付録(Appendix)

Rによる定量分析実装(Quantitative Analysis Implementation with R)

『ベインジアン機械学習・動学確率的応用一般均衡モデル』

"Bayesian Machine Learning and Dynamic Stochastic Applied General Equilibrium Models"

前提(Assumptions)

1. Rを用いる。(Using R)
2. メモリ容量の最大化(Maximize memory capacity)
3. 必要なライブラリの読込(Load required libraries)
4. 関数定義(Functions definition)
5. ローデータの目視確認(Visual check of raw data)

実装手順(Implementation Procedure)

1. 誤差項調整(Error Term Adjustment)
2. 多重共線性の実証分析(Empirical Analysis of Multicollinearity)
3. 無相関検定(Uncorrelated Tests)
4. 単位根検定(ADF検定) / Unit Root Test (ADF Test)
5. 共和分検定(Republican Test)
6. 偏グレンジャー因果性検定と非直交化インパルス応答関数(Partial Granger Causality Test and Non-Orthogonalized Impulse Response Function)
7. パネルVARモデルによる動的直接相関係数の導出(Derivation of Dynamic Direct Correlation Coefficients by Panel VAR Model)
8. 統計的最適化因果推論モデル(Optimized Statistical Inference Model)
9. Reproducibility by XGBoost
10. グラフ描画・出力(Graph drawing and output)

メモリ容量の最大化

Maximized Memory

In [1]:
```
suppressWarnings(memory.limit(suppressWarnings(memory.size(max = T))))
suppressWarnings(gc(verbose = getOption("verbose"), reset = T, full = T))
```

32176

A matrix: 2 × 6 of type dbl

	used	(Mb)	gc trigger	(Mb)	max used	(Mb)
Ncells	559836	29.9	1175941	62.9	559836	29.9
Vcells	1024332	7.9	8388608	64.0	1024332	7.9

必要なライブラリの読込

Load the required libraries.

In [2]:
```
# Libraries
load.lib <- c(
  "reader"
  , "magrittr"      # Preprocess
  , "tidyr"         # Preprocess
  , "dplyr"         # Preprocess
  , "tidyverse"     # Preprocess
  , "tseries"       # Preprocess
  , "urca"          # ADF tests
  , "aTSA"          # Republican tests
  , "plm"           # Form Panel data
  , "panelvar"      # Panel VAR Model
  , "Sim.DiffProc"  # GBM
  , "ggplot2"       # Graph Drawing
  , "gridExtra"     # Graph aggregation
  , "qgraph"        # Visualizing Correlation Matrices
  , "tsbox"         # Use ts_df function
  , "vars"          # Use to function definition
  , "NlinTS"        # Use to function definition
  , "tsDyn"         # Use to function definition
  , "Rtsne"         # Dimensional Compression
  , "psych"         # Factor analysis of exploration
  , "xgboost"       # ML metrics
  , "caret"         # ML metrics
  , "DiagrammeR"    # ML metrics
  , "dummies"       # ML metrics
)

install.lib <- load.lib[!load.lib %in% installed.packages()]
```

```r
for(lib in install.lib) capture.output(suppressWarnings(install.packages(lib,dependencies = T)))
capture.output(suppressWarnings(sapply(load.lib,require,character = T)))

# Recover Memory
rm(install.lib, load.lib, lib)
```

```
要求されたパッケージ reader をロード中です

要求されたパッケージ NCmisc をロード中です


次のパッケージを付け加えます: 'reader'


以下のオブジェクトは 'package:NCmisc' からマスクされています:

    cat.path, get.ext, rmv.ext


要求されたパッケージ magrittr をロード中です

要求されたパッケージ tidyr をロード中です


次のパッケージを付け加えます: 'tidyr'


以下のオブジェクトは 'package:magrittr' からマスクされています:

    extract


要求されたパッケージ dplyr をロード中です


次のパッケージを付け加えます: 'dplyr'


以下のオブジェクトは 'package:stats' からマスクされています:

    filter, lag


以下のオブジェクトは 'package:base' からマスクされています:

    intersect, setdiff, setequal, union


要求されたパッケージ tidyverse をロード中です

-- Attaching packages --------------------------------------------------------------------------------- tidyverse 1.3.1 --

v ggplot2 3.3.3     v purrr   0.3.4
v tibble  3.1.2     v stringr 1.4.0
v readr   1.4.0     v forcats 0.5.1

-- Conflicts ------------------------------------------------------------------------------------------ tidyverse_conflicts() --
x tidyr::extract()   masks magrittr::extract()
x dplyr::filter()    masks stats::filter()
x dplyr::lag()       masks stats::lag()
x purrr::set_names() masks magrittr::set_names()

要求されたパッケージ tseries をロード中です

Registered S3 method overwritten by 'quantmod':
  method            from
  as.zoo.data.frame zoo

要求されたパッケージ urca をロード中です

要求されたパッケージ aTSA をロード中です


次のパッケージを付け加えます: 'aTSA'


以下のオブジェクトは 'package:tseries' からマスクされています:

    adf.test, kpss.test, pp.test


以下のオブジェクトは 'package:graphics' からマスクされています:

    identify


要求されたパッケージ plm をロード中です


次のパッケージを付け加えます: 'plm'


以下のオブジェクトは 'package:dplyr' からマスクされています:

    between, lag, lead


要求されたパッケージ panelvar をロード中です

Welcome to panelvar! Please cite our package in your publications -- see citation("panelvar")


次のパッケージを付け加えます: 'panelvar'


以下のオブジェクトは 'package:tidyr' からマスクされています:

    extract


以下のオブジェクトは 'package:magrittr' からマスクされています:

    extract


要求されたパッケージ Sim.DiffProc をロード中です
```

```
Package 'Sim.DiffProc', version 4.8
browseVignettes('Sim.DiffProc') for more informations.

 次のパッケージを付け加えます: 'Sim.DiffProc'

 以下のオブジェクトは 'package:NCmisc' からマスクされています:

     Mode

 要求されたパッケージ gridExtra をロード中です

 次のパッケージを付け加えます: 'gridExtra'

 以下のオブジェクトは 'package:dplyr' からマスクされています:

     combine

 要求されたパッケージ qgraph をロード中です
 要求されたパッケージ tsbox をロード中です
 要求されたパッケージ vars をロード中です
 要求されたパッケージ MASS をロード中です

 次のパッケージを付け加えます: 'MASS'

 以下のオブジェクトは 'package:dplyr' からマスクされています:

     select

 要求されたパッケージ strucchange をロード中です
 要求されたパッケージ zoo をロード中です

 次のパッケージを付け加えます: 'zoo'

 以下のオブジェクトは 'package:base' からマスクされています:

     as.Date, as.Date.numeric

 要求されたパッケージ sandwich をロード中です

 次のパッケージを付け加えます: 'strucchange'

 以下のオブジェクトは 'package:stringr' からマスクされています:

     boundary

 要求されたパッケージ lmtest をロード中です

 次のパッケージを付け加えます: 'vars'

 以下のオブジェクトは 'package:panelvar' からマスクされています:

     stability

 以下のオブジェクトは 'package:aTSA' からマスクされています:

     arch.test

 要求されたパッケージ NlinTS をロード中です
 要求されたパッケージ Rcpp をロード中です
 要求されたパッケージ tsDyn をロード中です
 要求されたパッケージ Rtsne をロード中です
 要求されたパッケージ psych をロード中です

 次のパッケージを付け加えます: 'psych'

 以下のオブジェクトは 'package:ggplot2' からマスクされています:

     %+%, alpha

 要求されたパッケージ xgboost をロード中です

 次のパッケージを付け加えます: 'xgboost'

 以下のオブジェクトは 'package:dplyr' からマスクされています:

     slice

 要求されたパッケージ caret をロード中です
 要求されたパッケージ lattice をロード中です

 次のパッケージを付け加えます: 'caret'

 以下のオブジェクトは 'package:purrr' からマスクされています:
```

```
    lift

 要求されたパッケージ DiagrammeR をロード中です
 要求されたパッケージ dummies をロード中です
dummies-1.5.6 provided by Decision Patterns
```

' reader	magrittr	tidyr	dplyr	tidyverse	tseries '· '	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE '·
' urca	aTSA	plm	panelvar	Sim.DiffProc	ggplot2 '· '	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE '·
' gridExtra	qgraph	tsbox	vars	NlinTS	tsDyn '· '	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE '·
' Rtsne	psych	xgboost	caret	DiagrammeR	dummies '· '	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE '

In [3]:

```
# 対数差分系列に変換する。
# Convert to logarithmic difference series.
diff.log <- function(x) {
  y <- diff(log(x))
  return(y)
}
# プロビット写像
# Probit mappings
probit <- function(x) {
  y <- c(exp(((-x^2)/2))/sqrt(2 * pi))
  return(y)
}
# 偏グレンジャー因果性検定と非直交化インパルス応答関数
# Partial Granger Causality Tests and Non-Orthogonalized Impulse Response Functions
ts <- function(y1, y2) {
  temp  <- cbind(y1, y2) %>% as.data.frame
  model <- VAR(temp, p = 2, type = "both", ic = "AIC")
  wk_result_1  <- causality(model, cause = "y1")
  wk_result_2  <- causality(model, cause = "y2")
  granger      <- list(wk_result_1, wk_result_2)
  impulse_1 <- irf(model, impulse = "y1", response = "y2", boot = F)
  impulse_2 <- irf(model, impulse = "y2", response = "y1", boot = F)
  imp <- list(impulse_1, impulse_2)
  result <- list(granger, imp)
  return(result)
}
# ADF検定
# ADF Tests
ADF <- function(x) {
  result <- ur.df(x,type = c("drift"), lags = 1) %>%
    summary
  return(result)
}
# 標本分散
# Sample Variance
sigma <- function(x) {
  result <- var(x)*(length(x)-1)/length(x)
  return(result)
}
# 時系列プロット
fig <- function(data, y, title, label) {
  data %>%
    ggplot(aes(x = time, y = y)) +
    geom_point() +
    geom_line() +
    ggtitle(title) +
    labs(x = "年", y =  label)
}

# XGBoost Prediction
XGBoost <- function(df, indexes) {
  train = df[indexes, ]
  test  = df[-indexes, ]

  train_x = data.matrix(train[, -5])
  train_y = train[, 6]

  test_x = data.matrix(test[, -5])
  test_y = test[, 6]

  xgb_train = xgb.DMatrix(data = train_x, label = train_y)
  xgb_test = xgb.DMatrix(data = test_x, label = test_y)

  xgbc = xgboost(
    data = xgb_train
    , max.depth = 200
    , nrounds = 2000
    , objective = "reg:squarederror"
    , early_stopping_rounds = 50
    )
  print(xgbc)

  pred_y = predict(xgbc, xgb_test, se.fit = T, interval = "prediction",  type = "response")

  mse = weighted.mean((test_y - pred_y)^2)
  mae = caret::MAE(test_y, pred_y)
  rmse = caret::RMSE(test_y, pred_y)

  cat("MSE: ", mse, "MAE: ", mae, " RMSE: ", rmse)
```

```
  x = 1:length(test_y)
  plot(x, test_y, col = "red", type = "l")
  lines(x, pred_y, col = "blue", type = "l")
  legend(x = 1, y = 38,  legend = c("original test_y", "predicted test_y"),
         col = c("red", "blue"), box.lty = 1, cex = 0.7, lty = c(1, 1))
}
```

In [4]:

```
# 読込
# Load
raw_data <- read_csv("./0_input/raw_data.csv", col_types = cols(Y1   = col_number(),
                                                                Y2   = col_number(),
                                                                Y3   = col_number(),
                                                                Y4   = col_number(),
                                                                Y5   = col_number(),
                                                                Y6   = col_number(),
                                                                Y7   = col_number(),
                                                                Y8   = col_number(),
                                                                Y9   = col_number(),
                                                                Y10  = col_number(),
                                                                Y11  = col_number(),
                                                                time = col_number(),
                                                                id   = col_number()
                                                                )
                    )
# 要約統計量を求める。
# Obtain summary statistics.
raw_data %>%
  summary%>%
  print  %>%
  suppressWarnings()

# 誤差項調整
# Error Term Adjustment
adjusted <- bind_cols(
  raw_data$id[-1]
  , time = raw_data$time[-1]
  , Y1   = diff.log(raw_data$Y1)
  , Y2   = diff.log(raw_data$Y2)
  , Y3   = probit(raw_data$Y3) %>% diff.log
  , Y4   = diff.log(raw_data$Y4)
  , Y5   = diff.log(raw_data$Y5)
  , Y6   = diff.log(raw_data$Y6)
  , Y7   = diff.log(raw_data$Y7)
  , Y8   = diff.log(raw_data$Y8)
  , Y9   = diff.log(raw_data$Y9)
  , Y10  = diff.log(raw_data$Y10)
  , Y11  = probit(raw_data$Y11) %>% diff.log
) %>%
  as.data.frame %>%
  apply(2, as.numeric)

# 列名を戻す。
# Restore the column names.
colnames(adjusted) <- colnames(raw_data)

# 目視確認
# Visual confirmation
adjusted %>%
  print
```

```
       id               time            Y1               Y2
 Min.   :0.0000   Min.   :1986   Min.   :11.37   Min.   :1111019
 1st Qu.:0.0000   1st Qu.:1993   1st Qu.:13.86   1st Qu.:1315869
 Median :0.0000   Median :2000   Median :14.51   Median :1385835
 Mean   :0.4483   Mean   :2000   Mean   :14.44   Mean   :1352237
 3rd Qu.:1.0000   3rd Qu.:2007   3rd Qu.:15.46   3rd Qu.:1422453
 Max.   :3.0000   Max.   :2014   Max.   :15.74   Max.   :1478859
       Y3               Y4               Y5                Y6
 Min.   :0.0000   Min.   :15.90   Min.   :1.212e-313   Min.   : 36.20
 1st Qu.:0.0000   1st Qu.:22.40   1st Qu.:2.052e-313   1st Qu.: 41.90
 Median :0.0000   Median :31.80   Median :2.303e-313   Median : 69.50
 Mean   :0.2069   Mean   :44.78   Mean   :2.288e-313   Mean   : 77.77
 3rd Qu.:0.0000   3rd Qu.:71.49   3rd Qu.:2.531e-313   3rd Qu.:102.00
 Max.   :1.0000   Max.   :95.30   Max.   :3.176e-313   Max.   :149.50
       Y7               Y8               Y9              Y10
 Min.   : 85.90   Min.   :2.100   Min.   : 87.8   Min.   :24.79
 1st Qu.: 96.20   1st Qu.:2.800   1st Qu.:109.8   1st Qu.:47.60
 Median : 97.20   Median :4.000   Median :168.6   Median :49.38
 Mean   : 95.83   Mean   :3.731   Mean   :176.3   Mean   :50.20
 3rd Qu.: 97.70   3rd Qu.:4.700   3rd Qu.:201.9   3rd Qu.:58.59
 Max.   :100.10   Max.   :5.400   Max.   :439.7   Max.   :61.67
      Y11
 Min.   :0.0000
 1st Qu.:0.0000
 Median :0.0000
 Mean   :0.2759
 3rd Qu.:1.0000
 Max.   :1.0000
```

```
New names:
* `` -> ...1
```

```
      id time          Y1            Y2   Y3          Y4            Y5
 [1,]  0 1987  0.046607215 -0.0002078956  0.0  0.14329221  0.1707078336
 [2,]  0 1988  0.054685886  0.0659408662  0.0 -0.27232247  0.1875246946
 [3,]  0 1989  0.034524371  0.0250528266  0.0  0.19834206  0.0005499123
 [4,]  1 1990  0.038998671  0.0696834290  0.0  0.21128783  0.0213534085
 [5,]  0 1991  0.014394372  0.0108691005 -0.5 -0.15698568  0.1077704118
 [6,]  0 1992  0.008714600  0.0088384495  0.5 -0.03704127  0.0555237346
 [7,]  0 1993  0.010772713  0.0018245193  0.0 -0.15539469  0.1027742980
 [8,]  0 1994  0.034959773  0.0388160427  0.0 -0.02806837  0.0898896168
 [9,]  0 1995  0.031159245  0.0255089921 -0.5 -0.01487016  0.0913040437
[10,]  0 1996  0.015857216  0.0017373256  0.5  0.19217123 -0.1259988250
```

```
[11,]  0 1997  0.007429288 -0.0068458719  0.0 -0.01512484 -0.0896433402
[12,]  0 1998 -0.013352105 -0.0308981561  0.0 -0.33871590 -0.0915822665
[13,]  0 1999  0.024479115  0.0199589931 -0.5  0.34363431  0.1051332959
[14,]  0 2000  0.010736315  0.0051233463  0.5  0.45901574  0.0628943640
[15,]  1 2001 -0.012860210 -0.0130581957 -0.5 -0.10950287 -0.1242445967
[16,]  0 2002  0.014477534  0.0245535667  0.5  0.03522143 -0.0377329263
[17,]  1 2003 -0.009538650  0.0039634439  0.0  0.09713002  0.0843496711
[18,]  1 2004  0.013203359 -0.0004923830 -0.5  0.20097118  0.0890274168
[19,]  1 2005 -0.004302008  0.0087232322  0.5  0.31611580 -0.0094022598
[20,]  1 2006  0.002756154 -0.0097746472  0.0  0.16065287 -0.0484778223
[21,]  2 2007 -0.017173710  0.0245622798 -0.5  0.04150997 -0.0002505979
[22,]  0 2008 -0.072976198 -0.0535455057  0.5  0.23562571  0.1064363396
[23,]  0 2009 -0.018964601 -0.0709879183  0.0 -0.38749772  0.0376843968
[24,]  1 2010  0.042285908  0.0455902315  0.0  0.21075852  0.0715071253
[25,]  0 2011 -0.027442840  0.0337387012  0.0  0.17035756  0.0914818714
[26,]  0 2012 -0.012998704  0.0571105641  0.0  0.01671820  0.0146306523
[27,]  0 2013 -0.007562834 -0.1167735606  0.0 -0.00462769 -0.1828863972
[28,]  3 2014 -0.032698672 -0.0364950713  0.0 -0.06275503 -0.0603498860
                Y6           Y7          Y8           Y9           Y10  Y11
 [1,] -0.011862535  0.000000000  0.07410797  0.142432215  0.0000000000  0.0
 [2,] -0.036456042  0.006960585  0.00000000  0.328497539  0.0000000000  0.0
 [3,] -0.042990185  0.022858138 -0.11332869  0.232060601  0.0000000000  0.0
 [4,] -0.050341755  0.030052345 -0.08338161 -0.519724355 -0.0870144800  0.0
 [5,] -0.016438726  0.033426293 -0.09097178 -0.070368088  0.0000000000  0.0
 [6,]  0.019152432  0.015781495  0.00000000 -0.321780974 -0.2076436613 -0.5
 [7,]  0.078164773  0.013478690  0.04652002  0.015192971  0.0000000000  0.5
 [8,]  0.029631798  0.006160184  0.12783337  0.118167799  0.0000000000 -0.5
 [9,]  0.059049029 -0.001024066  0.14842001  0.008353525  0.0000000000  0.5
[10,]  0.060084811  0.001024066  0.09844007 -0.026863215  0.0868586003  0.0
[11,]  0.044357853  0.018256085  0.06062462 -0.256382432  0.0000000000 -0.5
[12,]  0.147635999  0.006012042  0.00000000 -0.103444736  0.0000000000  0.5
[13,]  0.123904093 -0.003001503  0.18721154  0.316258976  0.0000000000  0.0
[14,]  0.090286847 -0.007038742  0.13657554 -0.310307387  0.0195966413  0.0
[15,]  0.084129531 -0.007088637  0.00000000 -0.261116345  0.0000000000  0.0
[16,]  0.078820960 -0.009188426  0.06187540 -0.196926170  0.0000000000  0.0
[17,]  0.075329719 -0.003081667  0.07696104  0.221828367  0.0170148206  0.0
[18,]  0.082655722  0.000000000 -0.01869213  0.073310952  0.0000000000  0.0
[19,]  0.044905504 -0.002059733 -0.12014431  0.341250994  0.2223047186 -0.5
[20,]  0.002989539  0.002059733 -0.06595797  0.063789817  0.0000000000  0.5
[21,]  0.014815086  0.000000000 -0.07061757 -0.118048778  0.0000000000  0.0
[22,]  0.049723435  0.014300550 -0.05001042 -0.561164650  0.0000000000 -0.5
[23,]  0.118611879 -0.014300550  0.02531781  0.188591815 -0.9112279213  0.5
[24,]  0.054808236 -0.007227703  0.24294618 -0.023341674  0.0000000000 -0.5
[25,]  0.061593011 -0.002074690  0.00000000 -0.188344934  0.0000000000  0.5
[26,]  0.049632624 -0.001038961 -0.10318424  0.207581791  0.9044428289 -0.5
[27,]  0.028365790  0.004149384 -0.06744128  0.445140246  0.0000000000  0.0
[28,]  0.019588603  0.026559273 -0.07232066  0.042192672  0.0002122224  0.5
```

Functions Definition

In [5]:

```r
# 対数差分系列に変換する。
# Convert to logarithmic difference series.
diff.log <- function(x) {
  y <- diff(log(x))
  return(y)
}
# プロビット写像
# Probit mappings
probit <- function(x) {
  y <- c(exp(((-x^2)/2))/sqrt(2 * pi))
  return(y)
}
# 偏グレンジャー因果性検定と非直交化インパルス応答関数
# Partial Granger Causality Tests and Non-Orthogonalized Impulse Response Functions
ts <- function(y1, y2) {
  temp  <- cbind(y1, y2) %>% as.data.frame
  model <- VAR(temp, p = 2, type = "both", ic = "AIC")
  wk_result_1  <- causality(model, cause = "y1")
  wk_result_2  <- causality(model, cause = "y2")
  granger      <- list(wk_result_1, wk_result_2)
  impulse_1 <- irf(model, impulse = "y1", response = "y2", boot = F)
  impulse_2 <- irf(model, impulse = "y2", response = "y1", boot = F)
  imp <- list(impulse_1, impulse_2)
  result <- list(granger, imp)
  return(result)
}
# ADF検定
# ADF Tests
ADF <- function(x) {
  result <- ur.df(x,type = c("drift"), lags = 1) %>%
    summary
  return(result)
}
# 標本分散
# Sample Variance
sigma <- function(x) {
  result <- var(x)*(length(x)-1)/length(x)
  return(result)
}
# 時系列プロット
fig <- function(data, y, title, label) {
  data %>%
    ggplot(aes(x = time, y = y)) +
    geom_point() +
    geom_line() +
    ggtitle(title) +
    labs(x = "年", y =  label)
}

# XGBoost Prediction
XGBoost <- function(df, indexes) {
  train = df[indexes, ]
  test  = df[-indexes, ]
```

```
  train_x = data.matrix(train[, -5])
  train_y = train[, 6]

  test_x = data.matrix(test[, -5])
  test_y = test[, 6]

  xgb_train = xgb.DMatrix(data = train_x, label = train_y)
  xgb_test = xgb.DMatrix(data = test_x, label = test_y)

  xgbc = xgboost(
    data = xgb_train
    , max.depth = 200
    , nrounds = 2000
    , objective = "reg:squarederror"
    , early_stopping_rounds = 50
    )
  print(xgbc)

  pred_y = predict(xgbc, xgb_test, se.fit = T, interval = "prediction",  type = "response")

  mse = weighted.mean((test_y - pred_y)^2)
  mae = caret::MAE(test_y, pred_y)
  rmse = caret::RMSE(test_y, pred_y)

  cat("MSE: ", mse, "MAE: ", mae, " RMSE: ", rmse)

  x = 1:length(test_y)
  plot(x, test_y, col = "red", type = "l")
  lines(x, pred_y, col = "blue", type = "l")
  legend(x = 1, y = 38,  legend = c("original test_y", "predicted test_y"),
         col = c("red", "blue"), box.lty = 1, cex = 0.7, lty = c(1, 1))
}
```

