

# Package ‘dccmidas’

March 15, 2021

**Type** Package

**Title** DCC Models with GARCH-MIDAS Specifications in the Univariate Step

**Version** 0.1.0

**Description** Estimates a variety of Dynamic Conditional Correlation (DCC) models. More in detail, the 'dccmidas' package allows the estimation of the corrected DCC (cDCC) of Aielli (2013) <doi:10.1080/07350015.2013.771027>, the DCC-MIDAS of Colacito et al. (2011) <doi:10.1016/j.jeconom.2011.02.013>, the Asymmetric DCC of Cappiello et al. <doi:10.1093/jjfinec/nbl005>, and the Dynamic Equicorrelation (DECO) of Engle and Kelly (2012) <doi:10.1080/07350015.2011.652048>. 'dccmidas' offers the possibility of including standard GARCH <doi:10.1016/0304-4076(86)90063-1>, GARCH-MIDAS <doi:10.1162/REST\_a\_00300> and Double Asymmetric GARCH-MIDAS <doi:10.1016/j.econmod.2018.07.025> models in the univariate estimation. Finally, the package calculates also the var-cov matrix under two non-parametric models: the Moving Covariance and the RiskMetrics specifications.

**License** GPL-3

**LinkingTo** Rcpp, RcppArmadillo

**Encoding** UTF-8

**LazyData** true

**RoxygenNote** 7.1.1

**RdMacros** Rdpack

**Depends** R (>= 4.0.0)

**Imports** Rcpp (>= 1.0.5), maxLik (>= 1.3-8), rumidas (>= 0.1.1), rugarch (>= 1.4-4), roll (>= 1.1.4), xts (>= 0.12.0), tseries (>= 0.10.47), Rdpack (>= 1.0.0), lubridate (>= 1.7.9), zoo (>= 1.8.8), stats (>= 4.0.2), utils (>= 4.0.2)

**Suggests** knitr, rmarkdown

**NeedsCompilation** yes

**Author** Vincenzo Candila [aut, cre]

**Maintainer** Vincenzo Candila <vincenzo.candila@uniroma1.it>

**Repository** CRAN

**Date/Publication** 2021-03-15 10:00:07 UTC

## R topics documented:

cov_eval . . . . .	2
dcc_fit . . . . .	3
Det . . . . .	7
ftse100 . . . . .	7
indpro . . . . .	8
Inv . . . . .	9
nasdaq . . . . .	9
plot_dccmidas . . . . .	10
sp500 . . . . .	11
<b>Index</b>	<b>13</b>

---

cov_eval	<i>Var-cov matrix evaluation</i>
----------	----------------------------------

---

### Description

Evaluates the estimated var-cov matrix  $H_t$  with respect to a covariance proxy, under different robust loss functions (Laurent et al. 2013). The losses considered are also used in Amendola et al. (2020).

### Usage

```
cov_eval(H_t, cov_proxy = NULL, r_t = NULL, loss = "FROB")
```

### Arguments

<code>H_t</code>	Estimated covariance matrix, formatted as array
<code>cov_proxy</code>	<b>optional</b> Covariance matrix, formatted as array
<code>r_t</code>	<b>optional</b> List of daily returns used to calculate $H_t$ . If parameter 'cov_proxy' is not provided, then <code>r_t</code> must be included. In this case, a (noise) proxy will be automatically used
<code>loss</code>	Robust loss function to use. Valid choices are: "FROB" for Frobenius (by default), "SFROB" for Squared Frobenius, "EUCL" for Euclidean, "QLIKE" for QLIKE and "RMSE" for Root Mean Squared Errors

### Value

The value of the loss for each  $t$

## References

Amendola A, Braione M, Candila V, Storti G (2020). “A Model Confidence Set approach to the combination of multivariate volatility forecasts.” *International Journal of Forecasting*, **36**(3), 873 - 891. doi: [10.1016/j.ijforecast.2019.10.001](https://doi.org/10.1016/j.ijforecast.2019.10.001).

Laurent S, Rombouts JV, Violante F (2013). “On loss functions and ranking forecasting performances of multivariate volatility models.” *Journal of Econometrics*, **173**(1), 1–10. doi: [10.1016/j.jeconom.2012.08.004](https://doi.org/10.1016/j.jeconom.2012.08.004).

