

Package ‘EWS’

May 7, 2026

Type Package

Title Early Warning System

Version 0.2.0

Author Jean-Baptiste Hasse [aut], Quentin Lajaunie [aut, cre]

Maintainer Quentin Lajaunie <quentin_lajaunie@hotmail.fr>

Description

The purpose of Early Warning Systems (EWS) is to detect accurately the occurrence of a crisis, which is represented by a binary variable which takes the value of one when the event occurs, and the value of zero otherwise. EWS are a toolbox for policymakers to prevent or attenuate the impact of economic downturns. Modern EWS are based on the econometric framework of Kauppi and Saikkonen (2008) <doi:10.1162/rest.90.4.777>. Specifically, this framework includes four dichotomous models, relying on a logit approach to model the relationship between yield spreads and future recessions, controlling for recession risk factors. These models can be estimated in a univariate or a balanced panel framework as in Candelon, Dumitrescu and Hurlin (2014) <doi:10.1016/j.ijforecast.2014.03.015>. This package provides both methods for estimating these models and a dataset covering 13 OECD countries over a period of 45 years. In addition, this package also provides methods for the analysis of the propagation mechanisms of an exogenous shock, as well as robust confidence intervals for these response functions using a block-bootstrap method as in Lajaunie (2021). This package constitutes a useful toolbox (data and functions) for scholars as well as policymakers.

Depends R (>= 2.10)

License GPL-3

Encoding UTF-8

LazyData true

Imports numDeriv

NeedsCompilation no

Repository CRAN

Date/Publication 2021-02-24 10:30:06 UTC

Contents

BlockBootstrapp 2

data_panel	3
data_USA	4
EWS_AM_Criterion	5
EWS_CSA_Criterion	6
EWS_NSR_Criterion	8
GIRF_Dicho	9
GIRF_Index_CI	11
GIRF_Proba_CI	13
Logistic_Estimation	14
Matrix_lag	16
Simul_GIRF	17
Vector_Error	19
Vector_lag	20
Index	22

BlockBootstrapp	<i>Block Bootstrapp</i>
-----------------	-------------------------

Description

This function enables the estimation of the block size for resampling. The size of the blocks is computed as in Hall, Horowitz and Jing (1995). Then, the function returns in a matrix the new resampled input variables. These variables are then used to determine the confidence intervals of the response functions proposed by Lajaunie (2021).

Usage

```
BlockBootstrapp(Dicho_Y, Exp_X, Intercept, n_simul)
```

Arguments

Dicho_Y	Vector of the binary time series.
Exp_X	Vector or Matrix of explanatory time series.
Intercept	Boolean value: TRUE for an estimation with intercept, and FALSE otherwise.
n_simul	Numeric variable equal to the total number of replications.

Value

A matrix containing the replications of the new resampled input variables. The matrix contains $n \times S$ columns, where n denotes the number of input variables, and S denotes the number of replications.

Author(s)

Jean-Baptiste Hasse and Quentin Lajaunie

References

Hall, Peter, Joel L. Horowitz, and Bing-Yi Jing. "On blocking rules for the bootstrap with dependent data." *Biometrika* 82.3 (1995): 561-574.

Lajaunie, Quentin. Generalized Impulse Response Function for Dichotomous Models. No. 2852. Orleans Economics Laboratory/Laboratoire d'Economie d'Orleans (LEO), University of Orleans, 2021.

Examples

```
# NOT RUN {  
  
# Import data  
data("data_USA")  
  
# Data process  
Var_Y <- as.vector(data_USA$NBER)  
Var_X <- as.vector(data_USA$Spread)  
  
# Resample  
results <- BlockBootstrapp(Dicho_Y = Var_Y, Exp_X = Var_X, Intercept = TRUE, n_simul = 100)  
  
# print results  
results  
  
#}
```

data_panel

Historical data for 13 OECD countries

Description

data_USA contains: - OECD based Recession Indicators for 13 OECD countries from the Peak through the Trough from 1975:03 to 2019:05 - Yield Spread (10Years TB minus 3Months TB) for 13 OECD countries from 1975:03 to 2019:05

List of countries: Australia, Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, New Zealand, Sweden, Switzerland, the United Kingdom, the United States.

