R skripta VM

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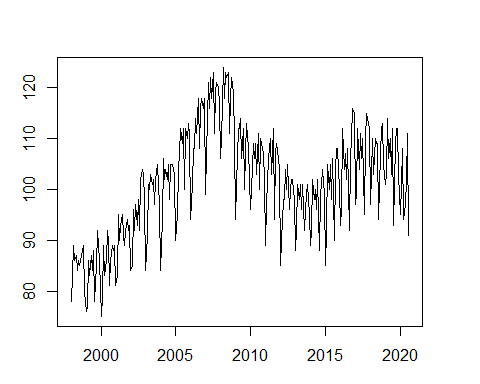
# 1. UVOD U UNIVARIJATNU ANALIZU VREMENSKIH NIZOVA

#### Slika 1.1.

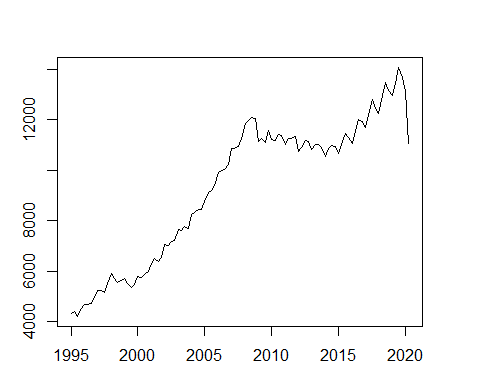
library(readxl)  
library(forecast)

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

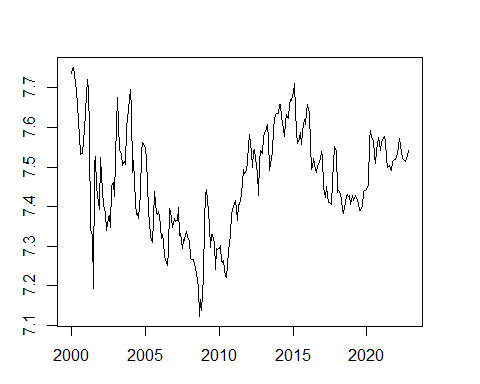
iip<-read.table("iip.txt",header=T,sep="\t")  
IIP<-ts(iip$IIP,start=c(1998,1),frequency=12)  
bdp<-read.table("bdp.txt",header=T,sep="\t")  
BDP<-ts(bdp$BDP,start=c(1995,1),frequency = 4)  
BDP<-BDP/decompose(BDP,type="multiplicative")$season  
tecaj <- read\_excel("tecaj.xlsx",sheet="List1")  
tecaj<-ts(tecaj$tecaj,start=c(2000,1),frequency = 12)  
dolasci<-read\_excel("msi-turizam.xlsx",sheet="List1")  
dolasci<-ts(dolasci$`dolasci, ukupno u 000`,start=c(2010,1),frequency = 12)  
des\_dolasci<-ma(dolasci,12,centre=T)  
  
par(mfrow = c(1,1),oma=c(1,1,1,1),mar=c(2,2,2,2))  
plot(IIP,xlab=NA,ylab=NA)



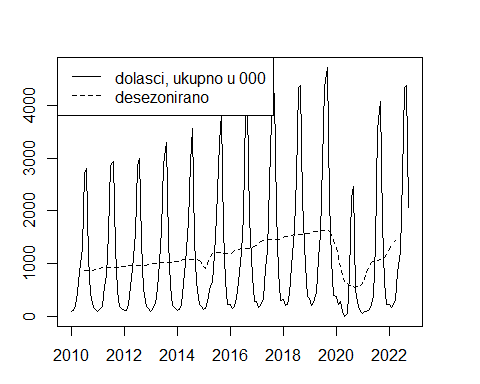
plot(BDP,xlab=NA,ylab=NA)



plot(tecaj,xlab=NA,ylab=NA)

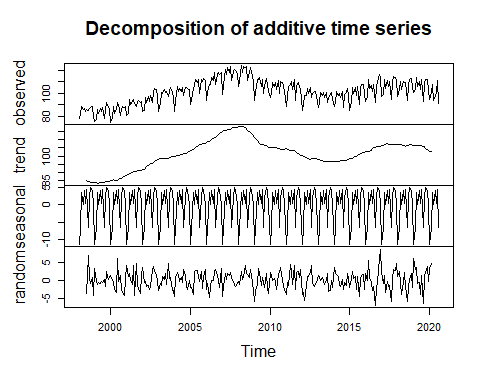


plot(dolasci,xlab=NA,ylab=NA)  
lines(des\_dolasci,lty="dashed")  
legend("topleft", legend=c("dolasci, ukupno u 000","desezonirano"),  
 col=c("black", "black"), lty=c(1,2))



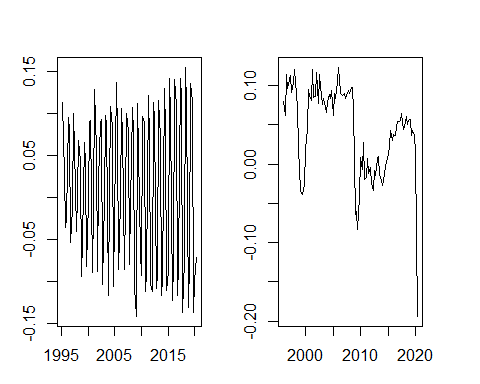
#### Slika 1.2.

iip<-read.table("iip.txt",header=T,sep="\t")  
IIP<-ts(iip$IIP,start=c(1998,1),frequency=12)  
plot(decompose(IIP,type="additive"))



#### Slika 1.3.

bdp<-read.table("bdp.txt",header=T,sep="\t")  
BDP<-ts(bdp$BDP,start=c(1995,1),frequency = 4)  
  
stopa\_a<-diff(log(BDP))  
stopa\_b<-diff(log(BDP),4)  
par(mfrow = c(1,2),oma=c(1,1,1,1),mar=c(2,2,2,2))  
plot(stopa\_a)  
plot(stopa\_b)



## Primjer 1.1.

#### Slika 1.4

iip<-read.table("iip.txt",header=T,sep="\t")  
IIP<-ts(iip$IIP,start=c(1998,1),frequency=12)  
library(forecast)  
binarne<-seasonaldummy(IIP)

#### Slika 1.5. je tablica binarne u gornjem desnom panelu R-studija

summary(lm(IIP~binarne))

##   
## Call:  
## lm(formula = IIP ~ binarne)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -21.6818 -4.7288 0.4565 6.1304 20.4783   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 101.6818 2.0036 50.748 < 2e-16 \*\*\*  
## binarneJan -12.1166 2.8026 -4.323 2.19e-05 \*\*\*  
## binarneFeb -7.2905 2.8026 -2.601 0.00982 \*\*   
## binarneMar 3.0138 2.8026 1.075 0.28321   
## binarneApr -0.9862 2.8026 -0.352 0.72522   
## binarneMay 2.9269 2.8026 1.044 0.29730   
## binarneJun -0.1601 2.8026 -0.057 0.95450   
## binarneJul 4.1877 2.8026 1.494 0.13633   
## binarneAug -7.1166 2.8026 -2.539 0.01169 \*   
## binarneSep 1.9091 2.8336 0.674 0.50108   
## binarneOct 4.5909 2.8336 1.620 0.10641   
## binarneNov 4.0000 2.8336 1.412 0.15925   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 9.398 on 260 degrees of freedom  
## Multiple R-squared: 0.2433, Adjusted R-squared: 0.2113   
## F-statistic: 7.599 on 11 and 260 DF, p-value: 2.405e-11

#### Slika 1.6.

summary(lm(IIP~binarne))

##   
## Call:  
## lm(formula = IIP ~ binarne)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -21.6818 -4.7288 0.4565 6.1304 20.4783   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 101.6818 2.0036 50.748 < 2e-16 \*\*\*  
## binarneJan -12.1166 2.8026 -4.323 2.19e-05 \*\*\*  
## binarneFeb -7.2905 2.8026 -2.601 0.00982 \*\*   
## binarneMar 3.0138 2.8026 1.075 0.28321   
## binarneApr -0.9862 2.8026 -0.352 0.72522   
## binarneMay 2.9269 2.8026 1.044 0.29730   
## binarneJun -0.1601 2.8026 -0.057 0.95450   
## binarneJul 4.1877 2.8026 1.494 0.13633   
## binarneAug -7.1166 2.8026 -2.539 0.01169 \*   
## binarneSep 1.9091 2.8336 0.674 0.50108   
## binarneOct 4.5909 2.8336 1.620 0.10641   
## binarneNov 4.0000 2.8336 1.412 0.15925   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 9.398 on 260 degrees of freedom  
## Multiple R-squared: 0.2433, Adjusted R-squared: 0.2113   
## F-statistic: 7.599 on 11 and 260 DF, p-value: 2.405e-11

#### Slika 1.7.

library(tsutils)  
sve.binarne<-seasdummy(length(IIP),12,y=IIP,type="bin",full=T)  
summary(lm(IIP~0+sve.binarne))

##   
## Call:  
## lm(formula = IIP ~ 0 + sve.binarne)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -21.6818 -4.7288 0.4565 6.1304 20.4783   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## sve.binarne1 89.565 1.960 45.71 <2e-16 \*\*\*  
## sve.binarne2 94.391 1.960 48.17 <2e-16 \*\*\*  
## sve.binarne3 104.696 1.960 53.43 <2e-16 \*\*\*  
## sve.binarne4 100.696 1.960 51.39 <2e-16 \*\*\*  
## sve.binarne5 104.609 1.960 53.38 <2e-16 \*\*\*  
## sve.binarne6 101.522 1.960 51.81 <2e-16 \*\*\*  
## sve.binarne7 105.870 1.960 54.03 <2e-16 \*\*\*  
## sve.binarne8 94.565 1.960 48.26 <2e-16 \*\*\*  
## sve.binarne9 103.591 2.004 51.70 <2e-16 \*\*\*  
## sve.binarne10 106.273 2.004 53.04 <2e-16 \*\*\*  
## sve.binarne11 105.682 2.004 52.74 <2e-16 \*\*\*  
## sve.binarne12 101.682 2.004 50.75 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 9.398 on 260 degrees of freedom  
## Multiple R-squared: 0.9918, Adjusted R-squared: 0.9914   
## F-statistic: 2627 on 12 and 260 DF, p-value: < 2.2e-16

## Primjer 1.2

#### Slika 1.8.

trend<-ts(1:length(IIP),start=c(1998,1),frequency=12)  
bin1<-c(rep(0,120),rep(1,72),rep(0,272-120-72))  
bin2<-c(rep(0,120+72),rep(1,272-120-72))  
summary(m1<-lm(IIP~binarne+trend+I(bin1\*trend)+I(bin2\*trend)))

##   
## Call:  
## lm(formula = IIP ~ binarne + trend + I(bin1 \* trend) + I(bin2 \*   
## trend))  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -14.0738 -3.5930 -0.2028 2.8054 22.3634   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 81.64248 1.70639 47.845 < 2e-16 \*\*\*  
## binarneJan -10.37087 1.84773 -5.613 5.15e-08 \*\*\*  
## binarneFeb -5.72549 1.84721 -3.100 0.002154 \*\*   
## binarneMar 4.39814 1.84675 2.382 0.017968 \*   
## binarneApr 0.21743 1.84634 0.118 0.906349   
## binarneMay 3.94976 1.84598 2.140 0.033325 \*   
## binarneJun 0.68209 1.84568 0.370 0.712015   
## binarneJul 4.84920 1.84543 2.628 0.009114 \*\*   
## binarneAug -6.63586 1.84523 -3.596 0.000387 \*\*\*  
## binarneSep 2.46322 1.86533 1.321 0.187834   
## binarneOct 4.96033 1.86519 2.659 0.008319 \*\*   
## binarneNov 4.18471 1.86511 2.244 0.025705 \*   
## trend 0.26826 0.01596 16.809 < 2e-16 \*\*\*  
## I(bin1 \* trend) -0.13086 0.01155 -11.326 < 2e-16 \*\*\*  
## I(bin2 \* trend) -0.17547 0.01251 -14.025 < 2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 6.186 on 257 degrees of freedom  
## Multiple R-squared: 0.6759, Adjusted R-squared: 0.6583   
## F-statistic: 38.29 on 14 and 257 DF, p-value: < 2.2e-16

## Primjer 1.3

#### Slika 1.9.

iip<-read.table("iip.txt",header=T,sep="\t")  
IIP<-ts(iip$IIP,start=c(1998,1),frequency=12)  
library(forecast)  
binarne<-seasonaldummy(IIP)  
trend<-ts(1:length(IIP),start=c(1998,1),frequency=12)  
bin1<-c(rep(0,120),rep(1,72),rep(0,272-120-72))  
bin2<-c(rep(0,120+72),rep(1,272-120-72))  
summary(m1<-lm(IIP~binarne+trend+I(bin1\*trend)+I(bin2\*trend)))

##   
## Call:  
## lm(formula = IIP ~ binarne + trend + I(bin1 \* trend) + I(bin2 \*   
## trend))  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -14.0738 -3.5930 -0.2028 2.8054 22.3634   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 81.64248 1.70639 47.845 < 2e-16 \*\*\*  
## binarneJan -10.37087 1.84773 -5.613 5.15e-08 \*\*\*  
## binarneFeb -5.72549 1.84721 -3.100 0.002154 \*\*   
## binarneMar 4.39814 1.84675 2.382 0.017968 \*   
## binarneApr 0.21743 1.84634 0.118 0.906349   
## binarneMay 3.94976 1.84598 2.140 0.033325 \*   
## binarneJun 0.68209 1.84568 0.370 0.712015   
## binarneJul 4.84920 1.84543 2.628 0.009114 \*\*   
## binarneAug -6.63586 1.84523 -3.596 0.000387 \*\*\*  
## binarneSep 2.46322 1.86533 1.321 0.187834   
## binarneOct 4.96033 1.86519 2.659 0.008319 \*\*   
## binarneNov 4.18471 1.86511 2.244 0.025705 \*   
## trend 0.26826 0.01596 16.809 < 2e-16 \*\*\*  
## I(bin1 \* trend) -0.13086 0.01155 -11.326 < 2e-16 \*\*\*  
## I(bin2 \* trend) -0.17547 0.01251 -14.025 < 2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 6.186 on 257 degrees of freedom  
## Multiple R-squared: 0.6759, Adjusted R-squared: 0.6583   
## F-statistic: 38.29 on 14 and 257 DF, p-value: < 2.2e-16

library(car)

## Loading required package: carData

ogranicenje<-c("binarneJan=0","binarneFeb=0","binarneMar=0",  
 "binarneApr=0","binarneMay=0","binarneJun=0",  
 "binarneJul=0","binarneAug=0","binarneSep=0",  
 "binarneOct=0","binarneNov=0")  
linearHypothesis(m1,ogranicenje,type="Chisq")

## Linear hypothesis test  
##   
## Hypothesis:  
## binarneJan = 0  
## binarneFeb = 0  
## binarneMar = 0  
## binarneApr = 0  
## binarneMay = 0  
## binarneJun = 0  
## binarneJul = 0  
## binarneAug = 0  
## binarneSep = 0  
## binarneOct = 0  
## binarneNov = 0  
##   
## Model 1: restricted model  
## Model 2: IIP ~ binarne + trend + I(bin1 \* trend) + I(bin2 \* trend)  
##   
## Res.Df RSS Df Sum of Sq F Pr(>F)   
## 1 268 16467.7   
## 2 257 9833.8 11 6634 15.761 < 2.2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## Primjer 1.4

iip<-read.table("iip.txt",header=T,sep="\t")  
IIP<-ts(iip$IIP,start=c(1998,1),frequency=12)  
library(forecast)  
binarne<-seasonaldummy(IIP)

#### Slika 1.10.

model<-lm(IIP~binarne)  
  
binarne<-seasonaldummy(ts(273:276,start=c(2020,9),frequency=12))  
binarne<-ts(binarne,start=c(2020,9),frequency=12)  
prognoza<-predict(model,newdata=binarne)  
procjene<-(fitted(model))  
zajedno<-c(procjene,prognoza)  
zajedno<-ts(zajedno,start=c(1998,1),frequency=12)  
cbind(IIP,zajedno)

## IIP zajedno  
## Jan 1998 78 89.56522  
## Feb 1998 83 94.39130  
## Mar 1998 89 104.69565  
## Apr 1998 86 100.69565  
## May 1998 87 104.60870  
## Jun 1998 84 101.52174  
## Jul 1998 86 105.86957  
## Aug 1998 85 94.56522  
## Sep 1998 87 103.59091  
## Oct 1998 88 106.27273  
## Nov 1998 89 105.68182  
## Dec 1998 80 101.68182  
## Jan 1999 76 89.56522  
## Feb 1999 77 94.39130  
## Mar 1999 86 104.69565  
## Apr 1999 83 100.69565  
## May 1999 87 104.60870  
## Jun 1999 84 101.52174  
## Jul 1999 88 105.86957  
## Aug 1999 78 94.56522  
## Sep 1999 85 103.59091  
## Oct 1999 92 106.27273  
## Nov 1999 89 105.68182  
## Dec 1999 86 101.68182  
## Jan 2000 75 89.56522  
## Feb 2000 79 94.39130  
## Mar 2000 89 104.69565  
## Apr 2000 83 100.69565  
## May 2000 86 104.60870  
## Jun 2000 92 101.52174  
## Jul 2000 90 105.86957  
## Aug 2000 81 94.56522  
## Sep 2000 86 103.59091  
## Oct 2000 89 106.27273  
## Nov 2000 88 105.68182  
## Dec 2000 89 101.68182  
## Jan 2001 81 89.56522  
## Feb 2001 83 94.39130  
## Mar 2001 95 104.69565  
## Apr 2001 90 100.69565  
## May 2001 93 104.60870  
## Jun 2001 95 101.52174  
## Jul 2001 91 105.86957  
## Aug 2001 89 94.56522  
## Sep 2001 92 103.59091  
## Oct 2001 94 106.27273  
## Nov 2001 92 105.68182  
## Dec 2001 93 101.68182  
## Jan 2002 84 89.56522  
## Feb 2002 85 94.39130  
## Mar 2002 96 104.69565  
## Apr 2002 92 100.69565  
## May 2002 97 104.60870  
## Jun 2002 93 101.52174  
## Jul 2002 98 105.86957  
## Aug 2002 92 94.56522  
## Sep 2002 102 103.59091  
## Oct 2002 104 106.27273  
## Nov 2002 103 105.68182  
## Dec 2002 98 101.68182  
## Jan 2003 84 89.56522  
## Feb 2003 91 94.39130  
## Mar 2003 101 104.69565  
## Apr 2003 100 100.69565  
## May 2003 103 104.60870  
## Jun 2003 101 101.52174  
## Jul 2003 102 105.86957  
## Aug 2003 97 94.56522  
## Sep 2003 102 103.59091  
## Oct 2003 105 106.27273  
## Nov 2003 101 105.68182  
## Dec 2003 97 101.68182  
## Jan 2004 84 89.56522  
## Feb 2004 94 94.39130  
## Mar 2004 106 104.69565  
## Apr 2004 102 100.69565  
## May 2004 104 104.60870  
## Jun 2004 102 101.52174  
## Jul 2004 105 105.86957  
## Aug 2004 98 94.56522  
## Sep 2004 105 103.59091  
## Oct 2004 105 106.27273  
## Nov 2004 104 105.68182  
## Dec 2004 103 101.68182  
## Jan 2005 90 89.56522  
## Feb 2005 95 94.39130  
## Mar 2005 104 104.69565  
## Apr 2005 107 100.69565  
## May 2005 112 104.60870  
## Jun 2005 109 101.52174  
## Jul 2005 112 105.86957  
## Aug 2005 100 94.56522  
## Sep 2005 112 103.59091  
## Oct 2005 110 106.27273  
## Nov 2005 113 105.68182  
## Dec 2005 111 101.68182  
## Jan 2006 94 89.56522  
## Feb 2006 101 94.39130  
## Mar 2006 108 104.69565  
## Apr 2006 108 100.69565  
## May 2006 114 104.60870  
## Jun 2006 111 101.52174  
## Jul 2006 118 105.86957  
## Aug 2006 108 94.56522  
## Sep 2006 116 103.59091  
## Oct 2006 118 106.27273  
## Nov 2006 116 105.68182  
## Dec 2006 118 101.68182  
## Jan 2007 99 89.56522  
## Feb 2007 107 94.39130  
## Mar 2007 121 104.69565  
## Apr 2007 116 100.69565  
## May 2007 122 104.60870  
## Jun 2007 118 101.52174  
## Jul 2007 123 105.86957  
## Aug 2007 111 94.56522  
## Sep 2007 119 103.59091  
## Oct 2007 121 106.27273  
## Nov 2007 120 105.68182  
## Dec 2007 117 101.68182  
## Jan 2008 106 89.56522  
## Feb 2008 110 94.39130  
## Mar 2008 124 104.69565  
## Apr 2008 118 100.69565  
## May 2008 123 104.60870  
## Jun 2008 122 101.52174  
## Jul 2008 123 105.86957  
## Aug 2008 111 94.56522  
## Sep 2008 118 103.59091  
## Oct 2008 122 106.27273  
## Nov 2008 119 105.68182  
## Dec 2008 110 101.68182  
## Jan 2009 94 89.56522  
## Feb 2009 101 94.39130  
## Mar 2009 112 104.69565  
## Apr 2009 112 100.69565  
## May 2009 114 104.60870  
## Jun 2009 106 101.52174  
## Jul 2009 112 105.86957  
## Aug 2009 100 94.56522  
## Sep 2009 107 103.59091  
## Oct 2009 113 106.27273  
## Nov 2009 108 105.68182  
## Dec 2009 102 101.68182  
## Jan 2010 96 89.56522  
## Feb 2010 100 94.39130  
## Mar 2010 109 104.69565  
## Apr 2010 106 100.69565  
## May 2010 109 104.60870  
## Jun 2010 103 101.52174  
## Jul 2010 111 105.86957  
## Aug 2010 100 94.56522  
## Sep 2010 110 103.59091  
## Oct 2010 109 106.27273  
## Nov 2010 107 105.68182  
## Dec 2010 102 101.68182  
## Jan 2011 89 89.56522  
## Feb 2011 97 94.39130  
## Mar 2011 106 104.69565  
## Apr 2011 108 100.69565  
## May 2011 110 104.60870  
## Jun 2011 103 101.52174  
## Jul 2011 112 105.86957  
## Aug 2011 94 94.56522  
## Sep 2011 107 103.59091  
## Oct 2011 109 106.27273  
## Nov 2011 106 105.68182  
## Dec 2011 104 101.68182  
## Jan 2012 85 89.56522  
## Feb 2012 90 94.39130  
## Mar 2012 98 104.69565  
## Apr 2012 98 100.69565  
## May 2012 104 104.60870  
## Jun 2012 100 101.52174  
## Jul 2012 105 105.86957  
## Aug 2012 96 94.56522  
## Sep 2012 100 103.59091  
## Oct 2012 102 106.27273  
## Nov 2012 102 105.68182  
## Dec 2012 98 101.68182  
## Jan 2013 88 89.56522  
## Feb 2013 92 94.39130  
## Mar 2013 101 104.69565  
## Apr 2013 98 100.69565  
## May 2013 101 104.60870  
## Jun 2013 96 101.52174  
## Jul 2013 101 105.86957  
## Aug 2013 92 94.56522  
## Sep 2013 96 103.59091  
## Oct 2013 99 106.27273  
## Nov 2013 101 105.68182  
## Dec 2013 95 101.68182  
## Jan 2014 89 89.56522  
## Feb 2014 92 94.39130  
## Mar 2014 102 104.69565  
## Apr 2014 98 100.69565  
## May 2014 100 104.60870  
## Jun 2014 96 101.52174  
## Jul 2014 102 105.86957  
## Aug 2014 88 94.56522  
## Sep 2014 99 103.59091  
## Oct 2014 101 106.27273  
## Nov 2014 104 105.68182  
## Dec 2014 99 101.68182  
## Jan 2015 85 89.56522  
## Feb 2015 92 94.39130  
## Mar 2015 105 104.69565  
## Apr 2015 100 100.69565  
## May 2015 105 104.60870  
## Jun 2015 98 101.52174  
## Jul 2015 106 105.86957  
## Aug 2015 90 94.56522  
## Sep 2015 104 103.59091  
## Oct 2015 108 106.27273  
## Nov 2015 108 105.68182  
## Dec 2015 100 101.68182  
## Jan 2016 93 89.56522  
## Feb 2016 96 94.39130  
## Mar 2016 112 104.69565  
## Apr 2016 104 100.69565  
## May 2016 107 104.60870  
## Jun 2016 102 101.52174  
## Jul 2016 108 105.86957  
## Aug 2016 92 94.56522  
## Sep 2016 106 103.59091  
## Oct 2016 110 106.27273  
## Nov 2016 116 105.68182  
## Dec 2016 115 101.68182  
## Jan 2017 97 89.56522  
## Feb 2017 99 94.39130  
## Mar 2017 112 104.69565  
## Apr 2017 104 100.69565  
## May 2017 111 104.60870  
## Jun 2017 106 101.52174  
## Jul 2017 110 105.86957  
## Aug 2017 95 94.56522  
## Sep 2017 110 103.59091  
## Oct 2017 115 106.27273  
## Nov 2017 114 105.68182  
## Dec 2017 112 101.68182  
## Jan 2018 97 89.56522  
## Feb 2018 103 94.39130  
## Mar 2018 110 104.69565  
## Apr 2018 103 100.69565  
## May 2018 110 104.60870  
## Jun 2018 109 101.52174  
## Jul 2018 109 105.86957  
## Aug 2018 94 94.56522  
## Sep 2018 107 103.59091  
## Oct 2018 112 106.27273  
## Nov 2018 113 105.68182  
## Dec 2018 105 101.68182  
## Jan 2019 101 89.56522  
## Feb 2019 103 94.39130  
## Mar 2019 114 104.69565  
## Apr 2019 106 100.69565  
## May 2019 110 104.60870  
## Jun 2019 103 101.52174  
## Jul 2019 112 105.86957  
## Aug 2019 93 94.56522  
## Sep 2019 109 103.59091  
## Oct 2019 112 106.27273  
## Nov 2019 112 105.68182  
## Dec 2019 103 101.68182  
## Jan 2020 95 89.56522  
## Feb 2020 101 94.39130  
## Mar 2020 108 104.69565  
## Apr 2020 94 100.69565  
## May 2020 97 104.60870  
## Jun 2020 102 101.52174  
## Jul 2020 111 105.86957  
## Aug 2020 91 94.56522  
## Sep 2020 NA 103.59091  
## Oct 2020 NA 106.27273  
## Nov 2020 NA 105.68182  
## Dec 2020 NA 101.68182

#### Slika 1.11.

#Slika 1.11. je zadnji dio ispisa koji se dobije s naredbom cbind(IIP,zajedno)

## Primjer 1.5

#### Slika 1.12.

crobex<-read.table("crobex.txt",header=T,sep="\t")  
prinos<-c(NA,diff(log(crobex$Crobex))\*100)  
cro<-lm(prinos~0+pon+uto+sri+cet+pet,data=crobex)  
#Newey-West korekcija:  
library(sandwich)  
mat<-NeweyWest(cro,lag=1)  
library(lmtest)

## Loading required package: zoo

##   
## Attaching package: 'zoo'

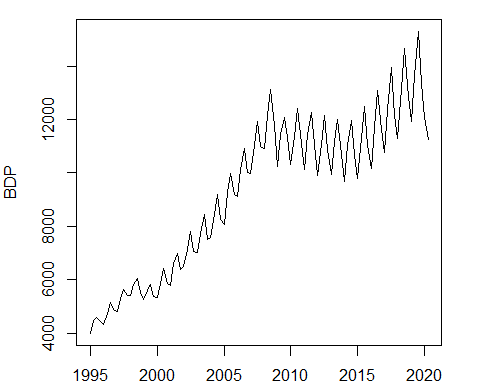
## The following objects are masked from 'package:base':  
##   
## as.Date, as.Date.numeric

coeftest(cro,vcov=mat)

##   
## t test of coefficients:  
##   
## Estimate Std. Error t value Pr(>|t|)   
## pon -0.254185 0.191298 -1.3287 0.18472   
## uto 0.202248 0.079776 2.5352 0.01163 \*  
## sri -0.121787 0.086194 -1.4129 0.15848   
## cet -0.090991 0.150527 -0.6045 0.54588   
## pet 0.141479 0.093878 1.5071 0.13261   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#### Slika 1.13.

bdp<-read.table("bdp.txt",header=T,sep="\t")  
bdp<-ts(bdp$BDP,start=c(1995,1),frequency = 4)  
  
par(mfrow = c(1,1),oma=c(1,0,0,1),mar=c(1,4,1,1))  
plot(bdp,xlab="godine",ylab="BDP")



#### Slika 1.14. i 1.15.

library(forecast)  
bin<-seasonaldummy(bdp)  
bin2<-c(rep(1,52),rep(0,102-52))  
trend<-ts(1:102,start=c(1995,1),frequency = 4)  
m1<-lm(bdp~bin)  
m2<-lm(bdp~bin+I(bin\*bin2))  
m3<-lm(bdp~bin+trend+I(bin\*bin2)+I(trend\*bin2))  
library(stargazer)

##   
## Please cite as:

## Hlavac, Marek (2022). stargazer: Well-Formatted Regression and Summary Statistics Tables.

## R package version 5.2.3. https://CRAN.R-project.org/package=stargazer

stargazer(list(m1,m2,m3),type="text")

##   
## ======================================================================================  
## Dependent variable:   
## ------------------------------------------------------------------  
## bdp   
## (1) (2) (3)   
## --------------------------------------------------------------------------------------  
## binQ1 -701.942 1,375.289\*\* -349.083   
## (807.241) (683.201) (347.149)   
##   
## binQ2 254.446 2,604.681\*\*\* 794.594\*\*   
## (807.241) (683.201) (348.891)   
##   
## binQ3 999.380 3,783.387\*\*\* 2,059.016\*\*\*   
## (815.117) (701.680) (354.479)   
##   
## trend 85.716\*\*\*   
## (4.648)   
##   
## I(bin \* bin2)Q1 -4,154.462\*\*\* -415.856   
## (783.686) (471.687)   
##   
## I(bin \* bin2)Q2 -4,700.469\*\*\* -990.609\*\*   
## (783.686) (474.755)   
##   
## I(bin \* bin2)Q3 -5,353.860\*\*\* -1,844.177\*\*\*   
## (799.846) (478.246)   
##   
## I(trend \* bin2) 28.745\*\*\*   
## (7.013)   
##   
## Constant 9,176.896\*\*\* 9,176.896\*\*\* 4,301.121\*\*\*   
## (576.375) (399.603) (308.517)   
##   
## --------------------------------------------------------------------------------------  
## Observations 102 102 102   
## R2 0.044 0.555 0.912   
## Adjusted R2 0.015 0.527 0.905   
## Residual Std. Error 2,881.873 (df = 98) 1,998.014 (df = 95) 895.741 (df = 93)   
## F Statistic 1.514 (df = 3; 98) 19.722\*\*\* (df = 6; 95) 121.051\*\*\* (df = 8; 93)  
## ======================================================================================  
## Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### Slika 1.16.

