# VAR

Code

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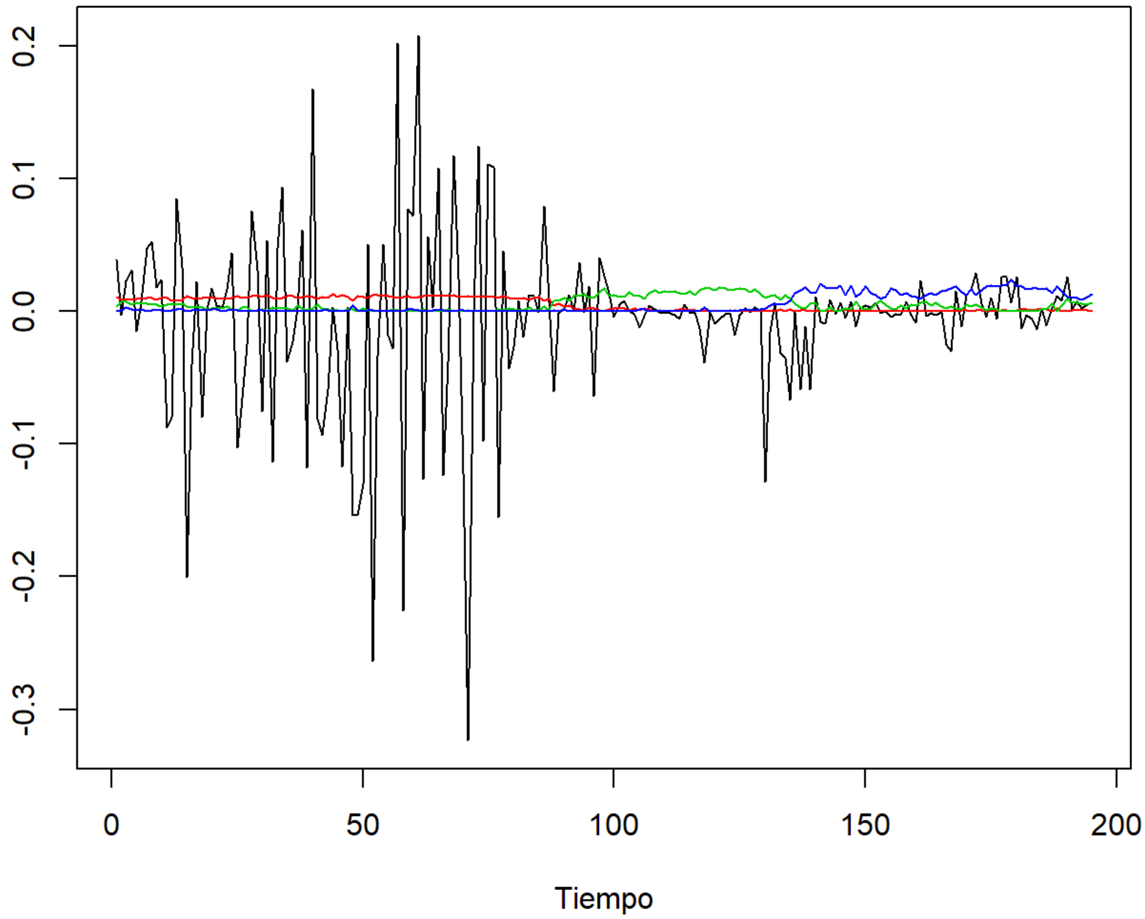
Code

# MODELO 1

Code

Code

Code




## Seleccion del LAG

Code

```
## $selection
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      3      2      2      3
##
## $criteria
##                    1             2             3             4
## AIC(n) -4.469808e+01 -4.506375e+01 -4.509536e+01 -4.502382e+01
## HQ(n)  -4.455644e+01 -4.480881e+01 -4.472711e+01 -4.454225e+01
## SC(n)  -4.434863e+01 -4.443474e+01 -4.418679e+01 -4.383569e+01
## FPE(n)  3.871628e-20  2.686562e-20  2.604615e-20  2.801063e-20
##                    5             6             7             8
## AIC(n) -4.501593e+01 -4.491821e+01 -4.476464e+01 -4.467046e+01
## HQ(n)  -4.442106e+01 -4.421003e+01 -4.394315e+01 -4.373566e+01
## SC(n)  -4.354825e+01 -4.317096e+01 -4.273783e+01 -4.236409e+01
## FPE(n)  2.828550e-20  3.127575e-20  3.660714e-20  4.042763e-20
##                    9            10
## AIC(n) -4.455927e+01 -4.441503e+01
## HQ(n)  -4.351116e+01 -4.325361e+01
## SC(n)  -4.197335e+01 -4.154954e+01
## FPE(n)  4.547849e-20  5.296714e-20
```

Code

### 1.2. Paso 2: EstimaciÓN del Modelo VAR

Code

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: tasa, w1, w2, w3
## Deterministic variables: const
## Sample size: 191
## Log Likelihood: 3284.883
## Roots of the characteristic polynomial:
## 0.7748 0.7748 0.7236 0.6486 0.6486 0.5171 0.445 0.445 0.429 0.429 0.330
7 0.09172
## Call:
## VAR(y = diff(as.matrix(series)), p = 3, type = c("const"))
##
##
## Estimation results for equation tasa:
## =====================================
## tasa = tasa.l1 + w1.l1 + w2.l1 + w3.l1 + tasa.l2 + w1.l2 + w2.l2 + w3.l
2 + tasa.l3 + w1.l3 + w2.l3 + w3.l3 + const
##
##           Estimate Std. Error t value Pr(>|t|)
## tasa.l1 -0.9145392  0.0694872 -13.161  < 2e-16 ***
## w1.l1    4.5606207  8.4067953   0.542    0.588
## w2.l1    4.1004098  4.8461699   0.846    0.399
## w3.l1    1.1423206  4.1904871   0.273    0.785
## tasa.l2 -0.7216917  0.0813307  -8.874 7.41e-16 ***
## w1.l2   10.8953247  9.3117591   1.170    0.244
## w2.l2    2.2505103  5.2313109   0.430    0.668
## w3.l2    1.1261359  4.6690239   0.241    0.810
## tasa.l3 -0.3907166  0.0694534  -5.626 7.06e-08 ***
## w1.l3    3.8539042  8.2612271   0.467    0.641
## w2.l3    2.8410369  4.7969373   0.592    0.554
## w3.l3    2.7899242  4.1441167   0.673    0.502
## const    0.0003641  0.0050822   0.072    0.943
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.06952 on 178 degrees of freedom
## Multiple R-Squared: 0.5268,  Adjusted R-squared: 0.4949
## F-statistic: 16.51 on 12 and 178 DF,  p-value: < 2.2e-16
##
##
##
## Covariance matrix of residuals:
##             tasa         w1         w2         w3
## tasa  4.833e-03 -3.375e-06 -3.045e-06 -2.787e-07
```

```
## w1   -3.375e-06  9.313e-07 -1.050e-06 -2.914e-07
## w2   -3.045e-06 -1.050e-06  3.778e-06 -1.895e-06
## w3   -2.787e-07 -2.914e-07 -1.895e-06  3.557e-06
##
## Correlation matrix of residuals:
##           tasa       w1       w2        w3
## tasa  1.000000 -0.05031 -0.02253 -0.002125
## w1   -0.050305  1.00000 -0.55995 -0.160076
## w2   -0.022534 -0.55995  1.00000 -0.516988
## w3   -0.002125 -0.16008 -0.51699  1.000000
```

Estabilidad en el modelo dado que son menores a uno En este ejemplo, estos estadisticos indican un ajuste sensiblemente pobre para ambas ecuaciones

### 1.3. Paso 3: EvaluaciÃ³n del Modelo

1.3.1. Prueba de Estacionariedad (Condicion de Estabilidad de los Estimadores) vamos a ver si cumple la condicion de estabilidad prueba de estacionariedad demultiple variables que mencionamos anteriormente

Recordemos que un proceso autorregresivo univariado es estacionario si todas las raices de Ï□$(z) = 0$ se encuentran fuera del circulo unitario.

Code

```
##  [1] 0.77478448 0.77478448 0.72361989 0.64855465 0.64855465 0.51710776
##  [7] 0.44504095 0.44504095 0.42899514 0.42899514 0.33067136 0.09172097
```

La comprobación de la estabilidad no indica que nuestro modelo este mal.

Code

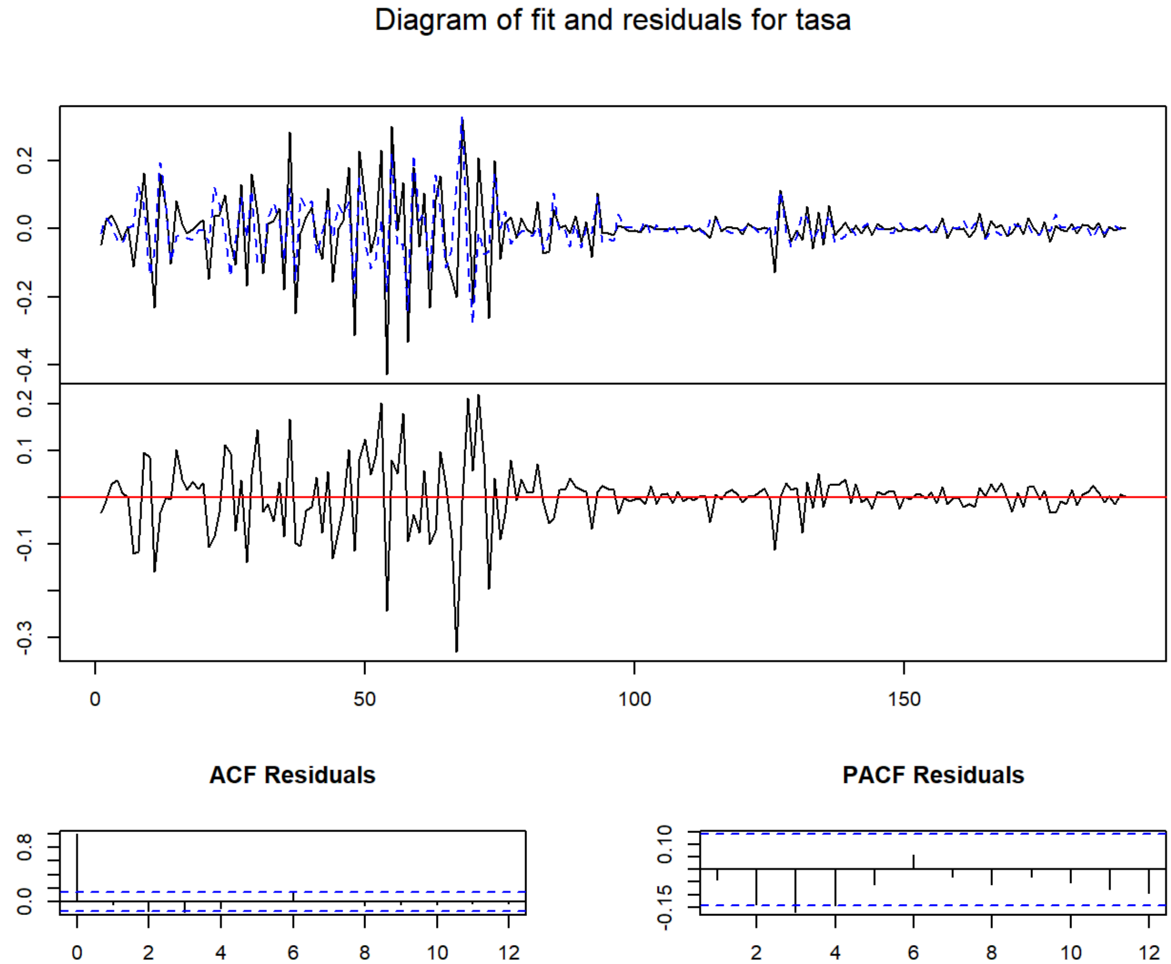


Diagram of fit and residuals for tasa
0.2
0.0
-0.2
-0.4
0.2
0.1
-0.1
-0.3
0
50
100
150
ACF Residuals
0.8
0.0
0
2
4
6
8
10
12
PACF Residuals
0.10
-0.15
2
4
6
8
10
12

Code

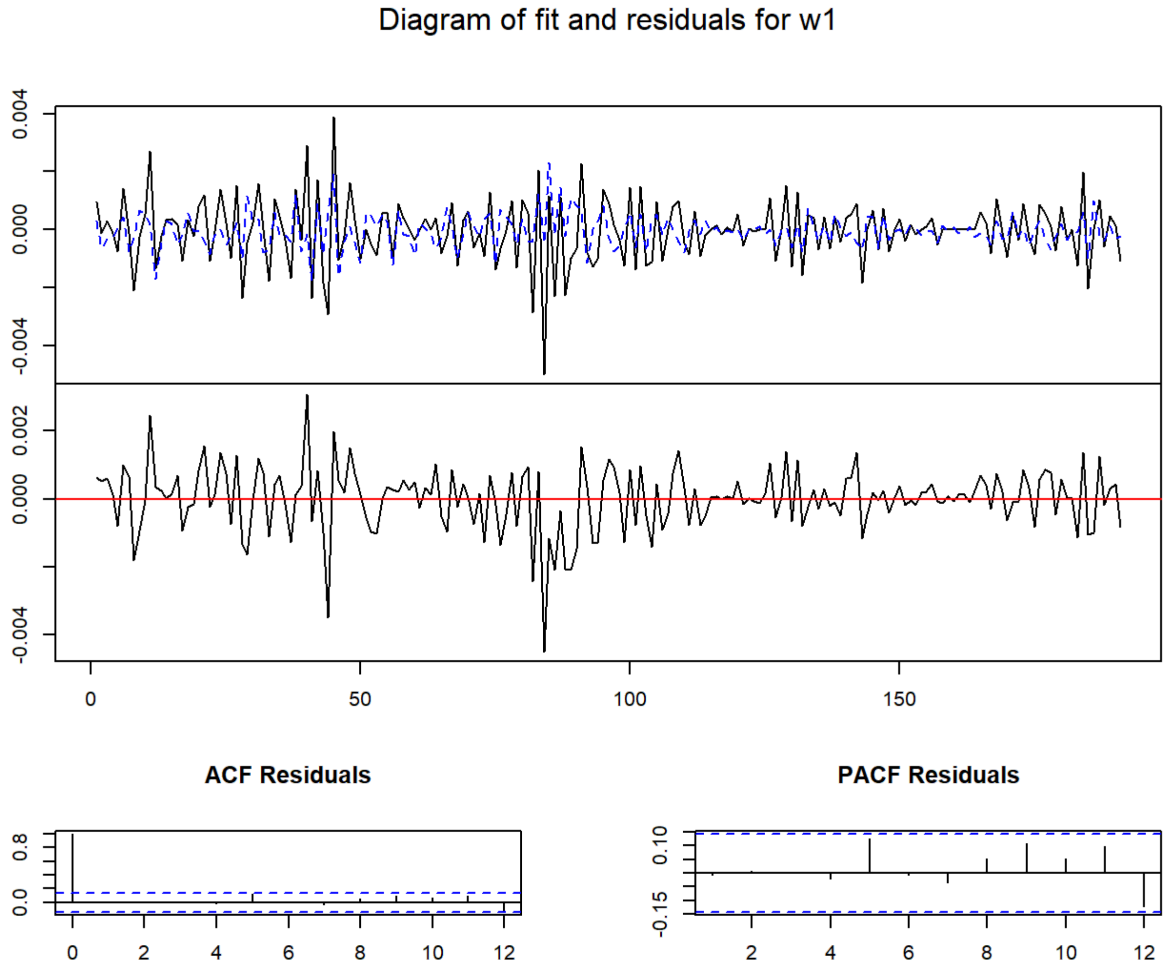


Diagram of fit and residuals for w1
0.004
0.000
-0.004
0.002
0.000
-0.004
0
50
100
150
ACF Residuals
0.8
0.0
0
2
4
6
8
10
12
PACF Residuals
0.10
-0.15
2
4
6
8
10
12

Code

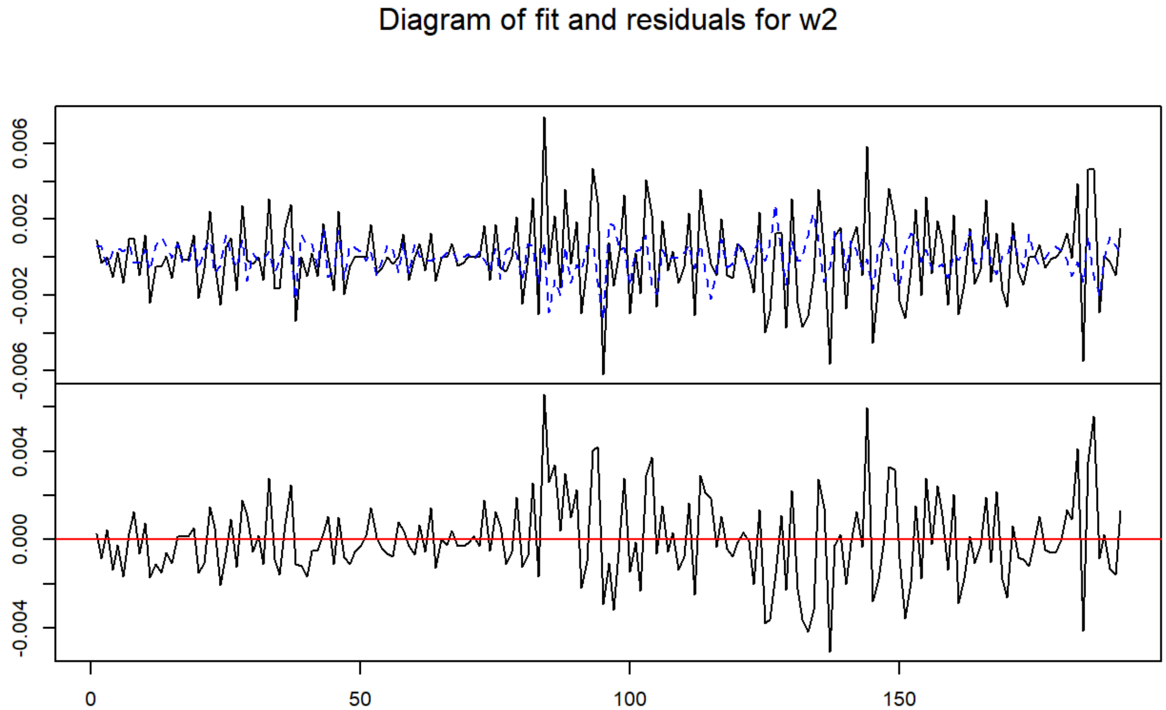
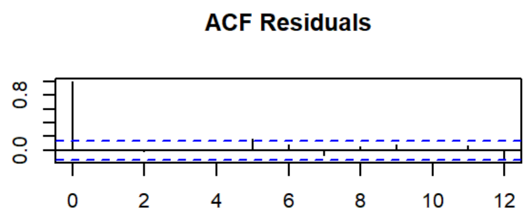
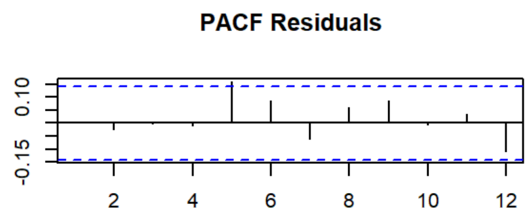
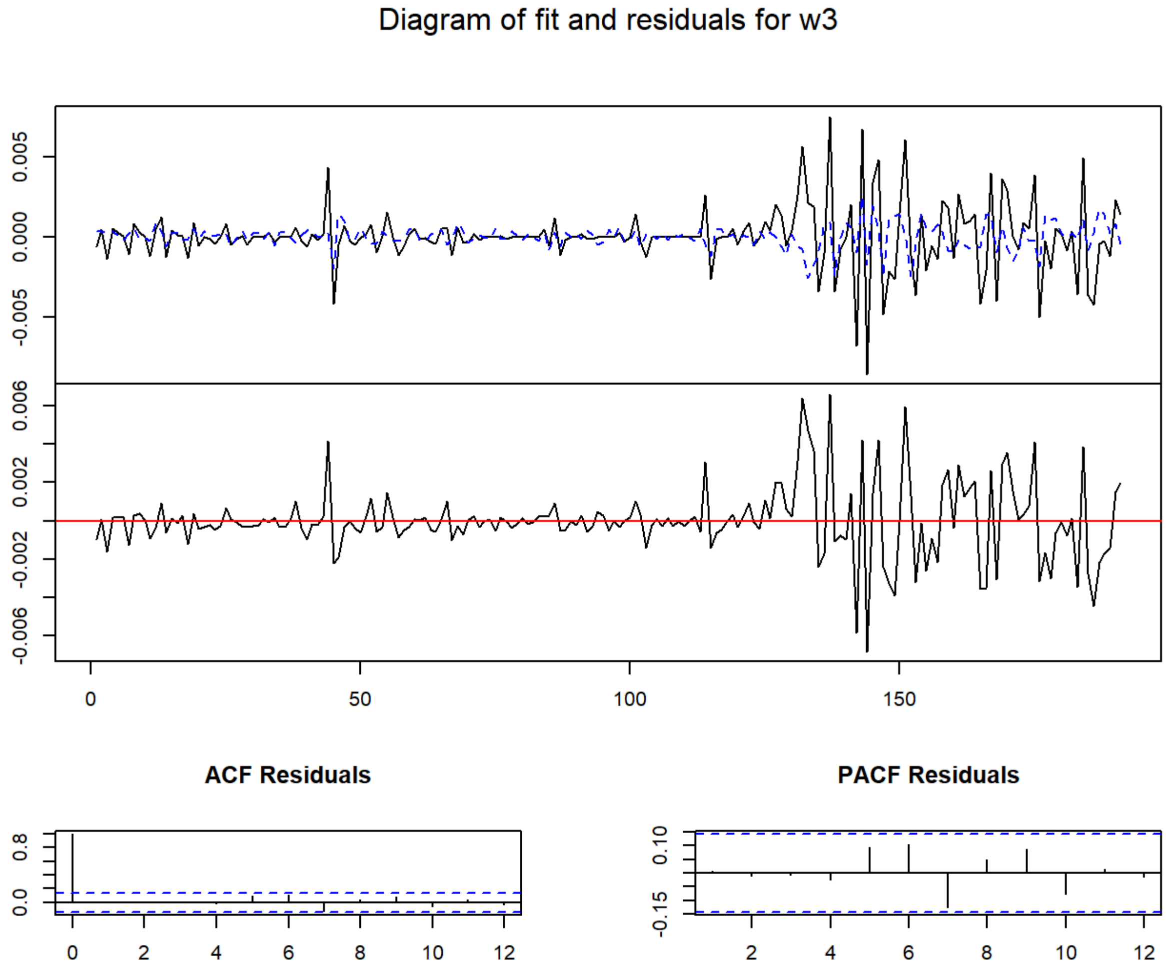


Diagram of fit and residuals for w2
0.006
0.002
-0.002
-0.006
0.004
0.000
-0.004
0
50
100
150


ACF Residuals
0.8
0.0
0
2
4
6
8
10
12


PACF Residuals
0.10
-0.15
2
4
6
8
10
12

Code




Code

Autocorrelación

Code

