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

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Abstra

In this pa ... gressive
conditio ... [A closed-
form est ...] to deal
with add ... e maximum
likelihoo ... lement and
does ... tification of
the clo ... by a robust
estimato ... filters. The
performa ... of the
GARCH(1 ... via intensive
Monte C ... r proposal
outperfo ... ures. Finally,
we fit the robust closed-form estimator and the benchmarks to one series of financial

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

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Notes

1. See [1 ... d]1;+∞[.

2. Resul...

3. The ... KSS=T/6 ... =1Tyt·2+3] and yt· a ... (0,1), then KSS and ...

4. The fi ... andard likelihoo...

$LR_{uc}=-2\log L(p;I_1,I_2,\dots,I_n)L(\hat{\pi};I_1,I_2,\dots,I_n)\sim_{asy}\chi^2(1)$, where $\{I_t\}_{t=1}^{n}$ is the indicator sequence,p is the theoretical coverage, $\hat{\pi}=n_1/(n_0+n_1)$ is the maximum likelihood estimate of the alternative failure rateπ, n_0 is the number of zeros and n_1 is 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

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

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

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

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

5. For computing [32]'s Dynamic Quantile test, $Ht(\alpha)$ is defined as $Ht(\alpha)=It(\alpha)-\alpha$ 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 $Ht(\alpha)$ given the past information must be zero. This assumption can be tested with the following linear regression model:

(20)

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zero me… $1=\cdots$

$=\beta P=\gamma 1$ … $P+K+1$

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$DQ=\hat{\Psi}T$ … in

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