Statistical Significance Tests

In [6]:

```
# 確率変数のみのデータフレーム
# Data frame with only random variables
relation <- adjusted[, !(colnames(adjusted) %in% c("id", "time"))] %>%
  apply(2, as.numeric) %>%
  as.data.frame %>%
  print

# 無相関検定
# Uncorrelated tests
# Y1～11
cor.test(relation$Y1, relation$Y2,   method = "pearson")
cor.test(relation$Y1, relation$Y3,   method = "pearson")
cor.test(relation$Y1, relation$Y4,   method = "pearson")
cor.test(relation$Y1, relation$Y5,   method = "pearson")
cor.test(relation$Y1, relation$Y6,   method = "pearson")
cor.test(relation$Y1, relation$Y7,   method = "pearson")
cor.test(relation$Y1, relation$Y8,   method = "pearson")
cor.test(relation$Y1, relation$Y9,   method = "pearson")
cor.test(relation$Y1, relation$Y10,  method = "pearson")
cor.test(relation$Y1, relation$Y11,  method = "pearson")
# Y2～11
cor.test(relation$Y2, relation$Y3,   method = "pearson")
cor.test(relation$Y2, relation$Y4,   method = "pearson")
cor.test(relation$Y2, relation$Y5,   method = "pearson")
cor.test(relation$Y2, relation$Y6,   method = "pearson")
cor.test(relation$Y2, relation$Y7,   method = "pearson")
cor.test(relation$Y2, relation$Y8,   method = "pearson")
cor.test(relation$Y2, relation$Y9,   method = "pearson")
cor.test(relation$Y2, relation$Y10,  method = "pearson")
cor.test(relation$Y2, relation$Y11,  method = "pearson")
# Y3～11
cor.test(relation$Y3, relation$Y4,   method = "pearson")
cor.test(relation$Y3, relation$Y5,   method = "pearson")
cor.test(relation$Y3, relation$Y6,   method = "pearson")
cor.test(relation$Y3, relation$Y7,   method = "pearson")
cor.test(relation$Y3, relation$Y8,   method = "pearson")
cor.test(relation$Y3, relation$Y9,   method = "pearson")
cor.test(relation$Y3, relation$Y10,  method = "pearson")
cor.test(relation$Y3, relation$Y11,  method = "pearson")
# Y4～11
cor.test(relation$Y4, relation$Y5,   method = "pearson")
cor.test(relation$Y4, relation$Y6,   method = "pearson")
cor.test(relation$Y4, relation$Y7,   method = "pearson")
cor.test(relation$Y4, relation$Y8,   method = "pearson")
cor.test(relation$Y4, relation$Y9,   method = "pearson")
cor.test(relation$Y4, relation$Y10,  method = "pearson")
cor.test(relation$Y4, relation$Y11,  method = "pearson")
# Y5～11
cor.test(relation$Y5, relation$Y6,   method = "pearson")
cor.test(relation$Y5, relation$Y7,   method = "pearson")
cor.test(relation$Y5, relation$Y8,   method = "pearson")
cor.test(relation$Y5, relation$Y9,   method = "pearson")
cor.test(relation$Y5, relation$Y10,  method = "pearson")
cor.test(relation$Y5, relation$Y11,  method = "pearson")
# Y6～11
cor.test(relation$Y6, relation$Y7,   method = "pearson")
cor.test(relation$Y6, relation$Y8,   method = "pearson")
cor.test(relation$Y6, relation$Y9,   method = "pearson")
cor.test(relation$Y6, relation$Y10,  method = "pearson")
```

```r
cor.test(relation$Y6, relation$Y11,  method = "pearson")
# Y7～11
cor.test(relation$Y7, relation$Y8,   method = "pearson")
cor.test(relation$Y7, relation$Y9,   method = "pearson")
cor.test(relation$Y7, relation$Y10,  method = "pearson")
cor.test(relation$Y7, relation$Y11,  method = "pearson")
# Y8～11
cor.test(relation$Y8, relation$Y9,   method = "pearson")
cor.test(relation$Y8, relation$Y10,  method = "pearson")
cor.test(relation$Y8, relation$Y11,  method = "pearson")
# Y9～11
cor.test(relation$Y9, relation$Y10,  method = "pearson")
cor.test(relation$Y9, relation$Y11,  method = "pearson")
# Y10～11
cor.test(relation$Y10,relation$Y11,  method = "pearson")

# 単位根検定(ADF検定)
# Unit Root Tests (ADF tests)
relation %>%
  apply(2, ADF)

# 共和分検定
# Republican tests
# Y1～11
coint.test(relation$Y1, relation$Y2,  nlag = 1) %>% summary
coint.test(relation$Y1, relation$Y3,  nlag = 1) %>% summary
coint.test(relation$Y1, relation$Y4,  nlag = 1) %>% summary
coint.test(relation$Y1, relation$Y5,  nlag = 1) %>% summary
coint.test(relation$Y1, relation$Y6,  nlag = 1) %>% summary
coint.test(relation$Y1, relation$Y7,  nlag = 1) %>% summary
coint.test(relation$Y1, relation$Y8,  nlag = 1) %>% summary
coint.test(relation$Y1, relation$Y9,  nlag = 1) %>% summary
coint.test(relation$Y1, relation$Y10, nlag = 1) %>% summary
coint.test(relation$Y1, relation$Y11, nlag = 1) %>% summary
# Y2～11
coint.test(relation$Y2, relation$Y3,  nlag = 1) %>% summary
coint.test(relation$Y2, relation$Y4,  nlag = 1) %>% summary
coint.test(relation$Y2, relation$Y6,  nlag = 1) %>% summary
coint.test(relation$Y2, relation$Y7,  nlag = 1) %>% summary
coint.test(relation$Y2, relation$Y8,  nlag = 1) %>% summary
coint.test(relation$Y2, relation$Y9,  nlag = 1) %>% summary
coint.test(relation$Y2, relation$Y10, nlag = 1) %>% summary
coint.test(relation$Y2, relation$Y11, nlag = 1) %>% summary
# Y3～11
coint.test(relation$Y3, relation$Y4,  nlag = 1) %>% summary
coint.test(relation$Y3, relation$Y5,  nlag = 1) %>% summary
coint.test(relation$Y3, relation$Y6,  nlag = 1) %>% summary
coint.test(relation$Y3, relation$Y7,  nlag = 1) %>% summary
coint.test(relation$Y3, relation$Y8,  nlag = 1) %>% summary
coint.test(relation$Y3, relation$Y9,  nlag = 1) %>% summary
coint.test(relation$Y3, relation$Y10, nlag = 1) %>% summary
coint.test(relation$Y3, relation$Y11, nlag = 1) %>% summary
# Y4～11
coint.test(relation$Y4, relation$Y5,  nlag = 1) %>% summary
coint.test(relation$Y4, relation$Y6,  nlag = 1) %>% summary
coint.test(relation$Y4, relation$Y7,  nlag = 1) %>% summary
coint.test(relation$Y4, relation$Y8,  nlag = 1) %>% summary
coint.test(relation$Y4, relation$Y9,  nlag = 1) %>% summary
coint.test(relation$Y4, relation$Y10, nlag = 1) %>% summary
coint.test(relation$Y4, relation$Y11, nlag = 1) %>% summary
#Y 5～11
coint.test(relation$Y5, relation$Y6,  nlag = 1) %>% summary
coint.test(relation$Y5, relation$Y7,  nlag = 1) %>% summary
coint.test(relation$Y5, relation$Y8,  nlag = 1) %>% summary
coint.test(relation$Y5, relation$Y9,  nlag = 1) %>% summary
coint.test(relation$Y5, relation$Y10, nlag = 1) %>% summary
coint.test(relation$Y5, relation$Y11, nlag = 1) %>% summary
# Y6～11
coint.test(relation$Y6, relation$Y7,  nlag = 1) %>% summary
coint.test(relation$Y6, relation$Y8,  nlag = 1) %>% summary
coint.test(relation$Y6, relation$Y9,  nlag = 1) %>% summary
coint.test(relation$Y6, relation$Y10, nlag = 1) %>% summary
coint.test(relation$Y6, relation$Y11, nlag = 1) %>% summary
# Y7～11
coint.test(relation$Y7, relation$Y8,  nlag = 1) %>% summary
coint.test(relation$Y7, relation$Y9,  nlag = 1) %>% summary
coint.test(relation$Y7, relation$Y10, nlag = 1) %>% summary
coint.test(relation$Y7, relation$Y11, nlag = 1) %>% summary
# Y8～11
coint.test(relation$Y8, relation$Y9,  nlag = 1) %>% summary
coint.test(relation$Y8, relation$Y10, nlag = 1) %>% summary
coint.test(relation$Y8, relation$Y11, nlag = 1) %>% summary
# Y9～11
coint.test(relation$Y9, relation$Y10, nlag = 1) %>% summary
coint.test(relation$Y9, relation$Y11, nlag = 1) %>% summary
# Y10～11
coint.test(relation$Y10, relation$Y11, nlag = 1) %>% summary

# 偏グレンジャー因果性検定と非直交化インパルス応答関数
# Partial Granger Causality Test and Non-Orthogonalized Impulse Response Functions
# Y1～11
ts(relation$Y1, relation$Y2)
ts(relation$Y1, relation$Y3)
ts(relation$Y1, relation$Y4)
ts(relation$Y1, relation$Y5)
ts(relation$Y1, relation$Y6)
```

```r
ts(relation$Y1, relation$Y7)
ts(relation$Y1, relation$Y8)
ts(relation$Y1, relation$Y9)
ts(relation$Y1, relation$Y10)
ts(relation$Y1, relation$Y11)
# Y2～11
ts(relation$Y2, relation$Y3)
ts(relation$Y2, relation$Y4)
ts(relation$Y2, relation$Y5)
ts(relation$Y2, relation$Y6)
ts(relation$Y2, relation$Y7)
ts(relation$Y2, relation$Y8)
ts(relation$Y2, relation$Y9)
ts(relation$Y2, relation$Y10)
ts(relation$Y2, relation$Y11)
# Y3～11
ts(relation$Y3, relation$Y4)
ts(relation$Y3, relation$Y5)
ts(relation$Y3, relation$Y6)
ts(relation$Y3, relation$Y7)
ts(relation$Y3, relation$Y8)
ts(relation$Y3, relation$Y9)
ts(relation$Y3, relation$Y10)
ts(relation$Y3, relation$Y11)
# Y4～11
ts(relation$Y4, relation$Y5)
ts(relation$Y4, relation$Y6)
ts(relation$Y4, relation$Y7)
ts(relation$Y4, relation$Y8)
ts(relation$Y4, relation$Y9)
ts(relation$Y4, relation$Y10)
ts(relation$Y4, relation$Y11)
# Y5～11
ts(relation$Y5, relation$Y6)
ts(relation$Y5, relation$Y7)
ts(relation$Y5, relation$Y8)
ts(relation$Y5, relation$Y9)
ts(relation$Y5, relation$Y10)
ts(relation$Y5, relation$Y11)
# Y6～11
ts(relation$Y6, relation$Y7)
ts(relation$Y6, relation$Y8)
ts(relation$Y6, relation$Y9)
ts(relation$Y6, relation$Y10)
ts(relation$Y6, relation$Y11)
# Y7～11
ts(relation$Y7, relation$Y8)
ts(relation$Y7, relation$Y9)
ts(relation$Y7, relation$Y10)
ts(relation$Y7, relation$Y11)
# Y8～11
ts(relation$Y8, relation$Y9)
ts(relation$Y8, relation$Y10)
ts(relation$Y8, relation$Y11)
# Y9～11
ts(relation$Y9, relation$Y10)
ts(relation$Y9, relation$Y11)
# Y10～11
ts(relation$Y10, relation$Y11)
```

```
             Y1            Y2   Y3          Y4            Y5           Y6
1   0.046607215 -0.0002078956  0.0  0.14329221  0.1707078336 -0.011862535
2   0.054685886  0.0659408662  0.0 -0.27232247  0.1875246946 -0.036456042
3   0.034524371  0.0250528266  0.0  0.19834206  0.0005499123 -0.042990185
4   0.038998671  0.0696834290  0.0  0.21128783  0.0213534085 -0.050341755
5   0.014394372  0.0108691005 -0.5 -0.15698568  0.1077704118 -0.016438726
6   0.008714600  0.0088384495  0.5 -0.03704127  0.0555237346  0.019152432
7   0.010772713  0.0018245193  0.0 -0.15539469  0.1027742980  0.078164773
8   0.034959773  0.0388160427  0.0 -0.02806837  0.0898896168  0.029631798
9   0.031159245  0.0255089921 -0.5 -0.01487016  0.0913040437  0.059049029
10  0.015857216  0.0017373256  0.5  0.19217123 -0.1259988250  0.060084811
11  0.007429288 -0.0068458719  0.0 -0.01512484 -0.0896433402  0.044357853
12 -0.013352105 -0.0308981561  0.0 -0.33871590 -0.0915822665  0.147635999
13  0.024479115  0.0199589931 -0.5  0.34363431  0.1051332959  0.123904093
14  0.010736315  0.0051233463  0.5  0.45901574  0.0628943640  0.090286847
15 -0.012860210 -0.0130581957 -0.5 -0.10950287 -0.1242445967  0.084129531
16  0.014477534  0.0245535667  0.5  0.03522143 -0.0377329263  0.078820960
17 -0.009538650  0.0039634439  0.0  0.09713002  0.0843496711  0.075329719
18  0.013203359 -0.0004923830 -0.5  0.20097118  0.0890274168  0.082655722
19 -0.004302008  0.0087232322  0.5  0.31611580 -0.0094022598  0.044905504
20  0.002756154 -0.0097746472  0.0  0.16065287 -0.0484778223  0.002989539
21 -0.017173710  0.0245622798 -0.5  0.04150997 -0.0002505979  0.014815086
22 -0.072976198 -0.0535455057  0.5  0.23562571  0.1064363396  0.049723435
23 -0.018964601 -0.0709879183  0.0 -0.38749772  0.0376843968  0.118611879
24  0.042285908  0.0455902315  0.0  0.21075852  0.0715071253  0.054808236
25 -0.027442840  0.0337387012  0.0  0.17035756  0.0914818714  0.061593011
26 -0.012998704  0.0571105641  0.0  0.01671820  0.0146306523  0.049632624
27 -0.007562834 -0.1167735606  0.0 -0.00462769 -0.1828863972  0.028365790
28 -0.032698672 -0.0364950713  0.0 -0.06275503 -0.0603498860  0.019588603
             Y7          Y8           Y9          Y10  Y11
1   0.000000000  0.07410797  0.142432215  0.0000000000  0.0
2   0.006960585  0.00000000  0.328497539  0.0000000000  0.0
3   0.022858138 -0.11332869  0.232060601  0.0000000000  0.0
4   0.030052345 -0.08338161 -0.519724355 -0.0870144800  0.0
5   0.033426293 -0.09097178 -0.070368088  0.0000000000  0.0
6   0.015781495  0.00000000 -0.321780974 -0.2076436613 -0.5
7   0.013478690  0.04652002  0.015192971  0.0000000000  0.5
8   0.006160184  0.12783337  0.118167799  0.0000000000 -0.5
9  -0.001024066  0.14842001  0.008353525  0.0000000000  0.5
10  0.001024066  0.09844007 -0.026863215  0.0868586003  0.0
11  0.018256085  0.06062462 -0.256382432  0.0000000000 -0.5
12  0.006012042  0.00000000 -0.103444736  0.0000000000  0.5
13 -0.003001503  0.18721154  0.316258976  0.0000000000  0.0
14 -0.007038742  0.13657554 -0.310307387  0.0195966413  0.0
15 -0.007088637  0.00000000 -0.261116345  0.0000000000  0.0
```

```
16 -0.009188426  0.06187540 -0.196926170  0.0000000000  0.0
17 -0.003081667  0.07696104  0.221828367  0.0170148206  0.0
18  0.000000000 -0.01869213  0.073310952  0.0000000000  0.0
19 -0.002059733 -0.12014431  0.341250994  0.2223047186 -0.5
20  0.002059733 -0.06595797  0.063789817  0.0000000000  0.5
21  0.000000000 -0.07061757 -0.118048778  0.0000000000  0.0
22  0.014300550 -0.05001042 -0.561164650  0.0000000000 -0.5
23 -0.014300550  0.02531781  0.188591815 -0.9112279213  0.5
24 -0.007227703  0.24294618 -0.023341674  0.0000000000 -0.5
25 -0.002074690  0.00000000 -0.188344934  0.0000000000  0.5
26 -0.001038961 -0.10318424  0.207581791  0.9044428289 -0.5
27  0.004149384 -0.06744128  0.445140246  0.0000000000  0.0
28  0.026559273 -0.07232066  0.042192672  0.0002122224  0.5
        Pearson's product-moment correlation

data:  relation$Y1 and relation$Y2
t = 3.5192, df = 26, p-value = 0.001615
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.2473684 0.7765392
sample estimates:
      cor
0.5680239
        Pearson's product-moment correlation

data:  relation$Y1 and relation$Y3
t = -0.82961, df = 26, p-value = 0.4143
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.5034989  0.2260314
sample estimates:
       cor
-0.1605874
        Pearson's product-moment correlation

data:  relation$Y1 and relation$Y4
t = 0.37222, df = 26, p-value = 0.7127
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3086556  0.4340912
sample estimates:
       cor
0.07280495
        Pearson's product-moment correlation

data:  relation$Y1 and relation$Y5
t = 1.6873, df = 26, p-value = 0.1035
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.06675539  0.61512889
sample estimates:
      cor
0.3141453
        Pearson's product-moment correlation

data:  relation$Y1 and relation$Y6
t = -2.0161, df = 26, p-value = 0.05423
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.651411333  0.006239047
sample estimates:
       cor
-0.3676937
        Pearson's product-moment correlation

data:  relation$Y1 and relation$Y7
t = 0.22034, df = 26, p-value = 0.8273
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3353049  0.4096515
sample estimates:
       cor
0.04317269
        Pearson's product-moment correlation

data:  relation$Y1 and relation$Y8
t = 2.2233, df = 26, p-value = 0.0351
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.03126576 0.67248257
sample estimates:
      cor
0.3996806
        Pearson's product-moment correlation

data:  relation$Y1 and relation$Y9
t = 1.4284, df = 26, p-value = 0.1651
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.1148885  0.5840500
sample estimates:
      cor
0.2697505
        Pearson's product-moment correlation

data:  relation$Y1 and relation$Y10
t = 0.013351, df = 26, p-value = 0.9894
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3708209  0.3753286
sample estimates:
        cor
0.002618298
        Pearson's product-moment correlation

data:  relation$Y1 and relation$Y11
t = -0.48014, df = 26, p-value = 0.6351
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4510497  0.2894523
sample estimates:
        cor
-0.09374834
        Pearson's product-moment correlation

data:  relation$Y2 and relation$Y3
t = -0.5077, df = 26, p-value = 0.6159
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
```

```
 -0.4553247  0.2845153
sample estimates:
        cor
-0.09907837
        Pearson's product-moment correlation

data:  relation$Y2 and relation$Y4
t = 1.1858, df = 26, p-value = 0.2464
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.1600924  0.5528691
sample estimates:
      cor
0.2265135
        Pearson's product-moment correlation

data:  relation$Y2 and relation$Y5
t = 2.7097, df = 26, p-value = 0.01176
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.1166096 0.7168467
sample estimates:
      cor
0.4692712
        Pearson's product-moment correlation

data:  relation$Y2 and relation$Y6
t = -1.7912, df = 26, p-value = 0.08491
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.62698322  0.04752009
sample estimates:
       cor
-0.3314327
        Pearson's product-moment correlation

data:  relation$Y2 and relation$Y7
t = 0.35592, df = 26, p-value = 0.7248
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3115373  0.4315001
sample estimates:
       cor
0.06963285
        Pearson's product-moment correlation

data:  relation$Y2 and relation$Y8
t = 0.86746, df = 26, p-value = 0.3936
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.2190701  0.5089462
sample estimates:
      cor
0.1677141
        Pearson's product-moment correlation

data:  relation$Y2 and relation$Y9
t = -0.56028, df = 26, p-value = 0.5801
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4634164  0.2750623
sample estimates:
      cor
-0.109223
        Pearson's product-moment correlation

data:  relation$Y2 and relation$Y10
t = 2.2109, df = 26, p-value = 0.03604
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.02904425 0.67126277
sample estimates:
      cor
0.3978106
        Pearson's product-moment correlation

data:  relation$Y2 and relation$Y11
t = -1.2436, df = 26, p-value = 0.2247
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.5604747  0.1493354
sample estimates:
       cor
-0.2369425
        Pearson's product-moment correlation

data:  relation$Y3 and relation$Y4
t = 1.2923, df = 26, p-value = 0.2076
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.1402566  0.5668019
sample estimates:
      cor
0.2456757
        Pearson's product-moment correlation

data:  relation$Y3 and relation$Y5
t = -0.66727, df = 26, p-value = 0.5105
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4796156  0.2556986
sample estimates:
       cor
-0.1297565
        Pearson's product-moment correlation

data:  relation$Y3 and relation$Y6
t = -0.029419, df = 26, p-value = 0.9768
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3780327  0.3680998
sample estimates:
         cor
-0.005769442
        Pearson's product-moment correlation

data:  relation$Y3 and relation$Y7
t = -0.21864, df = 26, p-value = 0.8286
alternative hypothesis: true correlation is not equal to 0
```

```
95 percent confidence interval:
 -0.4093734  0.3356014
sample estimates:
        cor
-0.04283918
        Pearson's product-moment correlation

data:  relation$Y3 and relation$Y8
t = -0.08408, df = 26, p-value = 0.9336
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3871826  0.3587967
sample estimates:
        cor
-0.01648723
        Pearson's product-moment correlation

data:  relation$Y3 and relation$Y9
t = -1.1614, df = 26, p-value = 0.256
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.5496236  0.1646318
sample estimates:
       cor
-0.2220857
        Pearson's product-moment correlation

data:  relation$Y3 and relation$Y10
t = 0.13456, df = 26, p-value = 0.894
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3501430  0.3955639
sample estimates:
       cor
0.02637999
        Pearson's product-moment correlation

data:  relation$Y3 and relation$Y11
t = -1.6543, df = 26, p-value = 0.1101
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.61130196  0.07285875
sample estimates:
       cor
-0.3086067
        Pearson's product-moment correlation

data:  relation$Y4 and relation$Y5
t = 0.49024, df = 26, p-value = 0.6281
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.2876439  0.4526195
sample estimates:
       cor
0.09570321
        Pearson's product-moment correlation

data:  relation$Y4 and relation$Y6
t = -0.43891, df = 26, p-value = 0.6644
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4446117  0.2968133
sample estimates:
        cor
-0.08576023
        Pearson's product-moment correlation

data:  relation$Y4 and relation$Y7
t = -0.59158, df = 26, p-value = 0.5592
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4681922  0.2694151
sample estimates:
       cor
-0.1152454
        Pearson's product-moment correlation

data:  relation$Y4 and relation$Y8
t = 0.79834, df = 26, p-value = 0.4319
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.2317682  0.4989660
sample estimates:
      cor
0.1546839
        Pearson's product-moment correlation

data:  relation$Y4 and relation$Y9
t = -0.64895, df = 26, p-value = 0.5221
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4768670  0.2590262
sample estimates:
       cor
-0.1262512
        Pearson's product-moment correlation

data:  relation$Y4 and relation$Y10
t = 1.7486, df = 26, p-value = 0.09216
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.05539499  0.62216755
sample estimates:
      cor
0.3243859
        Pearson's product-moment correlation

data:  relation$Y4 and relation$Y11
t = -1.8238, df = 26, p-value = 0.0797
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.63062382  0.04151056
sample estimates:
      cor
-0.336782
        Pearson's product-moment correlation

data:  relation$Y5 and relation$Y6
t = -0.83025, df = 26, p-value = 0.414
```

```
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.5035916  0.2259136
sample estimates:
       cor
-0.1607083
        Pearson's product-moment correlation

data:  relation$Y5 and relation$Y7
t = 0.048602, df = 26, p-value = 0.9616
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3648430  0.3812525
sample estimates:
        cor
0.009531276
        Pearson's product-moment correlation

data:  relation$Y5 and relation$Y8
t = 1.4276, df = 26, p-value = 0.1653
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.1150430  0.5839468
sample estimates:
      cor
0.2696053
        Pearson's product-moment correlation

data:  relation$Y5 and relation$Y9
t = 0.1897, df = 26, p-value = 0.851
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3406234  0.4046425
sample estimates:
       cor
0.03717803
        Pearson's product-moment correlation

data:  relation$Y5 and relation$Y10
t = -0.36764, df = 26, p-value = 0.7161
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4333642  0.3094655
sample estimates:
        cor
-0.07191429
        Pearson's product-moment correlation

data:  relation$Y5 and relation$Y11
t = -0.3284, df = 26, p-value = 0.7452
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4271069  0.3163922
sample estimates:
        cor
-0.06427117
        Pearson's product-moment correlation

data:  relation$Y6 and relation$Y7
t = -3.9711, df = 26, p-value = 0.0005041
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.8033582 -0.3131423
sample estimates:
       cor
-0.6144369
        Pearson's product-moment correlation

data:  relation$Y6 and relation$Y8
t = 2.5973, df = 26, p-value = 0.01526
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.09727328 0.70720369
sample estimates:
      cor
0.4538788
        Pearson's product-moment correlation

data:  relation$Y6 and relation$Y9
t = -0.0060965, df = 26, p-value = 0.9952
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3741057  0.3720473
sample estimates:
         cor
-0.001195629
        Pearson's product-moment correlation

data:  relation$Y6 and relation$Y10
t = -0.70264, df = 26, p-value = 0.4885
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4848906  0.2492632
sample estimates:
       cor
-0.1365082
        Pearson's product-moment correlation

data:  relation$Y6 and relation$Y11
t = 1.0574, df = 26, p-value = 0.3001
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.1839615  0.5355576
sample estimates:
      cor
0.2030512
        Pearson's product-moment correlation

data:  relation$Y7 and relation$Y8
t = -2.7066, df = 26, p-value = 0.01185
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.7165831 -0.1160749
sample estimates:
       cor
-0.4688484
        Pearson's product-moment correlation

data:  relation$Y7 and relation$Y9
```

```
t = -1.3994, df = 26, p-value = 0.1735
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.5804276  0.1202929
sample estimates:
       cor
-0.2646616
        Pearson's product-moment correlation

data:  relation$Y7 and relation$Y10
t = 0.32645, df = 26, p-value = 0.7467
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3167360  0.4267945
sample estimates:
       cor
0.06389073
        Pearson's product-moment correlation

data:  relation$Y7 and relation$Y11
t = -0.28724, df = 26, p-value = 0.7762
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4204961  0.3236252
sample estimates:
        cor
-0.05624227
        Pearson's product-moment correlation

data:  relation$Y8 and relation$Y9
t = -0.058966, df = 26, p-value = 0.9534
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3829881  0.3630799
sample estimates:
        cor
-0.01156338
        Pearson's product-moment correlation

data:  relation$Y8 and relation$Y10
t = -0.96936, df = 26, p-value = 0.3413
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.5233726  0.2002684
sample estimates:
       cor
-0.1867626
        Pearson's product-moment correlation

data:  relation$Y8 and relation$Y11
t = -0.20713, df = 26, p-value = 0.8375
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.4074949  0.3376005
sample estimates:
        cor
-0.04058856
        Pearson's product-moment correlation

data:  relation$Y9 and relation$Y10
t = 0.58027, df = 26, p-value = 0.5667
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.2714573  0.4664701
sample estimates:
      cor
0.1130708
        Pearson's product-moment correlation

data:  relation$Y9 and relation$Y11
t = 0.53731, df = 26, p-value = 0.5956
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.2791975  0.4598918
sample estimates:
      cor
0.1047951
        Pearson's product-moment correlation

data:  relation$Y10 and relation$Y11
t = -2.0247, df = 26, p-value = 0.05328
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.652309740  0.004676858
sample estimates:
      cor
-0.369044
$Y1

###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
-0.06802 -0.01276  0.00237  0.01493  0.05123

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0004843  0.0052101   0.093  0.92674
z.lag.1     -0.6311647  0.2209387  -2.857  0.00892 **
z.diff.lag  -0.0450070  0.1992158  -0.226  0.82326
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02523 on 23 degrees of freedom
Multiple R-squared:  0.3465,    Adjusted R-squared:  0.2897
F-statistic: 6.098 on 2 and 23 DF,  p-value: 0.0075


Value of test-statistic is: -2.8567 4.4176

Critical values for test statistics:
```

```
      1pct  5pct 10pct
tau2 -3.58 -2.93 -2.60
phi1  7.06  4.86  3.94


$Y2

###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
      Min        1Q    Median        3Q       Max
-0.120279 -0.012060  0.003403  0.018147  0.074868

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.003849   0.008635   0.446  0.65996
z.lag.1     -1.077094   0.329024  -3.274  0.00334 **
z.diff.lag   0.173688   0.252811   0.687  0.49894
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04106 on 23 degrees of freedom
Multiple R-squared:  0.4724,    Adjusted R-squared:  0.4265
F-statistic:  10.3 on 2 and 23 DF,  p-value: 0.0006405


Value of test-statistic is: -3.2736 5.6437

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.58 -2.93 -2.60
phi1  7.06  4.86  3.94


$Y3

###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
-0.50000  0.00000  0.05789  0.18421  0.31579

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.00000    0.04929   0.000  1.00000
z.lag.1     -2.40000    0.31789  -7.550 1.14e-07 ***
z.diff.lag   0.51579    0.17864   2.887  0.00831 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2513 on 23 degrees of freedom
Multiple R-squared:  0.8471,    Adjusted R-squared:  0.8338
F-statistic: 63.71 on 2 and 23 DF,  p-value: 4.178e-10


Value of test-statistic is: -7.5498 28.5

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.58 -2.93 -2.60
phi1  7.06  4.86  3.94


$Y4

###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
-0.42834 -0.12795  0.00796  0.13422  0.31986

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.08524    0.04169   2.045   0.0525 .
z.lag.1     -1.43324    0.28552  -5.020 4.44e-05 ***
z.diff.lag   0.29721    0.18973   1.566   0.1309
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1966 on 23 degrees of freedom
Multiple R-squared:  0.6125,    Adjusted R-squared:  0.5788
F-statistic: 18.17 on 2 and 23 DF,  p-value: 1.843e-05


Value of test-statistic is: -5.0198 12.6099

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.58 -2.93 -2.60
phi1  7.06  4.86  3.94


$Y5

###############################################
```

```
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
      Min        1Q    Median        3Q       Max
-0.171472 -0.027863 -0.001165  0.064972  0.105679

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.02027    0.01703   1.190 0.246262
z.lag.1     -1.03584    0.22304  -4.644 0.000113 ***
z.diff.lag   0.40543    0.19557   2.073 0.049558 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07872 on 23 degrees of freedom
Multiple R-squared:  0.4967,    Adjusted R-squared:  0.453
F-statistic: 11.35 on 2 and 23 DF,  p-value: 0.0003721


Value of test-statistic is: -4.6442 11.0683

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.58 -2.93 -2.60
phi1  7.06  4.86  3.94


$Y6

###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
      Min        1Q    Median        3Q       Max
-0.044331 -0.021287 -0.000129  0.009790  0.100182

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.01887    0.00998   1.890   0.0714 .
z.lag.1     -0.34762    0.15133  -2.297   0.0311 *
z.diff.lag   0.02227    0.19728   0.113   0.9111
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0353 on 23 degrees of freedom
Multiple R-squared:  0.202,     Adjusted R-squared:  0.1326
F-statistic: 2.911 on 2 and 23 DF,  p-value: 0.07464


Value of test-statistic is: -2.297 2.6965

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.58 -2.93 -2.60
phi1  7.06  4.86  3.94


$Y7

###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0269513 -0.0061571 -0.0009426  0.0027593  0.0210403

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.002465   0.002223   1.109   0.2788
z.lag.1     -0.382387   0.192007  -1.992   0.0584 .
z.diff.lag   0.094636   0.228577   0.414   0.6827
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01047 on 23 degrees of freedom
Multiple R-squared:  0.1537,    Adjusted R-squared:  0.08006
F-statistic: 2.088 on 2 and 23 DF,  p-value: 0.1468


Value of test-statistic is: -1.9915 2.0532

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.58 -2.93 -2.60
phi1  7.06  4.86  3.94


$Y8

###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)
```

```
Residuals:
     Min       1Q   Median       3Q      Max 
-0.15411 -0.05724 -0.00855  0.02925  0.20514 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)   
(Intercept)  0.009094   0.017567   0.518  0.60962   
z.lag.1     -0.634513   0.208216  -3.047  0.00572 **
z.diff.lag   0.258335   0.203640   1.269  0.21728   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.08707 on 23 degrees of freedom
Multiple R-squared:  0.2907,	Adjusted R-squared:  0.229 
F-statistic: 4.712 on 2 and 23 DF,  p-value: 0.01927


Value of test-statistic is: -3.0474 4.66 

Critical values for test statistics: 
      1pct  5pct 10pct
tau2 -3.58 -2.93 -2.60
phi1  7.06  4.86  3.94


$Y9

############################################### 
# Augmented Dickey-Fuller Test Unit Root Test # 
############################################### 

Test regression drift 


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.51030 -0.14007  0.03693  0.18080  0.42540 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.03088    0.05145  -0.600 0.554200    
z.lag.1     -1.14407    0.27811  -4.114 0.000424 ***
z.diff.lag   0.20340    0.20929   0.972 0.341234    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2604 on 23 degrees of freedom
Multiple R-squared:  0.5142,	Adjusted R-squared:  0.4719 
F-statistic: 12.17 on 2 and 23 DF,  p-value: 0.0002481


Value of test-statistic is: -4.1137 8.4689 

Critical values for test statistics: 
      1pct  5pct 10pct
tau2 -3.58 -2.93 -2.60
phi1  7.06  4.86  3.94


$Y10

############################################### 
# Augmented Dickey-Fuller Test Unit Root Test # 
############################################### 

Test regression drift 


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.91292 -0.00189 -0.00169  0.00027  0.90275 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)   
(Intercept)  0.001692   0.054196   0.031  0.97536   
z.lag.1     -0.987538   0.294867  -3.349  0.00278 **
z.diff.lag  -0.012505   0.208498  -0.060  0.95269   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2763 on 23 degrees of freedom
Multiple R-squared:  0.5001,	Adjusted R-squared:  0.4566 
F-statistic:  11.5 on 2 and 23 DF,  p-value: 0.0003445


Value of test-statistic is: -3.3491 5.6082 

Critical values for test statistics: 
      1pct  5pct 10pct
tau2 -3.58 -2.93 -2.60
phi1  7.06  4.86  3.94


$Y11

############################################### 
# Augmented Dickey-Fuller Test Unit Root Test # 
############################################### 

Test regression drift 


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.46569 -0.14461  0.03431  0.16850  0.35539 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.03431    0.04619  -0.743   0.4651    
```

```
z.lag.1     -2.78431    0.33307  -8.360    2e-08 ***
z.diff.lag   0.64216    0.18077   3.552   0.0017 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2332 on 23 degrees of freedom
Multiple R-squared:  0.8887,    Adjusted R-squared:  0.879
F-statistic: 91.81 on 2 and 23 DF,  p-value: 1.085e-11


Value of test-statistic is: -8.3595 35.0294

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.58 -2.93 -2.60
phi1  7.06  4.86  3.94

Response: relation$Y1
Input: relation$Y2
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -4.55    0.01
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.44    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.826   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-4.5544   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.9967   1st Qu.:0.055
 Median :1   Median :-1.4389   Median :0.100
 Mean   :1   Mean   :-1.7225   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.3065   3rd Qu.:0.100
 Max.   :1   Max.   : 0.8259   Max.   :0.100
Response: relation$Y1
Input: relation$Y3
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -3.3169  0.0308
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.54    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.04    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.3169   Min.   :0.03076
 1st Qu.:1   1st Qu.:-2.4277   1st Qu.:0.06538
 Median :1   Median :-1.5385   Median :0.10000
 Mean   :1   Mean   :-1.2721   Mean   :0.07692
 3rd Qu.:1   3rd Qu.:-0.2497   3rd Qu.:0.10000
 Max.   :1   Max.   : 1.0391   Max.   :0.10000
Response: relation$Y1
Input: relation$Y4
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -3.2421  0.0349
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.52    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.974   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.2421   Min.   :0.03493
 1st Qu.:1   1st Qu.:-2.3821   1st Qu.:0.06747
 Median :1   Median :-1.5221   Median :0.10000
 Mean   :1   Mean   :-1.2635   Mean   :0.07831
 3rd Qu.:1   3rd Qu.:-0.2742   3rd Qu.:0.10000
 Max.   :1   Max.   : 0.9737   Max.   :0.10000
Response: relation$Y1
Input: relation$Y5
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -3.6274  0.0134
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.36    0.10
```

```
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.04    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.6274   Min.   :0.01344
 1st Qu.:1   1st Qu.:-2.4913   1st Qu.:0.05672
 Median :1   Median :-1.3552   Median :0.10000
 Mean   :1   Mean   :-1.3128   Mean   :0.07115
 3rd Qu.:1   3rd Qu.:-0.1555   3rd Qu.:0.10000
 Max.   :1   Max.   : 1.0442   Max.   :0.10000
Response: relation$Y1
Input: relation$Y6
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -3.3000  0.0317
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.34    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.71    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.3000   Min.   :0.03170
 1st Qu.:1   1st Qu.:-2.3197   1st Qu.:0.06585
 Median :1   Median :-1.3394   Median :0.10000
 Mean   :1   Mean   :-0.9764   Mean   :0.07723
 3rd Qu.:1   3rd Qu.: 0.1854   3rd Qu.:0.10000
 Max.   :1   Max.   : 1.7101   Max.   :0.10000
Response: relation$Y1
Input: relation$Y7
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -3.3616  0.0283
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.52    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.07    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.3616   Min.   :0.02826
 1st Qu.:1   1st Qu.:-2.4391   1st Qu.:0.06413
 Median :1   Median :-1.5166   Median :0.10000
 Mean   :1   Mean   :-1.2683   Mean   :0.07609
 3rd Qu.:1   3rd Qu.:-0.2216   3rd Qu.:0.10000
 Max.   :1   Max.   : 1.0733   Max.   :0.10000
Response: relation$Y1
Input: relation$Y8
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -2.7384  0.0837
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.33    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.282   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-2.7384   Min.   :0.08369
 1st Qu.:1   1st Qu.:-2.0361   1st Qu.:0.09184
 Median :1   Median :-1.3337   Median :0.10000
 Mean   :1   Mean   :-1.2634   Mean   :0.09456
 3rd Qu.:1   3rd Qu.:-0.5258   3rd Qu.:0.10000
 Max.   :1   Max.   : 0.2820   Max.   :0.10000
Response: relation$Y1
Input: relation$Y9
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -3.1780  0.0385
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.63    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
```

```
   1.00    1.48    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG               p.value
 Min.   :1   Min.   :-3.17803   Min.   :0.03850
 1st Qu.:1   1st Qu.:-2.40490   1st Qu.:0.06925
 Median :1   Median :-1.63176   Median :0.10000
 Mean   :1   Mean   :-1.11147   Mean   :0.07950
 3rd Qu.:1   3rd Qu.:-0.07819   3rd Qu.:0.10000
 Max.   :1   Max.   : 1.47539   Max.   :0.10000
Response: relation$Y1
Input: relation$Y10
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -3.2911  0.0322
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.52    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.02    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.2911   Min.   :0.0322
 1st Qu.:1   1st Qu.:-2.4068   1st Qu.:0.0661
 Median :1   Median :-1.5225   Median :0.1000
 Mean   :1   Mean   :-1.2640   Mean   :0.0774
 3rd Qu.:1   3rd Qu.:-0.2504   3rd Qu.:0.1000
 Max.   :1   Max.   : 1.0217   Max.   :0.1000
Response: relation$Y1
Input: relation$Y11
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -3.2519  0.0344