# lines(ts(fitted(m1),start=c(1995,1),frequency = 4),lty="dashed")  
# lines(ts(fitted(m2),start=c(1995,1),frequency = 4),col="grey")  
# lines(ts(fitted(m3),start=c(1995,1),frequency = 4),col="black",type="b",lty=1)  
# legend("topleft", legend=c("BDP", "m1","m2","m3"),col=c("black", "black","grey","black"), lty=c(1,2,1,3))

#### Slika 1.17.

library(car)  
ogr<-c("binQ1=0","binQ2=0","binQ3=0")  
linearHypothesis(m3,ogr,type="Chisq")

## Linear hypothesis test  
##   
## Hypothesis:  
## binQ1 = 0  
## binQ2 = 0  
## binQ3 = 0  
##   
## Model 1: restricted model  
## Model 2: bdp ~ bin + trend + I(bin \* bin2) + I(trend \* bin2)  
##   
## Res.Df RSS Df Sum of Sq F Pr(>F)   
## 1 96 117242531   
## 2 93 74618789 3 42623742 17.708 3.57e-09 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#### Slika 1.18.

bin<-seasonaldummy(ts(103:104,start=c(2020,3),frequency=4))  
bin2<-c(1,1)  
trend<-ts(103:104,start=c(2020,3),frequency = 4)  
novo<-cbind(bin,bin2,trend)  
predict(m3,newdata=novo)

## 1 2   
## 16305.51 16205.13

#### Slika 1.19.

Box.test(resid(m3),lag=2,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: resid(m3)  
## X-squared = 107.8, df = 2, p-value < 2.2e-16

#### Slika 1.20.

bin<-seasonaldummy(bdp)  
bin2<-c(rep(1,52),rep(0,102-52))  
trend<-ts(1:102,start=c(1995,1),frequency = 4)  
bptest<-lm(residuals(m3)^2~bin+trend+I(bin\*bin2)+I(trend\*bin2))  
nobs(bptest)\*(summary(bptest))$r.squared

## [1] 9.123594

1-pchisq(nobs(bptest)\*(summary(bptest))$r.squared,8)

## [1] 0.3319773

#### Slika 1.21.

#White korekcija:  
library(car)  
mat<-hccm(m3,type="hc0")  
#t-test:  
library(lmtest)

#### Slika 1.22.

coeftest(m3)

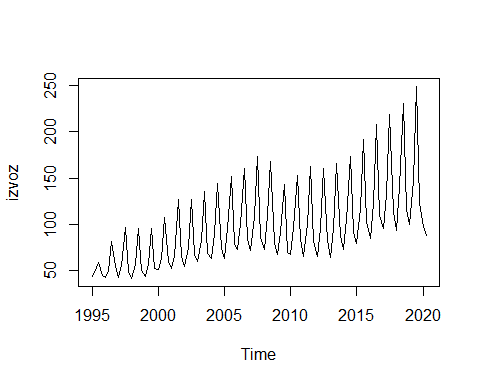
##   
## t test of coefficients:  
##   
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 4301.1210 308.5172 13.9413 < 2.2e-16 \*\*\*  
## binQ1 -349.0826 347.1488 -1.0056 0.3172314   
## binQ2 794.5935 348.8911 2.2775 0.0250489 \*   
## binQ3 2059.0161 354.4793 5.8086 8.733e-08 \*\*\*  
## trend 85.7162 4.6482 18.4405 < 2.2e-16 \*\*\*  
## I(bin \* bin2)Q1 -415.8556 471.6874 -0.8816 0.3802479   
## I(bin \* bin2)Q2 -990.6087 474.7555 -2.0866 0.0396641 \*   
## I(bin \* bin2)Q3 -1844.1775 478.2465 -3.8561 0.0002121 \*\*\*  
## I(trend \* bin2) 28.7454 7.0128 4.0990 8.868e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

coeftest(m3,vcov=mat)

##   
## t test of coefficients:  
##   
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 4301.1210 313.8567 13.7041 < 2.2e-16 \*\*\*  
## binQ1 -349.0826 407.7553 -0.8561 0.39414   
## binQ2 794.5935 417.5905 1.9028 0.06016 .   
## binQ3 2059.0161 371.2916 5.5455 2.733e-07 \*\*\*  
## trend 85.7162 4.4314 19.3429 < 2.2e-16 \*\*\*  
## I(bin \* bin2)Q1 -415.8556 473.4488 -0.8784 0.38202   
## I(bin \* bin2)Q2 -990.6087 472.0818 -2.0984 0.03858 \*   
## I(bin \* bin2)Q3 -1844.1775 451.0374 -4.0887 9.207e-05 \*\*\*  
## I(trend \* bin2) 28.7454 5.8540 4.9104 3.873e-06 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#### 1.5. Pitanja za ponavljanje, zadatak 12:

bdp<-read.table("bdp\_agregati.txt",header=T,sep="\t")  
izvoz<-ts(bdp$izvoz,start=c(1995,1),frequency = 4)  
plot(izvoz)



library(forecast)  
binarne<-seasonaldummy(izvoz)  
trend<-ts(1:length(izvoz),start=c(1995,1),frequency = 4)  
bin2<-c(rep(0,52),rep(1,length(izvoz)-52))  
  
#procjena i usporedba 4 modela:  
m1<-lm(izvoz~binarne)  
m2<-lm(izvoz~trend+binarne)  
m3<-lm(izvoz~trend+binarne+I(trend\*bin2))  
m4<-lm(izvoz~trend+binarne+I(binarne\*bin2))  
  
library(stargazer)  
stargazer(list(m1,m2,m3,m4),type="text")

##   
## ==================================================================================================================  
## Dependent variable:   
## ----------------------------------------------------------------------------------------------  
## izvoz   
## (1) (2) (3) (4)   
## ------------------------------------------------------------------------------------------------------------------  
## trend 0.878\*\*\* 1.276\*\*\* 0.953\*\*\*   
## (0.052) (0.131) (0.069)   
##   
## binarneQ1 -12.813 -11.934\*\*\* -11.202\*\*\* 0.474   
## (8.564) (4.349) (4.151) (4.957)   
##   
## binarneQ2 12.756 12.756\*\*\* 13.249\*\*\* 18.606\*\*\*   
## (8.564) (4.349) (4.147) (4.932)   
##   
## binarneQ3 71.996\*\*\* 72.874\*\*\* 73.120\*\*\* 64.183\*\*\*   
## (8.648) (4.392) (4.186) (4.907)   
##   
## I(trend \* bin2) -0.316\*\*\*   
## (0.096)   
##   
## I(binarne \* bin2)Q1 -24.668\*\*\*   
## (6.379)   
##   
## I(binarne \* bin2)Q2 -11.699\*   
## (6.379)   
##   
## I(binarne \* bin2)Q3 18.262\*\*\*   
## (6.393)   
##   
## Constant 79.136\*\*\* 33.455\*\*\* 24.624\*\*\* 29.576\*\*\*   
## (6.115) (4.125) (4.761) (4.490)   
##   
## ------------------------------------------------------------------------------------------------------------------  
## Observations 102 102 102 102   
## R2 0.537 0.882 0.894 0.914   
## Adjusted R2 0.523 0.877 0.888 0.908   
## Residual Std. Error 30.574 (df = 98) 15.526 (df = 97) 14.796 (df = 96) 13.428 (df = 94)   
## F Statistic 37.934\*\*\* (df = 3; 98) 181.070\*\*\* (df = 4; 97) 161.664\*\*\* (df = 5; 96) 143.429\*\*\* (df = 7; 94)  
## ==================================================================================================================  
## Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

library(car)  
ogr<-c("binarneQ1=0","binarneQ2=0","binarneQ3=0")  
linearHypothesis(m1,ogr,type="Chisq")

## Linear hypothesis test  
##   
## Hypothesis:  
## binarneQ1 = 0  
## binarneQ2 = 0  
## binarneQ3 = 0  
##   
## Model 1: restricted model  
## Model 2: izvoz ~ binarne  
##   
## Res.Df RSS Df Sum of Sq F Pr(>F)   
## 1 101 197981   
## 2 98 91605 3 106376 37.934 2.34e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

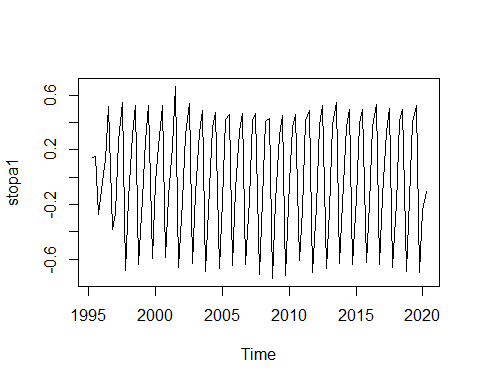
ogr<-"I(trend \* bin2)"  
linearHypothesis(m3,ogr,type="Chisq")

## Linear hypothesis test  
##   
## Hypothesis:  
## I(trend \* bin2) = 0  
##   
## Model 1: restricted model  
## Model 2: izvoz ~ trend + binarne + I(trend \* bin2)  
##   
## Res.Df RSS Df Sum of Sq F Pr(>F)   
## 1 97 23383   
## 2 96 21017 1 2366.1 10.808 0.001413 \*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

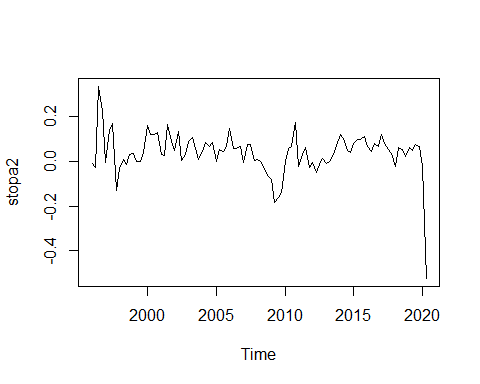
binarne<-seasonaldummy(ts(103:110,start=c(2020,3),frequency=4))  
binarne<-ts(binarne,start=c(2020,3),frequency=4)  
trend<-ts(103:110,start=c(2020,3),frequency=4)  
bin2<-ts(rep(1,8),start=c(2020,3),frequency=4)  
novo<-cbind(binarne,trend,bin2)  
prognoza<-predict(m4,newdata=novo)  
procjene<-(fitted(m4))  
zajedno<-c(procjene,prognoza)  
zajedno<-ts(zajedno,start=c(1995,1),frequency=4)  
cbind(izvoz,zajedno)

## izvoz zajedno  
## 1995 Q1 43.3 31.00285  
## 1995 Q2 50.0 50.08746  
## 1995 Q3 58.4 96.61823  
## 1995 Q4 44.4 33.38785  
## 1996 Q1 42.9 34.81519  
## 1996 Q2 48.7 53.89981  
## 1996 Q3 81.7 100.43058  
## 1996 Q4 55.7 37.20019  
## 1997 Q1 42.8 38.62754  
## 1997 Q2 55.9 57.71215  
## 1997 Q3 96.7 104.24292  
## 1997 Q4 48.9 41.01254  
## 1998 Q1 41.5 42.43989  
## 1998 Q2 56.4 61.52450  
## 1998 Q3 95.4 108.05527  
## 1998 Q4 50.4 44.82489  
## 1999 Q1 43.1 46.25223  
## 1999 Q2 56.4 65.33685  
## 1999 Q3 95.2 111.86762  
## 1999 Q4 52.5 48.63723  
## 2000 Q1 50.6 50.06458  
## 2000 Q2 63.5 69.14919  
## 2000 Q3 107.3 115.67996  
## 2000 Q4 59.8 52.44958  
## 2001 Q1 52.1 53.87692  
## 2001 Q2 65.1 72.96154  
## 2001 Q3 126.6 119.49231  
## 2001 Q4 65.3 56.26192  
## 2002 Q1 54.7 57.68927  
## 2002 Q2 74.4 76.77388  
## 2002 Q3 127.3 123.30465  
## 2002 Q4 67.5 60.07427  
## 2003 Q1 59.8 61.50161  
## 2003 Q2 82.8 80.58623  
## 2003 Q3 135.2 127.11700  
## 2003 Q4 68.0 63.88662  
## 2004 Q1 62.5 65.31396  
## 2004 Q2 90.1 84.39858  
## 2004 Q3 144.4 130.92935  
## 2004 Q4 74.1 67.69896  
## 2005 Q1 62.5 69.12631  
## 2005 Q2 95.2 88.21092  
## 2005 Q3 151.2 134.74169  
## 2005 Q4 79.3 71.51131  
## 2006 Q1 72.5 72.93865  
## 2006 Q2 101.0 92.02327  
## 2006 Q3 160.5 138.55404  
## 2006 Q4 84.9 75.32365  
## 2007 Q1 72.1 76.75100  
## 2007 Q2 109.0 95.83561  
## 2007 Q3 173.5 142.36638  
## 2007 Q4 85.4 79.13600  
## 2008 Q1 72.7 55.89516  
## 2008 Q2 109.2 87.94900  
## 2008 Q3 168.4 164.44043  
## 2008 Q4 80.3 82.94835  
## 2009 Q1 67.0 59.70750  
## 2009 Q2 91.1 91.76135  
## 2009 Q3 143.2 168.25278  
## 2009 Q4 69.8 86.76069  
## 2010 Q1 67.1 63.51985  
## 2010 Q2 96.7 95.57369  
## 2010 Q3 152.9 172.06512  
## 2010 Q4 83.2 90.57304  
## 2011 Q1 65.7 67.33219  
## 2011 Q2 99.9 99.38604  
## 2011 Q3 162.7 175.87747  
## 2011 Q4 81.0 94.38538  
## 2012 Q1 65.3 71.14454  
## 2012 Q2 95.2 103.19839  
## 2012 Q3 160.5 179.68981  
## 2012 Q4 82.2 98.19773  
## 2013 Q1 64.6 74.95688  
## 2013 Q2 95.3 107.01073  
## 2013 Q3 165.3 183.50216  
## 2013 Q4 88.1 102.01008  
## 2014 Q1 72.8 78.76923  
## 2014 Q2 105.6 110.82308  
## 2014 Q3 173.5 187.31451  
## 2014 Q4 91.9 105.82242  
## 2015 Q1 79.0 82.58158  
## 2015 Q2 116.7 114.63542  
## 2015 Q3 191.4 191.12685  
## 2015 Q4 102.6 109.63477  
## 2016 Q1 84.4 86.39392  
## 2016 Q2 122.3 118.44777  
## 2016 Q3 207.9 194.93920  
## 2016 Q4 109.6 113.44711  
## 2017 Q1 95.3 90.20627  
## 2017 Q2 132.4 122.26011  
## 2017 Q3 219.0 198.75154  
## 2017 Q4 113.4 117.25946  
## 2018 Q1 93.3 94.01861  
## 2018 Q2 140.7 126.07246  
## 2018 Q3 230.9 202.56389  
## 2018 Q4 116.1 121.07181  
## 2019 Q1 99.4 97.83096  
## 2019 Q2 147.9 129.88481  
## 2019 Q3 249.2 206.37624  
## 2019 Q4 124.0 124.88415  
## 2020 Q1 97.4 101.64331  
## 2020 Q2 87.7 133.69715  
## 2020 Q3 NA 210.18858  
## 2020 Q4 NA 128.69650  
## 2021 Q1 NA 105.45565  
## 2021 Q2 NA 137.50950  
## 2021 Q3 NA 214.00093  
## 2021 Q4 NA 132.50884  
## 2022 Q1 NA 109.26800  
## 2022 Q2 NA 141.32184

stopa1<-diff(log(izvoz))  
stopa1<-ts(stopa1,start=c(1995,2),frequency = 4)  
plot(stopa1)



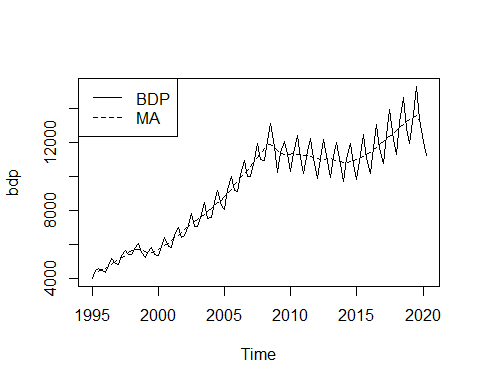
stopa2<-diff(log(izvoz),lag=4)  
stopa2<-ts(stopa2,start=c(1996,1),frequency = 4)  
plot(stopa2)



## Primjer 1.6.

#### Slika 1.23. i 1.24

bdp<-read.table("bdp.txt",header=T,sep="\t")  
bdp<-ts(bdp$BDP,start=c(1995,1),frequency = 4)  
  
library(forecast)  
bdp.pp<-ma(bdp,4,centre = T)  
plot(bdp)  
lines(bdp.pp,col="black",lty="dashed")  
legend("topleft", legend=c("BDP", "MA"),col=c("black", "black"), lty=c(1,2))

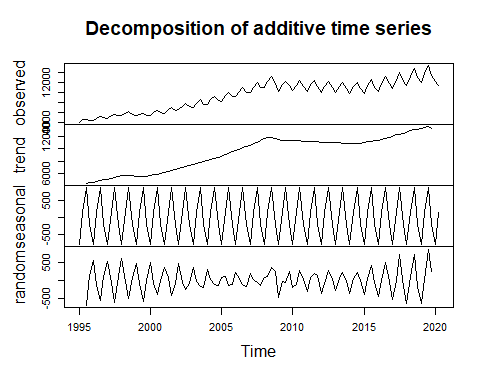


## Primjer 1.7

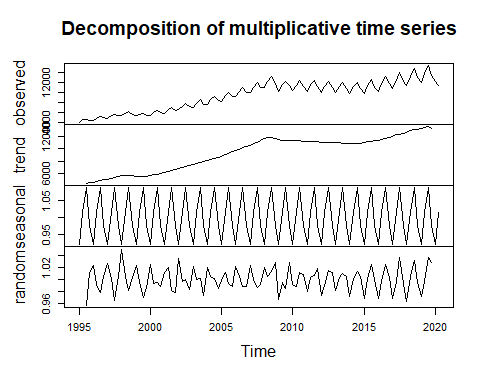
bdp<-read.table("bdp.txt",header=T,sep="\t")  
bdp<-ts(bdp$BDP,start=c(1995,1),frequency = 4)

#### Slika 1.25, 1.26. i 1.27

plot(decompose(bdp,type="additive"))

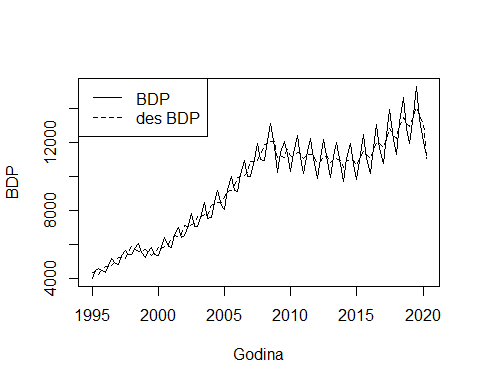


plot(decompose(bdp,type="multiplicative"))



#### Slika 1.28. i 1.29.

dekompozicija<-decompose(bdp,type="multiplicative")  
desezonirani.bdp<-bdp/dekompozicija$seasonal  
  
plot(bdp,xlab="Godina",ylab="BDP")  
lines(desezonirani.bdp,col="black",lty="dashed")  
legend("topleft", legend=c("BDP", "des BDP"),col=c("black", "black"), lty=c(1,2))



#### Slika 1.30.

dekompozicija$seasonal[1:4]

## [1] 0.9192557 1.0154841 1.0881047 0.9771555

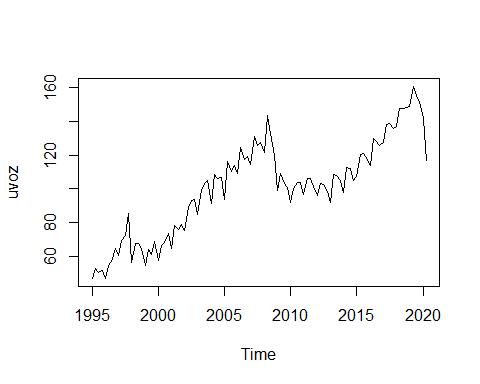
stope<-(dekompozicija$seasonal-1)\*100  
stope[1:4]

## [1] -8.074431 1.548415 8.810466 -2.284449

## 1.6.3. Primjer

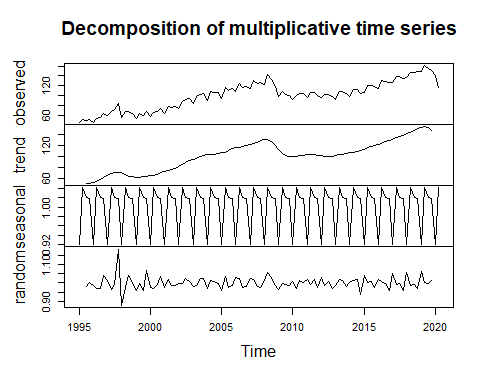
#### Slika 1.31. i 1.32

bdp<-read.table("bdp\_agregati.txt",header=T,sep="\t")  
uvoz<-ts(bdp$uvoz,start=c(1995,1),frequency = 4)  
desezonirani.uvoz<-uvoz/decompose(uvoz,type="multiplicative")$seasonal  
plot(uvoz)



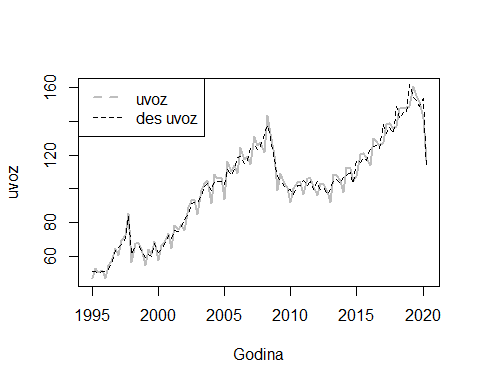
#### slika 1.33

plot(dekompozicija<-decompose(uvoz,type="multiplicative"))



#### Slika 1.34. i 1.35.

plot(uvoz, xlab="Godina", ylab="uvoz",col="grey",lwd=2)  
lines(desezonirani.uvoz,col="black",lty="dashed")  
legend("topleft",legend=c("uvoz","des uvoz"),col=c("grey","black"),lty=c(2,2),lwd=c(2,1))



#### Slika 1.36.

dekompozicija$seasonal[1:4]

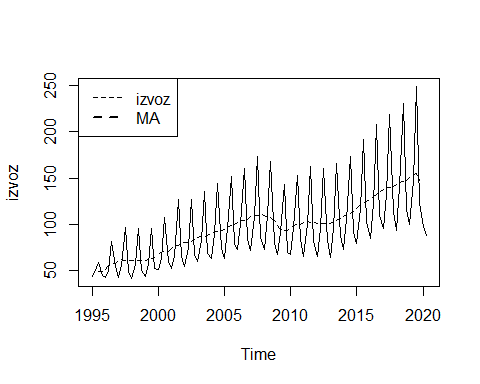
## [1] 0.9203829 1.0410812 1.0199325 1.0186033

stope<-(dekompozicija$seasonal-1)\*100  
stope[1:4]

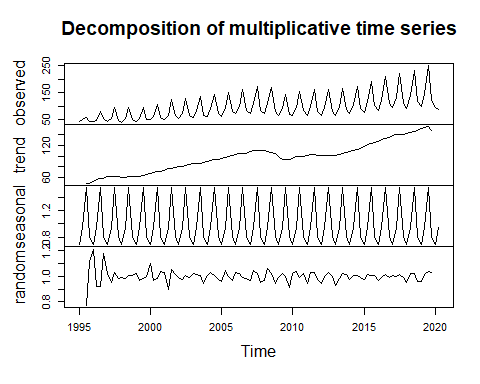
## [1] -7.961708 4.108123 1.993255 1.860330

#### 1.7. Pitanja za ponavljanje, zadatak 4

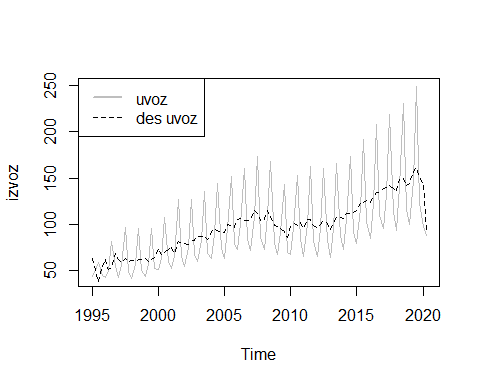
bdp<-read.table("bdp\_agregati.txt",header=T,sep="\t")  
izvoz<-ts(bdp$izvoz,start=c(1995,1),frequency = 4)  
plot(izvoz)  
lines(ma(izvoz,4,centre=T),type="l",lty="dashed")  
legend("topleft",legend=c("izvoz","MA"),col=c("black","black"),lty=c(2,2),lwd=c(1,2))



plot(dekompozicija<-decompose(izvoz,type="multiplicative"))



plot(izvoz,col="grey")  
lines(izvoz/decompose(izvoz,type="multiplicative")$seasonal,lty="dashed")  
legend("topleft",legend=c("uvoz","des uvoz"),col=c("grey","black"),lty=c(1,2),lwd=c(2,1))



#stope  
dekompozicija$seasonal[1:4]

## [1] 0.6876825 0.9488591 1.5466701 0.8167883

stope<-(dekompozicija$seasonal-1)\*100  
stope[1:4]

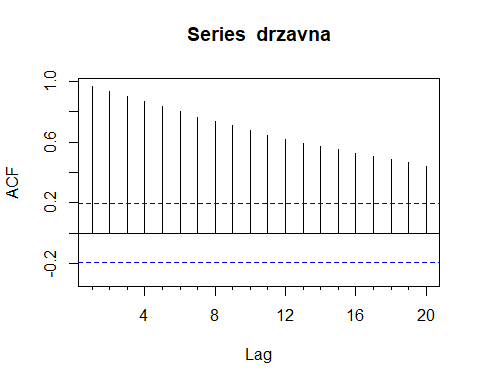
## [1] -31.231747 -5.114095 54.667012 -18.321170

## Primjer 1.8.

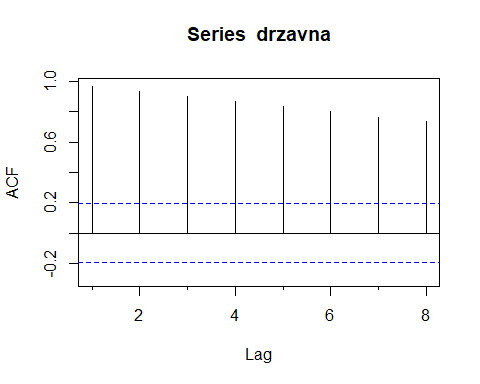
bdp<-read.table("bdp\_agregati.txt",header=T,sep="\t")  
drzavna<-ts(bdp$drzava,start=c(1995,1),frequency = 4)

#### Slika 1.37. i 1.38.

drzavna<-ts(bdp$drzava,start=c(1995,1),frequency = 4)  
library(forecast)  
acf.drz<-Acf(drzavna,lag.max = 20)



acf.drz<-Acf(drzavna,lag.max = 8)

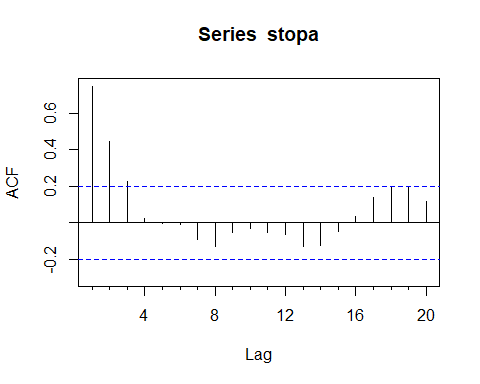


acf.koeficijenti<-matrix(acf.drz[["acf"]])  
t(acf.koeficijenti)

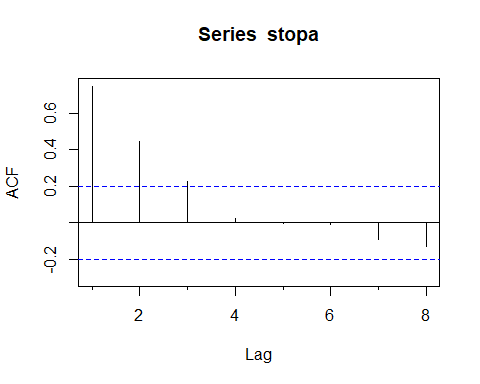
## [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8]  
## [1,] 1 0.9683576 0.933438 0.9035819 0.8719975 0.8377952 0.8015676 0.766668  
## [,9]  
## [1,] 0.734566

#### Slika 1.39. i 1.40.

stopa<-diff(log(drzavna),4)  
acf.drz<-Acf(stopa,lag.max = 20)



acf.drz<-Acf(stopa,lag.max = 8)

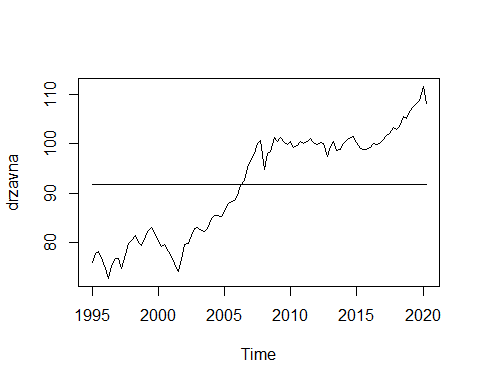


acf.koeficijenti<-matrix(acf.drz[["acf"]])  
t(acf.koeficijenti)

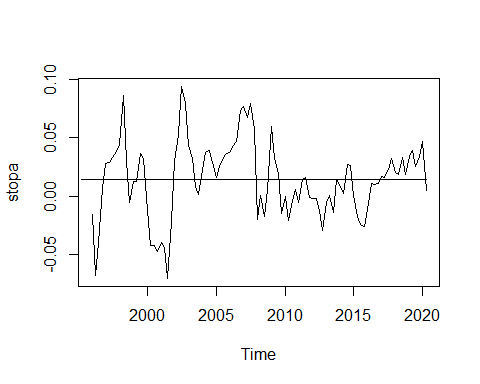
## [,1] [,2] [,3] [,4] [,5] [,6] [,7]  
## [1,] 1 0.7458894 0.447207 0.2266629 0.02491716 -0.005796723 -0.009734007  
## [,8] [,9]  
## [1,] -0.09135203 -0.1279069

