

1) Derive the GAS updating....

We have

$$p(y) = \frac{\exp\left\{-\frac{1(y-\mu)/\varphi^v}{2}\right\}}{2^{1+1/v} \varphi \Gamma\left(1+\frac{1}{v}\right)}$$

such that

$$\ln p(y) \propto -\ln \varphi - \frac{|y-\mu|^v}{2\varphi^v}$$

Note that $\varphi > 0$
such that $|\varphi| = \varphi$

the score with respect to φ is

$$\frac{\partial \ln p(y)}{\partial \varphi} = -\frac{1}{\varphi} + \frac{v |y-\mu|^v}{2\varphi^{v+1}} = \frac{1}{\varphi} \left(\frac{v}{2} \frac{|y-\mu|^v}{\varphi^v} - 1 \right)$$

Note that when $v=2$ we obtain $\frac{1}{\varphi} \left[\frac{(y-\mu)^2}{\varphi^2} - 1 \right]$

which is the score of the Gaussian distribution.

The GAS - GED model is defined as

$$\varphi_t = \exp\{\tilde{\varphi}_t\}$$

$$\tilde{\varphi}_t = \omega + \alpha s_{t-1} + \beta \tilde{\varphi}_{t-1}$$

$$\text{where } s_t = \frac{\partial \ln F(y)}{\partial \tilde{\varphi}_t} = \frac{\partial \varphi_t}{\partial \tilde{\varphi}_t} \frac{\partial \ln F(y)}{\partial \varphi_t} = \varphi_t \cdot \frac{1}{\varphi_t} \left[\frac{y}{2} \frac{|y|^\nu}{\varphi_t^\nu} - 1 \right]$$

$$= \frac{y}{2} \frac{|y|^\nu}{\varphi_t^\nu} - 1$$

$$\begin{aligned} E[s_t | \mathcal{F}_{t-1}] &= \int s_t P(y_t | \mathcal{F}_{t-1}) dy_t = \\ &= \int \frac{\partial \log P(y_t | \mathcal{F}_{t-1})}{\partial \tilde{\varphi}_t} P(y_t | \mathcal{F}_{t-1}) dy_t = \\ &= \int \frac{\partial P(y_t | \mathcal{F}_{t-1})}{\partial \tilde{\varphi}_t} \frac{1}{P(y_t | \mathcal{F}_{t-1})} P(y_t | \mathcal{F}_{t-1}) dy_t = \\ &= \int \frac{\partial P(y_t | \mathcal{F}_{t-1})}{\partial \tilde{\varphi}_t} dy_t = \\ &= \frac{\partial}{\partial \tilde{\varphi}_t} \int P(y_t | \mathcal{F}_{t-1}) dy_t = \frac{\partial}{\partial \tilde{\varphi}_t} 1 = 0. \end{aligned}$$

Also note that

$$E[S_t] = E[E[S_t | \mathcal{F}_{t-1}]] = E[0] = 0.$$

2) The log likelihood:

$$P(y_t | \mathcal{F}_{t-1}) = \frac{\exp\left\{-\frac{1}{2} \frac{y_t^2 / \varphi_t^\nu}{\varphi_t^\nu}\right\}}{2^{1+1/\nu} \varphi_t \Gamma\left(1 + \frac{1}{\nu}\right)}$$

$$\begin{aligned} \ln P(y_t | \mathcal{F}_{t-1}) = & -\left(1 + \frac{1}{\nu}\right) \ln 2 - \ln \varphi_t - \ln \Gamma\left(1 + \frac{1}{\nu}\right) + \\ & - \frac{1}{2} \frac{y_t^2 / \varphi_t^\nu}{\varphi_t^\nu} \end{aligned}$$

the log likelihood is

$$\begin{aligned} \mathcal{L}(y_{1:T} | \theta) = & -T\left(1 + \frac{1}{\nu}\right) \ln 2 - T \ln \Gamma\left(1 + \frac{1}{\nu}\right) + \\ & - \sum_{t=1}^T \ln \varphi_t - \frac{1}{2} \sum_{t=1}^T \frac{y_t^2 / \varphi_t^\nu}{\varphi_t^\nu} \end{aligned}$$

where $\varphi_t = \varphi_t(\theta)$, and $\theta = (\omega, \alpha, \beta, \nu)'$

Constraints to impose that $\tilde{\phi}_t$ is covariance stationary.

$$\tilde{\phi}_t = w + \alpha s_{t-1} + \beta \tilde{\phi}_{t-1}$$

can be written as

$$\tilde{\phi}_t = \frac{w}{1-\beta} + \alpha \sum_{s=0}^{\infty} \beta^s s_{t-1-s}$$

