

4.3. Mixing portmanteau test

- Null model:

$$Y_t = m(\theta, X_{t-1}) + \eta_t \sqrt{h(\theta, X_{t-1})}. \quad (1)$$

Given observations $\{Y_1, \dots, Y_n\}$ and the initial value Y_0 , the conditional log-LF (ignoring a constant) can be written as

$$L_n(\theta) = \sum_{t=1}^n \ell_t(\theta)$$

$$\ell_t(\theta) = - \left[\frac{1}{2} \log h_t(\theta) + \frac{\varepsilon_t^2(\theta)}{2h_t(\theta)} \right],$$

where $m_t(\theta) = m(\theta, Y_{t-1})$, $h_t(\theta) = h(\theta, Y_{t-1})$ and $\varepsilon_t(\theta) = Y_t - m_t(\theta)$.

The maximizer of $L_n(\theta)$ on the parameter spaces Θ , denoted by $\hat{\theta}_n$, is the QMLE of θ_0 . Denote

$$\begin{aligned}\eta_t(\theta) &= \frac{\varepsilon_t(\theta)}{\sqrt{h_t(\theta)}}, \\ D_t(\theta) &= \frac{\partial \ell_t(\theta)}{\partial \theta} = -U_t(\theta)\xi_t(\theta) \quad \text{and} \\ P_t(\theta) &= \frac{\partial^2 \ell_t(x)}{\partial \theta \partial \theta'} = -U_t(\theta)U_t'(\theta) - R_t(\theta),\end{aligned}$$

where

$$\begin{aligned}\xi_t(\theta) &= \left(\eta_t(\theta), \frac{1}{\sqrt{2}} [1 - \eta_t^2(\theta)] \right)', \\ U_t(\theta) &= \left[\frac{1}{\sqrt{h_t(\theta)}} \frac{\partial \varepsilon_t(\theta)}{\partial \theta}, \frac{1}{\sqrt{2}h_t(\theta)} \frac{\partial h_t(\theta)}{\partial \theta} \right], \\ R_t(\theta) &= \frac{1}{\partial h_t(\theta)} \left[\frac{\partial^2 h_t(\theta)}{\partial \theta \partial \theta'} - \frac{1}{h_t(\theta)} \frac{\partial h_t(\theta)}{\partial \theta} \frac{\partial h_t(\theta)}{\partial \theta'} \right] \\ &\quad \left[1 - \frac{\varepsilon_t^2(\theta)}{h_t(\theta)} \right].\end{aligned}$$

Furthermore, let $J = E(\xi_t(\theta_0)\xi_t'(\theta_0))$,

$$\Omega = E[U_t(\theta_0)JU_t'(\theta_0)] \quad \text{and} \quad \Sigma = E[U_t(\theta_0)U_t'(\theta_0)].$$

We assume:

Ω and Σ are positive definite and the estimator

$\hat{\theta}_n$ has the following expansion:

$$\sqrt{n}(\hat{\theta}_n - \theta_0) = \frac{\Sigma^{-1}}{\sqrt{n}} \sum_{t=1}^n D_t(\theta_0) + o_p(1).$$

The assumptions of Theorem 3.1 hold.

The lag- ℓ (standardized) residual ACF can be defined as

$$\tilde{\rho}_\ell = \sum_{t=\ell+1}^n \hat{\eta}_t \hat{\eta}_{t-\ell} / \sqrt{\sum_{t=\ell+1}^n \hat{\eta}_{t-\ell}^2 \sum_{t=1}^n \hat{\eta}_t^2}.$$

The lag- ℓ squared-residual (standardized) ACF as

$$\tilde{r}_\ell = \sum_{t=\ell+1}^n (\hat{\eta}_t^2 - \tilde{\varepsilon}) (\hat{\eta}_{t-\ell}^2 - \tilde{\varepsilon}) / \sum_{t=1}^n (\hat{\eta}_t^2 - \tilde{\varepsilon})^2,$$

where

$$\tilde{\varepsilon} = n^{-1} \sum_{t=1}^n \hat{\eta}_t^2 \quad \text{and} \quad \ell = 1, 2, \dots, M.$$

For the null model (1), the Ljung-Box and McLeod-Li tests are still used in SAS.

Ling and Li (1997) showed that

$$\begin{aligned} \sqrt{n}(\hat{\rho}_1, \dots, \hat{\rho}_M)' &= \sqrt{n}(\rho_1, \dots, \rho_M)' \\ &\quad - X_\rho \sqrt{n}(\hat{\theta}_n - \theta_0) + o_p(1), \end{aligned}$$

for any given integer M , where

$$\begin{aligned}\rho_\ell &= \frac{1}{n} \sum_{t=\ell+1}^n \eta_t \eta_{t-\ell}, \\ X_\rho &= (X_{\rho 1}, X_{\rho 2}, \dots, X_{\rho M})', \\ X_{\rho \ell} &= E \left[\frac{\partial \varepsilon_t(\theta_0)}{\partial \theta} \frac{\eta_{t-\ell}}{\sqrt{h_t}} \right], \quad \ell = 1, 2, \dots, M.\end{aligned}$$

Li and Mak (1994) and Ling and Li (1997) showed that

$$\begin{aligned}\sqrt{n}(\hat{r}_1, \dots, \hat{r}_M)' &= \sqrt{n}(r_1, \dots, r_M)' \\ &\quad - \frac{1}{\sigma_\varphi} X_r \sqrt{n}(\hat{\theta}_n - \theta_0) + o_p(1),\end{aligned}$$

where $X_r = (X_{r1}, X_{r2}, \dots, X_{rM})'$ and $X_{r\ell} = E \left\{ h_t^{-1} [\partial h_t(\theta_0) / \partial \theta] (\eta_{t-\ell}^2 - 1) \right\}$.