```
##
##  Portmanteau Test (asymptotic)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 92.352, df = 112, p-value = 0.912
```

Code

```
##
##  Portmanteau Test (asymptotic)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 180.81, df = 208, p-value = 0.9136
```

Code

## Normalidad

Code

```
## $tasa
##
##  JB-Test (univariate)
##
## data:  Residual of tasa equation
## Chi-squared = 176.4, df = 2, p-value < 2.2e-16
##
##
## $w1
##
##  JB-Test (univariate)
##
## data:  Residual of w1 equation
## Chi-squared = 107.99, df = 2, p-value < 2.2e-16
##
##
## $w2
##
##  JB-Test (univariate)
##
## data:  Residual of w2 equation
## Chi-squared = 14.478, df = 2, p-value = 0.0007179
##
##
## $w3
##
##  JB-Test (univariate)
##
## data:  Residual of w3 equation
## Chi-squared = 80.886, df = 2, p-value < 2.2e-16
##
##
## $JB
##
##  JB-Test (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 316.83, df = 8, p-value < 2.2e-16
##
##
## $Skewness
##
##  Skewness only (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 36.137, df = 4, p-value = 2.712e-07
```

```
##
##
## $Kurtosis
##
##  Kurtosis only (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 280.69, df = 4, p-value < 2.2e-16
```

Code

Habiendo estimado estos modelos, ¿podemos inferir algo mas? Si el sistema se somete a un shock de los topicos, ¿cual es el efecto en la trayectoria dinamica de la tasa de interes?

Code

```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w1), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df     F  Pr(>F)
## 1    187
## 2    189 -2 3.369 0.03653 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

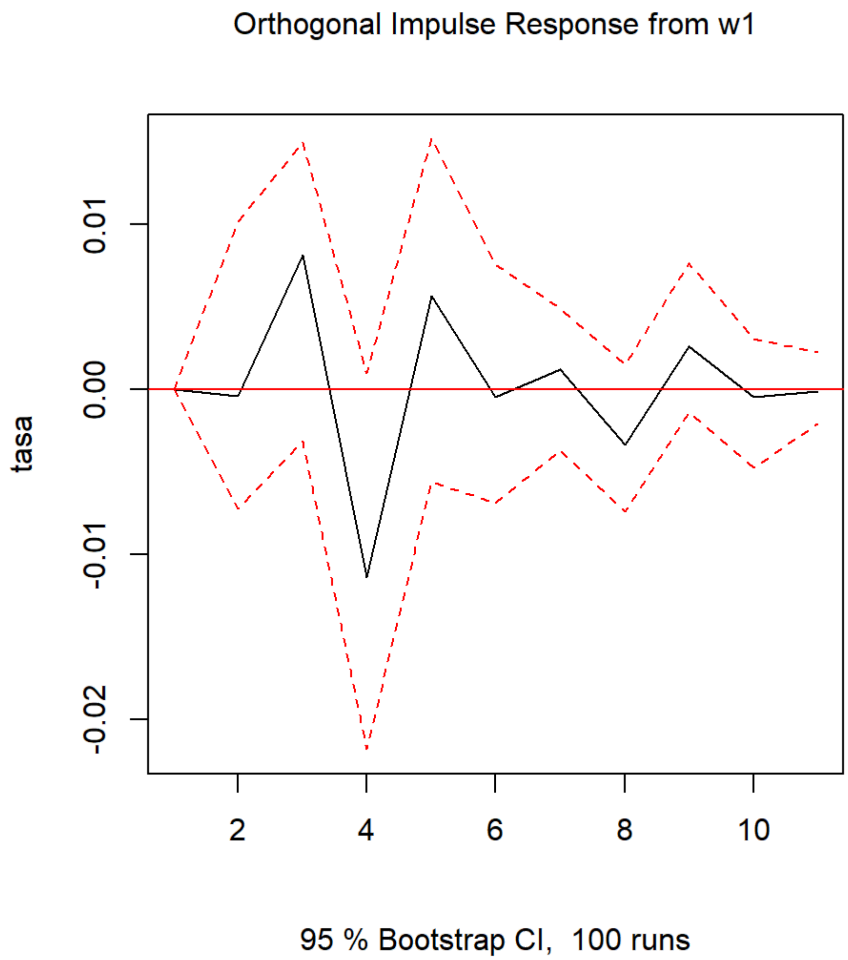
Code

```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w2), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df      F Pr(>F)
## 1    187
## 2    189 -2 1.4126 0.2461
```

Code

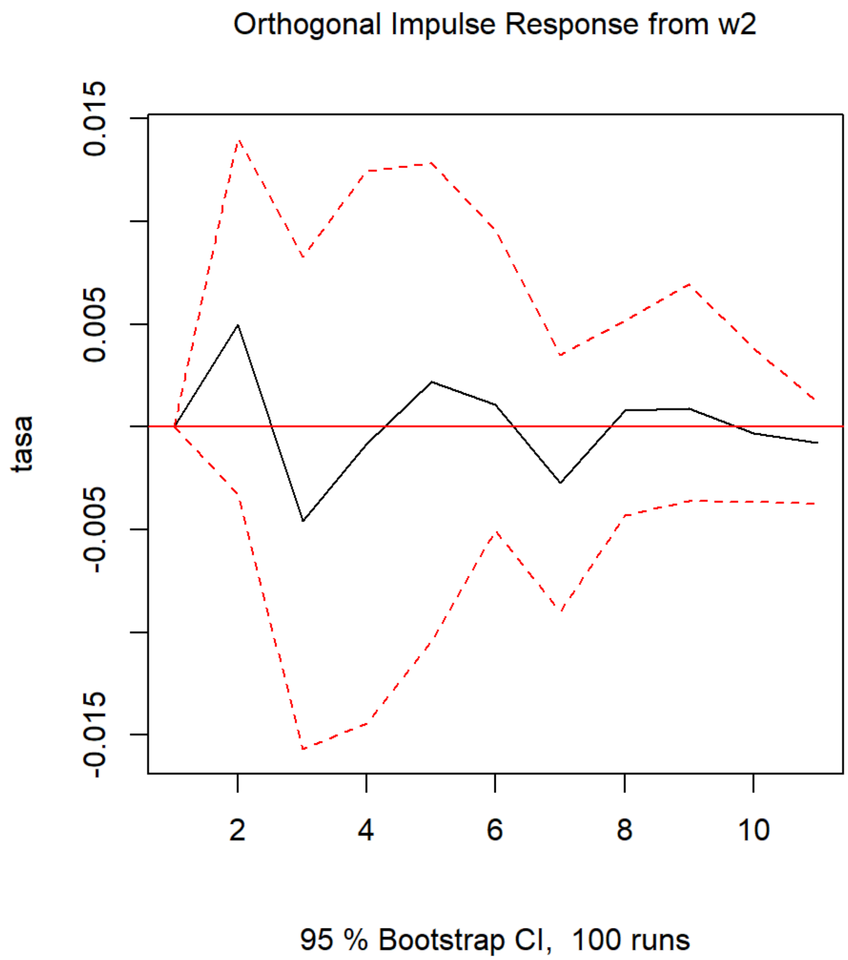
```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w3), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df      F Pr(>F)
## 1    187
## 2    189 -2 0.2249 0.7988
```