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.48    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.954   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.2519   Min.   :0.03438
 1st Qu.:1   1st Qu.:-2.3684   1st Qu.:0.06719
 Median :1   Median :-1.4849   Median :0.10000
 Mean   :1   Mean   :-1.2609   Mean   :0.07813
 3rd Qu.:1   3rd Qu.:-0.2654   3rd Qu.:0.10000
 Max.   :1   Max.   : 0.9540   Max.   :0.10000
Response: relation$Y2
Input: relation$Y3
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -4.65    0.01
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.04    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.01    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG               p.value
 Min.   :1   Min.   :-4.64596   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.84129   1st Qu.:0.055
 Median :1   Median :-1.03662   Median :0.100
 Mean   :1   Mean   :-1.55778   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.01369   3rd Qu.:0.100
 Max.   :1   Max.   : 1.00924   Max.   :0.100
Response: relation$Y2
Input: relation$Y4
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -4.60    0.01
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.12    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.952   0.100
-----------
```

```
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-4.60105   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.86161   1st Qu.:0.055
 Median :1   Median :-1.12217   Median :0.100
 Mean   :1   Mean   :-1.59034   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.08498   3rd Qu.:0.100
 Max.   :1   Max.   : 0.95220   Max.   :0.100
Response: relation$Y2
Input: relation$Y6
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -4.72    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.775   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
    1.0     1.6     0.1
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG             p.value
 Min.   :1   Min.   :-4.7159   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.7456   1st Qu.:0.055
 Median :1   Median :-0.7754   Median :0.100
 Mean   :1   Mean   :-1.2983   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.4105   3rd Qu.:0.100
 Max.   :1   Max.   : 1.5963   Max.   :0.100
Response: relation$Y2
Input: relation$Y7
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -4.58    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.969   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.02    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-4.57641   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.77293   1st Qu.:0.055
 Median :1   Median :-0.96945   Median :0.100
 Mean   :1   Mean   :-1.50750   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.02696   3rd Qu.:0.100
 Max.   :1   Max.   : 1.02337   Max.   :0.100
Response: relation$Y2
Input: relation$Y8
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -4.48    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.965   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.699   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG             p.value
 Min.   :1   Min.   :-4.4775   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.7210   1st Qu.:0.055
 Median :1   Median :-0.9645   Median :0.100
 Mean   :1   Mean   :-1.5812   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.1330   3rd Qu.:0.100
 Max.   :1   Max.   : 0.6985   Max.   :0.100
Response: relation$Y2
Input: relation$Y9
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -4.51    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.999   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.848   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
```

```
 Min.   :1   Min.   :-4.50577   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.75255   1st Qu.:0.055
 Median :1   Median :-0.99932   Median :0.100
 Mean   :1   Mean   :-1.55238   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.07568   3rd Qu.:0.100
 Max.   :1   Max.   : 0.84796   Max.   :0.100
Response: relation$Y2
Input: relation$Y10
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -3.88    0.01
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -1.13    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
    1.0     1.2     0.1
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.88207   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.50522   1st Qu.:0.055
 Median :1   Median :-1.12836   Median :0.100
 Mean   :1   Mean   :-1.27100   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.03454   3rd Qu.:0.100
 Max.   :1   Max.   : 1.19745   Max.   :0.100
Response: relation$Y2
Input: relation$Y11
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -4.34    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.977   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.881   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-4.34443   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.66085   1st Qu.:0.055
 Median :1   Median :-0.97727   Median :0.100
 Mean   :1   Mean   :-1.48012   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.04797   3rd Qu.:0.100
 Max.   :1   Max.   : 0.88133   Max.   :0.100
Response: relation$Y3
Input: relation$Y4
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -8.77    0.01
-----
 Type 2: linear trend
    lag      EG p.value
 1.0000  0.0447  0.1000
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000  -0.264   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-8.77391   Min.   :0.010
 1st Qu.:1   1st Qu.:-4.51906   1st Qu.:0.055
 Median :1   Median :-0.26422   Median :0.100
 Mean   :1   Mean   :-2.99782   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.10977   3rd Qu.:0.100
 Max.   :1   Max.   : 0.04467   Max.   :0.100
Response: relation$Y3
Input: relation$Y5
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -9.95    0.01
-----
 Type 2: linear trend
     lag       EG  p.value
 1.00000 -0.00191  0.10000
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000  -0.107   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG               p.value
 Min.   :1   Min.   :-9.946011   Min.   :0.010
 1st Qu.:1   1st Qu.:-5.026447   1st Qu.:0.055
 Median :1   Median :-0.106884   Median :0.100
```

```
 Mean   :1   Mean   :-3.351600   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.054395   3rd Qu.:0.100
 Max.   :1   Max.   :-0.001905   Max.   :0.100
Response: relation$Y3
Input: relation$Y6
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -9.93    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.215   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000  -0.161   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG               p.value
 Min.   :1   Min.   :-9.92875   Min.   :0.010
 1st Qu.:1   1st Qu.:-5.04467   1st Qu.:0.055
 Median :1   Median :-0.16060   Median :0.100
 Mean   :1   Mean   :-3.29161   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.02695   3rd Qu.:0.100
 Max.   :1   Max.   : 0.21451   Max.   :0.100
Response: relation$Y3
Input: relation$Y7
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -9.99    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.103   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000  -0.177   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG               p.value
 Min.   :1   Min.   :-9.98558   Min.   :0.010
 1st Qu.:1   1st Qu.:-5.08111   1st Qu.:0.055
 Median :1   Median :-0.17664   Median :0.100
 Mean   :1   Mean   :-3.35304   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.03677   3rd Qu.:0.100
 Max.   :1   Max.   : 0.10311   Max.   :0.100
Response: relation$Y3
Input: relation$Y8
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -9.94    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.195   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000  -0.127   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG               p.value
 Min.   :1   Min.   :-9.94315   Min.   :0.010
 1st Qu.:1   1st Qu.:-5.03483   1st Qu.:0.055
 Median :1   Median :-0.12651   Median :0.100
 Mean   :1   Mean   :-3.29150   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.03433   3rd Qu.:0.100
 Max.   :1   Max.   : 0.19517   Max.   :0.100
Response: relation$Y3
Input: relation$Y9
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -9.23    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.286   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000  -0.621   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-9.2342   Min.   :0.010
 1st Qu.:1   1st Qu.:-4.9275   1st Qu.:0.055
 Median :1   Median :-0.6207   Median :0.100
 Mean   :1   Mean   :-3.1898   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.1676   3rd Qu.:0.100
 Max.   :1   Max.   : 0.2855   Max.   :0.100
```

```
Response: relation$Y3
Input: relation$Y10
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -9.86    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.188   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000  -0.143   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-9.86300   Min.   :0.010
 1st Qu.:1   1st Qu.:-5.00297   1st Qu.:0.055
 Median :1   Median :-0.14294   Median :0.100
 Mean   :1   Mean   :-3.27278   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.02233   3rd Qu.:0.100
 Max.   :1   Max.   : 0.18760   Max.   :0.100
Response: relation$Y3
Input: relation$Y11
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -9.91    0.01
-----
 Type 2: linear trend
    lag      EG p.value
   1.00    0.19    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000  -0.265   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-9.91151   Min.   :0.010
 1st Qu.:1   1st Qu.:-5.08808   1st Qu.:0.055
 Median :1   Median :-0.26466   Median :0.100
 Mean   :1   Mean   :-3.32879   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.03744   3rd Qu.:0.100
 Max.   :1   Max.   : 0.18979   Max.   :0.100
Response: relation$Y4
Input: relation$Y5
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -5.67    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.411   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.332   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG             p.value
 Min.   :1   Min.   :-5.6652   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.6668   1st Qu.:0.055
 Median :1   Median : 0.3317   Median :0.100
 Mean   :1   Mean   :-1.6409   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.3713   3rd Qu.:0.100
 Max.   :1   Max.   : 0.4109   Max.   :0.100
Response: relation$Y4
Input: relation$Y6
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -5.56    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.401   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    0.47    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG             p.value
 Min.   :1   Min.   :-5.5603   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.5794   1st Qu.:0.055
 Median :1   Median : 0.4015   Median :0.100
 Mean   :1   Mean   :-1.5630   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.4357   3rd Qu.:0.100
 Max.   :1   Max.   : 0.4699   Max.   :0.100
Response: relation$Y4
Input: relation$Y7
Number of inputs: 1
```

```
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -6.05    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.196   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.331   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG             p.value
 Min.   :1   Min.   :-6.0521   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.9281   1st Qu.:0.055
 Median :1   Median : 0.1959   Median :0.100
 Mean   :1   Mean   :-1.8417   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.2635   3rd Qu.:0.100
 Max.   :1   Max.   : 0.3311   Max.   :0.100
Response: relation$Y4
Input: relation$Y8
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -5.44    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.353   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.109   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG             p.value
 Min.   :1   Min.   :-5.4426   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.6669   1st Qu.:0.055
 Median :1   Median : 0.1088   Median :0.100
 Mean   :1   Mean   :-1.6601   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.2311   3rd Qu.:0.100
 Max.   :1   Max.   : 0.3535   Max.   :0.100
Response: relation$Y4
Input: relation$Y9
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -5.55    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.339   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.208   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG             p.value
 Min.   :1   Min.   :-5.5530   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.6727   1st Qu.:0.055
 Median :1   Median : 0.2077   Median :0.100
 Mean   :1   Mean   :-1.6687   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.2734   3rd Qu.:0.100
 Max.   :1   Max.   : 0.3391   Max.   :0.100
Response: relation$Y4
Input: relation$Y10
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -5.67    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.226   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.581   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG             p.value
 Min.   :1   Min.   :-5.6703   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.7221   1st Qu.:0.055
 Median :1   Median : 0.2262   Median :0.100
 Mean   :1   Mean   :-1.6211   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.4035   3rd Qu.:0.100
 Max.   :1   Max.   : 0.5808   Max.   :0.100
Response: relation$Y4
Input: relation$Y11
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
```

```
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -5.17    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.329   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.268   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-5.1739   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.4531   1st Qu.:0.055
 Median :1   Median : 0.2678   Median :0.100
 Mean   :1   Mean   :-1.5256   Mean   :0.070
 3rd Qu.:1   3rd Qu.: 0.2985   3rd Qu.:0.100
 Max.   :1   Max.   : 0.3293   Max.   :0.100
Response: relation$Y5
Input: relation$Y6
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -3.78    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.705   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.388   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.7776   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.2413   1st Qu.:0.055
 Median :1   Median :-0.7051   Median :0.100
 Mean   :1   Mean   :-1.3650   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.1587   3rd Qu.:0.100
 Max.   :1   Max.   : 0.3877   Max.   :0.100
Response: relation$Y5
Input: relation$Y7
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -3.72    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.806   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.205   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.7180   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.2621   1st Qu.:0.055
 Median :1   Median :-0.8062   Median :0.100
 Mean   :1   Mean   :-1.4397   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.3006   3rd Qu.:0.100
 Max.   :1   Max.   : 0.2051   Max.   :0.100
Response: relation$Y5
Input: relation$Y8
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
  1.000  -3.528   0.019
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -0.71    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000  -0.133   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.5283   Min.   :0.01896
 1st Qu.:1   1st Qu.:-2.1192   1st Qu.:0.05948
 Median :1   Median :-0.7101   Median :0.10000
 Mean   :1   Mean   :-1.4571   Mean   :0.07299
 3rd Qu.:1   3rd Qu.:-0.4215   3rd Qu.:0.10000
 Max.   :1   Max.   :-0.1329   Max.   :0.10000
Response: relation$Y5
Input: relation$Y9
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
```

```
    lag      EG p.value
   1.00   -3.73    0.01
-----
 Type 2: linear trend
    lag      EG p.value
   1.00   -0.82    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.232   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.    :1   Min.    :-3.7271   Min.    :0.010
 1st Qu.:1   1st Qu.:-2.2737   1st Qu.:0.055
 Median :1   Median :-0.8204   Median :0.100
 Mean    :1   Mean    :-1.4386   Mean    :0.070
 3rd Qu.:1   3rd Qu.:-0.2944   3rd Qu.:0.100
 Max.    :1   Max.    : 0.2316   Max.    :0.100
Response: relation$Y5
Input: relation$Y10
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -3.85    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.811   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.179   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.    :1   Min.    :-3.8541   Min.    :0.010
 1st Qu.:1   1st Qu.:-2.3325   1st Qu.:0.055
 Median :1   Median :-0.8109   Median :0.100
 Mean    :1   Mean    :-1.4953   Mean    :0.070
 3rd Qu.:1   3rd Qu.:-0.3158   3rd Qu.:0.100
 Max.    :1   Max.    : 0.1792   Max.    :0.100
Response: relation$Y5
Input: relation$Y11
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -3.76    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.799   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.176   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.    :1   Min.    :-3.7604   Min.    :0.010
 1st Qu.:1   1st Qu.:-2.2798   1st Qu.:0.055
 Median :1   Median :-0.7992   Median :0.100
 Mean    :1   Mean    :-1.4611   Mean    :0.070
 3rd Qu.:1   3rd Qu.:-0.3114   3rd Qu.:0.100
 Max.    :1   Max.    : 0.1765   Max.    :0.100
Response: relation$Y6
Input: relation$Y7
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -3.0426  0.0461
-----
 Type 2: linear trend
    lag      EG p.value
   1.00    0.44    0.10
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.716   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.    :1   Min.    :-3.0426   Min.    :0.04606
 1st Qu.:1   1st Qu.:-1.3014   1st Qu.:0.07303
 Median :1   Median : 0.4398   Median :0.10000
 Mean    :1   Mean    :-0.6288   Mean    :0.08202
 3rd Qu.:1   3rd Qu.: 0.5781   3rd Qu.:0.10000
 Max.    :1   Max.    : 0.7163   Max.    :0.10000
Response: relation$Y6
Input: relation$Y8
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -3.4531  0.0232
-----
```

```
 Type 2: linear trend
    lag      EG p.value
  1.000   0.894   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000   0.669   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.4531   Min.   :0.02316
 1st Qu.:1   1st Qu.:-1.3922   1st Qu.:0.06158
 Median :1   Median : 0.6686   Median :0.10000
 Mean   :1   Mean   :-0.6303   Mean   :0.07439
 3rd Qu.:1   3rd Qu.: 0.7812   3rd Qu.:0.10000
 Max.   :1   Max.   : 0.8937   Max.   :0.10000
Response: relation$Y6
Input: relation$Y9
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -2.23    0.10
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.267   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.11    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-2.2285   Min.   :0.1
 1st Qu.:1   1st Qu.:-0.9806   1st Qu.:0.1
 Median :1   Median : 0.2673   Median :0.1
 Mean   :1   Mean   :-0.2838   Mean   :0.1
 3rd Qu.:1   3rd Qu.: 0.6885   3rd Qu.:0.1
 Max.   :1   Max.   : 1.1097   Max.   :0.1
Response: relation$Y6
Input: relation$Y10
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -2.16    0.10
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.263   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.12    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-2.1580   Min.   :0.1
 1st Qu.:1   1st Qu.:-0.9477   1st Qu.:0.1
 Median :1   Median : 0.2626   Median :0.1
 Mean   :1   Mean   :-0.2597   Mean   :0.1
 3rd Qu.:1   3rd Qu.: 0.6894   3rd Qu.:0.1
 Max.   :1   Max.   : 1.1163   Max.   :0.1
Response: relation$Y6
Input: relation$Y11
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -1.91    0.10
-----
 Type 2: linear trend
    lag      EG p.value
 1.0000  0.0381  0.1000
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.34    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-1.9064   Min.   :0.1
 1st Qu.:1   1st Qu.:-0.9342   1st Qu.:0.1
 Median :1   Median : 0.0381   Median :0.1
 Mean   :1   Mean   :-0.1773   Mean   :0.1
 3rd Qu.:1   3rd Qu.: 0.6873   3rd Qu.:0.1
 Max.   :1   Max.   : 1.3366   Max.   :0.1
Response: relation$Y7
Input: relation$Y8
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -2.6821  0.0918
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.462   0.100
```

```
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000  -0.382   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-2.6821   Min.   :0.09181
 1st Qu.:1   1st Qu.:-1.5723   1st Qu.:0.09590
 Median :1   Median :-0.4625   Median :0.10000
 Mean   :1   Mean   :-1.1754   Mean   :0.09727
 3rd Qu.:1   3rd Qu.:-0.4221   3rd Qu.:0.10000
 Max.   :1   Max.   :-0.3818   Max.   :0.10000
Response: relation$Y7
Input: relation$Y9
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -1.87    0.10
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.197   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00   -1.27    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-1.8717   Min.   :0.1
 1st Qu.:1   1st Qu.:-1.5702   1st Qu.:0.1
 Median :1   Median :-1.2686   Median :0.1
 Mean   :1   Mean   :-0.9809   Mean   :0.1
 3rd Qu.:1   3rd Qu.:-0.5355   3rd Qu.:0.1
 Max.   :1   Max.   : 0.1975   Max.   :0.1
Response: relation$Y7
Input: relation$Y10
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
    1.0    -2.1     0.1
-----
 Type 2: linear trend
    lag      EG p.value
 1.0000  0.0373  0.1000
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00   -1.03    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG               p.value
 Min.   :1   Min.   :-2.09866   Min.   :0.1
 1st Qu.:1   1st Qu.:-1.56302   1st Qu.:0.1
 Median :1   Median :-1.02738   Median :0.1
 Mean   :1   Mean   :-1.02959   Mean   :0.1
 3rd Qu.:1   3rd Qu.:-0.49505   3rd Qu.:0.1
 Max.   :1   Max.   : 0.03729   Max.   :0.1
Response: relation$Y7
Input: relation$Y11
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -2.11    0.10
-----
 Type 2: linear trend
    lag      EG p.value
 1.0000  0.0536  0.1000
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00   -1.05    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG               p.value
 Min.   :1   Min.   :-2.11205   Min.   :0.1
 1st Qu.:1   1st Qu.:-1.58009   1st Qu.:0.1
 Median :1   Median :-1.04812   Median :0.1
 Mean   :1   Mean   :-1.03553   Mean   :0.1
 3rd Qu.:1   3rd Qu.:-0.49727   3rd Qu.:0.1
 Max.   :1   Max.   : 0.05358   Max.   :0.1
Response: relation$Y8
Input: relation$Y9
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -2.9494  0.0533
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.374   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
```

```
   1.00    1.06    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-2.9494   Min.   :0.05325
 1st Qu.:1   1st Qu.:-1.6616   1st Qu.:0.07663
 Median :1   Median :-0.3737   Median :0.10000
 Mean   :1   Mean   :-0.7554   Mean   :0.08442
 3rd Qu.:1   3rd Qu.: 0.3415   3rd Qu.:0.10000
 Max.   :1   Max.   : 1.0568   Max.   :0.10000
Response: relation$Y8
Input: relation$Y10
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -3.1138  0.0421
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.344   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.06    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-3.1138   Min.   :0.04208
 1st Qu.:1   1st Qu.:-1.7289   1st Qu.:0.07104
 Median :1   Median :-0.3439   Median :0.10000
 Mean   :1   Mean   :-0.7989   Mean   :0.08069
 3rd Qu.:1   3rd Qu.: 0.3586   3rd Qu.:0.10000
 Max.   :1   Max.   : 1.0611   Max.   :0.10000
Response: relation$Y8
Input: relation$Y11
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
 1.0000 -2.9041  0.0598
-----
 Type 2: linear trend
    lag      EG p.value
  1.000  -0.365   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00    1.04    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-2.9041   Min.   :0.05979
 1st Qu.:1   1st Qu.:-1.6344   1st Qu.:0.07989
 Median :1   Median :-0.3647   Median :0.10000
 Mean   :1   Mean   :-0.7445   Mean   :0.08660
 3rd Qu.:1   3rd Qu.: 0.3353   3rd Qu.:0.10000
 Max.   :1   Max.   : 1.0353   Max.   :0.10000
Response: relation$Y9
Input: relation$Y10
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -4.99    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.213   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00   -1.07    0.10
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-4.9897   Min.   :0.010
 1st Qu.:1   1st Qu.:-3.0290   1st Qu.:0.055
 Median :1   Median :-1.0682   Median :0.100
 Mean   :1   Mean   :-1.9485   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.4278   3rd Qu.:0.100
 Max.   :1   Max.   : 0.2125   Max.   :0.100
Response: relation$Y9
Input: relation$Y11
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -4.77    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.219   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
   1.00   -1.05    0.10
-----------
```

```
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-4.7739   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.9112   1st Qu.:0.055
 Median :1   Median :-1.0485   Median :0.100
 Mean   :1   Mean   :-1.8679   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.4148   3rd Qu.:0.100
 Max.   :1   Max.   : 0.2188   Max.   :0.100
Response: relation$Y10
Input: relation$Y11
Number of inputs: 1
Model: y ~ X + 1
-------------------------------
Engle-Granger Cointegration Test
alternative: cointegrated

Type 1: no trend
    lag      EG p.value
   1.00   -4.42    0.01
-----
 Type 2: linear trend
    lag      EG p.value
  1.000   0.324   0.100
-----
 Type 3: quadratic trend
    lag      EG p.value
  1.000  -0.601   0.100
-----------
Note: p.value = 0.01 means p.value <= 0.01
    : p.value = 0.10 means p.value >= 0.10
      lag          EG              p.value
 Min.   :1   Min.   :-4.4199   Min.   :0.010
 1st Qu.:1   1st Qu.:-2.5104   1st Qu.:0.055
 Median :1   Median :-0.6009   Median :0.100
 Mean   :1   Mean   :-1.5657   Mean   :0.070
 3rd Qu.:1   3rd Qu.:-0.1386   3rd Qu.:0.100
 Max.   :1   Max.   : 0.3237   Max.   :0.100
[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 2.6256, df1 = 2, df2 = 40, p-value = 0.08484


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 7.1644, df = 1, p-value = 0.007437



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.16326, df1 = 2, df2 = 40, p-value = 0.8499


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 7.1644, df = 1, p-value = 0.007437




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  0.0217465331
 [2,]  0.0013100522
 [3,]  0.0045246853
 [4,] -0.0067526973
 [5,] -0.0068970660
 [6,]  0.0092147037
 [7,]  0.0039736520
 [8,] -0.0092305452
 [9,] -0.0006671813
[10,]  0.0078670658
[11,] -0.0018027779


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0008288689
 [3,]  0.0027036435
 [4,] -0.0001887940
 [5,] -0.0027562308
 [6,]  0.0010641781
 [7,]  0.0020658498
 [8,] -0.0015265323
 [9,] -0.0012500648
[10,]  0.0016329930
[11,]  0.0005278046


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2
```

```
data:  VAR object model
F-Test = 0.74651, df1 = 2, df2 = 40, p-value = 0.4805


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.032199, df = 1, p-value = 0.8576



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.5637, df1 = 2, df2 = 40, p-value = 0.2219


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.032199, df = 1, p-value = 0.8576




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -9.040977e-03
 [2,] -3.784293e-02
 [3,]  1.911729e-03
 [4,]  3.691991e-02
 [5,] -2.074645e-02
 [6,] -6.640440e-03
 [7,]  1.093324e-02
 [8,] -4.518784e-03
 [9,]  1.391421e-03
[10,]  7.750355e-05
[11,] -2.040931e-03


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,]  0.0046221443
 [3,]  0.0020075561
 [4,] -0.0062476015
 [5,]  0.0023742709
 [6,]  0.0017110317
 [7,] -0.0018783764
 [8,]  0.0006879277
 [9,] -0.0001110905
[10,] -0.0001815815
[11,]  0.0004287487


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 1.4966, df1 = 2, df2 = 40, p-value = 0.2362


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 1.5877, df = 1, p-value = 0.2077



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.77623, df1 = 2, df2 = 40, p-value = 0.4669


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 1.5877, df = 1, p-value = 0.2077




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,]  0.049694639
 [2,]  0.060199122
 [3,] -0.025674351
 [4,] -0.032148549
 [5,]  0.014708010
 [6,]  0.013561987
```

```
 [7,] -0.007651633
 [8,] -0.005308786
 [9,]  0.003744787
[10,]  0.001994851
[11,] -0.001769536


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.0000000000
 [2,] -0.0052748671
 [3,]  0.0005680558
 [4,]  0.0028751466
 [5,] -0.0005841470
 [6,] -0.0012564721
 [7,]  0.0003729502
 [8,]  0.0005159424
 [9,] -0.0002039720
[10,] -0.0002060324
[11,]  0.0001040500


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.77671, df1 = 2, df2 = 40, p-value = 0.4667


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.024614, df = 1, p-value = 0.8753



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 3.2556, df1 = 2, df2 = 40, p-value = 0.04898


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.024614, df = 1, p-value = 0.8753




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,]  2.448691e-03
 [2,] -3.870686e-03
 [3,] -1.900878e-02
 [4,] -2.815092e-04
 [5,]  1.401182e-02
 [6,]  2.688601e-03
 [7,] -5.233008e-03
 [8,] -2.122562e-03
 [9,] -3.220022e-05
[10,]  5.840635e-04
[11,]  1.470619e-03


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.000000e+00
 [2,]  2.725505e-05
 [3,]  9.260411e-03
 [4,]  1.678013e-03
 [5,] -6.995328e-03
 [6,] -2.033865e-03
 [7,]  2.646696e-03
 [8,]  1.179241e-03
 [9,] -3.232899e-05
[10,] -1.982043e-04
[11,] -6.809711e-04


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 3.1308, df1 = 2, df2 = 40, p-value = 0.05455


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 6.8459, df = 1, p-value = 0.008885
```

```
[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.1466, df1 = 2, df2 = 40, p-value = 0.3279


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 6.8459, df = 1, p-value = 0.008885



[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,] -0.019739860
 [2,] -0.027218278
 [3,] -0.017310674
 [4,] -0.006807237
 [5,] -0.006123428
 [6,] -0.006468563
 [7,] -0.004636910
 [8,] -0.002690773
 [9,] -0.001999658
[10,] -0.001728456
[11,] -0.001294256


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,]  5.464107e-03
 [3,] -2.739384e-04
 [4,] -4.650811e-04
 [5,]  3.218252e-04
 [6,]  7.261115e-04
 [7,]  1.940497e-04
 [8,]  7.267797e-06
 [9,]  8.988276e-05
[10,]  1.311073e-04
[11,]  6.753764e-05


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 4.4742, df1 = 2, df2 = 40, p-value = 0.01764


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.060658, df = 1, p-value = 0.8055


[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.1487, df1 = 2, df2 = 40, p-value = 0.3273


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.060658, df = 1, p-value = 0.8055



[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -0.0004454833
 [2,]  0.0050419635
 [3,]  0.0056006794
 [4,]  0.0016769547
 [5,]  0.0003230013
 [6,]  0.0010103273
 [7,]  0.0011592038
 [8,]  0.0005616860
 [9,]  0.0002051397
[10,]  0.0002312751
[11,]  0.0002510731


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
```

```
 [2,] -7.305935e-03
 [3,] -1.038472e-03
 [4,]  9.208687e-04
 [5,] -2.822756e-04
 [6,] -1.124965e-03
 [7,] -4.693709e-04
 [8,]  4.089431e-05
 [9,] -5.818749e-05
[10,] -2.001449e-04
[11,] -1.239648e-04


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 16.364, df1 = 2, df2 = 40, p-value = 6.414e-06


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 3.034, df = 1, p-value = 0.08154



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 3.1729, df1 = 2, df2 = 40, p-value = 0.0526


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 3.034, df = 1, p-value = 0.08154




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  0.0207611184
 [2,] -0.0267753604
 [3,] -0.0633002072
 [4,] -0.0161613794
 [5,]  0.0065730193
 [6,] -0.0009533390
 [7,]  0.0118288739
 [8,]  0.0152005372
 [9,]  0.0003001932
[10,] -0.0031545299
[11,] -0.0006869671


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,] -4.804039e-03
 [3,]  4.843799e-03
 [4,]  5.306380e-03
 [5,] -1.050245e-03
 [6,] -1.645999e-05
 [7,]  7.474339e-04
 [8,] -1.715662e-03
 [9,] -1.040745e-03
[10,]  5.359354e-04
[11,] -5.186834e-06


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.058468, df1 = 2, df2 = 40, p-value = 0.9433


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 3.7509, df = 1, p-value = 0.05278



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 3.7068, df1 = 2, df2 = 40, p-value = 0.03335


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1
```

```
data:  VAR object model
Chi-squared = 3.7509, df = 1, p-value = 0.05278



[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  0.1109406587
 [2,] -0.0117437910
 [3,] -0.0305054841
 [4,]  0.0055376933
 [5,]  0.0099605845
 [6,] -0.0023658523
 [7,] -0.0032784751
 [8,]  0.0009640955
 [9,]  0.0010715724
[10,] -0.0003802085
[11,] -0.0003471541


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,]  8.501453e-03
 [3,] -6.475907e-03
 [4,] -2.720434e-03
 [5,]  2.497963e-03
 [6,]  8.088718e-04
 [7,] -8.947906e-04
 [8,] -2.328369e-04
 [9,]  3.164147e-04
[10,]  6.420408e-05
[11,] -1.109847e-04


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 6.4521, df1 = 2, df2 = 40, p-value = 0.003727


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 2.7161, df = 1, p-value = 0.09934



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.1523, df1 = 2, df2 = 40, p-value = 0.8592


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 2.7161, df = 1, p-value = 0.09934




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,]  0.078363566
 [2,]  0.097042993
 [3,]  0.106491577
 [4,] -0.078240711
 [5,] -0.025550976
 [6,]  0.018734085
 [7,]  0.015770727
 [8,] -0.008003676
 [9,] -0.005917979
[10,]  0.002278810
[11,]  0.002654507


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,] -2.090325e-03
 [3,]  4.147930e-04
 [4,]  5.727758e-04
 [5,]  4.009764e-06
 [6,] -2.768447e-04
 [7,]  7.148052e-07
 [8,]  9.740639e-05
 [9,]  1.203366e-05
[10,] -3.913617e-05
[11,] -6.818662e-06


[[1]]
```

```
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 1.2832, df1 = 2, df2 = 40, p-value = 0.2883


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.017627, df = 1, p-value = 0.8944



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.8624, df1 = 2, df2 = 40, p-value = 0.1685


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.017627, df = 1, p-value = 0.8944




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,] -0.006130665
 [2,]  0.080975452
 [3,] -0.099064627
 [4,]  0.030697140
 [5,]  0.031065837
 [6,] -0.040973875
 [7,]  0.026491143
 [8,] -0.011460432
 [9,] -0.002930762
[10,]  0.013780543
[11,] -0.014484067


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,]  0.0009923127
 [3,] -0.0054772536
 [4,]  0.0052885568
 [5,] -0.0007368249
 [6,] -0.0022961889
 [7,]  0.0022846683
 [8,] -0.0013071972
 [9,]  0.0004550914
[10,]  0.0003554046
[11,] -0.0008809601


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.60519, df1 = 2, df2 = 40, p-value = 0.5509


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.17194, df = 1, p-value = 0.6784



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.0107, df1 = 2, df2 = 40, p-value = 0.3731


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.17194, df = 1, p-value = 0.6784




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -0.0210875782
```

```
 [2,] -0.0369769122
 [3,]  0.0154968552
 [4,]  0.0255958037
 [5,] -0.0229555840
 [6,]  0.0012027095
 [7,]  0.0080307351
 [8,] -0.0060840681
 [9,]  0.0026815857
[10,] -0.0001033958
[11,] -0.0017841071


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,]  0.0018193104
 [3,]  0.0073167656
 [4,] -0.0089579673
 [5,]  0.0016186544
 [6,]  0.0037112074
 [7,] -0.0034918623
 [8,]  0.0012379064
 [9,]  0.0003729919
[10,] -0.0010088890
[11,]  0.0009039057


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 1.1385, df1 = 2, df2 = 40, p-value = 0.3305


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 2.8955, df = 1, p-value = 0.08883



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.072797, df1 = 2, df2 = 40, p-value = 0.9299


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 2.8955, df = 1, p-value = 0.08883




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,]  0.070083862
 [2,]  0.025642767
 [3,] -0.082173365
 [4,]  0.001989872
 [5,]  0.040118317
 [6,] -0.007079365
 [7,] -0.016561868
 [8,]  0.005352092
 [9,]  0.006327168
[10,] -0.003117536
[11,] -0.002260731


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,] -1.896397e-03
 [3,] -2.102965e-03
 [4,]  1.604203e-03
 [5,]  8.947346e-04
 [6,] -8.859306e-04
 [7,] -2.758519e-04
 [8,]  4.229241e-04
 [9,]  6.092708e-05
[10,] -1.879797e-04
[11,] -8.110571e-07


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 1.7675, df1 = 2, df2 = 40, p-value = 0.1838


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2
```

```
data:  VAR object model
Chi-squared = 4.6109, df = 1, p-value = 0.03177



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.93047, df1 = 2, df2 = 40, p-value = 0.4027


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 4.6109, df = 1, p-value = 0.03177




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,]  0.0353448844
 [2,] -0.0042898988
 [3,] -0.0442086636
 [4,] -0.0046770498
 [5,]  0.0211154771
 [6,]  0.0074449585
 [7,] -0.0024867403
 [8,] -0.0040905107
 [9,] -0.0041066441
[10,]  0.0001877894
[11,]  0.0034310461


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.0000000000
 [2,]  0.0006978687
 [3,]  0.0086085751
 [4,]  0.0011413146
 [5,] -0.0057696640
 [6,] -0.0018899400
 [7,]  0.0015608904
 [8,]  0.0012174947
 [9,]  0.0005295759
[10,] -0.0002512570
[11,] -0.0007779936


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.14776, df1 = 2, df2 = 40, p-value = 0.8631


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 4.2637, df = 1, p-value = 0.03894



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.01028, df1 = 2, df2 = 40, p-value = 0.9898


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 4.2637, df = 1, p-value = 0.03894




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,] -0.0166348771
 [2,] -0.0150693559
 [3,] -0.0112602725
 [4,] -0.0055338618
 [5,] -0.0032846217
