Package ‘segMGarch’

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Multiple Change-Point Detection for High-Dimensional GARCH Processes

Description

Implements a segmentation algorithm for multiple change-point detection in high-dimensional GARCH processes described in Cho and Korkas (2018) ("High-dimensional GARCH process segmentation with an application to Value-at-Risk." arXiv preprint arXiv:1706.01155). It simultaneously segments GARCH processes by identifying 'common' change-points, each of which can be shared by a subset or all of the component time series as a change-point in their within-series and/or cross-sectional correlation structure. We adopt the Double CUSUM Binary Segmentation procedure Cho (2016), which achieves consistency in estimating both the total number and locations of the multiple change-points while permitting within-series and cross-sectional correlations, for simultaneous segmentation of the panel data of transformed time series.

It also provides additional functions and methods that relate to risk management measures and backtests.

Details

We develop a segmentation algorithm for multiple change-point detection in high-dimensional GARCH processes. It simultaneously segments GARCH processes by identifying 'common' change-points, each of which can be shared by a subset or all of the component time series as a change-point in their within-series and/or cross-sectional correlation structure. The methodology first transforms the $d$-dimensional time series into $d(d+1)/2$-dimensional panel data consisting of empirical residual series and their cross-products, whereby change-points in the complex ((un)conditional variance and covariance) structure are made detectable as change-points in the simpler (mean) structure of the panel data at the price of the increased dimensionality. The main routine is garchNseg.

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References


### DQtest

**Examples**

```r
## Not run:
#w.CCC.obj <- new("simGarch")
#pw.CCC.obj <- pc_cccsim(pw.CCC.obj)
#pw.CCC.obj@d=10
#pw.CCC.obj@n=1000
#pw.CCC.obj@changepoints=c(250,750)
#pw.CCC.obj <- pc_cccsim(pw.CCC.obj)
#dcs.obj=garch.seg(pw.CCC.obj@y)
#dcs.obj$est cps
#ts.plot(t(pw.CCC.obj@y),col="grey");grid()
#abline(v=dcs.obj$est cps,col="red"
)#abline(v=pw.CCC.obj@changepoints,col="blue"
)#legend("bottom", legend=c("Estimated change-points", "Real change-points"),
#col=c("red", "blue"), lty=1:2, cex=0.8)

## End(Not run)
```

---

**DQtest**

A regression-based test to backtest VaR models proposed by Engle and Manganelli (2004)

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### Description

Typical VaR tests cannot control for the dependence of violations, i.e., violations may cluster while the overall (unconditional) average of violations is not significantly different from $\alpha = 1 - \text{VaR}$. The conditional expectation should also be zero meaning that $H_{it}(\alpha)$ is uncorrelated with its own past and other lagged variables (such as $r_t$, $r_t^2$ or the one-step ahead forecast VaR). To test this assumption, the dynamic conditional quantile (DQ) test is used which involves the following statistic

$$DQ = H_{it}^T X (X^T X)^{-1} X^T H_{it}/\alpha(1 - \alpha)$$

where $X$ is the matrix of explanatory variables (e.g., raw and squared past returns) and $H_{it}$ the vector collecting $H_{it}(\alpha)$. Under the null hypothesis, Engle and Manganelli (2004) show that the proposed statistic $DQ$ follows a $\chi^2_q$ where $q = \text{rank}(X)$.

### Usage

```r
dQtest(y, VaR, VaR_level, lag = 1, lag_hit = 1, lag_var = 1)
```

### Arguments

- **y**
  - The time series to apply a VaR model (a single asset return or portfolio return).
- **VaR**
  - The forecast VaR.
- **VaR_level**
  - The VaR level, typically 95% or 99%.
The chosen lag for y. Default is 1.

The chosen lag for hit. Default is 1.

The chosen lag for VaR forecasts. Default is 1.

References


Examples

```r
#VaR_level=0.95
#y=rnorm(1000,0,4)
#VaR=rep(quantile(y,1-VaR_level),length(y))
#y[c(17,18,19,20,100,101,102,103,104)]=-8
#lag=5
#DQtest(y,VaR,VaR_level,lag)
```

---

**garch.seg-class**

An S4 method to detect the change-points in a high-dimensional GARCH process.