Code

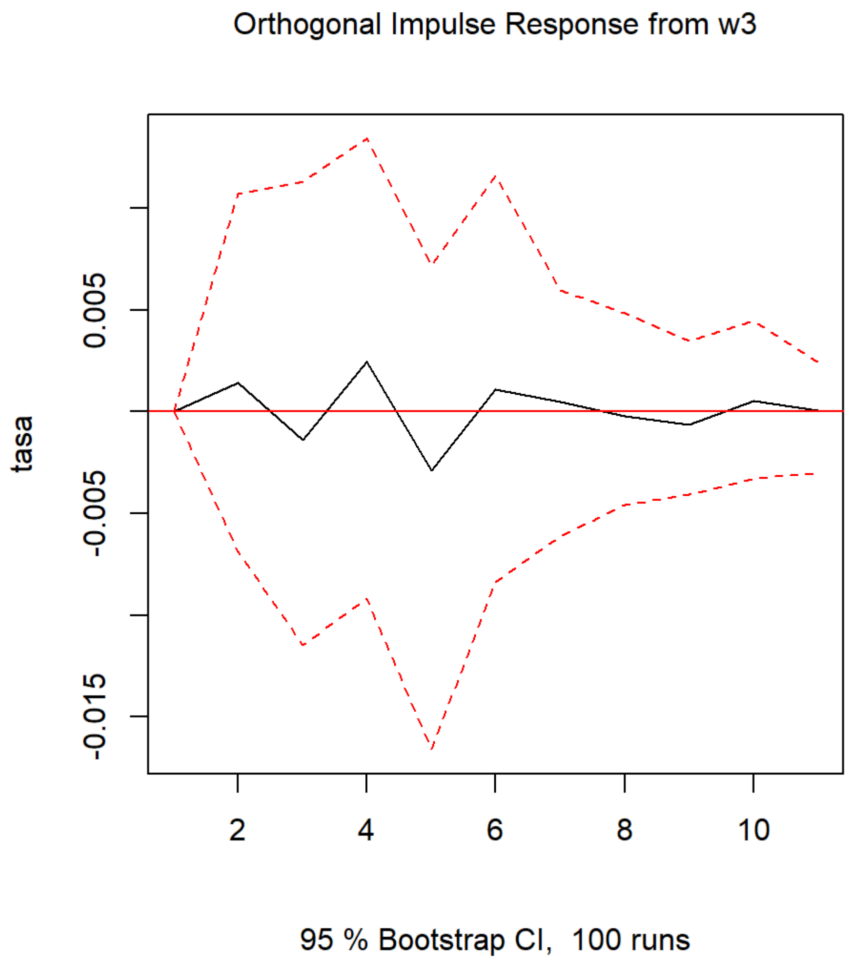


Orthogonal Impulse Response from w1
tasa
0.01
0.00
-0.01
-0.02
2
4
6
8
10
95 % Bootstrap CI, 100 runs


Code


Orthogonal Impulse Response from w2
tasa
0.015
0.005
-0.005
-0.015
2
4
6
8
10
95 % Bootstrap CI, 100 runs

Code




# Modelo 2

Pre-crisis

Code

Seleccion del LAG

Code

```
## $selection
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      3      2      2      3
##
## $criteria
##                    1             2             3             4
## AIC(n) -4.601622e+01 -4.679419e+01 -4.685218e+01 -4.672584e+01
## HQ(n)  -4.576614e+01 -4.634405e+01 -4.620198e+01 -4.587557e+01
## SC(n)  -4.538870e+01 -4.566465e+01 -4.522062e+01 -4.459226e+01
## FPE(n)  1.037008e-20  4.783333e-21  4.560619e-21  5.276505e-21
##                    5             6             7             8
## AIC(n) -4.670467e+01 -4.663572e+01 -4.672481e+01 -4.685188e+01
## HQ(n)  -4.565434e+01 -4.538533e+01 -4.527436e+01 -4.520136e+01
## SC(n)  -4.406908e+01 -4.349811e+01 -4.308518e+01 -4.271023e+01
## FPE(n)  5.564727e-21  6.258265e-21  6.138153e-21  5.954845e-21
##                    9            10
## AIC(n) -4.660283e+01 -4.645792e+01
## HQ(n)  -4.475225e+01 -4.440728e+01
## SC(n)  -4.195916e+01 -4.131223e+01
## FPE(n)  8.710308e-21  1.200187e-20
```

Code

### 1.2. Paso 2: Estimacion del Modelo VAR

Code

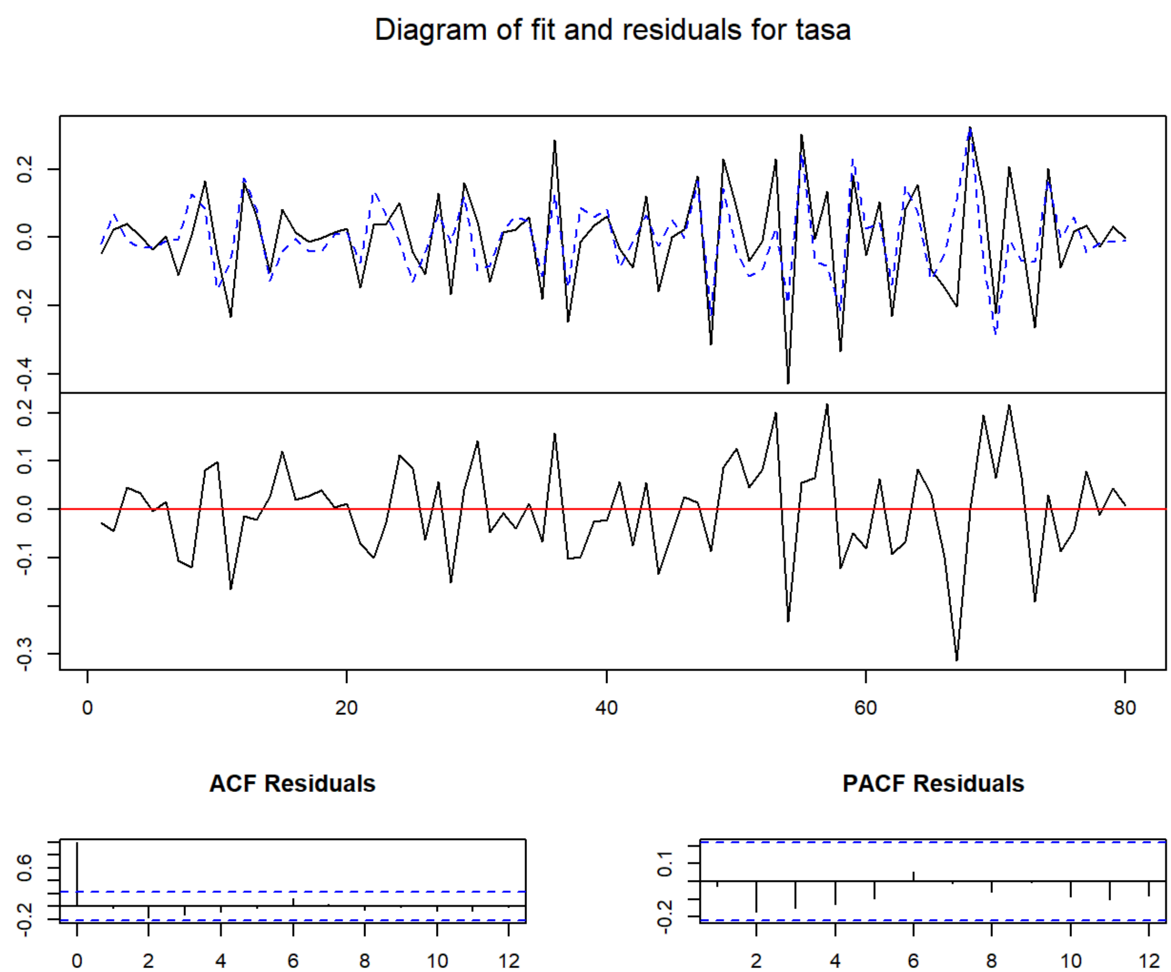
```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: tasa, w1, w2, w3
## Deterministic variables: const
## Sample size: 80
## Log Likelihood: 1479.686
## Roots of the characteristic polynomial:
## 0.8105 0.8105 0.7972 0.7972 0.7589 0.7589 0.7215 0.7215 0.5425 0.5425
0.4591 0.06181
## Call:
## VAR(y = diff(as.matrix(series)), p = 3, type = c("const"))
##
##
## Estimation results for equation tasa:
## =====================================
## tasa = tasa.l1 + w1.l1 + w2.l1 + w3.l1 + tasa.l2 + w1.l2 + w2.l2 + w3.l
2 + tasa.l3 + w1.l3 + w2.l3 + w3.l3 + const
##
##           Estimate Std. Error t value Pr(>|t|)
## tasa.l1 -9.000e-01  1.177e-01  -7.645 1.05e-10 ***
## w1.l1    3.998e+00  2.271e+01   0.176  0.86080
## w2.l1    8.999e+00  1.910e+01   0.471  0.63914
## w3.l1   -2.638e+00  2.188e+01  -0.121  0.90441
## tasa.l2 -7.279e-01  1.362e-01  -5.345 1.17e-06 ***
## w1.l2    7.115e+00  2.359e+01   0.302  0.76393
## w2.l2    8.168e-01  1.980e+01   0.041  0.96722
## w3.l2   -1.545e+01  2.214e+01  -0.698  0.48756
## tasa.l3 -3.740e-01  1.182e-01  -3.164  0.00234 **
## w1.l3    7.517e+00  2.075e+01   0.362  0.71831
## w2.l3    1.018e+01  1.862e+01   0.546  0.58656
## w3.l3    9.655e+00  1.970e+01   0.490  0.62568
## const   -7.537e-06  1.244e-02  -0.001  0.99952
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.1069 on 67 degrees of freedom
## Multiple R-Squared: 0.5524,  Adjusted R-squared: 0.4723
## F-statistic: 6.892 on 12 and 67 DF,  p-value: 6.285e-08
##
##
##
## Covariance matrix of residuals:
##            tasa         w1         w2         w3
## tasa  1.142e-02 -1.728e-06 -1.847e-05 -4.029e-06
```

```
## w1   -1.728e-06  1.049e-06 -7.553e-07 -4.067e-07
## w2   -1.847e-05 -7.553e-07  1.164e-06  8.097e-08
## w3   -4.029e-06 -4.067e-07  8.097e-08  5.342e-07
##
## Correlation matrix of residuals:
##          tasa       w1      w2       w3
## tasa  1.00000 -0.01578 -0.1602 -0.05158
## w1   -0.01578  1.00000 -0.6834 -0.54311
## w2   -0.16020 -0.68337  1.0000  0.10267
## w3   -0.05158 -0.54311  0.1027  1.00000
```

1.3. Paso 3: Evaluacion del Modelo 1.3.1. Prueba de Estacionariedad (Condicion de Estabilidad de los Estimadores)

1.3.2. Analisis de Autocorrelacion en los Residuales

Code




Code

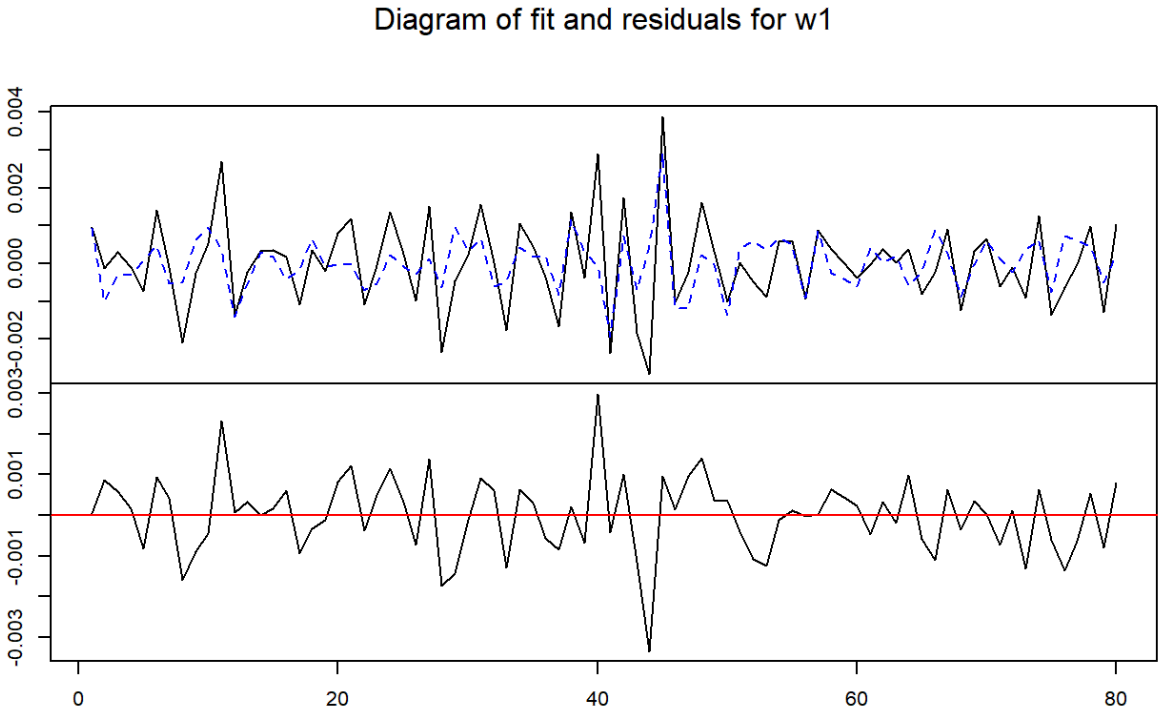
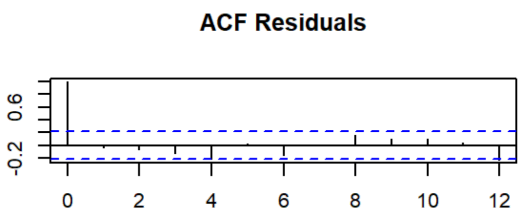
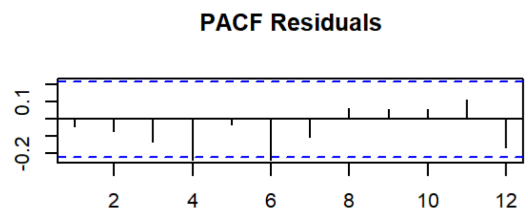


Diagram of fit and residuals for w1
0.004
0.002
0.000
-0.002
0.003
0.001
-0.001
-0.003
0
20
40
60
80