 [6,] -0.0026640571
 [7,] -0.0017415985
 [8,] -0.0009529771
 [9,] -0.0006238601
[10,] -0.0004516596
[11,] -0.0002824915


[[2]][[2]]
```

```
Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,] -9.621562e-05
 [3,]  9.823884e-04
 [4,]  5.159198e-04
 [5,]  3.018297e-05
 [6,]  8.688193e-05
 [7,]  1.400713e-04
 [8,]  6.085596e-05
 [9,]  1.689397e-05
[10,]  2.212801e-05
[11,]  1.979156e-05


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.54611, df1 = 2, df2 = 40, p-value = 0.5835


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.074809, df = 1, p-value = 0.7845



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.47375, df1 = 2, df2 = 40, p-value = 0.6261


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.074809, df = 1, p-value = 0.7845




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  5.797382e-04
 [2,]  1.343455e-03
 [3,]  3.692294e-03
 [4,]  9.516470e-04
 [5,] -4.850143e-04
 [6,] -3.676530e-04
 [7,] -9.911605e-05
 [8,]  1.887854e-05
 [9,]  3.627038e-05
[10,]  1.610929e-05
[11,]  1.164464e-07


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,] -9.042499e-03
 [3,] -4.699633e-03
 [4,]  3.895610e-04
 [5,]  1.067293e-03
 [6,]  4.499776e-04
 [7,]  3.735419e-05
 [8,] -8.477796e-05
 [9,] -5.839446e-05
[10,] -1.179485e-05
[11,]  7.029314e-06


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 5.1284, df1 = 2, df2 = 40, p-value = 0.01041


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.12946, df = 1, p-value = 0.719



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.79266, df1 = 2, df2 = 40, p-value = 0.4596
```

```
[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.12946, df = 1, p-value = 0.719




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -0.0053339711
 [2,] -0.0498020620
 [3,] -0.0524463653
 [4,]  0.0045881232
 [5,]  0.0167399007
 [6,]  0.0068667596
 [7,]  0.0033779845
 [8,] -0.0014675162
 [9,] -0.0034187092
[10,] -0.0010654484
[11,]  0.0003593281


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0023316368
 [3,]  0.0081684808
 [4,]  0.0025143218
 [5,] -0.0021888251
 [6,] -0.0006512846
 [7,] -0.0004462382
 [8,] -0.0003122734
 [9,]  0.0003493642
[10,]  0.0002475316
[11,] -0.0000109905


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.21367, df1 = 2, df2 = 40, p-value = 0.8085


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.25585, df = 1, p-value = 0.613



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.35738, df1 = 2, df2 = 40, p-value = 0.7017


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.25585, df = 1, p-value = 0.613




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -2.673040e-02
 [2,]  3.337111e-02
 [3,]  3.035267e-02
 [4,] -2.093324e-02
 [5,] -1.285846e-02
 [6,]  1.035943e-02
 [7,]  3.865490e-03
 [8,] -4.593211e-03
 [9,] -7.347455e-04
[10,]  1.865192e-03
[11,] -6.620248e-05


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,]  6.075678e-03
 [3,]  2.152135e-03
 [4,] -3.509197e-03
 [5,] -8.616035e-04
 [6,]  1.574180e-03
 [7,]  1.627621e-04
 [8,] -6.307831e-04
 [9,]  3.708014e-05
```

```
[10,]  2.308771e-04
[11,] -5.620002e-05


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 4.8775, df1 = 2, df2 = 40, p-value = 0.01272


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 7.7259, df = 1, p-value = 0.005444



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 6.2369, df1 = 2, df2 = 40, p-value = 0.004389


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 7.7259, df = 1, p-value = 0.005444




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,]  0.1568808987
 [2,]  0.1096710237
 [3,] -0.0160909739
 [4,] -0.0320966019
 [5,] -0.0483066420
 [6,] -0.0006760752
 [7,]  0.0074205709
 [8,]  0.0170643233
 [9,]  0.0031436859
[10,] -0.0013299935
[11,] -0.0055370094


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.0000000000
 [2,] -0.0200584223
 [3,] -0.0006715028
 [4,] -0.0017913163
 [5,]  0.0064833802
 [6,]  0.0011095398
 [7,]  0.0009692683
 [8,] -0.0018587104
 [9,] -0.0006550300
[10,] -0.0004537605
[11,]  0.0004829488


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.94092, df1 = 2, df2 = 40, p-value = 0.3987


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.034083, df = 1, p-value = 0.8535



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 5.4117, df1 = 2, df2 = 40, p-value = 0.008316


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.034083, df = 1, p-value = 0.8535




[[2]]
[[2]][[1]]
```

```
Impulse response coefficients
$y1
                 y2
 [1,]  0.0086598165
 [2,] -0.0179121171
 [3,] -0.0548028308
 [4,]  0.0705975624
 [5,] -0.0142205169
 [6,] -0.0242888245
 [7,]  0.0183683655
 [8,] -0.0044077187
 [9,]  0.0011436834
[10,] -0.0001509064
[11,] -0.0029021119


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,]  8.685913e-03
 [3,] -1.699990e-02
 [4,]  9.340407e-03
 [5,]  2.695466e-03
 [6,] -5.882327e-03
 [7,]  2.901571e-03
 [8,] -6.089616e-04
 [9,] -3.733559e-05
[10,]  5.639294e-04
[11,] -9.015934e-04


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 3.5364, df1 = 2, df2 = 40, p-value = 0.03853


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.69652, df = 1, p-value = 0.404



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.31297, df1 = 2, df2 = 40, p-value = 0.733


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.69652, df = 1, p-value = 0.404




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -2.979481e-02
 [2,] -8.041679e-02
 [3,]  6.958993e-02
 [4,]  1.489466e-02
 [5,] -4.733313e-02
 [6,]  2.593392e-02
 [7,] -7.061473e-05
 [8,] -1.136751e-02
 [9,]  1.193434e-02
[10,] -6.251137e-03
[11,] -1.120401e-03


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0404928689
 [3,]  0.0390175103
 [4,] -0.0013156930
 [5,] -0.0216092944
 [6,]  0.0177062068
 [7,] -0.0046005032
 [8,] -0.0045325780
 [9,]  0.0071139371
[10,] -0.0047474889
[11,]  0.0004846754


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.22556, df1 = 2, df2 = 40, p-value = 0.7991
```

```
[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.50844, df = 1, p-value = 0.4758



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.17163, df1 = 2, df2 = 40, p-value = 0.8429


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.50844, df = 1, p-value = 0.4758




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -1.153313e-02
 [2,]  4.583665e-03
 [3,]  8.658650e-03
 [4,] -5.419306e-03
 [5,] -1.000543e-03
 [6,]  1.287946e-03
 [7,] -8.339275e-04
 [8,]  1.008723e-03
 [9,] -7.294425e-05
[10,] -7.157121e-04
[11,]  4.195769e-04


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0185920945
 [3,]  0.0399390998
 [4,] -0.0102960390
 [5,] -0.0161619194
 [6,]  0.0114832251
 [7,] -0.0025085011
 [8,] -0.0004700521
 [9,]  0.0030150131
[10,] -0.0033411278
[11,]  0.0005589427


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.1286, df1 = 2, df2 = 40, p-value = 0.8797


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 7.5113e-05, df = 1, p-value = 0.9931



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.30739, df1 = 2, df2 = 40, p-value = 0.7371


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 7.5113e-05, df = 1, p-value = 0.9931




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -6.390028e-05
 [2,]  2.960940e-03
 [3,] -4.669622e-04
 [4,]  2.642040e-04
 [5,]  9.161452e-04
 [6,] -3.681112e-04
 [7,]  2.300059e-04
 [8,]  2.348515e-04
 [9,] -1.698651e-04
```

```
[10,]  1.325537e-04
[11,]  3.807201e-05


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,]  0.0412697681
 [3,] -0.0494956281
 [4,]  0.0129479941
 [5,]  0.0080908601
 [6,] -0.0180861459
 [7,]  0.0092642589
 [8,] -0.0005078221
 [9,] -0.0055126587
[10,]  0.0044673910
[11,] -0.0015670057


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.050906, df1 = 2, df2 = 40, p-value = 0.9504


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.044612, df = 1, p-value = 0.8327



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.072732, df1 = 2, df2 = 40, p-value = 0.93


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.044612, df = 1, p-value = 0.8327




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -4.583256e-04
 [2,] -5.714054e-04
 [3,] -7.021123e-04
 [4,]  1.484339e-04
 [5,] -4.241339e-05
 [6,] -1.024306e-04
 [7,]  1.174048e-04
 [8,] -3.969554e-05
 [9,] -1.991119e-05
[10,]  4.153039e-05
[11,] -2.603162e-05


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0139426834
 [3,] -0.0099348656
 [4,]  0.0040525221
 [5,] -0.0028156846
 [6,] -0.0006206693
 [7,]  0.0020846055
 [8,] -0.0013677407
 [9,]  0.0002263545
[10,]  0.0005636796
[11,] -0.0006150914


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.33956, df1 = 2, df2 = 40, p-value = 0.7141


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.59666, df = 1, p-value = 0.4399



[[1]][[2]]
[[1]][[2]]$Granger
```

```
        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.035971, df1 = 2, df2 = 40, p-value = 0.9647


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.59666, df = 1, p-value = 0.4399




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  0.0139783828
 [2,]  0.0183492318
 [3,]  0.0131141675
 [4,] -0.0066119390
 [5,] -0.0012093949
 [6,]  0.0008218609
 [7,] -0.0022211732
 [8,]  0.0011447457
 [9,]  0.0004259822
[10,] -0.0006996187
[11,]  0.0004840044


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0137164602
 [3,]  0.0155473312
 [4,] -0.0011613710
 [5,] -0.0045948213
 [6,]  0.0047532801
 [7,] -0.0023214409
 [8,] -0.0007468103
 [9,]  0.0017767952
[10,] -0.0011401865
[11,]  0.0001259634


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.84534, df1 = 2, df2 = 40, p-value = 0.4369


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 1.2149, df = 1, p-value = 0.2704



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.6856, df1 = 2, df2 = 40, p-value = 0.1982


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 1.2149, df = 1, p-value = 0.2704




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -0.0576095916
 [2,]  0.0484212703
 [3,] -0.0246275754
 [4,] -0.0024809321
 [5,]  0.0174881800
 [6,] -0.0138301831
 [7,]  0.0025308642
 [8,]  0.0044927840
 [9,] -0.0049101549
[10,]  0.0021241736
[11,]  0.0004931497


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.000000000
 [2,]  0.015312928
 [3,] -0.107907951
 [4,]  0.076403574
```

```
 [5,]  0.013749969
 [6,] -0.045013008
 [7,]  0.024794336
 [8,] -0.001306060
 [9,] -0.008927528
[10,]  0.009125187
[11,] -0.004163034


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.60425, df1 = 2, df2 = 40, p-value = 0.5514


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.3928, df = 1, p-value = 0.5308



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.26815, df1 = 2, df2 = 40, p-value = 0.7662


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.3928, df = 1, p-value = 0.5308




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,] -0.035395219
 [2,] -0.035406384
 [3,]  0.049130981
 [4,] -0.025511786
 [5,] -0.003153488
 [6,]  0.016839845
 [7,] -0.013869697
 [8,]  0.003648410
 [9,]  0.004193285
[10,] -0.005873720
[11,]  0.003148961


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.000000000
 [2,] -0.038591069
 [3,]  0.016259033
 [4,]  0.005960022
 [5,] -0.014189631
 [6,]  0.009888841
 [7,] -0.001411534
 [8,] -0.004091282
 [9,]  0.004558268
[10,] -0.001986784
[11,] -0.000648826


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.090058, df1 = 2, df2 = 40, p-value = 0.9141


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 3.9334, df = 1, p-value = 0.04734



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.29394, df1 = 2, df2 = 40, p-value = 0.7469


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 3.9334, df = 1, p-value = 0.04734
```

```
[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
               y2
 [1,] -0.105085570
 [2,]  0.138705164
 [3,] -0.093923709
 [4,]  0.012295785
 [5,]  0.052029056
 [6,] -0.068746408
 [7,]  0.043322430
 [8,] -0.003398047
 [9,] -0.024187870
[10,]  0.028629058
[11,] -0.015893069


[[2]][[2]]

Impulse response coefficients
$y2
               y1
 [1,]  0.000000000
 [2,] -0.039476583
 [3,]  0.053105421
 [4,] -0.022429714
 [5,] -0.024249220
 [6,]  0.049655807
 [7,] -0.039834737
 [8,]  0.008707723
 [9,]  0.019072704
[10,] -0.027675898
[11,]  0.017777564


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 2.3354, df1 = 2, df2 = 40, p-value = 0.1098


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.16208, df = 1, p-value = 0.6873



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.19329, df1 = 2, df2 = 40, p-value = 0.825


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.16208, df = 1, p-value = 0.6873




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,]  0.0058887794
 [2,] -0.0219879796
 [3,] -0.0316795457
 [4,]  0.0106731675
 [5,]  0.0223303238
 [6,] -0.0009330474
 [7,] -0.0112450014
 [8,] -0.0025839101
 [9,]  0.0043678784
[10,]  0.0026176941
[11,] -0.0011053035


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.0000000000
 [2,]  0.0197859324
 [3,]  0.0085047007
 [4,] -0.0122471668
 [5,] -0.0076412625
 [6,]  0.0045614341
 [7,]  0.0048436663
 [8,] -0.0007325248
 [9,] -0.0024466784
[10,] -0.0004955515
[11,]  0.0009701684


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger
```

```
        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.07351, df1 = 2, df2 = 40, p-value = 0.9293


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 7.6804, df = 1, p-value = 0.005582



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.1447, df1 = 2, df2 = 40, p-value = 0.3285


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 7.6804, df = 1, p-value = 0.005582




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -0.0244088741
 [2,] -0.0142906696
 [3,] -0.0092152338
 [4,] -0.0070896362
 [5,] -0.0044715720
 [6,] -0.0026449434
 [7,] -0.0018247648
 [8,] -0.0012439608
 [9,] -0.0007704212
[10,] -0.0004953600
[11,] -0.0003357527


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,] 0.0000000000
 [2,] 0.0156419774
 [3,] 0.0357493974
 [4,] 0.0160592386
 [5,] 0.0050410905
 [6,] 0.0065304115
 [7,] 0.0050959152
 [8,] 0.0022213149
 [9,] 0.0014471524
[10,] 0.0012549739
[11,] 0.0007509063


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.12298, df1 = 2, df2 = 40, p-value = 0.8846


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 1.1721, df = 1, p-value = 0.279



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 4.2907, df1 = 2, df2 = 40, p-value = 0.0205


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 1.1721, df = 1, p-value = 0.279




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  2.393442e-03
 [2,]  6.949787e-04
 [3,] -3.985533e-04
 [4,]  8.299318e-06
```

```
 [5,]  1.357457e-04
 [6,] -4.948525e-05
 [7,] -4.958725e-05
 [8,]  1.614628e-05
 [9,]  8.299980e-06
[10,] -7.876350e-06
[11,] -1.063969e-06


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.1231163323
 [3,] -0.0565399243
 [4,]  0.0115433282
 [5,]  0.0018574882
 [6,] -0.0066879239
 [7,]  0.0014051083
 [8,]  0.0028188713
 [9,] -0.0003579063
[10,] -0.0005012625
[11,]  0.0003207122


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 5.0203, df1 = 2, df2 = 40, p-value = 0.01134


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.00035453, df = 1, p-value = 0.985



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.43562, df1 = 2, df2 = 40, p-value = 0.6499


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.00035453, df = 1, p-value = 0.985




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  0.0002794416
 [2,] -0.0480123878
 [3,] -0.0219359086
 [4,]  0.0109919220
 [5,]  0.0099322377
 [6,]  0.0015918491
 [7,] -0.0005910777
 [8,] -0.0008482821
 [9,] -0.0008282068
[10,] -0.0002262998
[11,]  0.0002198682


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0127275063
 [3,]  0.0297504465
 [4,]  0.0203733094
 [5,] -0.0048853809
 [6,] -0.0071946614
 [7,] -0.0016102574
 [8,]  0.0001609362
 [9,]  0.0004246063
[10,]  0.0005764942
[11,]  0.0002479218


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.81114, df1 = 2, df2 = 40, p-value = 0.4515


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.36905, df = 1, p-value = 0.5435
```

```
[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 4.4455, df1 = 2, df2 = 40, p-value = 0.01806


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.36905, df = 1, p-value = 0.5435




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -0.0312731464
 [2,] -0.0745063119
 [3,]  0.0047529714
 [4,]  0.0228763228
 [5,] -0.0032719392
 [6,] -0.0074513557
 [7,]  0.0015614130
 [8,]  0.0023830228
 [9,] -0.0006726943
[10,] -0.0007513107
[11,]  0.0002721808


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,]  0.1106834177
 [3,] -0.0190417278
 [4,] -0.0334787202
 [5,]  0.0082533922
 [6,]  0.0106748639
 [7,] -0.0034369414
 [8,] -0.0033375416
 [9,]  0.0013585602
[10,]  0.0010256501
[11,] -0.0005182996


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.07748, df1 = 2, df2 = 40, p-value = 0.9256


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 3.4211, df = 1, p-value = 0.06437



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.12421, df1 = 2, df2 = 40, p-value = 0.8835


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 3.4211, df = 1, p-value = 0.06437




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  1.141128e-01
 [2,] -2.427940e-03
 [3,]  2.105769e-02
 [4,] -4.038503e-03
 [5,] -8.145532e-03
 [6,]  2.421846e-03
 [7,]  1.932755e-03
 [8,] -9.307473e-04
 [9,] -3.635543e-04
[10,]  2.954502e-04
[11,]  4.761636e-05


[[2]][[2]]

Impulse response coefficients
$y2
```

```
                 y1
 [1,]  0.000000e+00
 [2,] -1.073367e-02
 [3,] -1.779275e-02
 [4,]  6.382453e-03
 [5,]  4.871147e-03
 [6,] -2.460116e-03
 [7,] -9.488868e-04
 [8,]  7.822027e-04
 [9,]  1.258858e-04
[10,] -2.199111e-04
[11,]  1.904798e-06


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 2.3952, df1 = 2, df2 = 40, p-value = 0.1041


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.22935, df = 1, p-value = 0.632



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 6.843, df1 = 2, df2 = 40, p-value = 0.00278


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.22935, df = 1, p-value = 0.632




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  0.0211853680
 [2,] -0.0006971279
 [3,] -0.0933895582
 [4,]  0.1042061218
 [5,] -0.0311350939
 [6,] -0.0211703212
 [7,]  0.0333997817
 [8,] -0.0393332115
 [9,]  0.0367291081
[10,] -0.0135252902
[11,] -0.0136358497


[[2]][[2]]

Impulse response coefficients
$y2
               y1
 [1,]  0.00000000
 [2,]  0.10401463
 [3,] -0.05820516
 [4,] -0.04664983
 [5,]  0.05919241
 [6,] -0.02507554
 [7,]  0.01625165
 [8,] -0.01047758
 [9,] -0.01328261
[10,]  0.02835429
[11,] -0.02006116


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 4.4736, df1 = 2, df2 = 40, p-value = 0.01765


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.90622, df = 1, p-value = 0.3411



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.0147, df1 = 2, df2 = 40, p-value = 0.3716


[[1]][[2]]$Instant
```

```
        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.90622, df = 1, p-value = 0.3411




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -5.976553e-03
 [2,] -1.776267e-03
 [3,] -1.947377e-02
 [4,] -1.718498e-02
 [5,] -4.195423e-03
 [6,]  3.604792e-03
 [7,] -5.483062e-06
 [8,] -5.624350e-03
 [9,] -5.041408e-03
[10,] -3.762738e-04
[11,]  1.911192e-03


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.000000000
 [2,]  0.008844547
 [3,] -0.011991923
 [4,] -0.016244982
 [5,] -0.005395408
 [6,]  0.004825091
 [7,]  0.003144898
 [8,] -0.003649624
 [9,] -0.005256667
[10,] -0.001102018
[11,]  0.002215679


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 3.4344, df1 = 2, df2 = 40, p-value = 0.04203


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.97468, df = 1, p-value = 0.3235



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.6042, df1 = 2, df2 = 40, p-value = 0.2137


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.97468, df = 1, p-value = 0.3235




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  0.0018870996
 [2,] -0.0024681227
 [3,]  0.0007164136
 [4,]  0.0027903109
 [5,]  0.0020681860
 [6,] -0.0001417288
 [7,] -0.0012170059
 [8,] -0.0005580130
 [9,]  0.0005174249
[10,]  0.0007436314
[11,]  0.0001650703


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0081235331
 [3,]  0.0210427841
 [4,]  0.0268253972
 [5,]  0.0099050389
 [6,] -0.0078520945
 [7,] -0.0094517732
 [8,]  0.0002788632
 [9,]  0.0070875121
[10,]  0.0047851581
[11,] -0.0013291547
```

```
[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.57076, df1 = 2, df2 = 40, p-value = 0.5696


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 1.4093, df = 1, p-value = 0.2352



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 2.452, df1 = 2, df2 = 40, p-value = 0.09897


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 1.4093, df = 1, p-value = 0.2352




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  0.0215946289
 [2,] -0.0013161168
 [3,] -0.0148350383
 [4,] -0.0052949044
 [5,]  0.0048789527
 [6,]  0.0035911326
 [7,] -0.0014087358
 [8,] -0.0020949238
 [9,]  0.0001041116
[10,]  0.0010243458
[11,]  0.0002284921


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,]  0.0106113712
 [3,] -0.0242627326
 [4,] -0.0314835342
 [5,] -0.0068603684
 [6,]  0.0090581312
 [7,]  0.0042945940
 [8,] -0.0035501070
 [9,] -0.0030858753
[10,]  0.0008458853
[11,]  0.0017008659


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.4473, df1 = 2, df2 = 40, p-value = 0.6425


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.76627, df = 1, p-value = 0.3814



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.34189, df1 = 2, df2 = 40, p-value = 0.7125


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.76627, df = 1, p-value = 0.3814




[[2]]
[[2]][[1]]

Impulse response coefficients
```

```
$y1
                 y2
 [1,] -4.620027e-02
 [2,]  4.306575e-02
 [3,]  3.248012e-02
 [4,] -1.590631e-02
 [5,] -1.880688e-02
 [6,]  8.229412e-04
 [7,]  8.048730e-03
 [8,]  2.741067e-03
 [9,] -2.263436e-03
[10,] -2.109499e-03
[11,]  8.782955e-05


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,] -3.062323e-03
 [3,] -1.526315e-02
 [4,] -3.117116e-03
 [5,]  7.698952e-03
 [6,]  4.008399e-03
 [7,] -2.060072e-03
 [8,] -2.477708e-03
 [9,] -7.911246e-05
[10,]  1.022710e-03
[11,]  4.543459e-04


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.22049, df1 = 2, df2 = 40, p-value = 0.8031


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.0072128, df = 1, p-value = 0.9323



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 4.9053, df1 = 2, df2 = 40, p-value = 0.01244


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.0072128, df = 1, p-value = 0.9323




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -0.0048491853
 [2,] -0.0059185073
 [3,]  0.0315454235
 [4,]  0.0087346872
 [5,] -0.0102136254
 [6,] -0.0074972984
 [7,]  0.0008359199
 [8,]  0.0035575404
 [9,]  0.0012641122
[10,] -0.0009572949
[11,] -0.0009729775


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0441398354
 [3,] -0.0286590787
 [4,]  0.0119928874
 [5,]  0.0168579529
 [6,]  0.0021561293
 [7,] -0.0061026227
 [8,] -0.0036817979
 [9,]  0.0009469562
[10,]  0.0020057898
[11,]  0.0004970752


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.81602, df1 = 2, df2 = 40, p-value = 0.4494


[[1]][[1]]$Instant
```

```
        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.065022, df = 1, p-value = 0.7987



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.13476, df1 = 2, df2 = 40, p-value = 0.8743


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.065022, df = 1, p-value = 0.7987




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,]  0.0120371978
 [2,] -0.0432871493
 [3,] -0.0124419454
 [4,]  0.0368542994
 [5,] -0.0119905297
 [6,] -0.0001735252
 [7,]  0.0010610820
 [8,] -0.0074696293
 [9,]  0.0087669848
[10,] -0.0022224948
[11,] -0.0023870677


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,]  0.0067383716
 [3,] -0.0038387341
 [4,] -0.0015660218
 [5,]  0.0019654450
 [6,] -0.0012553818
 [7,]  0.0011891386
 [8,] -0.0002421695
 [9,] -0.0008084550
[10,]  0.0008283135
[11,] -0.0003728871


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 6.603, df1 = 2, df2 = 40, p-value = 0.003327


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 3.5786, df = 1, p-value = 0.05853



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 2.6733, df1 = 2, df2 = 40, p-value = 0.08134


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 3.5786, df = 1, p-value = 0.05853




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -3.436351e-03
 [2,] -4.883403e-03
 [3,] -4.619349e-03
 [4,] -2.880491e-03
 [5,] -1.415285e-03
 [6,] -4.612444e-04
 [7,] -8.343113e-06
 [8,]  1.393631e-04
 [9,]  1.388870e-04
[10,]  9.215656e-05
[11,]  4.631360e-05
```

```
[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.0000000000
 [2,]  0.0192658739
 [3,]  0.0126107842
 [4,]  0.0081368548
 [5,]  0.0034008973
 [6,]  0.0009335414
 [7,] -0.0002169094
 [8,] -0.0004919044
 [9,] -0.0004187496
[10,] -0.0002531690
[11,] -0.0001160284


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 19.141, df1 = 2, df2 = 40, p-value = 1.472e-06


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.0037974, df = 1, p-value = 0.9509



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.88834, df1 = 2, df2 = 40, p-value = 0.4193


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.0037974, df = 1, p-value = 0.9509




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,]  0.0006566363
 [2,]  0.0715030941
 [3,]  0.0487583250
 [4,]  0.0102634485
 [5,] -0.0043352292
 [6,] -0.0064779944
 [7,] -0.0058755823
 [8,] -0.0040515712
 [9,] -0.0018230108
[10,] -0.0002302849
[11,]  0.0004732102


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.000000e+00
 [2,]  8.200878e-03
 [3,]  7.835571e-03
 [4,]  3.596718e-03
 [5,]  7.915618e-04
 [6,] -3.607974e-04
 [7,] -7.221566e-04
 [8,] -6.673396e-04
 [9,] -4.168480e-04
[10,] -1.666428e-04
[11,] -9.171496e-06


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.54756, df1 = 2, df2 = 40, p-value = 0.5826


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.13517, df = 1, p-value = 0.7131



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1
```

```
data:  VAR object model
F-Test = 7.8382, df1 = 2, df2 = 40, p-value = 0.001342


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.13517, df = 1, p-value = 0.7131




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,] -1.907485e-02
 [2,]  5.873935e-02
 [3,] -9.543727e-03
 [4,] -6.444629e-03
 [5,]  5.408614e-04
 [6,]  1.582902e-03
 [7,] -5.398579e-06
 [8,] -1.833858e-04
 [9,]  4.698496e-05
[10,]  7.969486e-05
[11,]  2.760679e-05


[[2]][[2]]

Impulse response coefficients
$y2
               y1
 [1,]  0.000000000
 [2,] -0.023115656
 [3,] -0.017968780
 [4,] -0.009559617
 [5,] -0.006923813
 [6,] -0.005916916
 [7,] -0.004533223
 [8,] -0.003294897
 [9,] -0.002464339
[10,] -0.001877414
[11,] -0.001418543


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.36644, df1 = 2, df2 = 40, p-value = 0.6955


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 2.6481, df = 1, p-value = 0.1037



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.01038, df1 = 2, df2 = 40, p-value = 0.9897


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 2.6481, df = 1, p-value = 0.1037




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
               y2
 [1,] -0.097336235
 [2,] -0.008698907
 [3,]  0.038784461
 [4,]  0.026631719
 [5,]  0.019578834
 [6,]  0.012763426
 [7,]  0.008177499
 [8,]  0.005174288
 [9,]  0.003255560
[10,]  0.002043684
[11,]  0.001281386


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.000000e+00
 [2,] -1.320523e-04
 [3,] -1.234045e-03
 [4,] -7.857208e-04
 [5,] -5.574709e-04
 [6,] -3.594645e-04
```

```
 [7,] -2.289556e-04
 [8,] -1.445307e-04
 [9,] -9.083167e-05
[10,] -5.699009e-05
[11,] -3.572410e-05


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 3.497, df1 = 2, df2 = 40, p-value = 0.03984


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 1.7003, df = 1, p-value = 0.1922



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 3.7178, df1 = 2, df2 = 40, p-value = 0.03304


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 1.7003, df = 1, p-value = 0.1922




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
               y2
 [1,]  0.05692722
 [2,] -0.12937773
 [3,]  0.17072695
 [4,] -0.04025403
 [5,] -0.01558308
 [6,]  0.07943264
 [7,] -0.07062798
 [8,]  0.03278208
 [9,]  0.00946108
[10,] -0.03653585
[11,]  0.03560880


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0136444807
 [3,] -0.0009508779
 [4,] -0.0021786468
 [5,] -0.0040218076
 [6,]  0.0032444002
 [7,] -0.0018527659
 [8,]  0.0001741941
 [9,]  0.0015748676
[10,] -0.0016176405
[11,]  0.0010864211


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 9.5503, df1 = 2, df2 = 40, p-value = 0.0004068


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 4.4892, df = 1, p-value = 0.03411



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.7433, df1 = 2, df2 = 40, p-value = 0.188


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 4.4892, df = 1, p-value = 0.03411
```

```
[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -0.030301622
 [2,] -0.061560380
 [3,]  0.020799773
 [4,]  0.035835506
 [5,]  0.027342575
 [6,]  0.022990724
 [7,]  0.006806457
 [8,] -0.008002935
 [9,] -0.013446002
[10,] -0.012670379
[11,] -0.007515900


[[2]][[2]]

Impulse response coefficients
$y2
                  y1
 [1,]  0.0000000000
 [2,] -0.0021881730
 [3,] -0.0033383389
 [4,] -0.0020321631
 [5,] -0.0006421774
 [6,]  0.0004735426
 [7,]  0.0011848241
 [8,]  0.0011899255
 [9,]  0.0007262350
[10,]  0.0001478107
[11,] -0.0003120188


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.0037757, df1 = 2, df2 = 40, p-value = 0.9962


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.68696, df = 1, p-value = 0.4072



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 4.6537, df1 = 2, df2 = 40, p-value = 0.01524


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.68696, df = 1, p-value = 0.4072




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                  y2
 [1,] -0.0446331304
 [2,] -0.0011793739
 [3,]  0.0040999918
 [4,] -0.0024040258
 [5,] -0.0026171945
 [6,] -0.0009093545
 [7,] -0.0004818500
 [8,] -0.0005132834
 [9,] -0.0003952204
[10,] -0.0002506671
[11,] -0.0001728649


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,] 0.0000000000
 [2,] 0.0043424960
 [3,] 0.0071086811
 [4,] 0.0040954722
 [5,] 0.0021994713
 [6,] 0.0017350860
 [7,] 0.0013629846
 [8,] 0.0009394510
 [9,] 0.0006452158
[10,] 0.0004643939
[11,] 0.0003345525


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2
```

```
data:  VAR object model
F-Test = 1.0529, df1 = 2, df2 = 40, p-value = 0.3584


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 2.5449, df = 1, p-value = 0.1106



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.33, df1 = 2, df2 = 40, p-value = 0.2759


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 2.5449, df = 1, p-value = 0.1106




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,]  0.092206964
 [2,] -0.091606995
 [3,] -0.048588512
 [4,] -0.029674907
 [5,]  0.004294772
 [6,]  0.012731573
 [7,]  0.010744213
 [8,]  0.003535347
 [9,] -0.001259841
[10,] -0.002681108
[11,] -0.001796998


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,]  1.941366e-04
 [3,]  3.614636e-03
 [4,]  2.253150e-03
 [5,]  8.200843e-04
 [6,] -3.674969e-04
 [7,] -6.210375e-04
 [8,] -4.091188e-04
 [9,] -8.920744e-05
[10,]  9.258246e-05
[11,]  1.203135e-04


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 1.23, df1 = 2, df2 = 40, p-value = 0.3031


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.0045908, df = 1, p-value = 0.946



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 0.39508, df1 = 2, df2 = 40, p-value = 0.6762


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.0045908, df = 1, p-value = 0.946




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,]  0.003135304
 [2,] -0.082099442
 [3,]  0.017303506
 [4,] -0.004915302
 [5,] -0.022794047
 [6,]  0.028507410
```

```
 [7,] -0.017964180
 [8,]  0.002282935
 [9,]  0.011035512
[10,] -0.015107835
[11,]  0.010659662


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,]  1.916817e-03
 [3,]  6.359499e-04
 [4,] -4.138973e-04
 [5,]  7.600240e-04
 [6,] -4.573573e-04
 [7,]  2.745819e-06
 [8,]  2.978184e-04
 [9,] -3.959660e-04
[10,]  2.603320e-04
[11,] -3.410048e-05


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.58518, df1 = 2, df2 = 40, p-value = 0.5617


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.040087, df = 1, p-value = 0.8413



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 11.063, df1 = 2, df2 = 40, p-value = 0.0001499


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.040087, df = 1, p-value = 0.8413




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -1.035021e-02
 [2,] -3.464042e-02
 [3,]  1.882703e-02
 [4,]  2.467958e-02
 [5,]  2.855129e-04
 [6,]  7.330690e-04
 [7,]  3.233094e-03
 [8,] -2.870152e-03
 [9,] -3.128941e-03
[10,] -1.533883e-05
[11,]  1.367073e-05


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0003990350
 [3,] -0.0638406995
 [4,] -0.0405678119
 [5,]  0.0023388751
 [6,]  0.0028518889
 [7,]  0.0022699268
 [8,]  0.0084934523
 [9,]  0.0047164793
[10,] -0.0007061074
[11,] -0.0007500051


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 4.2859, df1 = 2, df2 = 40, p-value = 0.02058


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 1.6725, df = 1, p-value = 0.1959
```

```
[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.554, df1 = 2, df2 = 40, p-value = 0.2239


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 1.6725, df = 1, p-value = 0.1959




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -0.0645597949
 [2,] -0.0272612070
 [3,]  0.1227786054
 [4,]  0.0669878166
 [5,]  0.0314894809
 [6,] -0.0193043135
 [7,] -0.0199559070
 [8,] -0.0133848302
 [9,]  0.0006943244
[10,]  0.0045755677
[11,]  0.0044483816


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
 [2,] -2.808926e-02
 [3,] -6.887717e-03
 [4,] -2.753397e-03
 [5,]  5.971615e-03
 [6,]  3.064552e-03
 [7,]  1.659313e-03
 [8,] -9.437486e-04
 [9,] -9.241639e-04
[10,] -6.719455e-04
[11,]  3.141335e-05


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 4.1557, df1 = 2, df2 = 40, p-value = 0.02292


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.14797, df = 1, p-value = 0.7005



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.2625, df1 = 2, df2 = 40, p-value = 0.294


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.14797, df = 1, p-value = 0.7005




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,] -0.015897912
 [2,]  0.147432315
 [3,] -0.144641097
 [4,]  0.046265389
 [5,]  0.017016557
 [6,] -0.059797930
 [7,]  0.063450346
 [8,] -0.031038984
 [9,] -0.003656091
[10,]  0.025321805
[11,] -0.028745615


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.000000e+00
```

```
 [2,]  1.098137e-02
 [3,] -1.271698e-02
 [4,]  4.557000e-03
 [5,]  8.090224e-04
 [6,] -4.548403e-03
 [7,]  5.367884e-03
 [8,] -2.910650e-03
 [9,]  1.318016e-05
[10,]  1.914223e-03
[11,] -2.392381e-03


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.63316, df1 = 2, df2 = 40, p-value = 0.5361


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.59555, df = 1, p-value = 0.4403



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 1.0202, df1 = 2, df2 = 40, p-value = 0.3697


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.59555, df = 1, p-value = 0.4403




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,]  0.0436973131
 [2,]  0.0494480612
 [3,]  0.0350570124
 [4,] -0.0150019398
 [5,] -0.0062602010
 [6,]  0.0064019215
 [7,]  0.0005124686
 [8,] -0.0021392317
 [9,]  0.0003385100
[10,]  0.0005972814
[11,] -0.0002465641


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.0000000000
 [2,]  0.0765903961
 [3,]  0.0260430988
 [4,] -0.0238644742
 [5,] -0.0016963421
 [6,]  0.0080840360
 [7,] -0.0013313112
 [8,] -0.0022413601
 [9,]  0.0009450773
[10,]  0.0004878071
[11,] -0.0004127437


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

	Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 1.6971, df1 = 2, df2 = 40, p-value = 0.1961


[[1]][[1]]$Instant

	H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.15945, df = 1, p-value = 0.6897



[[1]][[2]]
[[1]][[2]]$Granger

	Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 2.2174, df1 = 2, df2 = 40, p-value = 0.1221


[[1]][[2]]$Instant

	H0: No instantaneous causality between: y2 and y1
```

```
data:  VAR object model
Chi-squared = 0.15945, df = 1, p-value = 0.6897




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                y2
 [1,] -0.018159119
 [2,]  0.045711993
 [3,]  0.040821109
 [4,] -0.073999227
 [5,]  0.035983029
 [6,] -0.003276566
 [7,] -0.013012096
 [8,]  0.024414522
 [9,] -0.023673095
[10,]  0.010325598
[11,]  0.003860160


[[2]][[2]]

Impulse response coefficients
$y2
                 y1
 [1,]  0.0000000000
 [2,] -0.0687494005
 [3,] -0.0208199587
 [4,]  0.0769429415
 [5,] -0.0432415674
 [6,]  0.0083680943
 [7,]  0.0073442407
 [8,] -0.0210247875
 [9,]  0.0249378423
[10,] -0.0139378422
[11,] -0.0006391833


[[1]]
[[1]][[1]]
[[1]][[1]]$Granger

        Granger causality H0: y1 do not Granger-cause y2

data:  VAR object model
F-Test = 0.033704, df1 = 2, df2 = 40, p-value = 0.9669


[[1]][[1]]$Instant

        H0: No instantaneous causality between: y1 and y2

data:  VAR object model
Chi-squared = 0.24038, df = 1, p-value = 0.6239



[[1]][[2]]
[[1]][[2]]$Granger

        Granger causality H0: y2 do not Granger-cause y1

data:  VAR object model
F-Test = 2.4985, df1 = 2, df2 = 40, p-value = 0.09496


[[1]][[2]]$Instant

        H0: No instantaneous causality between: y2 and y1

data:  VAR object model
Chi-squared = 0.24038, df = 1, p-value = 0.6239




[[2]]
[[2]][[1]]

Impulse response coefficients
$y1
                 y2
 [1,] -2.411141e-02
 [2,]  2.379493e-02
 [3,]  1.662515e-03
 [4,] -1.498251e-02
 [5,]  1.584177e-02
 [6,] -8.669036e-03
 [7,] -3.410830e-04
 [8,]  6.040227e-03
 [9,] -6.728445e-03
[10,]  3.814677e-03
[11,] -1.340125e-05


[[2]][[2]]

Impulse response coefficients
$y2
                y1
 [1,]  0.000000000
 [2,]  0.098766309
 [3,] -0.080180938
 [4,]  0.028235958
 [5,]  0.017897705
 [6,] -0.039271788
 [7,]  0.033603223
 [8,] -0.013104072
 [9,] -0.006777444
[10,]  0.016325095
[11,] -0.014381143
```