**Description**

An S4 method to detect the change-points in a high-dimensional GARCH process using the DCBS methodology described in Cho and Korkas (2018). If a `tvmGarch` is specified then it returns a `tvmGarch` object is returned. Otherwise a list of features is returned.

**Usage**

```r
garch.seg(object, x = 1, q = 0, f = NULL, sig.level = 0.05, 
  Bsim = 200, off.diag = TRUE, dw = NULL, do.pp = TRUE, 
  do.parallel = 4)
```

```
## S4 method for signature 'ANY'
garch.seg(object = NULL, x = 1, q = 0, f = NULL, 
  sig.level = 0.05, Bsim = 200, off.diag = TRUE, dw = NULL, 
  do.pp = TRUE, do.parallel = 4)
```

```
## S4 method for signature 'tvMgarch'
garch.seg(object, p = 1, q = 0, f = NULL, 
  sig.level = 0.05, Bsim = 200, off.diag = TRUE, dw = NULL, 
  do.pp = TRUE, do.parallel = 4)
```
gen_pc_coef-class

Arguments

object A tvMGarch object. Not necessary if x is used.
x Input data matrix, with each row representing the component time series.
p Choose the ARCH order. Default is 1.
q Choose the GARCH order. Default is 0.
f The dampening factor. If NULL then f is selected automatically. Default is NULL.
sig.level Indicates the quantile of bootstrap test statistics to be used for threshold selection. Default is 0.05.
Bsim Number of bootstrap samples for threshold selection. Default is 200.
off.diag If TRUE allows to look at the cross-sectional correlation structure.
dw The length of boundaries to be trimmed off.
do.pp Allows further post processing of the estimated change-points to reduce the risk of undersegmentation.
do.parallel Number of copies of R running in parallel, if do.parallel = 0, %do% operator is used, see also foreach.

References


Examples

#pw.CCC.obj <- new("simMGarch")
#pw.CCC.obj@d=10
#pw.CCC.obj@n=1000
#pw.CCC.obj@changepoints=c(250,750)
#pw.CCC.obj <- pc_cccsim(pw.CCC.obj)
#dcs.obj=garch.seg(x=empirObj@y,do.parallel = 4)

generate_pc_coef <- function(object, coef) {
  # S4 method for signature 'simMGarch'
  gen_pc_coef(object, coef)
}

Description

An auxiliary method to calculate piecewise constant coefficients for a user-specified vector of coefficients. The change-points are controlled by the changepoints slot in the simMGarch object.

Usage

gen_pc_coef(object, coef)

# S4 method for signature 'simMGarch'
gen_pc_coef(object, coef)
Arguments

object  A simMGarch object.
coef    A vector of coefficients.

References


Examples

pw.CCC.obj <- new("simMGarch")
coef.vector <- gen_pc_coef(pw.CCC.obj,c(0.2,0.4))
ts.plot(coef.vector,main="piecewise constant coefficients",ylab="coefficient",xlab="time")

kupiec(y, VaR, VaR_level, verbose = TRUE, test = "PoF")

# S4 method for signature 'ANY'
kupiec(y, VaR, VaR_level, verbose = TRUE, test = "PoF")

Description

An S4 method that performs backtest for VaR models using the Kupiec statistics. For a sample of \( n \) observations, the Kupiec test statistics takes the form of likelihood ratio

\[
LR_{PoF} = -2 \log \left( \frac{(1-\alpha)^{n_f} \alpha^{n_f} (t_f)}{(1-\frac{1}{n_f})^{n_f} \left( \frac{1}{n_f} \right)^{t_f}} \right),
\]

\[
LR_{TFF} = -2 \log \left( \frac{\alpha^{(1-\alpha)^{t_f-1}} \left( \frac{1}{t_f} \right)^{(1-\frac{1}{t_f})^{n_f} \left( \frac{1}{t_f} \right)^{t_f}}} \right),
\]

where \( n_f \) denotes the number of failures occurred and \( t_f \) the number of days until the first failure within the \( n \) observations. Under \( H_0 \), both \( LR_{PoF} \) and \( LR_{TFF} \) are asymptotically \( \chi^2 \)-distributed, and their exceedance of the critical value implies that the VaR model is inadequate.

