PS5

WARM UP

1. **Explain in detail why we care whether a time series process is covariance stationary.**
    a. Having all three conditions met under covariance stationary is essential to understanding the stability of probability. If we are able to create a stable model, then we will be able to better use our historical data to forecast.
    b. Additionally, when understanding the dependence, we are able to identify if the model has a unit root, which is critical to solving in your model (through differencing).

EXERCISES

<u>Wooldridge, 18.7</u>

Let *gM* be the annual growth in the money supply and let *unem* be the unemployment rate. Assuming that *unem* follows a stable AR(1) process, explain in detail how you would test whether *gM* Granger causes *unem*.

1. AR(1): yt = ryt−1 + et
2. In order to separate cause from effect, assumed weak dependence, which means that the correlation between the observations get smaller as time increases.
3. We would then test to see if these data covary, in which we would attempt to understand if the data is highly persistent or trending.
4. If ρ =1, then there is a unit root, which means we need to difference so that we can untangle to determine causality.

<u>Wooldridge, 18.9</u>

1. **Let *yt* be an I(1) sequence. Suppose that *gn* is the one-step-ahead forecast of *delta yn* and let *fn = gn + yn* be the one-step-ahead forecast of *yn +1* . Explain why the forecast errors for forecasting delta *yn + 1 and yn +1* are identical.**
    a. In order to forecast y_{t+1} with an I(1) process, you must use delta y_{t+1}.
    b. The computation for the forecast interval is as follows
        i. $$se\left(\hat{e}_{T+1}\right) = \sqrt{\left[se\left(\hat{f}_T\right)\right]^2 + \hat{\sigma}^2}$$
    c. The standard errors will be smaller the sigma, but will equal the corresponding value (so that they are identical)

COMPUTER EXCERCISES

Wooldridge, 11.C10

Use all the data in PHILLIPS to answer this question. You should now use 56 years of data.

1. **Reestimate equation (11.19) and report the results in the usual form. Do the intercept and slope estimates change notably when you add the recent years of data?**
    a. $\text{In}f_t - \text{in}f^{e}_t = \text{B1}(\text{unemt} - \text{u0}) + e_t$

```
> tidy(est)
# A tibble: 2 x 5
  term        estimate std.error statistic p.value
  <chr>          <dbl>     <dbl>     <dbl>   <dbl>
1 (Intercept)    1.05      1.55      0.681  0.499
2 unem           0.502     0.266     1.89   0.0639

> tidy(est.delta)
 # A tibble: 2 x 5
   term        estimate std.error statistic p.value
   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
 1 (Intercept)    2.83      1.22       2.31  0.0249
 2 unem          -0.518     0.209     -2.48  0.0165
```

    a. Intercepts and estimates change considerably. The variable Unem's coefficient flips signs completely.

2. **Obtain a new estimate of the natural rate of unemployment. Compare this new estimate with that reported in Example 11.5.**
    a. Non lag:
        i. 1.05/0.502 = 2.091633% unemployment
        ii. 2.83/-0.518 = -5.46332% unemployment

3. **Compute the first order autocorrelation for unem. In your opinion, is the root close to one?**
    a. There is a 49.17 change the variable has a unit root.
    b. P value = . 4917

4. **Use cunem as the explanatory variable instead of unem. Which explanatory variable gives a higher R-squared?**
    a. Model 1: R2 = 0.1037
    b. Model 2: R2 = 0.1348
    c. "cunem" gives a higher R^2

COMPUTER EXCERCISES *(Cont'd)*

<u>Wooldridge, 18.C3</u>

Use the data in VOLAT for this exercise.

1. **Estimate an AR(3) model for *pcip*. Now, add a fourth lag and verify that it is very insignificant.**

```
Coefficients:
             Estimate Std. Error t value
(Intercept)  1.80419    0.54804   3.292
pcip_1       0.34912    0.04252   8.210
pcip_2       0.07080    0.04495   1.575
pcip_3       0.06737    0.04253   1.584
```

   a. cip_1 significant, rest are not.
   b. Add in 4th lag (very insignificant):

```
Coefficients:
              Estimate Std. Error t value
(Intercept)  1.787332   0.554904   3.221
pcip_1       0.349382   0.042716   8.179
pcip_2       0.070236   0.045132   1.556
pcip_3       0.065750   0.045128   1.457
lag(pcip, 4) 0.004317   0.042696   0.101
```

2. **To the AR(3) model from part (i), add three lags of *pcsp* to test whether *pcsp* Granger causes *pcip*. Carefully, state your conclusion.**
   a. It appears that the lag of pcsp does effect pcip; however, as time continues, a greater weight seems to be placed on lags that are closer to time 0.

3. **To the model in part (ii), add three lags of the change in *i3*, the three-month T-bill rate. Does *pcsp* Granger cause *pcip*conditional on past ?**

```
Coefficients:
             Estimate Std. Error t value
(Intercept)  1.42708    0.55741   2.560
pcip_1       0.30172    0.04278   7.052
pcip_2       0.04875    0.04456   1.094
pcip_3       0.07579    0.04183   1.812
pcsp_1         0.02639    0.01332   1.981
pcsp_2         0.02647    0.01371   1.931
pcsp_3         0.01765    0.01327   1.329
ci3            3.57487    1.11803   3.197
ci3_1          0.58382    1.16459   0.501
ci3_2          1.72886    1.13868   1.518
```

   a. pcsp has a lesser effect on pcip when you add in these variables.
   b. It appears that it does not cause this.

COOL DOWN

Wooldridge, 10.1

Decide if you agree or disagree with each of the following statements and give a brief explanation of your decision:

1. **Like cross-sectional observations, we can assume that most time series observations are independently distributed.**
    a. Disagree. Identical distribution is common in times series data.

2. **The OLS estimator in a time series regression is unbiased under the first three Gauss-Markov assumptions.**
    a. Agree. If time series meets first three then unbiased.

3. **A trending variable cannot be used as the dependent variable in multiple regression analysis.**
    a. Disagree. Remove the trends, but we can still use the variable as the dependent variable.

4. **Seasonality is not an issue when using annual time series observations.**
    a. Agree because seasonality mostly effects quarters or months. You may have to deal with trending data year over year, but it is likely that annual data will suffice.