Usage

```
data("data_panel")
```

Format

A data frame with 6903 observations on the following 4 variables.

country List of countries.

Date Vector of dates.

YIESPR historical yield spread for the 13 OECD countries.

OECD Historical binary variable related to historical recessions for the 13 OECD countries.

Source

<https://fred.stlouisfed.org/>

Examples

```
data("data_panel")
head("data_panel")
```

data_USA

Historical data for the United States

Description

data_USA contains: - NBER based Recession Indicators for the United States from 1953:04 to 2020:01 - 10Years TB for the United States from 1953:04 to 2020:01 - 3Months TB for the United States from 1953:04 to 2020:01 - Yield Spread (10Years TB minus 3Months TB) for the United States from 1975:03 to 2019:05

Usage

```
data("data_USA")
```

Format

A data frame with 268 observations on the following 5 variables.

Date Vector of dates.

X10Y Historical 10 years Treasury bond.

X3M Historical 3 months Treasury bond.

Spread Historical yield spread.

NBER Historical binary variable related to historical recessions.

Source

<https://fred.stlouisfed.org/>

Examples

```
data("data_USA")
head("data_USA")
```

EWS_AM_Criterion	<i>AM Threshold - optimal cut-off</i>
------------------	---------------------------------------

Description

This function provides a method to compute the optimal AM (Accuracy Measure) criterion. As defined in Candelon, Dumitrescu and Hurlin (2012), this approach consists in aggregating the number of crisis and calm periods correctly identified by the EWS. The optimal cut-off maximizes the number of correctly identified periods.

Usage

```
EWS_AM_Criterion(Var_Proba, Dicho_Y, cutoff_interval)
```

Arguments

Var_Proba	Vector containing the estimated probabilities obtained with the Logistic Estimation function.
Dicho_Y	Vector of the binary time series.
cutoff_interval	Numeric variable between 0 and 1.

Value

A numeric variable containing the optimal cut-off that maximizes the higher proportion of calm and crisis periods correctly identified.

Author(s)

Jean-Baptiste Hasse and Quentin Lajaunie

References

Candelon, Bertrand, Elena-Ivona Dumitrescu, and Christophe Hurlin. "How to evaluate an early-warning system: Toward a unified statistical framework for assessing financial crises forecasting methods." *IMF Economic Review* 60.1 (2012): 75-113.

Lajaunie, Quentin. Generalized Impulse Response Function for Dichotomous Models. No. 2852. Orleans Economics Laboratory/Laboratoire d'Economie d'Orleans (LEO), University of Orleans, 2021.

Examples

```
# NOT RUN {  
  
# Import data  
data("data_USA")
```

```

# Data process
Var_Y <- as.vector(data_USA$NBER)
Var_X <- as.vector(data_USA$Spread)

# Estimate the logit regression
Logistic_results <- Logistic_Estimation(Dicho_Y = Var_Y, Exp_X = Var_X, Intercept = TRUE,
                                       Nb_Id = 1, Lag = 1, type_model = 4)

# Vector of probabilities
vector_proba <- as.vector(rep(0,length(Var_Y)-1))
vector_proba <- Logistic_results$prob

# Vector of binary variables
Lag <- 1
vector_binary <- as.vector(rep(0,length(Var_Y)-1))
vector_binary <- Var_Y[(1+Lag):length(Var_Y)]

# optimal cut-off that maximizes the AM criterion
results <- EWS_AM_Criterion(Var_Proba = vector_proba, Dicho_Y = vector_binary,
                           cutoff_interval = 0.0001)

# print results
results

#}

```

EWS_CSA_Criterion *CSA Threshold - optimal cut-off*

Description

This function provides a method to compute the optimal CSA (Credit-Scoring Approach) criterion. As defined in Candelon, Dumitrescu and Hurlin (2012), this approach consists of calculating the difference between the sensitivity and the specificity. Sensitivity represents the proportion of crisis periods correctly identified by the EWS. Specificity is the proportion of calm periods correctly identified by the EWS. The optimal cut-off minimizes the absolute value of this difference.

