Package 'rumidas'

March 18, 2025

Title Univariate GARCH-MIDAS, Double-Asymmetric GARCH-MIDAS and
MEM-MIDAS

Version 0.1.3

Description Adds the MIxing-Data Sampling (MIDAS, Ghy-
sels et al. (2007) <doi:10.1080/07474930600972467>) components to a vari-
ety of GARCH and MEM (Engle (2002) <doi:10.1002/jae.683>, En-
gle and Gallo (2006) <doi:10.1016/j.jeconom.2005.01.018>, and Amen-
dola et al. (2024) <doi:10.1016/j.seps.2023.101764>) models, with the aim of predict-
ing the volatility with additional low-frequency (that is, MIDAS) terms. The estima-
tion takes place through simple functions, which provide in-sample and (if present) and out-of-
sample evaluations. 'rumidas' also offers a summary tool, which synthesizes the main informa-
tion of the estimated model. There is also the possibility of generating one-step-ahead and multi-
step-ahead forecasts.

License GPL-3

Encoding UTF-8

LazyData true

RoxygenNote 7.2.3

RdMacros Rdpack

Depends R (>= 4.0.0), maxLik (>= 1.3-8)

Imports 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 no

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Contents

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beta_function   *Beta function*

Description

Represents a tool able to accommodate various lag structures for the additional MIDAS variable observed each "low-frequency" period t. It can have a monotonically increasing, decreasing weighting scheme or a hump-shaped weighting scheme. The Beta function is:

$$\delta_k(\omega) = \frac{(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K}(j/K)^{\omega_1-1}(1-j/K)^{\omega_2-1}}.$$

For additional details, see Ghysels et al. (2007).

Usage

```
beta_function(k, K, w1, w2)
```

Arguments

k	Lag of interest.
K	Number of (lagged) realizations to consider.
w1, w2	Parameters governing the weights of each k lag.

Value

The weights associated to each lag k, with $k = 1, \cdots, K$.

References

Ghysels E, Sinko A, Valkanov R (2007). "MIDAS regressions: Further results and new directions." *Econometric Reviews*, **26**(1), 53–90. doi:10.1080/07474930600972467.

Examples

```
# suppose to have four lags:
# K<-4
# w1<-1 # by setting w1=1, only a monotonically decreasing weighting scheme is allowed
#(more recent observations weigh more)
# w2<-5
beta_function(1:4,K=4,w1=1,w2=5)
```

---

exp_almon   *Exponential Almon Lag*

Description

Represents a tool able to accommodate various lag structures for the additional MIDAS variable observed each "low-frequency" period t. It can have a monotonically increasing, decreasing weighting scheme or a hump-shaped weighting scheme. As in Ghysels et al. (2007), here the function form uses only two parameters:

$$\delta_k(\omega_1, \omega_2) = \frac{exp(\omega_1 k + \omega_2 k^2)}{\sum_{k=1}^{K} exp(\omega_1 k + \omega_2 k^2)}.$$

For additional details, see Almon (1965) and Ghysels et al. (2007).

Usage

```
exp_almon(k, K, w1, w2)
```

Arguments

k	Lag of interest.
K	Number of (lagged) realizations to consider.
w1, w2	Parameters governing the weights of each k lag.

Value

The weights associated to each lag k, with $k = 1, \cdots, K$.

References

Almon S (1965). "The distributed lag between capital appropriations and expenditures." *Econometrica: Journal of the Econometric Society*, 178–196. doi:10.2307/1911894.

Ghysels E, Sinko A, Valkanov R (2007). "MIDAS regressions: Further results and new directions." *Econometric Reviews*, **26**(1), 53–90. doi:10.1080/07474930600972467.