Usage

kupiec(y, VaR, VaR_level, verbose = TRUE, test = "PoF")

Arguments

y  The time series to apply a VaR model (a single asset return or portfolio return).
VaR  The forecast VaR.
VaR_level   The VaR level, typically 95% or 99%.
verbose  If TRUE show the outcome. Default is TRUE.
test   Choose between PoF or TFF. Default is PoF.
References


Examples

```r
pw.CCC.obj = new("simMGarch")
pw.CCC.obj@d = 10
pw.CCC.obj@n = 1000
pw.CCC.obj@changepoints = c(250,750)
pw.CCC.obj = pc_cccsim(pw.CCC.obj)
y_out_of_sample = t(pw.CCC.obj@y[,900:1000])
weights = rep(1/pw.CCC.obj@d,pw.CCC.obj@n) # an equally weighted portfolio
VaR = quantile(t(pw.CCC.obj@y[,1:899]),0.05)
#ts.plot(y_out_of_sample,ylab="portfolio return");abline(h=VaR,col="red")
#kupiec(y_out_of_sample,rep(VaR,100),.95,verbose=TRUE,test="PoF")
```

---

**pc_cccsim-class**

A method to simulate nonstationary high-dimensional CCC GARCH models.

---

Description

A S4 method that takes as an input a `simMGarch` object and outputs a simulated nonstationary CCC model. The formulation of the of the piecewise constant CCC model is given in the `simMGarch` class.

Usage

```r
pc_cccsim(object)
```

Arguments

- `object` : a `simMGarch` object

References


Examples

```r
pw.CCC.obj <- new("simMGarch")
pw.CCC.obj <- pc_cccsim(pw.CCC.obj)
par(mfrow=c(1,2))
ts.plot(pw.CCC.obj@y[1,],main="a single simulated time series",ylab="series")
ts.plot(pw.CCC.obj@h[1,],main="a single simulated conditional variance",ylab="variance")
```
Method to simulate correlated variables with change-points

Description

An S4 method that takes a simMGarch object and outputs simulated correlated time series with a piecewise constant covariance matrix. The correlations are generated as \( \sigma_{i,i'} = \rho|i-i'| \) with \( \rho \) taking values from \((-1, 1)\). The exact variables that will contain a change-point are randomly selected and controlled by \( r \) in the simMGarch object.

Usage

\[
\text{pcSigma}(\text{object})
\]

## S4 method for signature 'simMGarch'

\[
\text{pcSigma}(\text{object})
\]

Arguments

\[
\text{object} \quad \text{A simMGarch object.}
\]

References


Examples

\[
\text{cp}=500 \\
\text{n}=2000 \\
\text{pwCCC.obj} <- \text{new("simMGarch")} \\
\text{pwCCC.obj@change-points}=\text{cp} \\
\text{pwCCC.obj@n}=\text{n} \\
\text{pcSigma.obj} <- \text{pcSigma(pwCCC.obj)} \\
\text{par(mfrow=c(1,2))} \\
# requires corrplot library \\
# correlation matrix before the changepoint \\
\text{corrplot::corrplot.mixed(cor(pcSigma.obj@cor_errors[1:cp,], order="hclust", tl.col="black")} \\
# correlation matrix after the changepoint \\
\text{corrplot::corrplot.mixed(cor(pcSigma.obj@cor_errors[(cp+1):n,], order="hclust", tl.col="black")}
\]
### simMGarch-class

An S4 class for a nonstationary CCC model.

#### Description

A specification class to create an object of a simulated piecewise constant conditional correlation (CCC) model denoted by \( r_t = (r_{1,t}, \ldots, r_{n,t})^T, t = 1, \ldots, n \) with \( r_{i,t} = \sqrt{h_{i,t}} \epsilon_{i,t} \) where \( h_{i,t} = \omega_i(t) + \sum_{j=1}^{p} \alpha_{i,j}(t) r_{i,t-j}^2 + \sum_{k=1}^{q} \beta_{i,k}(t) h_{i,t-k} \). In this package, we assume a piecewise constant CCC with \( p = q = 1 \).