Usage

```
EWS_CSA_Criterion(Var_Proba, Dicho_Y, cutoff_interval)
```

Arguments

Var_Proba	Vector containing the estimated probabilities obtained with the Logistic Estimation function.
Dicho_Y	Vector of the binary time series.
cutoff_interval	Numeric variable between 0 and 1.

Value

A numeric variable containing the optimal cut-off that minimizes the absolute value of the difference between the sensitivity and the specificity.

Author(s)

Jean-Baptiste Hasse and Quentin Lajaunie

References

Basel Committee on Banking Supervision, 2005, "Studies on the Validation of Internal Rating Systems", working paper no.14, Bank for International Settlements.

Candelon, Bertrand, Elena-Ivona Dumitrescu, and Christophe Hurlin. "How to evaluate an early-warning system: Toward a unified statistical framework for assessing financial crises forecasting methods." *IMF Economic Review* 60.1 (2012): 75-113.

Examples

```
# NOT RUN {  
  
# Import data  
data("data_USA")  
  
# Data process  
Var_Y <- as.vector(data_USA$NBER)  
Var_X <- as.vector(data_USA$spread)  
  
# Estimate the logit regression  
Logistic_results <- Logistic_Estimation(Dicho_Y = Var_Y, Exp_X = Var_X, Intercept = TRUE,  
                                       Nb_Id = 1, Lag = 1, type_model = 4)  
  
# Vector of probabilities  
vector_proba <- as.vector(rep(0,length(Var_Y)-1))  
vector_proba <- Logistic_results$prob  
  
# Vector of binary variables  
Lag <- 1  
vector_binary <- as.vector(rep(0,length(Var_Y)-1))  
vector_binary <- Var_Y[(1+Lag):length(Var_Y)]  
  
# optimal cut-off that minimizes the CSA criterion  
results <- EWS_CSA_Criterion(Var_Proba = vector_proba, Dicho_Y = vector_binary,  
                           cutoff_interval = 0.0001)  
  
# print results  
results  
  
#}
```

EWS_NSR_Criterion *NSR Threshold - optimal cut-off*

Description

This function provides a method to compute the optimal NSR (Noise to Signal Ratio) criterion proposed by Kaminsky, Lizondo and Reinhart (1998). As defined in Candelon, Dumitrescu and Hurlin (2012), the NSR represents the ratio of the false alarms (type II error) to the number of crises correctly identified by the EWS for a given cut-off. The optimal cut-off minimizes the NSR criterion.

Usage

```
EWS_NSR_Criterion(Var_Proba, Dicho_Y, cutoff_interval)
```

Arguments

Var_Proba	Vector containing the estimated probabilities obtained with the Logistic Estimation function.
Dicho_Y	Vector of the binary time series.
cutoff_interval	Numeric variable between 0 and 1.

Value

A numeric variable containing the optimal cut-off that minimizes the NSR criterion.

Author(s)

Jean-Baptiste Hasse and Quentin Lajaunie

References

Candelon, Bertrand, Elena-Ivona Dumitrescu, and Christophe Hurlin. "How to evaluate an early-warning system: Toward a unified statistical framework for assessing financial crises forecasting methods." *IMF Economic Review* 60.1 (2012): 75-113.

Kaminsky, Graciela, Saul Lizondo, and Carmen M. Reinhart. "Leading indicators of currency crises." *IMF Staff Papers* 45.1 (1998): 1-48.

Examples

```
# NOT RUN {  
  
# Import data  
data("data_USA")  
  
# Data process
```

```

Var_Y <- as.vector(data_USA$NBER)
Var_X <- as.vector(data_USA$Spread)

# Estimate the logit regression
Logistic_results <- Logistic_Estimation(Dicho_Y = Var_Y, Exp_X = Var_X, Intercept = TRUE,
                                       Nb_Id = 1, Lag = 1, type_model = 4)

# Vector of probabilities
vector_proba <- as.vector(rep(0,length(Var_Y)-1))
vector_proba <- Logistic_results$prob

# Vector of binary variables
Lag <- 1
vector_binary <- as.vector(rep(0,length(Var_Y)-1))
vector_binary <- Var_Y[(1+Lag):length(Var_Y)]

# optimal cut-off that minimizes the NSR criterion
results <- EWS_NSR_Criterion(Var_Proba = vector_proba, Dicho_Y = vector_binary,
                             cutoff_interval = 0.0001)

# print results
results

#}

```

GIRF_Dicho

GIRF for Dichotomous models

Description

This function estimates the response functions of dichotomous models in a univariate framework using the method proposed by Lajaunie (2021). The response functions are based on the 4 specifications proposed by Kauppi & Saikkonen (2008).