#### Slika 1.41.

prosjek1<-mean(drzavna)  
prosjek1<-ts(rep(prosjek1,102),start=c(1995,1),frequency = 4)  
plot(drzavna)  
lines(prosjek1)



prosjek2<-mean(stopa)  
prosjek2<-ts(rep(prosjek2,101),start=c(1995,2),frequency = 4)  
plot(stopa)  
lines(prosjek2)

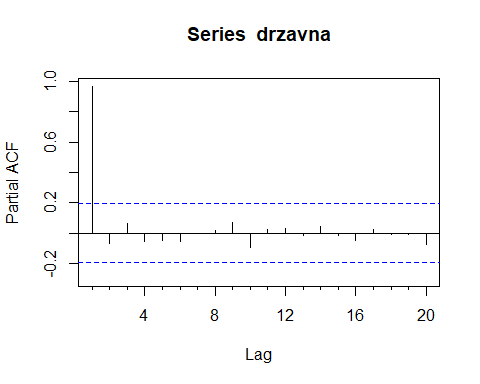


## Primjer 1.9.

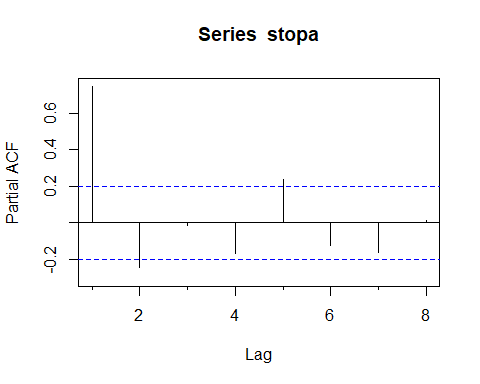
bdp<-read.table("bdp\_agregati.txt",header=T,sep="\t")  
drzavna<-ts(bdp$drzava,start=c(1995,1),frequency = 4)  
stopa<-diff(log(drzavna),4)

#### Slika 1.42. i 1.43.

pacf.drz<-Pacf(drzavna,lag.max=20)



pacf.drz<-Pacf(stopa,lag.max = 8)

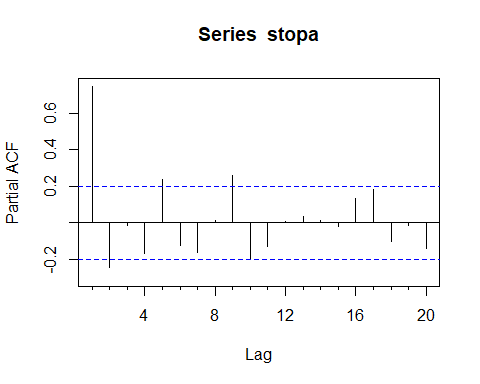


pacf.koeficijenti<-matrix(pacf.drz[["acf"]])  
t(pacf.koeficijenti)

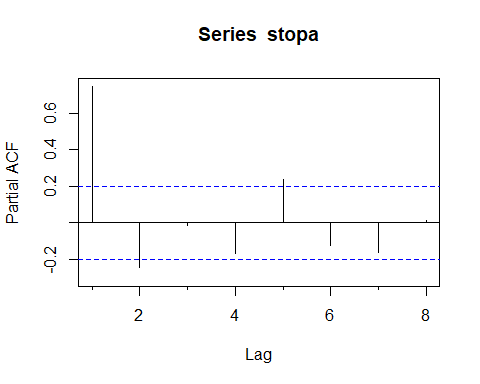
## [,1] [,2] [,3] [,4] [,5] [,6]  
## [1,] 0.7458894 -0.2460144 -0.01311639 -0.1695555 0.2353942 -0.1208143  
## [,7] [,8]  
## [1,] -0.1609853 0.01225773

#### Slika 1.44 i 1.45

acf.drz<-Pacf(stopa,lag.max = 20)



acf.drz<-Pacf(stopa,lag.max = 8)



acf.koeficijenti<-matrix(acf.drz[["acf"]])  
t(acf.koeficijenti)

## [,1] [,2] [,3] [,4] [,5] [,6]  
## [1,] 0.7458894 -0.2460144 -0.01311639 -0.1695555 0.2353942 -0.1208143  
## [,7] [,8]  
## [1,] -0.1609853 0.01225773

## Primjer 1.10

bdp<-read.table("bdp\_agregati.txt",header=T,sep="\t")  
drzavna<-ts(bdp$drzava,start=c(1995,1),frequency = 4)  
stopa<-diff(log(drzavna),4)

#### Slika 1.46

Box.test(drzavna,lag=3,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: drzavna  
## X-squared = 267.8, df = 3, p-value < 2.2e-16

Box.test(drzavna,lag=3,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: drzavna  
## X-squared = 278.4, df = 3, p-value < 2.2e-16

#### Slika 1.47.

Box.test(stopa,lag=3,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: stopa  
## X-squared = 79.157, df = 3, p-value < 2.2e-16

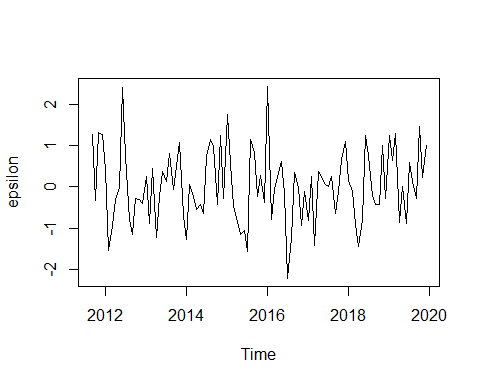
Box.test(stopa,lag=3,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: stopa  
## X-squared = 81.925, df = 3, p-value < 2.2e-16

## Primjer 1.11

#### Slika 1.48. i 1.49.

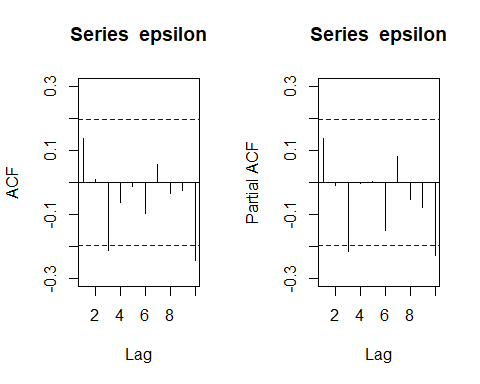
set.seed(0)  
epsilon<-rnorm(100,0,1)  
epsilon<-ts(epsilon,start=c(2011,9),frequency=12)  
plot(epsilon)



#spremiti epsilon za primjere ispod

#### Slika 1.50. i 1.51.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(epsilon,lag.max=10)  
Pacf(epsilon,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.52.

Box.test(epsilon,lag = 10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: epsilon  
## X-squared = 14.312, df = 10, p-value = 0.1592

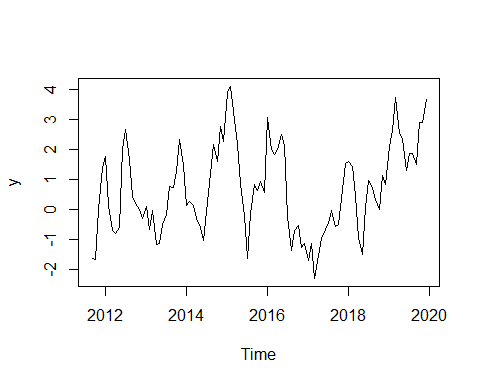
Box.test(epsilon,lag = 10,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: epsilon  
## X-squared = 15.565, df = 10, p-value = 0.1128

## Primjer 1.12

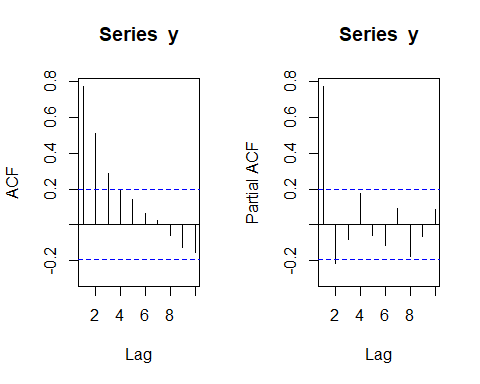
#### Slika 1.53. i 1.54

#spremiti epsilon iz primjera 1.11  
library(stats)  
y<-arima.sim(model=list(ar = 0.88), n=100, innov = epsilon)   
y<-1+y  
y<-ts(y,start=c(2011,9),frequency=12)  
plot(y)



#### Slika 1.55.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y,lag.max=10)  
Pacf(y,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.56.

Box.test(y,lag = 10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y  
## X-squared = 105.1, df = 10, p-value < 2.2e-16

Box.test(y,lag = 10,type="Ljung-Box")

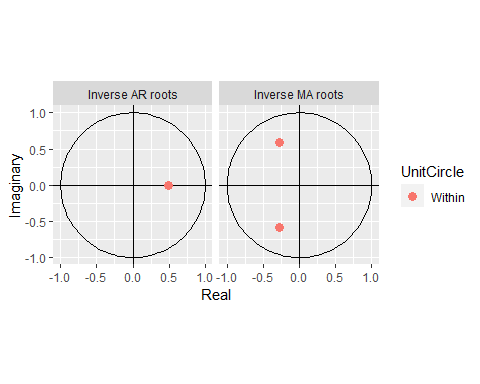
##   
## Box-Ljung test  
##   
## data: y  
## X-squared = 109.39, df = 10, p-value < 2.2e-16

#### Slika 1.57. i 1.58.

ar\_1<-auto.arima(y,d=0) #ako tu ne dobijete ar(1) (provjeriti uz summary(ar\_1)), onda "rucno"  
#Procijeniti uz ar\_1<-arima(y,order=c(1,0,0))  
summary(ar\_1)

## Series: y   
## ARIMA(1,0,2) with non-zero mean   
##   
## Coefficients:  
## ar1 ma1 ma2 mean  
## 0.4875 0.5426 0.423 0.6863  
## s.e. 0.1494 0.1475 0.147 0.3125  
##   
## sigma^2 = 0.7143: log likelihood = -123.75  
## AIC=257.51 AICc=258.14 BIC=270.53  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.01246233 0.8280871 0.664114 166.711 478.0543 0.4262967  
## ACF1  
## Training set -0.01786834

korijeni<-autoplot(ar\_1)  
plot(korijeni)



korijeni$data$roots

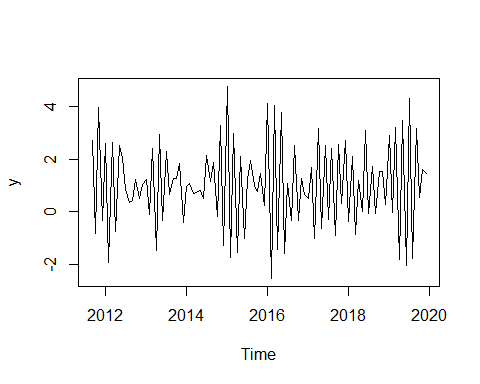
## [1] 2.051353+0.000000i -0.641412+1.397357i -0.641412-1.397357i

## Primjer 1.13

#spremiti epsilon iz primjera 1.11  
  
library(stats)  
y<-arima.sim(model=list(ar = -0.88), n=100, innov = epsilon)  
y<-1+y  
y<-ts(y,start=c(2011,9),frequency=12)

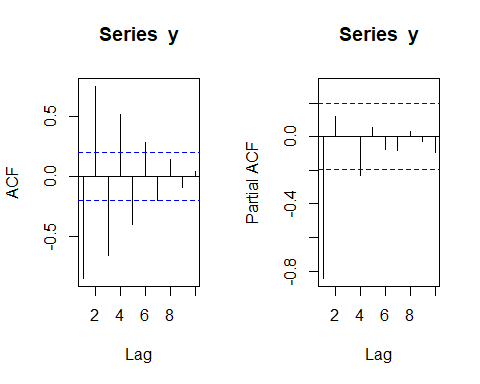
#### Slika 1.59.

plot(y)



#### Slika 1.60.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y,lag.max=10)  
Pacf(y,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.61.

Box.test(y,lag = 10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y  
## X-squared = 225.87, df = 10, p-value < 2.2e-16

Box.test(y,lag = 10,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: y  
## X-squared = 236.64, df = 10, p-value < 2.2e-16

ar\_1<-auto.arima(y,d=0) # ako tu ne dobijete ar(1) (provjeriti uz summary(ar\_1)), onda "rucno"  
#Procijeniti uz ar\_1<-arima(y,order=c(1,0,0))  
summary(ar\_1)

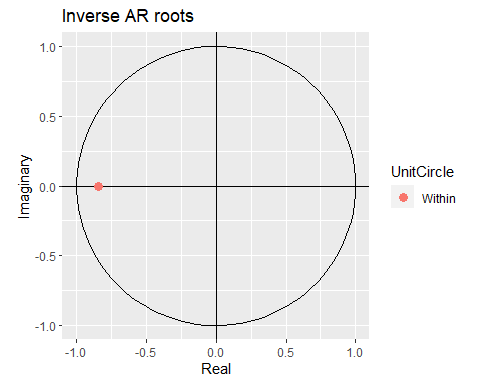
## Series: y   
## ARIMA(1,0,0) with non-zero mean   
##   
## Coefficients:  
## ar1 mean  
## -0.8451 1.0067  
## s.e. 0.0518 0.0475  
##   
## sigma^2 = 0.7763: log likelihood = -128.85  
## AIC=263.69 AICc=263.94 BIC=271.51  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.006526875 0.8722027 0.696973 -35.70159 139.5314 0.4037507  
## ACF1  
## Training set 0.1051673

korijeni<-autoplot(ar\_1)  
korijeni$data$roots

## [1] -1.18325+0i

#### Slika 1.62.

plot(korijeni)

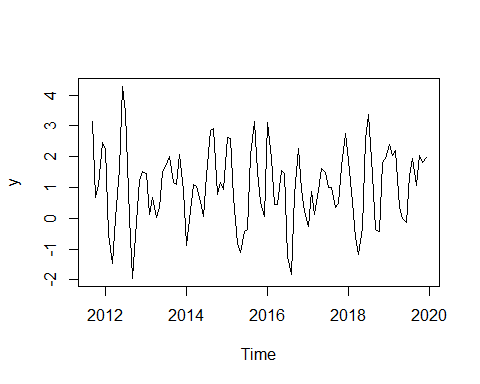


## Primjer 1.14

#spremiti epsilon iz primjera 1.11  
library(stats)  
y<-arima.sim(model=list(ar=c(0.6,-0.5)), n=100, innov = epsilon)  
y<-1+y  
y<-ts(y,start=c(2011,9),frequency=12)

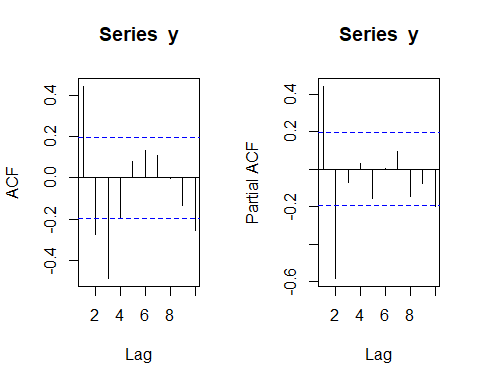
#### Slika 1.63.

plot(y)



#### Slika 1.64.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y,lag.max=10)  
Pacf(y,lag.max=10)



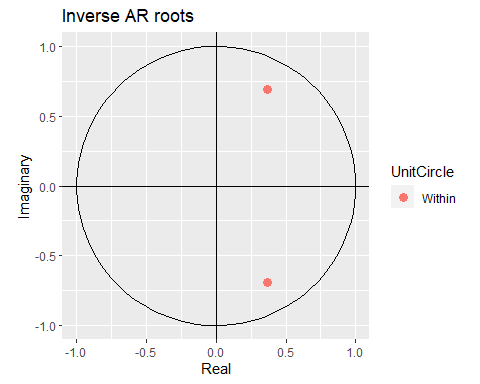
par(mfrow = c(1, 1))

#### Slika 1.65. i 1.66.

ar\_2<-auto.arima(y,d=0) # ako tu ne dobijete ar(2) (provjeriti uz summary(ar\_2)), onda "rucno"  
#Procijeniti uz ar\_2<-arima(y,order=c(2,0,0))  
summary(ar\_2)

## Series: y   
## ARIMA(2,0,0) with non-zero mean   
##   
## Coefficients:  
## ar1 ar2 mean  
## 0.7402 -0.6158 1.0254  
## s.e. 0.0804 0.0793 0.1003  
##   
## sigma^2 = 0.7859: log likelihood = -128.92  
## AIC=265.84 AICc=266.26 BIC=276.26  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set -0.002300032 0.8731119 0.6960635 -117.5874 296.6644 0.5505024  
## ACF1  
## Training set -0.02989651

korijeni<-autoplot(ar\_2)  
plot(korijeni)



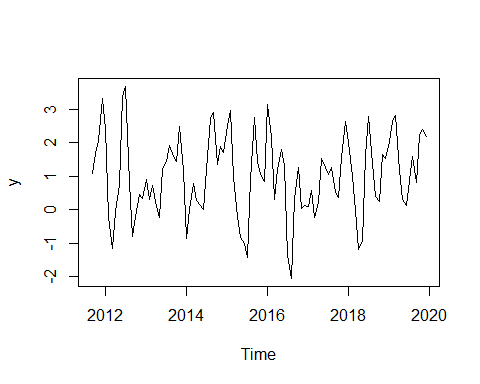
korijeni$data$roots

## [1] 0.600971+1.123671i 0.600971-1.123671i

## Primjer 1.15

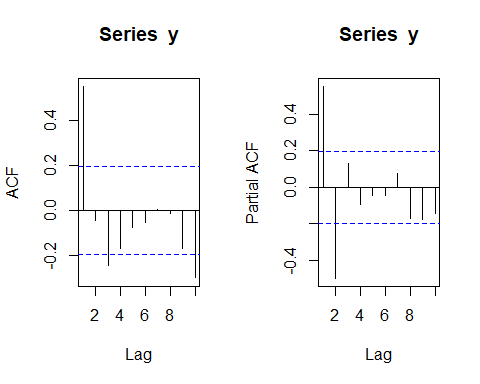
#### Slika 1.67. i 1.68.

#spremiti epsilon iz primjera 1.11  
y<- arima.sim(model = list(ma =0.8), n = 100,innov=epsilon)  
y<-1+y  
y<-ts(y,start=c(2011,9),frequency=12)  
plot(y)



#### Slika 1.69.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y,lag.max=10)  
Pacf(y,lag.max=10)



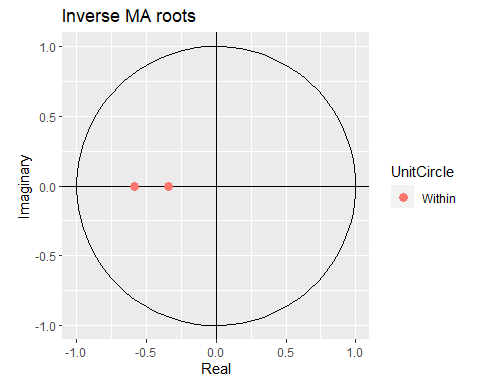
par(mfrow = c(1, 1))

#### Slika 1.70. i 1.71.

ma\_1<-auto.arima(y,d=0) # ako tu ne dobijete ma(1) (provjeriti uz summary(ma\_1)), onda "rucno"  
#Procijeniti uz ma\_1<-arima(y,order=c(0,0,1))  
summary(ma\_1)

## Series: y   
## ARIMA(0,0,2) with non-zero mean   
##   
## Coefficients:  
## ma1 ma2 mean  
## 0.9312 0.2024 1.0271  
## s.e. 0.0929 0.1337 0.1823  
##   
## sigma^2 = 0.7622: log likelihood = -127.29  
## AIC=262.58 AICc=263.01 BIC=273.01  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.001515295 0.8598366 0.6898768 -29.01707 426.1071 0.5659239  
## ACF1  
## Training set 0.01131931

korijeni<-autoplot(ma\_1)  
plot(korijeni)



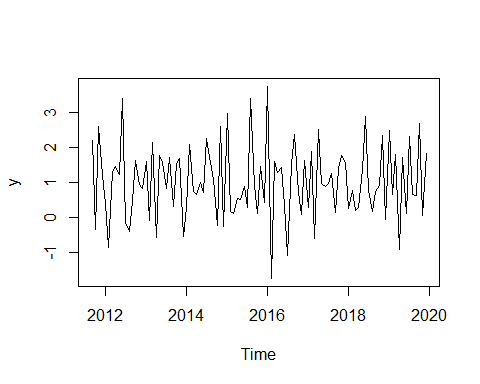
korijeni$data$roots

## [1] -1.707311+0i -2.894188-0i

## Primjer 1.16

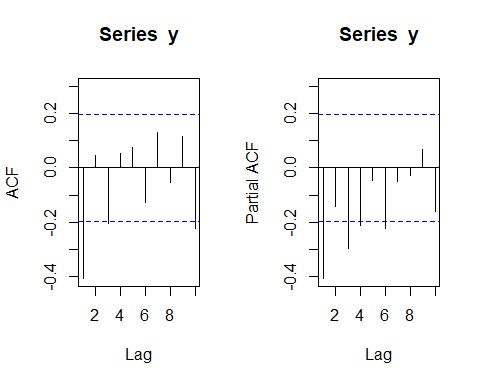
#### Slika 1.72.

#spremiti epsilon iz primjera 1.11  
y<- arima.sim(model = list(ma = -0.8), n = 100,innov=epsilon)  
y<-1+y  
y<-ts(y,start=c(2011,9),frequency=12)  
plot(y)



#### Slika 1.73.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y,lag.max=10)  
Pacf(y,lag.max=10)

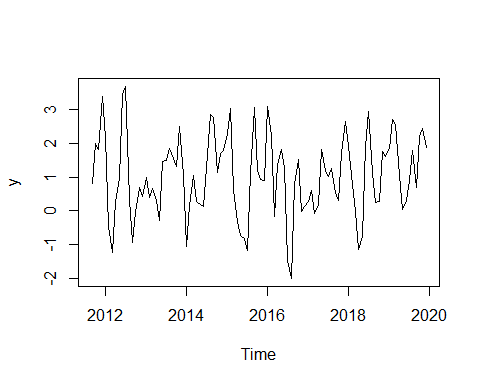


par(mfrow = c(1, 1))

## Primjer 1.17

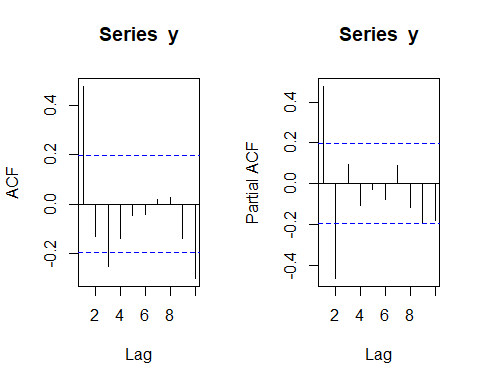
#### Slika 1.74. i 1.75.

#spremiti epsilon iz primjera 1.11  
y<- arima.sim(model = list(ma =c( 0.8,-0.2)), n = 100,innov=epsilon)  
y<-1+y  
y<-ts(y,start=c(2011,9),frequency=12)  
plot(y)



#### Slika 1.76.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y,lag.max=10)  
Pacf(y,lag.max=10)



par(mfrow = c(1, 1))  
  
ma\_2<-arima(y,order=c(0,0,2))  
korijeni<-autoplot(ma\_2)

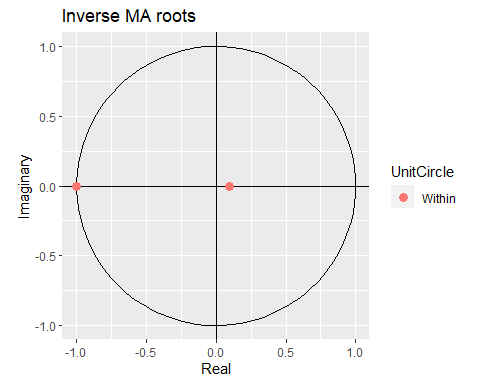
#### Slika 1.77.

korijeni$data$roots

## [1] -1.000007+0i 10.849410-0i

#### Slika 1.78.

plot(korijeni)



## Primjer 1.18

#### Slika 1.79.

library("FitARMA")

## Loading required package: FitAR

## Loading required package: lattice

## Loading required package: leaps

## Warning: package 'leaps' was built under R version 4.2.2

## Loading required package: ltsa

## Loading required package: bestglm

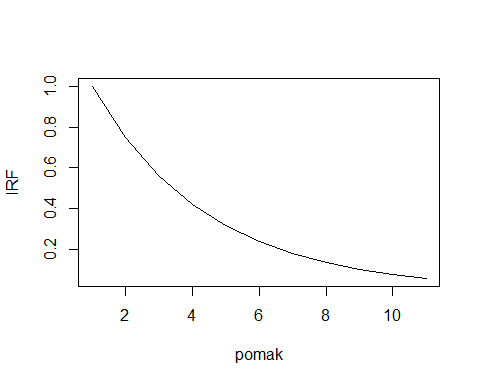
## Warning: package 'bestglm' was built under R version 4.2.2

##   
## Attaching package: 'FitAR'

## The following object is masked from 'package:car':  
##   
## Boot

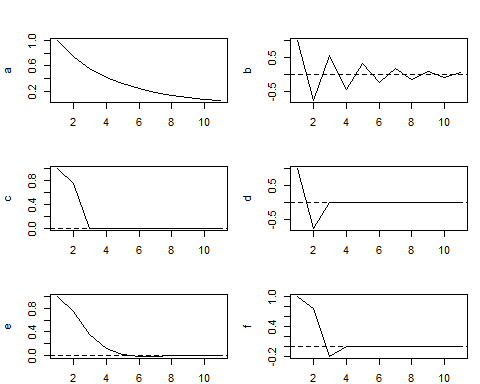
## The following object is masked from 'package:forecast':  
##   
## BoxCox

z<-ImpulseCoefficientsARMA(phi=.75, theta=0, lag.max=10)  
plot(z,type="l",ylab="IRF",xlab="pomak")



#### Slika 1.80.

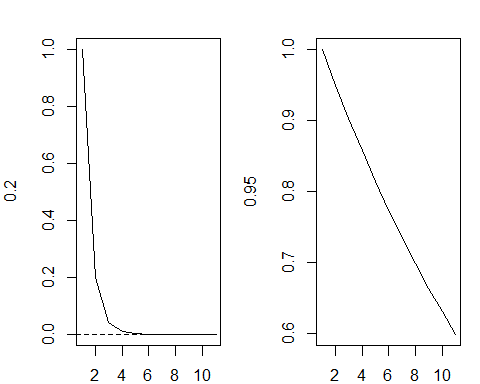
z1 <- ImpulseCoefficientsARMA(phi=0.75, theta=0,  
 lag.max=10)  
z2 <- ImpulseCoefficientsARMA(phi=-0.75, theta=0,  
 lag.max=10)  
z3 <- ImpulseCoefficientsARMA(phi=0, theta=-0.75,  
 lag.max=10)  
z4 <- ImpulseCoefficientsARMA(phi=0, theta=+0.75,  
 lag.max=10)  
z5 <- ImpulseCoefficientsARMA(phi=c(0.75,-0.2), theta=0,  
 lag.max=10)  
z6 <- ImpulseCoefficientsARMA(phi=0, theta=c(-0.75,+0.2),  
 lag.max=10)  
  
par(mfrow = c(3, 2),oma=c(0,0,0,0),mar=c(2,4,3,1))  
plot(z1,type="l",ylab="a",xlab="pomak")  
abline(h=0,lty="dashed")  
plot(z2,type="l",ylab="b",xlab="pomak")  
abline(h=0,lty="dashed")  
plot(z3,type="l",ylab="c",xlab="pomak")  
abline(h=0,lty="dashed")  
plot(z4,type="l",ylab="d",xlab="pomak")  
abline(h=0,lty="dashed")  
plot(z5,type="l",ylab="e",xlab="pomak")  
abline(h=0,lty="dashed")  
plot(z6,type="l",ylab="f",xlab="pomak")  
abline(h=0,lty="dashed")



## Primjer 1.19

#### Slika 1.81.

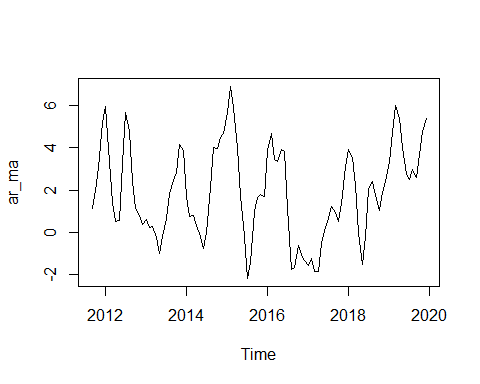
library("FitARMA")  
z7 <- ImpulseCoefficientsARMA(phi=0.2, theta=0,lag.max=10)  
z8 <- ImpulseCoefficientsARMA(phi=0.95,theta=0,lag.max=10)  
par(mfrow = c(1, 2),oma=c(0,0,0,0),mar=c(2,4,2,1))  
plot(z7,type="l",ylab="0.2",xlab="pomak")  
abline(h=0,lty="dashed")  
plot(z8,type="l",ylab="0.95",xlab="pomak")  
abline(h=0,lty="dashed")



## Primjer 1.20

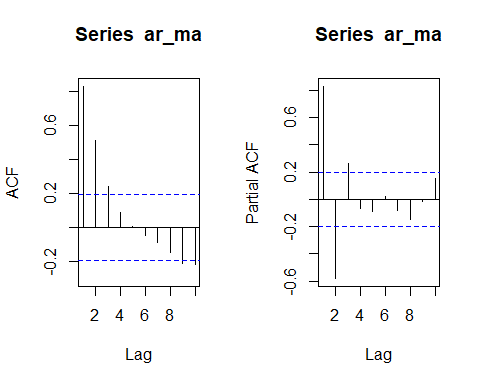
#### Slika 1.82. i 1.83.