## Examples

```
require(xts)
# open to close daily log-returns
r_t_s<-log(sp500['2010/2019'][,3])-log(sp500['2010/2019'][,1])
r_t_n<-log(nasdaq['2010/2019'][,3])-log(nasdaq['2010/2019'][,1])
r_t_f<-log(ftse100['2010/2019'][,3])-log(ftse100['2010/2019'][,1])
db_m<-merge.xts(r_t_s,r_t_n,r_t_f)
db_m<-db_m[complete.cases(db_m),]
colnames(db_m)<-c("S&P500","NASDAQ","FTSE100")
# list of returns
r_t<-list(db_m[,1],db_m[,2],db_m[,3])
# estimation
K_c<-144
N_c<-36
cdcc_est<-dcc_fit(r_t,univ_model="sGARCH",distribution="norm",
corr_model="DCCMIDAS",N_c=N_c,K_c=K_c)
cov_eval(cdcc_est$H_t,r_t=r_t)[(K_c+1):dim(cdcc_est$H_t)[3]]
```

---

dcc\_fit

*DCC fit (first and second steps)*

---

## Description

Obtains the estimation of a variety of DCC models, using as univariate models both GARCH and GARCH-MIDAS specifications.

## Usage

```
dcc_fit(
  r_t,
  univ_model = "sGARCH",
  distribution = "norm",
  MV = NULL,
  K = NULL,
  corr_model = "cDCC",
  lag_fun = "Beta",
```

```

    N_c = NULL,
    K_c = NULL
)

```

### Arguments

<code>r_t</code>	List of daily returns on which estimate a DCC model. Each daily return must be an 'xts' object. Note that the sample period of the returns should be the same. Otherwise, a merge is performed
<code>univ_model</code>	Specification of the univariate model. Valid choices are: some of the specifications used in the <code>rugarch</code> ( <a href="#">ugarchspec</a> ) and <code>rumidas</code> ( <a href="#">ugmfit</a> ) packages. More in detail, the models coming from <code>rugarch</code> are: <code>model</code> Valid models (currently implemented) are 'sGARCH', 'eGARCH', 'gjrGARCH', 'iGARCH', and 'csGARCH'. The models implemented from <code>rumidas</code> are: 'GM_skew', 'GM_noskew', 'DAGM_skew', and 'DAGM_noskew'
<code>distribution</code>	<b>optional</b> Distribution chosen for the univariate estimation. Valid choices are: "norm" (by default) and "std", respectively, for the Normal and Student's t distributions
<code>MV</code>	<b>optional</b> MIDAS variable to include in the univariate estimation, if the model specified is a GARCH-MIDAS (GM, Engle et al. (2013)) or a Double Asymmetric GM (DAGM, Engle et al. (2013)). In the case of MIDAS-based models, please provide a list of the MIDAS variables obtained from the <a href="#">mv_into_mat</a> function. If the same MV variable is used, then provide always a list, with the same (transformed) variable repeated
<code>K</code>	<b>optional</b> The number of lagged realization of MV variable to use, if 'univ_model' has a MIDAS term
<code>corr_model</code>	Correlation model used. Valid choices are: "cDCC" (the corrected DCC of Aielli (2013)), "aDCC" (the asymmetric DCC model of Cappiello et al. (2006)), "DECO" (Dynamic equicorrelation of Engle and Kelly (2012)), and "DCCMIDAS" (the DCC-MIDAS of Colacito et al. (2011)). By default, it is "cDCC"
<code>lag_fun</code>	<b>optional.</b> Lag function to use. Valid choices are "Beta" (by default) and "Almon", for the Beta and Exponential Almon lag functions, respectively, if 'univ_model' has a MIDAS term and/or if 'corr_model' is "DCCMIDAS"
<code>N_c</code>	<b>optional</b> Number of (lagged) realizations to use for the standardized residuals forming the long-run correlation, if 'corr_model' is "DCCMIDAS"
<code>K_c</code>	<b>optional</b> Number of (lagged) realizations to use for the long-run correlation, if 'corr_model' is "DCCMIDAS"

### Details

Function `dcc_fit` implements the two-steps estimation of the DCC models. In the first step, a variety of univariate models are considered. These models can be selected using for the parameter 'univ\_model' one of the following choices: 'sGARCH' (standard GARCH of Bollerslev (1986)), 'eGARCH' of Nelson (1991), 'gjrGARCH' of Glosten et al. (1993), 'iGARCH' (Integrated GARCH of Engle and Bollerslev (1986)), 'csGARCH' (the Component GARCH of Engle and Lee (1999)), 'GM\_noskew' and 'GM\_skew' (the GARCH-MIDAS model of Engle et al. (2013), respectively, without and with the asymmetric term in the short-run component), and 'DAGM\_noskew'

and 'DAGM\_skew' (the Double Asymmetric GARCH-MIDAS model of Amendola et al. (2019), respectively, without and with the asymmetric term in the short-run component).