ACF Residuals
0.6
-0.2
0
2
4
6
8
10
12


PACF Residuals
0.1
-0.2
2
4
6
8
10
12

Code

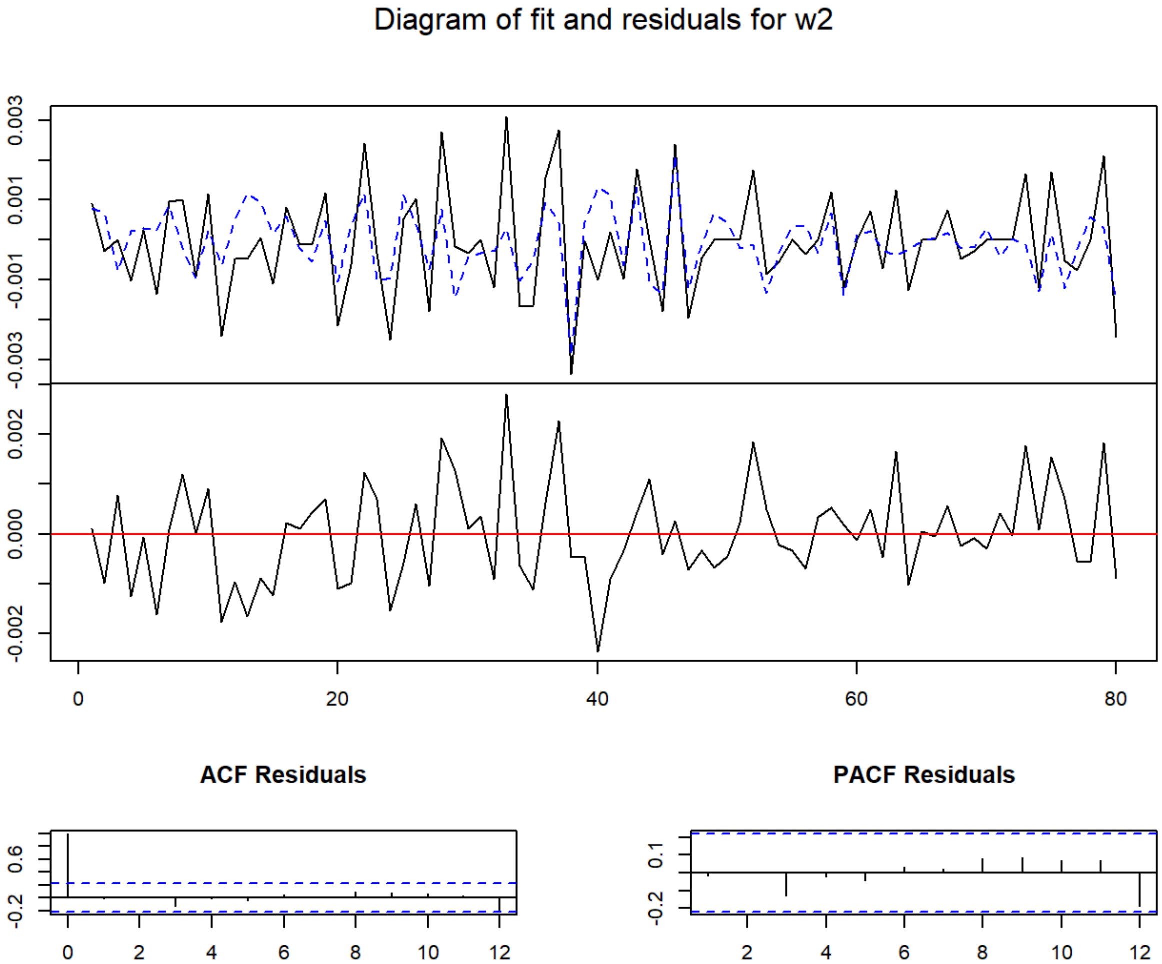
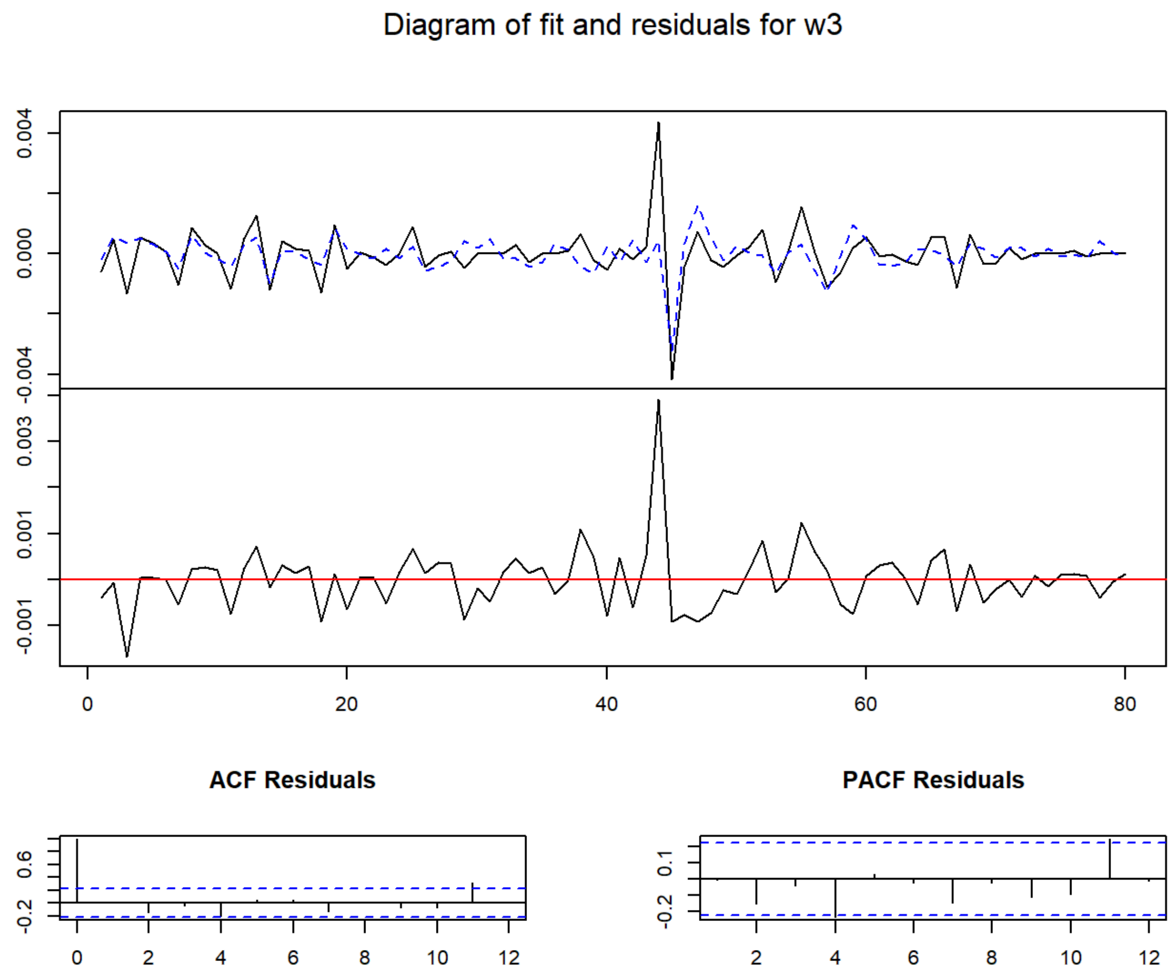


Diagram of fit and residuals for w2
0.003
0.001
-0.001
-0.003
0.002
0.000
-0.002
0
20
40
60
80
ACF Residuals
0.6
0.2
-0.2
0
2
4
6
8
10
12
PACF Residuals
0.1
-0.2
2
4
6
8
10
12

Code




Code

## Prueba Portmanteau Multivariada

Code

```
##
##  Portmanteau Test (asymptotic)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 117.36, df = 112, p-value = 0.3458
```

Code

```
##
##  Portmanteau Test (asymptotic)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 193.06, df = 208, p-value = 0.7635
```

Code

### 1.3.3. Prueba de Normalidad de los Residuales

Code

```
## $tasa
##
##  JB-Test (univariate)
##
## data:  Residual of tasa equation
## Chi-squared = 2.1386, df = 2, p-value = 0.3432
##
##
## $w1
##
##  JB-Test (univariate)
##
## data:  Residual of w1 equation
## Chi-squared = 10.37, df = 2, p-value = 0.005601
##
##
## $w2
##
##  JB-Test (univariate)
##
## data:  Residual of w2 equation
## Chi-squared = 2.1075, df = 2, p-value = 0.3486
##
##
## $w3
##
##  JB-Test (univariate)
##
## data:  Residual of w3 equation
## Chi-squared = 617.62, df = 2, p-value < 2.2e-16
##
##
## $JB
##
##  JB-Test (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 45.317, df = 8, p-value = 3.204e-07
##
##
## $Skewness
##
##  Skewness only (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 11.202, df = 4, p-value = 0.02438
```

```
##
##
## $Kurtosis
##
##  Kurtosis only (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 34.115, df = 4, p-value = 7.058e-07
```

2. Resumiendo Relaciones Temporales en un VAR 2.1. Prueba de Causalidad Granger

Code

```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w1), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df      F  Pr(>F)
## 1     76
## 2     78 -2 2.5407 0.08549 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Code

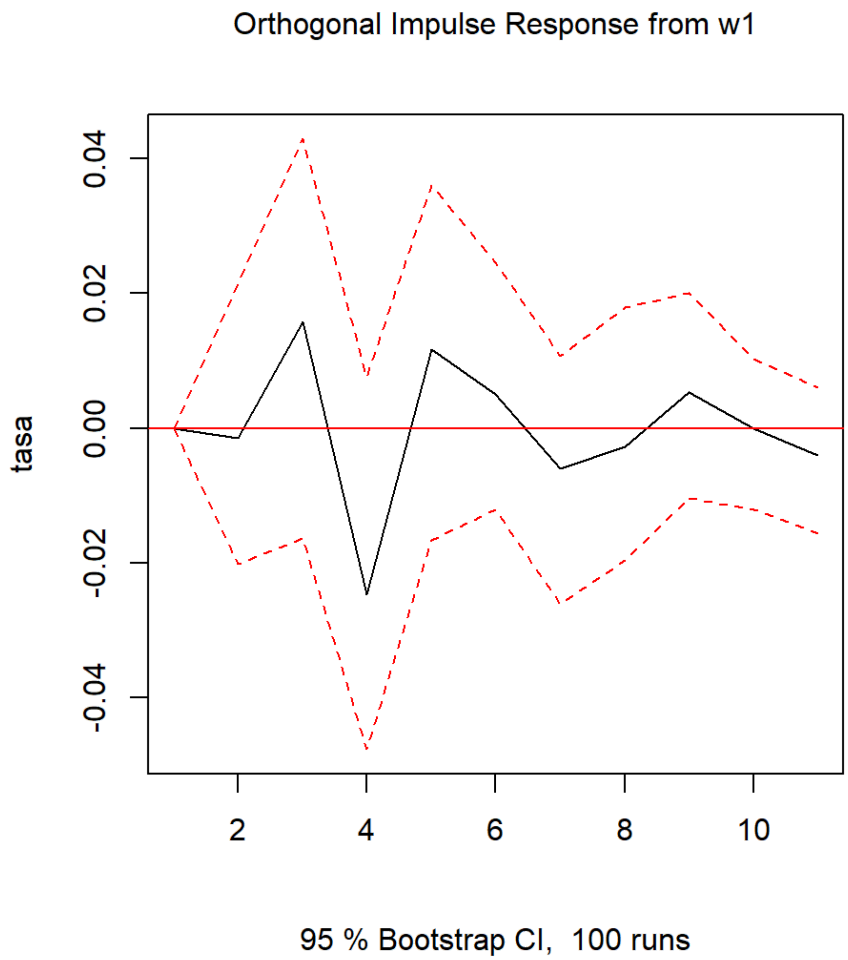
```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w2), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df      F Pr(>F)
## 1     76
## 2     78 -2 1.4584  0.239
```

Code

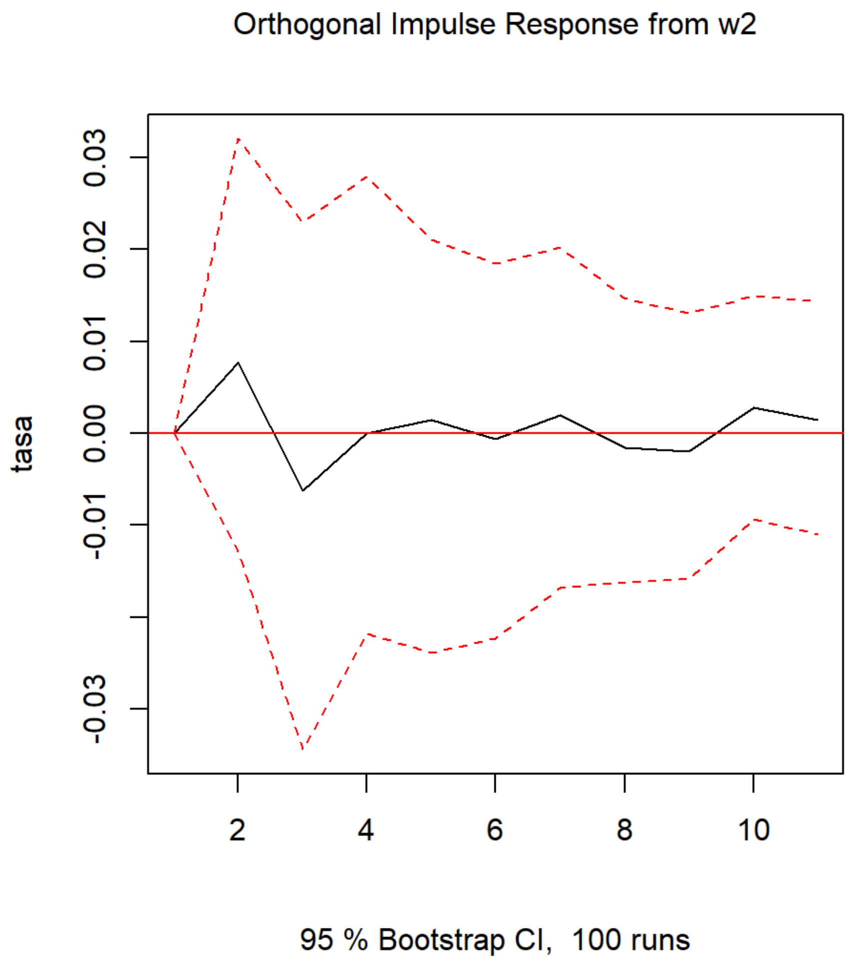
```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w3), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df      F Pr(>F)
## 1     76
## 2     78 -2 1.6982 0.1899
```

Las funciones de impulso respuesta muestran los efectos de los shock en la trayectoria de ajuste de las variables.

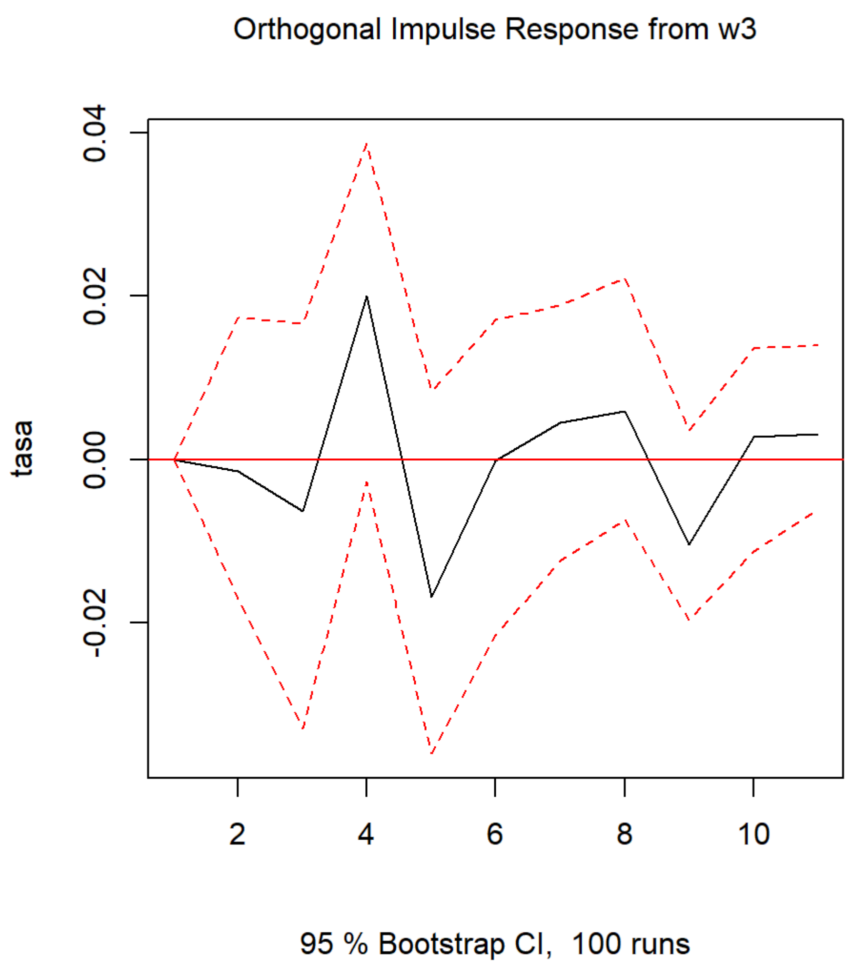
Code


Orthogonal Impulse Response from w1
tasa
0.04
0.02
0.00
-0.02
-0.04
2
4
6
8
10
95 % Bootstrap CI, 100 runs

Code


Orthogonal Impulse Response from w2
tasa
0.03
0.02
0.01
0.00
-0.01
-0.03
2
4
6
8
10
95 % Bootstrap CI, 100 runs

Code




# Modelo 3

Code

SelecciÃ³n del LAG

Code