#spremiti epsilon iz primjera 1.11  
  
ar\_ma<-arima.sim(model=list(ar=0.8,ma=0.8),n=100,innov=epsilon)  
ar\_ma<-2+ar\_ma  
ar\_ma<-ts(ar\_ma,start=c(2011,9),frequency=12)  
plot(ar\_ma)



#### Slika 1.84.

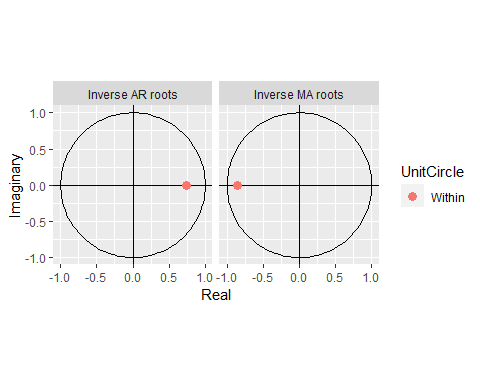
library(forecast)  
par(mfrow = c(1, 2))  
Acf(ar\_ma,lag.max=10)  
Pacf(ar\_ma,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.85. i 1.86.

ar\_ma\_11<-arima(ar\_ma,order=c(1,0,1))  
korijeni<-autoplot(ar\_ma\_11)  
plot(korijeni)

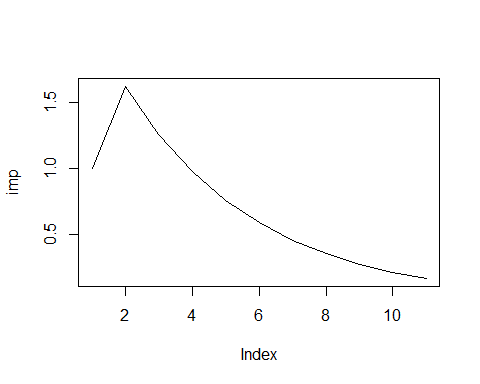


korijeni$data$roots

## [1] 1.355337+0i -1.173552+0i

#### Slika 1.87.

imp<- ImpulseCoefficientsARMA(phi=.775, theta=-0.8491,  
 lag.max=10)  
plot(imp,type="l")  
abline(h=0,lty="dashed")

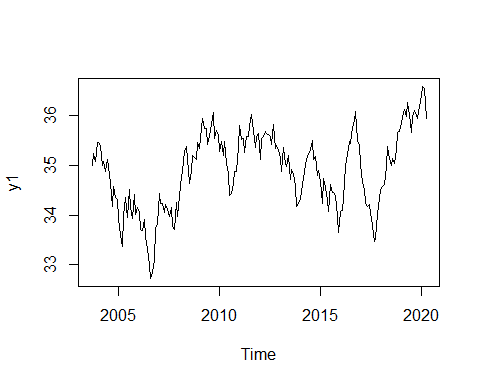


## 1.9.9 Primjer

nizovi<-read.table("gen\_nizovi.txt",header=T,sep="\t")

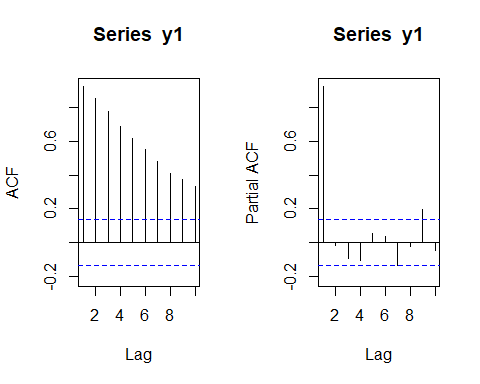
#### Slika 1.88.

y1<-ts(nizovi$Y1,start=c(2003,9),frequency=12)  
plot(y1)



#### Slika 1.89.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y1,lag.max=10)  
Pacf(y1,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.90.

Box.test(y1,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y1  
## X-squared = 801.42, df = 10, p-value < 2.2e-16

Box.test(y1,lag=10,type="Ljung-Box")

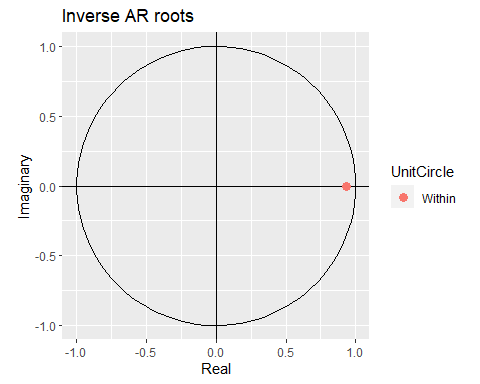
##   
## Box-Ljung test  
##   
## data: y1  
## X-squared = 825.14, df = 10, p-value < 2.2e-16

#### Slika 1.91.

m1<-auto.arima(y1,d=0)  
summary(m1)

## Series: y1   
## ARIMA(1,0,0) with non-zero mean   
##   
## Coefficients:  
## ar1 mean  
## 0.9302 34.9706  
## s.e. 0.0251 0.2691  
##   
## sigma^2 = 0.0803: log likelihood = -31.59  
## AIC=69.18 AICc=69.31 BIC=79.08  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set -7.046532e-05 0.2819608 0.2392335 -0.006993027 0.6870978 0.3179367  
## ACF1  
## Training set -0.01726027

korijeni<-autoplot(m1)  
plot(korijeni)

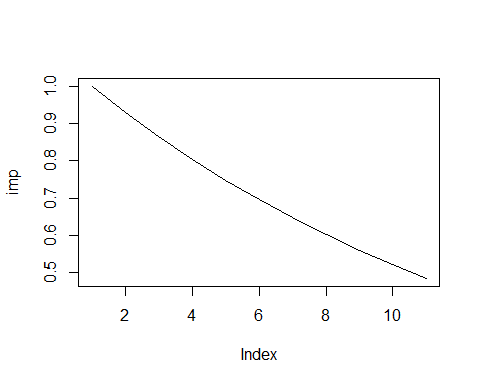


korijeni$data$roots

## [1] 1.075056+0i

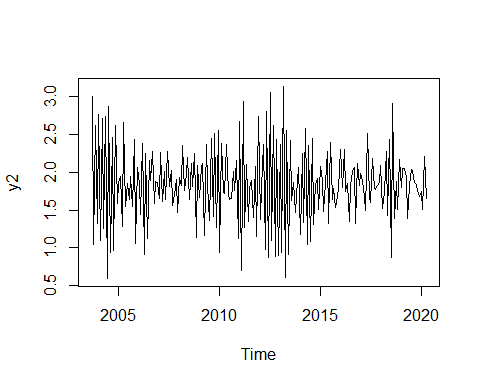
#### Slika 1.92.

imp<- ImpulseCoefficientsARMA(phi=0.9302, theta=0,  
 lag.max=10)  
plot(imp,type="l")



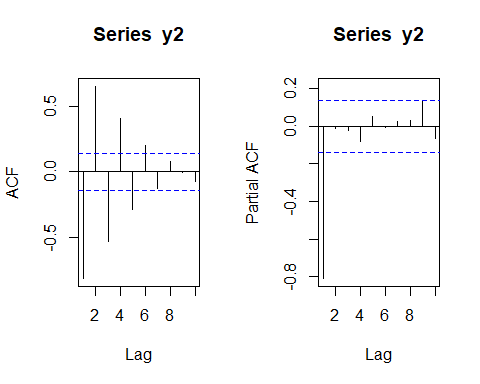
#### Slika 1.93.

y2<-ts(nizovi$Y2,start=c(2003,9),frequency=12)  
plot(y2)



#### Slika 1.94.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y2,lag.max=10)  
Pacf(y2,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.95.

Box.test(y2,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y2  
## X-squared = 332.09, df = 10, p-value < 2.2e-16

Box.test(y2,lag=10,type="Ljung-Box")

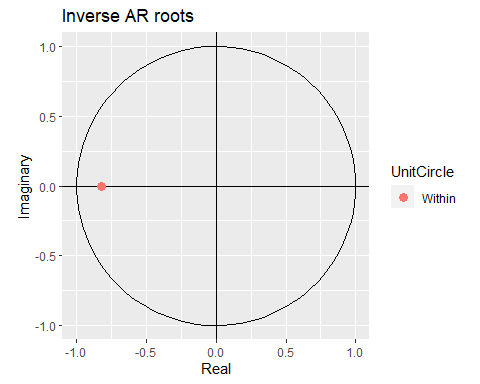
##   
## Box-Ljung test  
##   
## data: y2  
## X-squared = 339.33, df = 10, p-value < 2.2e-16

#### Slika 1.96.

m1<-auto.arima(y2,d=0)  
summary(m1)

## Series: y2   
## ARIMA(1,0,0) with non-zero mean   
##   
## Coefficients:  
## ar1 mean  
## -0.8258 1.8328  
## s.e. 0.0406 0.0115  
##   
## sigma^2 = 0.08876: log likelihood = -41.17  
## AIC=88.35 AICc=88.47 BIC=98.24  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.002274523 0.2964348 0.2596211 -3.168637 15.99956 0.4278454  
## ACF1  
## Training set 0.001202566

korijeni<-autoplot(m1)  
plot(korijeni)

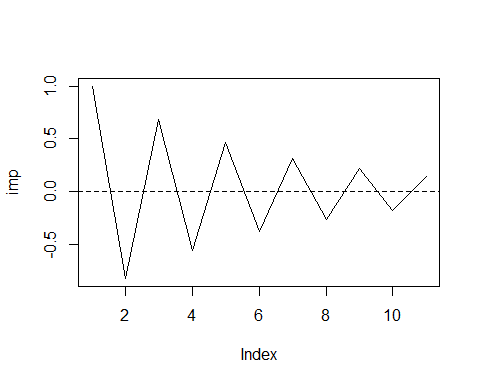


korijeni$data$roots

## [1] -1.210896+0i

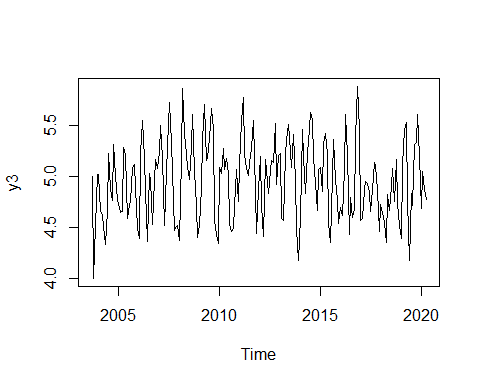
#### Slika 1.97.

imp<- ImpulseCoefficientsARMA(phi=-0.8258, theta=0,  
 lag.max=10)  
plot(imp,type="l")  
abline(h=0,lty="dashed")



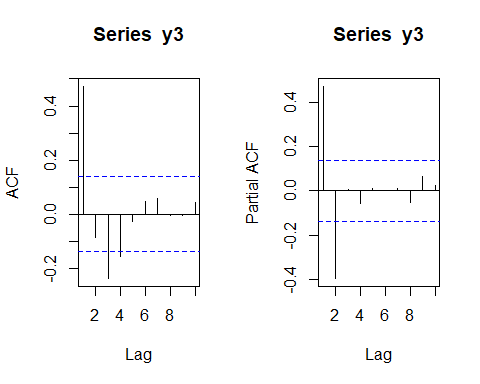
#### Slika 1.98.

y3<-ts(nizovi$Y3,start=c(2003,9),frequency=12)  
plot(y3)



#### Slika 1.99.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y3,lag.max=10)  
Pacf(y3,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.100.

Box.test(y3,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y3  
## X-squared = 63.64, df = 10, p-value = 7.371e-10

Box.test(y3,lag=10,type="Ljung-Box")

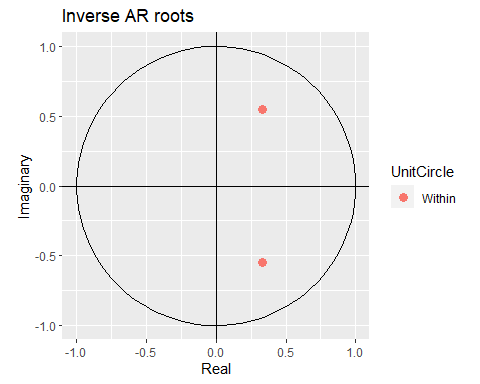
##   
## Box-Ljung test  
##   
## data: y3  
## X-squared = 64.851, df = 10, p-value = 4.328e-10

#### Slika 1.101.

m1<-auto.arima(y3,d=0)  
summary(m1)

## Series: y3   
## ARIMA(2,0,0) with non-zero mean   
##   
## Coefficients:  
## ar1 ar2 mean  
## 0.6661 -0.4107 4.9674  
## s.e. 0.0649 0.0657 0.0285  
##   
## sigma^2 = 0.09111: log likelihood = -43.02  
## AIC=94.03 AICc=94.24 BIC=107.23  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set -0.001594886 0.2995702 0.2520564 -0.3998839 5.119613 0.6272004  
## ACF1  
## Training set -0.001328095

korijeni<-autoplot(m1)  
plot(korijeni)

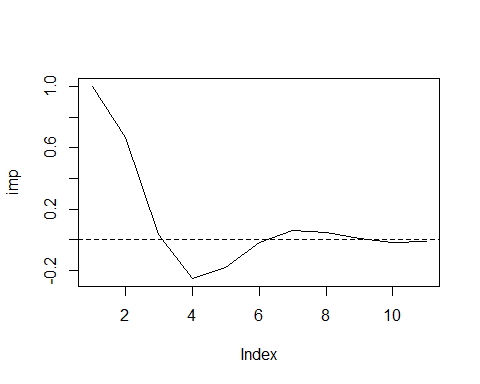


korijeni$data$roots

## [1] 0.81109+1.333151i 0.81109-1.333151i

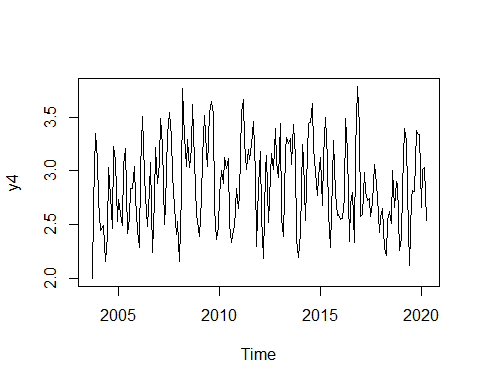
#### Slika 1.102.

imp<- ImpulseCoefficientsARMA(phi=c(.6661,-.4107), theta=0,lag.max=10)  
plot(imp,type="l")  
abline(h=0,lty="dashed")



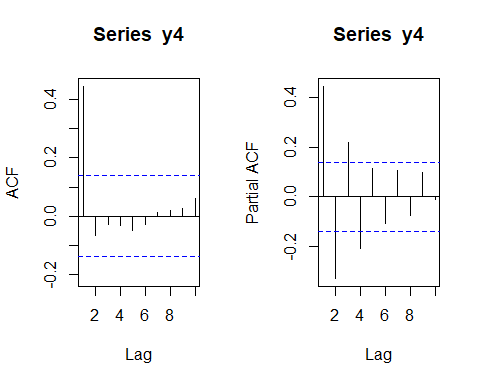
#### Slika 1.103.

y4<-ts(nizovi$Y4,start=c(2003,9),frequency=12)  
plot(y4)



#### Slika 1.104.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y4,lag.max=10)  
Pacf(y4,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.105.

Box.test(y4,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y4  
## X-squared = 42.326, df = 10, p-value = 6.56e-06

Box.test(y4,lag=10,type="Ljung-Box")

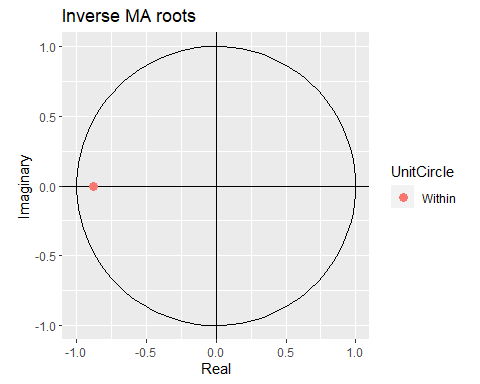
##   
## Box-Ljung test  
##   
## data: y4  
## X-squared = 43.032, df = 10, p-value = 4.908e-06

#### Slika 1.106.

m1<-arima(y4,order=c(0,0,1))  
summary(m1)

##   
## Call:  
## arima(x = y4, order = c(0, 0, 1))  
##   
## Coefficients:  
## ma1 intercept  
## 0.8799 2.8817  
## s.e. 0.0324 0.0394  
##   
## sigma^2 estimated as 0.08813: log likelihood = -41.64, aic = 89.28  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.001370848 0.2968671 0.2467319 -1.024279 8.800314 0.7441584  
## ACF1  
## Training set -0.05060556

korijeni<-autoplot(m1)  
plot(korijeni)

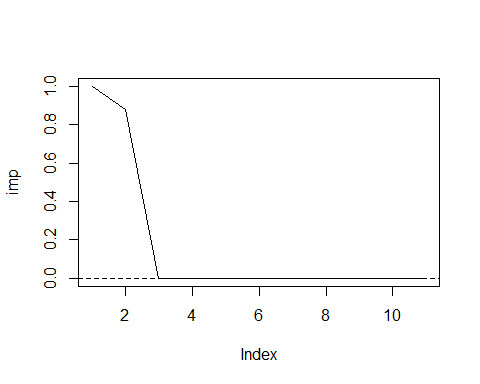


korijeni$data$roots

## [1] -1.136501+0i

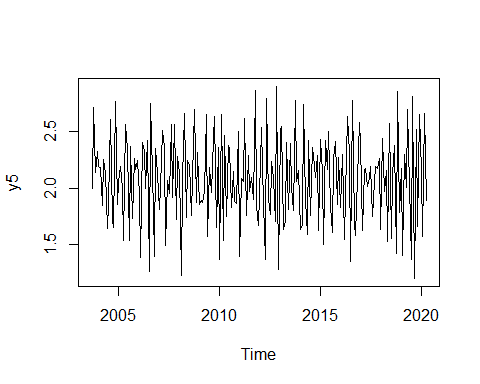
#### Slika 1.107.

imp<- ImpulseCoefficientsARMA(phi=0, theta=-0.8799,lag.max=10)  
plot(imp,type="l")  
abline(h=0,lty="dashed")



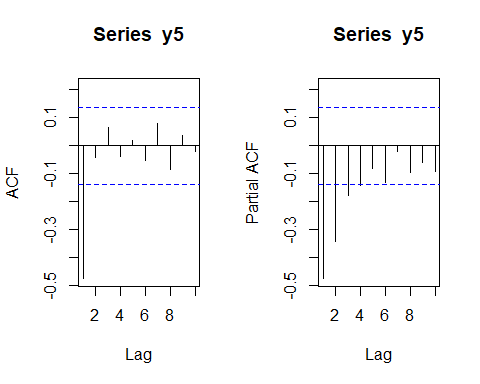
#### Slika 1.108.

y5<-ts(nizovi$Y5,start=c(2003,9),frequency=12)  
plot(y5)



#### Slika 1.109.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y5,lag.max=10)  
Pacf(y5,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.110.

Box.test(y5,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y5  
## X-squared = 50.068, df = 10, p-value = 2.593e-07

Box.test(y5,lag=10,type="Ljung-Box")

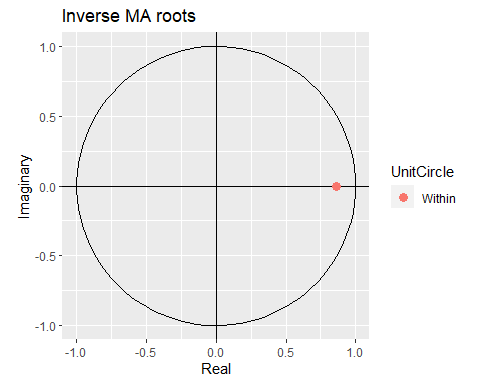
##   
## Box-Ljung test  
##   
## data: y5  
## X-squared = 50.967, df = 10, p-value = 1.771e-07

#### Slika 1.111.

m1<-arima(y5,order=c(0,0,1))  
summary(m1)

##   
## Call:  
## arima(x = y5, order = c(0, 0, 1))  
##   
## Coefficients:  
## ma1 intercept  
## -0.8636 2.0734  
## s.e. 0.0384 0.0030  
##   
## sigma^2 estimated as 0.09202: log likelihood = -45.9, aic = 97.8  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.009575107 0.3033514 0.2499786 -1.869811 12.89392 0.4445203  
## ACF1  
## Training set 0.050539

korijeni<-autoplot(m1)  
plot(korijeni)

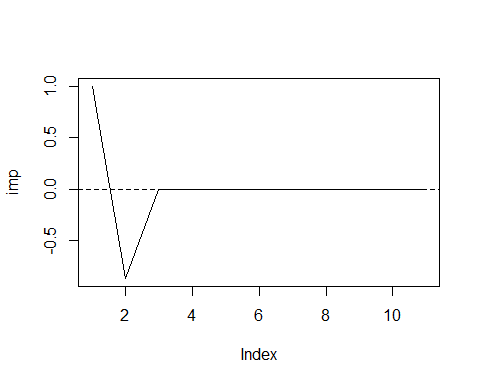


korijeni$data$roots

## [1] 1.157941+0i

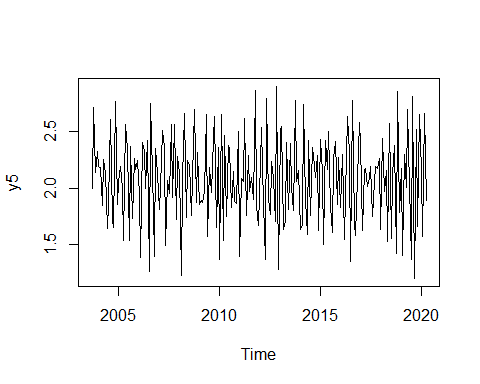
#### Slika 1.112.

imp<-ImpulseCoefficientsARMA(phi=0,theta=0.8636,lag.max=10)  
plot(imp,type="l")  
abline(h=0,lty="dashed")



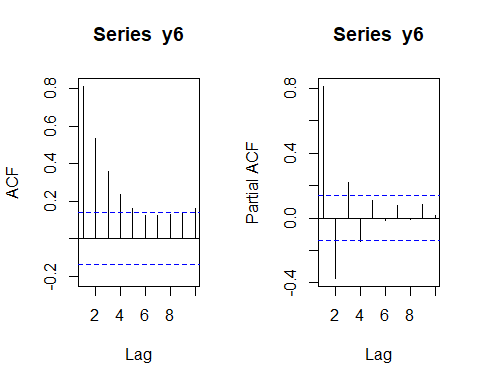
#### Slika 1.113.

y6<-ts(nizovi$Y6,start=c(2003,9),frequency=12)  
plot(y5)



#### Slika 1.114.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y6,lag.max=10)  
Pacf(y6,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.115.

Box.test(y6,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y6  
## X-squared = 248.79, df = 10, p-value < 2.2e-16

Box.test(y6,lag=10,type="Ljung-Box")

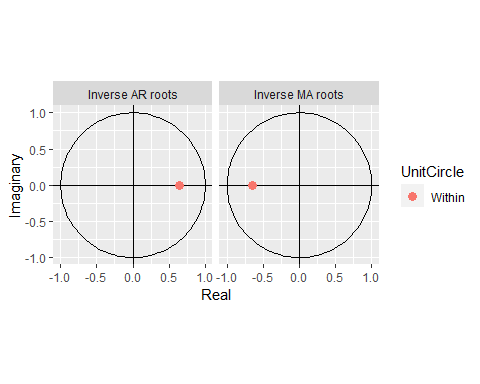
##   
## Box-Ljung test  
##   
## data: y6  
## X-squared = 254.08, df = 10, p-value < 2.2e-16

#### Slika 1.116.

m1<-arima(y6,order=c(1,0,1))  
summary(m1)

##   
## Call:  
## arima(x = y6, order = c(1, 0, 1))  
##   
## Coefficients:  
## ar1 ma1 intercept  
## 0.6462 0.6499 15.8726  
## s.e. 0.0601 0.0653 0.0961  
##   
## sigma^2 estimated as 0.08672: log likelihood = -40.17, aic = 88.34  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.002856574 0.2944754 0.249341 -0.01643764 1.572383 0.865998  
## ACF1  
## Training set -0.01878241

korijeni<-autoplot(m1)  
plot(korijeni)

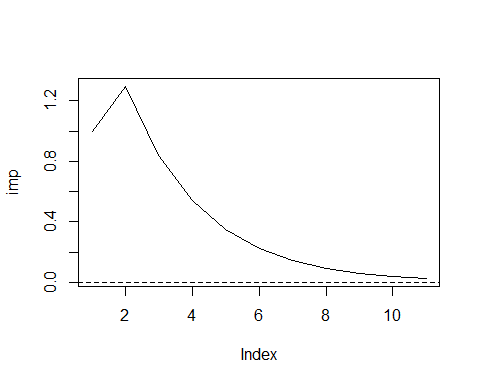


korijeni$data$roots

## [1] 1.547603+0i -1.538605+0i

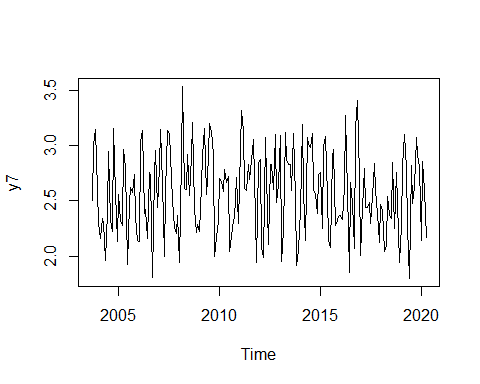
#### Slika 1.117.

imp<-ImpulseCoefficientsARMA(phi=0.646,theta=-0.6499,lag.max=10)  
plot(imp,type="l")  
abline(h=0,lty="dashed")



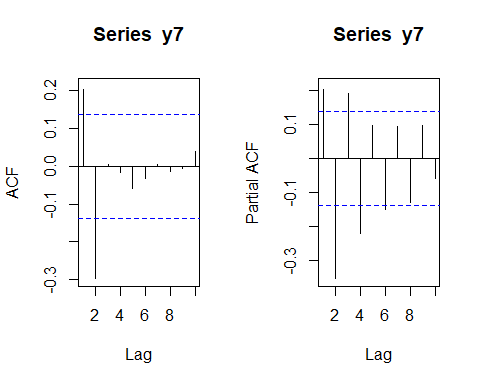
#### Slika 1.118.

y7<-ts(nizovi$Y7,start=c(2003,9),frequency=12)  
plot(y7)



#### Slika 1.119.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y7,lag.max=10)  
Pacf(y7,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.120.

Box.test(y7,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y7  
## X-squared = 27.308, df = 10, p-value = 0.002328

Box.test(y7,lag=10,type="Ljung-Box")

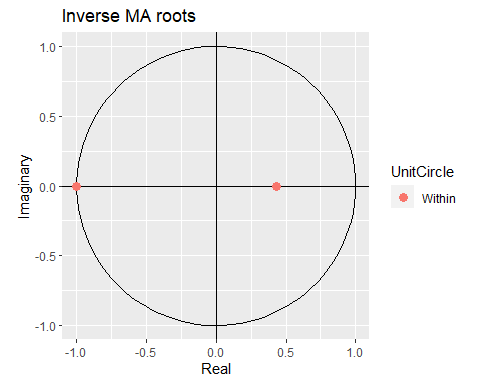
##   
## Box-Ljung test  
##   
## data: y7  
## X-squared = 27.848, df = 10, p-value = 0.001909

#### Slika 1.121.

m1<-arima(y7,order=c(0,0,2))  
summary(m1)

##   
## Call:  
## arima(x = y7, order = c(0, 0, 2))  
##   
## Coefficients:  
## ma1 ma2 intercept  
## 0.5679 -0.4321 2.5787  
## s.e. 0.0688 0.0677 0.0236  
##   
## sigma^2 estimated as 0.08607: log likelihood = -40.93, aic = 89.85  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 0.000184768 0.2933789 0.2492797 -1.385873 9.886612 0.6692948  
## ACF1  
## Training set 0.02180044

korijeni<-autoplot(m1)  
plot(korijeni)

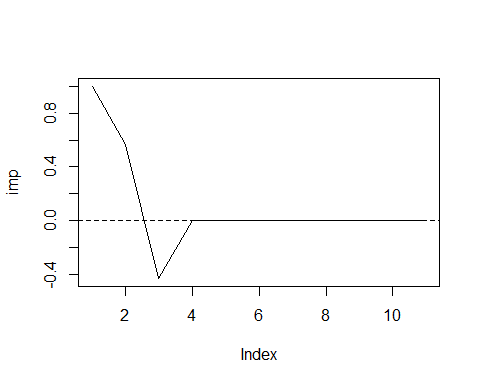


korijeni$data$roots

## [1] -1.00000-0i 2.31421+0i

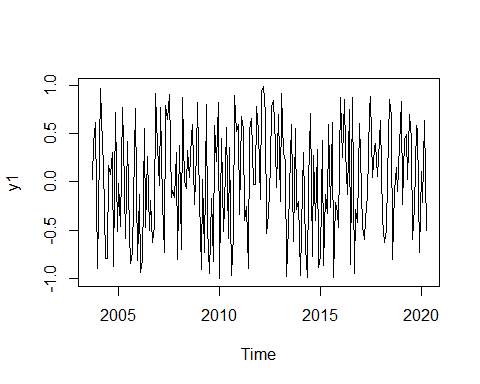
#### Slika 1.122.

imp<-ImpulseCoefficientsARMA(phi=0, theta=c(-.5679,.4321),lag.max=10)  
plot(imp,type="l")  
abline(h=0,lty="dashed")

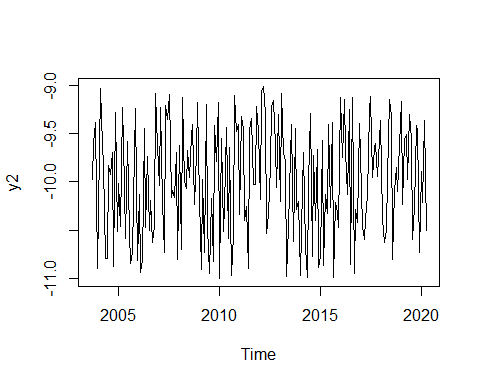


#### 1.9.10. Pitanja za ponavljanje, zadatak 35:

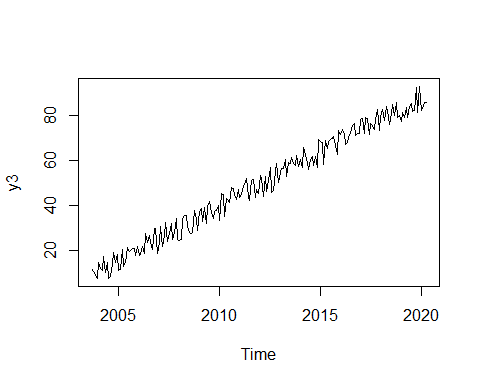
nizovi<-read.table("vremenski2.txt",header=T,sep="\t")  
y1<-ts(nizovi$y1,start=c(2003,9),frequency=12)  
y2<-ts(nizovi$y2,start=c(2003,9),frequency=12)  
y3<-ts(nizovi$y3,start=c(2003,9),frequency=12)  
y4<-ts(nizovi$y4,start=c(2003,9),frequency=12)  
  
plot(y1)