Usage

```
GIRF_Dicho(Dicho_Y, Exp_X, Lag, Int, t_mod, horizon, shock_size, OC)
```

Arguments

Dicho_Y	Vector of the binary time series.
Exp_X	Vector or Matrix of explanatory time series.
Lag	Number of lags used for the estimation.
Int	Boolean value: TRUE for an estimation with intercept, and FALSE otherwise.
t_mod	Model number: 1, 2, 3 or 4. -> 1 for the static model:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta' X_t)$$

-> 2 for the dynamic model with lag binary variable:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta'X_t + \gamma Y_{t-1})$$

-> 3 for the dynamic model with lag index variable:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta'X_t + \eta\pi_{t-1})$$

-> 4 for the dynamic model with both lag binary variable and lag index variable:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta'X_t + \eta\pi_{t-1} + \gamma Y_{t-1})$$

horizon	Numeric variable corresponding to the horizon target for the GIRF analysis.
shock_size	Numeric variable equal to the size of the shock. It can be estimated with the Vector_Error function.
OC	Numeric variable equal to the Optimal Cut-off (threshold). This threshold can be considered arbitrarily, with a value between 0 and 1, or it can be estimated with one of the functions EWS_AM_Criterion, EWS_CSA_Criterion, or EWS_NSR_Criterion.

Value

Matrix with 7 columns:

column 1	horizon
column 2	index
column 3	index with shock
column 4	probability associated to the index
column 5	probability associated to the index with shock
column 6	binary variable associated to the index
column 7	binary variable associated to the index with shock

Author(s)

Jean-Baptiste Hasse and Quentin Lajaunie

References

Kauppi, Heikki, and Pentti Saikkonen. "Predicting US recessions with dynamic binary response models." *The Review of Economics and Statistics* 90.4 (2008): 777-791.

Lajaunie, Quentin. Generalized Impulse Response Function for Dichotomous Models. No. 2852. Orleans Economics Laboratory/Laboratoire d'Economie d'Orleans (LEO), University of Orleans, 2021.

Examples

```

# NOT RUN {

# Import data
data("data_USA")

# Data process
Var_Y <- as.vector(data_USA$NBER)
Var_X <- as.vector(data_USA$Spread)

# Estimate the logit regression
Logistic_results <- Logistic_Estimation(Dicho_Y = Var_Y, Exp_X = Var_X, Intercept = TRUE,
                                       Nb_Id = 1, Lag = 1, type_model = 1)

# Vector of probabilities
vector_proba <- as.vector(rep(0,length(Var_Y)-1))
vector_proba <- Logistic_results$prob

# Vector of binary variables
Lag <- 1
vector_binary <- as.vector(rep(0,length(Var_Y)-1))
vector_binary <- Var_Y[(1+Lag):length(Var_Y)]

# optimal cut-off that maximizes the AM criterion
Threshold_AM <- EWS_AM_Criterion(Var_Proba = vector_proba, Dicho_Y = vector_binary,
                                cutoff_interval = 0.0001)

# Estimate the estimation errors
Residuals <- Vector_Error(Dicho_Y = Var_Y, Exp_X = Var_X, Intercept = TRUE,
                          Nb_Id = 1, Lag = 1, type_model = 1)

# Initialize the shock
size_shock <- quantile(Residuals,0.95)

# GIRF Analysis
results <- GIRF_Dicho(Dicho_Y = Var_Y, Exp_X = Var_X, Lag = 1, Int = TRUE, t_mod = 1,
                    horizon = 3, shock_size = size_shock, OC = Threshold_AM)

# print results
results

#}

```

Description

From the results of the Simulation_GIRF function, this function calculates the values of the upper and lower bounds of the confidence intervals, as well as the average of the different response functions for the index.