```
## Warning in log(sigma.det): Se han producido NaNs

## Warning in log(sigma.det): Se han producido NaNs

## Warning in log(sigma.det): Se han producido NaNs
```

```
## $selection
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      9      9      1     10
##
## $criteria
##                     1             2             3             4
## AIC(n) -4.712582e+01 -4.707803e+01 -4.683902e+01 -4.684164e+01
## HQ(n)  -4.682506e+01 -4.653667e+01 -4.605705e+01 -4.581907e+01
## SC(n)  -4.631482e+01 -4.561824e+01 -4.473043e+01 -4.408426e+01
## FPE(n)  3.429493e-21  3.668094e-21  4.893399e-21  5.375660e-21
##                     5             6             7             8
## AIC(n) -4.683396e+01 -4.673109e+01 -4.730869e+01 -4.781997e+01
## HQ(n)  -4.557079e+01 -4.522731e+01 -4.556430e+01 -4.583498e+01
## SC(n)  -4.342778e+01 -4.267611e+01 -4.260491e+01 -4.246740e+01
## FPE(n)  6.409062e-21  9.359704e-21  8.186690e-21  1.015495e-20
##                     9            10
## AIC(n) -4.905304e+01           NaN
## HQ(n)  -4.682744e+01           NaN
## SC(n)  -4.305167e+01           NaN
## FPE(n)  1.067743e-20 -8.381684e-36
```

Code

### 1.2. Paso 2: EstimaciÃ³n del Modelo VAR

Code

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: tasa, w1, w2, w3
## Deterministic variables: const
## Sample size: 52
## Log Likelihood: 965.211
## Roots of the characteristic polynomial:
## 0.6827 0.6827 0.629 0.629 0.3618 0.3618 0.3196 0.3196
## Call:
## VAR(y = diff(as.matrix(series)), p = 2, type = c("const"))
##
##
## Estimation results for equation tasa:
## =====================================
## tasa = tasa.l1 + w1.l1 + w2.l1 + w3.l1 + tasa.l2 + w1.l2 + w2.l2 + w3.l
2 + const
##
##          Estimate Std. Error t value Pr(>|t|)
## tasa.l1 -0.736812   0.136775  -5.387 2.83e-06 ***
## w1.l1    2.441808   6.751227   0.362   0.7194
## w2.l1    5.273322   3.122797   1.689   0.0985 .
## w3.l1    0.500641   4.048455   0.124   0.9022
## tasa.l2 -0.273428   0.129835  -2.106   0.0411 *
## w1.l2   -2.458961   6.626578  -0.371   0.7124
## w2.l2   -0.485887   3.141562  -0.155   0.8778
## w3.l2    4.830316   4.491280   1.075   0.2882
## const   -0.002243   0.004674  -0.480   0.6338
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.03061 on 43 degrees of freedom
## Multiple R-Squared: 0.4805,  Adjusted R-squared: 0.3838
## F-statistic: 4.971 on 8 and 43 DF,  p-value: 0.0002131
##
##
##
## Covariance matrix of residuals:
##            tasa         w1         w2         w3
## tasa  9.371e-04 -1.008e-05  1.848e-05  4.006e-06
## w1   -1.008e-05  8.295e-07 -1.268e-06 -1.178e-07
## w2    1.848e-05 -1.268e-06  4.393e-06 -1.004e-06
## w3    4.006e-06 -1.178e-07 -1.004e-06  1.757e-06
##
## Correlation matrix of residuals:
```

```
##           tasa       w1      w2       w3
## tasa  1.00000 -0.36148  0.2880  0.09874
## w1   -0.36148  1.00000 -0.6643 -0.09763
## w2    0.28805 -0.66430  1.0000 -0.36147
## w3    0.09874 -0.09763 -0.3615  1.00000
```

A continuacion solicitaremos un resumen de cada ecuaciÃ³n por separado:

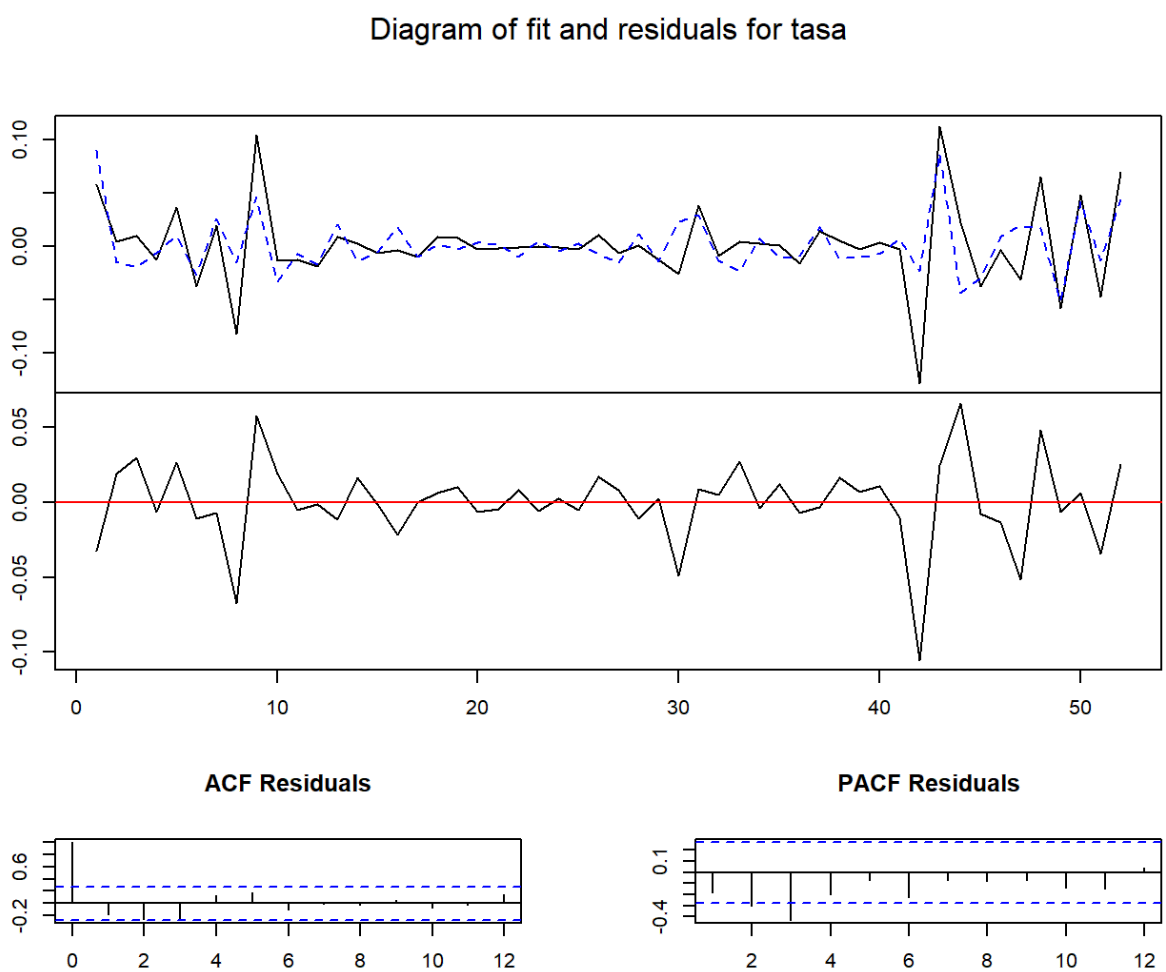
1.3. Paso 3: EvaluaciÃ³n del Modelo 1.3.1. Prueba de Estacionariedad (CondiciÃ³n de Estabilidad de los Estimadores)

Code

```
## [1] 0.6826996 0.6826996 0.6289609 0.6289609 0.3617651 0.3617651 0.31955
35
## [8] 0.3195535
```

Code

Code



Code

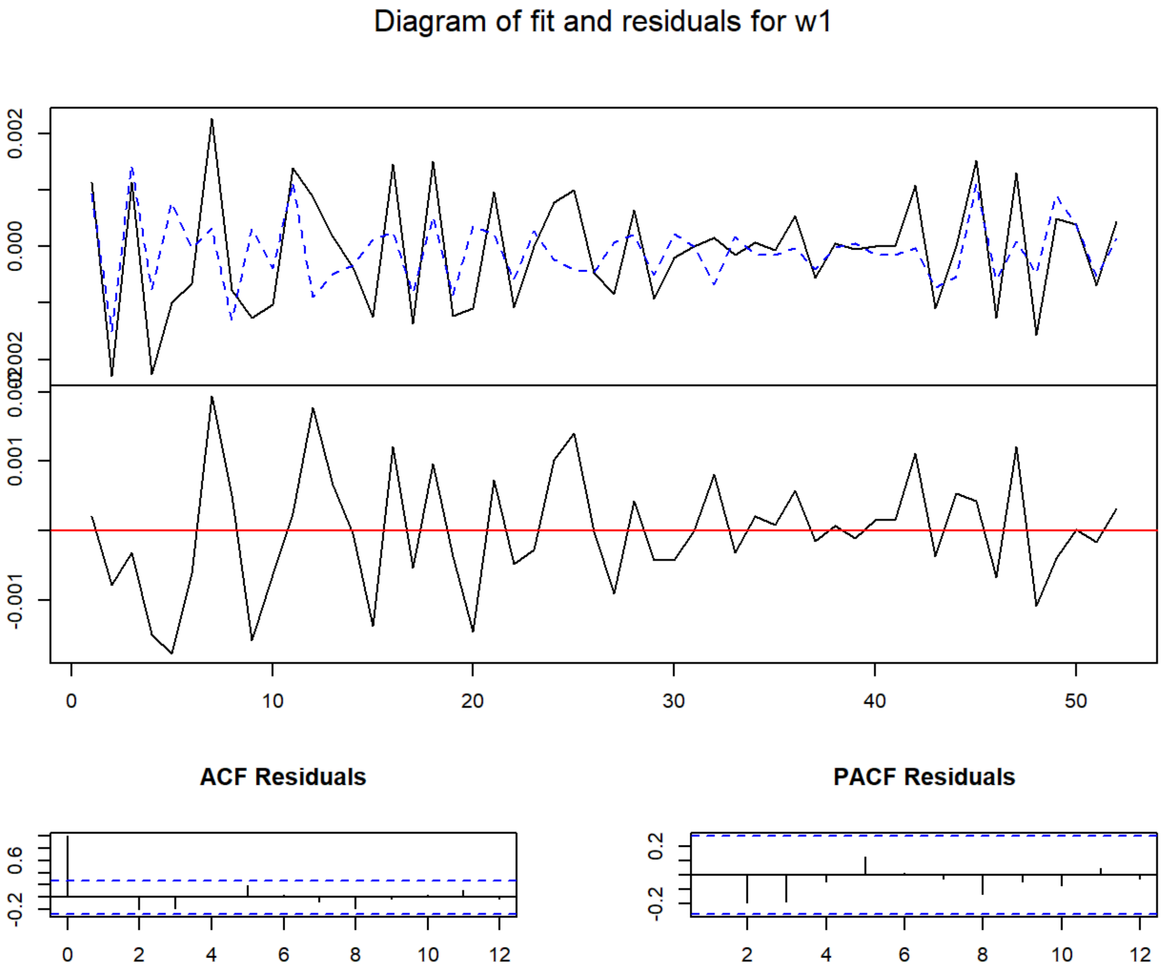


Diagram of fit and residuals for w1
0.002
0.000
-0.002
0.001
-0.001
0
10
20
30
40
50
ACF Residuals
0.6
0.2
-0.2
PACF Residuals


Code

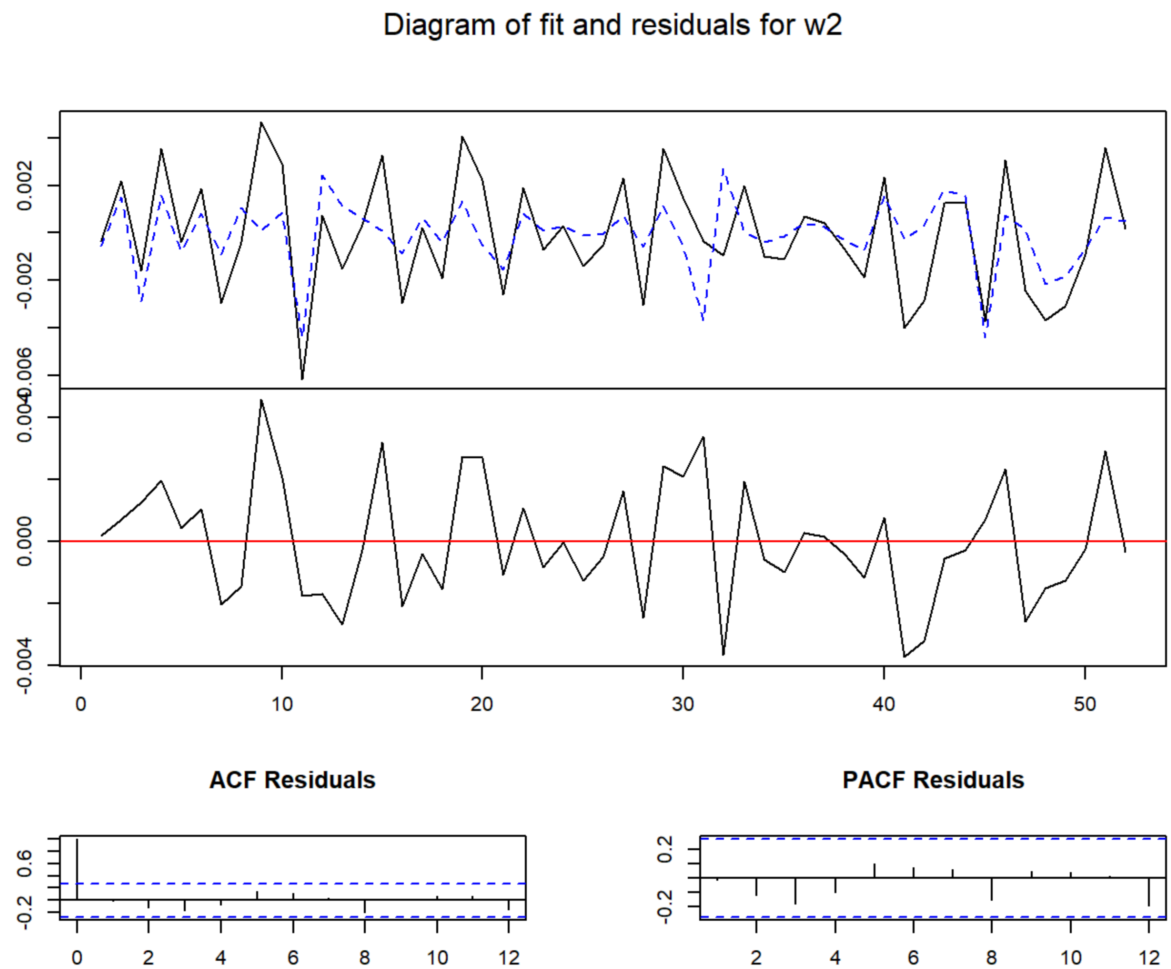
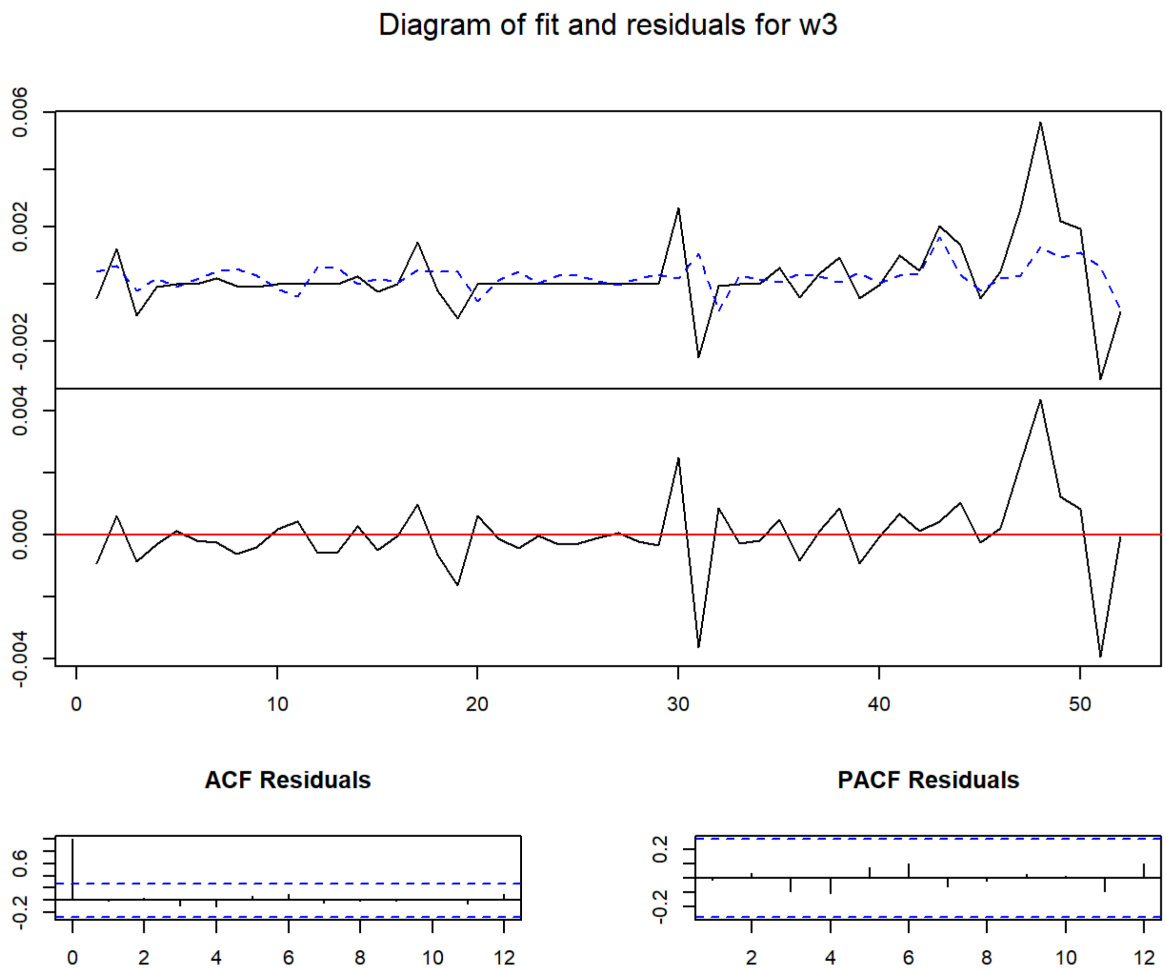