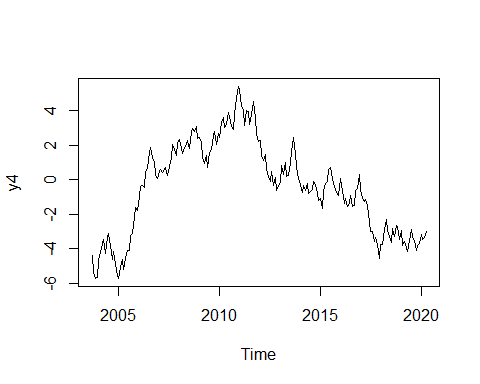
plot(y2)



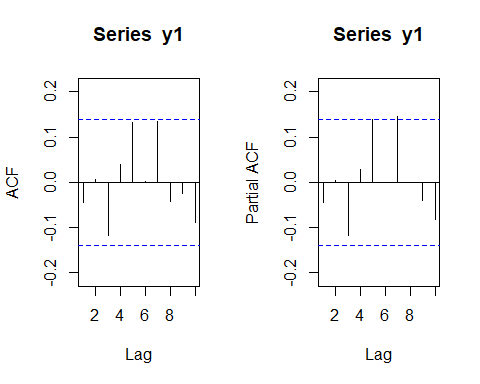
plot(y3)



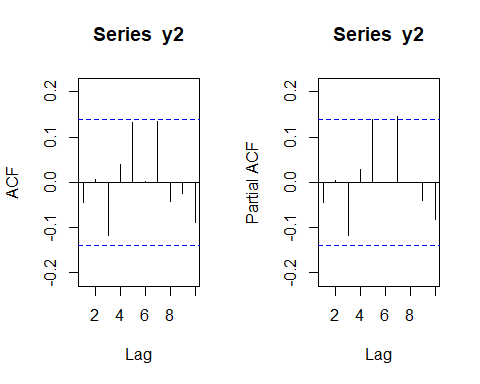
plot(y4)



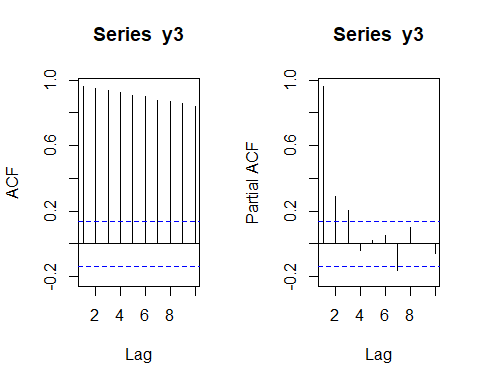
library(forecast)  
par(mfrow = c(1, 2))  
Acf(y1,lag.max=10)  
Pacf(y1,lag.max=10)



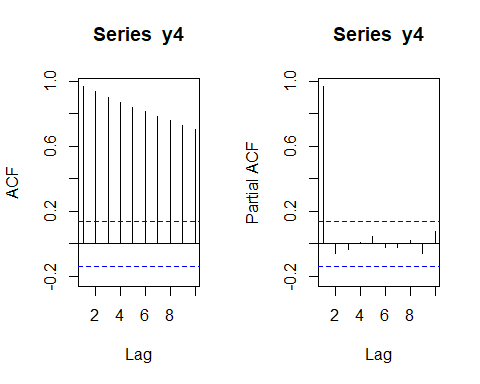
par(mfrow = c(1, 1))  
  
par(mfrow = c(1, 2))  
Acf(y2,lag.max=10)  
Pacf(y2,lag.max=10)



par(mfrow = c(1, 1))  
  
par(mfrow = c(1, 2))  
Acf(y3,lag.max=10)  
Pacf(y3,lag.max=10)



par(mfrow = c(1, 1))  
  
par(mfrow = c(1, 2))  
Acf(y4,lag.max=10)  
Pacf(y4,lag.max=10)



par(mfrow = c(1, 1))  
  
Box.test(y1,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y1  
## X-squared = 12.592, df = 10, p-value = 0.2474

Box.test(y1,lag=10,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: y1  
## X-squared = 13.096, df = 10, p-value = 0.2184

Box.test(y2,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y2  
## X-squared = 12.592, df = 10, p-value = 0.2474

Box.test(y2,lag=10,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: y2  
## X-squared = 13.096, df = 10, p-value = 0.2184

Box.test(y3,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y3  
## X-squared = 1629.9, df = 10, p-value < 2.2e-16

Box.test(y3,lag=10,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: y3  
## X-squared = 1690.9, df = 10, p-value < 2.2e-16

Box.test(y4,lag=10,type="Box-Pierce")

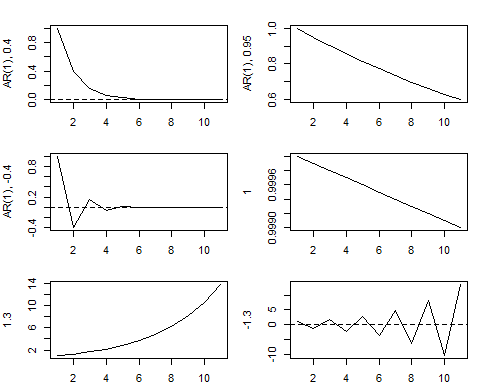
##   
## Box-Pierce test  
##   
## data: y4  
## X-squared = 1396.5, df = 10, p-value < 2.2e-16

Box.test(y4,lag=10,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: y4  
## X-squared = 1446.3, df = 10, p-value < 2.2e-16

#### 1.9.10. Pitanja za ponavljanje, zadatak 36:

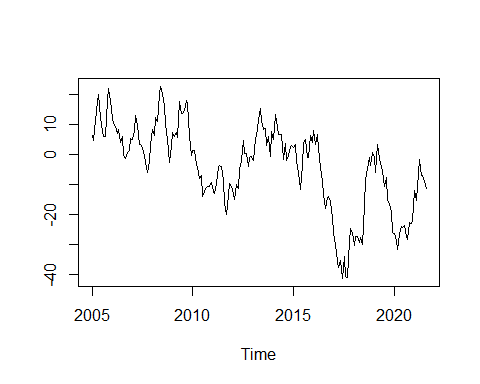
x1 <- ImpulseCoefficientsARMA(phi=c(0.4),theta=0,lag.max=10)  
x2 <- ImpulseCoefficientsARMA(phi=0.95,theta=0,lag.max=10)  
x3 <- ImpulseCoefficientsARMA(phi=-0.4,theta=0,lag.max=10)  
x4 <- ImpulseCoefficientsARMA(phi=0.9999,theta=0,lag.max=10)  
x5 <- ImpulseCoefficientsARMA(phi=1.3,theta=0,lag.max=10)  
x6 <- ImpulseCoefficientsARMA(phi=-1.3,theta=0,lag.max=10)  
  
par(mfrow = c(3,2),oma=c(0,0,0,0),mar=c(2,4,2,1))  
plot(x1,type="l",ylab="AR(1), 0.4",xlab="pomak")  
abline(h=0,lty="dashed")  
plot(x2,type="l",ylab="AR(1), 0.95",xlab="pomak")  
abline(h=0,lty="dashed")  
plot(x3,type="l",ylab="AR(1), -0.4",xlab="pomak")  
abline(h=0,lty="dashed")  
plot(x4,type="l",ylab="1",xlab="pomak")  
abline(h=0,lty="dashed")  
plot(x5,type="l",ylab="1.3",xlab="pomak")  
abline(h=0,lty="dashed")  
plot(x6,type="l",ylab="-1.3",xlab="pomak")  
abline(h=0,lty="dashed")



## Primjer 1.21

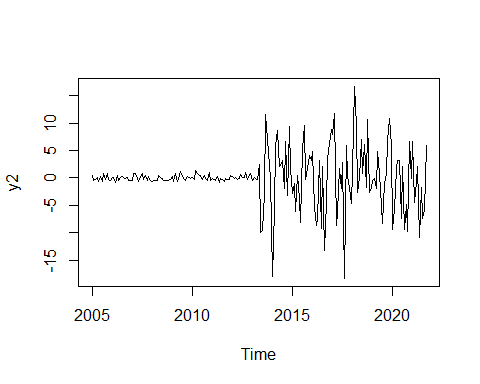
#### Slika 1.123. lijevi panel:

set.seed(0)  
epsilon<-rnorm(200,0,1)  
epsilon<-ts(epsilon,start=c(2005,1),frequency = 12)  
trend<-ts((1:200),start=c(2005,1),frequency = 12)  
y1<-cumsum(5\*epsilon)  
y1<-ts(y1,start=c(2005,1),frequency = 12)  
plot(y1,ylab=NA)



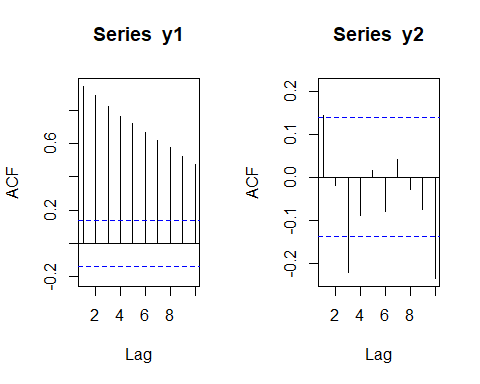
#### Slika 1.123. desni panel:

y2<-c((diff((y1/10))),-1.5\*diff((y1)))  
y2<-y2[100:300]  
y2<-ts(y2,start=c(2005,1),frequency = 12)  
plot(y2)



#### Slika 1.124.

library(forecast)  
par(mfrow = c(1, 2))  
Acf(y1,lag.max=10)  
Acf(y2,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.125 lijevi panel

Box.test(y1,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y1  
## X-squared = 1025, df = 10, p-value < 2.2e-16

Box.test(y1,lag=10,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: y1  
## X-squared = 1058.4, df = 10, p-value < 2.2e-16

#### Slika 1.125 desni panel

Box.test(y2,lag=10,type="Box-Pierce")

##   
## Box-Pierce test  
##   
## data: y2  
## X-squared = 29.6, df = 10, p-value = 0.0009957

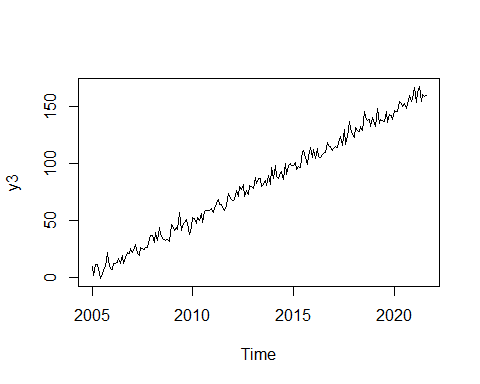
Box.test(y2,lag=10,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: y2  
## X-squared = 30.796, df = 10, p-value = 0.000634

## Primjer 1.22

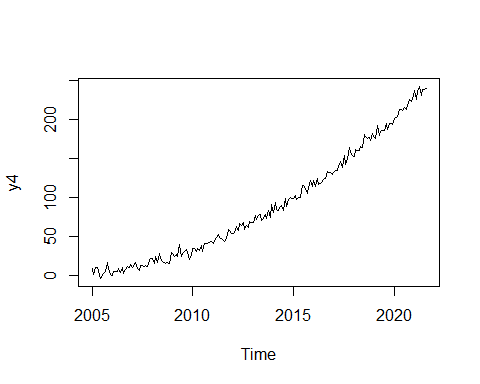
#### Slika 1.126. lijevi panel:

#imati spremeljen epsilon iz primjera 1.21.  
y3<-ts(2+.8\*trend+5\*epsilon,start=c(2005,1),frequency = 12)  
plot(y3)



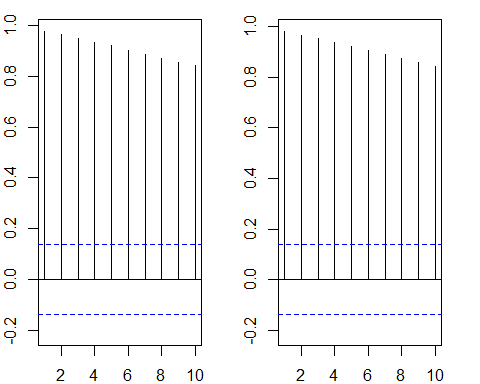
#### Slika 1.126. desni panel:

y4<-ts(2+.2\*trend+5\*epsilon+.005\*trend^2,start=c(2005,1),frequency = 12)  
plot(y4)



#### Slika 1.127.

library(forecast)  
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
Acf(y3,lag.max=10)  
Acf(y4,lag.max=10)

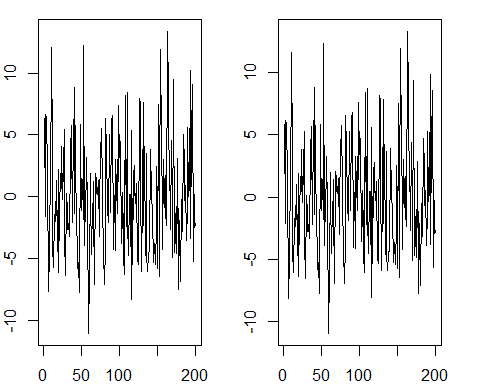


par(mfrow = c(1, 1))

## Primjer 1.23

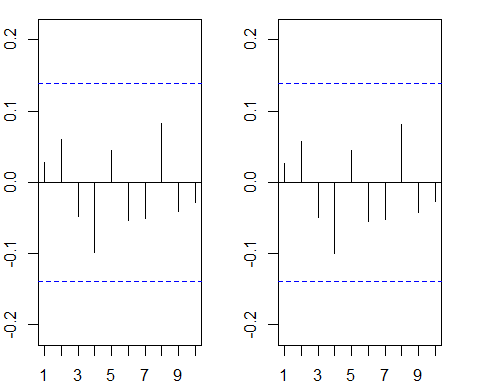
#### Slika 1.128.

# imati spremljeno sve u primjeru 1.22  
rez1<-resid(lm(y3~trend))  
rez2<-resid(lm(y4~trend+I(trend^2)))  
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
plot(rez1,type="l",ylab=NA)  
plot(rez2,type="l",ylab=NA)



#### Slika 1.129.

library(forecast)  
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
Acf(rez1,lag.max=10)  
Acf(rez2,lag.max=10)



par(mfrow = c(1, 1))

#### Slika 1.130.

Box.test(rez1,lag = 10,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: rez1  
## X-squared = 6.8487, df = 10, p-value = 0.7397

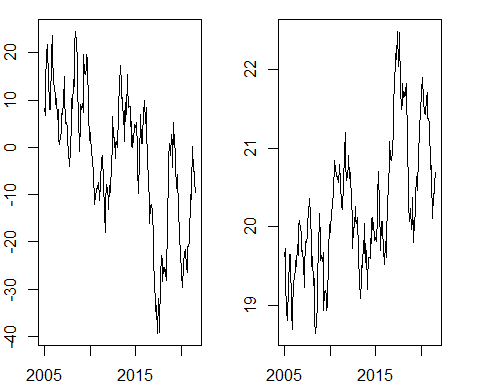
Box.test(rez2,lag = 10,type="Ljung-Box")

##   
## Box-Ljung test  
##   
## data: rez2  
## X-squared = 6.9211, df = 10, p-value = 0.7329

## Primjer 1.23

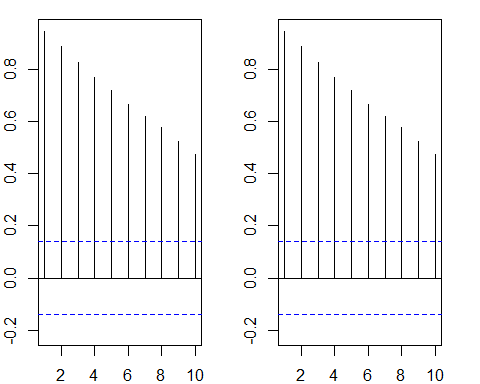
#### Slika 1.131.

#imati spremeljen epsilon iz primjera 1.21.  
y5<-2+cumsum(5\*epsilon)  
y5<-ts(y5,start=c(2005,1),frequency = 12)  
y6<-20+cumsum(-.3\*epsilon)  
y6<-ts(y6,start=c(2005,1),frequency = 12)  
  
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
plot(y5)  
plot(y6)



#### Slika 1.132.

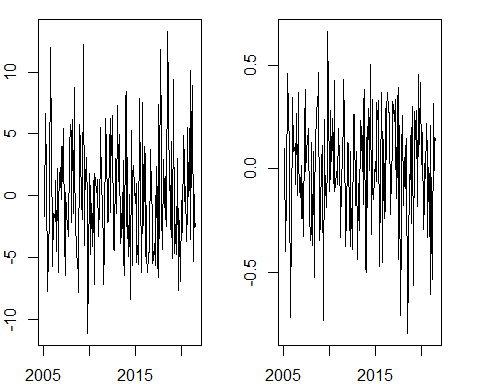
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
Acf(y5,lag.max=10)  
Acf(y6,lag.max=10)



## Primjer 1.24

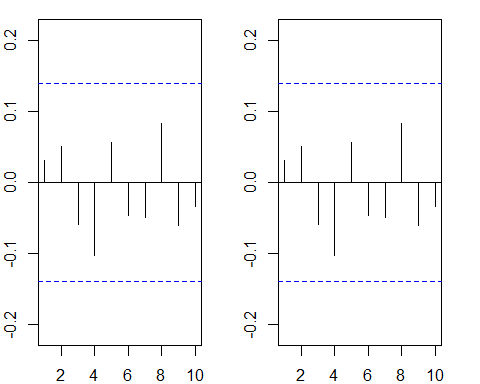
#### Slika 1.133.

#prvo provesti primjer 1.23  
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
plot(diff(y5))  
plot(diff(y6))



#### Slika 1.134.

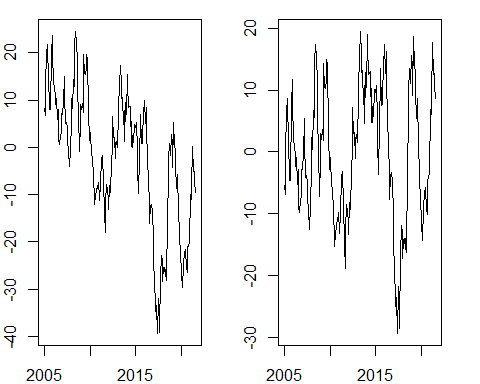
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
Acf(diff(y5),lag.max=10)  
Acf(diff(y6),lag.max=10)



## Primjer 1.25

#### Slika 1.135.

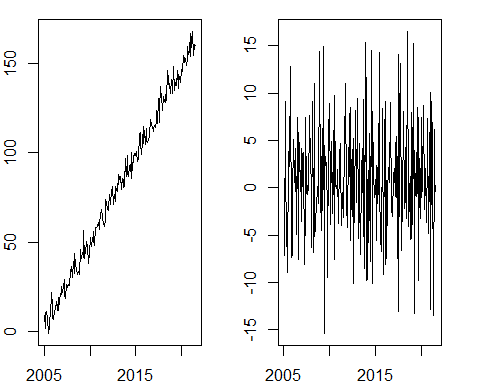
#prvo provesti primjer 1.23  
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
plot(y5)  
rez<-resid(lm(y5~trend))  
rez<-ts(rez,start=c(2005,1),frequency = 12)  
plot(rez)



## Primjer 1.26

#### Slika 1.136.

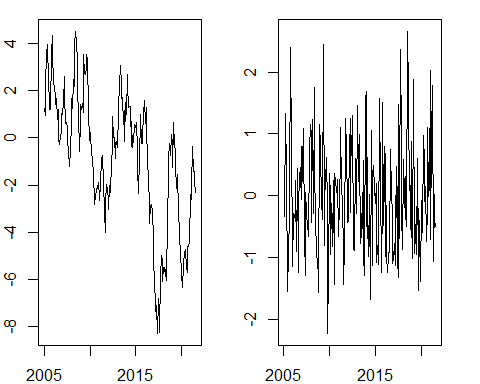
#prvo provesti primjer 1.22  
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
plot(y3)  
rez2<-(diff(y3))  
rez2<-ts(rez2,start=c(2005,2),frequency = 12)  
plot(rez2)



## Primjer 1.27

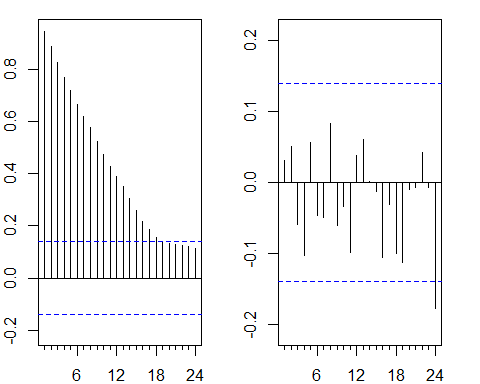
#### Slika 1.137.

par(mfrow = c(1, 2),mar=c(2,2,1,2))  
set.seed(0)  
epsilon<-rnorm(200,0,1)  
y7<-cumsum(epsilon)  
y7<-ts(y7,start=c(2005,1),frequency = 12)  
plot(y7)  
dy7<-ts(diff(y7),start=c(2005,2),frequency=12)  
plot(dy7)



#### Slika 1.138.

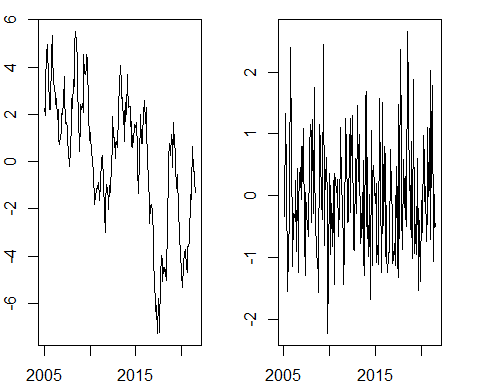
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
Acf((y7),lag.max=24)  
Acf((dy7),lag.max=24)



## Primjer 1.28

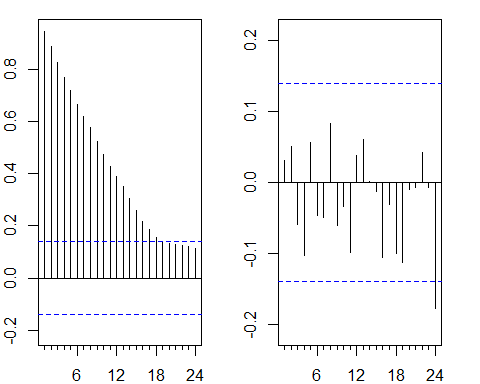
#### Slika 1.139.

#imati epsilon iz primjera 1.27.  
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
  
y8<-1+cumsum(epsilon)  
y8<-ts(y8,start=c(2005,1),frequency=12)  
plot(y8)  
dy8<-ts(diff(y8),start=c(2005,2),frequency=12)  
plot(dy8)



#### Slika 1.140.

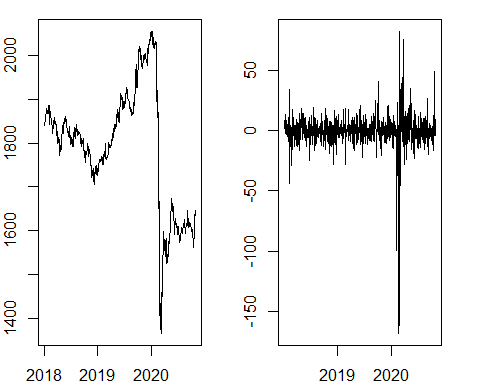
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
Acf((y8),lag.max=24)  
Acf((dy8),lag.max=24)



## Primjer 1.29

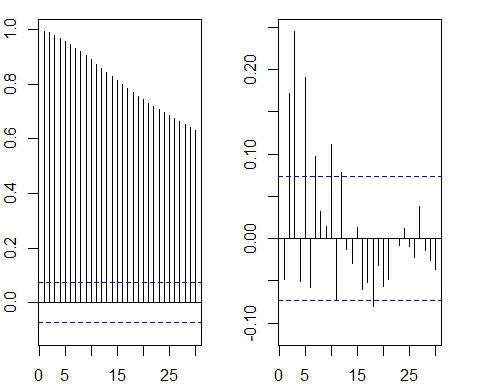
#### Slika 1.141.

par(mfrow = c(1, 2),mar=c(2,2,1,2))  
cro<-read.table("crobex\_dnevno.txt",sep="\t",head=T)  
cro<-ts(cro$Price,start=c(2018,1,2),frequency = 252)  
plot(cro,xaxt="n",xlab=NA)  
axis(1, at=2018:2020)  
prinos<-ts(diff(cro),start=c(2018,1,3),frequency = 252)  
plot(prinos,xaxt="n")  
axis(1,at=2019:2020)



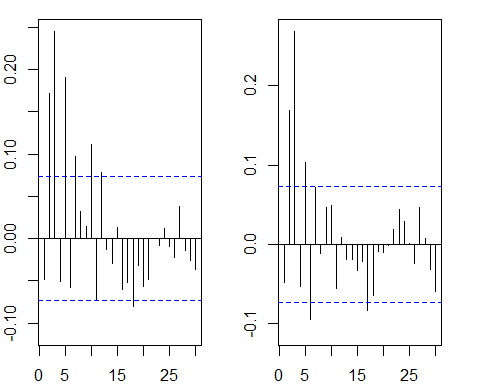
#### Slika 1.142.

par(mfrow = c(1, 2),mar=c(2,2,1,2))  
Acf(cro,lag.max=30)  
Acf(prinos,lag.max=30)



#### Slika 1.143.

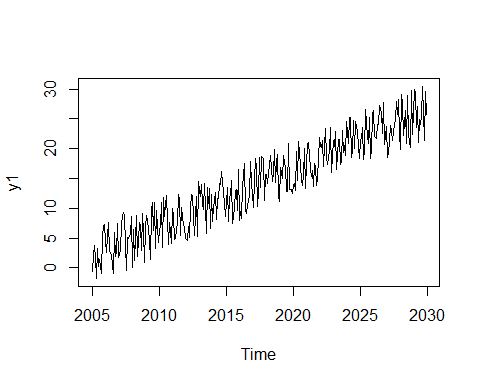
par(mfrow = c(1, 2),mar=c(2,2,1,2))  
Acf(prinos,lag.max=30)  
Pacf(prinos,lag.max=30)



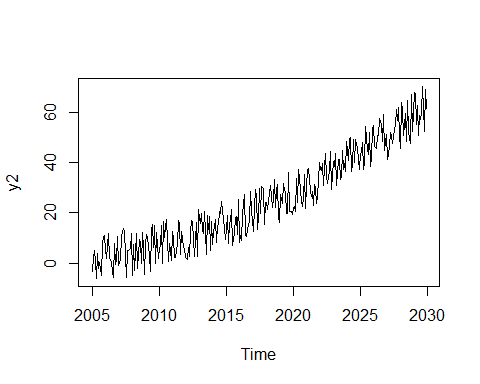
## 1.10.5. Primjer

#### Slika 1.144., 1.145., 1.146. i 1.147.

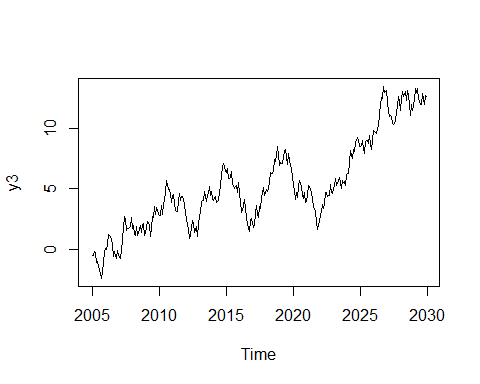
nestac<-read.table("nestac.txt",head=T,sep="\t")  
y1<-ts(nestac$y1,start=c(2005,1),frequency = 12)  
y2<-ts(nestac$y2,start=c(2005,1),frequency = 12)  
y3<-ts(nestac$y3,start=c(2005,1),frequency = 12)  
plot(y1)



plot(y2)

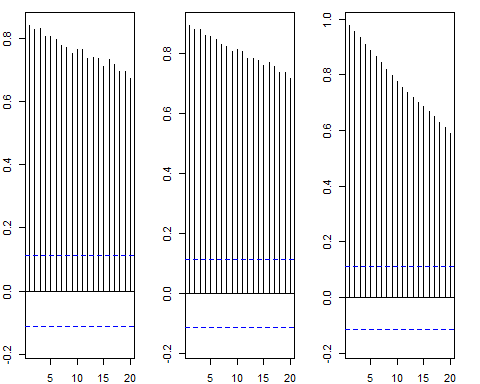


plot(y3)



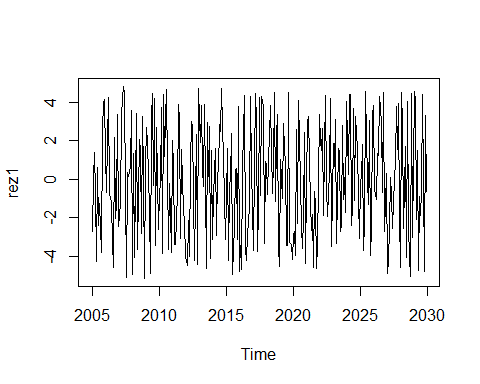
#### Slika 1.148. i 1.149.

par(mfrow = c(1, 3),mar=c(2,2,1,2))  
Acf(y1,20)  
Acf(y2,20)  
Acf(y3,20)

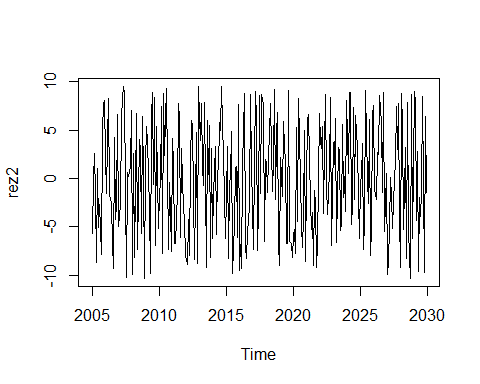


#### Slika 1.150., 1.151., 1.152. i 1.153.

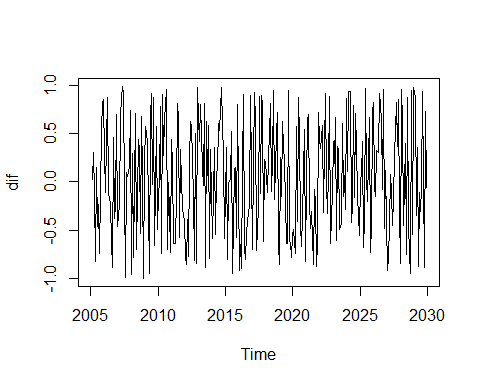
trend<-ts(1:length(y1),start=c(2005,1),frequency = 12)  
rez1<-resid(lm(y1~trend))  
rez2<-resid(lm(y2~trend+I(trend^2)))  
dif<-diff(y3)  
rez1<-ts(rez1,start=c(2005,1),frequency = 12)  
rez2<-ts(rez2,start=c(2005,1),frequency = 12)  
dif<-ts(dif,start=c(2005,2),frequency = 12)  
plot(rez1)



plot(rez2)