Examples

```
# suppose to have four lags:
# K<-4 # Note: the number of lags to consider
# w1<-1
# w2<- -0.5 # by setting w2<0, the monotonically decreasing weighting scheme is used
exp_almon(1:4,K=4,w1=0.1,w2=-0.5)
```

---

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, Scognamillo 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)
```

multi_step_ahead_pred | *Multi–step–ahead predictions of the GARCH–MIDAS–based models with and without the '–X' part.*

Description

Calculates the multi–step–ahead predictions for the GARCH–MIDAS and DAGM models, according to the procedure suggested by Amendola et al. (2021).

Usage

```
multi_step_ahead_pred(est, h, X = NULL)
```

Arguments

est   The estimation object as resulting by the `ugmfit` function

h   The length of the multi-step-ahead predictions

X   **optional**. The '–X' variable. NULL by default. It hat to be equal to the 'X' used in the `ugmfit` function

Details

The multi–step–ahead procedure calculates the volatility predictions keeping fixed the information set at the last observation available and projecting forward the forecasts. The procedure calculates the volatility predictions conditionally to the parameters estimated in the in-sample period. Therefore, the estimation object (through the `ugmfit` function) has to be provided. For additional details, see Eq. (20) in Amendola et al. (2021).

Value

The multi-step-ahead predictions, for the following h days, starting from the last day of the chosen in-sample period adopted in the 'est' object.

References

Amendola A, Candila V, Gallo GM (2021). "Choosing the frequency of volatility components within the Double Asymmetric GARCH–MIDAS–X model." *Economic and Statistics*. doi:10.1016/ j.ecosta.2020.11.001.

Examples

```
r_t<-sp500['2008']
X<-(rv5['2008'])^0.5
mv_m<-mv_into_mat(r_t,diff(indpro),K=12,"monthly")
fit<-ugmfit(model="GMX",skew="YES",distribution="norm",r_t,mv_m,K=12,X=X)
### ten days predictions
multi_step_ahead_pred(fit,h=10,X)
```

---

mv_into_mat   *MIDAS variable matrix transformation*

Description

Implements the transformation of the MIDAS variable into a matrix, whose dimension is $(K+1) \times N$, where K is the number of lagged realizations to consider and N is the length of the variable x.

Usage

```
mv_into_mat(x, mv, K, type)
```

Arguments

x	Variable according to which the MIDAS term has to be aligned. It must be an 'xts' object.
mv	MIDAS variable, observed each period t. It must be an 'xts' object.
K	Number of (lagged) realizations of the MIDAS variable to consider.
type	The frequency of the period of observations for the MIDAS variable. It can be 'weekly', 'monthly', 'quarterly' or 'yearly'.

Value

The resulting matrix has as many rows as the number of lagged realizations (plus one) of the MIDAS variable to consider, and as many columns as the length of x.

Examples

```
require(xts)
# weekly frequency
# obtain weekly MIDAS variable after daily aggregation
RV_weekly_sum<-apply.weekly(rv5^0.5,sum) #realized volatility
# then allocate correctly the information
RV_weekly<-as.xts(coredata(RV_weekly_sum),seq(as.Date("2000-01-10"),
by = "week", length.out = length(RV_weekly_sum)))
# use mv_into_mat
mv_into_mat(sp500['2002/2003-12-26'],diff(RV_weekly['/2003-12']),K=4,type="weekly")

# monthly frequency
r_t<-sp500['2005/2010']
mv_into_mat(r_t,diff(indpro),K=12,type="monthly")

# quarterly frequency
RV_quarterly_sum<-apply.quarterly(rv5,sum)
RV_quarterly<-as.xts(coredata(RV_quarterly_sum),seq(as.Date("2000-04-01"),
by = "quarter", length.out = length(RV_quarterly_sum)))
mv_into_mat(sp500['2004/2010'],diff(RV_quarterly),K=10,type="quarterly")
```

```
# yearly frequency
RV_yearly_sum<-apply.yearly(rv5,sum)
RV_yearly<-as.xts(coredata(RV_yearly_sum),seq(as.Date("2001-01-01"),
by = "year", length.out = length(RV_yearly_sum)))
mv_into_mat(sp500['2006/2010'],diff(RV_yearly),K=2,type="yearly")
```

---

rv5   *S&P 500 realized variance at 5-minutes*

Description

Daily data on the realized variance of the S&P 500 collected from the realized library of the Oxford-Man Institute (Heber et al. 2009). The realized variance has been calculated using intradaily intervals of five minutes (Andersen and Bollerslev 1998).

Usage

```
data(rv5)
```

Format

An object of class "xts".

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(rv5)
summary(rv5)
plot(rv5)
```

---

sp500   *S&P 500 daily log-returns*

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"`.