### Value

`dcc_fit` returns an object of class 'dccmidas'. The function `summary.dccmidas` can be used to print a summary of the results. Moreover, an object of class 'dccmidas' is a list containing the following components:

- `assets`: Names of the assets considered.
- `model`: Univariate model used in the first step.
- `est_univ_model`: List of matrixes of estimated coefficients of the univariate model, with the QML (Bollerslev and Wooldridge 1992) standard errors.
- `corr_coef_mat`: Matrix of estimated coefficients of the correlation model, with the QML standard errors.
- `mult_model`: Correlation model used in the second step.
- `obs`: The number of daily observations used for the estimation.
- `period`: The period of the estimation.
- `H_t`: Conditional covariance matrix, reported as an array.
- `R_t`: Conditional correlation matrix, reported as an array.
- `R_t_bar`: Conditional long-run correlation matrix, reported as an array, if the correlation matrix includes a MIDAS specification.
- `est_time`: Time of estimation.
- `Days`: Days of the sample period.
- `llk`: The value of the log-likelihood (for the second step) at the maximum.

### References

- Aielli GP (2013). "Dynamic conditional correlation: on properties and estimation." *Journal of Business & Economic Statistics*, **31**(3), 282–299. doi: [10.1080/07350015.2013.771027](https://doi.org/10.1080/07350015.2013.771027).
- Amendola A, Candila V, Gallo GM (2019). "On the asymmetric impact of macro-variables on volatility." *Economic Modelling*, **76**, 135–152. doi: [10.1016/j.econmod.2018.07.025](https://doi.org/10.1016/j.econmod.2018.07.025).
- Bollerslev T (1986). "Generalized autoregressive conditional heteroskedasticity." *Journal of Econometrics*, **31**(3), 307–327. doi: [10.1016/03044076\(86\)900631](https://doi.org/10.1016/03044076(86)900631).
- Bollerslev T, Wooldridge JM (1992). "Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances." *Econometric Reviews*, **11**, 143–172. doi: [10.1080/07474939208800229](https://doi.org/10.1080/07474939208800229).
- Cappiello L, Engle RF, Sheppard K (2006). "Asymmetric dynamics in the correlations of global equity and bond returns." *Journal of Financial Econometrics*, **4**(4), 537–572. doi: [10.1093/jjfinec/nbl005](https://doi.org/10.1093/jjfinec/nbl005).
- Colacito R, Engle RF, Ghysels E (2011). "A component model for dynamic correlations." *Journal*

of *Econometrics*, **164**(1), 45–59. doi: [10.1016/j.jeconom.2011.02.013](https://doi.org/10.1016/j.jeconom.2011.02.013).

Engle R, Kelly B (2012). “Dynamic equicorrelation.” *Journal of Business & Economic Statistics*, **30**(2), 212–228. doi: [10.1080/07350015.2011.652048](https://doi.org/10.1080/07350015.2011.652048).

Engle RF, Bollerslev T (1986). “Modelling the persistence of conditional variances.” *Econometric Reviews*, **5**(1), 1–50. doi: [10.1080/07474938608800095](https://doi.org/10.1080/07474938608800095).

Engle RF, Ghysels E, Sohn B (2013). “Stock market volatility and macroeconomic fundamentals.” *Review of Economics and Statistics*, **95**(3), 776–797. doi: [10.1162/REST\\_a\\_00300](https://doi.org/10.1162/REST_a_00300).

Engle RF, Lee GJ (1999). “A Long-run and Short-run Component Model of Stock Return Volatility.” In Engle RF, White H (eds.), *Cointegration, Causality, and Forecasting: A Festschrift in Honor of Clive W. J. Granger*, 475–497. Oxford University Press, Oxford.

Glosten LR, Jagannathan R, Runkle DE (1993). “On the relation between the expected value and the volatility of the nominal excess return on stocks.” *The Journal of Finance*, **48**(5), 1779–1801. doi: [10.1111/j.15406261.1993.tb05128.x](https://doi.org/10.1111/j.15406261.1993.tb05128.x).

Nelson DB (1991). “Conditional heteroskedasticity in asset returns: A new approach.” *Econometrica*, **59**, 347–370. doi: [10.2307/2938260](https://doi.org/10.2307/2938260).