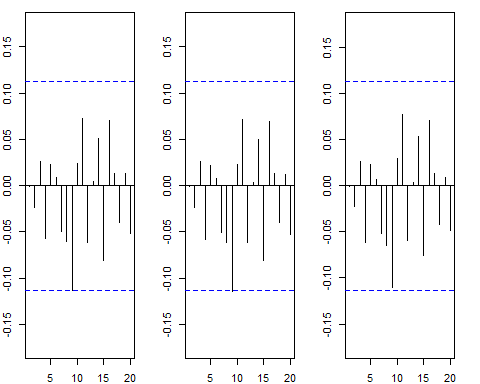


plot(dif)



#### Slika 1.154.

par(mfrow = c(1, 3),mar=c(2,2,1,2))  
Acf(rez1,20)  
Acf(rez2,20)  
Acf(dif,20)



## Primjer 1.30.

#### Slika 1.155.

set.seed(0)  
y<-cumsum(rnorm(200,0,1))  
x<-cumsum(rnorm(200,0,1))  
summary(lm(y~x))

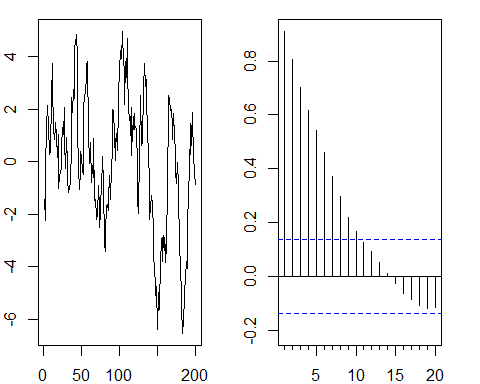
##   
## Call:  
## lm(formula = y ~ x)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -6.5347 -1.4539 0.2548 1.8674 4.9780   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2.17610 0.45048 4.831 2.72e-06 \*\*\*  
## x -0.50974 0.07002 -7.280 7.69e-12 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 2.532 on 198 degrees of freedom  
## Multiple R-squared: 0.2111, Adjusted R-squared: 0.2072   
## F-statistic: 53 on 1 and 198 DF, p-value: 7.686e-12

library(car)  
durbinWatsonTest(lm(y~x))

## lag Autocorrelation D-W Statistic p-value  
## 1 0.9106073 0.1765369 0  
## Alternative hypothesis: rho != 0

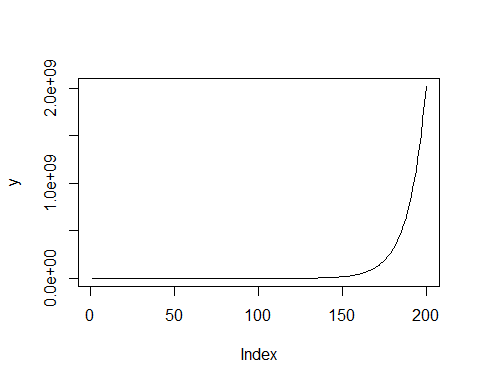
#### Slika 1.156.

par(mfrow = c(1, 2),mar=c(2,2,1,2))  
plot(resid(lm(y~x)),type="l")  
Acf(resid(lm(y~x)),20)



#### Slika 1.157.

y<-rep(NA,200)  
y[1]<-1  
for (i in 2:200) {  
 y[i]<-1+1.1\*y[i-1]+epsilon[i]  
}  
plot(y,type="l")



## Primjer 1.31

#### Slika 1.158., 1.159, 1.160, 1.161. i 1.162.

#prvo provesti primjer 1.30  
library(urca)

## Warning: package 'urca' was built under R version 4.2.2

summary(ur.df(x,type="trend",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression trend   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.65595 -0.61460 0.03191 0.58374 3.09116   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.676577 0.173333 3.903 0.000131 \*\*\*  
## z.lag.1 -0.201783 0.040909 -4.932 1.74e-06 \*\*\*  
## tt 0.005588 0.001786 3.129 0.002025 \*\*   
## z.diff.lag 0.107765 0.070253 1.534 0.126670   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.9464 on 194 degrees of freedom  
## Multiple R-squared: 0.1147, Adjusted R-squared: 0.101   
## F-statistic: 8.381 on 3 and 194 DF, p-value: 2.883e-05  
##   
##   
## Value of test-statistic is: -4.9324 8.5128 12.5478   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau3 -3.99 -3.43 -3.13  
## phi2 6.22 4.75 4.07  
## phi3 8.43 6.49 5.47

summary(ur.df(x,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # 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   
## -2.9615 -0.6274 0.0243 0.5414 3.4159   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.66962 0.17718 3.779 0.000209 \*\*\*  
## z.lag.1 -0.10559 0.02759 -3.827 0.000175 \*\*\*  
## z.diff.lag 0.05473 0.06970 0.785 0.433282   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.9675 on 195 degrees of freedom  
## Multiple R-squared: 0.07005, Adjusted R-squared: 0.06052   
## F-statistic: 7.345 on 2 and 195 DF, p-value: 0.0008406  
##   
##   
## Value of test-statistic is: -3.8269 7.5344   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

summary(ur.df(x,type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.8499 -0.5282 0.0952 0.6787 3.3282   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)  
## z.lag.1 -0.009498 0.011073 -0.858 0.392  
## z.diff.lag 0.022307 0.071472 0.312 0.755  
##   
## Residual standard error: 0.9997 on 196 degrees of freedom  
## Multiple R-squared: 0.004009, Adjusted R-squared: -0.006154   
## F-statistic: 0.3945 on 2 and 196 DF, p-value: 0.6746  
##   
##   
## Value of test-statistic is: -0.8578   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

summary(ur.df(y,type="trend",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression trend   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.2074 -0.7644 -0.0966 0.6268 2.7003   
##   
## Coefficients: (1 not defined because of singularities)  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1.002e+00 1.411e-01 7.098e+00 2.29e-11 \*\*\*  
## z.lag.1 1.000e-01 2.630e-10 3.803e+08 < 2e-16 \*\*\*  
## tt -3.103e-04 1.363e-03 -2.280e-01 0.82   
## z.diff.lag NA NA NA NA   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.9274 on 195 degrees of freedom  
## Multiple R-squared: 1, Adjusted R-squared: 1   
## F-statistic: 1.01e+17 on 2 and 195 DF, p-value: < 2.2e-16  
##   
##   
## Value of test-statistic is: 380271892 91.5597 183.1128   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau3 -3.99 -3.43 -3.13  
## phi2 6.22 4.75 4.07  
## phi3 8.43 6.49 5.47

summary(ur.df(y,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # 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   
## -2.19751 -0.76893 -0.09193 0.61871 2.67970   
##   
## Coefficients: (1 not defined because of singularities)  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 9.736e-01 6.954e-02 14 <2e-16 \*\*\*  
## z.lag.1 1.000e-01 2.219e-10 450635062 <2e-16 \*\*\*  
## z.diff.lag NA NA NA NA   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.9251 on 196 degrees of freedom  
## Multiple R-squared: 1, Adjusted R-squared: 1   
## F-statistic: 2.031e+17 on 1 and 196 DF, p-value: < 2.2e-16  
##   
##   
## Value of test-statistic is: 450635062 183.9576   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

summary(ur.df(y,type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -1.5973 0.1248 0.7742 1.5287 3.5986   
##   
## Coefficients: (1 not defined because of singularities)  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 1.00e-01 2.96e-10 337862204 <2e-16 \*\*\*  
## z.diff.lag NA NA NA NA   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1.305 on 197 degrees of freedom  
## Multiple R-squared: 1, Adjusted R-squared: 1   
## F-statistic: 1.142e+17 on 1 and 197 DF, p-value: < 2.2e-16  
##   
##   
## Value of test-statistic is: 337862204   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

## Primjer 1.32

#### Slika 1.163. i 1.164.

# prvo provesti primjer 1.31  
library(urca)  
  
dx<-diff(x)  
dy<-diff(y)  
summary(ur.df(dx,type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.8009 -0.6274 0.0211 0.6133 3.2388   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -1.04118 0.09972 -10.441 <2e-16 \*\*\*  
## z.diff.lag 0.06449 0.07103 0.908 0.365   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.9978 on 195 degrees of freedom  
## Multiple R-squared: 0.4931, Adjusted R-squared: 0.4879   
## F-statistic: 94.83 on 2 and 195 DF, p-value: < 2.2e-16  
##   
##   
## Value of test-statistic is: -10.4412   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

summary(ur.df(dy,type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.45363 -0.78393 -0.06921 0.70155 3.08627   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 0.15088 0.00613 24.613 < 2e-16 \*\*\*  
## z.diff.lag -0.55962 0.06743 -8.299 1.71e-14 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1.105 on 195 degrees of freedom  
## Multiple R-squared: 1, Adjusted R-squared: 1   
## F-statistic: 6.575e+14 on 2 and 195 DF, p-value: < 2.2e-16  
##   
##   
## Value of test-statistic is: 24.6126   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

## Primjer 1.33

#### Slika 1.165. i 1.166.

#prvo provesti 1.10.5. Primjer  
library(urca)  
  
summary(ur.df(y1,type="trend",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression trend   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -5.1056 -2.5411 -0.0808 2.7330 4.8772   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2.268763 0.384441 5.901 9.91e-09 \*\*\*  
## z.lag.1 -1.024805 0.082496 -12.422 < 2e-16 \*\*\*  
## tt 0.082545 0.006936 11.901 < 2e-16 \*\*\*  
## z.diff.lag 0.023907 0.058352 0.410 0.682   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 2.945 on 294 degrees of freedom  
## Multiple R-squared: 0.5007, Adjusted R-squared: 0.4956   
## F-statistic: 98.27 on 3 and 294 DF, p-value: < 2.2e-16  
##   
##   
## Value of test-statistic is: -12.4224 51.6259 77.1581   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau3 -3.98 -3.42 -3.13  
## phi2 6.15 4.71 4.05  
## phi3 8.34 6.30 5.36

summary(ur.df(y1,type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -7.3099 -2.5599 0.8519 2.7192 9.3164   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -0.01014 0.01316 -0.770 0.442   
## z.diff.lag -0.48219 0.05131 -9.398 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 3.623 on 296 degrees of freedom  
## Multiple R-squared: 0.2395, Adjusted R-squared: 0.2343   
## F-statistic: 46.6 on 2 and 296 DF, p-value: < 2.2e-16  
##   
##   
## Value of test-statistic is: -0.7704   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

#### Slika 1.167.

summary(ur.df(resid(lm((y1~trend))),type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -5.1217 -2.5501 -0.0828 2.7466 4.9085   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -1.02475 0.08222 -12.464 <2e-16 \*\*\*  
## z.diff.lag 0.02389 0.05815 0.411 0.682   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 2.935 on 296 degrees of freedom  
## Multiple R-squared: 0.5007, Adjusted R-squared: 0.4973   
## F-statistic: 148.4 on 2 and 296 DF, p-value: < 2.2e-16  
##   
##   
## Value of test-statistic is: -12.464   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

## Primjer 1.34

#### Slika 1.168. i 1.169.

set.seed(0)  
epsilon<-rnorm(200,0,1)  
summary(ur.df(epsilon,type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.2552 -0.7553 -0.1481 0.6124 2.6545   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -0.91123 0.09925 -9.181 <2e-16 \*\*\*  
## z.diff.lag -0.05897 0.07102 -0.830 0.407   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -9.1814   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

epsilon2<-rnorm(200,5,1)  
summary(ur.df(epsilon2,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # 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   
## -2.8353 -0.6715 -0.0273 0.5740 3.1952   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 5.32901 0.50699 10.511 <2e-16 \*\*\*  
## z.lag.1 -1.05637 0.09965 -10.600 <2e-16 \*\*\*  
## z.diff.lag 0.07237 0.07107 1.018 0.31   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -10.6004 56.1901   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

## Primjer 1.35

#### Slika 1.170. i 1.171.

#prvo provesti 1.10.5. Primjer  
y2<-ts(nizovi$y2,start=c(2003,9),frequency=12)  
summary(ur.df(y2,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # 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   
## -1.04286 -0.49022 -0.00813 0.52685 1.00958   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -10.37264 1.03287 -10.042 <2e-16 \*\*\*  
## z.lag.1 -1.03947 0.10345 -10.048 <2e-16 \*\*\*  
## z.diff.lag -0.00403 0.07188 -0.056 0.955   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -10.0477 50.4805   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

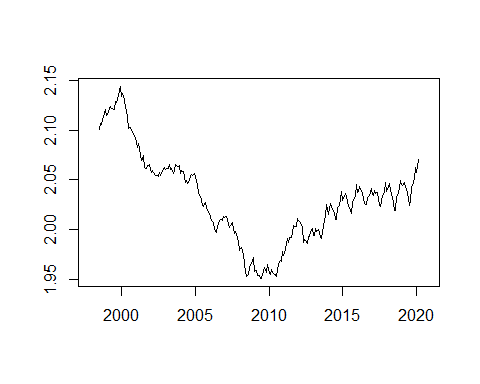
y4<-ts(nizovi$y4,start=c(2003,9),frequency=12)  
summary(ur.df(y4,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # 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   
## -0.96311 -0.46007 0.02978 0.42309 0.99787   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -0.0003547 0.0403394 -0.009 0.9930   
## z.lag.1 -0.0287624 0.0150640 -1.909 0.0577 .  
## z.diff.lag 0.0013526 0.0708127 0.019 0.9848   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -1.9093 1.8685   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

## Primjer 1.36

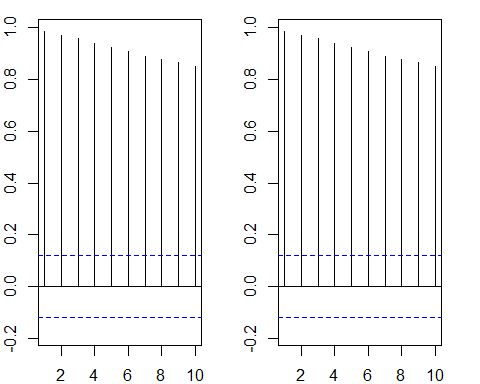
#### Slika 1.172. i 1.173.

ppp<-read.table("ppp.txt",header=T,sep="\t")  
tecaj<-ts(ppp$tecaj, start=c(1998,1),frequency = 12)  
library(forecast)  
tecaj<-ma(tecaj,12,centre = T)  
  
r<-log(tecaj)+log(ppp$aut)-log(ppp$cro)  
plot(r,ylab=NA,xlab=NA)



#### Slika 1.174.

par(mfrow = c(1, 2),mar=c(2,2,1,2))  
Acf(r,lag.max=10)  
Acf(r,lag.max=10)



#### Slika 1.175.

r<-r[7:267]  
summary(ur.df(r,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression drift   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)  
## (Intercept) 0.02284 0.01489 1.534 0.126  
## z.lag.1 -0.01131 0.00733 -1.543 0.124  
## z.diff.lag 0.08533 0.06205 1.375 0.170  
##   
## Value of test-statistic is: -1.5433 1.2671   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.44 -2.87 -2.57  
## phi1 6.47 4.61 3.79

## Primjer 1.37

#### Slika 1.176. i 1.177.

cro<-read.table("crobex\_dnevno.txt",sep="\t",head=T)  
cro<-ts(cro$Price,start=c(2018,1,2),frequency = 252)  
summary(ur.df(cro,type="drift",selectlags="BIC"))  
summary(ur.df(diff(cro),type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression drift   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)  
## (Intercept) 8.354926 7.272842 1.149 0.251  
## z.lag.1 -0.004831 0.004050 -1.193 0.233  
## z.diff.lag -0.045838 0.037543 -1.221 0.223  
##   
## Value of test-statistic is: -1.1928 0.8444   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.43 -2.86 -2.57  
## phi1 6.43 4.59 3.78

summary(ur.df(diff(cro),type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -0.87031 0.05359 -16.240 < 2e-16 \*\*\*  
## z.diff.lag -0.16976 0.03702 -4.585 5.35e-06 \*\*\*  
##   
## Value of test-statistic is: -16.2404   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

## Primjer 1.38

ppp<-read.table("ppp.txt",header=T,sep="\t")  
tecaj<-ts(ppp$tecaj, start=c(1998,1),frequency = 12)  
library(forecast)  
tecaj<-ma(tecaj,12,centre = T)

#### Slika 1.178.

summary(ur.df(tecaj[7:267],type="trend",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression trend   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 5.970e-02 1.534e-02 3.891 0.000128 \*\*\*  
## z.lag.1 -8.054e-03 2.058e-03 -3.914 0.000117 \*\*\*  
## tt 2.874e-06 3.218e-06 0.893 0.372653   
## z.diff.lag 9.240e-01 2.017e-02 45.808 < 2e-16 \*\*\*  
##   
## Value of test-statistic is: -3.9136 5.2892 7.9332   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau3 -3.98 -3.42 -3.13  
## phi2 6.15 4.71 4.05  
## phi3 8.34 6.30 5.36

summary(ur.df(tecaj[7:267],type="drift",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression drift   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.059543 0.015337 3.882 0.000132 \*\*\*  
## z.lag.1 -0.007983 0.002056 -3.883 0.000131 \*\*\*  
## z.diff.lag 0.921364 0.019941 46.205 < 2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -3.8834 7.5409   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.44 -2.87 -2.57  
## phi1 6.47 4.61 3.79

## Primjer 1.39

#### Slika 1.179.

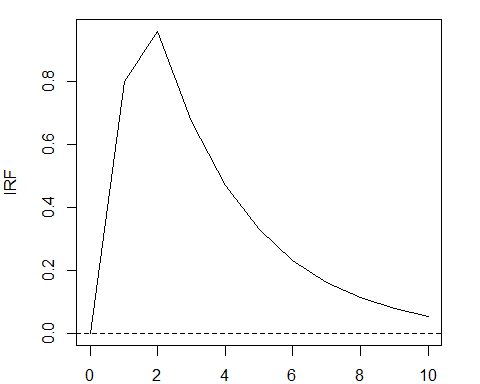
ardl<-read.table("ardl.txt",header=T, sep="\t")  
ardl<-ts(ardl,start=c(2004,1),frequency = 12)  
  
library(dynlm)

dynlm(y~L(y)+x+L(x),data=ardl)

##   
## Time series regression with "ts" data:  
## Start = 2004(2), End = 2021(6)  
##   
## Call:  
## dynlm(formula = y ~ L(y) + x + L(x), data = ardl)  
##   
## Coefficients:  
## (Intercept) L(y) x L(x)   
## 20.0 0.7 0.8 0.4

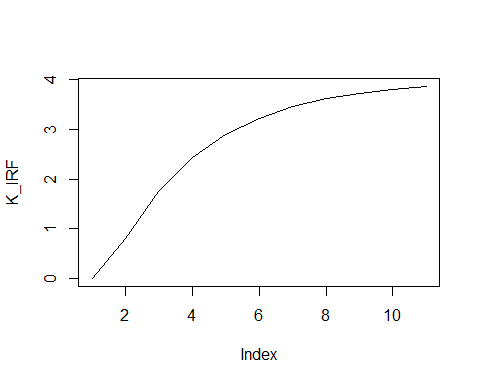
#### Slika 1.180.

#ardl(1,1): y=a+bx+cx(-1)+dy(-1)  
  
b<-0.8  
c<-0.4  
d<-0.7  
  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
par(mfrow = c(1,1),oma=c(1,0,0,1),mar=c(1,4,1,1))  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



#### Slika 1.181.

#kumulativno:  
k\_irf<-cumsum(irf)  
plot(k\_irf,type="l",ylab="K\_IRF")



## Primjer 1.40.

library(dynlm)  
  
ardl<-read.table("ardl.txt",header=T, sep="\t")  
ardl<-ts(ardl,start=c(2004,1),frequency = 12)

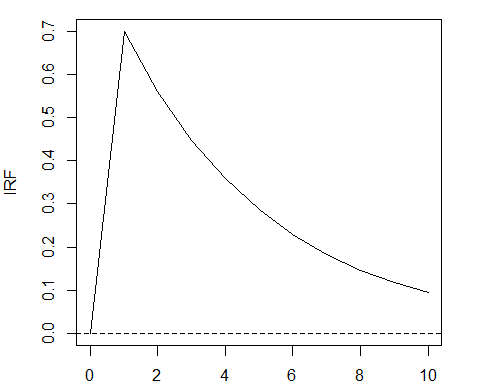
#### Slika 1.182.

dynlm(z~L(z)+x,data=ardl)

##   
## Time series regression with "ts" data:  
## Start = 2004(2), End = 2021(6)  
##   
## Call:  
## dynlm(formula = z ~ L(z) + x, data = ardl)  
##   
## Coefficients:  
## (Intercept) L(z) x   
## 20.0 0.8 0.7

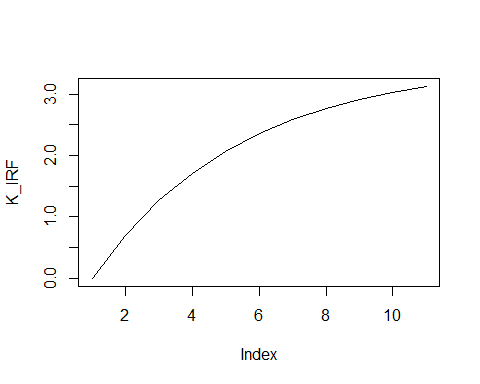
#### Slika 1.183.

#ardl(1,1): y=a+bx+cx(-1)+dy(-1)  
  
b<-0.7  
c<-0  
d<-0.8  
  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
par(mfrow = c(1,1),oma=c(1,0,0,1),mar=c(1,4,1,1))  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



#### Slika 1.184.

#kumulativno:  
k\_irf<-cumsum(irf)  
plot(k\_irf,type="l",ylab="K\_IRF")



## Primjer 1.41.

library(dynlm)  
  
ardl<-read.table("ardl.txt",header=T, sep="\t")  
ardl<-ts(ardl,start=c(2004,1),frequency = 12)

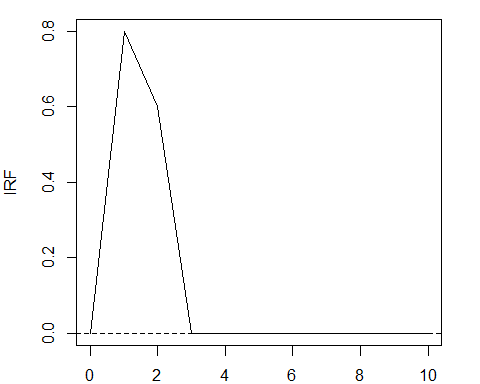
#### Slika 1.185.

dynlm(w~L(x)+x,data=ardl)

##   
## Time series regression with "ts" data:  
## Start = 2004(2), End = 2021(6)  
##   
## Call:  
## dynlm(formula = w ~ L(x) + x, data = ardl)  
##   
## Coefficients:  
## (Intercept) L(x) x   
## 20.0 0.6 0.8

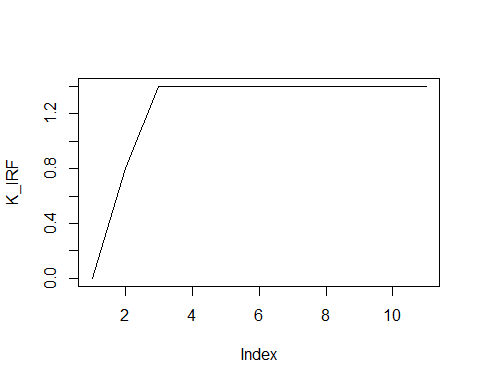
#### Slika 1.186.

#ardl(1,1): y=a+bx+cx(-1)+dy(-1)  
  
b<-0.8  
c<-0.6  
d<-0  
  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
par(mfrow = c(1,1),oma=c(1,0,0,1),mar=c(1,4,1,1))  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



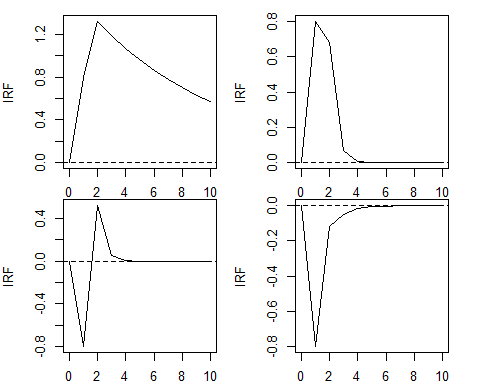
#### Slika 1.187.

#kumulativno:  
k\_irf<-cumsum(irf)  
plot(k\_irf,type="l",ylab="K\_IRF")



##Primjer 1.42.

library(dynlm)  
  
par(mfrow = c(2,2),oma=c(1,0,0,1),mar=c(1,4,1,1))  
  
b<-(0.8)  
c<-0.6  
d<-0.9  
  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")  
  
b<-(0.8)  
c<-0.6  
d<-0.1  
  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")  
  
b<-(-0.8)  
c<-0.6  
d<-0.1  
  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")  
  
b<-(-0.8)  
c<-(0.2)  
d<-(.4)  
  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



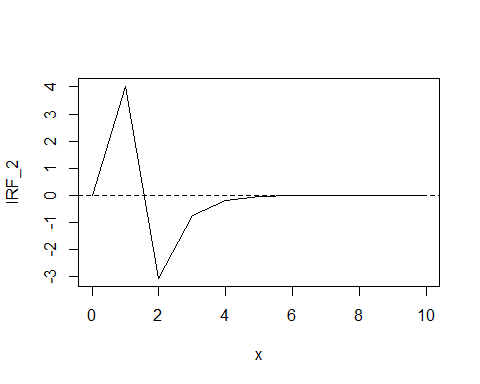
##Primjer 1.43 #### Slika 1.189. i 1.190.

ardl2<-read.table("ardl2.txt",sep="\t",header=T)  
dolasci<-ts(ardl2$S\_dol,start=c(1998,1),frequency = 12)  
dolasci<-dolasci/decompose(dolasci,type="multiplicative")$seasonal  
cijene<-ts(ardl2$S\_hicp,start=c(1998,1),frequency = 12)  
cijene<-cijene/decompose(cijene,type="multiplicative")$seasonal  
  
stopa.cijene<-diff(log(cijene),12)  
stopa.dolasci<-diff(log(dolasci),12)  
  
library(dynlm)  
m1<-dynlm(stopa.dolasci~L(stopa.dolasci)+stopa.cijene+L(stopa.cijene))  
m2<-dynlm(stopa.dolasci~L(stopa.dolasci)+stopa.cijene)  
m3<-dynlm(stopa.dolasci~stopa.cijene+L(stopa.cijene))  
library(stargazer)  
stargazer(list(m1,m2,m3),type="text")

##   
## =======================================================================================  
## Dependent variable:   
## -------------------------------------------------------------------  
## stopa.dolasci   
## (1) (2) (3)   
## ---------------------------------------------------------------------------------------  
## L(stopa.dolasci) 0.239\*\*\* 0.231\*\*\*   
## (0.060) (0.061)   
##   
## stopa.cijene 4.019\*\*\* 0.147 3.819\*\*\*   
## (1.312) (0.355) (1.350)   
##   
## L(stopa.cijene) -4.020\*\*\* -3.792\*\*\*   
## (1.313) (1.350)   
##   
## Constant 0.030\*\*\* 0.028\*\*\* 0.039\*\*\*   
## (0.009) (0.009) (0.009)   
##   
## ---------------------------------------------------------------------------------------  
## Observations 252 252 252   
## R2 0.090 0.055 0.031   
## Adjusted R2 0.079 0.048 0.024   
## Residual Std. Error 0.084 (df = 248) 0.086 (df = 249) 0.087 (df = 249)   
## F Statistic 8.140\*\*\* (df = 3; 248) 7.279\*\*\* (df = 2; 249) 4.048\*\* (df = 2; 249)  
## =======================================================================================  
## Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

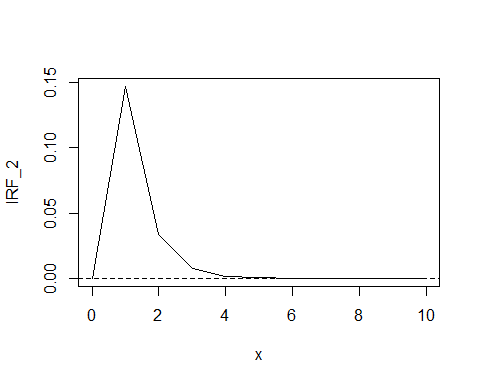
#### Slika 1.191.

#ardl(1,1): y=a+bx+cx(-1)+dy(-1)  
b<-(4.019)  
c<-(-4.020)  
d<-(0.239)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF\_2",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



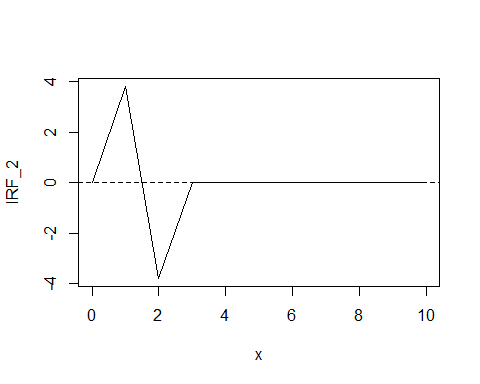
#### Slika 1.192.