Source

Realized library of the Oxford-Man Institute

References

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)
plot(sp500)
```

---

summary.rumidas   *Summary method for 'rumidas' class*

Description

Summary method for 'rumidas' class

Usage

```
## S3 method for class 'rumidas'
summary(object, ...)
```

Arguments

object	An object of class 'rumidas', that is the result of a call to ugmfit or umemfit.
...	Additional arguments affecting the summary produced.

Examples

```
r_t<-sp500['2003/2010']
real<-(rv5['2003/2010'])^0.5 # realized volatility
fit<-umemfit(model="MEM",skew="NO",x=real)
summary.rumidas(fit)
```

---

ugmfit	*Methods for obtaining (and evaluating) a variety of GARCH-MIDAS-based models*

Description

Estimates several GARCH-MIDAS-based models, according to two errors' conditional distributions: Normal and Student-t, and the presence of asymmetric terms in the short- and long-run components.

Usage

```
ugmfit(
  model,
  skew,
  distribution,
  daily_ret,
  mv_m,
  mv_m_2 = NULL,
  K,
  K_2 = NULL,
  lag_fun = "Beta",
  X = NULL,
  out_of_sample = NULL,
  vol_proxy = NULL,
  R = 100
)
```

Arguments

model	Model to estimate. Valid choices are: "GM" for GARCH-MIDAS, "GM2M" for GARCH-MIDAS with two MIDAS variables, "GMX" for GARCH-MIDAS-X, "DAGM" for Double Asymmetric GARCH-MIDAS (DAGM), "DAGM2M" for DAGM with two MIDAS variables, and "DAGMX" for DAGM-X
skew	The skewness parameter to include in the short–run equation. Valid choices are: "YES" and "NO"
distribution	The conditional density to use for the innovations. At the moment, valid choices are "norm" and "std", for the Normal and Student-t distribution, respectively
daily_ret	Daily returns, which must be an "xts" objectparamter

mv_m	(first) MIDAS variable already transformed into a matrix, through `mv_into_mat` function
mv_m_2	**optional** second MIDAS variable already transformed into a matrix, through `mv_into_mat` function
K	Number of (lagged) realizations of the (first) MIDAS variable to consider
K_2	**optional** Number of (lagged) realizations of the (second) MIDAS variable to consider
lag_fun	**optional** Lag function to use. Valid choices are "Beta" (by default) and "Almon", for the Beta and Exponential Almon lag functions, respectively
X	**optional** Additional "X" variable, which must be an "xts" object. Moreover, "X" must be observed for the same days of daily_ret
out_of_sample	**optional** A positive integer indicating the number of periods before the last to keep for out of sample forecasting
vol_proxy	**optional** If present, the 'vol_proxy' is the volatility proxy used for the in-sample and out-of-sample (again, if present) evaluation. It could be the realized variance. If it left unspecified, vol_proxy is replaced by the squared daily returns
R	**optional**. A positive integer indicating the number of replications used to find the best starting values. Equal to 100 by default

Details

Function ugmfit implements the estimation and evaluation of the GARCH–MIDAS–based models, with and without the asymmetric term linked to negative lagged daily returns, according to two distributions for the error term. The general framework assumes that:

$$r_{i,t} = \sqrt{\tau_t \times g_{i,t}}\,\epsilon_{i,t},$$

where

- $r_{i,t}$ is the daily return for the i-th day ($i = 1, \ldots, N_t$) of the period t (for example, a week, a month or a quarter; $t = 1, \ldots, T$);