Usage

```
GIRF_Index_CI(results_simul_GIRF, CI_bounds, n_simul, horizon_forecast)
```

Arguments

```
results_simul_GIRF
    Matrix containing results of the Simulation_GIRF function.
CI_bounds
    Numeric variable between 0 and 1 for the size of the confidence intervals.
n_simul
    Numeric variable equal to the total number of replications.
horizon_forecast
    Numeric variable corresponding to the horizon target for the GIRF analysis.
```

Value

A list with:

```
Simulation_CI  a matrix containing the set of simulations belonging to the confidence interval.
values_CI      a matrix containing three columns: the lower bound of the CI, the average of the
                IRFs, and the upper bound of the CI.
```

Author(s)

Jean-Baptiste Hasse and Quentin Lajaunie

References

Lajaunie, Quentin. Generalized Impulse Response Function for Dichotomous Models. No. 2852. Orleans Economics Laboratory/Laboratoire d'Economie d'Orleans (LEO), University of Orleans, 2021.

Examples

```
# NOT RUN {

# Import data
data("data_USA")

# Data process
Var_Y <- as.vector(data_USA$NBER)
Var_X <- as.vector(data_USA$Spread)

# Simulation for the GIRF analysis
results_simulation <- Simul_GIRF(Var_Y, Var_X, TRUE, 1, 1, 2, 0.95, 3, "AM")

# Confidence intervals for the index
results <- GIRF_Index_CI(results_simulation, 0.95, 2, 3)

# print results
results

#}
```

GIRF_Proba_CI *Confidence Intervals for the Probability - GIRF Analysis*

Description

From the results of the Simulation_GIRF function, this function calculates the values of the upper and lower bounds of the confidence intervals, as well as the average of the different response functions for the probability.

Usage

```
GIRF_Proba_CI(results_simul_GIRF, CI_bounds, n_simul, horizon_forecast)
```

Arguments

results_simul_GIRF Matrix containing results of the Simulation_GIRF function.

CI_bounds Numeric variable between 0 and 1 for the size of the confidence intervals.

n_simul Numeric variable equal to the total number of replications.

horizon_forecast Numeric variable corresponding to the horizon target for the GIRF analysis.

Value

A list with:

horizon Numeric vector containing the horizon target.

Simulation_CI_proba_shock a matrix containing the set of simulations of probabilities with shock belonging to the confidence interval.

Simulation_CI_proba a matrix containing the set of simulations of probabilities belonging to the confidence interval.

CI_proba_shock a matrix containing three columns: the lower bound of the CI, the average of the IRFs, and the upper bound of the CI for the probabilities with shock.

CI_proba a matrix containing three columns: the lower bound of the CI, the average of the IRFs, and the upper bound of the CI for the probabilities.

Author(s)

Jean-Baptiste Hasse and Quentin Lajaunie

References

Lajaunie, Quentin. Generalized Impulse Response Function for Dichotomous Models. No. 2852. Orleans Economics Laboratory/Laboratoire d'Economie d'Orleans (LEO), University of Orleans, 2021.

Examples

```
# NOT RUN {

# Import data
data("data_USA")

# Data process
Var_Y <- as.vector(data_USA$NBER)
Var_X <- as.vector(data_USA$Spread)

# Simulation for the GIRF analysis
results_simulation <- Simul_GIRF(Var_Y, Var_X, TRUE, 1, 1, 2, 0.95, 3, "AM")

# Confidence intervals for the index
results <- GIRF_Proba_CI(results_simulation, 0.95, 2, 3)

# print results
results

#}
```

Logistic_Estimation *Logistic Estimation for Dichotomous Analysis*

Description

This function provides methods for estimating the four dichotomous models as in Kauppi & Saikkonen (2008). Based on a logit approach, models are estimated in a univariate or a balanced panel framework as in Candelon, Dumitrescu and Hurlin (2014). This estimation has been used in recent papers such in Ben Naceur, Candelon and Lajaunie (2019) and Hasse and Lajaunie (2020).