Diagram of fit and residuals for w2
0.002
-0.002
-0.006
0.004
0.000
-0.004
0
10
20
30
40
50
ACF Residuals
0.6
0.2
-0.2
0
2
4
6
8
10
12
PACF Residuals
0.2
-0.2
2
4
6
8
10
12

Code




Code

Code

```
##
##  Portmanteau Test (asymptotic)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 101.41, df = 128, p-value = 0.96
```

Code

```
##
##  Portmanteau Test (asymptotic)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 161.96, df = 224, p-value = 0.9994
```

Code

```
## $tasa
##
##  JB-Test (univariate)
##
## data:  Residual of tasa equation
## Chi-squared = 31.701, df = 2, p-value = 1.307e-07
##
##
## $w1
##
##  JB-Test (univariate)
##
## data:  Residual of w1 equation
## Chi-squared = 0.089976, df = 2, p-value = 0.956
##
##
## $w2
##
##  JB-Test (univariate)
##
## data:  Residual of w2 equation
## Chi-squared = 0.99149, df = 2, p-value = 0.6091
##
##
## $w3
##
##  JB-Test (univariate)
##
## data:  Residual of w3 equation
## Chi-squared = 50.849, df = 2, p-value = 9.086e-12
##
##
## $JB
##
##  JB-Test (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 53.902, df = 8, p-value = 7.211e-09
##
##
## $Skewness
##
##  Skewness only (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 13.148, df = 4, p-value = 0.01057
```

```
##
##
## $Kurtosis
##
##  Kurtosis only (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 40.754, df = 4, p-value = 3.022e-08
```

Code

```
## [1] "tasa" "w1"   "w2"   "w3"
```

Code

```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w1), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df      F Pr(>F)
## 1     47
## 2     49 -2 1.0014 0.3751
```

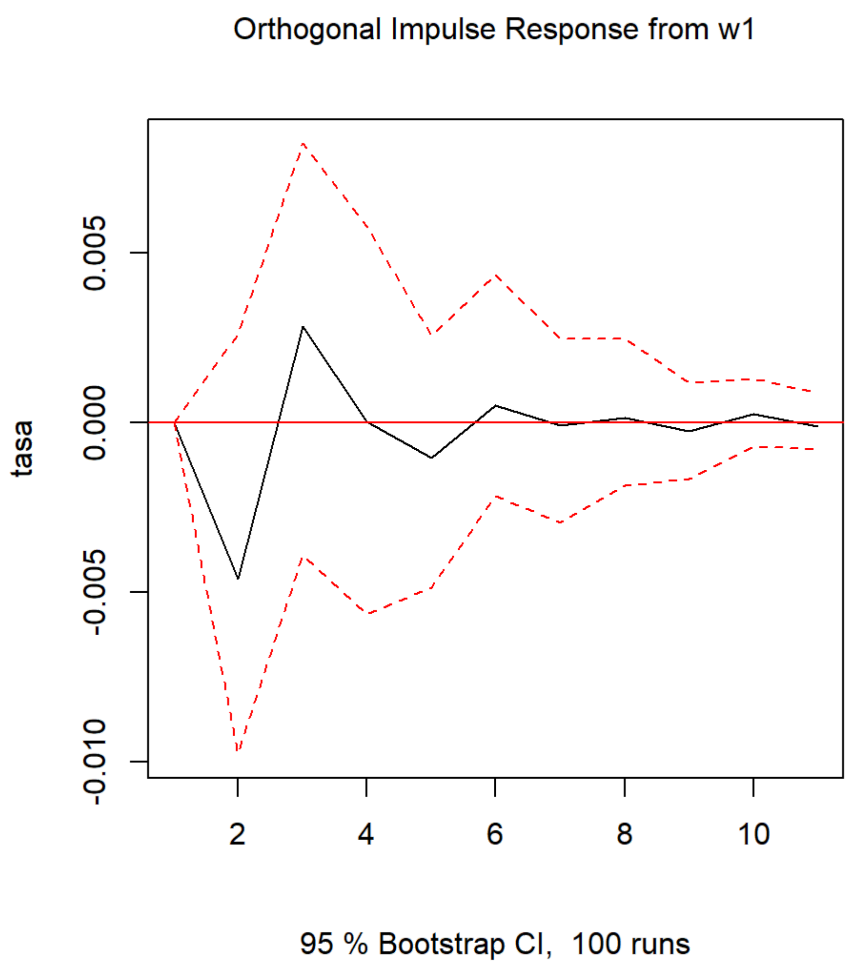
Code

```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w2), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df      F  Pr(>F)
## 1     47
## 2     49 -2 2.4611 0.09627 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

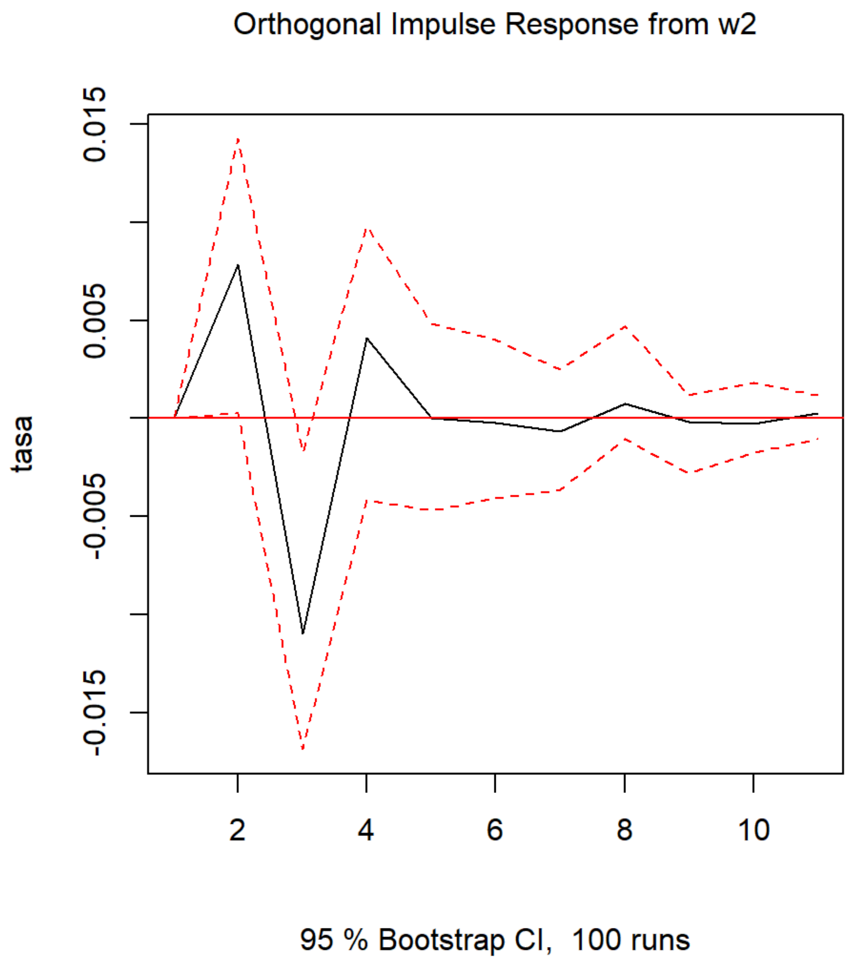
Code

```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w3), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df      F Pr(>F)
## 1     47
## 2     49 -2 0.4557 0.6368
```

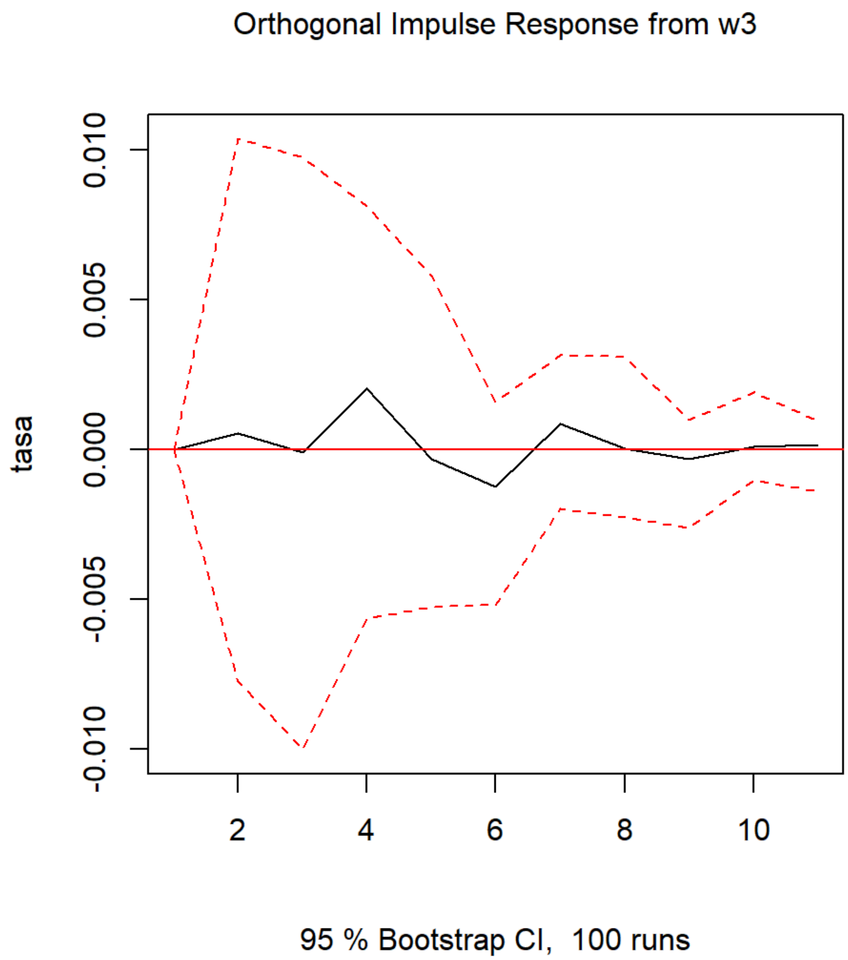
Code


Orthogonal Impulse Response from w1
tasa
0.005
0.000
-0.005
-0.010
2
4
6
8
10
95 % Bootstrap CI, 100 runs

Code


Orthogonal Impulse Response from w2
tasa
0.015
0.005
-0.005
-0.015
2
4
6
8
10
95 % Bootstrap CI, 100 runs

Code




# Modelo 4

post-crisis

Code

SelecciÃ³n del LAG

Code

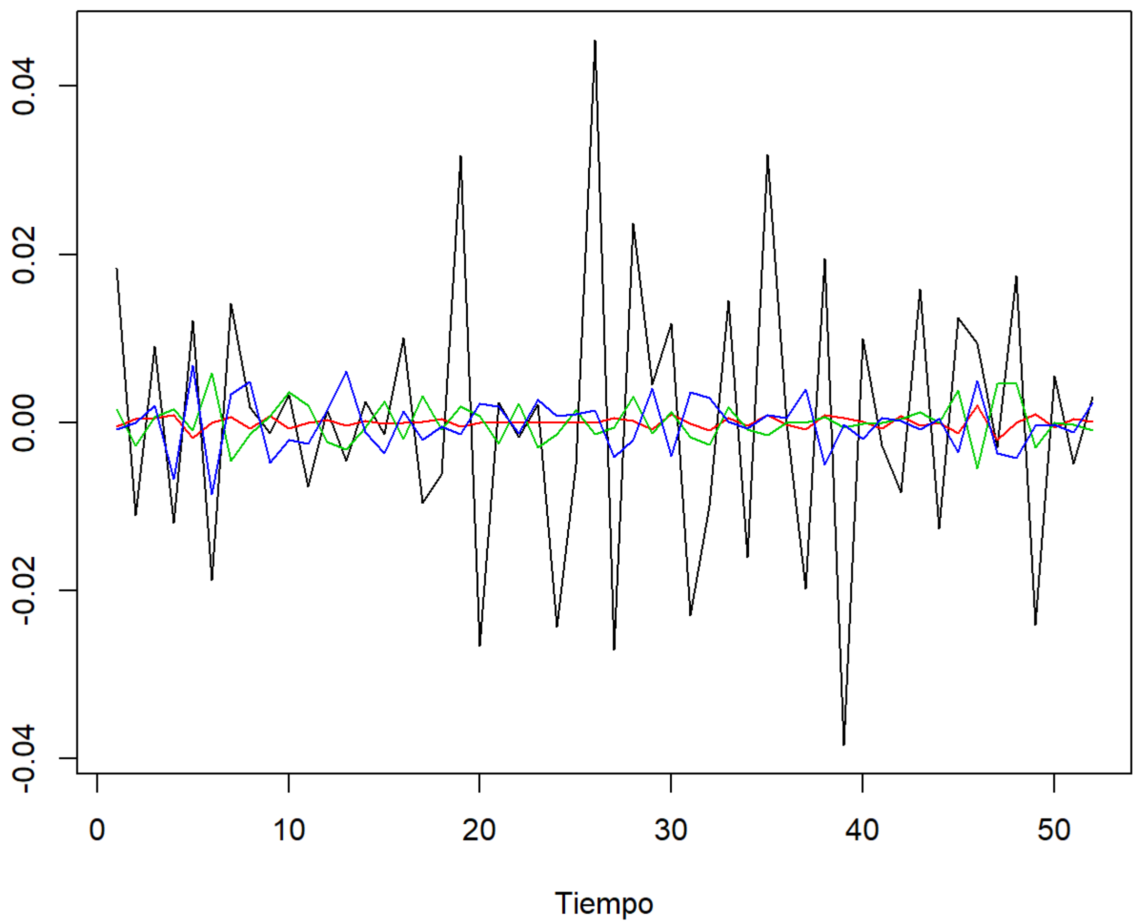
```
## Warning in log(sigma.det): Se han producido NaNs