- τ_t is the long-run component, varying each period t;
- $g_{i,t}$ is the short–run term, varying each day i of the period t;
- $\epsilon_{i,t}$ is an iid error term which has a zero mean and unit variance.

The short–run component of the GARCH–MIDAS (parameter "model" set to "GM"), DAGM (parameter "model" set to "DAGM"), and DAGM with two MIDAS variables (parameter "model" set to "DAGM2M") models is as follows. When the parameter "skew" is present (set to "YES"):

$$g_{i,t} = (1 - \alpha - \gamma/2 - \beta) + \left(\alpha + \gamma \cdot I_{(r_{i-1,t}<0)}\right)\frac{\left(r_{i-1,t}\right)^2}{\tau_t} + \beta g_{i-1,t},$$

where $I_{(\cdot)}$ is an indicator function. The short–run component of the GARCH–MIDAS–X (parameter "model" set to "GMX") and DAGM–X (parameter "model" set to "DAGMX"), when the parameter "skew" is set to "YES", is:

$$g_{i,t} = (1 - \alpha - \gamma/2 - \beta) + \left(\alpha + \gamma \cdot I_{(r_{i-1,t}<0)}\right)\frac{\left(r_{i-1,t}\right)^2}{\tau_t} + \beta g_{i-1,t} + z \cdot \left(X_{i-1,t} - E(X_{i-1,t})\right).$$

When, for the models GARCH–MIDAS, GARCH–MIDAS–X, DAGM, and DAGM–X, the parameter "skew" is set to "NO", parameter γ disappears. For details on the GARCH–MIDAS–X and DAGM–X models, see Amendola et al. (2021). The long-run component of the GARCH-MIDAS and GARCH–MIDAS–X models is:

$$\tau_t = \exp\left\{ m + \theta \sum_{j=1}^{K} \delta_j(\omega) X_{t-j} \right\},$$

where X_t is the MIDAS term and $\delta_j(\omega)$ is the chosen weighting function, which can be the Beta (`beta_function`) or Exponential Almon lag (`exp_almon`) functions. The long-run component of the DAGM and DAGM–X models is:

$$\tau_t = \exp\left(m + \theta^+ \sum_{k=1}^{K} \delta_k(\omega)^+ X_{t-k} I_{(X_{t-k} \geq 0)} + \theta^- \sum_{k=1}^{K} \delta_k(\omega)^- X_{t-k} I_{(X_{t-k} < 0)} \right).$$

Value

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

- model: The model used for the estimation.
- rob_coef_mat: The matrix of estimated coefficients, with the QML standard errors. For details, see: Bollerslev and Wooldridge (1992).
- obs: The number of daily observations used for the (in-sample) estimation.
- period: The period of the in-sample estimation.
- loglik: The value of the log-likelihood at the maximum.
- inf_criteria: The AIC and BIC information criteria.
- loss_in_s: The in-sample MSE and QLIKE averages, calculated considering the distance with respect to the volatility proxy (if provided) or the squared daily returns.
- est_in_s: The one-step-ahead volatility, for the in-sample period, that is: $\sqrt{\hat{\tau}_t \times \hat{g}_{i,t}}$.
- est_lr_in_s: The one-step-ahead long-run volatility, for the in-sample period.
- loss_oos: The out-of-sample MSE and QLIKE averages, calculated considering the distance with respect to the volatility proxy (if provided) or the squared daily returns.
- est_oos: The one-step-ahead volatility, for the out-of-sample period, that is: $\sqrt{\hat{\tau}_t \times \hat{g}_{i,t}}$.
- est_lr_oos: The one-step-ahead long-run volatility, for the out-of-sample period.

References

Amendola A, Candila V, Gallo GM (2021). "Choosing the frequency of volatility components within the Double Asymmetric GARCH–MIDAS–X model." *Economic and Statistics*. doi:10.1016/j.ecosta.2020.11.001.

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.

See Also

mv_into_mat.

Examples

