

# Non-stationary and non-linear models

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## 1 Cointegrated VAR

- Example 1:

$$\begin{pmatrix} x_{1t} \\ x_{2t} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} x_{1t-1} \\ x_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Error correction model:

$$\begin{pmatrix} \Delta x_{1t} \\ \Delta x_{2t} \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \begin{pmatrix} 1 & -1 \end{pmatrix} \begin{pmatrix} x_{1t-1} \\ x_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

where  $\Delta x_{it} = x_{it} - x_{it-1}$ . The cointegration vector is:  $\begin{pmatrix} 1 & -1 \end{pmatrix}$

- Example 2:

$$\begin{pmatrix} x_{1t} \\ x_{2t} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0.001 & 0.999 \end{pmatrix} \begin{pmatrix} x_{1t-1} \\ x_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Error correction model:

$$\begin{pmatrix} \Delta x_{1t} \\ \Delta x_{2t} \end{pmatrix} = \begin{pmatrix} 0 \\ 0.001 \end{pmatrix} \begin{pmatrix} 1 & -1 \end{pmatrix} \begin{pmatrix} x_{1t-1} \\ x_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

## 2 ARCH, GARCH, leptokurtic distributions

### 2.1 General framework

$$x_t = \mu_t + \sigma_t u_t$$

where  $u_t$  is *iid* with  $E(u_t) = 0$  and  $V(u_t) = 1$ . Hence:

$$\begin{aligned} E_{t-1}(x_t) &= \mu_t \\ V_{t-1}(x_t) &= \sigma_t^2 \end{aligned}$$

## 2.2 Distribution of the standardised residuals

### 2.2.1 Normal

$$u_{1,t} \sim N(0, 1)$$

- Moments:  $E(u_{1,t}) = 0$ ,  $V(u_{1,t}) = 1$ ,  $E(u_{1,t}^3) = 0$ ,  $E(u_{1,t}^4) = 3$

### 2.2.2 Student $t$ with $\nu$ degrees of freedom

- Usual parametrisation:

$$f(v_t) \propto \left(1 + \frac{v_t^2}{\nu}\right)^{-\frac{(\nu+1)}{2}}$$

Then, for  $\nu > 2$ :  $E(v_t) = 0$ ,  $V(v_t) = \nu/(\nu - 2)$ . Hence,  $u_{2,t} = \sqrt{(\nu - 2)/\nu} v_t$  will have zero mean and unit variance.

- Simulation

$$u_{2,t} = \sqrt{\frac{\nu - 2}{z_t}} u_{1,t}$$

where  $u_{1,t} \sim N(0, 1)$  and  $z_t$  is a Gamma variate with mean  $\nu$  and variance  $2\nu$ . When  $\nu$  is an integer,  $z_t \sim \chi_\nu^2$

- For  $\nu = 10$ :

```
genr chi2=randgen(X,10)
series r=8/chi2
series u2=r^.5*u1
```

- Moments ( $\nu > 4$ ):  $E(u_{2,t}) = 0$ ,  $V(u_{2,t}) = 1$ ,  $E(u_{2,t}^3) = 0$ , and

$$E(u_{2,t}^4) = 3 \frac{\nu - 2}{\nu - 4} > 3$$

### 2.2.3 Asymmetric $t$ with $\nu$ degrees of freedom

- Simulation

$$u_{3,t} = c(\beta, \nu) \beta \left( \frac{\nu - 2}{z_t} - 1 \right) + \sqrt{\frac{\nu - 2}{z_t}} c(\beta, \nu) u_{1,t}$$

where

$$c(\beta, \nu) = \frac{-1 + \sqrt{1 + \frac{8\beta^2}{\nu - 4}}}{\frac{4\beta^2}{\nu - 4}}$$

- Moments ( $\nu > 8$ ):  $E(u_{3,t}) = 0$ ,  $V(u_{3,t}) = 1$ ,

$$E(u_{3,t}^3) = \begin{cases} > 0 & \text{si } \beta > 0 \\ < 0 & \text{si } \beta < 0 \end{cases}$$

and  $E(u_{2,t}^4) > 3$

- For  $\nu = 10$  and  $\beta = -10$ :

$$\text{series } u3 = -1.588534 * (r-1) + (r * .158853)^{.5} * u1$$

## 2.2.4 Normal Inverse Gaussian

- Simulation

$$u_{4,t} = c(\beta, \gamma) \beta \left( \frac{\gamma}{w_t} - 1 \right) + \sqrt{\frac{\gamma}{w_t} c(\beta, \gamma)} u_{1,t}$$

where  $\gamma \geq 0$ ,

$$c(\beta, \gamma) = \frac{-1 + \sqrt{1 + \frac{4\beta^2}{\gamma}}}{\frac{2\beta^2}{\gamma}}$$

and  $w_t$  is Inverse Gaussian or  $IG(1, \gamma)$  for short.

