

# Methods of Economic Investigation II (EC403)

## Solutions to Problem Set #5

October 25, 2002

### Solutions

1. (a) The process  $u_t$  is a Moving Average process of order 1. The autocorrelation function of  $u_t$  is:

$$\begin{aligned}\rho(1) &= \frac{\gamma(1)}{\gamma(0)} = \frac{\text{cov}(u_t, u_{t-1})}{\text{var}(u_t)} \\ \rho(s) &= 0 \quad \forall s \geq 2.\end{aligned}$$

We calculate first the variance:

$$\text{var}(u_t) = \text{var}(\varepsilon_t) + 0.25\text{var}(\varepsilon_{t-1}) - 2 \times 0.5\text{cov}(\varepsilon_t, \varepsilon_{t-1}) = 1.25$$

then the covariance:

$$\text{cov}(u_t, u_{t-1}) = E(u_t u_{t-1}) = E[(\varepsilon_t - 0.5\varepsilon_{t-1})(\varepsilon_{t-1} - 0.5\varepsilon_{t-2})] = -0.5E(\varepsilon_{t-1}^2) = -0.5$$

using the independence between the  $\varepsilon_t$ 's. We get

$$\begin{aligned}\rho(1) &= \frac{-0.5}{1.25} = -0.4 \\ \rho(s) &= 0 \quad \forall s \geq 2.\end{aligned}$$

(b) The process generating  $u_t$  is (weakly) stationary, its mean, variance, and autocovariance do not depend on  $t$ . The process generating  $y_t$  is not stationary because it is composed by deterministic trend. We can anyway calculate its mean and variance to prove it:

$$\begin{aligned}E(y_t) &= \beta t \\ \text{var}(y_t) &= 1.25\end{aligned}$$

We say that  $y_t$  is trend stationary because  $y_t - \beta t$  is stationary.

(c) To construct the confidence interval of  $\hat{\beta}$  we need its variance and mean:

$$\hat{\beta} = \frac{\sum_{t=1}^T ty_t}{\sum_{t=1}^T t^2} = \beta + \frac{\sum_{t=1}^T tu_t}{\sum_{t=1}^T t^2}$$

and  $\hat{\beta}$  is an unbiased estimator of  $\beta$ . The variance is given by

$$\text{var}(\hat{\beta}) = \frac{1}{\left(\sum_{t=1}^T t^2\right)^2} \text{var}\left(\sum_{t=1}^T tu_t\right) = \frac{1}{\left(\sum_{t=1}^T t^2\right)^2} E\left[\left(\sum_{t=1}^T tu_t\right)^2\right],$$

where

$$\begin{aligned} E\left[\left(\sum_{t=1}^T tu_t\right)^2\right] &= E\left[\sum_{t=1}^T \sum_{s=1}^T tsu_t u_s\right] = E\left[\sum_{t=1}^T t^2 u_t^2\right] + E\left[t \neq s \sum \sum tsu_t u_s\right] \\ &= \sum_{t=1}^T t^2 E(u_t^2) + 2 \sum_{t=1}^T t(t-1) E[u_t u_{t-1}] \\ &= 1.25 \sum_{t=1}^T t^2 + 2(-0.5) \sum_{t=1}^T t(t-1) \\ &= 1.25 \sum_{t=1}^T t^2 - \sum_{t=1}^T t^2 + \sum_{t=1}^T t = 0.25 \sum_{t=1}^T t^2 + \sum_{t=1}^T t. \end{aligned}$$

Therefore,

$$\text{var}(\hat{\beta}) = \frac{0.25 \sum_{t=1}^T t^2 + \sum_{t=1}^T t}{\left(\sum_{t=1}^T t^2\right)^2}$$

and the confidence interval is hence

$$\hat{\beta} \pm z_{\alpha/2} \sqrt{\text{var}(\hat{\beta})}.$$

Assuming  $\varepsilon_t \sim i.i.d. N(0, 1)$  this is exact, otherwise it is approximate.

2. (a)  $x_t$  is an AR(1) with drift, its mean and variance are hence:

$$\begin{aligned} E(x_t) &= \frac{\alpha}{1-\rho} = E(x_{t-1}) = \dots \\ \text{var}(x_t) &= \frac{s^2}{1-\rho^2} = \text{var}(x_{t-1}) = \dots \end{aligned}$$

Hence the autocovariance function is

$$\begin{aligned} \gamma(1) &= \text{cov}(x_t, x_{t-1}) = E(x_t x_{t-1}) - E(x_t)E(x_{t-1}) = E[(\alpha + \rho x_{t-1} + u_t)(x_{t-1})] - \frac{\alpha^2}{(1-\rho)^2} = \\ &= E[\alpha x_{t-1} + \rho x_{t-1}^2 + u_t x_{t-1}] - \frac{\alpha^2}{(1-\rho)^2} = \frac{\alpha^2}{1-\rho} + \rho E(x_{t-1}^2) - \frac{\alpha^2}{(1-\rho)^2} = \end{aligned}$$

$$= \frac{\alpha^2}{1-\rho} + \frac{s^2}{1-\rho^2} + \frac{\alpha^2}{1-\rho^2} - \frac{\alpha^2}{(1-\rho)^2} = \rho \frac{s^2}{1-\rho^2} = \rho\gamma(0).$$