Denote $\hat{\rho} = (\hat{\rho}_1, \dots, \hat{\rho}_M)'$ and $\hat{r} = (\hat{r}_1, \dots, \hat{r}_M)'$.

We get the following expansion:

$$\sqrt{n} \begin{pmatrix} \hat{\rho} \\ \hat{r} \end{pmatrix} = \sqrt{n} V \begin{bmatrix} \rho \\ r \\ \frac{1}{n} \sum_{t=1}^n D_t(\theta_0) \end{bmatrix} + o_p(1),$$

$$\text{where } V = \begin{bmatrix} I_M & 0 & -X_\rho \Sigma^{-1} \\ 0 & I_M & -X_r \Sigma^{-1} / \sigma_\varphi \end{bmatrix}.$$

Denote

$$Z_n = \sqrt{n} \left[\rho', r', \frac{1}{n} \sum_{t=1}^n D'_t(\theta_0) \right]'.$$

It is easy to show that

$$\begin{aligned} Z_n &= \frac{1}{\sqrt{n}} \sum_{t=1}^n \left[\eta_t \eta_{t-1}, \dots, \eta_t \eta_{t-M}, \right. \\ &\quad \frac{(\eta_t^2 - 1)(\eta_{t-1}^2 - 1)}{\sigma_\varphi}, \\ &\quad \left. \dots, \frac{(\eta_t^2 - 1)(\eta_{t-M}^2 - 1)}{\sigma_\varphi}, D'_t(\theta_0) \right]' + o_p(1) \\ &\equiv \frac{1}{\sqrt{n}} \sum_{t=1}^n \nu_t + o_p, \end{aligned}$$

where ν_t is a martingale difference in terms of \mathcal{F}_t with

$$E(\nu_t \nu_t') \equiv \tilde{\Omega}.$$

Thus,

$$Z_n \rightarrow_{\mathcal{L}} N(0, \tilde{\Omega}) \text{ and } \sqrt{n} \begin{pmatrix} \hat{\rho} \\ \hat{r} \end{pmatrix} \rightarrow_{\mathcal{L}} N(0, V \tilde{\Omega} V').$$

Wong and Ling (2005) define the following statistic:

$$Q_M = n \begin{pmatrix} \rho \\ r \end{pmatrix}' (V \Omega V^1)^{-1} \begin{pmatrix} \hat{\rho} \\ \hat{r} \end{pmatrix}.$$

$$Q_M \longrightarrow_{\mathcal{L}} \chi^2(2M) \text{ as } n \rightarrow \infty.$$

We can use Q_M to test the hypothesis H_0 : Model (1) is correct.

When η_t is $N(0, 1)$, $\Omega = I$, and

$$\hat{\Omega} = \begin{bmatrix} I_M & 0 & X_\rho \\ 0 & I_M & X_r \\ X'_\rho & X'_r & \Sigma^{-1} \end{bmatrix}$$

$$V\hat{\Omega}V' = \begin{bmatrix} I_M - X_\rho\Sigma^{-1}X'_\rho & 2^{-1}X_\rho\Sigma^{-1}X'_r \\ 2^{-1}X_r\Sigma^{-1}X'_\rho & I_M - \frac{1}{4}X_r\Sigma^{-1}X'_r \end{bmatrix}.$$

When $X_\rho \approx 0$, Q_M can be further simplified as

$$Q_{0M} \approx n \sum_{l=1}^M \hat{\rho}_l^2 + n\hat{r}' \left[I_M - \frac{1}{4}X_r\Sigma^{-1}X'_r \right]^{-1} \hat{r}.$$

This is the mixed statistic of Box-Pierce and Li-Mak test statistics.

In many time series model $X_{\rho l} \approx 0$ when l is large enough. In this case, we can use the following modified statistics.

$$Q_{1M} \approx n \sum_{l=L_0}^M \hat{\rho}_l^2 + n\hat{r}' \left[I_M - \frac{1}{4} X_r \Sigma^{-1} X_r' \right]^{-1} \hat{r} \\ \rightarrow_{\mathcal{L}} \chi^2(2M - L_0 + 1).$$

The Q_{1M} statistic can be used for diagnostic checking the mean and variance part of model (2.1) jointly.

This statistic is very simple.

Simulation results show that Q_{1M} seems to work reasonably well when $L_0 = 1$.