Panel VAPCR-SPDE Models

In [7]:

```
# パネルデータの生成
# Generating panel data
index <- adjusted[, 1:2] %>%
  apply(2, as.character) %>%
  as.data.frame

# Recover Memory
rm(adjusted)

panel <- bind_cols(index, relation) %>%
  plm::pdata.frame(index = c("id", "time")) %>%
  print

# 要約統計量を求める。
# Find summary statistics.
panel %>%
  summary %>%
  print

# モデルの形成
# Model formation
model <- pvargmm(dependent_vars = c("Y1", "Y2", "Y3","Y4", "Y5", "Y6", "Y7", "Y8", "Y9", "Y10",  "Y11"),
                 predet_vars = c("Y3", "Y10",  "Y11"),
                 exog_vars = c("Y1", "Y2"),
                 lags = 1,
                 transformation = c("fod"),
                 data = panel,
                 panel_identifier =  c("id", "time"),
                 steps = c("twostep"),
                 pca_instruments = T,
                 pca_eigenvalue = 1,
                 system_instruments = T,
                 system_constant = T,
                 max_instr_dependent_vars = 11L,
                 max_instr_predet_vars = 3L,
                 min_instr_dependent_vars = 1L,
                 min_instr_predet_vars = 1L,
                 collapse = F,
                 progressbar = F
) %>%
  suppressWarnings

# 詳細結果の目視確認
# Visual confirmation of detailed results
model %>%
  summary %>%
  print

# P-value
model %>%
  pvalue %>%
  print

# 主成分回偏帰係数
# Principal Component Regression Coefficient
coefficient <- model %>%
  coef %>%
  print

# モデルの標準誤差
# Standard Error of Model
SE <- model %>%
  se %>%
  print

# 主成分標準偏回帰係数
# SPDE based on Standard Partial Regression Coefficient
SE_coefficient <- coefficient / SE %>%
  apply(2, as.numeric) %>%
  as.data.frame %>%
  print

# 確率偏微分方程式(絶対値)
# SPDE (abs)
SPDE <- SE_coefficient %>%
  abs
  as.data.frame %>%
  print
```

```
        id time           Y1            Y2   Y3          Y4            Y5
0-1987   0 1987  0.046607215 -0.0002078956  0.0  0.14329221  0.1707078336
0-1988   0 1988  0.054685886  0.0659408662  0.0 -0.27232247  0.1875246946
0-1989   0 1989  0.034524371  0.0250528266  0.0  0.19834206  0.0005499123
0-1991   0 1991  0.014394372  0.0108691005 -0.5 -0.15698568  0.1077704118
0-1992   0 1992  0.008714600  0.0088384495  0.5 -0.03704127  0.0555237346
0-1993   0 1993  0.010772713  0.0018245193  0.0 -0.15539469  0.1027742980
0-1994   0 1994  0.034959773  0.0388160427  0.0 -0.02806837  0.0898896168
0-1995   0 1995  0.031159245  0.0255089921 -0.5 -0.01487016  0.0913040437
0-1996   0 1996  0.015857216  0.0017373256  0.5  0.19217123 -0.1259988250
0-1997   0 1997  0.007429288 -0.0068458719  0.0 -0.01512484 -0.0896433402
0-1998   0 1998 -0.013352105 -0.0308981561  0.0 -0.33871590 -0.0915822665
0-1999   0 1999  0.024479115  0.0199589931 -0.5  0.34363431  0.1051332959
0-2000   0 2000  0.010736315  0.0051233463  0.5  0.45901574  0.0628943640
0-2002   0 2002  0.014477534  0.0245535667  0.5  0.03522143 -0.0377329263
0-2008   0 2008 -0.072976198 -0.0535455057  0.5  0.23562571  0.1064363396
0-2009   0 2009 -0.018964601 -0.0709879183  0.0 -0.38749772  0.0376843968
```

```
0-2011  0 2011 -0.027442840  0.0337387012  0.0  0.17035756  0.0914818714
0-2012  0 2012 -0.012998704  0.0571105641  0.0  0.01671820  0.0146306523
0-2013  0 2013 -0.007562834 -0.1167735606  0.0 -0.00462769 -0.1828863972
1-1990  1 1990  0.038998671  0.0696834290  0.0  0.21128783  0.0213534085
1-2001  1 2001 -0.012860210 -0.0130581957 -0.5 -0.10950287 -0.1242445967
1-2003  1 2003 -0.009538650  0.0039634439  0.0  0.09713002  0.0843496711
1-2004  1 2004  0.013203359 -0.0004923830 -0.5  0.20097118  0.0890274168
1-2005  1 2005 -0.004302008  0.0087232322  0.5  0.31611580 -0.0094022598
1-2006  1 2006  0.002756154 -0.0097746472  0.0  0.16065287 -0.0484778223
1-2010  1 2010  0.042285908  0.0455902315  0.0  0.21075852  0.0715071253
2-2007  2 2007 -0.017173710  0.0245622798 -0.5  0.04150997 -0.0002505979
3-2014  3 2014 -0.032698672 -0.0364950713  0.0 -0.06275503 -0.0603498860
                 Y6           Y7          Y8           Y9           Y10  Y11
0-1987 -0.011862535  0.000000000  0.07410797  0.142432215  0.0000000000  0.0
0-1988 -0.036456042  0.006960585  0.00000000  0.328497539  0.0000000000  0.0
0-1989 -0.042990185  0.022858138 -0.11332869  0.232060601  0.0000000000  0.0
0-1991 -0.016438726  0.033426293 -0.09097178 -0.070368088  0.0000000000  0.0
0-1992  0.019152432  0.015781495  0.00000000 -0.321780974 -0.2076436613 -0.5
0-1993  0.078164773  0.013478690  0.04652002  0.015192971  0.0000000000  0.5
0-1994  0.029631798  0.006160184  0.12783337  0.118167799  0.0000000000 -0.5
0-1995  0.059049029 -0.001024066  0.14842001  0.008353525  0.0000000000  0.5
0-1996  0.060084811  0.001024066  0.09844007 -0.026863215  0.0868586003  0.0
0-1997  0.044357853  0.018256085  0.06062462 -0.256382432  0.0000000000 -0.5
0-1998  0.147635999  0.006012042  0.00000000 -0.103444736  0.0000000000  0.5
0-1999  0.123904093 -0.003001503  0.18721154  0.316258976  0.0000000000  0.0
0-2000  0.090286847 -0.007038742  0.13657554 -0.310307387  0.0195966413  0.0
0-2002  0.078820960 -0.009188426  0.06187540 -0.196926170  0.0000000000  0.0
0-2008  0.049723435  0.014300550 -0.05001042 -0.561164650  0.0000000000 -0.5
0-2009  0.118611879 -0.014300550  0.02531781  0.188591815 -0.9112279213  0.5
0-2011  0.061593011 -0.002074690  0.00000000 -0.188344934  0.0000000000  0.5
0-2012  0.049632624 -0.001038961 -0.10318424  0.207581791  0.9044428289 -0.5
0-2013  0.028365790  0.004149384 -0.06744128  0.445140246  0.0000000000  0.0
1-1990 -0.050341755  0.030052345 -0.08338161 -0.519724355 -0.0870144800  0.0
1-2001  0.084129531 -0.007088637  0.00000000 -0.261116345  0.0000000000  0.0
1-2003  0.075329719 -0.003081667  0.07696104  0.221828367  0.0170148206  0.0
1-2004  0.082655722  0.000000000 -0.01869213  0.073310952  0.0000000000  0.0
1-2005  0.044905504 -0.002059733 -0.12014431  0.341250994  0.2223047186 -0.5
1-2006  0.002989539  0.002059733 -0.06595797  0.063789817  0.0000000000  0.5
1-2010  0.054808236 -0.007227703  0.24294618 -0.023341674  0.0000000000 -0.5
2-2007  0.014815086  0.000000000 -0.07061757 -0.118048778  0.0000000000  0.0
3-2014  0.019588603  0.026559273 -0.07232066  0.042192672  0.0002122224  0.5
 id        time          Y1                  Y2                  Y3
 0:19   1987    : 1   Min.   :-0.072976   Min.   :-0.116774   Min.   :-0.5
 1: 7   1988    : 1   1st Qu.:-0.012895   1st Qu.:-0.007578   1st Qu.: 0.0
 2: 1   1989    : 1   Median : 0.009725   Median : 0.006923   Median : 0.0
 3: 1   1990    : 1   Mean   : 0.006292   Mean   : 0.004733   Mean   : 0.0
        1991    : 1   3rd Qu.: 0.026149   3rd Qu.: 0.025167   3rd Qu.: 0.0
        1992    : 1   Max.   : 0.054686   Max.   : 0.069683   Max.   : 0.5
        (Other):22
       Y4                 Y5                 Y6                 Y7
 Min.   :-0.38750   Min.   :-0.18289   Min.   :-0.05034   Min.   :-0.014301
 1st Qu.:-0.04347   1st Qu.:-0.04042   1st Qu.: 0.01807   1st Qu.:-0.002306
 Median : 0.03837   Median : 0.04660   Median : 0.04968   Median : 0.000512
 Mean   : 0.05178   Mean   : 0.02571   Mean   : 0.04501   Mean   : 0.005141
 3rd Qu.: 0.19900   3rd Qu.: 0.09135   3rd Qu.: 0.07833   3rd Qu.: 0.013684
 Max.   : 0.45902   Max.   : 0.18752   Max.   : 0.14764   Max.   : 0.033426

       Y8                 Y9                  Y10                 Y11
 Min.   :-0.12014   Min.   :-0.561165   Min.   :-0.911228   Min.   :-0.500
 1st Qu.:-0.06824   1st Qu.:-0.190490   1st Qu.: 0.000000   1st Qu.:-0.125
 Median : 0.00000   Median : 0.011773   Median : 0.000000   Median : 0.000
 Mean   : 0.01539   Mean   :-0.007613   Mean   : 0.001591   Mean   : 0.000
 3rd Qu.: 0.07482   3rd Qu.: 0.193339   3rd Qu.: 0.000000   3rd Qu.: 0.125
 Max.   : 0.24295   Max.   : 0.445140   Max.   : 0.904443   Max.   : 0.500
```

```
---------------------------------------------------
Dynamic Panel VAR estimation, two-step GMM
---------------------------------------------------
Transformation: Forward orthogonal deviations
Group variable: id
Time variable: time
Number of observations = 12
Number of groups = 4
Obs per group: min = 2
               avg = 6
               max = 10
Number of instruments = 363

=====================================================================================================================
           Y1         Y2         Y3         Y4         Y5         Y6         Y7         Y8         Y9         Y10        Y11
---------------------------------------------------------------------------------------------------------------------
lag1_Y1    -0.0000    -0.0002     0.0002    -0.0002    -0.0004     0.0001     0.0000    -0.0003     0.0006    -0.0000     0.0000
           (0.0000)   (0.0001)   (0.0002)   (0.0002)   (0.0003)   (0.0001)   (0.0000)   (0.0002)   (0.0007)   (0.0000)   (0.0003)
lag1_Y2    -0.0000    -0.0002     0.0004    -0.0003    -0.0005     0.0001     0.0000    -0.0004     0.0007     0.0002    -0.0004
           (0.0000)   (0.0002)   (0.0003)   (0.0004)   (0.0004)   (0.0001)   (0.0000)   (0.0003)   (0.0008)   (0.0002)   (0.0002)
lag1_Y3     0.0000     0.0000    -0.0005    -0.0002    -0.0002    -0.0000    -0.0000     0.0002     0.0002    -0.0001     0.0005
           (0.0001)   (0.0000)   (0.0008)   (0.0001)   (0.0002)   (0.0001)   (0.0000)   (0.0007)   (0.0001)   (0.0001)   (0.0008)
lag1_Y4    -0.0001    -0.0010     0.0014    -0.0019    -0.0026     0.0005     0.0001    -0.0027     0.0060    -0.0000    -0.0003
           (0.0001)   (0.0008)   (0.0010)   (0.0022)   (0.0022)   (0.0005)   (0.0001)   (0.0019)   (0.0064)   (0.0000)   (0.0012)
lag1_Y5     0.0000    -0.0012     0.0010    -0.0024    -0.0033     0.0006     0.0001    -0.0024     0.0063     0.0003    -0.0001
           (0.0003)   (0.0010)   (0.0019)   (0.0029)   (0.0027)   (0.0006)   (0.0001)   (0.0014)   (0.0069)   (0.0002)   (0.0021)
lag1_Y6     0.0000    -0.0011     0.0011    -0.0021    -0.0029     0.0006     0.0001    -0.0024     0.0062     0.0001    -0.0001
           (0.0002)   (0.0009)   (0.0015)   (0.0025)   (0.0024)   (0.0006)   (0.0001)   (0.0015)   (0.0067)   (0.0001)   (0.0019)
lag1_Y7     0.0000    -0.0001     0.0001    -0.0002    -0.0004     0.0001     0.0000    -0.0003     0.0007     0.0000     0.0000
           (0.0000)   (0.0001)   (0.0002)   (0.0003)   (0.0003)   (0.0001)   (0.0000)   (0.0002)   (0.0008)   (0.0000)   (0.0002)
lag1_Y8     0.0001    -0.0006    -0.0001    -0.0014    -0.0017     0.0004     0.0000    -0.0010     0.0040    -0.0003     0.0009
           (0.0002)   (0.0005)   (0.0013)   (0.0017)   (0.0015)   (0.0004)   (0.0000)   (0.0005)   (0.0043)   (0.0003)   (0.0019)
lag1_Y9    -0.0001    -0.0002     0.0012     0.0008    -0.0000    -0.0000     0.0001    -0.0007    -0.0010    -0.0000    -0.0009
           (0.0001)   (0.0001)   (0.0008)   (0.0007)   (0.0003)   (0.0000)   (0.0001)   (0.0004)   (0.0010)   (0.0000)   (0.0006)
lag1_Y10   -0.0002    -0.0012     0.0030    -0.0017    -0.0030     0.0005     0.0002    -0.0034     0.0044     0.0014    -0.0030
           (0.0001)   (0.0010)   (0.0017)   (0.0022)   (0.0024)   (0.0005)   (0.0001)   (0.0024)   (0.0050)   (0.0014)   (0.0018)
lag1_Y11    0.0001     0.0014    -0.0021     0.0018     0.0036    -0.0006    -0.0002     0.0037    -0.0069     0.0004     0.0002
           (0.0001)   (0.0012)   (0.0013)   (0.0022)   (0.0030)   (0.0006)   (0.0001)   (0.0028)   (0.0075)   (0.0004)   (0.0016)
Y3          0.0000    -0.0003     0.0029    -0.0002    -0.0009     0.0005     0.0001    -0.0005     0.0009    -0.0002    -0.0024
           (0.0001)   (0.0002)   (0.0022)   (0.0004)   (0.0008)   (0.0005)   (0.0000)   (0.0003)   (0.0012)   (0.0003)   (0.0018)
Y10        -0.0002     0.0002     0.0017     0.0010     0.0009    -0.0002     0.0000    -0.0005    -0.0028     0.0013    -0.0030
           (0.0002)   (0.0002)   (0.0015)   (0.0010)   (0.0010)   (0.0002)   (0.0000)   (0.0004)   (0.0028)   (0.0013)   (0.0028)
Y11         0.0001    -0.0018    -0.0069    -0.0034    -0.0036    -0.0001     0.0001    -0.0042     0.0138     0.0001     0.0085
           (0.0002)   (0.0017)   (0.0078)   (0.0037)   (0.0033)   (0.0001)   (0.0001)   (0.0036)   (0.0140)   (0.0000)   (0.0093)
Y1         -0.0001     0.0001     0.0013     0.0000     0.0004    -0.0000     0.0000    -0.0002    -0.0015     0.0014    -0.0027
           (0.0001)   (0.0001)   (0.0010)   (0.0000)   (0.0005)   (0.0000)   (0.0000)   (0.0002)   (0.0014)   (0.0014)   (0.0025)
Y2          0.0003     0.0004     0.0014    -0.0001     0.0001     0.0006    -0.0001     0.0033    -0.0035    -0.0016    -0.0006
           (0.0003)   (0.0004)   (0.0017)   (0.0001)   (0.0001)   (0.0006)   (0.0001)   (0.0032)   (0.0036)   (0.0015)   (0.0009)
const      -0.0001    -0.0210     0.0224    -0.0390    -0.0561     0.0108     0.0027    -0.0468     0.1127     0.0035    -0.0049
           (0.0039)   (0.0174)   (0.0285)   (0.0481)   (0.0465)   (0.0107)   (0.0016)   (0.0291)   (0.1231)   (0.0023)   (0.0332)
=====================================================================================================================
*** p < 0.001; ** p < 0.01; * p < 0.05

---------------------------------------------------
```

```
Instruments for  equation
 Standard
  FOD.(Y1 Y2)
 GMM-type
  Dependent vars: L(1, 10)
  Predet vars: L(1, 3)
  Collapse =  FALSE
--------------------------------------------------

Hansen test of overid. restrictions: chi2(176) = 0 Prob > chi2 = 1
(Robust, but weakened by many instruments.)        fod_lag1_Y1 fod_lag1_Y2 fod_lag1_Y3 fod_lag1_Y4 fod_lag1_Y5 fod_lag1_Y6
fod_Y1     0.8613707  0.68408138  0.83185380   0.7031931  0.93208471  0.96055904
fod_Y2     0.2287994  0.21217399  0.48086271   0.2356250  0.22221101  0.22799766
fod_Y3     0.3896317  0.15473280  0.53517173   0.1822397  0.59190382  0.47334757
fod_Y4     0.4817619  0.45938863  0.10531820   0.4014726  0.41667276  0.41593228
fod_Y5     0.2179918  0.19805368  0.52915343   0.2251185  0.22908034  0.22704383
fod_Y6     0.3132275  0.30317840  0.74937446   0.3218325  0.31278115  0.31373026
fod_Y7     0.1076402  0.11260092  0.39725946   0.1078251  0.07869682  0.08690607
fod_Y8     0.0923920  0.09554111  0.75380609   0.1526707  0.08869824  0.10795082
fod_Y9     0.3735294  0.38432069  0.09988176   0.3507196  0.36196916  0.35790161
fod_Y10    0.5194131  0.28998361  0.48972022   0.4757248  0.13573033  0.09744780
fod_Y11    0.9881089  0.09534946  0.49467262   0.7949590  0.95376668  0.95644654
        fod_lag1_Y7 fod_lag1_Y8 fod_lag1_Y9 fod_lag1_Y10 fod_lag1_Y11
fod_Y1    0.98274520  0.64831582  0.09663730   0.14811379     0.3533666
fod_Y2    0.23535600  0.23354818  0.10923919   0.22163252     0.2463935
fod_Y3    0.48123155  0.92770380  0.11588711   0.07556081     0.1005906
fod_Y4    0.41206921  0.40039459  0.25980323   0.44267482     0.4198043
fod_Y5    0.23731541  0.25014286  0.98853922   0.20893544     0.2286216
fod_Y6    0.31014262  0.31064776  0.60066160   0.30284005     0.3077327
fod_Y7    0.09303982  0.09597969  0.16992201   0.14074673     0.1561788
fod_Y8    0.11720562  0.07858183  0.08849803   0.14571435     0.1785648
fod_Y9    0.35811791  0.35241654  0.27865913   0.37535761     0.3538455
fod_Y10   0.28335986  0.44654356  0.07884891   0.30894779     0.2955334
fod_Y11   0.99456821  0.63597757  0.12313798   0.08721312     0.9211973
            fod_Y3    fod_Y10    fod_Y11     fod_Y1     fod_Y2       const
fod_Y1  0.93396637 0.2632595 0.5790433 0.1228267 0.2765449 0.98646695
fod_Y2  0.26555028 0.3592389 0.2891128 0.4927595 0.3068539 0.22779962
fod_Y3  0.18394567 0.2527324 0.3804484 0.2062177 0.3942069 0.43191267
fod_Y4  0.65702502 0.2987503 0.3473178 0.4211789 0.1579884 0.41728268
fod_Y5  0.23768890 0.3491415 0.2796785 0.4288939 0.5316634 0.22783431
fod_Y6  0.32912031 0.3171702 0.2535165 0.2147889 0.3145441 0.31144204
fod_Y7  0.13367259 0.2461034 0.1763535 0.1462918 0.2698507 0.09013312
fod_Y8  0.08810939 0.1868710 0.2439906 0.1380930 0.2919140 0.10858363
fod_Y9  0.46082784 0.3133287 0.3272337 0.3147314 0.3233942 0.35987599
fod_Y10 0.34924434 0.3205717 0.1058571 0.3180966 0.2881626 0.13155121
fod_Y11 0.17371797 0.2884023 0.3610860 0.2796713 0.5162491 0.88352597
          fod_lag1_Y1   fod_lag1_Y2   fod_lag1_Y3   fod_lag1_Y4   fod_lag1_Y5
fod_Y1  -4.852096e-06 -1.304199e-05  2.337883e-05 -5.151298e-05  2.198802e-05
fod_Y2  -1.597617e-04 -1.953098e-04  3.402263e-05 -9.658157e-04 -1.163208e-03
fod_Y3   1.876814e-04  3.763487e-04 -4.877163e-04  1.359683e-03  1.007864e-03
fod_Y4  -1.680080e-04 -2.752273e-04 -2.426439e-04 -1.859539e-03 -2.354014e-03
fod_Y5  -3.796035e-04 -4.605542e-04 -1.509973e-04 -2.628573e-03 -3.256684e-03
fod_Y6   7.016313e-05  8.969570e-05 -1.782087e-05  4.945400e-04  6.138152e-04
fod_Y7   2.363290e-05  3.391005e-05 -2.258142e-05  1.234640e-04  1.382325e-04
fod_Y8  -3.262680e-04 -4.490049e-04  2.163686e-04 -2.686235e-03 -2.391455e-03
fod_Y9   6.316522e-04  7.014408e-04  1.998669e-04  5.981811e-03  6.274882e-03
fod_Y10 -2.755047e-05  2.110560e-04 -9.188789e-05 -3.050582e-05  2.571255e-04
fod_Y11  4.482819e-06 -3.790530e-04  5.222028e-04 -3.118482e-04 -1.237699e-04
          fod_lag1_Y6   fod_lag1_Y7   fod_lag1_Y8   fod_lag1_Y9  fod_lag1_Y10
fod_Y1   1.083015e-05  5.091184e-07  8.330484e-05 -1.033701e-04 -0.0001834999
fod_Y2  -1.088933e-03 -1.307729e-04 -6.046575e-04 -1.769559e-04 -0.0011870725
fod_Y3   1.089089e-03  1.216076e-04 -1.202708e-04  1.208502e-03  0.0030250011
fod_Y4  -2.063488e-03 -2.460038e-04 -1.401414e-03  8.292099e-04 -0.0016967562
fod_Y5  -2.871227e-03 -3.533832e-04 -1.695942e-03 -4.551140e-06 -0.0029537393
fod_Y6   5.793615e-04  6.702357e-05  3.670855e-04 -6.763523e-06  0.0004977768
fod_Y7   1.338707e-04  1.585944e-05  4.738641e-05  7.662999e-05  0.0002203255
fod_Y8  -2.441074e-03 -2.866233e-04 -9.628769e-04 -6.543600e-04 -0.0034201530
fod_Y9   6.166765e-03  7.177257e-04  4.020012e-03 -1.033098e-03  0.0044488836
fod_Y10  9.032125e-05  7.142670e-06 -2.559057e-04 -4.671065e-05  0.0013895776
fod_Y11 -1.013071e-04  1.513499e-06  8.975292e-04 -8.814656e-04 -0.0030440063
          fod_lag1_Y11        fod_Y3       fod_Y10       fod_Y11        fod_Y1
fod_Y1    0.0001148238  7.943620e-06 -1.966953e-04  1.332073e-04 -8.269873e-05
fod_Y2    0.0014354348 -2.754388e-04  1.881534e-04 -1.806175e-03  9.223063e-05
fod_Y3   -0.0020818889  2.921497e-03  1.704205e-03 -6.878844e-03  1.265551e-03
fod_Y4    0.0018144848 -1.619004e-04  1.019782e-03 -3.449143e-03  3.687249e-05
fod_Y5    0.0036247521 -9.440873e-04  9.002690e-04 -3.596212e-03  4.286386e-04
fod_Y6   -0.0006247789  5.080815e-04 -2.447348e-04 -6.907678e-05 -3.278630e-05
fod_Y7   -0.0002120644  5.228996e-05  4.729487e-05  1.370978e-04  3.575100e-05
fod_Y8    0.0037250360 -4.894409e-04 -5.325304e-04 -4.227095e-03 -2.455414e-04
fod_Y9   -0.0069478959  8.895460e-04 -2.804162e-03  1.375622e-02 -1.456711e-03
fod_Y10   0.0003725246 -2.475471e-04  1.275051e-03  6.010935e-05  1.428821e-03
fod_Y11   0.0001591057 -2.406455e-03 -2.970714e-03  8.491703e-03 -2.703904e-03
               fod_Y2         const
fod_Y1   2.832819e-04 -6.688844e-05
fod_Y2   4.470703e-04 -2.097511e-02
fod_Y3   1.415068e-03  2.237321e-02
fod_Y4  -1.446809e-04 -3.904364e-02
fod_Y5   8.660383e-05 -5.612809e-02
fod_Y6   5.987304e-04  1.078641e-02
fod_Y7  -1.009274e-04  2.652534e-03
fod_Y8   3.346611e-03 -4.675761e-02
fod_Y9  -3.508610e-03  1.127451e-01
fod_Y10 -1.553688e-03  3.537590e-03
fod_Y11 -5.917321e-04 -4.868801e-03
              [,1]         [,2]         [,3]         [,4]         [,5]
 [1,] 2.778508e-05 3.205206e-05 1.101089e-04 1.351998e-04 2.580080e-04
 [2,] 1.327523e-04 1.565471e-04 4.826483e-05 8.143519e-04 9.529258e-04
 [3,] 2.181618e-04 2.644734e-04 7.864735e-04 1.019336e-03 1.880066e-03
 [4,] 2.388270e-04 3.720022e-04 1.498172e-04 2.216391e-03 2.898293e-03
 [5,] 3.081483e-04 3.578186e-04 2.399453e-04 2.166949e-03 2.707741e-03
 [6,] 6.957364e-05 8.711354e-05 5.578361e-05 4.991828e-04 6.080970e-04
 [7,] 1.468894e-05 2.137264e-05 2.667540e-05 7.677891e-05 7.861723e-05
 [8,] 1.938710e-04 2.693708e-04 6.898966e-04 1.878274e-03 1.404834e-03
 [9,] 7.098160e-04 8.062882e-04 1.214681e-04 6.410037e-03 6.883226e-03
[10,] 4.276362e-05 1.994561e-04 1.330255e-04 4.277343e-05 1.723499e-04
[11,] 3.007842e-04 2.272732e-04 7.646887e-04 1.199986e-03 2.134798e-03
              [,6]         [,7]         [,8]         [,9]        [,10]
 [1,] 2.190030e-04 2.354047e-05 1.826447e-04 6.221942e-05 0.0001268819
 [2,] 9.032797e-04 1.102011e-04 5.075745e-04 1.104854e-04 0.0009712599
 [3,] 1.518862e-03 1.726588e-04 1.325529e-03 7.686335e-04 0.0017022646
 [4,] 2.536561e-03 2.999104e-04 1.666531e-03 7.358613e-04 0.0022102268
 [5,] 2.376826e-03 2.990405e-04 1.474729e-03 3.168337e-04 0.0023507710
 [6,] 5.750911e-04 6.603809e-05 3.620659e-04 1.292107e-05 0.0004831086
 [7,] 7.819784e-05 9.442524e-06 2.846604e-05 5.583427e-05 0.0001495744
 [8,] 1.518579e-03 1.829575e-04 5.474081e-04 3.841551e-04 0.0023508837
 [9,] 6.707592e-03 7.810218e-04 4.323002e-03 9.536261e-04 0.0050185806
[10,] 5.449724e-05 6.657956e-06 3.361916e-04 2.657934e-05 0.0013657690
[11,] 1.854990e-03 2.223187e-04 1.896201e-03 5.717361e-04 0.0017798236
             [,11]        [,12]        [,13]        [,14]        [,15]
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 [1,] 0.0001237221 9.587308e-05 1.758217e-04 2.401072e-04 5.359548e-05
 [2,] 0.0012383471 2.473924e-04 2.052248e-04 1.703826e-03 1.344614e-04
 [3,] 0.0012679006 2.198757e-03 1.490031e-03 7.842979e-03 1.001200e-03
 [4,] 0.0022490986 3.646206e-04 9.813923e-04 3.670064e-03 4.583978e-05
 [5,] 0.0030107983 7.995434e-04 9.615631e-04 3.326617e-03 5.418358e-04
 [6,] 0.0006125337 5.206354e-04 2.446639e-04 6.049550e-05 2.642982e-05
 [7,] 0.0001495475 3.486519e-05 4.077615e-05 1.013986e-04 2.460910e-05
 [8,] 0.0027691579 2.869853e-04 4.034651e-04 3.628189e-03 1.655785e-04
 [9,] 0.0074937716 1.206190e-03 2.781184e-03 1.404124e-02 1.448968e-03
[10,] 0.0003561217 2.644576e-04 1.283672e-03 3.717112e-05 1.431144e-03
[11,] 0.0016083358 1.768992e-03 2.798249e-03 9.297847e-03 2.501164e-03
             [,16]       [,17]
 [1,] 2.603421e-04 0.003943433
 [2,] 4.375125e-04 0.017391630
 [3,] 1.660852e-03 0.028467439
 [4,] 1.024747e-04 0.048134006
 [5,] 1.384623e-04 0.046542388
 [6,] 5.953176e-04 0.010656392
 [7,] 9.146889e-05 0.001565198
 [8,] 3.175357e-03 0.029139873
 [9,] 3.552997e-03 0.123137776
[10,] 1.462761e-03 0.002345862
[11,] 9.115659e-04 0.033233934
             V1           V2           V3           V4           V5
1  2.778508e-05 3.205206e-05 1.101089e-04 1.351998e-04 2.580080e-04
2  1.327523e-04 1.565471e-04 4.826483e-05 8.143519e-04 9.529258e-04
3  2.181618e-04 2.644734e-04 7.864735e-04 1.019336e-03 1.880066e-03
4  2.388270e-04 3.720022e-04 1.498172e-04 2.216391e-03 2.898293e-03
5  3.081483e-04 3.578186e-04 2.399453e-04 2.166949e-03 2.707741e-03
6  6.957364e-05 8.711354e-05 5.578361e-05 4.991828e-04 6.080970e-04
7  1.468894e-05 2.137264e-05 2.667540e-05 7.677891e-05 7.861723e-05
8  1.938710e-04 2.693708e-04 6.898966e-04 1.878274e-03 1.404834e-03
9  7.098160e-04 8.062882e-04 1.214681e-04 6.410037e-03 6.883226e-03
10 4.276362e-05 1.994561e-04 1.330255e-04 4.277343e-05 1.723499e-04
11 3.007842e-04 2.272732e-04 7.646887e-04 1.199986e-03 2.134798e-03
             V6           V7           V8           V9          V10
1  2.190030e-04 2.354047e-05 1.826447e-04 6.221942e-05 0.0001268819
2  9.032797e-04 1.102011e-04 5.075745e-04 1.104854e-04 0.0009712599
3  1.518862e-03 1.726588e-04 1.325529e-03 7.686335e-04 0.0017022646
4  2.536561e-03 2.999104e-04 1.666531e-03 7.358613e-04 0.0022102268
5  2.376826e-03 2.990405e-04 1.474729e-03 3.168337e-04 0.0023507710
6  5.750911e-04 6.603809e-05 3.620659e-04 1.292107e-05 0.0004831086
7  7.819784e-05 9.442524e-06 2.846604e-05 5.583427e-05 0.0001495744
8  1.518579e-03 1.829575e-04 5.474081e-04 3.841551e-04 0.0023508837
9  6.707592e-03 7.810218e-04 4.323002e-03 9.536261e-04 0.0050185806
10 5.449724e-05 6.657956e-06 3.361916e-04 2.657934e-05 0.0013657690
11 1.854990e-03 2.223187e-04 1.896201e-03 5.717361e-04 0.0017798236
            V11          V12          V13          V14          V15
1  0.0001237221 9.587308e-05 1.758217e-04 2.401072e-04 5.359548e-05
2  0.0012383471 2.473924e-04 2.052248e-04 1.703826e-03 1.344614e-04
3  0.0012679006 2.198757e-03 1.490031e-03 7.842979e-03 1.001200e-03
4  0.0022490986 3.646206e-04 9.813923e-04 3.670064e-03 4.583978e-05
5  0.0030107983 7.995434e-04 9.615631e-04 3.326617e-03 5.418358e-04
6  0.0006125337 5.206354e-04 2.446639e-04 6.049550e-05 2.642982e-05
7  0.0001495475 3.486519e-05 4.077615e-05 1.013986e-04 2.460910e-05
8  0.0027691579 2.869853e-04 4.034651e-04 3.628189e-03 1.655785e-04
9  0.0074937716 1.206190e-03 2.781184e-03 1.404124e-02 1.448968e-03
10 0.0003561217 2.644576e-04 1.283672e-03 3.717112e-05 1.431144e-03
11 0.0016083358 1.768992e-03 2.798249e-03 9.297847e-03 2.501164e-03
            V16         V17
1  2.603421e-04 0.003943433
2  4.375125e-04 0.017391630
3  1.660852e-03 0.028467439
4  1.024747e-04 0.048134006
5  1.384623e-04 0.046542388
6  5.953176e-04 0.010656392
7  9.146889e-05 0.001565198
8  3.175357e-03 0.029139873
9  3.552997e-03 0.123137776
10 1.462761e-03 0.002345862
11 9.115659e-04 0.033233934
function (x, row.names = NULL, optional = FALSE, ...)
{
    if (is.null(x))
        return(as.data.frame(list()))
    UseMethod("as.data.frame")
}
<bytecode: 0x000000000c809b80>
<environment: namespace:base>
```