Usage

```
Logistic_Estimation(Dicho_Y, Exp_X, Intercept, Nb_Id, Lag, type_model)
```

Arguments

Dicho_Y	Vector of the binary time series.
Exp_X	Vector or Matrix of explanatory time series.
Intercept	Boolean value: TRUE for an estimation with intercept, and FALSE otherwise.
Nb_Id	Number of individuals studied for a panel approach. Nb_Id=1 in the univariate case.
Lag	Number of lags used for the estimation.
type_model	Model number: 1, 2, 3 or 4. -> 1 for the static model:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta' X_t)$$

-> 2 for the dynamic model with lag binary variable:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta' X_t + \gamma Y_{t-1})$$

-> 3 for the dynamic model with lag index variable:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta' X_t + \eta \pi_{t-1})$$

-> 4 for the dynamic model with both lag binary variable and lag index variable:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta' X_t + \eta \pi_{t-1} + \gamma Y_{t-1})$$

Value

A list with:

Estimation	a dataframe containing the coefficients of the logitic estimation, the Standard Error for each coefficient, the Z-score and the associated critical probability
AIC	a numeric vector containing the Akaike information criterion
BIC	a numeric vector containing the Bayesian information criterion
R2	a numeric vector containing the Pseudo R Square
index	a numeric vector containing the estimated index
prob	a numeric vector containing the estimated probabilities
LogLik	a numeric vector containing the Log likelihood value of the estimation
VCM	a numeric matrix of the Variance Covariance of the estimation

Note

For the panel estimation, data must be stacked one after the other for each country or for each individual.

Author(s)

Jean-Baptiste Hasse and Quentin Lajaunie

References

- Candelon, Bertrand, Elena-Ivona Dumitrescu, and Christophe Hurlin. "Currency crisis early warning systems: Why they should be dynamic." *International Journal of Forecasting* 30.4 (2014): 1016-1029.
- Hasse, Jean-Baptiste, Lajaunie Quentin. "Does the Yield Curve Signal Recessions? New Evidence from an International Panel Data Analysis." (2020)
- Kauppi, Heikki, and Pentti Saikkonen. "Predicting US recessions with dynamic binary response models." *The Review of Economics and Statistics* 90.4 (2008): 777-791.
- Naceur, Sami Ben, Bertrand Candelon, and Quentin Lajaunie. "Taming financial development to reduce crises." *Emerging Markets Review* 40 (2019): 100618.

Examples

```
# NOT RUN {  
  
# Import data  
data("data_USA")  
  
# Data process  
Var_Y <- as.vector(data_USA$NBER)  
Var_X <- as.vector(data_USA$Spread)  
  
# Estimate the logit regression  
results <- Logistic_Estimation(Dicho_Y = Var_Y, Exp_X = Var_X, Intercept = TRUE,  
                               Nb_Id = 1, Lag = 1, type_model = 1)  
  
# print results  
results  
  
# }
```

Matrix_lag

Matrix Lag - data processing

Description

Compute a lagged version of a time series, shifting the time base back by a given number of observations defined by the user. The user must enter three parameters for this function: the matrix, the number of lags, and of boolean variable calls 'beginning'. If 'beginning'=TRUE, then the lag will be applied at the beginning of the matrix whereas if 'beginning'=FALSE, then the lag will be applied at the end of the matrix.

Usage

```
Matrix_lag(Matrix_target, Nb_lag, beginning)
```

Arguments

Matrix_target	Initial Matrix
Nb_lag	Number of lag
beginning	Boolean variable. If 'place'=TRUE, the lag is applied at the beginning of the matrix. If 'place'=FALSE, the lag is applied at the end of the matrix.

Value

A numeric Matrix.

Examples

```
# NOT RUN {

# Initialize the following matrix
Matrix_example <- matrix(data=(1:10), nrow=5, ncol=2)

# Use Matrix_lag
new_matrix <- Matrix_lag(Matrix_target = Matrix_example, Nb_lag = 1, beginning = TRUE)

new_matrix

# Results:
#> new_matrix
#      [,1] [,2]
#[1,]    2    7
#[2,]    3    8
#[3,]    4    9
#[4,]    5   10

#}
```

 Simul_GIRF

GIRF Simulations

Description

This function calls the BlockBootstrap function of the EWS package and then calculates response functions for each simulation. It then measures the confidence intervals as in Lajaunie (2021). The response functions are based on the 4 specifications proposed by Kauppi & Saikkonen (2008).