## Examples

```
require(xts)
# open to close daily log-returns
r_t_s<-log(sp500['2005/2008'][,3])-log(sp500['2005/2008'][,1])
r_t_n<-log(nasdaq['2005/2008'][,3])-log(nasdaq['2005/2008'][,1])
r_t_f<-log(ftse100['2005/2008'][,3])-log(ftse100['2005/2008'][,1])
db_m<-merge.xts(r_t_s,r_t_n,r_t_f)
db_m<-db_m[complete.cases(db_m),]
colnames(db_m)<-c("S&P500","NASDAQ","FTSE100")
# list of returns
r_t<-list(db_m[,1],db_m[,2],db_m[,3])
# MV transformation (same MV for all the stocks)
require(rumidas)
mv_m<-mv_into_mat(r_t[[1]],diff(indpro),K=12,"monthly")
# list of MV
MV<-list(mv_m,mv_m,mv_m)
# estimation
K_c<-144
N_c<-36
dccmidas_est<-dcc_fit(r_t,univ_model="GM_noskew",distribution="norm",
MV=MV,K=12,corr_model="DCCMIDAS",N_c=N_c,K_c=K_c)
dccmidas_est
summary.dccmidas(dccmidas_est)
```

---

Det	<i>Matrix determinant</i>
-----	---------------------------

---

**Description**

Calculates the determinant of a numeric matrix.

**Usage**

```
Det(x)
```

**Arguments**

x                    a numeric matrix

**Value**

The determinant of x.

**Examples**

```
x<-matrix(sample(1:25,25,replace=TRUE),ncol=5)
Det(x)
```

---

ftse100	<i>FTSE 100 data</i>
---------	----------------------

---

**Description**

Daily data on FTSE 100 collected from the realized library of the Oxford-Man Institute (Heber et al. 2009).

**Usage**

```
data(ftse100)
```

**Format**

An object of class "xts".

**Details**

ftse100 includes the open price (open\_price), the realized variance (rv5), and the close price (close\_price). The realized variance has been calculated using intradaily intervals of five minutes (Andersen and Bollerslev 1998).

**Source**

Realized library of the [Oxford-Man Institute](#)

**References**

Andersen TG, Bollerslev T (1998). “Answering the Skeptics: Yes, Standard Volatility Models do Provide Accurate Forecasts.” *International Economic Review*, **39**, 885–905. doi: [10.2307/2527343](#).

Heber G, Lunde A, Shephard N, Sheppard K (2009). “OMI’s realised library, version 0.1.” Oxford–Man Institute, University of Oxford.

**Examples**

```
head(ftse100)
summary(ftse100)
```

---

indpro

*Monthly U.S. Industrial Production*

---

**Description**

Monthly data on the U.S. Industrial Production index (IP, index 2012=100, seasonally adjusted) collected from the Federal Reserve Economic Data (FRED) archive. The IP has been used as MIDAS term in different contributions (see, for instance, Engle et al. (2013), Conrad and Loch (2015), and Amendola et al. (2017)).

**Usage**

```
data(indpro)
```

**Format**

An object of class "xts".

**Source**

Archive of the Federal Reserve Economic Data ([FRED](#))

**References**

Amendola A, Candila V, Scognamiglio A (2017). “On the influence of US monetary policy on crude oil price volatility.” *Empirical Economics*, **52**(1), 155–178. doi: [10.1007/s0018101610695](#).

Conrad C, Loch K (2015). “Anticipating Long-Term Stock Market Volatility.” *Journal of Applied Econometrics*, **30**(7), 1090–1114. doi: [10.1002/jae.2404](#).

Engle RF, Ghysels E, Sohn B (2013). “Stock market volatility and macroeconomic fundamentals.” *Review of Economics and Statistics*, **95**(3), 776–797. doi: [10.1162/REST\\_a\\_00300](#).



**Examples**

```
head(indpro)
summary(indpro)
plot(indpro)
```

---

Inv	<i>Inverse of a matrix</i>
-----	----------------------------

---

**Description**

Calculates the inverse of a numeric matrix

**Usage**

```
Inv(x)
```

**Arguments**

x                    a numeric matrix

**Value**

The inverse of x.

**Examples**

```
x<-matrix(sample(1:25,25,replace=TRUE),ncol=5)
Inv(x)
```

---

nasdaq	<i>NASDAQ data</i>
--------	--------------------

---

**Description**

Daily data on NASDAQ collected from the realized library of the Oxford-Man Institute (Heber et al. 2009).