XGBoost Prediction with Metrics

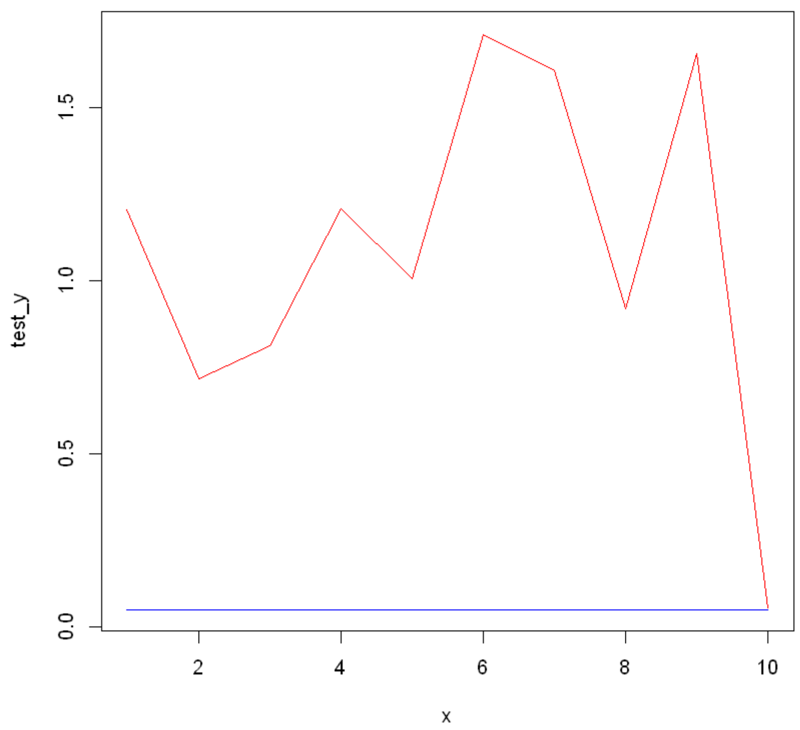
In [8]:

```
XGBoost(SPDE, SPDE$V1)
ggsave("./1_output/XGBoost_Y1.jpg") %>%
 suppressWarnings()
```

```
[1]	train-rmse:0.337911
Will train until train_rmse hasn't improved in 50 rounds.

[2]	train-rmse:0.253433
[3]	train-rmse:0.190075
[4]	train-rmse:0.142556
[5]	train-rmse:0.106917
[6]	train-rmse:0.080188
[7]	train-rmse:0.060141
[8]	train-rmse:0.045106
[9]	train-rmse:0.033829
[10]	train-rmse:0.025372
[11]	train-rmse:0.019029
[12]	train-rmse:0.014272
[13]	train-rmse:0.010704
[14]	train-rmse:0.008028
[15]	train-rmse:0.006021
[16]	train-rmse:0.004516
[17]	train-rmse:0.003387
[18]	train-rmse:0.002540
[19]	train-rmse:0.001905
[20]	train-rmse:0.001429
[21]	train-rmse:0.001072
[22]	train-rmse:0.000804
[23]	train-rmse:0.000603
[24]	train-rmse:0.000452
[25]	train-rmse:0.000339
[26]	train-rmse:0.000254
[27]	train-rmse:0.000191
```

```
[28]	train-rmse:0.000143
[29]	train-rmse:0.000107
[30]	train-rmse:0.000080
[31]	train-rmse:0.000060
[32]	train-rmse:0.000045
[33]	train-rmse:0.000034
[34]	train-rmse:0.000025
[35]	train-rmse:0.000019
[36]	train-rmse:0.000014
[37]	train-rmse:0.000011
[38]	train-rmse:0.000008
[39]	train-rmse:0.000006
[40]	train-rmse:0.000005
[41]	train-rmse:0.000003
[42]	train-rmse:0.000003
[43]	train-rmse:0.000002
[44]	train-rmse:0.000001
[45]	train-rmse:0.000001
[46]	train-rmse:0.000001
[47]	train-rmse:0.000001
[48]	train-rmse:0.000000
[49]	train-rmse:0.000000
[50]	train-rmse:0.000000
[51]	train-rmse:0.000000
[52]	train-rmse:0.000000
[53]	train-rmse:0.000000
[54]	train-rmse:0.000000
[55]	train-rmse:0.000000
[56]	train-rmse:0.000000
[57]	train-rmse:0.000000
[58]	train-rmse:0.000000
[59]	train-rmse:0.000000
[60]	train-rmse:0.000000
[61]	train-rmse:0.000000
[62]	train-rmse:0.000000
[63]	train-rmse:0.000000
[64]	train-rmse:0.000000
[65]	train-rmse:0.000000
[66]	train-rmse:0.000000
[67]	train-rmse:0.000000
[68]	train-rmse:0.000000
[69]	train-rmse:0.000000
[70]	train-rmse:0.000000
[71]	train-rmse:0.000000
[72]	train-rmse:0.000000
[73]	train-rmse:0.000000
[74]	train-rmse:0.000000
[75]	train-rmse:0.000000
[76]	train-rmse:0.000000
[77]	train-rmse:0.000000
[78]	train-rmse:0.000000
[79]	train-rmse:0.000000
[80]	train-rmse:0.000000
[81]	train-rmse:0.000000
[82]	train-rmse:0.000000
[83]	train-rmse:0.000000
[84]	train-rmse:0.000000
[85]	train-rmse:0.000000
[86]	train-rmse:0.000000
[87]	train-rmse:0.000000
[88]	train-rmse:0.000000
[89]	train-rmse:0.000000
[90]	train-rmse:0.000000
[91]	train-rmse:0.000000
[92]	train-rmse:0.000000
[93]	train-rmse:0.000000
[94]	train-rmse:0.000000
[95]	train-rmse:0.000000
[96]	train-rmse:0.000000
[97]	train-rmse:0.000000
[98]	train-rmse:0.000000
Stopping. Best iteration:
[48]	train-rmse:0.000000

##### xgb.Booster
raw: 43 Kb
call:
  xgb.train(params = params, data = dtrain, nrounds = nrounds,
    watchlist = watchlist, verbose = verbose, print_every_n = print_every_n,
    early_stopping_rounds = early_stopping_rounds, maximize = maximize,
    save_period = save_period, save_name = save_name, xgb_model = xgb_model,
    callbacks = callbacks, max.depth = 200, objective = "reg:squarederror")
params (as set within xgb.train):
  max_depth = "200", objective = "reg:squarederror", validate_parameters = "TRUE"
xgb.attributes:
  best_iteration, best_msg, best_ntreelimit, best_score, niter
callbacks:
  cb.print.evaluation(period = print_every_n)
  cb.evaluation.log()
  cb.early.stop(stopping_rounds = early_stopping_rounds, maximize = maximize,
    verbose = verbose)
# of features: 16
niter: 98
best_iteration : 48
best_ntreelimit : 48
best_score : 0
best_msg : [48] train-rmse:0.000000
nfeatures : 16
evaluation_log:
    iter train_rmse
       1   0.337911
       2   0.253433
---
      97   0.000000
      98   0.000000
MSE:  1.315938 MAE:  1.040774  RMSE:  1.147144
```

```
Saving 6.67 x 6.67 in image
```

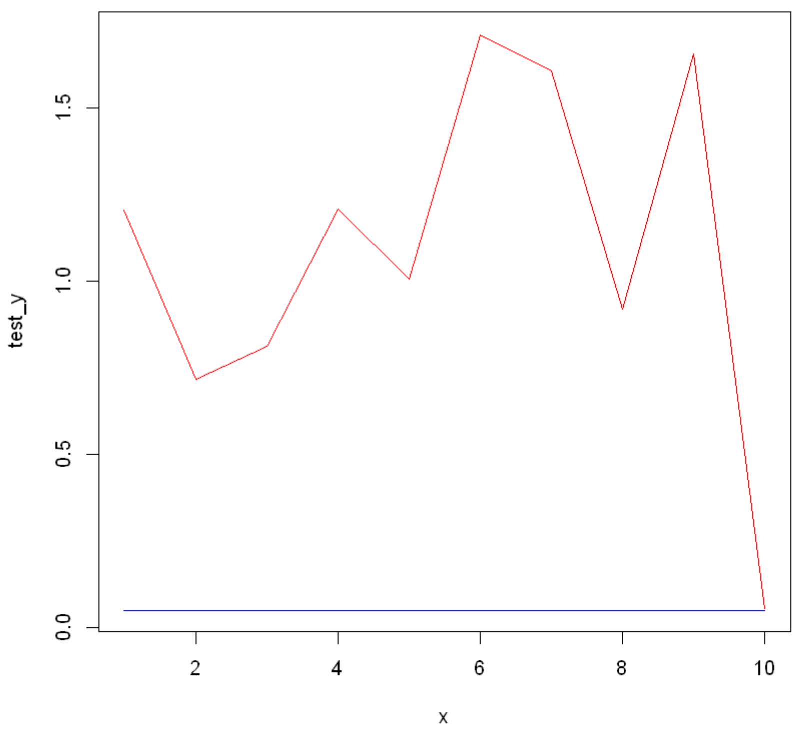


In [9]:

```
XGBoost(SPDE, SPDE$V2)
ggsave("./1_output/XGBoost_Y2.jpg") %>%
 suppressWarnings()
```

```
[1]	train-rmse:0.330402
Will train until train_rmse hasn't improved in 50 rounds.

[2]	train-rmse:0.242295
[3]	train-rmse:0.177683
[4]	train-rmse:0.130301
[5]	train-rmse:0.095554
[6]	train-rmse:0.070073
[7]	train-rmse:0.051387
[8]	train-rmse:0.037684
[9]	train-rmse:0.027635
[10]	train-rmse:0.020265
[11]	train-rmse:0.014861
[12]	train-rmse:0.010898
[13]	train-rmse:0.007992
[14]	train-rmse:0.005861
[15]	train-rmse:0.004298
[16]	train-rmse:0.003152
[17]	train-rmse:0.002311
[18]	train-rmse:0.001695
[19]	train-rmse:0.001243
[20]	train-rmse:0.000912
[21]	train-rmse:0.000668
[22]	train-rmse:0.000490
[23]	train-rmse:0.000359
[24]	train-rmse:0.000264
[25]	train-rmse:0.000193
[26]	train-rmse:0.000142
[27]	train-rmse:0.000104
[28]	train-rmse:0.000076
[29]	train-rmse:0.000056
[30]	train-rmse:0.000041
[31]	train-rmse:0.000030
[32]	train-rmse:0.000022
[33]	train-rmse:0.000016
[34]	train-rmse:0.000012
[35]	train-rmse:0.000009
[36]	train-rmse:0.000006
[37]	train-rmse:0.000005
[38]	train-rmse:0.000003
[39]	train-rmse:0.000003
[40]	train-rmse:0.000002
[41]	train-rmse:0.000001
[42]	train-rmse:0.000001
[43]	train-rmse:0.000001
[44]	train-rmse:0.000001
[45]	train-rmse:0.000000
[46]	train-rmse:0.000000
[47]	train-rmse:0.000000
[48]	train-rmse:0.000000
[49]	train-rmse:0.000000
[50]	train-rmse:0.000000
[51]	train-rmse:0.000000
[52]	train-rmse:0.000000
[53]	train-rmse:0.000000
[54]	train-rmse:0.000000
[55]	train-rmse:0.000000
[56]	train-rmse:0.000000
[57]	train-rmse:0.000000
[58]	train-rmse:0.000000
[59]	train-rmse:0.000000
[60]	train-rmse:0.000000
[61]	train-rmse:0.000000
[62]	train-rmse:0.000000
[63]	train-rmse:0.000000
[64]	train-rmse:0.000000
[65]	train-rmse:0.000000
[66]	train-rmse:0.000000
[67]	train-rmse:0.000000
[68]	train-rmse:0.000000
[69]	train-rmse:0.000000
[70]	train-rmse:0.000000
[71]	train-rmse:0.000000
[72]	train-rmse:0.000000
[73]	train-rmse:0.000000
[74]	train-rmse:0.000000
[75]	train-rmse:0.000000
[76]	train-rmse:0.000000
[77]	train-rmse:0.000000
```

```
[78]	train-rmse:0.000000
[79]	train-rmse:0.000000
[80]	train-rmse:0.000000
[81]	train-rmse:0.000000
[82]	train-rmse:0.000000
[83]	train-rmse:0.000000
[84]	train-rmse:0.000000
[85]	train-rmse:0.000000
[86]	train-rmse:0.000000
[87]	train-rmse:0.000000
[88]	train-rmse:0.000000
[89]	train-rmse:0.000000
[90]	train-rmse:0.000000
[91]	train-rmse:0.000000
[92]	train-rmse:0.000000
[93]	train-rmse:0.000000
[94]	train-rmse:0.000000
[95]	train-rmse:0.000000
Stopping. Best iteration:
[45]	train-rmse:0.000000

##### xgb.Booster
raw: 41.8 Kb
call:
  xgb.train(params = params, data = dtrain, nrounds = nrounds,
    watchlist = watchlist, verbose = verbose, print_every_n = print_every_n,
    early_stopping_rounds = early_stopping_rounds, maximize = maximize,
    save_period = save_period, save_name = save_name, xgb_model = xgb_model,
    callbacks = callbacks, max.depth = 200, objective = "reg:squarederror")
params (as set within xgb.train):
  max_depth = "200", objective = "reg:squarederror", validate_parameters = "TRUE"
xgb.attributes:
  best_iteration, best_msg, best_ntreelimit, best_score, niter
callbacks:
  cb.print.evaluation(period = print_every_n)
  cb.evaluation.log()
  cb.early.stop(stopping_rounds = early_stopping_rounds, maximize = maximize,
    verbose = verbose)
# of features: 16
niter: 95
best_iteration : 45
best_ntreelimit : 45
best_score : 0
best_msg : [45] train-rmse:0.000000
nfeatures : 16
evaluation_log:
    iter train_rmse
       1   0.330402
       2   0.242295
---
      94   0.000000
      95   0.000000
MSE:  1.315939 MAE:  1.040774  RMSE:  1.147144
Saving 6.67 x 6.67 in image
```



In [10]:

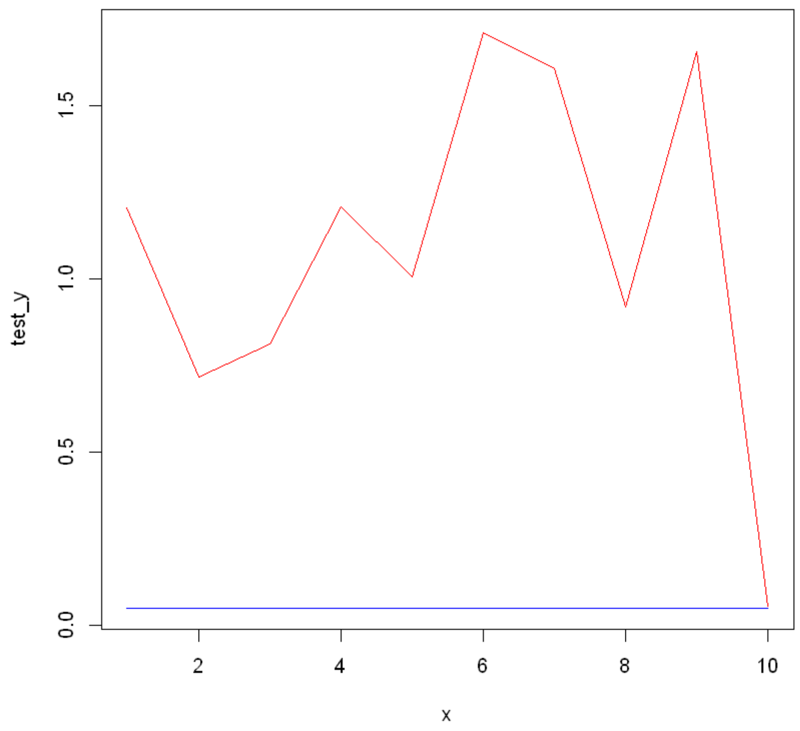
```
XGBoost(SPDE, SPDE$V3)
ggsave("./1_output/XGBoost_Y3.jpg") %>%
 suppressWarnings()
```

```
[1]	train-rmse:0.360438
Will train until train_rmse hasn't improved in 50 rounds.

[2]	train-rmse:0.288351
[3]	train-rmse:0.230681
[4]	train-rmse:0.184544
[5]	train-rmse:0.147636
[6]	train-rmse:0.118108
[7]	train-rmse:0.094487
[8]	train-rmse:0.075589
[9]	train-rmse:0.060472
[10]	train-rmse:0.048377
[11]	train-rmse:0.038702
[12]	train-rmse:0.030961
[13]	train-rmse:0.024769
[14]	train-rmse:0.019815
[15]	train-rmse:0.015852
[16]	train-rmse:0.012682
[17]	train-rmse:0.010145
[18]	train-rmse:0.008116
[19]	train-rmse:0.006493
[20]	train-rmse:0.005194
[21]	train-rmse:0.004156
[22]	train-rmse:0.003324
```

```
[23]	train-rmse:0.002660
[24]	train-rmse:0.002128
[25]	train-rmse:0.001702
[26]	train-rmse:0.001362
[27]	train-rmse:0.001089
[28]	train-rmse:0.000871
[29]	train-rmse:0.000697
[30]	train-rmse:0.000558
[31]	train-rmse:0.000446
[32]	train-rmse:0.000357
[33]	train-rmse:0.000286
[34]	train-rmse:0.000228
[35]	train-rmse:0.000183
[36]	train-rmse:0.000146
[37]	train-rmse:0.000117
[38]	train-rmse:0.000094
[39]	train-rmse:0.000075
[40]	train-rmse:0.000060
[41]	train-rmse:0.000048
[42]	train-rmse:0.000038
[43]	train-rmse:0.000031
[44]	train-rmse:0.000025
[45]	train-rmse:0.000020
[46]	train-rmse:0.000016
[47]	train-rmse:0.000013
[48]	train-rmse:0.000010
[49]	train-rmse:0.000008
[50]	train-rmse:0.000006
[51]	train-rmse:0.000005
[52]	train-rmse:0.000004
[53]	train-rmse:0.000003
[54]	train-rmse:0.000003
[55]	train-rmse:0.000002
[56]	train-rmse:0.000002
[57]	train-rmse:0.000001
[58]	train-rmse:0.000001
[59]	train-rmse:0.000001
[60]	train-rmse:0.000001
[61]	train-rmse:0.000001
[62]	train-rmse:0.000000
[63]	train-rmse:0.000000
[64]	train-rmse:0.000000
[65]	train-rmse:0.000000
[66]	train-rmse:0.000000
[67]	train-rmse:0.000000
[68]	train-rmse:0.000000
[69]	train-rmse:0.000000
[70]	train-rmse:0.000000
[71]	train-rmse:0.000000
[72]	train-rmse:0.000000
[73]	train-rmse:0.000000
[74]	train-rmse:0.000000
[75]	train-rmse:0.000000
[76]	train-rmse:0.000000
[77]	train-rmse:0.000000
[78]	train-rmse:0.000000
[79]	train-rmse:0.000000
[80]	train-rmse:0.000000
[81]	train-rmse:0.000000
[82]	train-rmse:0.000000
[83]	train-rmse:0.000000
[84]	train-rmse:0.000000
[85]	train-rmse:0.000000
[86]	train-rmse:0.000000
[87]	train-rmse:0.000000
[88]	train-rmse:0.000000
[89]	train-rmse:0.000000
[90]	train-rmse:0.000000
[91]	train-rmse:0.000000
[92]	train-rmse:0.000000
[93]	train-rmse:0.000000
[94]	train-rmse:0.000000
[95]	train-rmse:0.000000
[96]	train-rmse:0.000000
[97]	train-rmse:0.000000
[98]	train-rmse:0.000000
[99]	train-rmse:0.000000
[100]	train-rmse:0.000000
[101]	train-rmse:0.000000
[102]	train-rmse:0.000000
[103]	train-rmse:0.000000
[104]	train-rmse:0.000000
[105]	train-rmse:0.000000
[106]	train-rmse:0.000000
[107]	train-rmse:0.000000
[108]	train-rmse:0.000000
[109]	train-rmse:0.000000
[110]	train-rmse:0.000000
[111]	train-rmse:0.000000
[112]	train-rmse:0.000000
Stopping. Best iteration:
[62]	train-rmse:0.000000

##### xgb.Booster
raw: 48.8 Kb
call:
  xgb.train(params = params, data = dtrain, nrounds = nrounds,
    watchlist = watchlist, verbose = verbose, print_every_n = print_every_n,
    early_stopping_rounds = early_stopping_rounds, maximize = maximize,
    save_period = save_period, save_name = save_name, xgb_model = xgb_model,
    callbacks = callbacks, max.depth = 200, objective = "reg:squarederror")
params (as set within xgb.train):
  max_depth = "200", objective = "reg:squarederror", validate_parameters = "TRUE"
xgb.attributes:
  best_iteration, best_msg, best_ntreelimit, best_score, niter
callbacks:
  cb.print.evaluation(period = print_every_n)
  cb.evaluation.log()
  cb.early.stop(stopping_rounds = early_stopping_rounds, maximize = maximize,
    verbose = verbose)
# of features: 16
niter: 112
best_iteration : 62
best_ntreelimit : 62
best_score : 0
best_msg : [62] train-rmse:0.000000
nfeatures : 16
evaluation_log:
    iter train_rmse
```

```
       1    0.360438
       2    0.288351
---
     111    0.000000
     112    0.000000
MSE:  1.315938 MAE:  1.040774  RMSE:  1.147144
```

```
Saving 6.67 x 6.67 in image
```