- For  $\gamma = 1$  and  $\beta = -10$ :

$$\begin{aligned} &\text{genr } v = \text{normal}() \\ &\text{genr } s = \text{randgen}(X, 1) \\ &\text{series } q = 1 - .5 * ((s^2 + 4 * s)^{.5} - s) \\ &\text{series } w = (v <= (1 / (1 + q))) * q + (v > (1 / (1 + q))) * (1 / q) \\ &\text{series } u4 = -0.951249 * (w - 1) + (.0951249 * w)^{.5} * u1 \end{aligned}$$

## 2.3 Models for the mean $\mu_t$

- See session 1. We will assume that  $\mu_t = 0, \forall t$

## 2.4 Models for $\sigma_t^2$

### 2.4.1 ARCH(1)

- Model:  $x_t = \sigma_t u_t$

$$\sigma_t^2 = \alpha_0 + \alpha_1 x_{t-1}^2$$

- Kurtosis

$$E(x_t^4) = \frac{\kappa \alpha_0^2 (1 + \alpha_1)}{(1 - \alpha_1)(1 - \kappa \alpha_1^2)}$$

where  $\kappa = E(u_t^4)$ .

- Let  $\alpha_0 = .6, \alpha_1 = .4$
- Simulation:

```

smpl 1 100000
series sig2arch1=1
smpl 2 100000
sig2arch1=.6+.4*sig2arch1(-1)*u1(-1)^2
smpl 1 100000
series x1=sig2arch1^0.5*u1

```

### 2.4.2 GARCH(1,1)

- Model:  $x_t = \sigma_t u_t$

$$\sigma_t^2 = \alpha_0 + \alpha_1 x_{t-1}^2 + \alpha_2 \sigma_{t-1}^2$$

- Kurtosis

$$E(x_t^4) = \frac{\kappa \alpha_0^2 (1 + \alpha_1 + \alpha_2)}{(1 - \alpha_1 - \alpha_2)(1 - \kappa \alpha_1^2 - \alpha_2^2 - 2\alpha_1 \alpha_2)}$$

where  $\kappa = E(u_t^4)$ .

- Let  $\alpha_0 = .05, \alpha_1 = .1, \alpha_2 = .85$
- Simulation:

```

smpl 1 100000
series sig2garch1=1
smpl 2 100000
sig2garch1=.05+.1*sig2garch1(-1)*u1(-1)^2+.85*sig2garch1(-1)
smpl 1 100000
series x2=sig2garch1^0.5*u1

```

## 3 ARG

- $y_t$  follows an autoregressive Gamma process of order 1, or  $ARG(1)$  for short, if the distribution of  $x_t = 2y_t/c$  conditional on information known at  $t-1$  is a non-central chi-square with non-centrality parameter  $2\beta y_{t-1}$  and degrees of freedom  $2\delta$ .

- The ARG(1) is an autoregressive heteroskedastic process for positive distributions:

$$\begin{aligned} E_{t-1}(y_t) &= c\delta + c\beta y_{t-1}, \\ V_{t-1}(y_t) &= c^2\delta + 2c^2\beta y_{t-1}, \\ E(y_t) &= \frac{c\delta}{1 - c\beta}, \\ V(y_t) &= c^2\delta \frac{1 + c\beta}{(1 - c\beta)(1 - c^2\beta^2)} \end{aligned}$$

- In terms of autocorrelations, it behaves as an AR(1):

$$\text{corr}(y_t, y_{t-k}) = (c\beta)^k.$$

- Simulation. Let  $\delta = 1/2$ , then we can simulate  $y_t$  as

$$y_t = \frac{c}{2} z_t^2,$$

where  $z_t \sim N(\sqrt{2\beta y_{t-1}}, 1)$ .

## 4 AR with Markov chain

$$y_t = \begin{cases} \phi_{00} + \phi_{10}y_{t-1} + \sigma_0 u_t^0 & \text{si } s_t = 0 \\ \phi_{01} + \phi_{11}y_{t-1} + \sigma_1 u_t^1 & \text{si } s_t = 1 \end{cases}$$

where  $s_t$  is a Markov chain with  $s_1 = 0$  and

$$\begin{aligned} \Pr(s_t = 1 | s_{t-1} = 0) &= 1 - p \\ \Pr(s_t = 1 | s_{t-1} = 1) &= q \end{aligned}$$

- Let

$$\begin{aligned} \phi_{00} &= -.00001 & \phi_{01} &= .06 \\ \phi_{10} &= .9999 & \phi_{11} &= .4 \\ \sigma_0^2 &= 1.28 & \sigma_1^2 &= .16 \\ p &= .95 & q &= .95 \end{aligned}$$