First moment

$$\begin{aligned} E[\tilde{\phi}_t] &= E\left[\frac{w}{1-\beta} + \alpha \sum_{k=0}^{\infty} \beta^k s_{t-1-k}\right] = \\ &= \frac{w}{1-\beta} + \alpha E\left[\sum_{k=0}^{\infty} \beta^k s_{t-1-k}\right] = \frac{w}{1-\beta} + \alpha \sum_{k=0}^{\infty} \beta^k E[s_{t-1-k}] \end{aligned}$$

and since $E[s_t] = 0 \quad \forall t$

$$E[\tilde{\phi}_t] = \frac{w}{1-\beta} < \infty \quad \text{if } |\beta| < 1 \quad \text{and } |w| < \infty$$

Second moment

$$E[\tilde{\phi}_t^2] = E\left[\left(\frac{w}{1-\beta} + \alpha \sum_{k=0}^{\infty} \beta^k s_{t-1-k}\right)^2\right]$$

$$\begin{aligned}
&= \frac{w^2}{(1-\beta)^2} + \alpha^2 \mathbb{E} \left[\left(\sum_{k=0}^{\infty} \beta^k s_{t-1-k} \right)^2 \right] + \\
&\quad + \frac{2\alpha w}{1-\beta} \mathbb{E} \left[\sum_{k=0}^{\infty} \beta^k s_{t-1-k} \right] = \\
&= \frac{w^2}{(1-\beta)^2} + \alpha^2 \mathbb{E} \left[\sum_{k=0}^{\infty} \sum_{l=0}^{\infty} \beta^k \beta^l s_{t-1-k} s_{t-1-l} \right] + \frac{2\alpha w}{1-\beta} \underbrace{\sum_{k=0}^{\infty} \mathbb{E} \left[\beta^k s_{t-1-k} \right]}_{=0} \\
&= \frac{w^2}{(1-\beta)^2} + \alpha^2 \sum_{k=0}^{\infty} \sum_{l=0}^{\infty} \beta^k \beta^l \mathbb{E} [s_{t-1-k} s_{t-1-l}]
\end{aligned}$$

by assumption

Consider

$$\mathbb{E} [s_{t-1-k} s_{t-1-l}] = \begin{cases} \mathbb{E} [s_{t-1-k}^2] = c < \infty & \text{if } k=l \\ \mathbb{E} [s_{t-1-k} s_{t-1-l}] & \text{if } k \neq l \end{cases}$$

Assume $k < l$

$$\mathbb{E} [s_{t-1-k} s_{t-1-l}] = \mathbb{E} \left[\mathbb{E} [s_{t-1-k} s_{t-1-l} | \mathcal{F}_{t-1-k}] \right] = \mathbb{E} [s_{t-1-k} \mathbb{E} [s_{t-1-l} | \mathcal{F}_{t-1-k}]]$$

but

$$\begin{aligned}
\mathbb{E} [s_{t-1-l} | \mathcal{F}_{t-1-k}] &= \mathbb{E} \left[\mathbb{E} [s_{t-1-l} | \mathcal{F}_{t-2-l}] \middle| \mathcal{F}_{t-1-k} \right] = \\
&= \mathbb{E} [0 | \mathcal{F}_{t-1-k}] = 0
\end{aligned}$$

if $k > l$ the same applies.

$$\text{so } E[S_{t-1-k} S_{t-1-l}] = \begin{cases} e & \text{if } k=l \\ 0 & \text{if } k \neq l \end{cases}$$

then

$$\sum_{k=0}^{\infty} \sum_{l=0}^{\infty} \beta^k \beta^l E[S_{t-1-k} S_{t-1-l}] = \sum_{k=0}^{\infty} \beta^{2k} e = \frac{e}{1-\beta^2}$$

and

$$E[\tilde{\varphi}_t^2] = \frac{w^2}{(1-\beta)^2} + \frac{\alpha^2 e}{1-\beta^2} < \infty \quad \text{if } \begin{cases} |\alpha| < \infty \\ |w| < \infty \\ |\beta| < 1 \end{cases}$$

The autocovariance

$$\begin{aligned} \text{cov}(\tilde{\varphi}_t, \tilde{\varphi}_{t-k}) &= E[\tilde{\varphi}_t \tilde{\varphi}_{t-k}] - E[\tilde{\varphi}_t] E[\tilde{\varphi}_{t-k}] \\ &= E[\tilde{\varphi}_t \tilde{\varphi}_{t-k}] - \frac{w^2}{(1-\beta^2)} \end{aligned}$$