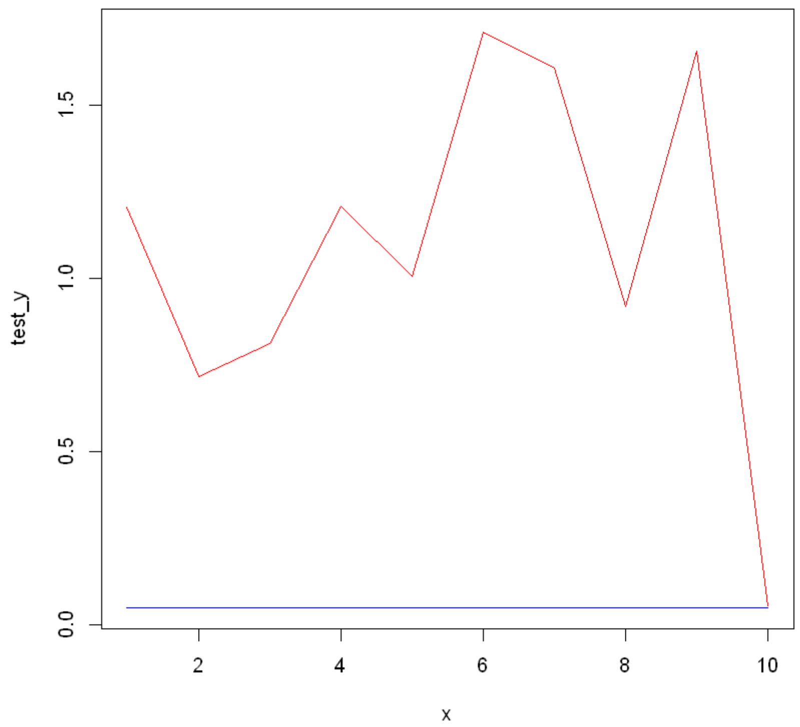


In [11]:

```
XGBoost(SPDE, SPDE$V4)
ggsave("./1_output/XGBoost_Y4.jpg") %>%
 suppressWarnings()
```

```
[1]	train-rmse:0.337911
Will train until train_rmse hasn't improved in 50 rounds.

[2]	train-rmse:0.253433
[3]	train-rmse:0.190075
[4]	train-rmse:0.142556
[5]	train-rmse:0.106917
[6]	train-rmse:0.080188
[7]	train-rmse:0.060141
[8]	train-rmse:0.045106
[9]	train-rmse:0.033829
[10]	train-rmse:0.025372
[11]	train-rmse:0.019029
[12]	train-rmse:0.014272
[13]	train-rmse:0.010704
[14]	train-rmse:0.008028
[15]	train-rmse:0.006021
[16]	train-rmse:0.004516
[17]	train-rmse:0.003387
[18]	train-rmse:0.002540
[19]	train-rmse:0.001905
[20]	train-rmse:0.001429
[21]	train-rmse:0.001072
[22]	train-rmse:0.000804
[23]	train-rmse:0.000603
[24]	train-rmse:0.000452
[25]	train-rmse:0.000339
[26]	train-rmse:0.000254
[27]	train-rmse:0.000191
[28]	train-rmse:0.000143
[29]	train-rmse:0.000107
[30]	train-rmse:0.000080
[31]	train-rmse:0.000060
[32]	train-rmse:0.000045
[33]	train-rmse:0.000034
[34]	train-rmse:0.000025
[35]	train-rmse:0.000019
[36]	train-rmse:0.000014
[37]	train-rmse:0.000011
[38]	train-rmse:0.000008
[39]	train-rmse:0.000006
[40]	train-rmse:0.000005
[41]	train-rmse:0.000003
[42]	train-rmse:0.000003
[43]	train-rmse:0.000002
[44]	train-rmse:0.000001
[45]	train-rmse:0.000001
[46]	train-rmse:0.000001
[47]	train-rmse:0.000001
[48]	train-rmse:0.000000
[49]	train-rmse:0.000000
[50]	train-rmse:0.000000
[51]	train-rmse:0.000000
[52]	train-rmse:0.000000
[53]	train-rmse:0.000000
[54]	train-rmse:0.000000
[55]	train-rmse:0.000000
[56]	train-rmse:0.000000
[57]	train-rmse:0.000000
[58]	train-rmse:0.000000
[59]	train-rmse:0.000000
[60]	train-rmse:0.000000
[61]	train-rmse:0.000000
[62]	train-rmse:0.000000
[63]	train-rmse:0.000000
[64]	train-rmse:0.000000
[65]	train-rmse:0.000000
[66]	train-rmse:0.000000
[67]	train-rmse:0.000000
[68]	train-rmse:0.000000
[69]	train-rmse:0.000000
```

```
[70]	train-rmse:0.000000
[71]	train-rmse:0.000000
[72]	train-rmse:0.000000
[73]	train-rmse:0.000000
[74]	train-rmse:0.000000
[75]	train-rmse:0.000000
[76]	train-rmse:0.000000
[77]	train-rmse:0.000000
[78]	train-rmse:0.000000
[79]	train-rmse:0.000000
[80]	train-rmse:0.000000
[81]	train-rmse:0.000000
[82]	train-rmse:0.000000
[83]	train-rmse:0.000000
[84]	train-rmse:0.000000
[85]	train-rmse:0.000000
[86]	train-rmse:0.000000
[87]	train-rmse:0.000000
[88]	train-rmse:0.000000
[89]	train-rmse:0.000000
[90]	train-rmse:0.000000
[91]	train-rmse:0.000000
[92]	train-rmse:0.000000
[93]	train-rmse:0.000000
[94]	train-rmse:0.000000
[95]	train-rmse:0.000000
[96]	train-rmse:0.000000
[97]	train-rmse:0.000000
[98]	train-rmse:0.000000
Stopping. Best iteration:
[48]	train-rmse:0.000000

##### xgb.Booster
raw: 43 Kb
call:
  xgb.train(params = params, data = dtrain, nrounds = nrounds,
    watchlist = watchlist, verbose = verbose, print_every_n = print_every_n,
    early_stopping_rounds = early_stopping_rounds, maximize = maximize,
    save_period = save_period, save_name = save_name, xgb_model = xgb_model,
    callbacks = callbacks, max.depth = 200, objective = "reg:squarederror")
params (as set within xgb.train):
  max_depth = "200", objective = "reg:squarederror", validate_parameters = "TRUE"
xgb.attributes:
  best_iteration, best_msg, best_ntreelimit, best_score, niter
callbacks:
  cb.print.evaluation(period = print_every_n)
  cb.evaluation.log()
  cb.early.stop(stopping_rounds = early_stopping_rounds, maximize = maximize,
    verbose = verbose)
# of features: 16
niter: 98
best_iteration : 48
best_ntreelimit : 48
best_score : 0
best_msg : [48] train-rmse:0.000000
nfeatures : 16
evaluation_log:
    iter train_rmse
       1   0.337911
       2   0.253433
---
      97   0.000000
      98   0.000000
MSE:  1.315938 MAE:  1.040774  RMSE:  1.147144
Saving 6.67 x 6.67 in image
```



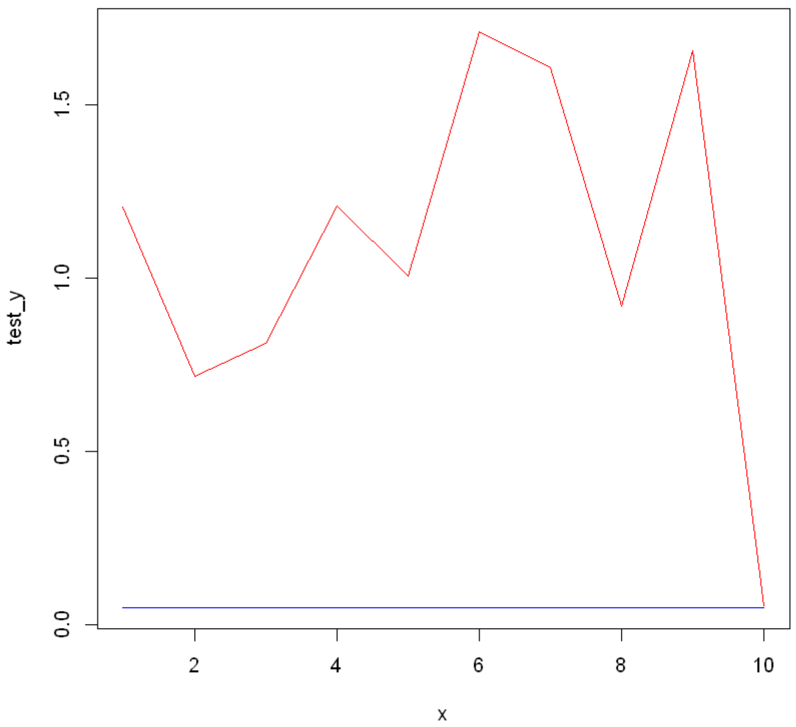
In [12]:

```
XGBoost(SPDE, SPDE$V5)
ggsave("./1_output/XGBoost_Y5.jpg") %>%
 suppressWarnings()
```

```
[1]	train-rmse:0.334693
Will train until train_rmse hasn't improved in 50 rounds.

[2]	train-rmse:0.248629
[3]	train-rmse:0.184696
[4]	train-rmse:0.137203
[5]	train-rmse:0.101922
[6]	train-rmse:0.075713
[7]	train-rmse:0.056244
[8]	train-rmse:0.041781
[9]	train-rmse:0.031038
[10]	train-rmse:0.023057
[11]	train-rmse:0.017128
```

```
[12]	train-rmse:0.012723
[13]	train-rmse:0.009452
[14]	train-rmse:0.007021
[15]	train-rmse:0.005216
[16]	train-rmse:0.003875
[17]	train-rmse:0.002878
[18]	train-rmse:0.002138
[19]	train-rmse:0.001588
[20]	train-rmse:0.001180
[21]	train-rmse:0.000877
[22]	train-rmse:0.000651
[23]	train-rmse:0.000484
[24]	train-rmse:0.000359
[25]	train-rmse:0.000267
[26]	train-rmse:0.000198
[27]	train-rmse:0.000147
[28]	train-rmse:0.000109
[29]	train-rmse:0.000081
[30]	train-rmse:0.000060
[31]	train-rmse:0.000045
[32]	train-rmse:0.000033
[33]	train-rmse:0.000025
[34]	train-rmse:0.000018
[35]	train-rmse:0.000014
[36]	train-rmse:0.000010
[37]	train-rmse:0.000008
[38]	train-rmse:0.000006
[39]	train-rmse:0.000004
[40]	train-rmse:0.000003
[41]	train-rmse:0.000002
[42]	train-rmse:0.000002
[43]	train-rmse:0.000001
[44]	train-rmse:0.000001
[45]	train-rmse:0.000001
[46]	train-rmse:0.000001
[47]	train-rmse:0.000000
[48]	train-rmse:0.000000
[49]	train-rmse:0.000000
[50]	train-rmse:0.000000
[51]	train-rmse:0.000000
[52]	train-rmse:0.000000
[53]	train-rmse:0.000000
[54]	train-rmse:0.000000
[55]	train-rmse:0.000000
[56]	train-rmse:0.000000
[57]	train-rmse:0.000000
[58]	train-rmse:0.000000
[59]	train-rmse:0.000000
[60]	train-rmse:0.000000
[61]	train-rmse:0.000000
[62]	train-rmse:0.000000
[63]	train-rmse:0.000000
[64]	train-rmse:0.000000
[65]	train-rmse:0.000000
[66]	train-rmse:0.000000
[67]	train-rmse:0.000000
[68]	train-rmse:0.000000
[69]	train-rmse:0.000000
[70]	train-rmse:0.000000
[71]	train-rmse:0.000000
[72]	train-rmse:0.000000
[73]	train-rmse:0.000000
[74]	train-rmse:0.000000
[75]	train-rmse:0.000000
[76]	train-rmse:0.000000
[77]	train-rmse:0.000000
[78]	train-rmse:0.000000
[79]	train-rmse:0.000000
[80]	train-rmse:0.000000
[81]	train-rmse:0.000000
[82]	train-rmse:0.000000
[83]	train-rmse:0.000000
[84]	train-rmse:0.000000
[85]	train-rmse:0.000000
[86]	train-rmse:0.000000
[87]	train-rmse:0.000000
[88]	train-rmse:0.000000
[89]	train-rmse:0.000000
[90]	train-rmse:0.000000
[91]	train-rmse:0.000000
[92]	train-rmse:0.000000
[93]	train-rmse:0.000000
[94]	train-rmse:0.000000
[95]	train-rmse:0.000000
[96]	train-rmse:0.000000
[97]	train-rmse:0.000000
Stopping. Best iteration:
[47]	train-rmse:0.000000

##### xgb.Booster
raw: 42.6 Kb
call:
  xgb.train(params = params, data = dtrain, nrounds = nrounds,
    watchlist = watchlist, verbose = verbose, print_every_n = print_every_n,
    early_stopping_rounds = early_stopping_rounds, maximize = maximize,
    save_period = save_period, save_name = save_name, xgb_model = xgb_model,
    callbacks = callbacks, max.depth = 200, objective = "reg:squarederror")
params (as set within xgb.train):
  max_depth = "200", objective = "reg:squarederror", validate_parameters = "TRUE"
xgb.attributes:
  best_iteration, best_msg, best_ntreelimit, best_score, niter
callbacks:
  cb.print.evaluation(period = print_every_n)
  cb.evaluation.log()
  cb.early.stop(stopping_rounds = early_stopping_rounds, maximize = maximize,
    verbose = verbose)
# of features: 16
niter: 97
best_iteration : 47
best_ntreelimit : 47
best_score : 0
best_msg : [47] train-rmse:0.000000
nfeatures : 16
evaluation_log:
    iter train_rmse
       1   0.334693
       2   0.248629
---
      96   0.000000
```

```
      97   0.000000
MSE:  1.315939 MAE:  1.040774  RMSE:  1.147144
Saving 6.67 x 6.67 in image
```



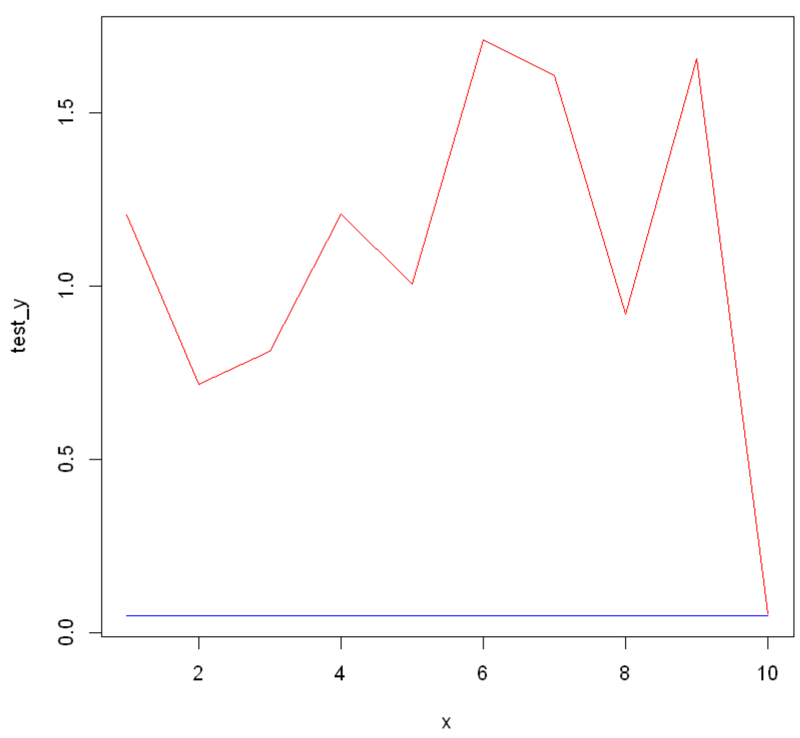
In [13]:

```
XGBoost(SPDE, SPDE$V6)
ggsave("./1_output/XGBoost_Y6.jpg") %>%
 suppressWarnings()
```

```
[1]	train-rmse:0.334693
Will train until train_rmse hasn't improved in 50 rounds.

[2]	train-rmse:0.248629
[3]	train-rmse:0.184696
[4]	train-rmse:0.137203
[5]	train-rmse:0.101922
[6]	train-rmse:0.075713
[7]	train-rmse:0.056244
[8]	train-rmse:0.041781
[9]	train-rmse:0.031038
[10]	train-rmse:0.023057
[11]	train-rmse:0.017128
[12]	train-rmse:0.012723
[13]	train-rmse:0.009452
[14]	train-rmse:0.007021
[15]	train-rmse:0.005216
[16]	train-rmse:0.003875
[17]	train-rmse:0.002878
[18]	train-rmse:0.002138
[19]	train-rmse:0.001588
[20]	train-rmse:0.001180
[21]	train-rmse:0.000877
[22]	train-rmse:0.000651
[23]	train-rmse:0.000484
[24]	train-rmse:0.000359
[25]	train-rmse:0.000267
[26]	train-rmse:0.000198
[27]	train-rmse:0.000147
[28]	train-rmse:0.000109
[29]	train-rmse:0.000081
[30]	train-rmse:0.000060
[31]	train-rmse:0.000045
[32]	train-rmse:0.000033
[33]	train-rmse:0.000025
[34]	train-rmse:0.000018
[35]	train-rmse:0.000014
[36]	train-rmse:0.000010
[37]	train-rmse:0.000008
[38]	train-rmse:0.000006
[39]	train-rmse:0.000004
[40]	train-rmse:0.000003
[41]	train-rmse:0.000002
[42]	train-rmse:0.000002
[43]	train-rmse:0.000001
[44]	train-rmse:0.000001
[45]	train-rmse:0.000001
[46]	train-rmse:0.000001
[47]	train-rmse:0.000000
[48]	train-rmse:0.000000
[49]	train-rmse:0.000000
[50]	train-rmse:0.000000
[51]	train-rmse:0.000000
[52]	train-rmse:0.000000
[53]	train-rmse:0.000000
[54]	train-rmse:0.000000
[55]	train-rmse:0.000000
[56]	train-rmse:0.000000
[57]	train-rmse:0.000000
[58]	train-rmse:0.000000
[59]	train-rmse:0.000000
[60]	train-rmse:0.000000
[61]	train-rmse:0.000000
[62]	train-rmse:0.000000
[63]	train-rmse:0.000000
[64]	train-rmse:0.000000
[65]	train-rmse:0.000000
[66]	train-rmse:0.000000
[67]	train-rmse:0.000000
[68]	train-rmse:0.000000
[69]	train-rmse:0.000000
[70]	train-rmse:0.000000
[71]	train-rmse:0.000000
[72]	train-rmse:0.000000
[73]	train-rmse:0.000000
```

```
[74]	train-rmse:0.000000
[75]	train-rmse:0.000000
[76]	train-rmse:0.000000
[77]	train-rmse:0.000000
[78]	train-rmse:0.000000
[79]	train-rmse:0.000000
[80]	train-rmse:0.000000
[81]	train-rmse:0.000000
[82]	train-rmse:0.000000
[83]	train-rmse:0.000000
[84]	train-rmse:0.000000
[85]	train-rmse:0.000000
[86]	train-rmse:0.000000
[87]	train-rmse:0.000000
[88]	train-rmse:0.000000
[89]	train-rmse:0.000000
[90]	train-rmse:0.000000
[91]	train-rmse:0.000000
[92]	train-rmse:0.000000
[93]	train-rmse:0.000000
[94]	train-rmse:0.000000
[95]	train-rmse:0.000000
[96]	train-rmse:0.000000
[97]	train-rmse:0.000000
Stopping. Best iteration:
[47]	train-rmse:0.000000

##### xgb.Booster
raw: 42.6 Kb
call:
  xgb.train(params = params, data = dtrain, nrounds = nrounds,
    watchlist = watchlist, verbose = verbose, print_every_n = print_every_n,
    early_stopping_rounds = early_stopping_rounds, maximize = maximize,
    save_period = save_period, save_name = save_name, xgb_model = xgb_model,
    callbacks = callbacks, max.depth = 200, objective = "reg:squarederror")
params (as set within xgb.train):
  max_depth = "200", objective = "reg:squarederror", validate_parameters = "TRUE"
xgb.attributes:
  best_iteration, best_msg, best_ntreelimit, best_score, niter
callbacks:
  cb.print.evaluation(period = print_every_n)
  cb.evaluation.log()
  cb.early.stop(stopping_rounds = early_stopping_rounds, maximize = maximize,
    verbose = verbose)
# of features: 16
niter: 97
best_iteration : 47
best_ntreelimit : 47
best_score : 0
best_msg : [47] train-rmse:0.000000
nfeatures : 16
evaluation_log:
    iter train_rmse
       1   0.334693
       2   0.248629
---
      96   0.000000
      97   0.000000
MSE:  1.315939 MAE:  1.040774  RMSE:  1.147144
```

```
Saving 6.67 x 6.67 in image
```



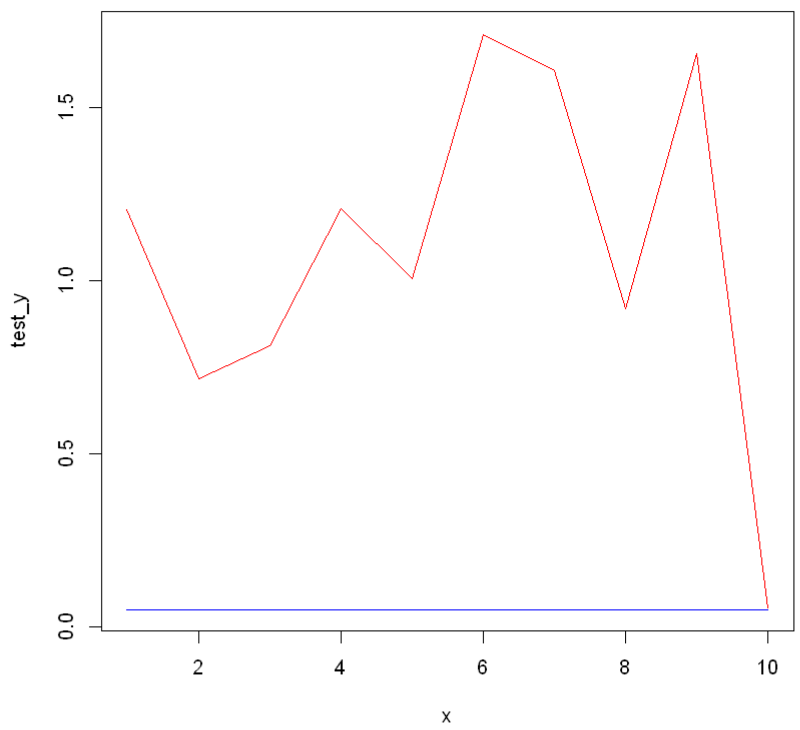
In [14]:

```r
XGBoost(SPDE, SPDE$V7)
fig_7 <- ggsave("./1_output/XGBoost_Y7.jpg") %>%
 suppressWarnings()
```

```
[1]	train-rmse:0.334693
Will train until train_rmse hasn't improved in 50 rounds.

[2]	train-rmse:0.248629
[3]	train-rmse:0.184696
[4]	train-rmse:0.137203
[5]	train-rmse:0.101922
[6]	train-rmse:0.075713
[7]	train-rmse:0.056244
[8]	train-rmse:0.041781
[9]	train-rmse:0.031038
[10]	train-rmse:0.023057
[11]	train-rmse:0.017128
[12]	train-rmse:0.012723
[13]	train-rmse:0.009452
[14]	train-rmse:0.007021
[15]	train-rmse:0.005216
[16]	train-rmse:0.003875
```

```
[17]	train-rmse:0.002878
[18]	train-rmse:0.002138
[19]	train-rmse:0.001588
[20]	train-rmse:0.001180
[21]	train-rmse:0.000877
[22]	train-rmse:0.000651
[23]	train-rmse:0.000484
[24]	train-rmse:0.000359
[25]	train-rmse:0.000267
[26]	train-rmse:0.000198
[27]	train-rmse:0.000147
[28]	train-rmse:0.000109
[29]	train-rmse:0.000081
[30]	train-rmse:0.000060
[31]	train-rmse:0.000045
[32]	train-rmse:0.000033
[33]	train-rmse:0.000025
[34]	train-rmse:0.000018
[35]	train-rmse:0.000014
[36]	train-rmse:0.000010
[37]	train-rmse:0.000008
[38]	train-rmse:0.000006
[39]	train-rmse:0.000004
[40]	train-rmse:0.000003
[41]	train-rmse:0.000002
[42]	train-rmse:0.000002
[43]	train-rmse:0.000001
[44]	train-rmse:0.000001
[45]	train-rmse:0.000001
[46]	train-rmse:0.000001
[47]	train-rmse:0.000000
[48]	train-rmse:0.000000
[49]	train-rmse:0.000000
[50]	train-rmse:0.000000
[51]	train-rmse:0.000000
[52]	train-rmse:0.000000
[53]	train-rmse:0.000000
[54]	train-rmse:0.000000
[55]	train-rmse:0.000000
[56]	train-rmse:0.000000
[57]	train-rmse:0.000000
[58]	train-rmse:0.000000
[59]	train-rmse:0.000000
[60]	train-rmse:0.000000
[61]	train-rmse:0.000000
[62]	train-rmse:0.000000
[63]	train-rmse:0.000000
[64]	train-rmse:0.000000
[65]	train-rmse:0.000000
[66]	train-rmse:0.000000
[67]	train-rmse:0.000000
[68]	train-rmse:0.000000
[69]	train-rmse:0.000000
[70]	train-rmse:0.000000
[71]	train-rmse:0.000000
[72]	train-rmse:0.000000
[73]	train-rmse:0.000000
[74]	train-rmse:0.000000
[75]	train-rmse:0.000000
[76]	train-rmse:0.000000
[77]	train-rmse:0.000000
[78]	train-rmse:0.000000
[79]	train-rmse:0.000000
[80]	train-rmse:0.000000
[81]	train-rmse:0.000000
[82]	train-rmse:0.000000
[83]	train-rmse:0.000000
[84]	train-rmse:0.000000
[85]	train-rmse:0.000000
[86]	train-rmse:0.000000
[87]	train-rmse:0.000000
[88]	train-rmse:0.000000
[89]	train-rmse:0.000000
[90]	train-rmse:0.000000
[91]	train-rmse:0.000000
[92]	train-rmse:0.000000
[93]	train-rmse:0.000000
[94]	train-rmse:0.000000
[95]	train-rmse:0.000000
[96]	train-rmse:0.000000
[97]	train-rmse:0.000000
Stopping. Best iteration:
[47]	train-rmse:0.000000

##### xgb.Booster
raw: 42.6 Kb
call:
  xgb.train(params = params, data = dtrain, nrounds = nrounds,
    watchlist = watchlist, verbose = verbose, print_every_n = print_every_n,
    early_stopping_rounds = early_stopping_rounds, maximize = maximize,
    save_period = save_period, save_name = save_name, xgb_model = xgb_model,
    callbacks = callbacks, max.depth = 200, objective = "reg:squarederror")
params (as set within xgb.train):
  max_depth = "200", objective = "reg:squarederror", validate_parameters = "TRUE"
xgb.attributes:
  best_iteration, best_msg, best_ntreelimit, best_score, niter
callbacks:
  cb.print.evaluation(period = print_every_n)
  cb.evaluation.log()
  cb.early.stop(stopping_rounds = early_stopping_rounds, maximize = maximize,
    verbose = verbose)
# of features: 16
niter: 97
best_iteration : 47
best_ntreelimit : 47
best_score : 0
best_msg : [47] train-rmse:0.000000
nfeatures : 16
evaluation_log:
    iter train_rmse
       1   0.334693
       2   0.248629
---
      96   0.000000
      97   0.000000
MSE:  1.315939 MAE:  1.040774  RMSE:  1.147144
```

```
Saving 6.67 x 6.67 in image
```

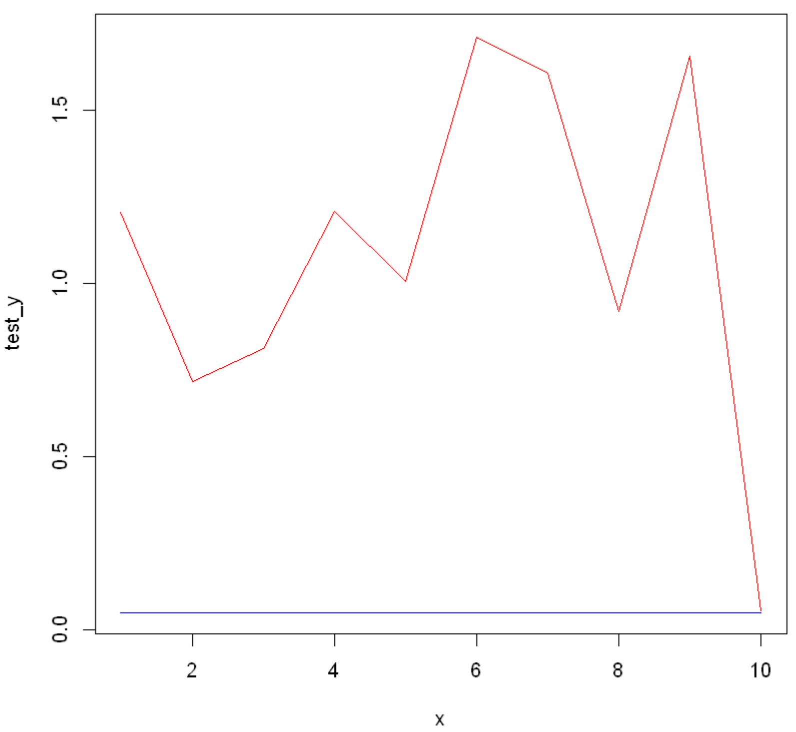


In [15]:

```
XGBoost(SPDE, SPDE$V8)
ggsave("./1_output/XGBoost_Y8.jpg") %>%
 suppressWarnings()
```

```
[1]	train-rmse:0.337911
Will train until train_rmse hasn't improved in 50 rounds.

[2]	train-rmse:0.253433
[3]	train-rmse:0.190075
[4]	train-rmse:0.142556
[5]	train-rmse:0.106917
[6]	train-rmse:0.080188
[7]	train-rmse:0.060141
[8]	train-rmse:0.045106
[9]	train-rmse:0.033829
[10]	train-rmse:0.025372
[11]	train-rmse:0.019029
[12]	train-rmse:0.014272
[13]	train-rmse:0.010704
[14]	train-rmse:0.008028
[15]	train-rmse:0.006021
[16]	train-rmse:0.004516
[17]	train-rmse:0.003387
[18]	train-rmse:0.002540
[19]	train-rmse:0.001905
[20]	train-rmse:0.001429
[21]	train-rmse:0.001072
[22]	train-rmse:0.000804
[23]	train-rmse:0.000603
[24]	train-rmse:0.000452
[25]	train-rmse:0.000339
[26]	train-rmse:0.000254
[27]	train-rmse:0.000191
[28]	train-rmse:0.000143
[29]	train-rmse:0.000107
[30]	train-rmse:0.000080
[31]	train-rmse:0.000060
[32]	train-rmse:0.000045
[33]	train-rmse:0.000034
[34]	train-rmse:0.000025
[35]	train-rmse:0.000019
[36]	train-rmse:0.000014
[37]	train-rmse:0.000011
[38]	train-rmse:0.000008
[39]	train-rmse:0.000006
[40]	train-rmse:0.000005
[41]	train-rmse:0.000003
[42]	train-rmse:0.000003
[43]	train-rmse:0.000002
[44]	train-rmse:0.000001
[45]	train-rmse:0.000001
[46]	train-rmse:0.000001
[47]	train-rmse:0.000001
[48]	train-rmse:0.000000
[49]	train-rmse:0.000000
[50]	train-rmse:0.000000
[51]	train-rmse:0.000000
[52]	train-rmse:0.000000
[53]	train-rmse:0.000000
[54]	train-rmse:0.000000
[55]	train-rmse:0.000000
[56]	train-rmse:0.000000
[57]	train-rmse:0.000000
[58]	train-rmse:0.000000
[59]	train-rmse:0.000000
[60]	train-rmse:0.000000
[61]	train-rmse:0.000000
[62]	train-rmse:0.000000
[63]	train-rmse:0.000000
[64]	train-rmse:0.000000
[65]	train-rmse:0.000000
[66]	train-rmse:0.000000
[67]	train-rmse:0.000000
[68]	train-rmse:0.000000
[69]	train-rmse:0.000000
[70]	train-rmse:0.000000
[71]	train-rmse:0.000000
[72]	train-rmse:0.000000
[73]	train-rmse:0.000000
[74]	train-rmse:0.000000
[75]	train-rmse:0.000000
[76]	train-rmse:0.000000
[77]	train-rmse:0.000000
```

```
[78]	train-rmse:0.000000
[79]	train-rmse:0.000000
[80]	train-rmse:0.000000
[81]	train-rmse:0.000000
[82]	train-rmse:0.000000
[83]	train-rmse:0.000000
[84]	train-rmse:0.000000
[85]	train-rmse:0.000000
[86]	train-rmse:0.000000
[87]	train-rmse:0.000000
[88]	train-rmse:0.000000
[89]	train-rmse:0.000000
[90]	train-rmse:0.000000
[91]	train-rmse:0.000000
[92]	train-rmse:0.000000
[93]	train-rmse:0.000000
[94]	train-rmse:0.000000
[95]	train-rmse:0.000000
[96]	train-rmse:0.000000
[97]	train-rmse:0.000000
[98]	train-rmse:0.000000
Stopping. Best iteration:
[48]	train-rmse:0.000000

##### xgb.Booster
raw: 43 Kb
call:
  xgb.train(params = params, data = dtrain, nrounds = nrounds,
    watchlist = watchlist, verbose = verbose, print_every_n = print_every_n,
    early_stopping_rounds = early_stopping_rounds, maximize = maximize,
    save_period = save_period, save_name = save_name, xgb_model = xgb_model,
    callbacks = callbacks, max.depth = 200, objective = "reg:squarederror")
params (as set within xgb.train):
  max_depth = "200", objective = "reg:squarederror", validate_parameters = "TRUE"
xgb.attributes:
  best_iteration, best_msg, best_ntreelimit, best_score, niter
callbacks:
  cb.print.evaluation(period = print_every_n)
  cb.evaluation.log()
  cb.early.stop(stopping_rounds = early_stopping_rounds, maximize = maximize,
    verbose = verbose)
# of features: 16
niter: 98
best_iteration : 48
best_ntreelimit : 48
best_score : 0
best_msg : [48] train-rmse:0.000000
nfeatures : 16
evaluation_log:
    iter train_rmse
       1   0.337911
       2   0.253433
---
      97   0.000000
      98   0.000000
MSE:  1.315938 MAE:  1.040774  RMSE:  1.147144
Saving 6.67 x 6.67 in image
```