- Hence:

$$\begin{aligned} E(y_t | s_t = 0) &= -.1 & V(y_t | s_t = 0) &= 2 \\ E(y_t | s_t = 1) &= .1 & V(y_t | s_t = 1) &= 1 \end{aligned}$$

- Simulation

```

smpl 1 100000
series s=0
series y=0
series b=uniform()
smpl 2 100000
s=(1-s(-1))*(b<.05)+s(-1)*(b<.95)
y=(1-s)*(-.00001+.9999*y(-1)+1.28^.5*u1)+s*(.06+.4*y(-1)+.16^.5*u1)

```

- Filtering: probability of the regimes conditional on observable information.

$$\begin{aligned}
\Pr(s_t = 1|I_{t-1}) &= \Pr(s_t = 1|s_{t-1} = 1, I_{t-1}) \Pr(s_{t-1} = 1|I_{t-1}) \\
&\quad + \Pr(s_t = 1|s_{t-1} = 0, I_{t-1})[1 - \Pr(s_{t-1} = 1|I_{t-1})], \\
&= q \Pr(s_{t-1} = 1|I_{t-1}) + (1 - p)[1 - \Pr(s_{t-1} = 1|I_{t-1})],
\end{aligned}$$

$$\Pr(s_t = 1|I_t) = \frac{f(y_t|s_t = 1, I_{t-1}) \Pr(s_t = 1|I_{t-1})}{f(y_t|s_t = 0, I_{t-1})[1 - \Pr(s_t = 1|I_{t-1})] + f(y_t|s_t = 1, I_{t-1}) \Pr(s_t = 1|I_{t-1})},$$

where  $I_t = \{y_t, y_{t-1}, y_{t-2}, \dots\}$ . We initialise the filter with the unconditional probability

$$\Pr(s_0 = 1|I_0) = \frac{1 - p}{2 - p - q}.$$

## A Gamma distribution

- Notation:  $z \sim \Gamma(a, b)$
- Density function:

$$\frac{a^b}{\Gamma(b)} z^{b-1} \exp(-az)$$

where  $\Gamma()$  is the Gamma function.

- Moments:

$$E(z^r) = a^{-r} \frac{\Gamma(b+r)}{\Gamma(b)}$$

- For the Student  $t$  and the Asymmetric  $t$ ,  $a = \nu/2$  y  $b = 1/2$ . If  $\nu$  is an integer,  $z \sim \chi_\nu^2$ .

## B Inverse Gaussian distribution

- Notation:  $w \sim IG(1, \gamma)$
- Density:

$$\frac{\exp(\gamma)}{\sqrt{2\pi}} w^{-3/2} \exp\left[-\frac{1}{2}(w^{-1} + \gamma^2 w)\right]$$

where  $\gamma \geq 0$  y  $w > 0$ .

- Moments:

$$\begin{aligned} E(w) &= \gamma^{-1} \\ E(w^2) &= \gamma^{-2}(1 + \gamma^{-1}) \\ E(w^3) &= \gamma^{-3}(1 + 3\gamma^{-1} + 3\gamma^{-2}) \end{aligned}$$

- Simulation:

1. Generate  $u \sim Unif(0, 1)$  and  $s \sim \chi_1^2$  independent of  $u$ .

2. Let

$$q = 1 - (1/2)\gamma^{-1} \left( \sqrt{s^2 + 4\gamma s} - s \right)$$

3. Finally:

$$w = \begin{cases} \frac{q}{\gamma} & \text{si } u \leq (1+q)^{-1} \\ \frac{1}{\gamma q} & \text{si } u > (1+q)^{-1} \end{cases}$$

## C Non-central chi-square distribution

- Two parameters:
  - Degrees of freedom:  $\nu$ ,
  - Non-centrality:  $\lambda$ .
- Probability density function:

$$f_{NC2}(x; \nu, \lambda) = \sum_{j=0}^{\infty} \frac{(\lambda/2)^j \exp(-\lambda/2)}{j!} f_{\chi^2}(x; \nu + 2j)$$

for  $x \geq 0$ , where  $f_{\chi^2}(\cdot; \nu)$  is the pdf of a chi-square distribution with  $\nu$  degrees of freedom.

- First non-centred moments:

$$\begin{aligned}\mu'_1 = E(x) &= \nu + \lambda, \\ \mu'_2 = E(x^2) &= 2(2\lambda + \nu) + (\lambda + \nu)^2.\end{aligned}$$

- Property: If  $\nu = k$  is an integer, then it is possible to generate this distribution as

$$\sum_{i=1}^k x_i^2$$

where  $x_i \sim N(\mu_i, 1)$ , so that  $\lambda = \sum_{i=1}^k \mu_i^2$ .