Usage

```
Simul_GIRF(Dicho_Y, Exp_X, Int, Lag, t_mod, n_simul, centile_shock, horizon, OC)
```

Arguments

Dicho_Y	Vector of the binary time series.
Exp_X	Vector or Matrix of explanatory time series.
Int	Boolean value: TRUE for an estimation with intercept, and FALSE otherwise.
Lag	Number of lags used for the estimation.
t_mod	Model number: 1, 2, 3 or 4. -> 1 for the static model:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta' X_t)$$

-> 2 for the dynamic model with lag binary variable:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta'X_t + \gamma Y_{t-1})$$

-> 3 for the dynamic model with lag index variable:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta'X_t + \eta\pi_{t-1})$$

-> 4 for the dynamic model with both lag binary variable and lag index variable:

$$P_{t-1}(Y_t) = F(\pi_t) = F(\alpha + \beta'X_t + \eta\pi_{t-1} + \gamma Y_{t-1})$$

n_simul	Numeric variable equal to the total number of replications.
centile_shock	Numeric variable corresponding to the centile of the shock following Koop, Pesaran and Potter (1996).
horizon	Numeric variable corresponding to the horizon target for the GIRF analysis.
OC	Either a numeric variable equal to the optimal cut-off (threshold) or a character variable of the method chosen to calculate the optimal cut-off ("NSR", "CSA", "AM").

Value

A matrix containing the GIRF analysis for each replication. For each replication, the function returns 7 columns with:

column 1	horizon
column 2	index
column 3	index with shock
column 4	probability associated to the index
column 5	probability associated to the index with shock
column 6	binary variable associated to the index
column 7	binary variable associated to the index with shock

The matrix contains $7 \times S$ columns, where S denotes the number of replications.

Author(s)

Jean-Baptiste Hasse and Quentin Lajaunie

References

- Kauppi, Heikki, and Pentti Saikkonen. "Predicting US recessions with dynamic binary response models." *The Review of Economics and Statistics* 90.4 (2008): 777-791.
- Koop, Gary, M. Hashem Pesaran, and Simon M. Potter. "Impulse response analysis in nonlinear multivariate models." *Journal of econometrics* 74.1 (1996): 119-147.
- Lajaunie, Quentin. *Generalized Impulse Response Function for Dichotomous Models*. No. 2852. Orleans Economics Laboratory/Laboratoire d'Economie d'Orleans (LEO), University of Orleans, 2021.

Examples

```

# NOT RUN {

# Import data
data("data_USA")

# Data process
Var_Y <- as.vector(data_USA$NBER)
Var_X <- as.vector(data_USA$Spread)

# Simulations
results <- Simul_GIRF(Dicho_Y = Var_Y, Exp_X = Var_X, Int = TRUE, Lag = 1, t_mod = 1 ,
                     n_simul = 2 , centile_shock = 0.95, horizon = 3, OC = "AM")

# print results
results

#}

```

Vector_Error

Vector of Errors

Description

The function measures the estimation errors from the logistic estimation, and stores them in a vector. This function is used to initialize a shock in impulse response analysis as in Koop, Pesaran and Potter (1996).

Usage

```
Vector_Error(Dicho_Y, Exp_X, Intercept, Nb_Id, Lag, type_model)
```

Arguments

Dicho_Y	Vector of the binary time series.
Exp_X	Vector or Matrix of explanatory time series.
Intercept	Boolean value: TRUE for an estimation with intercept, and FALSE otherwise.
Nb_Id	Number of individuals studied for a panel approach. Nb_Id=1 in the univariate case.
Lag	Number of lags used for the estimation.
type_model	Model number: 1, 2, 3 or 4.

Value

A numeric vector containing estimation errors.

Author(s)

Jean-Baptiste Hasse and Quentin Lajaunie

References

Kauppi, Heikki, and Pentti Saikkonen. "Predicting US recessions with dynamic binary response models." *The Review of Economics and Statistics* 90.4 (2008): 777-791.