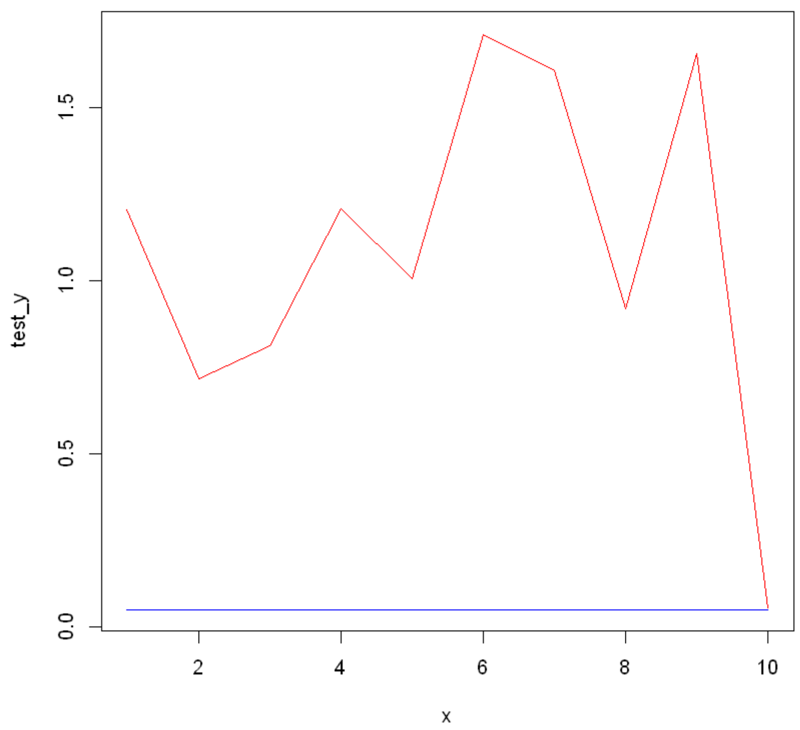
In [16]:

```
XGBoost(SPDE, SPDE$V9)
ggsave("./1_output/XGBoost_Y9.jpg") %>%
 suppressWarnings()
```

```
[1]	train-rmse:0.328900
Will train until train_rmse hasn't improved in 50 rounds.

[2]	train-rmse:0.240097
[3]	train-rmse:0.175271
[4]	train-rmse:0.127948
[5]	train-rmse:0.093402
[6]	train-rmse:0.068183
[7]	train-rmse:0.049774
[8]	train-rmse:0.036335
[9]	train-rmse:0.026524
[10]	train-rmse:0.019363
[11]	train-rmse:0.014135
[12]	train-rmse:0.010318
[13]	train-rmse:0.007532
[14]	train-rmse:0.005499
[15]	train-rmse:0.004014
[16]	train-rmse:0.002930
[17]	train-rmse:0.002139
[18]	train-rmse:0.001562
[19]	train-rmse:0.001140
```

```
[20]	train-rmse:0.000832
[21]	train-rmse:0.000607
[22]	train-rmse:0.000443
[23]	train-rmse:0.000324
[24]	train-rmse:0.000236
[25]	train-rmse:0.000173
[26]	train-rmse:0.000126
[27]	train-rmse:0.000092
[28]	train-rmse:0.000067
[29]	train-rmse:0.000049
[30]	train-rmse:0.000036
[31]	train-rmse:0.000026
[32]	train-rmse:0.000019
[33]	train-rmse:0.000014
[34]	train-rmse:0.000010
[35]	train-rmse:0.000007
[36]	train-rmse:0.000005
[37]	train-rmse:0.000004
[38]	train-rmse:0.000003
[39]	train-rmse:0.000002
[40]	train-rmse:0.000002
[41]	train-rmse:0.000001
[42]	train-rmse:0.000001
[43]	train-rmse:0.000001
[44]	train-rmse:0.000000
[45]	train-rmse:0.000000
[46]	train-rmse:0.000000
[47]	train-rmse:0.000000
[48]	train-rmse:0.000000
[49]	train-rmse:0.000000
[50]	train-rmse:0.000000
[51]	train-rmse:0.000000
[52]	train-rmse:0.000000
[53]	train-rmse:0.000000
[54]	train-rmse:0.000000
[55]	train-rmse:0.000000
[56]	train-rmse:0.000000
[57]	train-rmse:0.000000
[58]	train-rmse:0.000000
[59]	train-rmse:0.000000
[60]	train-rmse:0.000000
[61]	train-rmse:0.000000
[62]	train-rmse:0.000000
[63]	train-rmse:0.000000
[64]	train-rmse:0.000000
[65]	train-rmse:0.000000
[66]	train-rmse:0.000000
[67]	train-rmse:0.000000
[68]	train-rmse:0.000000
[69]	train-rmse:0.000000
[70]	train-rmse:0.000000
[71]	train-rmse:0.000000
[72]	train-rmse:0.000000
[73]	train-rmse:0.000000
[74]	train-rmse:0.000000
[75]	train-rmse:0.000000
[76]	train-rmse:0.000000
[77]	train-rmse:0.000000
[78]	train-rmse:0.000000
[79]	train-rmse:0.000000
[80]	train-rmse:0.000000
[81]	train-rmse:0.000000
[82]	train-rmse:0.000000
[83]	train-rmse:0.000000
[84]	train-rmse:0.000000
[85]	train-rmse:0.000000
[86]	train-rmse:0.000000
[87]	train-rmse:0.000000
[88]	train-rmse:0.000000
[89]	train-rmse:0.000000
[90]	train-rmse:0.000000
[91]	train-rmse:0.000000
[92]	train-rmse:0.000000
[93]	train-rmse:0.000000
[94]	train-rmse:0.000000
Stopping. Best iteration:
[44]	train-rmse:0.000000

##### xgb.Booster
raw: 41.4 Kb
call:
  xgb.train(params = params, data = dtrain, nrounds = nrounds,
    watchlist = watchlist, verbose = verbose, print_every_n = print_every_n,
    early_stopping_rounds = early_stopping_rounds, maximize = maximize,
    save_period = save_period, save_name = save_name, xgb_model = xgb_model,
    callbacks = callbacks, max.depth = 200, objective = "reg:squarederror")
params (as set within xgb.train):
  max_depth = "200", objective = "reg:squarederror", validate_parameters = "TRUE"
xgb.attributes:
  best_iteration, best_msg, best_ntreelimit, best_score, niter
callbacks:
  cb.print.evaluation(period = print_every_n)
  cb.evaluation.log()
  cb.early.stop(stopping_rounds = early_stopping_rounds, maximize = maximize,
    verbose = verbose)
# of features: 16
niter: 94
best_iteration : 44
best_ntreelimit : 44
best_score : 0
best_msg : [44] train-rmse:0.000000
nfeatures : 16
evaluation_log:
    iter train_rmse
       1   0.328900
       2   0.240097
---
      93   0.000000
      94   0.000000
MSE:  1.315938 MAE:  1.040774  RMSE:  1.147144
```

```
Saving 6.67 x 6.67 in image
```



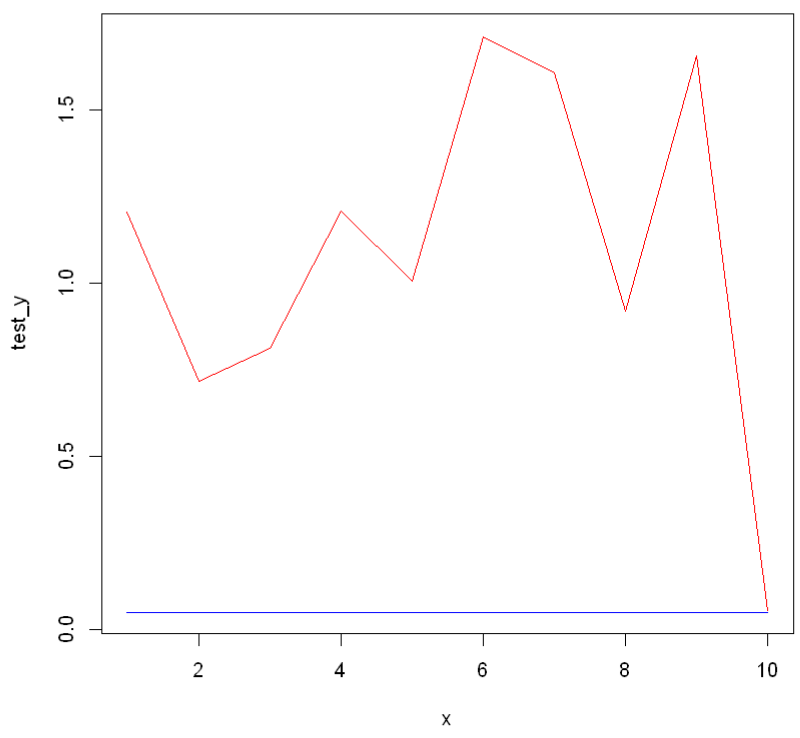
In [17]:

```
XGBoost(SPDE, SPDE$V10)
ggsave("./1_output/XGBoost_Y10.jpg") %>%
 suppressWarnings()
```

```
[1]	train-rmse:0.328900
Will train until train_rmse hasn't improved in 50 rounds.

[2]	train-rmse:0.240097
[3]	train-rmse:0.175271
[4]	train-rmse:0.127948
[5]	train-rmse:0.093402
[6]	train-rmse:0.068183
[7]	train-rmse:0.049774
[8]	train-rmse:0.036335
[9]	train-rmse:0.026524
[10]	train-rmse:0.019363
[11]	train-rmse:0.014135
[12]	train-rmse:0.010318
[13]	train-rmse:0.007532
[14]	train-rmse:0.005499
[15]	train-rmse:0.004014
[16]	train-rmse:0.002930
[17]	train-rmse:0.002139
[18]	train-rmse:0.001562
[19]	train-rmse:0.001140
[20]	train-rmse:0.000832
[21]	train-rmse:0.000607
[22]	train-rmse:0.000443
[23]	train-rmse:0.000324
[24]	train-rmse:0.000236
[25]	train-rmse:0.000173
[26]	train-rmse:0.000126
[27]	train-rmse:0.000092
[28]	train-rmse:0.000067
[29]	train-rmse:0.000049
[30]	train-rmse:0.000036
[31]	train-rmse:0.000026
[32]	train-rmse:0.000019
[33]	train-rmse:0.000014
[34]	train-rmse:0.000010
[35]	train-rmse:0.000007
[36]	train-rmse:0.000005
[37]	train-rmse:0.000004
[38]	train-rmse:0.000003
[39]	train-rmse:0.000002
[40]	train-rmse:0.000002
[41]	train-rmse:0.000001
[42]	train-rmse:0.000001
[43]	train-rmse:0.000001
[44]	train-rmse:0.000000
[45]	train-rmse:0.000000
[46]	train-rmse:0.000000
[47]	train-rmse:0.000000
[48]	train-rmse:0.000000
[49]	train-rmse:0.000000
[50]	train-rmse:0.000000
[51]	train-rmse:0.000000
[52]	train-rmse:0.000000
[53]	train-rmse:0.000000
[54]	train-rmse:0.000000
[55]	train-rmse:0.000000
[56]	train-rmse:0.000000
[57]	train-rmse:0.000000
[58]	train-rmse:0.000000
[59]	train-rmse:0.000000
[60]	train-rmse:0.000000
[61]	train-rmse:0.000000
[62]	train-rmse:0.000000
[63]	train-rmse:0.000000
[64]	train-rmse:0.000000
[65]	train-rmse:0.000000
[66]	train-rmse:0.000000
[67]	train-rmse:0.000000
[68]	train-rmse:0.000000
[69]	train-rmse:0.000000
[70]	train-rmse:0.000000
[71]	train-rmse:0.000000
[72]	train-rmse:0.000000
[73]	train-rmse:0.000000
[74]	train-rmse:0.000000
[75]	train-rmse:0.000000
[76]	train-rmse:0.000000
[77]	train-rmse:0.000000
```

```
[78]	train-rmse:0.000000
[79]	train-rmse:0.000000
[80]	train-rmse:0.000000
[81]	train-rmse:0.000000
[82]	train-rmse:0.000000
[83]	train-rmse:0.000000
[84]	train-rmse:0.000000
[85]	train-rmse:0.000000
[86]	train-rmse:0.000000
[87]	train-rmse:0.000000
[88]	train-rmse:0.000000
[89]	train-rmse:0.000000
[90]	train-rmse:0.000000
[91]	train-rmse:0.000000
[92]	train-rmse:0.000000
[93]	train-rmse:0.000000
[94]	train-rmse:0.000000
Stopping. Best iteration:
[44]	train-rmse:0.000000

##### xgb.Booster
raw: 41.4 Kb
call:
  xgb.train(params = params, data = dtrain, nrounds = nrounds,
    watchlist = watchlist, verbose = verbose, print_every_n = print_every_n,
    early_stopping_rounds = early_stopping_rounds, maximize = maximize,
    save_period = save_period, save_name = save_name, xgb_model = xgb_model,
    callbacks = callbacks, max.depth = 200, objective = "reg:squarederror")
params (as set within xgb.train):
  max_depth = "200", objective = "reg:squarederror", validate_parameters = "TRUE"
xgb.attributes:
  best_iteration, best_msg, best_ntreelimit, best_score, niter
callbacks:
  cb.print.evaluation(period = print_every_n)
  cb.evaluation.log()
  cb.early.stop(stopping_rounds = early_stopping_rounds, maximize = maximize,
    verbose = verbose)
# of features: 16
niter: 94
best_iteration : 44
best_ntreelimit : 44
best_score : 0
best_msg : [44] train-rmse:0.000000
nfeatures : 16
evaluation_log:
    iter train_rmse
       1   0.328900
       2   0.240097
---
      93   0.000000
      94   0.000000
MSE:  1.315938 MAE:  1.040774  RMSE:  1.147144
```

```
Saving 6.67 x 6.67 in image
```

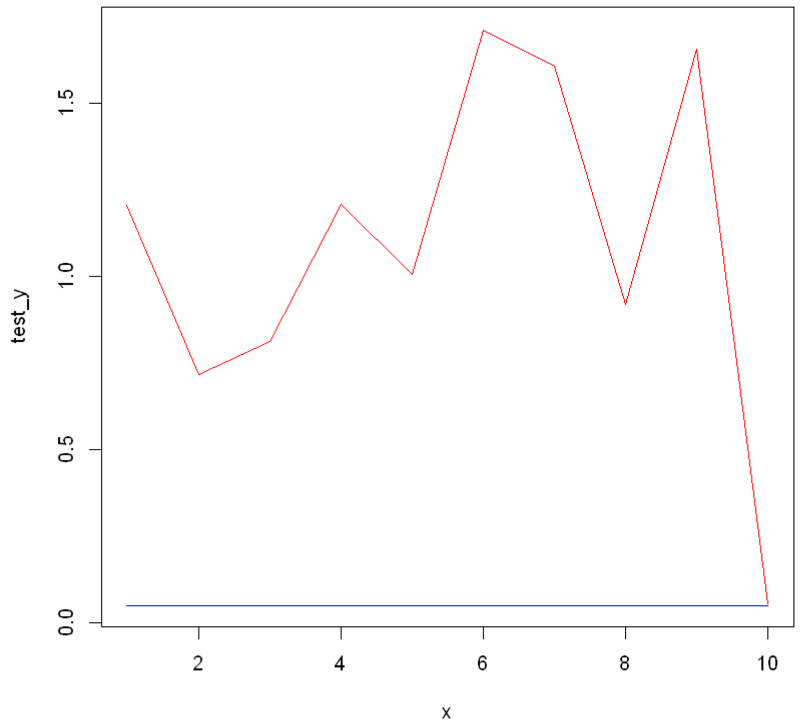


In [18]:

```
XGBoost(SPDE, SPDE$V11)
ggsave("./1_output/XGBoost_Y11.jpg") %>%
 suppressWarnings()
```

```
[1]	train-rmse:0.332279
Will train until train_rmse hasn't improved in 50 rounds.

[2]	train-rmse:0.245056
[3]	train-rmse:0.180729
[4]	train-rmse:0.133287
[5]	train-rmse:0.098299
[6]	train-rmse:0.072496
[7]	train-rmse:0.053466
[8]	train-rmse:0.039431
[9]	train-rmse:0.029080
[10]	train-rmse:0.021447
[11]	train-rmse:0.015817
[12]	train-rmse:0.011665
[13]	train-rmse:0.008603
[14]	train-rmse:0.006345
[15]	train-rmse:0.004679
[16]	train-rmse:0.003451
[17]	train-rmse:0.002545
[18]	train-rmse:0.001877
[19]	train-rmse:0.001384
[20]	train-rmse:0.001021
[21]	train-rmse:0.000753
[22]	train-rmse:0.000555
[23]	train-rmse:0.000410
```

```
[24]	train-rmse:0.000302
[25]	train-rmse:0.000223
[26]	train-rmse:0.000164
[27]	train-rmse:0.000121
[28]	train-rmse:0.000089
[29]	train-rmse:0.000066
[30]	train-rmse:0.000049
[31]	train-rmse:0.000036
[32]	train-rmse:0.000026
[33]	train-rmse:0.000019
[34]	train-rmse:0.000014
[35]	train-rmse:0.000011
[36]	train-rmse:0.000008
[37]	train-rmse:0.000006
[38]	train-rmse:0.000004
[39]	train-rmse:0.000003
[40]	train-rmse:0.000002
[41]	train-rmse:0.000002
[42]	train-rmse:0.000001
[43]	train-rmse:0.000001
[44]	train-rmse:0.000001
[45]	train-rmse:0.000001
[46]	train-rmse:0.000000
[47]	train-rmse:0.000000
[48]	train-rmse:0.000000
[49]	train-rmse:0.000000
[50]	train-rmse:0.000000
[51]	train-rmse:0.000000
[52]	train-rmse:0.000000
[53]	train-rmse:0.000000
[54]	train-rmse:0.000000
[55]	train-rmse:0.000000
[56]	train-rmse:0.000000
[57]	train-rmse:0.000000
[58]	train-rmse:0.000000
[59]	train-rmse:0.000000
[60]	train-rmse:0.000000
[61]	train-rmse:0.000000
[62]	train-rmse:0.000000
[63]	train-rmse:0.000000
[64]	train-rmse:0.000000
[65]	train-rmse:0.000000
[66]	train-rmse:0.000000
[67]	train-rmse:0.000000
[68]	train-rmse:0.000000
[69]	train-rmse:0.000000
[70]	train-rmse:0.000000
[71]	train-rmse:0.000000
[72]	train-rmse:0.000000
[73]	train-rmse:0.000000
[74]	train-rmse:0.000000
[75]	train-rmse:0.000000
[76]	train-rmse:0.000000
[77]	train-rmse:0.000000
[78]	train-rmse:0.000000
[79]	train-rmse:0.000000
[80]	train-rmse:0.000000
[81]	train-rmse:0.000000
[82]	train-rmse:0.000000
[83]	train-rmse:0.000000
[84]	train-rmse:0.000000
[85]	train-rmse:0.000000
[86]	train-rmse:0.000000
[87]	train-rmse:0.000000
[88]	train-rmse:0.000000
[89]	train-rmse:0.000000
[90]	train-rmse:0.000000
[91]	train-rmse:0.000000
[92]	train-rmse:0.000000
[93]	train-rmse:0.000000
[94]	train-rmse:0.000000
[95]	train-rmse:0.000000
[96]	train-rmse:0.000000
Stopping. Best iteration:
[46]	train-rmse:0.000000

##### xgb.Booster
raw: 42.2 Kb
call:
  xgb.train(params = params, data = dtrain, nrounds = nrounds,
    watchlist = watchlist, verbose = verbose, print_every_n = print_every_n,
    early_stopping_rounds = early_stopping_rounds, maximize = maximize,
    save_period = save_period, save_name = save_name, xgb_model = xgb_model,
    callbacks = callbacks, max.depth = 200, objective = "reg:squarederror")
params (as set within xgb.train):
  max_depth = "200", objective = "reg:squarederror", validate_parameters = "TRUE"
xgb.attributes:
  best_iteration, best_msg, best_ntreelimit, best_score, niter
callbacks:
  cb.print.evaluation(period = print_every_n)
  cb.evaluation.log()
  cb.early.stop(stopping_rounds = early_stopping_rounds, maximize = maximize,
    verbose = verbose)
# of features: 16
niter: 96
best_iteration : 46
best_ntreelimit : 46
best_score : 0
best_msg : [46] train-rmse:0.000000
nfeatures : 16
evaluation_log:
    iter train_rmse
       1   0.332279
       2   0.245056
---
      95   0.000000
      96   0.000000
MSE:  1.315939 MAE:  1.040774  RMSE:  1.147144
Saving 6.67 x 6.67 in image
```



Drawing Graphs

In [19]:

```
# ローデータの多変量時系列プロット
# Multivariate Time Series Plot of Raw Data
## 各グラフの作成
## Create each graph
fig_1  <- fig(raw_data, raw_data$Y1, "Final Energy Consumption(EJ)", "Descriptive Statistics")
fig_2  <- fig(raw_data, raw_data$Y2, "GHG(t-CO2)", "Descriptive Statistics")
fig_3  <- fig(raw_data, raw_data$Y3, "Nuclear power plant accidents and abnormal events (presence/absence)", "Descriptive Statistics")
fig_4  <- fig(raw_data, raw_data$Y4, "Average crude oil price(Real US$/bbl)", "Descriptive Statistics")
fig_5  <- fig(raw_data, raw_data$Y5, "Real GDP(US$)", "記述統計値(Descriptive Statistics)")
fig_6  <- fig(raw_data, raw_data$Y6, "Japan GDP / the national debt residual(%)", "escriptive Statistics")
fig_7  <- fig(raw_data, raw_data$Y7, "Average consumer price index for the year)(JFY2015 = 100)", "Descriptive Statistics)")
fig_8  <- fig(raw_data, raw_data$Y8, "Average complete unemployment rate over the year)(%)","Descriptive Statistics")
fig_9  <- fig(raw_data, raw_data$Y9, "Nikkei Stock Average Closing Price)(Real Yen)", "Descriptive Statistics")
fig_10 <- fig(raw_data, raw_data$Y10, "Japan LDP's share of House of Representatives seats won(%)", "Descriptive Statistics")
fig_11 <- fig(raw_data, raw_data$Y11, "Agreement on climate change measures (yes/no)", "Descriptive Statistics")
fig_12 <- fig(raw_data, raw_data$id,  "Formulation and revision of the basic energy plan (yes/no)", "Descriptive Statistics")

## 一枚に集約して出力する。
## Consolidate and output to a single sheet.
grid.arrange(fig_1, fig_2, fig_3, fig_4, fig_5, fig_6, fig_7, fig_8, fig_9, fig_10, fig_11, fig_12)
ggsave("./1_output/Multivariate_Time_Series_Plot_raw_data.jpg") %>%
  suppressWarnings() %>%
  capture.output

# 誤差項調整多変量時系列プロット
# Multivariate Time Series Plot with Error Term Adjusted
## 各グラフの作成
## Create each graph
fig_1  <- fig(panel, panel$Y1,  "Final Energy Consumption(EJ)(EJ)", "Logarithmic differential series")
fig_2  <- fig(panel, panel$Y2,  "GHG(t-CO2)", "Logarithmic differential series")
fig_3  <- fig(panel, panel$Y3,  "Nuclear power plant accidents and abnormal events (presence/absence)", "Logarithmic differential series)")
fig_4  <- fig(panel, panel$Y4,  "Average crude oil price(Real US$/bbl)", "Logarithmic differential series")
fig_5  <- fig(panel, panel$Y5,  "Real GDP(US$)", "Logarithmic differential series")
fig_6  <- fig(panel, panel$Y6,  "Japan GDP / the national debt residual(%)", "Logarithmic differential series")
fig_7  <- fig(panel, panel$Y7,  "Average consumer price index for the year)(JFY2015 = 100)","Logarithmic differential series")
fig_8  <- fig(panel, panel$Y8,  "Average complete unemployment rate over the year(%)", "Logarithmic differential series")
fig_9  <- fig(panel, panel$Y9,  "Nikkei Stock Average Closing Price(Real Yen)", "Logarithmic differential series")
fig_10 <- fig(panel, panel$Y10, "Japan LDP's share of House of Representatives seats won(%)", "Logarithmic differential series")
fig_11 <- fig(panel, panel$Y11, "Agreement on climate change measures (yes/no)", "Logarithmic differential series")
fig_12 <- fig(panel, panel$id,  "Formulation and revision of the basic energy plan (yes/no)", "Logarithmic differential series")

## 一枚に集約して出力する。
## Consolidate and output to a single sheet.
grid.arrange(fig_1, fig_2, fig_3, fig_4, fig_5, fig_6, fig_7, fig_8, fig_9, fig_10, fig_11, fig_12)
ggsave("./1_output/Multivariate_Time_Series_Plot_adjusted.jpg") %>%
  suppressWarnings() %>%
  capture.output

# 相関行列の可視化による多重共線性の目視確認
# Visual confirmation of multicollinearity by visualizing the correlation matrix
qgraph(cor(relation), edge.labels = TRUE)
ggsave("./1_output/relation_vector.jpg") %>%
  suppressWarnings() %>%
  capture.output
```

```
Saving 6.67 x 6.67 in image
```

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geom_path: Each group consists of only one observation. Do you need to adjust
the group aesthetic?

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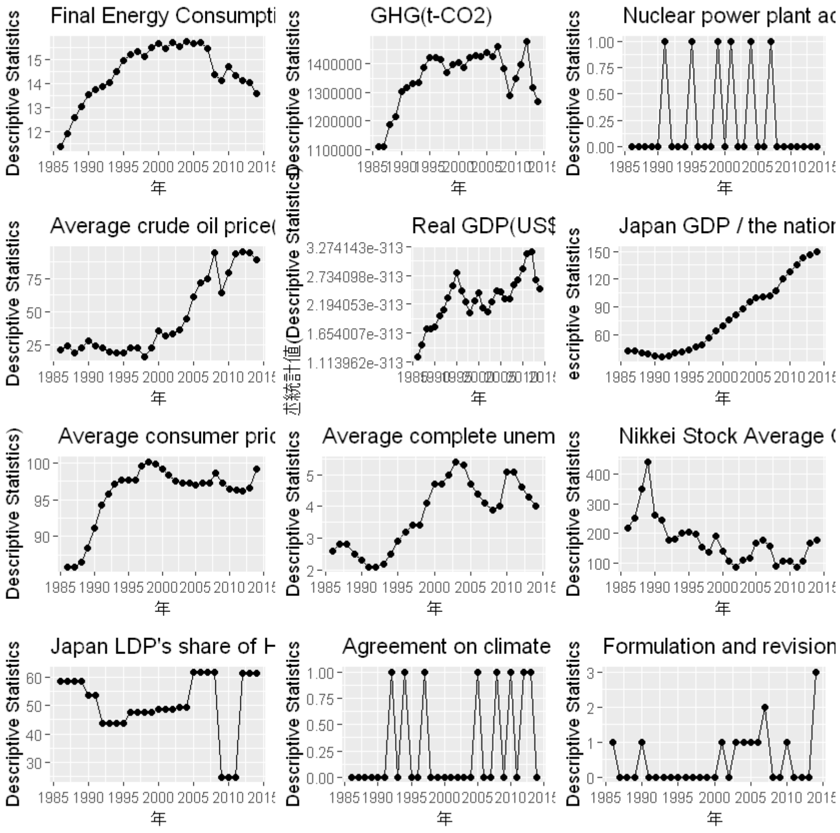
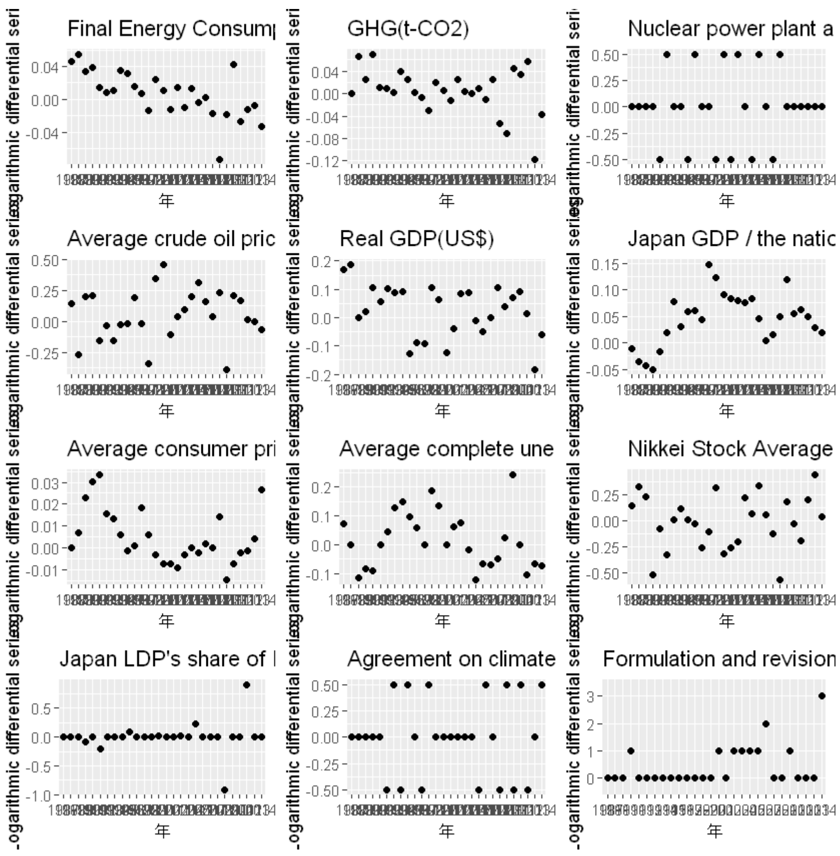



```
Saving 6.67 x 6.67 in image

geom_path: Each group consists of only one observation. Do you need to adjust
the group aesthetic?
```

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Saving 6.67 x 6.67 in image

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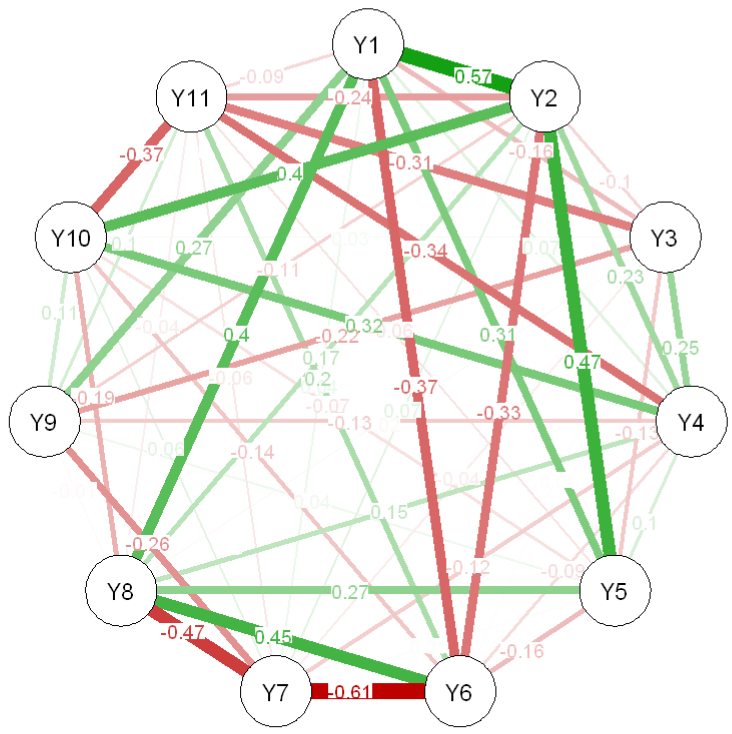
Y1
Y2
Y3
Y4
Y5
Y6
Y7
Y8
Y9
Y10
Y11
0.57
-0.24
-0.37
-0.31
0.4
-0.34
0.27
0.23
0.25
0.32
0.47
0.31
0.4
-0.37
-0.33
-0.26
0.27
-0.47
0.45
-0.61
0.15
-0.16