We have to study $E[\tilde{\psi}_t \tilde{\psi}_{t-n}]$

Consider the case $k=1$

$$\begin{aligned} E[\tilde{\psi}_t \tilde{\psi}_{t-1}] &= E[(w + \alpha S_{t-1} + \beta \tilde{\psi}_{t-1}) \tilde{\psi}_{t-1}] = \\ &= w E[\tilde{\psi}_{t-1}] + \alpha \underbrace{E[S_{t-1} \tilde{\psi}_{t-1}]}_{=0} + \beta E[\tilde{\psi}_{t-1}^2] \end{aligned}$$

Consider the case $k=2$

$$\begin{aligned} E[\tilde{\psi}_t \tilde{\psi}_{t-2}] &= E[(w + \alpha S_{t-1} + \beta \tilde{\psi}_{t-1}) \tilde{\psi}_{t-2}] = \\ &= w E[\tilde{\psi}_{t-2}] + \alpha \underbrace{E[S_{t-1} \tilde{\psi}_{t-2}]}_{=0} + \beta E[\tilde{\psi}_{t-1} \tilde{\psi}_{t-2}] \end{aligned}$$

$$= w E[\tilde{\psi}_{t-2}] + \beta \left\{ w E[\tilde{\psi}_{t-1}] + \beta E[\tilde{\psi}_{t-1}^2] \right\}$$

$$= w E[\tilde{\psi}_{t-2}] + \beta w E[\tilde{\psi}_{t-1}] + \beta^2 E[\tilde{\psi}_{t-1}^2]$$

However, we know that $E[\tilde{\psi}_{t-1}] = E[\tilde{\psi}_{t-2}] = \frac{w}{1-\beta}$

$$= w \left(E[\tilde{\psi}_{t-1}] + \beta E[\tilde{\psi}_{t-1}] \right) + \beta^2 E[\tilde{\psi}_{t-1}^2]$$

By iterative substitutions we obtain

$$\begin{aligned} E[\tilde{\varphi}_t \tilde{\varphi}_{t-k}] &= w E[\tilde{\varphi}_{t-1}] \sum_{l=0}^{k-1} \beta^l + \beta^k E[\tilde{\varphi}_{t-1}^2] \\ &= \frac{w^2}{1-\beta} \sum_{l=0}^{k-1} \beta^l + \beta^k \left[\frac{w^2}{(1-\beta)^2} + \frac{\sigma_c^2}{1-\beta^2} \right] \end{aligned}$$

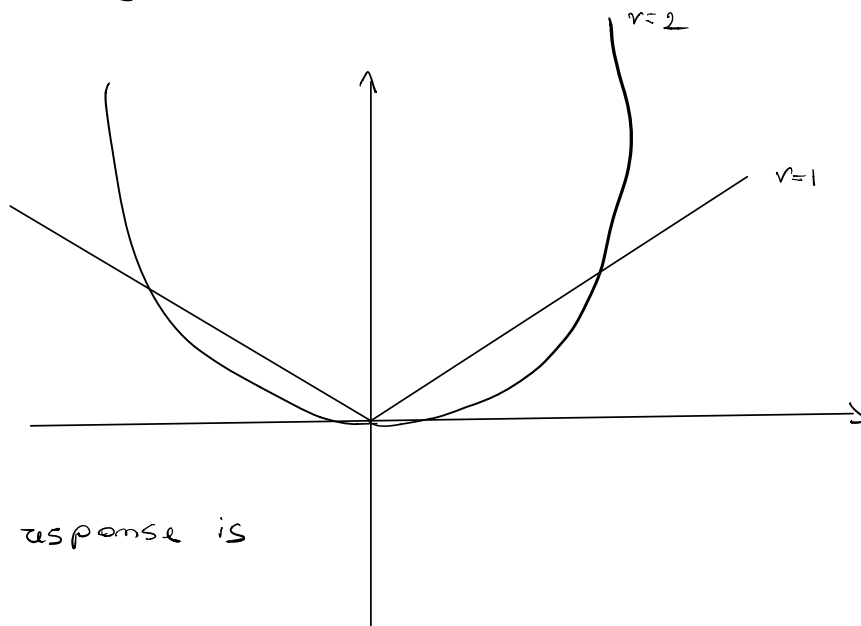
which does not depend from t

So, conditions for covariance stationarity are

$$\boxed{|\beta| < 1, |w| < \infty, |\sigma_c| < \infty}$$

3) When $r=2$ we have

$$S_t = \frac{y_t^2}{\varphi_t^2} - 1$$



when $r=2$ the response is quadratic

when $r=1$ the response is piecewise linear