**Usage**

```
data(nasdaq)
```

**Format**

An object of class "xts".

## Details

nasdaq includes the open price (open\_price), the realized variance (rv5), and the close price (close\_price). The realized variance has been calculated using intradaily intervals of five minutes (Andersen and Bollerslev 1998).

## Source

Realized library of the [Oxford-Man Institute](#)

## References

Andersen TG, Bollerslev T (1998). “Answering the Skeptics: Yes, Standard Volatility Models do Provide Accurate Forecasts.” *International Economic Review*, **39**, 885–905. doi: [10.2307/2527343](#).

Heber G, Lunde A, Shephard N, Sheppard K (2009). “OMI’s realised library, version 0.1.” Oxford–Man Institute, University of Oxford.

## Examples

```
head(nasdaq)
summary(nasdaq)
```

---

plot_dccmidas	<i>Plot method for 'dccmidas' class</i>
---------------	---

---

## Description

Plots of the conditional volatilities on the main diagonal and of the conditional correlations on the extra-diagonal elements.

## Usage

```
plot_dccmidas(  
  x,  
  K_c = NULL,  
  vol_col = "black",  
  long_run_col = "red",  
  cex_axis = 0.75,  
  LWD = 2,  
  asset_sub = NULL  
)
```

**Arguments**

x	An object of class 'dccmidas', that is the result of a call to <code>dcc_fit</code> .
K_c	<b>optional</b> Number of (lagged) realizations to use for the long-run correlation, , if 'corr_model' is "DCCMIDAS"
vol_col	<b>optional</b> Color of the volatility and correlation plots. "black" by default
long_run_col	<b>optional</b> Color of the long-run correlation plots, if present. "red" by default
cex_axis	<b>optional</b> Size of the x-axis. Default to 0.75
LWD	<b>optional</b> Width of the plotted lines. Default to 2
asset_sub	<b>optional</b> Numeric vector of selected assets to consider for the plot. NULL by default

**Value**

No return value, called for side effects

**Examples**

```
require(xts)
# open to close daily log-returns
r_t_s<-log(sp500['2010/2019'][,3])-log(sp500['2010/2019'][,1])
r_t_n<-log(nasdaq['2010/2019'][,3])-log(nasdaq['2010/2019'][,1])
r_t_f<-log(ftse100['2010/2019'][,3])-log(ftse100['2010/2019'][,1])
db_m<-merge.xts(r_t_s,r_t_n,r_t_f)
db_m<-db_m[complete.cases(db_m),]
colnames(db_m)<-c("S&P500","NASDAQ","FTSE100")
# list of returns
r_t<-list(db_m[,1],db_m[,2],db_m[,3])
# estimation
K_c<-144
N_c<-36
cdcc_est<-dcc_fit(r_t,univ_model="sGARCH",distribution="norm",
corr_model="DCCMIDAS",N_c=N_c,K_c=K_c)
plot_dccmidas(cdcc_est,K_c=144)
```

---

sp500

*S&P 500 data*


---

**Description**

Daily data on S&P 500 collected from the realized library of the Oxford-Man Institute (Heber et al. 2009).

**Usage**

```
data(sp500)
```

**Format**

An object of class "xts".

**Details**

sp500 includes the open price (open\_price), the realized variance (rv5), and the close price (close\_price). The realized variance has been calculated using intradaily intervals of five minutes (Andersen and Bollerslev 1998).

**Source**

Realized library of the [Oxford-Man Institute](#)

**References**

Andersen TG, Bollerslev T (1998). "Answering the Skeptics: Yes, Standard Volatility Models do Provide Accurate Forecasts." *International Economic Review*, **39**, 885–905. doi: [10.2307/2527343](#).

Heber G, Lunde A, Shephard N, Sheppard K (2009). "OMI's realised library, version 0.1." Oxford–Man Institute, University of Oxford.

**Examples**

```
head(sp500)
summary(sp500)
```

# Index

## \* datasets

ftse100, 7

indpro, 8

nasdaq, 9

sp500, 11

cov\_eval, 2

dcc\_fit, 3, 11

Det, 7

ftse100, 7

indpro, 8

Inv, 9

mv\_into\_mat, 4

nasdaq, 9

plot\_dccmidas, 10

sp500, 11

summary.dccmidas, 5

ugarchspec, 4

ugmfit, 4