Simulation Study:

We further modify Q_{1M} to rectify the conservative nature of BP statistic as follows.

$$Q_s \approx n(n+2) \sum_{l=1}^M \frac{\hat{\rho}_l^2}{n-l} + n(n+2) \sum_{l=1}^M \frac{\hat{r}_l^2}{n-l}.$$

Replications are 1000 and the sample size $n = 100, 200$ and 400

The first null model is the AR(1) model,

$$(a). \quad Y_t = 0.5Y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim iidN(0, 1).$$

The following five alternative models are used to study the powers of Q_M and Q_s :

$$(b). \quad Y_t = 0.2Y_{t-1} + \varepsilon_t,$$

$$E(\varepsilon_t^2 | F_{t-1}) = h_t$$

$$h_t = 0.2 + 0.2\varepsilon_{t-1}^2 + 0.2\varepsilon_{t-2}^2.$$

$$(c). \quad Y_t = 0.3Y_{t-1} + \varepsilon_t,$$

$$h_t = 0.3 + 0.3\varepsilon_{t-1}^2 + 0.3h_{t-1}.$$

$$(d). \quad Y_t = 0.6Y_{t-1} + 0.3Y_{t-1}\varepsilon_{t-1} + \varepsilon_t,$$

$$\varepsilon_t \sim iidN(0, 1).$$

$$(e). \quad Y_t = 0.7Y_{t-1} + 0.2Y_{t-2} + \varepsilon_t,$$

$$h_t = 0.01 + 0.2\varepsilon_{t-1}^2.$$

Following Li and Mak (1994), we choose $M=6$ in the simulations.

Table I. Size and power of Q_M , Q_S , Q_{LB} and Q_{ML}

Models		(a)	(b)	(c)	(d)	(e)
100	Q_M	0.060	0.346	0.363	0.435	0.362
	Q_S	0.070	0.359	0.374	0.445	0.379
	Q_{LB}	0.062	0.108	0.105	0.244	0.324
	Q_{ML}	0.060	0.381	0.401	0.377	0.226
200	Q_M	0.048	0.635	0.683	0.762	0.659
	Q_S	0.054	0.639	0.686	0.769	0.665
	Q_{LB}	0.050	0.104	0.114	0.344	0.560
	Q_{ML}	0.056	0.673	0.717	0.720	0.428
400	Q_M	0.048	0.908	0.923	0.976	0.937
	Q_S	0.050	0.912	0.924	0.976	0.939
	Q_{LB}	0.054	0.096	0.106	0.560	0.863
	Q_{ML}	0.044	0.939	0.945	0.962	0.710

The second null model is AR(1)-ARCH(1) model:

$$(f). \quad Y_t = 0.5Y_{t-1} + \varepsilon_t, \quad h_t = 0.01 + 0.4\varepsilon_{t-1}^2.$$

The following five models are the alternative models:

$$(g). \quad Y_t = 0.5Y_{t-1} + \varepsilon_t,$$

$$h_t = 0.01 + 0.4\varepsilon_{t-1}^2 + 0.3\varepsilon_{t-2}^2,$$

$$(h). \quad Y_t = 0.5Y_{t-1} + \varepsilon_t,$$

$$h_t = 0.01 + 0.4\varepsilon_{t-1}^2 + 0.5h_{t-1},$$

$$(i). \quad Y_t = 0.5Y_{t-1} + 0.2Y_{t-2} + \varepsilon_t,$$

$$h_t = 0.01 + 0.4\varepsilon_{t-1}^2,$$

$$(j). \quad Y_t = 0.5Y_{t-1} + 0.1Y_{t-2} + \varepsilon_t,$$

$$h_t = 0.01 + 0.4\varepsilon_{t-1}^2 + 0.1\varepsilon_{t-2}^2,$$

$$(k). \quad Y_t = 0.5Y_{t-1} + 0.2Y_{t-2} + \varepsilon_t,$$

$$h_t = 0.01 + 0.4\varepsilon_{t-1}^2 + 0.2\varepsilon_{t-2}^2.$$

Table II. Size and power of Q_M , Q_{1M} , Q_{BP} , and Q_{LM}

M.		(f)	(g)	(h)	(i)	(j)	(k)
100	Q_M	0.057	0.248	0.289	0.220	0.142	0.369
	Q_{1M}	0.040	0.241	0.295	0.184	0.112	0.348
	Q_{BP}	0.030	0.076	0.064	0.222	0.102	0.324
	Q_{LM}	0.036	0.277	0.333	0.073	0.079	0.195
200	Q_M	0.061	0.492	0.472	0.406	0.235	0.706
	Q_{1M}	0.047	0.481	0.477	0.362	0.195	0.685
	Q_{BP}	0.033	0.091	0.075	0.499	0.139	0.602
	Q_{LM}	0.055	0.547	0.509	0.094	0.164	0.427
400	Q_M	0.053	0.782	0.548	0.723	0.441	0.953
	Q_{1M}	0.047	0.782	0.558	0.735	0.398	0.950
	Q_{BP}	0.038	0.079	0.092	0.871	0.261	0.923
	Q_{LM}	0.055	0.844	0.561	0.154	0.300	0.727