```
# estimate a GARH-MIDAS model, without the skewness parameter
r_t<-sp500['2008']
mv_m<-mv_into_mat(r_t,diff(indpro),K=12,"monthly")
fit<-ugmfit(model="GM",skew="NO",distribution="norm",r_t,mv_m,K=12)
fit
summary.rumidas(fit)
names(fit)

# to see the estimated coefficients with the QML standard errors:
fit$rob_coef_mat

# estimate a DAGM model, with the skewness parameter,
# including the volatility proxy (realized variance), and
# leaving the last 100 observations for the out-of-sample evaluation
r_t<-sp500['2002/2020']
mv_m<-mv_into_mat(r_t,diff(indpro),K=12,"monthly")
fit_2<-ugmfit(model="DAGM",skew="YES",distribution="norm",r_t,
mv_m,K=12,vol_proxy=rv5['2002/2020'],out_of_sample=100)
fit_2
summary.rumidas(fit_2)
# estimate a GM-X model, without the skewness parameter
r_t<-sp500['2010/2013']
X<-vix['2010/2013']
mv_m<-mv_into_mat(r_t,diff(indpro),K=36,"monthly")
fit_3<-ugmfit(model="GMX",skew="NO",distribution="norm",r_t,mv_m,K=36,X=X)
summary.rumidas(fit_3)
```

---

umemfit   *Methods for obtaining (and evaluating) a variety of MEM(-MIDAS)-*
                               based models

Description

Estimates several MEM and MEM-MIDAS-based models. For details, see Amendola et al. (2024)

Usage