#### Slots

- **y**  The \( n \times d \) time series.
- **cor_errors**  The \( n \times d \) matrix of the errors.
- **h**  The \( n \times d \) matrix of the time-varying variances.
- **n**  Size of the time series.
- **d**  The number of variables (assets).
- **r**  A sparsity parameter to control the impact of changepoint across the series.
- **mutp**  A parameter to control the covariance of errors.
- **changepoints**  The vector with the location of the changepoints.
- **pw**  A logical parameter to allow for changepoints in the error covariance matrix.
- **a0**  The vector of the parameters \( a0 \) in the individual GARCH processes denoted by \( \omega_i(t) \) in the above formula.
- **a1**  The vector of the parameters \( a1 \) in the individual GARCH processes denoted by \( \alpha_i(t) \) in the above formula.
- **b1**  The vector of the parameters \( b1 \) in the individual GARCH processes denoted by \( \beta_i(t) \) in the above formula.
- **BurnIn**  The size of the burn-in sample. Note that this only applies at the first simulated segment. Default is 50.

#### References


#### Examples

```r
pw.CCC.obj <- new("simMGarch")
pw.CCC.obj <- pc_cccsim(pw.CCC.obj)
par(mfrow=c(2,2))
ts.plot(pw.CCC.obj@y[1,]); ts.plot(pw.CCC.obj@y[2,])
ts.plot(pw.CCC.obj@h[1,]); ts.plot(pw.CCC.obj@h[1,])
```
Method to backtest VaR violation using the Traffic Light (TL) approach of Basel

Description

A method that performs backtest for VaR models using the TL approach. According to Basel, a VaR model is deemed valid if the cumulative probability of observing up to \(n_f\) failures is less than 0.95 (green zone) under the binomial distribution with \(n\) (sample size) and Var level as the parameters. If the cumulative probability is between 0.95 and 0.9999 a VaR model is in yellow zone. Otherwise (>0.9999) a VaR model is in red zone.

Usage

```r
TL(y, n = NULL, no_fail = NULL, VaR, VaR_level)
```

### S4 method for signature 'ANY'
```r
TL(y, n = NULL, no_fail = NULL, VaR, VaR_level)
```

Arguments

- **y**: The time series to apply a VaR model (a single asset return or portfolio return).
- **n**: If \(y\) is not provided, then insert sample size. Default is NULL.
- **no_fail**: If \(y\) is not provided, then insert number of fails. Default is NULL.
- **VaR**: The forecast VaR.
- **VaR_level**: The VaR level, typically 95% or 99%.

References


Examples

```r
pw.CCC.obj = new("simMGarch")
pw.CCC.obj@d = 10
pw.CCC.obj@n = 1000
pw.CCC.obj@changepoints = c(250, 750)
pw.CCC.obj = pc_cccsim(pw.CCC.obj)
y_out_of_sample = t(pw.CCC.obj@y[900:1000])
w = rep(1/pw.CCC.obj@d, pw.CCC.obj@d) # an equally weighted portfolio
# VaR = quantile(t(pw.CCC.obj@y[,1:899])%>%w, 0.05)
# ts.plot(y_out_of_sample%>%w, ylab="portfolio return"); abline(h=VaR, col="red")
TL(y=y_out_of_sample%>%w, VaR=rep(VaR,100), VaR_level = 0.95)
```
tvMGarch-class

An S4 class for a nonstationary multivariate class model.

Description

A specification class to create an object of a nonstationary multivariate class model reserved for real (empirical) applications. It inherits from simMGarch.

Slots

- out_of_sample_prop Proportion of y to keep for out-of-sample forecasting expressed in %.
- out_of_sample_y The out of sample y matrix reserved for forecasting and backtesting exercises.
- in_sample_y The in-sample y matrix reserved for estimation (calibration) and change-point detection.

References


Examples

```r
simobj <- new("simMGarch")
simobj@d <- 10
simobj@n <- 1000
simobj@changepoints <- c(250,750)
simobj <- pc_cccsim(simobj)
empirObj <- new("tvMGarch") # simulated, but treated as a real dataset for illustration
empirObj@y <- simobj@y
empirObj@out_of_sample_prop <- 0.1
# empirObj=garch.seg(object=empirObj,do.parallel = 4)#Not run
```
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