hat{\pi}}{se_{\pi}} = \frac{\hat{\rho} - 1}{se_{\hat{\rho}}}$$

3. Double check that you get the same $t - tests$ values in (1) and (2), you made a mistake if this is not the case.

4. Compare the former t-test with the critical values provided by Dickey and Fuller (see my slides). Take a 5% significance level and the column with constant and trend as there is a trend in (1) and (2). What do you conclude about the type of trend: deterministic vs. stochastic?

5. The distribution of the unit roots tests, that is the DF critical values, for (1) or (2) is not correct if the error term ε_t is autocorrelated. Test the null of no autocorrelation in (2). If you have some autocorrelation, add lags until you do not have autocorrelation anymore (white noise), namely use a regression like in (2) but with some additional past values of the dependent variable. This is the ADF test

$$t - test : \frac{\hat{\pi}}{se_{\pi}}$$

but now in regression (3).

$$\Delta \ln Y_t = \alpha + \beta trend + \pi \ln Y_{t-1} + \delta_1 \Delta \ln Y_{t-1} + ... + \delta_p \Delta \ln Y_{t-p} + \varepsilon_t \quad (3)$$

Make sure you see the differences between (2) and (3). Hint: now it is Dlog(y) c @trend log(y(-1)) Dlog(y(-1)) Dlog(y(-2)) in EViews with e.g. 2 lags. And we look at the coefficient and t-test for log(y(-1)).

6. Perform ADF tests (3) on the commodity series using EViews drop down menu. Choose the option with intercept and trend. Take an information criteria (in EViews window of the unit root test) to decide about the number of lags p needed to whiten for the presence of autocorrelation in (3). For the same model with the same number of lags p you must get the same numerical values for the t-test.

7. Now that you are comfortable with the test, perform the ADF unit root test on your own main series. Plot the series before. If you observe a trend in the series, the adequate model is (1), (2) or (3). Indeed we need to have the possibility to get a deterministic trend under the alternative. Some series do not have a trend (some unemployment, some current account, some interest rates). The same DF (or ADF) test can be performed but as we do not believe that the series is moving around a positive/negative trend but around an horizontal line, the ADF tests with a constant only is recommended, that is

$$\Delta \ln Y_t = \alpha + \pi \ln Y_{t-1} + \delta_1 \Delta \ln Y_{t-1} + ... + \delta_p \Delta \ln Y_{t-p} + \varepsilon_t \qquad (4)$$

The procedure is the same, only the critical values change (EViews knows which ones to take). Note that it's not wrong to leave the trend in but it's not necessary. The null is the unit root, the alternative is that the variable is stationary around a mean. As an example, the US unemployment rate seems moving around 6% in the US.

8. Whatever the results above in item 7 (of course you will continue with the correct specification for your final project), estimate on your main series both a trend stationary (TS) and a difference stationary (DS) specification without the last 20 observations, namely

$$\begin{aligned} a)\ \ln(Y_t) &= \alpha_0 + \alpha_1 trend + \varepsilon_t \quad \text{(TS)} \\ b)\ \Delta \ln(Y_t) &= \beta_0 + u_t \qquad\qquad\quad \text{(DS)} \end{aligned}$$

with $t = 1...T-20$. Then forecast both series Y_t (go back to the level and ask for dynamic forecasts) on the last 20 observations and pay attention to what confidence intervals look like. Note that

$$\Delta \ln Y_t = \ln(Y_t) - \ln(Y_{t-1}) \approx \frac{Y_t - Y_{t-1}}{Y_{t-1}}$$

Hint: do not generate the series before the regressions, instead write y, log(y), dlog(y) or d(y) in the estimation equation window. This is equivalent to do the regression on generated series but it has the advantage in EViews to get forecasts for the level of the original variable as well. EViews understands that you have modified the series and proposes to go back to the untransformed variable we are interested in.

9. Perform the Diebold Mariano test between two static forecasts (DS and TS for the levels).

10. For your series (TS or DS), find the best ARMA(p,q) using the automatic model selection. We will use the correlogram next week to identify ARMA. By now, define and generate your stationary variable, open it, then go `Proc -> automatic ARIMA forecasting`. On the right panel, choose no transformation. On the left panel, choose no differencing. Indeed you did spend time on that with unit root tests, graphs, etc. Use BIC as an information criteria in icon option. Take AR and MA of max 4. In the box regressors you can add your deterministic trend or seasonal components if you have them on your data. Report the ARMA(p,q) numbers.