Koop, Gary, M. Hashem Pesaran, and Simon M. Potter. "Impulse response analysis in nonlinear multivariate models." *Journal of econometrics* 74.1 (1996): 119-147.

Lajaunie, Quentin. Generalized Impulse Response Function for Dichotomous Models. No. 2852. Orleans Economics Laboratory/Laboratoire d'Economie d'Orleans (LEO), University of Orleans, 2021.

Examples

```
# NOT RUN {

# Import data
data("data_USA")

# Data process
Var_Y <- as.vector(data_USA$NBER)
Var_X <- as.vector(data_USA$Spread)

# Estimate the estimation errors
results <- Vector_Error(Dicho_Y = Var_Y, Exp_X = Var_X, Intercept = TRUE,
                        Nb_Id = 1, Lag = 1, type_model = 4)

# print results
results

#}
```

Vector_lag

Vector lag - data processing

Description

Compute a lagged version of a time series, shifting the time base back by a given number of observations defined by the user. The user must enter three parameters for this function: the vector, the number of lags, and a boolean variable named 'beginning'. If 'beginning'=TRUE, then the lag will be applied at the beginning of the vector whereas if 'beginning'=FALSE, then the lag will be applied at the end of the vector.

Usage

```
Vector_lag(Vector_target, Nb_lag, beginning)
```

Arguments

Vector_target	Initial vector
Nb_lag	Number of lag
beginning	Boolean variable. If 'beginning'=TRUE, the lag is applied at the beginning of the vector. If 'beginning'=FALSE, the lag is applied at the end of the vector.

Value

A numeric Vector.

Examples

```
# NOT RUN {  
  
# Initialize the following vector  
vector_example <- as.vector(1:10)  
  
# Use Vector_lag  
new_vector <- Vector_lag(Vector_target = vector_example, Nb_lag = 2, beginning = TRUE)  
  
new_vector  
# Results:  
#> new_vector  
#[1] 3 4 5 6 7 8 9 10  
  
#}
```

Index

- * **Bootstrapp**
 - BlockBootstrapp, 2
- * **Confidence-Intervals**
 - BlockBootstrapp, 2
 - GIRF_Index_CI, 11
 - GIRF_Proba_CI, 13
 - Simul_GIRF, 17
- * **Dichotomous**
 - EWS_AM_Criterion, 5
 - EWS_CSA_Criterion, 6
 - EWS_NSR_Criterion, 8
 - GIRF_Dicho, 9
 - GIRF_Index_CI, 11
 - GIRF_Proba_CI, 13
 - Logistic_Estimation, 14
 - Simul_GIRF, 17
 - Vector_Error, 19
- * **Econometrics**
 - BlockBootstrapp, 2
 - EWS_AM_Criterion, 5
 - EWS_CSA_Criterion, 6
 - EWS_NSR_Criterion, 8
 - GIRF_Dicho, 9
 - GIRF_Index_CI, 11
 - GIRF_Proba_CI, 13
 - Logistic_Estimation, 14
 - Simul_GIRF, 17
 - Vector_Error, 19
- * **IRF**
 - GIRF_Dicho, 9
 - GIRF_Index_CI, 11
 - GIRF_Proba_CI, 13
 - Simul_GIRF, 17
- * **Panel**
 - Logistic_Estimation, 14
- * **Shock**
 - Vector_Error, 19
- * **Threshold**
 - EWS_AM_Criterion, 5
 - EWS_CSA_Criterion, 6
 - EWS_NSR_Criterion, 8
- * **datasets**
 - data_panel, 3
 - data_USA, 4
- BlockBootstrapp, 2
- data_panel, 3
- data_USA, 4
- EWS_AM_Criterion, 5
- EWS_CSA_Criterion, 6
- EWS_NSR_Criterion, 8
- GIRF_Dicho, 9
- GIRF_Index_CI, 11
- GIRF_Proba_CI, 13
- Logistic_Estimation, 14
- Matrix_lag, 16
- Simul_GIRF, 17
- Vector_Error, 19
- Vector_lag, 20