Generalizing,

$$\gamma(j) = \rho^j \gamma(0) = \rho^j \frac{s^2}{1-\rho^2}.$$

(b) The point estimate of  $x_{t+r}$  is obtained using the best linear predictor; suppose to know  $\{x_t, x_{t-1}, \dots\}$  and the actual value of the parameters, therefore

$$\hat{x}_{t+1|t} = E[x_{t+1} | x_t, x_{t-1}, \dots] = \alpha + \rho x_t,$$

which is the one period ahead estimate of  $x_{t+1}$ . We can proceed in the same fashion for the two periods ahead:

$$\begin{aligned} \hat{x}_{t+2|t} &= E[x_{t+2} | x_t, x_{t-1}, \dots] = E[\alpha + \rho x_{t+1} + u_{t+2} | x_t, x_{t-1}, \dots] \\ &= \alpha + \rho(\alpha + \rho x_t) = \alpha + \alpha\rho + \rho^2 x_t. \end{aligned}$$

Repeating this process for the r-period forward given the sample information available at time  $t$ ,  $I_t$ , we have

$$\hat{x}_{t+r|t} = \alpha \sum_{j=0}^{r-1} \rho^j + \rho^r x_t,$$

which is, as already said, the best linear predictor of  $x_{t+r|t}$ . To calculate the interval forecast we need the variance of this forecast which is obtained from the one period ahead forecast error

$$e_{t+1} = x_{t+1} - \hat{x}_{t+1|t} = x_{t+1} - \alpha - \rho x_t = u_{t+1}.$$

The 2-periods ahead forecast error is

$$e_{t+2} = x_{t+2} - \hat{x}_{t+2|t} = x_{t+2} - [\alpha(1+\rho) + \rho^2 x_t] = u_{t+2} + \rho u_{t+1}$$

after substituting for  $x_{t+2}$ . In general we have

$$e_{t+r} = u_{t+r} + \rho u_{t+r-1} + \rho^2 u_{t+r-2} + \dots + \rho^r u_{t+1} = \sum_{j=1}^r \rho^{r-j} u_{t+j}.$$

The forecast variance is thus

$$\text{var}(e_{t+r} | I_t) = \sum_{j=1}^r \rho^{2(r-j)} \text{var}(u_{t+j}) = s^2 \sum_{j=1}^r \rho^{2(r-j)}$$

under the assumption we have about the errors. Hence the interval forecast is

$$(\hat{x}_{t+r|t-1}) \pm z_{\alpha/2} \sqrt{s^2 \sum_{j=1}^r \rho^{2(r-j)}}$$

(c) We can do the same for  $y_t$ .

$$y_t = \gamma y_{t-1} + \beta E(x_{t+1} | I_t) + \varepsilon_t$$

and substituting for  $E(x_{t+1} | I_t)$

$$y_t = \alpha\beta + \gamma y_{t-1} + \beta x_t + \varepsilon_t$$

then

$$\hat{y}_{t+1|t} = E(y_{t+1} | I_t) = \alpha\beta + \gamma y_t + \beta\rho E(x_{t+1} | I_t) = \alpha\beta + \gamma y_t + \beta\rho(\alpha + \rho x_t)$$

the associated error is

$$e_{t+1|t} = y_{t+1} - \hat{y}_{t+1|t} = \varepsilon_{t+1} + \beta\rho [x_{t+1} - \hat{x}_{t+1|t}] = \varepsilon_{t+1} + \beta\rho(u_{t+1})$$

hence the variance of the error forecast is

$$\text{var}(e_{t+1} | I_t) = \sigma^2 + \beta^2 \rho^2 s^2$$

then the interval forecast is

$$\hat{y}_{t+1|t} \pm z_{\alpha/2} \sqrt{\sigma^2 + \beta^2 \rho^2 s^2}$$

(d) The estimation of the parameters proceed as follows:

- from the Ar(1) process

$$x_{t+1} = \alpha + \rho x_t + u_{t+1}$$

we get  $\hat{\alpha}$  and  $\hat{\rho}$  by OLS

- from

$$y_t = \theta_0 + \theta_1 y_{t-1} + \theta_2 x_t + \varepsilon_t$$

we get  $\hat{\theta}_0, \hat{\theta}_1, \hat{\theta}_2$ .

- Then using the relationship given by

$$y_t = \alpha\beta + \gamma y_{t-1} + \beta\rho x_t + \varepsilon_t$$

we have that

$$\begin{aligned} \hat{\beta} &= \frac{\hat{\theta}_0}{\hat{\alpha}} \\ \hat{\gamma} &= \hat{\theta}_1 \\ \hat{\beta} &= \frac{\hat{\theta}_2}{\hat{\rho}} \end{aligned}$$

Note that there's an alternative estimate of  $\beta$ .