#ardl(1,1): y=a+bx+cx(-1)+dy(-1)  
b<-(0.147)  
c<-(0)  
d<-(0.231)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF\_2",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



#### Slika 1.193.

#ardl(1,1): y=a+bx+cx(-1)+dy(-1)  
b<-(3.819)  
c<-(-3.792)  
d<-(0)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF\_2",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



m4<-dynlm(stopa.dolasci~L(stopa.dolasci)+stopa.cijene+L(stopa.cijene),end=c(2007,12))  
m5<-dynlm(stopa.dolasci~L(stopa.dolasci)+stopa.cijene+L(stopa.cijene),start=c(2008,1))  
m4$coefficients

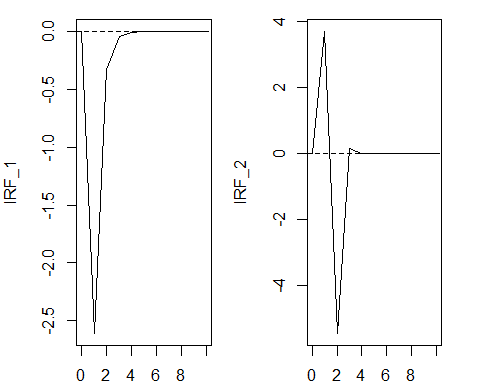
## (Intercept) L(stopa.dolasci) stopa.cijene L(stopa.cijene)   
## 0.14652293 0.14100783 -2.60851966 0.03838064

m5$coefficients

## (Intercept) L(stopa.dolasci) stopa.cijene L(stopa.cijene)   
## 0.03514457 -0.02923156 3.69706994 -5.35397142

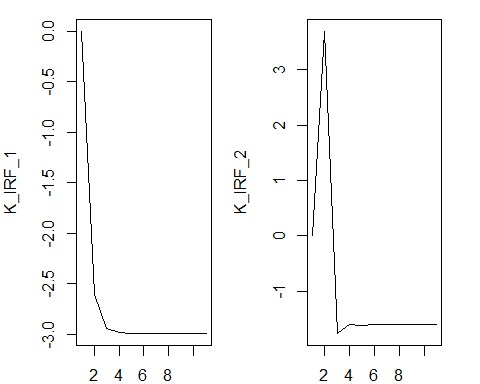
#### Slika 1.194.

par(mfrow = c(1,2),oma=c(1,0,0,1),mar=c(1,4,1,1))  
  
b<-(-2.609)  
c<-(0.038)  
d<-(0.141)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF\_1",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")  
  
  
b<-(3.697)  
c<-(-5.354)  
d<-(-0.029)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF\_2",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



#### Slika 1.195.

par(mfrow = c(1,2),oma=c(1,0,0,1),mar=c(1,4,1,1))  
  
b<-(-2.609)  
c<-(0.038)  
d<-(0.141)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
k\_irf<-cumsum(irf)  
plot(k\_irf,type="l",ylab="K\_IRF\_1")  
  
  
b<-(3.697)  
c<-(-5.354)  
d<-(-0.029)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
k\_irf<-cumsum(irf)  
plot(k\_irf,type="l",ylab="K\_IRF\_2")



## Primjer 1.44.

ardl2<-read.table("ardl2.txt",sep="\t",header=T)  
dolasci<-ts(ardl2$I\_dol,start=c(1998,1),frequency = 12)  
dolasci<-dolasci/decompose(dolasci,type="multiplicative")$seasonal  
cijene<-ts(ardl2$I\_hicp,start=c(1998,1),frequency = 12)  
cijene<-cijene/decompose(cijene,type="multiplicative")$seasonal  
  
stopa.cijene<-diff(log(cijene),12)  
stopa.dolasci<-diff(log(dolasci),12)

#### Slika 1.196.

m6<-dynlm(stopa.dolasci~L(stopa.dolasci)+stopa.cijene,end=c(2007,12))  
m7<-dynlm(stopa.dolasci~L(stopa.dolasci)+stopa.cijene,start=c(2008,1))  
m6$coefficients

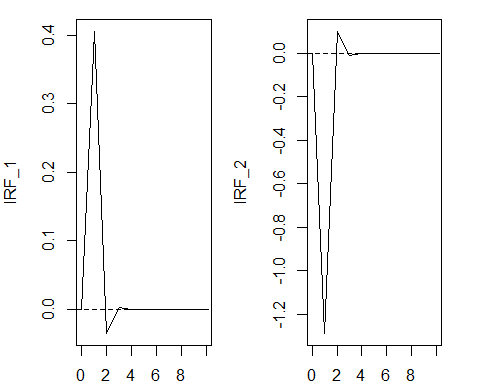
## (Intercept) L(stopa.dolasci) stopa.cijene   
## 0.02214917 -0.08708713 0.40630577

m7$coefficients

## (Intercept) L(stopa.dolasci) stopa.cijene   
## 0.03802875 -0.07903659 -1.28841439

#### Slika 1.197.

par(mfrow = c(1,2),oma=c(1,0,0,1),mar=c(1,4,1,1))  
  
b<-(.406)  
c<-(0)  
d<-(-.087)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF\_1",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")  
  
b<-(-1.288)  
c<-(0)  
d<-(-0.079)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF\_2",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



## Primjer 1.45.

#### Slika 1.198.

ardl2<-read.table("ardl2.txt",sep="\t",header=T)  
dolasci<-ts(ardl2$S\_dol,start=c(1998,1),frequency = 12)  
dolasci<-dolasci/decompose(dolasci,type="multiplicative")$seasonal  
cijene<-ts(ardl2$S\_hicp,start=c(1998,1),frequency = 12)  
cijene<-cijene/decompose(cijene,type="multiplicative")$seasonal  
  
library(lmtest)  
grangertest(diff(cijene),diff(dolasci),1)

## Granger causality test  
##   
## Model 1: diff(dolasci) ~ Lags(diff(dolasci), 1:1) + Lags(diff(cijene), 1:1)  
## Model 2: diff(dolasci) ~ Lags(diff(dolasci), 1:1)  
## Res.Df Df F Pr(>F)  
## 1 260   
## 2 261 -1 1.3043 0.2545

grangertest(diff(cijene),diff(dolasci),2)

## Granger causality test  
##   
## Model 1: diff(dolasci) ~ Lags(diff(dolasci), 1:2) + Lags(diff(cijene), 1:2)  
## Model 2: diff(dolasci) ~ Lags(diff(dolasci), 1:2)  
## Res.Df Df F Pr(>F)  
## 1 257   
## 2 259 -2 0.5857 0.5575

grangertest(diff(cijene),diff(dolasci),3)

## Granger causality test  
##   
## Model 1: diff(dolasci) ~ Lags(diff(dolasci), 1:3) + Lags(diff(cijene), 1:3)  
## Model 2: diff(dolasci) ~ Lags(diff(dolasci), 1:3)  
## Res.Df Df F Pr(>F)   
## 1 254   
## 2 257 -3 2.1637 0.09278 .  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#### Slika 1.199.

library(lmtest)  
grangertest(diff(dolasci),diff(cijene),1)

## Granger causality test  
##   
## Model 1: diff(cijene) ~ Lags(diff(cijene), 1:1) + Lags(diff(dolasci), 1:1)  
## Model 2: diff(cijene) ~ Lags(diff(cijene), 1:1)  
## Res.Df Df F Pr(>F)   
## 1 260   
## 2 261 -1 7.2763 0.007444 \*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(diff(dolasci),diff(cijene),2)

## Granger causality test  
##   
## Model 1: diff(cijene) ~ Lags(diff(cijene), 1:2) + Lags(diff(dolasci), 1:2)  
## Model 2: diff(cijene) ~ Lags(diff(cijene), 1:2)  
## Res.Df Df F Pr(>F)   
## 1 257   
## 2 259 -2 10.904 2.849e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(diff(dolasci),diff(cijene),3)

## Granger causality test  
##   
## Model 1: diff(cijene) ~ Lags(diff(cijene), 1:3) + Lags(diff(dolasci), 1:3)  
## Model 2: diff(cijene) ~ Lags(diff(cijene), 1:3)  
## Res.Df Df F Pr(>F)   
## 1 254   
## 2 257 -3 7.2523 0.0001096 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#### Slika 1.200.

library(lmtest)  
grangertest(diff(cijene),diff(dolasci),1)

## Granger causality test  
##   
## Model 1: diff(dolasci) ~ Lags(diff(dolasci), 1:1) + Lags(diff(cijene), 1:1)  
## Model 2: diff(dolasci) ~ Lags(diff(dolasci), 1:1)  
## Res.Df Df F Pr(>F)  
## 1 260   
## 2 261 -1 1.3043 0.2545

grangertest(diff(cijene),diff(dolasci),2)

## Granger causality test  
##   
## Model 1: diff(dolasci) ~ Lags(diff(dolasci), 1:2) + Lags(diff(cijene), 1:2)  
## Model 2: diff(dolasci) ~ Lags(diff(dolasci), 1:2)  
## Res.Df Df F Pr(>F)  
## 1 257   
## 2 259 -2 0.5857 0.5575

grangertest(diff(cijene),diff(dolasci),3)

## Granger causality test  
##   
## Model 1: diff(dolasci) ~ Lags(diff(dolasci), 1:3) + Lags(diff(cijene), 1:3)  
## Model 2: diff(dolasci) ~ Lags(diff(dolasci), 1:3)  
## Res.Df Df F Pr(>F)   
## 1 254   
## 2 257 -3 2.1637 0.09278 .  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#### Slika 1.201.

library(lmtest)  
grangertest(diff(dolasci),diff(cijene),1)

## Granger causality test  
##   
## Model 1: diff(cijene) ~ Lags(diff(cijene), 1:1) + Lags(diff(dolasci), 1:1)  
## Model 2: diff(cijene) ~ Lags(diff(cijene), 1:1)  
## Res.Df Df F Pr(>F)   
## 1 260   
## 2 261 -1 7.2763 0.007444 \*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(diff(dolasci),diff(cijene),2)

## Granger causality test  
##   
## Model 1: diff(cijene) ~ Lags(diff(cijene), 1:2) + Lags(diff(dolasci), 1:2)  
## Model 2: diff(cijene) ~ Lags(diff(cijene), 1:2)  
## Res.Df Df F Pr(>F)   
## 1 257   
## 2 259 -2 10.904 2.849e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(diff(dolasci),diff(cijene),3)

## Granger causality test  
##   
## Model 1: diff(cijene) ~ Lags(diff(cijene), 1:3) + Lags(diff(dolasci), 1:3)  
## Model 2: diff(cijene) ~ Lags(diff(cijene), 1:3)  
## Res.Df Df F Pr(>F)   
## 1 254   
## 2 257 -3 7.2523 0.0001096 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## Primjer 1.46.

#### Slika 1.203. lijevi panel

koin<-read.table("kointegracija.txt",header = T,sep="\t")  
x<-ts(koin$x1,start=c(2002,1),frequency = 12)  
y1<-ts(koin$y1,start=c(2002,1),frequency = 12)  
y2<-ts(koin$y2,start=c(2002,1),frequency = 12)  
  
library(urca)  
summary(ur.df(x,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression drift   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.51942 0.19782 2.626 0.00927 \*\*  
## z.lag.1 -0.05494 0.02218 -2.477 0.01401 \*   
## z.diff.lag -0.02076 0.06822 -0.304 0.76114   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -2.4772 3.4746   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

#### Slika 1.203. desni panel

summary(ur.df(y1,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression drift   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1.05113 0.36462 2.883 0.00434 \*\*  
## z.lag.1 -0.06327 0.02293 -2.759 0.00630 \*\*  
## z.diff.lag -0.01944 0.06805 -0.286 0.77542   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -2.7588 4.1915   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

#### Slika 1.204. lijevi panel

summary(ur.df(diff(x),type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -1.12504 0.09942 -11.316 <2e-16 \*\*\*  
## z.diff.lag 0.07860 0.06868 1.144 0.254   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -11.3164   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

#### Slika 1.204. desni panel

summary(ur.df(diff(y1),type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -1.08045 0.09976 -10.830 <2e-16 \*\*\*  
## z.diff.lag 0.03470 0.06885 0.504 0.615   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -10.83   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

#### Slika 1.205.

rez1<-resid(lm(y1~x))  
summary(ur.df(rez1,type="none",selectlags = "BIC"))

##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -0.10218 0.03054 -3.346 0.000967 \*\*\*  
## z.diff.lag -0.01499 0.06801 -0.220 0.825742   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -3.3458   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

#### Slika 1.206. lijevi panel

summary(ur.df(y2,type="drift",selectlags="BIC"))

##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.430033 0.201066 2.139 0.0336 \*  
## z.lag.1 0.003331 0.003080 1.081 0.2807   
## z.diff.lag -0.088506 0.068653 -1.289 0.1987   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: 1.0815 10.8131   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

#### Slika 1.206. desni panel

summary(ur.df(diff(y2),type="none",selectlags="BIC"))

##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -0.90210 0.09577 -9.419 <2e-16 \*\*\*  
## z.diff.lag -0.08791 0.06811 -1.291 0.198   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -9.419   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

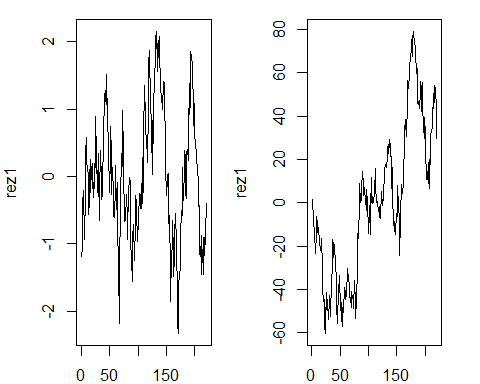
#### Slika 1.207.

rez2<-resid(lm(y2~x))  
summary(ur.df(rez2,type="none",selectlags = "BIC"))

##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -17.0290 -5.3107 0.0685 4.8270 16.1864   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)  
## z.lag.1 -0.02032 0.01443 -1.408 0.160  
## z.diff.lag -0.01703 0.06874 -0.248 0.805  
##   
## Residual standard error: 7.415 on 216 degrees of freedom  
## Multiple R-squared: 0.009906, Adjusted R-squared: 0.0007386   
## F-statistic: 1.081 on 2 and 216 DF, p-value: 0.3412  
##   
##   
## Value of test-statistic is: -1.4082   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

#### Slika 1.208.

par(mfrow = c(1,2),oma=c(1,0,0,1),mar=c(1,4,1,1))  
  
plot(rez1,type="l",ylab="rez1",xlab=NA)  
plot(rez2,type="l",ylab="rez1",xlab=NA)



## Primjer 1.48.

#### Slika 1.209.

ardl2<-read.table("ardl2.txt",sep="\t",header=T)  
dolasci<-ts(ardl2$S\_dol,start=c(1998,1),frequency = 12)  
dolasci<-dolasci/decompose(dolasci,type="multiplicative")$seasonal  
cijene<-ts(ardl2$S\_hicp,start=c(1998,1),frequency = 12)  
cijene<-cijene/decompose(cijene,type="multiplicative")$seasonal  
  
dolasci<-log(dolasci)  
cijene<-log(cijene)  
#dugi rok:  
lm(dolasci~cijene)

##   
## Call:  
## lm(formula = dolasci ~ cijene)  
##   
## Coefficients:  
## (Intercept) cijene   
## 8.848 1.429

reziduali<-ts(resid(lm(dolasci~cijene)),start=c(1998,1),frequency = 12)  
  
#korekcija:  
dynlm(diff(dolasci)~diff(cijene)+L(reziduali))

##   
## Time series regression with "ts" data:  
## Start = 1998(2), End = 2020(1)  
##   
## Call:  
## dynlm(formula = diff(dolasci) ~ diff(cijene) + L(reziduali))  
##   
## Coefficients:  
## (Intercept) diff(cijene) L(reziduali)   
## -0.002354 3.473550 -0.280365

#### Slika 1.211.

dolasci<-ts(ardl2$I\_dol,start=c(1998,1),frequency = 12)  
dolasci<-dolasci/decompose(dolasci,type="multiplicative")$seasonal  
cijene<-ts(ardl2$I\_hicp,start=c(1998,1),frequency = 12)  
cijene<-cijene/decompose(cijene,type="multiplicative")$seasonal  
  
dolasci<-log(dolasci)  
cijene<-log(cijene)  
#dugi rok:  
lm(dolasci~cijene)

##   
## Call:  
## lm(formula = dolasci ~ cijene)  
##   
## Coefficients:  
## (Intercept) cijene   
## 10.8174 0.9977

reziduali<-ts(resid(lm(dolasci~cijene)),start=c(1998,1),frequency = 12)  
  
#korekcija:  
dynlm(diff(dolasci)~diff(cijene)+L(reziduali))

##   
## Time series regression with "ts" data:  
## Start = 1998(2), End = 2020(1)  
##   
## Call:  
## dynlm(formula = diff(dolasci) ~ diff(cijene) + L(reziduali))  
##   
## Coefficients:  
## (Intercept) diff(cijene) L(reziduali)   
## 4.745e-05 1.036e+00 -6.561e-01

## 1.16. Primjer

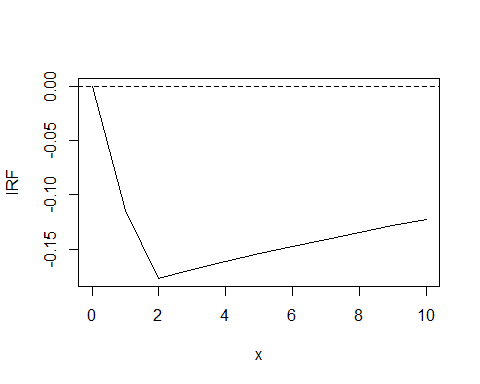
#### Slika 1.212.

dinamicki<-read.table("rh\_dinamicki.txt",sep="\t",header=T)  
iip<-ts(dinamicki$hr\_iip,start=c(2000,1),frequency = 12)  
nez<-ts(dinamicki$hr\_nez,start=c(2000,1),frequency = 12)  
  
s.iip<-diff(log(iip/decompose(iip,type="multiplicative")$seasonal),12)  
s.nez<-diff(log(nez/decompose(nez,type="multiplicative")$seasonal),12)  
  
library(dynlm)  
dynlm(s.nez~L(s.nez)+s.iip+L(s.iip))

##   
## Time series regression with "ts" data:  
## Start = 2001(2), End = 2020(9)  
##   
## Call:  
## dynlm(formula = s.nez ~ L(s.nez) + s.iip + L(s.iip))  
##   
## Coefficients:  
## (Intercept) L(s.nez) s.iip L(s.iip)   
## 0.0003051 0.9552513 -0.1141376 -0.0682544

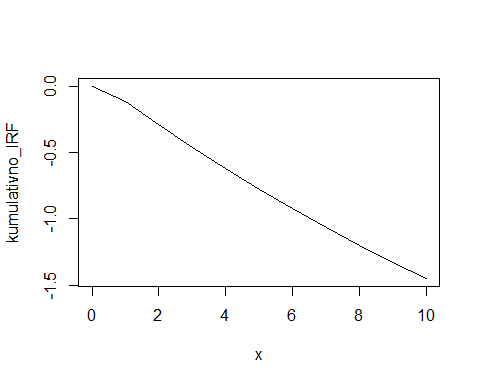
#### Slika 1.213.

b<-(-0.1141)  
c<-(-.068)  
d<-(0.9552)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



#### Slika 1.214.

irf<-cumsum(irf)  
plot(x,irf,ylab="kumulativno\_IRF",xlim=c(0,10),type="l")



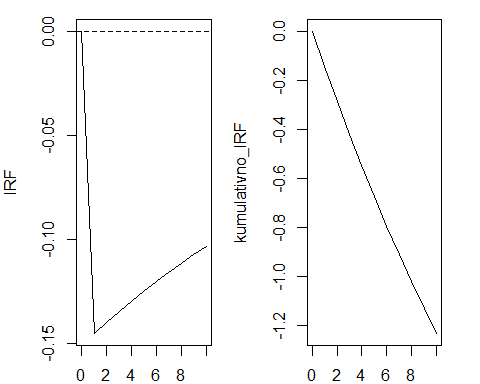
#### Slika 1.215.

library(dynlm)  
dynlm(s.nez~L(s.nez)+s.iip)

##   
## Time series regression with "ts" data:  
## Start = 2001(2), End = 2020(9)  
##   
## Call:  
## dynlm(formula = s.nez ~ L(s.nez) + s.iip)  
##   
## Coefficients:  
## (Intercept) L(s.nez) s.iip   
## 0.000308 0.963276 -0.145049

#### Slika 1.216.

par(mfrow = c(1,2),oma=c(1,0,0,1),mar=c(1,4,1,1))  
  
b<-(-0.145)  
c<-(0)  
d<-(0.963)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")  
  
irf<-cumsum(irf)  
plot(x,irf,ylab="kumulativno\_IRF",xlim=c(0,10),type="l")



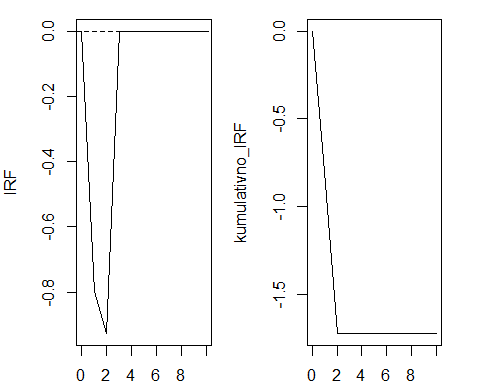
#### Slika 1.217.

library(dynlm)  
dynlm(s.nez~s.iip+L(s.iip))

##   
## Time series regression with "ts" data:  
## Start = 2001(2), End = 2020(9)  
##   
## Call:  
## dynlm(formula = s.nez ~ s.iip + L(s.iip))  
##   
## Coefficients:  
## (Intercept) s.iip L(s.iip)   
## -0.02623 -0.79815 -0.92707

#### Slika 1.218.

par(mfrow = c(1,2),oma=c(1,0,0,1),mar=c(1,4,1,1))  
b<-(-0.798)  
c<-(-.927)  
d<-(0)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")  
irf<-cumsum(irf)  
plot(x,irf,ylab="kumulativno\_IRF",xlim=c(0,10),type="l")



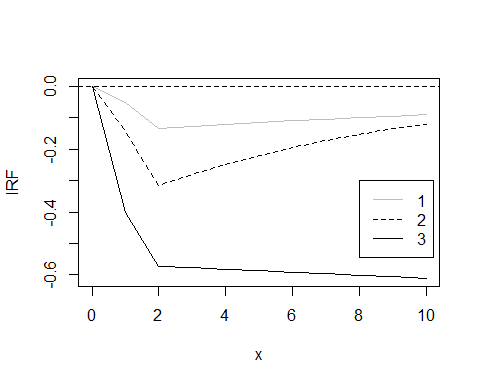
#### Slika 1.219.

m1<-dynlm(s.nez~L(s.nez)+s.iip+L(s.iip),end=c(2017,12))  
m2<-dynlm(s.nez~L(s.nez)+s.iip+L(s.iip),start=c(2008,1),end=c(2015,12))  
m3<-dynlm(s.nez~L(s.nez)+s.iip+L(s.iip),start=c(2016,1))  
library(stargazer)  
stargazer(list(m1,m2,m3),type="text")

##   
## ================================================================================================  
## Dependent variable:   
## ----------------------------------------------------------------------------  
## s.nez   
## (1) (2) (3)   
## ------------------------------------------------------------------------------------------------  
## L(s.nez) 0.953\*\*\* 0.886\*\*\* 1.008\*\*\*   
## (0.015) (0.022) (0.035)   
##   
## s.iip -0.052\* -0.143\*\*\* -0.402\*\*\*   
## (0.031) (0.043) (0.109)   
##   
## L(s.iip) -0.083\*\*\* -0.189\*\*\* -0.168   
## (0.032) (0.045) (0.113)   
##   
## Constant -0.001 -0.003 0.016\*\*   
## (0.001) (0.002) (0.008)   
##   
## ------------------------------------------------------------------------------------------------  
## Observations 203 96 57   
## R2 0.979 0.981 0.949   
## Adjusted R2 0.979 0.980 0.947   
## Residual Std. Error 0.018 (df = 199) 0.017 (df = 92) 0.036 (df = 53)   
## F Statistic 3,088.425\*\*\* (df = 3; 199) 1,543.069\*\*\* (df = 3; 92) 331.628\*\*\* (df = 3; 53)  
## ================================================================================================  
## Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### Slika 1.220.

b<-(-.402)  
c<-(-.168)  
d<-(1.008)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")  
b<-(-.052)  
c<-(-.083)  
d<-(0.953)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
lines(x,irf,col="grey")  
b<-(-.143)  
c<-(-.189)  
d<-(0.886)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
lines(x,irf,col="black",lty="dashed")  
  
legend(8,-.3,legend=c("1","2","3"),  
 col=c( "grey","black","black"), lty=c(1,2,1))



#### Slika 1.221.

grangertest(s.iip,s.nez,1)

## Granger causality test  
##   
## Model 1: s.nez ~ Lags(s.nez, 1:1) + Lags(s.iip, 1:1)  
## Model 2: s.nez ~ Lags(s.nez, 1:1)  
## Res.Df Df F Pr(>F)   
## 1 233   
## 2 234 -1 12.744 0.0004337 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(s.iip,s.nez,2)

## Granger causality test  
##   
## Model 1: s.nez ~ Lags(s.nez, 1:2) + Lags(s.iip, 1:2)  
## Model 2: s.nez ~ Lags(s.nez, 1:2)  
## Res.Df Df F Pr(>F)   
## 1 230   
## 2 232 -2 2.8606 0.05928 .  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(s.iip,s.nez,3)

## Granger causality test  
##   
## Model 1: s.nez ~ Lags(s.nez, 1:3) + Lags(s.iip, 1:3)  
## Model 2: s.nez ~ Lags(s.nez, 1:3)  
## Res.Df Df F Pr(>F)   
## 1 227   
## 2 230 -3 3.0519 0.02935 \*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#### Slika 1.222.

grangertest(s.nez,s.iip,1)

## Granger causality test  
##   
## Model 1: s.iip ~ Lags(s.iip, 1:1) + Lags(s.nez, 1:1)  
## Model 2: s.iip ~ Lags(s.iip, 1:1)  
## Res.Df Df F Pr(>F)   
## 1 233   
## 2 234 -1 17.241 4.622e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(s.nez,s.iip,2)

## Granger causality test  
##   
## Model 1: s.iip ~ Lags(s.iip, 1:2) + Lags(s.nez, 1:2)  
## Model 2: s.iip ~ Lags(s.iip, 1:2)  
## Res.Df Df F Pr(>F)   
## 1 230   
## 2 232 -2 4.7863 0.009192 \*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(s.nez,s.iip,3)

## Granger causality test  
##   
## Model 1: s.iip ~ Lags(s.iip, 1:3) + Lags(s.nez, 1:3)  
## Model 2: s.iip ~ Lags(s.iip, 1:3)  
## Res.Df Df F Pr(>F)   
## 1 227   
## 2 230 -3 3.8042 0.01089 \*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

iip<-iip/decompose(iip,type="multiplicative")$seasonal  
nez<-nez/decompose(nez,type="multiplicative")$seasonal

#### Slika 1.223.

lm(nez~iip)

##   
## Call:  
## lm(formula = nez ~ iip)  
##   
## Coefficients:  
## (Intercept) iip   
## 581.963 -3.206

rez<-resid(lm(nez~iip))  
rez<-ts(rez,start=c(2001,1),frequency = 12)  
library(dynlm)  
dynlm(diff(nez)~diff(iip)+L(rez))

##   
## Time series regression with "ts" data:  
## Start = 2001(2), End = 2020(9)  
##   
## Call:  
## dynlm(formula = diff(nez) ~ diff(iip) + L(rez))  
##   
## Coefficients:  
## (Intercept) diff(iip) L(rez)   
## -0.48103 0.02880 -0.01843

#### Slika 1.224. lijevi panel:

summary(ur.df(iip,type="drift",selectlags = "BIC"))

##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 6.84518 2.74211 2.496 0.0132 \*   
## z.lag.1 -0.06232 0.02523 -2.470 0.0142 \*   
## z.diff.lag -0.46201 0.05667 -8.153 1.87e-14 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -2.4701 3.1271   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

#### Slika 1.224. desni panel:

summary(ur.df(nez,type="drift",selectlags = "BIC"))

##   
## ###############################################   
## # 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   
## -11.9354 -2.4495 0.3065 2.5192 15.0202   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.747693 1.033493 0.723 0.470   
## z.lag.1 -0.003937 0.004245 -0.927 0.355   
## z.diff.lag 0.636595 0.049814 12.779 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 3.942 on 244 degrees of freedom  
## Multiple R-squared: 0.4011, Adjusted R-squared: 0.3962   
## F-statistic: 81.7 on 2 and 244 DF, p-value: < 2.2e-16  
##   
##   
## Value of test-statistic is: -0.9274 0.6912   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

#### Slika 1.225. lijevi panel:

summary(ur.df(diff(iip),type="none",selectlags = "BIC"))

##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -2.00417 0.10388 -19.293 < 2e-16 \*\*\*  
## z.diff.lag 0.34574 0.06064 5.701 3.42e-08 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -19.293   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

#### Slika 1.225. desni panel:

summary(ur.df(diff(nez),type="none",selectlags = "BIC"))

##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -0.39687 0.05428 -7.311 3.78e-12 \*\*\*  
## z.diff.lag 0.08285 0.06356 1.304 0.194   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -7.3111   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

#### Slika 1.226.

rez2<-resid(lm(nez~iip))  
summary(ur.df(rez2,type="none",selectlags = "BIC"))

##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -0.02860 0.02044 -1.399 0.163   
## z.diff.lag -0.35752 0.06030 -5.929 1.03e-08 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Value of test-statistic is: -1.3992   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

## Primjer 1.49.

#### Slika 1.227.

nizovi<-read.table("gen\_nizovi.txt",header=T,sep="\t")  
  
y<-ts(nizovi$Y1,start=c(2003,9),frequency=12)  
  
library("ICglm")

ar\_1<-arima(y,order=c(1,0,0))  
ar\_2<-arima(y,order=c(2,0,0))  
ma\_1<-arima(y,order=c(0,0,1))  
ma\_2<-arima(y,order=c(0,0,2))  
arma<-arima(y,order=c(1,0,1))  
  
aic\_ar\_1<-AIC(ar\_1);bic\_ar\_1<-BIC(ar\_1);hqc\_ar\_1<-HQIC(ar\_1)  
aic\_ar\_2<-AIC(ar\_2);bic\_ar\_2<-BIC(ar\_2);hqc\_ar\_2<-HQIC(ar\_2)  
aic\_ma\_1<-AIC(ma\_1);bic\_ma\_1<-BIC(ma\_1);hqc\_ma\_1<-HQIC(ma\_1)  
aic\_ma\_2<-AIC(ma\_2);bic\_ma\_2<-BIC(ma\_2);hqc\_ma\_2<-HQIC(ma\_2)  
aic\_arma<-AIC(arma);bic\_arma<-BIC(arma);hqc\_arma<-HQIC(arma)  
  
aic<-c(aic\_ar\_1,aic\_ar\_2,aic\_ma\_1,aic\_ma\_2,aic\_arma)  
bic<-c(bic\_ar\_1,bic\_ar\_2,bic\_ma\_1,bic\_ma\_2,bic\_arma)  
hqc<-c(hqc\_ar\_1,hqc\_ar\_2,hqc\_ma\_1,hqc\_ma\_2,hqc\_arma)  
  
tablica<-cbind(aic,bic,hqc)  
row.names(tablica)<-c("ar\_1","ar\_2","ma\_1","ma\_2","arma")  
tablica

## aic bic hqc  
## ar\_1 69.18479 79.07975 73.18913  
## ar\_2 71.06863 84.26190 76.40774  
## ma\_1 287.78625 297.68120 291.79058  
## ma\_2 207.58605 220.77932 212.92517  
## arma 71.08860 84.28187 76.42772

#### Slika 2.228.

tablica

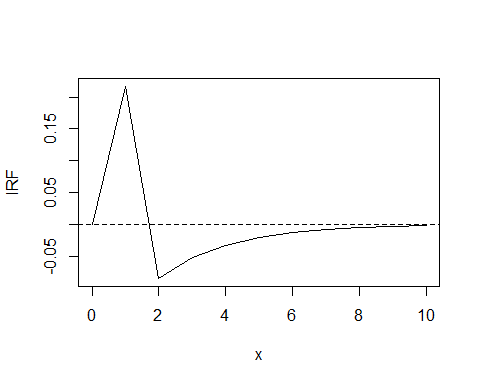
## aic bic hqc  
## ar\_1 69.18479 79.07975 73.18913  
## ar\_2 71.06863 84.26190 76.40774  
## ma\_1 287.78625 297.68120 291.79058  
## ma\_2 207.58605 220.77932 212.92517  
## arma 71.08860 84.28187 76.42772