## Warning in log(sigma.det): Se han producido NaNs

## Warning in log(sigma.det): Se han producido NaNs
```

```
## $selection
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      9      1      1     10
##
## $criteria
##                    1             2             3             4
## AIC(n) -4.837919e+01 -4.830903e+01 -4.778719e+01 -4.783906e+01
## HQ(n)  -4.807589e+01 -4.776310e+01 -4.699862e+01 -4.680785e+01
## SC(n)  -4.755173e+01 -4.681960e+01 -4.563579e+01 -4.502569e+01
## FPE(n)  9.798431e-22  1.074916e-21  1.917563e-21  2.037618e-21
##                    5             6             7             8
## AIC(n) -4.737709e+01 -4.751909e+01 -4.819758e+01 -4.838586e+01
## HQ(n)  -4.610324e+01 -4.600260e+01 -4.643845e+01 -4.638410e+01
## SC(n)  -4.390175e+01 -4.338178e+01 -4.339830e+01 -4.292461e+01
## FPE(n)  3.941837e-21  4.755082e-21  4.152956e-21  8.703848e-21
##                    9         10
## AIC(n) -5.023909e+01        NaN
## HQ(n)  -4.799469e+01        NaN
## SC(n)  -4.411587e+01        NaN
## FPE(n)  8.228622e-21 -7.579e-67
```

Code




## 1.2. Paso 2: EstimaciÃ³n del Modelo VAR

Code

```
##
## VAR Estimation Results:
## =======================
##
## Estimated coefficients for equation tasa:
## =========================================
## Call:
## tasa = tasa.l1 + w1.l1 + w2.l1 + w3.l1 + const
##
##       tasa.l1         w1.l1         w2.l1         w3.l1         const
## -5.546496e-01 -2.034381e+00 -1.309496e-01 -3.560342e-01  2.960478e-05
##
##
## Estimated coefficients for equation w1:
## =======================================
## Call:
## w1 = tasa.l1 + w1.l1 + w2.l1 + w3.l1 + const
##
##       tasa.l1         w1.l1         w2.l1         w3.l1         const
##  2.063699e-03 -4.899761e-01  2.666233e-02 -1.441551e-02  1.994429e-05
##
##
## Estimated coefficients for equation w2:
## =======================================
## Call:
## w2 = tasa.l1 + w1.l1 + w2.l1 + w3.l1 + const
##
##       tasa.l1         w1.l1         w2.l1         w3.l1         const
##  8.062044e-04 -7.174511e-01 -4.437227e-01 -3.708154e-02  9.297143e-05
##
##
## Estimated coefficients for equation w3:
## =======================================
## Call:
## w3 = tasa.l1 + w1.l1 + w2.l1 + w3.l1 + const
##
##       tasa.l1         w1.l1         w2.l1         w3.l1         const
## -0.0042983481  0.5073311903 -0.2329743068 -0.5078518229 -0.0001865885
```

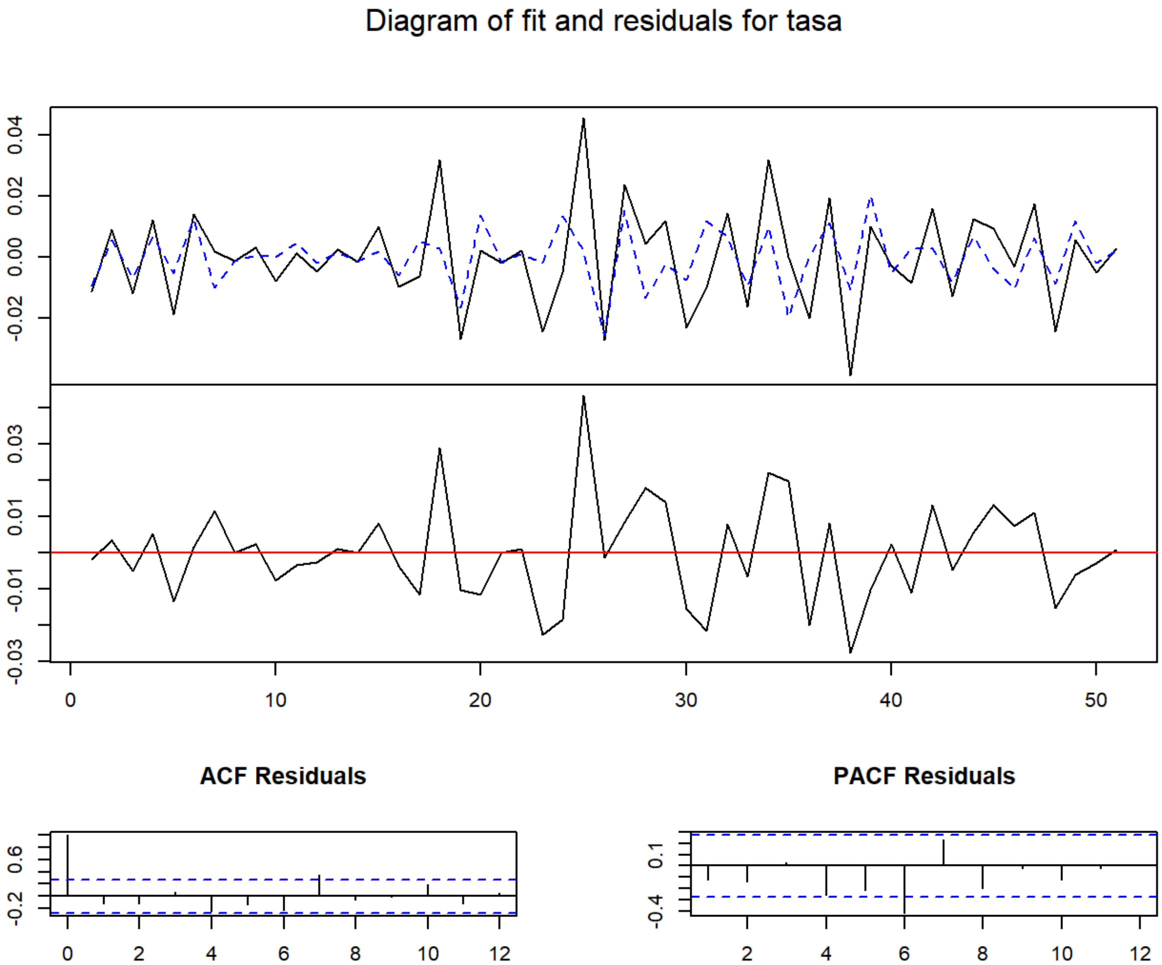
Code

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: tasa, w1, w2, w3
## Deterministic variables: const
## Sample size: 51
## Log Likelihood: 958.693
## Roots of the characteristic polynomial:
## 0.5721 0.5721 0.4576 0.4576
## Call:
## VAR(y = diff(as.matrix(series)), p = 1, type = c("const"))
##
##
## Estimation results for equation tasa:
## =====================================
## tasa = tasa.l1 + w1.l1 + w2.l1 + w3.l1 + const
##
##           Estimate Std. Error t value Pr(>|t|)
## tasa.l1 -0.5546496  0.1212691  -4.574 3.62e-05 ***
## w1.l1   -2.0343814  3.6128131  -0.563    0.576
## w2.l1   -0.1309496  1.5475189  -0.085    0.933
## w3.l1   -0.3560342  1.1130276  -0.320    0.751
## const    0.0000296  0.0019684   0.015    0.988
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.01403 on 46 degrees of freedom
## Multiple R-Squared: 0.3238,  Adjusted R-squared: 0.265
## F-statistic: 5.507 on 4 and 46 DF,  p-value: 0.001043
##
##
##
## Covariance matrix of residuals:
##            tasa         w1         w2         w3
## tasa  1.969e-04 -2.870e-07  2.325e-06  2.416e-07
## w1   -2.870e-07  4.053e-07 -5.337e-07 -2.285e-07
## w2    2.325e-06 -5.337e-07  5.197e-06 -5.060e-06
## w3    2.416e-07 -2.285e-07 -5.060e-06  8.894e-06
##
## Correlation matrix of residuals:
##           tasa       w1       w2        w3
## tasa  1.000000 -0.03213  0.07268  0.005773
## w1   -0.032128  1.00000 -0.36775 -0.120333
## w2    0.072678 -0.36775  1.00000 -0.744301
## w3    0.005773 -0.12033 -0.74430  1.000000
```

### 1.3. Paso 3: EvaluaciÃ³n del Modelo 1.3.1. Prueba de Estacionariedad (CondiciÃ³n de Estabilidad de los Estimadores)

### 1.3.2. Analisis de Autocorrelacion en los Residuales

Code




Code

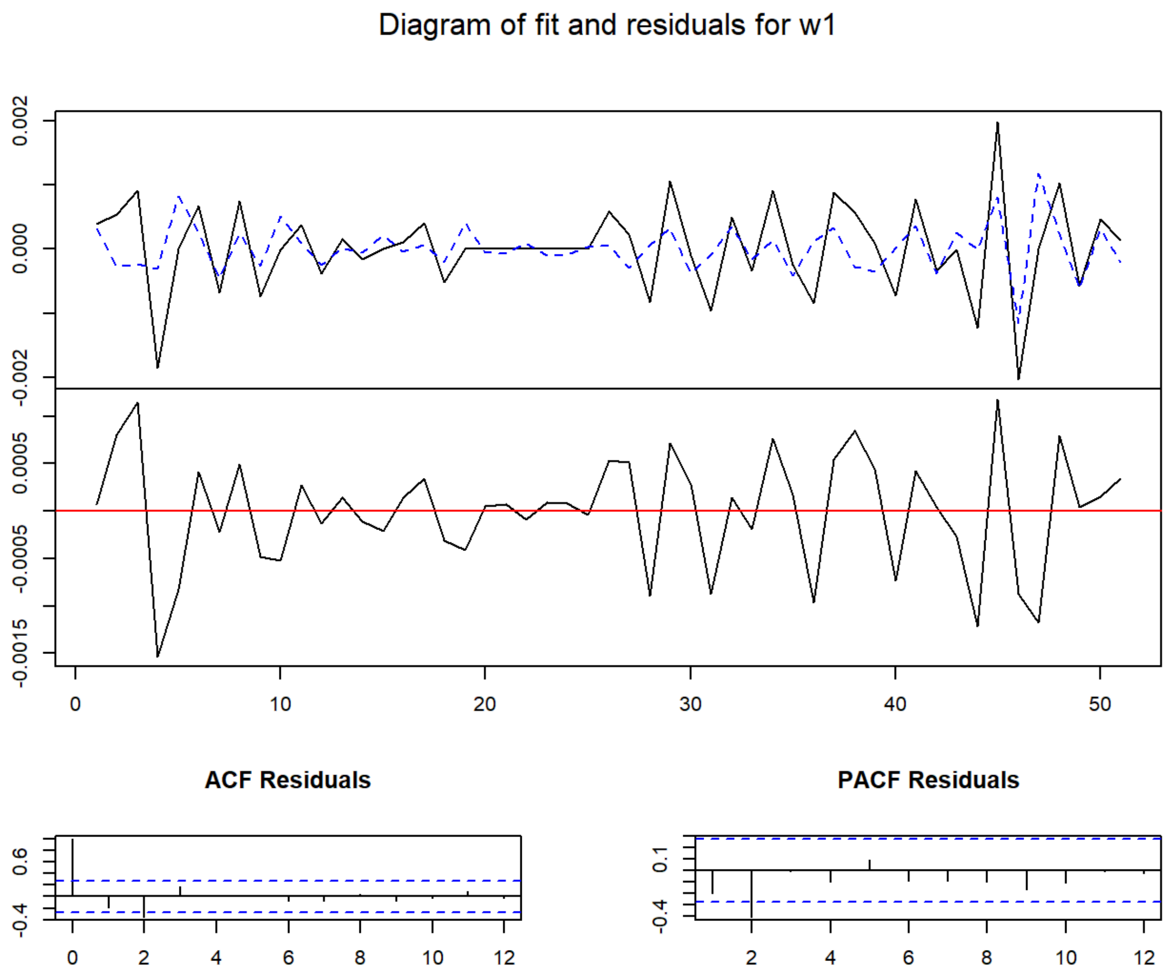


Diagram of fit and residuals for w1
0.002
0.000
-0.002
0.0005
-0.0005
-0.0015
0
10
20
30
40
50
ACF Residuals
0.6
-0.4
0
2
4
6
8
10
12
PACF Residuals
0.1
-0.4
2
4
6
8
10
12