```
umemfit(
  model,
  skew,
  x,
  daily_ret = NULL,
  mv_m = NULL,
```

```
    K = NULL,
    z = NULL,
    out_of_sample = NULL,
    R = 100
)
```

Arguments

model	Model to estimate. Valid choices are: "MEMMIDAS" for MEM-MIDAS, "MEM" for base MEM, "MEMX" for the base MEM with an X term, "MEMMIDASX" for the MEM-MIDAS-X
skew	The skewness parameter linked to lagged daily returns. Valid choices are: "YES" and "NO"
x	Dependent variable to predict. Usually the realized volatility. It must be positive and "xts" object
daily_ret	**optional**. Daily returns, which must be an "xts" object. NULL by default
mv_m	**optional**. MIDAS variable already transformed into a matrix, through `mv_into_mat` function. NULL by default
K	**optional**. Number of (lagged) realizations of the MIDAS variable to consider. NULL by default for the Beta and Exponential Almon lag functions, respectively
z	**optional**. Additional daily variable, which must be an "xts" object, and with the same length of x. NULL by default
out_of_sample	**optional**. A positive integer indicating the number of periods before the last to keep for out of sample forecasting
R	**optional**. A positive integer indicating the number of replications used to find the best starting values. Equal to 100 by default

Details

Function `umemfit` implements the estimation and evaluation of the MEM, MEM-MIDAS MEM-X and MEM-MIDAS-X models, with and without the asymmetric term linked to negative lagged daily returns. The general framework assumes that:

$$x_{i,t} = \mu_{i,t}\epsilon_{i,t} = \tau_t\xi_{i,t}\epsilon_{i,t},$$

where

- $x_{i,t}$ is a time series coming from a non-negative discrete time process for the i-th day ($i = 1, \ldots, N_t$) of the period t (for example, a week, a month or a quarter; $t = 1, \ldots, T$);

- τ_t is the long-run component, determining the average level of the conditional mean, varying each period t;

- $\xi_{i,t}$ is a factor centered around one, labelled as the short–run term, which plays the role of dumping or amplifying $\tau_{i,t}$;

- $\epsilon_{i,t}$ is an *iid* error term which, conditionally on the information set, has a unit mean, an unknown variance, and a probability density function defined over a non-negative support.

The short–run component of the MEM-MIDAS-X is:

$$\xi_{i,t} = (1 - \alpha - \gamma/2 - \beta) + \left(\alpha + \gamma \cdot I_{(r_{i-1,t}<0)}\right) \frac{x_{i-1,t}}{\tau_t} + \beta \xi_{i-1,t} + \delta \left(Z_{i-1,t} - E(Z)\right),$$

where $I_{(\cdot)}$ is an indicator function, $r_{i,t}$ is the daily return of the day i of the period t and Z is an additional X term (for instance, the VIX). When the X part is absent, then the parameter δ cancels. The long-run component of the MEM-MIDAS and MEM-MIDAS-X is:

$$\tau_t = \exp\left\{m + \theta \sum_{k=1}^{K} \delta_k(\omega) X_{t-k}\right\},$$

where X_t is the MIDAS term. When the "skew" parameter is set to "NO", γ disappears. The MEM and MEM-X models do not have the long- and short-run components. Therefore, they directly evolve according to $\mu_{i,t}$. When the "skew" and X parameters are present, the MEM-X is:

$$\mu_{i,t} = (1 - \alpha - \gamma/2 - \beta)\mu + (\alpha + \gamma I_{(r_{i-1,t}<0)})x_{i-1,t} + \beta\mu_{i-1,t} + \delta\left(Z_{i-1,t} - E(Z)\right),$$

where $\mu = E(x_{i,t})$. When the "skew" parameter is set to "NO", in the previous equation γ cancels. Finally, when the additional X part is not present, then we have the MEM model, where δ disappears.

Value

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

- model: The model used for the estimation.
- rob_coef_mat: The matrix of estimated coefficients, with the QML standard errors.
- obs: The number of daily observations used for the (in-sample) estimation.
- period: The period of the in-sample estimation.
- loglik: The value of the log-likelihood at the maximum.
- inf_criteria: The AIC and BIC information criteria.
- loss_in_s: The in-sample MSE and QLIKE averages, calculated considering the distance with respect to the dependent variable.
- est_in_s: The in-sample predicted dependent variable.
- est_lr_in_s: The in-sample predicted long-run component (if present) of the dependent variable.
- loss_oos: The out-of-sample MSE and QLIKE averages, calculated considering the distance with respect to the dependent variable.
- est_oos: The out-of-sample predicted dependent variable.
- est_lr_oos: The out-of-sample predicted long-run component (if present) of the dependent variable.

References

Amendola A, Candila V, Cipollini F, Gallo GM (2024). "Doubly multiplicative error models with long-and short-run components." *Socio-Economic Planning Sciences*, **91**, 101764. doi:10.1016/j.seps.2023.101764.

See Also

[mv_into_mat](#).

Examples

```
# estimate the base MEM, without the asymmetric term linked to negative lagged returns
real<-(rv5['2003/2010'])^0.5 # realized volatility
fit<-umemfit(model="MEM",skew="NO",x=real)
fit
summary.rumidas(fit)
# to see the estimated coefficients with the QML standard errors:
fit$rob_coef_mat

# All the other elements of fit are:
names(fit)

# estimate the MEM-MIDAS, with the asymmetric term linked to negative lagged returns,
# leaving the last 200 observations for the out-of-sample analysis
r_t<-sp500['2003/2010']
real<-(rv5['2003/2010'])^0.5 # realized volatility
mv_m<-mv_into_mat(real,diff(indpro),K=12,"monthly")
fit_2<-umemfit(model="MEMMIDAS",skew="YES",x=real,daily_ret=r_t,mv_m=mv_m,K=12,out_of_sample=200)
fit_2
summary.rumidas(fit_2)
# to see the estimated coefficients with the QML standard errors:
fit_2$rob_coef_mat
```

---

vix   *VIX daily data*

Description

Daily data on VIX collected from Yahoo Finance site. The VIX data have been de-annualized and multiplied by 100^{-1}.

Usage

```
data(vix)
```

Format

An object of class "xts".

Source

[Yahoo Finance](#)

Examples

```
head(vix)
summary(vix)
plot(vix)
```

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