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A robust closed-form estimator for the GARCH(1,1) model

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Abstract

In this paper we extend the closed-form estimator for the generalized autoregressive conditional heteroscedastic (GARCH(1,1)) proposed by Kristensen and Linton [A closed-form estimator for the GARCH(1,1) model. Econom Theory. 2006;22:323–337] to deal with additive outliers. It has the advantage that is per se more robust that the maximum likelihood estimator (ML) often used to estimate this model, it is easy to implement and does not require the use of any numerical optimization procedure. The robustification of
the close … by a robust
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returns and analyse their performances in estimating and forecasting the volatility and the value-at-risk.

Keywords: additive outliers autocorrelations robustness value-at-risk volatility forecasting

JEL Classifications: C22 C53 C58

Disclosure statement

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Notes

1. See [19] for dealing with estimates of φ that are in the intervals $]-\infty;0[$ and $]1;+\infty[$.

2. Results are available from the authors upon request.

3. The Kiefer and Salmon [30] test is given by $KSN=(KSS)^2+(KSK)^2$, where $KSS=T/6[(1/T)\sum_{t=1}^{T}y_{t\cdot}^{3}-(3/T)\sum_{t=1}^{T}y_{t\cdot}]$, $KSK=T/24[(1/T)\sum_{t=1}^{T}y_{t\cdot}^{4}-(6/T)\sum_{t=1}^{T}y_{t\cdot}^{2}+3]$ and $y_{t\cdot}$ are the standardized returns. If the distribution of $y_{t\cdot}$ is conditional $N(0,1)$, then KSS and

4. The fi andard likeliho

LRuc= ndicator sequenc lihood estimate the number of ones in the sequence $\{I_t\}_{t=1}^{n}$. The second tests for the independence part of the conditional coverage hypothesis (denoted LR_{ind}) and it is also a likelihood ratio test

$$LR_{ind} = -2\log \frac{L(\hat{\Pi}_2; I_1, I_2, \ldots, I_n)}{L(\hat{\Pi}_1; I_1, I_2, \ldots, I_n)} \sim_{asy} \chi^2(1), \text{ where}$$

$$\hat{\Pi}_1 = \begin{pmatrix} \frac{n_{00}}{(n_{00}+n_{01})} & \frac{n_{01}}{(n_{00}+n_{01})} \\ \frac{n_{10}}{(n_{10}+n_{11})} & \frac{n_{11}}{(n_{10}+n_{11})} \end{pmatrix}, \hat{\Pi}_2 = \begin{pmatrix} 1-\hat{\pi}_2 & \hat{\pi}_2 \\ 1-\hat{\pi}_2 & \hat{\pi}_2 \end{pmatrix},$$

n_{ij} is the number of observations with value i followed by j and $\hat{\pi}_2 = (n_{01}+n_{11})/(n_{00}+n_{10}+n_{01}+n_{11})$. Finally, the third is a joint test of coverage and independence (denoted LR_{cc}) given by

$$LR_{cc} = -2\log \frac{L(p; I_1, I_2, \ldots, I_n)}{L(\hat{\Pi}_1; I_1, I_2, \ldots, I_n)} \sim_{asy} \chi^2(1).$$

5. For computing [32]'s Dynamic Quantile test, $H_t(\alpha)$ is defined as $H_t(\alpha) = I_t(\alpha) - \alpha$ where $I(\alpha)$ is a vector composed by ones (VaR violations) and zeros (VaR no violations). By the definition of VaR, we expect that the conditional expectation of $H_t(\alpha)$ given the past information must be zero. This assumption can be tested with the following linear regression model:

$$H_t(\alpha) = \beta_0 + \sum_{i=1}^{P} \beta_i H_{t-i}(\alpha) + \sum_{j=1}^{K} \gamma_j g_j(z_{t-j}) + \varepsilon_t, \quad (20)$$

where ε_t is an i.i.d process with zero mean and $g(\cdot)$ is a function of the past of variable z_t. Consider $H_0: \beta_0 = \beta_1 = \cdots = \beta_P = \gamma_1 = \cdots = \gamma_K = 0$, and denote $\Psi = (\beta_0, \beta_1, \ldots, \beta_P, \gamma_1, \ldots, \gamma_K)^T$ the vector of the $P+K+1$ parameters of the model. The test statistics is given by

$$DQ = \frac{\hat{\Psi}^T X^T X \hat{\Psi}}{\alpha(1-\alpha)} \xrightarrow{L} \chi^2(P+K+1),$$

where X denotes the covariates matrix in Equation (20). In our study, we select $P=4$, $K=4$ and $g(z_t) = VaR_t$ to account the influence of past exceedances up to four days (see [34], for more details).

Relate