Code

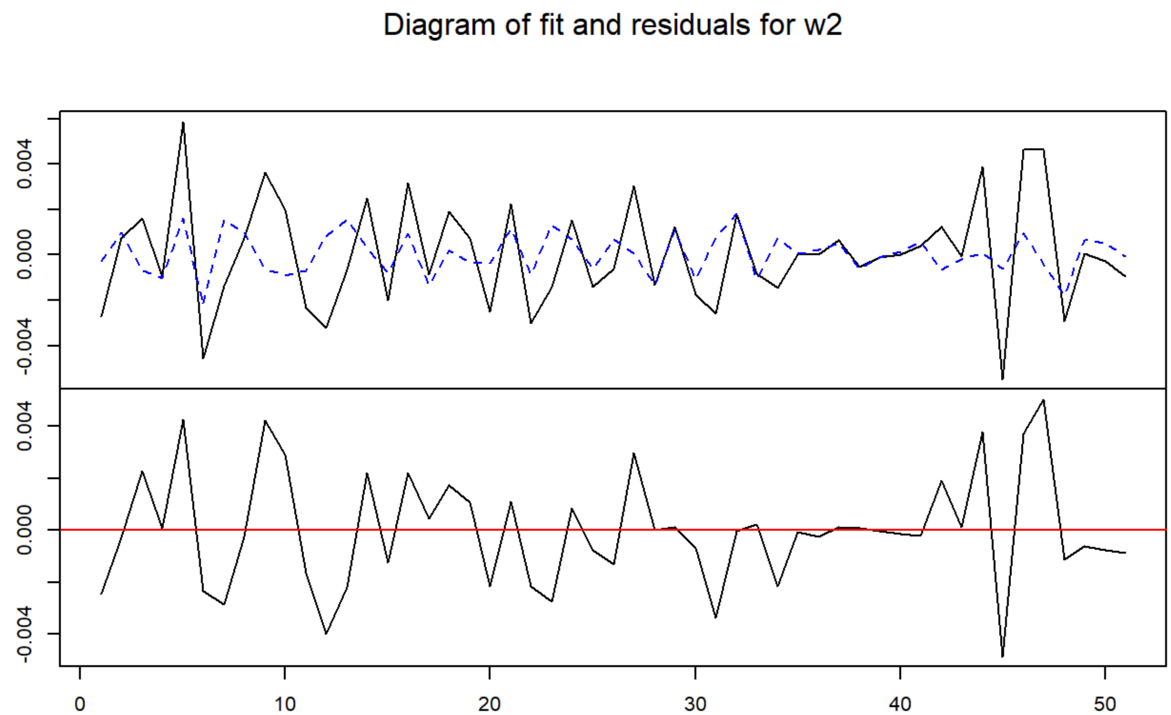
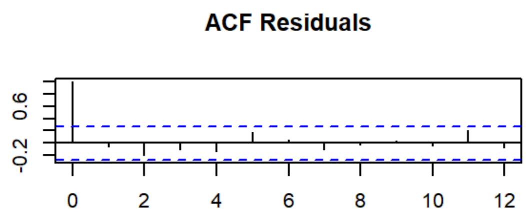
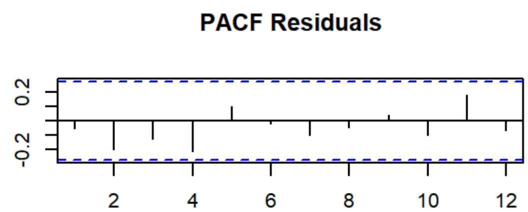
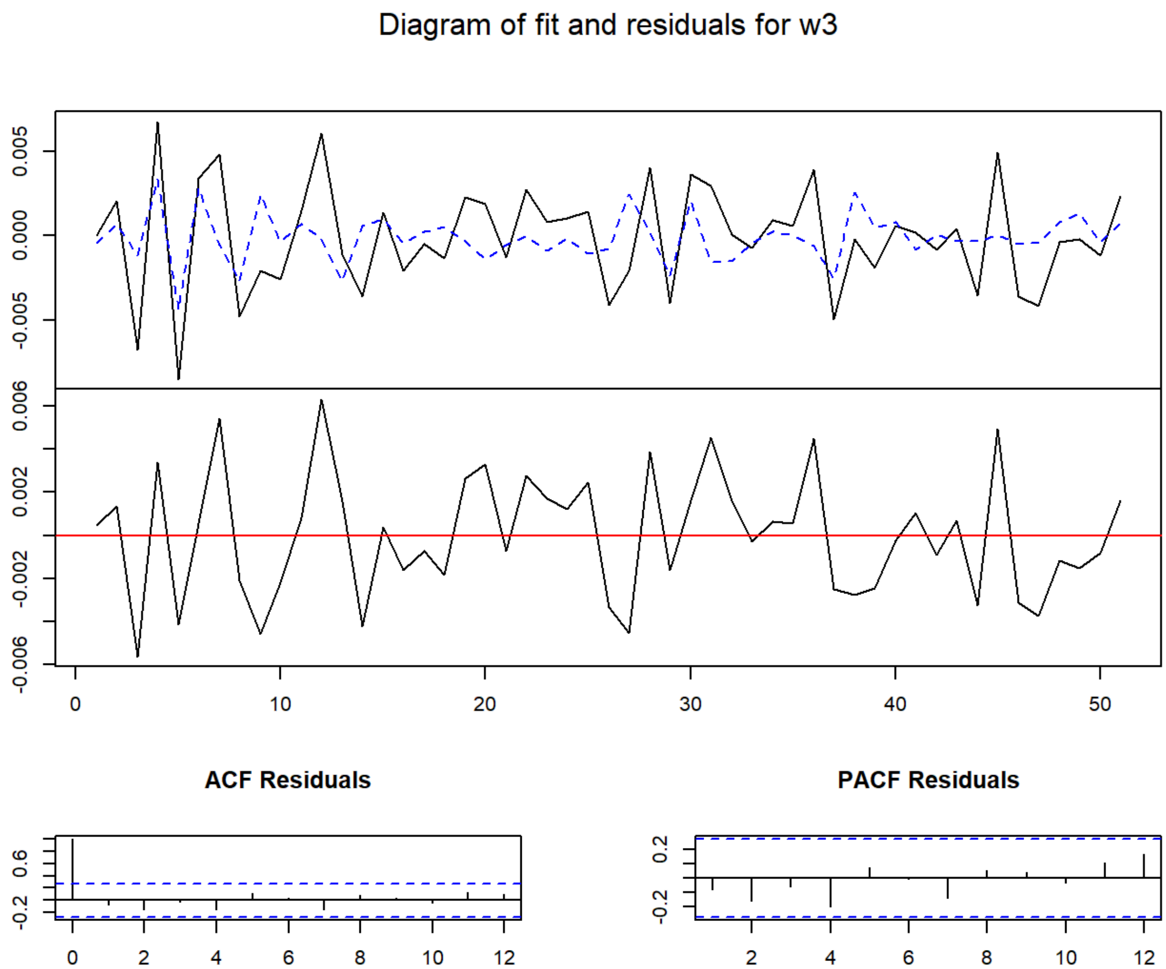


Diagram of fit and residuals for w2
0.004
0.000
-0.004
0.004
0.000
-0.004
0
10
20
30
40
50


ACF Residuals
0.6
0.2
-0.2
0
2
4
6
8
10
12


PACF Residuals
0.2
-0.2
2
4
6
8
10
12

Code




Code

```
##
##  Portmanteau Test (asymptotic)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 115.52, df = 144, p-value = 0.9611
```

Code

```
##
##  Portmanteau Test (asymptotic)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 190.45, df = 240, p-value = 0.992
```

Code

```
## $tasa
##
##  JB-Test (univariate)
##
## data:  Residual of tasa equation
## Chi-squared = 4.6678, df = 2, p-value = 0.09692
##
##
## $w1
##
##  JB-Test (univariate)
##
## data:  Residual of w1 equation
## Chi-squared = 1.5972, df = 2, p-value = 0.45
##
##
## $w2
##
##  JB-Test (univariate)
##
## data:  Residual of w2 equation
## Chi-squared = 0.71371, df = 2, p-value = 0.6999
##
##
## $w3
##
##  JB-Test (univariate)
##
## data:  Residual of w3 equation
## Chi-squared = 1.0874, df = 2, p-value = 0.5806
##
##
## $JB
##
##  JB-Test (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 7.2301, df = 8, p-value = 0.512
##
##
## $Skewness
##
##  Skewness only (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 4.1424, df = 4, p-value = 0.3871
```

```
##
##
## $Kurtosis
##
##  Kurtosis only (multivariate)
##
## data:  Residuals of VAR object modelo
## Chi-squared = 3.0877, df = 4, p-value = 0.5433
```

2. Resumiendo Relaciones Temporales en un VAR 2.1. Prueba de Causalidad Granger

Code

```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w1), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df      F Pr(>F)
## 1     45
## 2     47 -2 0.1376 0.8718
```

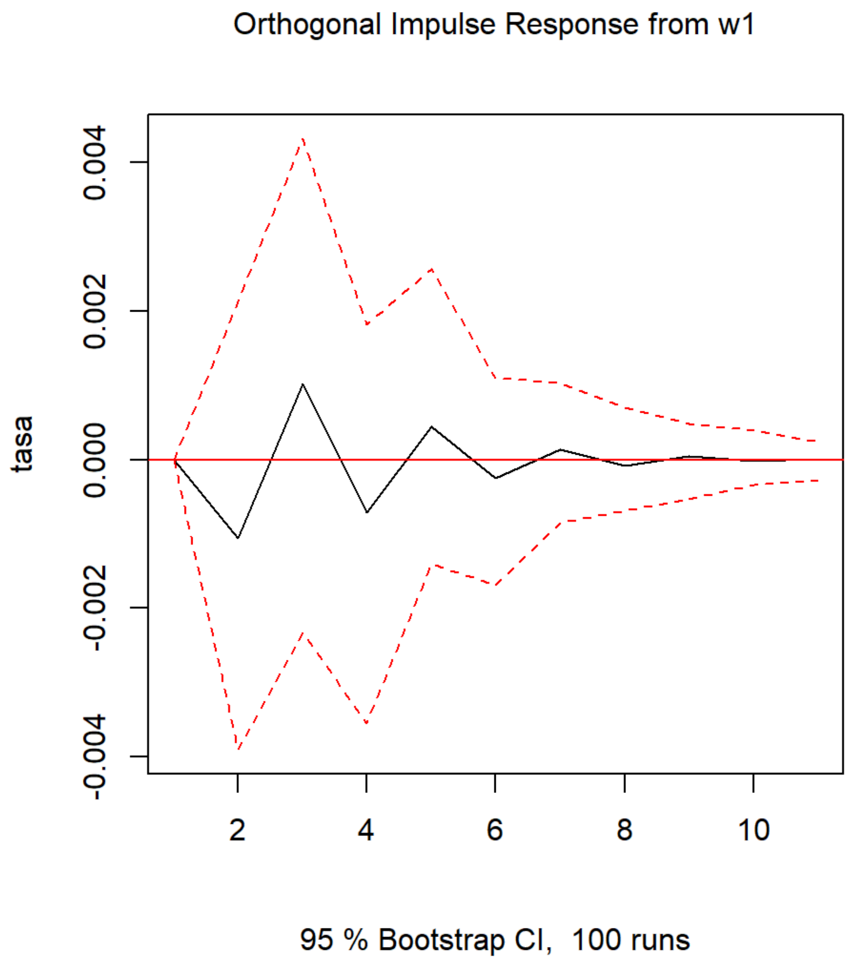
Code

```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w2), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df    F Pr(>F)
## 1     45
## 2     47 -2 0.14 0.8698
```

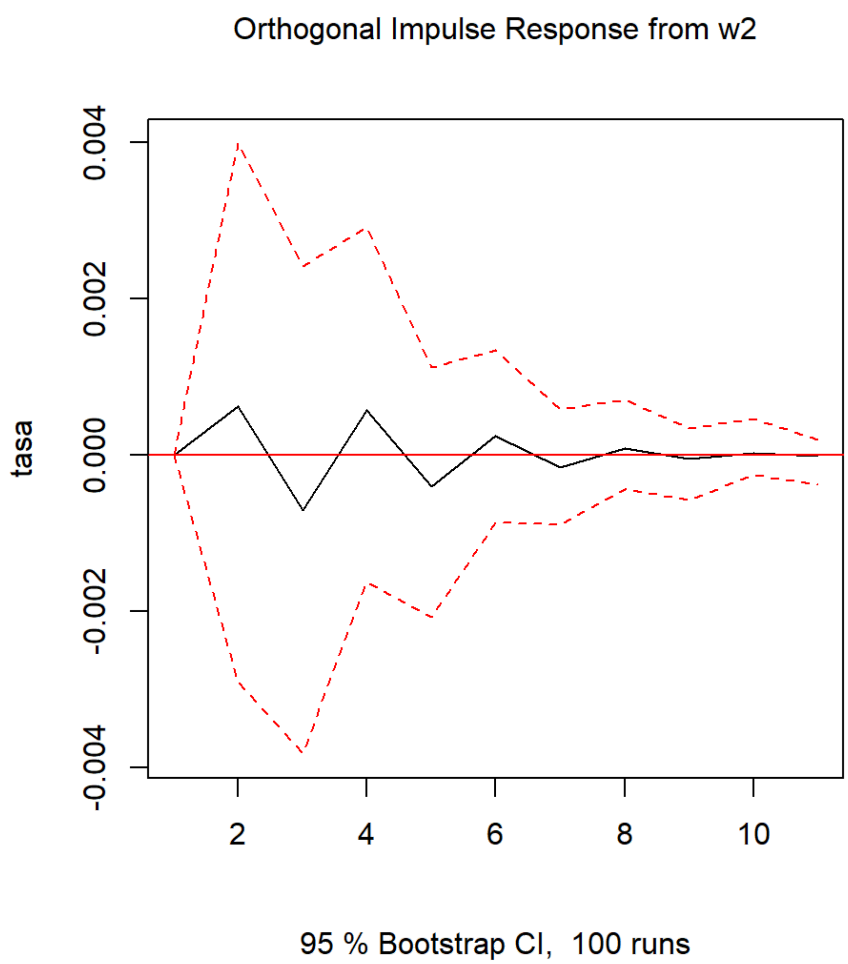
Code

```
## Granger causality test
##
## Model 1: diff(tasa) ~ Lags(diff(tasa), 1:2) + Lags(diff(w3), 1:2)
## Model 2: diff(tasa) ~ Lags(diff(tasa), 1:2)
##   Res.Df Df      F Pr(>F)
## 1     45
## 2     47 -2 0.0936 0.9108
```

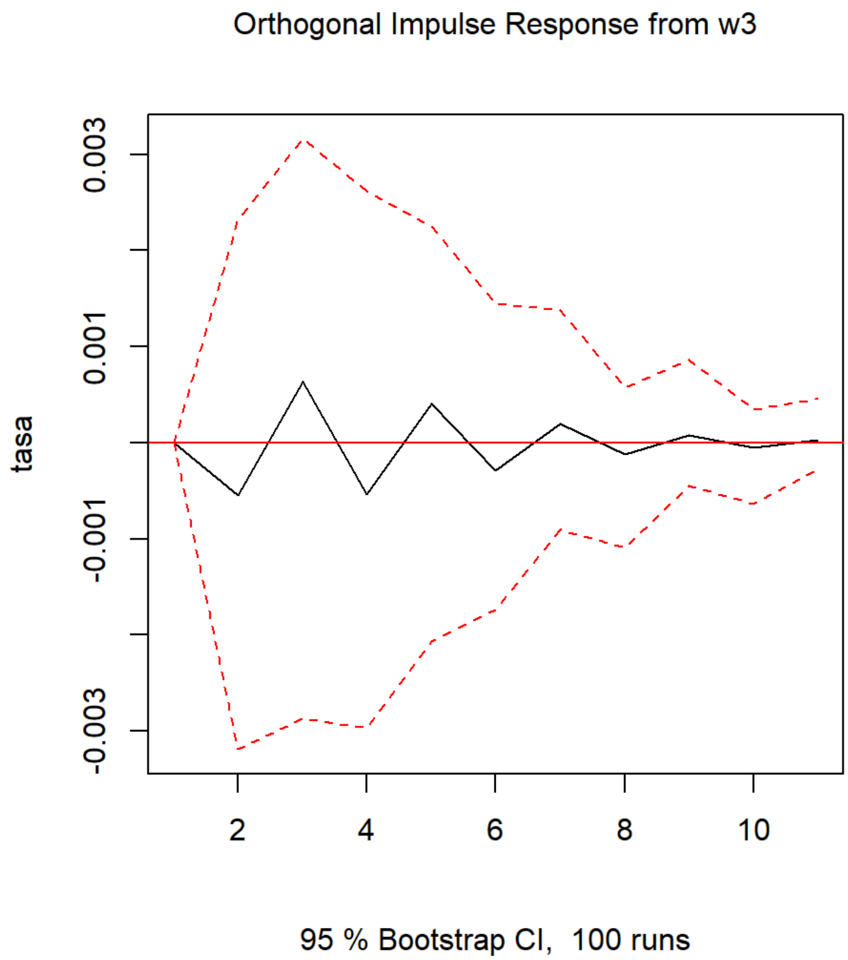
Code


Orthogonal Impulse Response from w1
tasa
0.004
0.002
0.000
-0.002
-0.004
2
4
6
8
10
95 % Bootstrap CI, 100 runs

Code


Orthogonal Impulse Response from w2
tasa
0.004
0.002
0.000
-0.002
-0.004
2
4
6
8
10
95 % Bootstrap CI, 100 runs

Code


Orthogonal Impulse Response from w3
tasa
0.003
0.001
-0.001
-0.003
2
4
6
8
10
95 % Bootstrap CI, 100 runs