#### 1.18. pitanja za ponavljanje, zadatak 13:

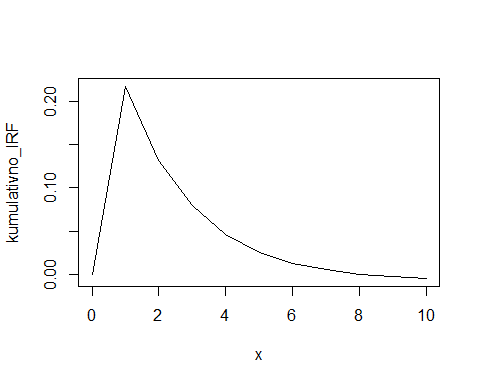
pod<-read.table("it\_dinamicki.txt",sep="\t",header=T)  
  
iip<-ts(pod$it\_iip,start=c(1990,1),frequency = 12)  
nez<-ts(pod$it\_nez,start=c(1990,1),frequency = 12)  
  
s.iip<-diff(log(iip/decompose(iip,type="multiplicative")$seasonal),12)  
s.nez<-diff(log(nez/decompose(nez,type="multiplicative")$seasonal),12)  
  
library(dynlm)  
dynlm(s.iip~s.nez+L(s.nez)+L(s.iip))

##   
## Time series regression with "ts" data:  
## Start = 1991(2), End = 2020(9)  
##   
## Call:  
## dynlm(formula = s.iip ~ s.nez + L(s.nez) + L(s.iip))  
##   
## Coefficients:  
## (Intercept) s.nez L(s.nez) L(s.iip)   
## -0.00215 0.21688 -0.21964 0.62153

b<-(.21688)  
c<-(-.21964)  
d<-(.62153)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



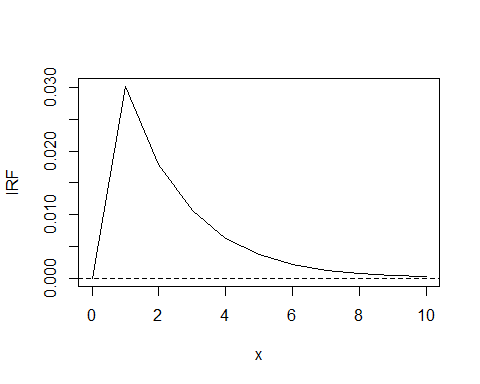
irf<-cumsum(irf)  
plot(x,irf,ylab="kumulativno\_IRF",xlim=c(0,10),type="l")



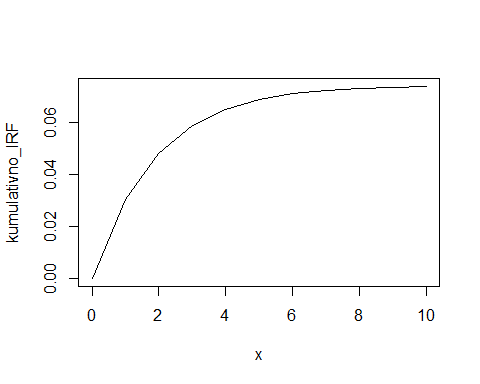
dynlm(s.iip~s.nez+L(s.iip))

##   
## Time series regression with "ts" data:  
## Start = 1991(2), End = 2020(9)  
##   
## Call:  
## dynlm(formula = s.iip ~ s.nez + L(s.iip))  
##   
## Coefficients:  
## (Intercept) s.nez L(s.iip)   
## -0.002385 0.030176 0.593624

b<-(.030176)  
c<-(0)  
d<-(.5936)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



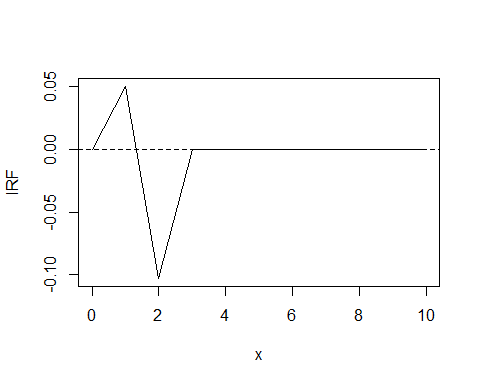
irf<-cumsum(irf)  
plot(x,irf,ylab="kumulativno\_IRF",xlim=c(0,10),type="l")



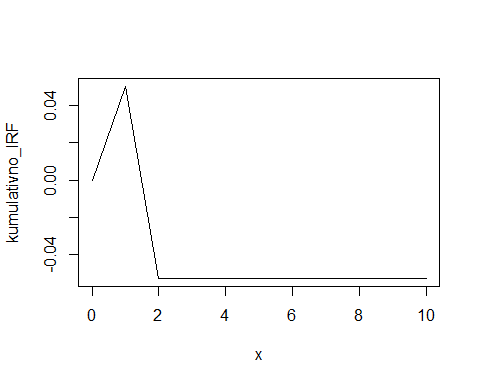
dynlm(s.iip~s.nez+L(s.nez))

##   
## Time series regression with "ts" data:  
## Start = 1991(2), End = 2020(9)  
##   
## Call:  
## dynlm(formula = s.iip ~ s.nez + L(s.nez))  
##   
## Coefficients:  
## (Intercept) s.nez L(s.nez)   
## -0.005341 0.050190 -0.102739

b<-(.05019)  
c<-(-.102739)  
d<-(0)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l")  
abline(h=0,lty="dashed")



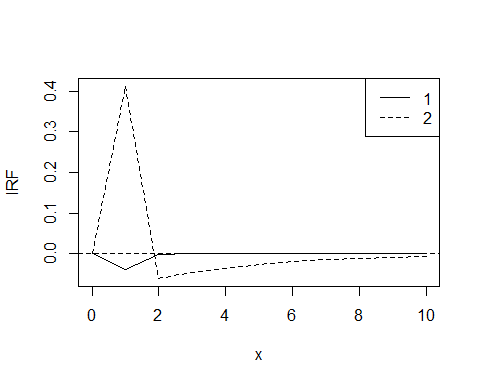
irf<-cumsum(irf)  
plot(x,irf,ylab="kumulativno\_IRF",xlim=c(0,10),type="l")



m1<-dynlm(s.iip~s.nez+L(s.iip)+L(s.nez),end=c(2007,12))  
m2<-dynlm(s.iip~s.nez+L(s.iip)+L(s.nez),start=c(2008,1))  
  
library(stargazer)  
stargazer(list(m1,m2),type="text")

##   
## =================================================================  
## Dependent variable:   
## ---------------------------------------------  
## s.iip   
## (1) (2)   
## -----------------------------------------------------------------  
## s.nez -0.040 0.412\*\*\*   
## (0.070) (0.073)   
##   
## L(s.iip) 0.183\*\*\* 0.762\*\*\*   
## (0.070) (0.058)   
##   
## L(s.nez) 0.006 -0.375\*\*\*   
## (0.070) (0.073)   
##   
## Constant 0.010\*\*\* -0.008   
## (0.003) (0.006)   
##   
## -----------------------------------------------------------------  
## Observations 203 153   
## R2 0.039 0.543   
## Adjusted R2 0.024 0.534   
## Residual Std. Error 0.046 (df = 199) 0.063 (df = 149)   
## F Statistic 2.658\*\* (df = 3; 199) 59.056\*\*\* (df = 3; 149)  
## =================================================================  
## Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

b<-(.412)  
c<-(-.375)  
d<-(.762)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
x<-0:10  
plot(x,irf,ylab="IRF",xlim=c(0,10),type="l",lty="dashed")  
abline(h=0,lty="dashed")  
  
  
b<-(-.04)  
c<-(.006)  
d<-(.183)  
irf<-c(0,b,d\*b+c,d\*(d\*b+c),d^2\*(d\*b+c),d^3\*(d\*b+c),d^4\*(d\*b+c),  
 d^5\*(d\*b+c),d^6\*(d\*b+c),d^7\*(d\*b+c),d^8\*(d\*b+c))  
lines(x,irf)  
legend("topright",legend=c("1","2"),lty=c(1,2))



library(lmtest)  
grangertest(s.iip,s.nez,1)

## Granger causality test  
##   
## Model 1: s.nez ~ Lags(s.nez, 1:1) + Lags(s.iip, 1:1)  
## Model 2: s.nez ~ Lags(s.nez, 1:1)  
## Res.Df Df F Pr(>F)   
## 1 353   
## 2 354 -1 17.557 3.528e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(s.iip,s.nez,2)

## Granger causality test  
##   
## Model 1: s.nez ~ Lags(s.nez, 1:2) + Lags(s.iip, 1:2)  
## Model 2: s.nez ~ Lags(s.nez, 1:2)  
## Res.Df Df F Pr(>F)   
## 1 350   
## 2 352 -2 12.469 5.875e-06 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(s.iip,s.nez,3)

## Granger causality test  
##   
## Model 1: s.nez ~ Lags(s.nez, 1:3) + Lags(s.iip, 1:3)  
## Model 2: s.nez ~ Lags(s.nez, 1:3)  
## Res.Df Df F Pr(>F)   
## 1 347   
## 2 350 -3 8.7377 1.332e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(s.nez,s.iip,1)

## Granger causality test  
##   
## Model 1: s.iip ~ Lags(s.iip, 1:1) + Lags(s.nez, 1:1)  
## Model 2: s.iip ~ Lags(s.iip, 1:1)  
## Res.Df Df F Pr(>F)  
## 1 353   
## 2 354 -1 1.8654 0.1729

grangertest(s.nez,s.iip,2)

## Granger causality test  
##   
## Model 1: s.iip ~ Lags(s.iip, 1:2) + Lags(s.nez, 1:2)  
## Model 2: s.iip ~ Lags(s.iip, 1:2)  
## Res.Df Df F Pr(>F)   
## 1 350   
## 2 352 -2 3.723 0.02512 \*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

grangertest(s.nez,s.iip,3)

## Granger causality test  
##   
## Model 1: s.iip ~ Lags(s.iip, 1:3) + Lags(s.nez, 1:3)  
## Model 2: s.iip ~ Lags(s.iip, 1:3)  
## Res.Df Df F Pr(>F)   
## 1 347   
## 2 350 -3 4.3784 0.004833 \*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

iip<-iip/decompose(iip,type="multiplicative")$seasonal  
nez<-nez/decompose(nez,type="multiplicative")$seasonal  
  
lm(iip~nez)

##   
## Call:  
## lm(formula = iip ~ nez)  
##   
## Coefficients:  
## (Intercept) nez   
## 151.48000 -0.01538

rez<-resid(lm(iip~nez))  
rez<-ts(rez,start=c(1990,1),frequency = 12)  
library(dynlm)  
dynlm(diff(iip)~diff(nez)+L(rez))

##   
## Time series regression with "ts" data:  
## Start = 1990(2), End = 2020(9)  
##   
## Call:  
## dynlm(formula = diff(iip) ~ diff(nez) + L(rez))  
##   
## Coefficients:  
## (Intercept) diff(nez) L(rez)   
## -0.036488 -0.002892 -0.272546

library(urca)  
summary(ur.df(iip,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # 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   
## -34.829 -3.825 0.258 4.064 22.668   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 13.08607 3.41729 3.829 0.000151 \*\*\*  
## z.lag.1 -0.11374 0.02948 -3.858 0.000135 \*\*\*  
## z.diff.lag -0.38113 0.04889 -7.796 6.78e-14 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 6.947 on 364 degrees of freedom  
## Multiple R-squared: 0.2209, Adjusted R-squared: 0.2167   
## F-statistic: 51.61 on 2 and 364 DF, p-value: < 2.2e-16  
##   
## Value of test-statistic is: -3.8585 7.4462   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.44 -2.87 -2.57  
## phi1 6.47 4.61 3.79

summary(ur.df(nez,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # 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   
## -728.79 -73.46 5.35 85.68 450.70   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 102.74127 39.34777 2.611 0.00940 \*\*  
## z.lag.1 -0.04274 0.01639 -2.608 0.00949 \*\*  
## z.diff.lag -0.14346 0.05186 -2.766 0.00596 \*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 146.3 on 364 degrees of freedom  
## Multiple R-squared: 0.04504, Adjusted R-squared: 0.0398   
## F-statistic: 8.585 on 2 and 364 DF, p-value: 0.0002275  
##   
## Value of test-statistic is: -2.6079 3.4376   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.44 -2.87 -2.57  
## phi1 6.47 4.61 3.79

summary(ur.df(diff(iip),type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -37.352 -3.330 0.039 3.819 30.165   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -1.95351 0.08320 -23.479 < 2e-16 \*\*\*  
## z.diff.lag 0.36273 0.04951 7.326 1.54e-12 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 6.617 on 364 degrees of freedom  
## Multiple R-squared: 0.7515, Adjusted R-squared: 0.7502   
## F-statistic: 550.4 on 2 and 364 DF, p-value: < 2.2e-16  
##   
## Value of test-statistic is: -23.4794   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

summary(ur.df(diff(nez),type="none",selectlags="BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -725.99 -74.98 6.23 91.37 498.53   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -1.35860 0.07887 -17.227 < 2e-16 \*\*\*  
## z.diff.lag 0.16600 0.05168 3.212 0.00144 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 145.6 on 364 degrees of freedom  
## Multiple R-squared: 0.5941, Adjusted R-squared: 0.5919   
## F-statistic: 266.4 on 2 and 364 DF, p-value: < 2.2e-16  
##   
## Value of test-statistic is: -17.2267   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

rez2<-resid(lm(iip~nez))  
summary(ur.df(rez2,type="none",selectlags = "BIC"))

##   
## ###############################################   
## # Augmented Dickey-Fuller Test Unit Root Test #   
## ###############################################   
##   
## Test regression none   
##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -44.643 -3.872 0.111 4.350 22.760   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## z.lag.1 -0.20904 0.03822 -5.469 8.41e-08 \*\*\*  
## z.diff.lag -0.27872 0.05056 -5.512 6.71e-08 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 7.235 on 365 degrees of freedom  
## Multiple R-squared: 0.2103, Adjusted R-squared: 0.206   
## F-statistic: 48.6 on 2 and 365 DF, p-value: < 2.2e-16  
##   
## Value of test-statistic is: -5.469   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau1 -2.58 -1.95 -1.62

# 2. VEKTORSKI AUTOREGRESIJSKI MODELI

## Primjer 2.3.

pod<-read.table("rh\_dinamicki.txt",sep="\t",header = T)  
iip<-ts(pod$hr\_iip,start=c(2001,1),frequency = 12)  
nez<-ts(pod$hr\_nez,start=c(2001,1),frequency = 12)  
  
#desezoniranje:  
iip<-iip/decompose(iip,type="multiplicative")$seasonal  
nez<-nez/decompose(nez,type="multiplicative")$seasonal  
  
#stope rasta:  
s.iip<-diff(log(iip),12)  
s.nez<-diff(log(nez),12)

#### Slika 2.1.

library(vars)  
matrica<-cbind(s.iip,s.nez)  
m1<-VAR(matrica,p=1,type="const")  
summary(m1)

##   
## VAR Estimation Results:  
## =========================   
## Endogenous variables: s.iip, s.nez   
## Deterministic variables: const   
## Sample size: 236   
## Log Likelihood: 943.5   
## Roots of the characteristic polynomial:  
## 0.9886 0.443  
## Call:  
## VAR(y = matrica, p = 1, type = "const")  
##   
##   
## Estimation results for equation s.iip:   
## ======================================   
## s.iip = s.iip.l1 + s.nez.l1 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## s.iip.l1 0.4653245 0.0589947 7.888 1.19e-13 \*\*\*  
## s.nez.l1 -0.0962168 0.0231725 -4.152 4.62e-05 \*\*\*  
## const 0.0002102 0.0029718 0.071 0.944   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.0439 on 233 degrees of freedom  
## Multiple R-Squared: 0.4003, Adjusted R-squared: 0.3952   
## F-statistic: 77.77 on 2 and 233 DF, p-value: < 2.2e-16   
##   
##   
## Estimation results for equation s.nez:   
## ======================================   
## s.nez = s.iip.l1 + s.nez.l1 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## s.iip.l1 -0.1213654 0.0339972 -3.570 0.000434 \*\*\*  
## s.nez.l1 0.9662333 0.0133537 72.357 < 2e-16 \*\*\*  
## const 0.0002811 0.0017125 0.164 0.869770   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.0253 on 233 degrees of freedom  
## Multiple R-Squared: 0.9701, Adjusted R-squared: 0.9698   
## F-statistic: 3780 on 2 and 233 DF, p-value: < 2.2e-16   
##   
##   
## Covariance matrix of residuals:  
## s.iip s.nez  
## s.iip 0.0019270 -0.0002199  
## s.nez -0.0002199 0.0006399  
##   
## Correlation matrix of residuals:  
## s.iip s.nez  
## s.iip 1.0000 -0.1981  
## s.nez -0.1981 1.0000

## Primjer 2.4.

pod<-read.table("rh\_dinamicki.txt",sep="\t",header = T)  
iip<-ts(pod$hr\_iip,start=c(2001,1),frequency = 12)  
nez<-ts(pod$hr\_nez,start=c(2001,1),frequency = 12)  
  
#desezoniranje:  
iip<-iip/decompose(iip,type="multiplicative")$seasonal  
nez<-nez/decompose(nez,type="multiplicative")$seasonal  
  
#stope rasta:  
s.iip<-diff(log(iip),12)  
s.nez<-diff(log(nez),12)  
library(vars)  
matrica<-cbind(s.iip,s.nez)

#### Slika 2.2.

m2<-VAR(matrica,p=2,type="const")  
summary(m2)

##   
## VAR Estimation Results:  
## =========================   
## Endogenous variables: s.iip, s.nez   
## Deterministic variables: const   
## Sample size: 235   
## Log Likelihood: 994.285   
## Roots of the characteristic polynomial:  
## 0.9361 0.7804 0.5484 0.4447  
## Call:  
## VAR(y = matrica, p = 2, type = "const")  
##   
##   
## Estimation results for equation s.iip:   
## ======================================   
## s.iip = s.iip.l1 + s.nez.l1 + s.iip.l2 + s.nez.l2 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## s.iip.l1 0.316681 0.062721 5.049 9.03e-07 \*\*\*  
## s.nez.l1 -0.291998 0.108593 -2.689 0.00769 \*\*   
## s.iip.l2 0.329149 0.062578 5.260 3.30e-07 \*\*\*  
## s.nez.l2 0.243562 0.106020 2.297 0.02250 \*   
## const 0.001014 0.002793 0.363 0.71692   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.04105 on 230 degrees of freedom  
## Multiple R-Squared: 0.4818, Adjusted R-squared: 0.4728   
## F-statistic: 53.45 on 4 and 230 DF, p-value: < 2.2e-16   
##   
##   
## Estimation results for equation s.nez:   
## ======================================   
## s.nez = s.iip.l1 + s.nez.l1 + s.iip.l2 + s.nez.l2 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## s.iip.l1 -0.0723975 0.0327235 -2.212 0.0279 \*   
## s.nez.l1 1.5035686 0.0566568 26.538 <2e-16 \*\*\*  
## s.iip.l2 0.0032895 0.0326488 0.101 0.9198   
## s.nez.l2 -0.5388676 0.0553141 -9.742 <2e-16 \*\*\*  
## const -0.0005543 0.0014573 -0.380 0.7040   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.02142 on 230 degrees of freedom  
## Multiple R-Squared: 0.9788, Adjusted R-squared: 0.9784   
## F-statistic: 2650 on 4 and 230 DF, p-value: < 2.2e-16   
##   
##   
## Covariance matrix of residuals:  
## s.iip s.nez  
## s.iip 0.0016852 -0.0001291  
## s.nez -0.0001291 0.0004587  
##   
## Correlation matrix of residuals:  
## s.iip s.nez  
## s.iip 1.0000 -0.1468  
## s.nez -0.1468 1.0000

## Primjer 2.5

pod<-read.table("rh\_dinamicki.txt",sep="\t",header = T)  
iip<-ts(pod$hr\_iip,start=c(2001,1),frequency = 12)  
nez<-ts(pod$hr\_nez,start=c(2001,1),frequency = 12)  
iip<-iip/decompose(iip,type="multiplicative")$seasonal  
nez<-nez/decompose(nez,type="multiplicative")$seasonal  
s.iip<-diff(log(iip),12)  
s.nez<-diff(log(nez),12)  
library(vars)  
matrica<-cbind(s.iip,s.nez)  
m1<-VAR(matrica,p=1,type="const")

#### Slika 2.3.

causality(m1,cause = "s.iip")$Granger

##   
## Granger causality H0: s.iip do not Granger-cause s.nez  
##   
## data: VAR object m1  
## F-Test = 12.744, df1 = 1, df2 = 466, p-value = 0.0003942

causality(m1,cause = "s.nez")$Granger

##   
## Granger causality H0: s.nez do not Granger-cause s.iip  
##   
## data: VAR object m1  
## F-Test = 17.241, df1 = 1, df2 = 466, p-value = 3.917e-05

m2<-VAR(matrica,p=2,type="const")

#### Slika 2.4.

causality(m2,cause = "s.iip")$Granger

##   
## Granger causality H0: s.iip do not Granger-cause s.nez  
##   
## data: VAR object m2  
## F-Test = 2.8606, df1 = 2, df2 = 460, p-value = 0.05826

causality(m2,cause = "s.nez")$Granger

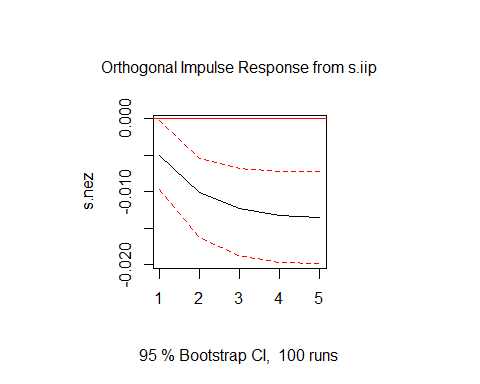
##   
## Granger causality H0: s.nez do not Granger-cause s.iip  
##   
## data: VAR object m2  
## F-Test = 4.7863, df1 = 2, df2 = 460, p-value = 0.008763

## Primjer 2.8

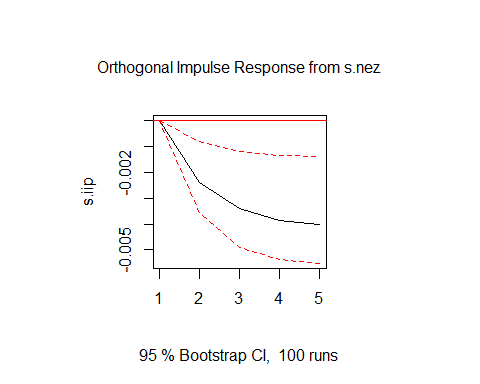
## provesti primjer 2.5.

#### Slika 2.5.

irf1<-irf(m1,n.ahead=4,ortho=T,ci=0.95,impulse="s.iip",response="s.nez")  
irf2<-irf(m1,n.ahead=4,ortho=T,ci=0.95,impulse="s.nez",response="s.iip")  
plot(irf1)

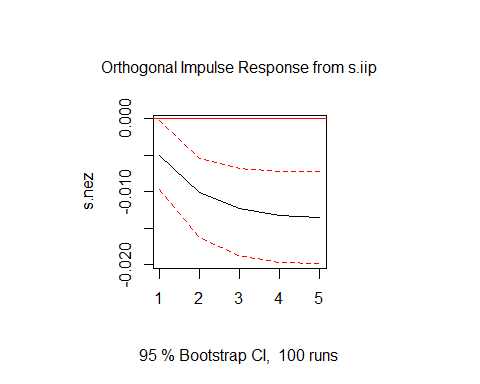


plot(irf2)



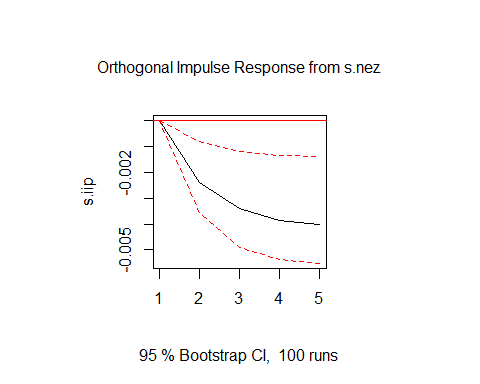
#### Slika 2.6. lijevi panel

plot(irf1)



#### Slika 2.6. desni panel

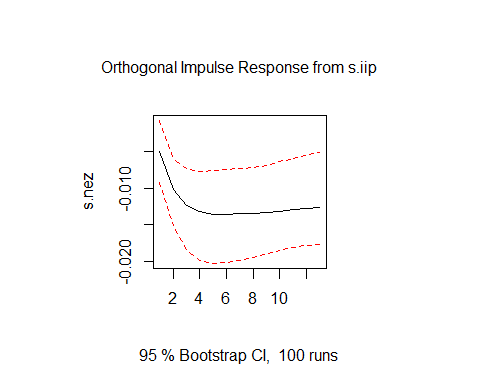
plot(irf2)



irf1<-irf(m1,n.ahead=12,ortho=T,ci=0.95,impulse="s.iip",response="s.nez")  
irf2<-irf(m1,n.ahead=12,ortho=T,ci=0.95,impulse="s.nez",response="s.iip")

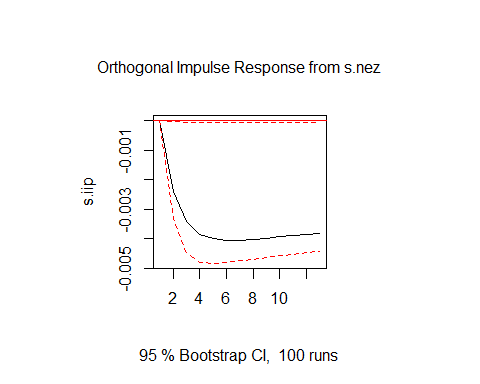
#### Slika 2.7. lijevi panel

plot(irf1)



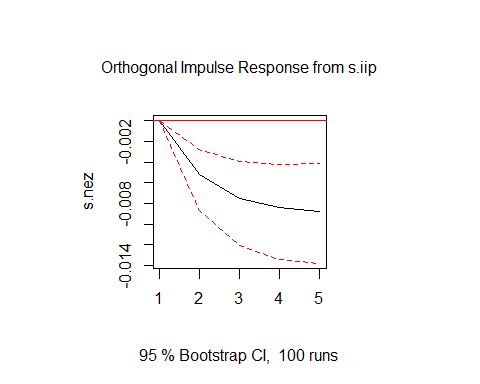
#### Slika 2.7. desni panel

plot(irf2)

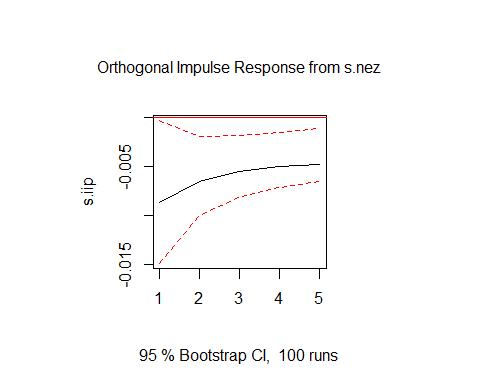


#### Slika 2.8.

matrica2<-cbind(s.nez,s.iip)  
m3<-VAR(matrica2,p=1,type="const")  
irf3<-irf(m3,n.ahead=4,ortho=T,ci=0.95,impulse="s.iip",response="s.nez")  
irf4<-irf(m3,n.ahead=4,ortho=T,ci=0.95,impulse="s.nez",response="s.iip")  
plot(irf3)

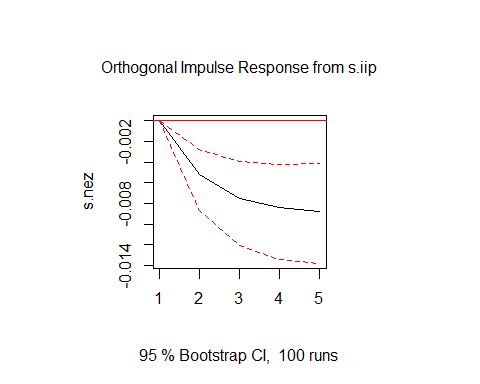


plot(irf4)



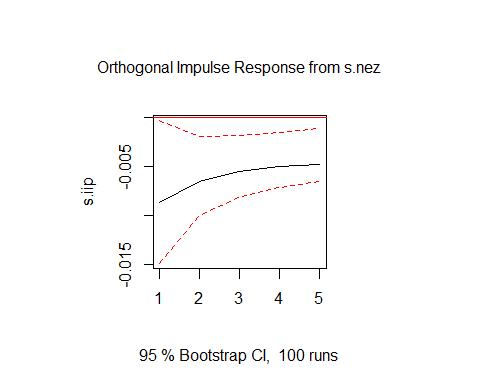
#### Slika 2.9. lijevi panel

plot(irf3)



#### Slika 2.9. desni panel

plot(irf4)

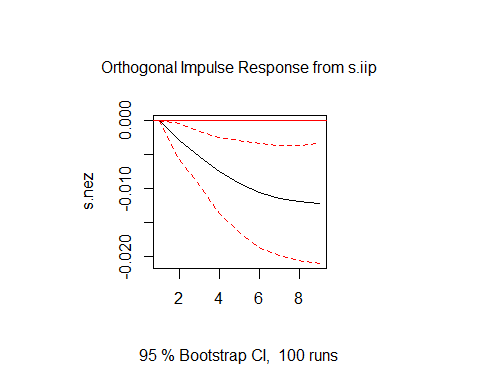


## Primjer 2.9

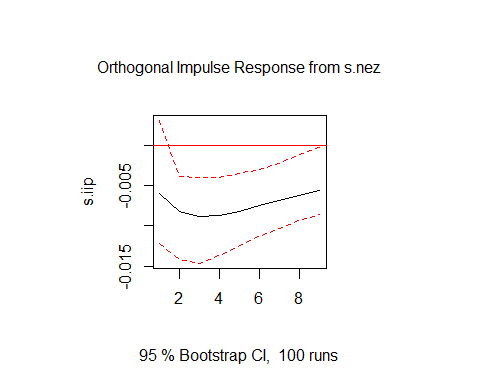
## provesti primjer 2.5.

#### Slika 2.10.

mat2<-cbind(s.nez,s.iip)  
var2<-VAR(mat2,p=2,type="const")  
irf5<-irf(var2,n.ahead=8,ortho=T,ci=0.95,impulse="s.iip",response="s.nez")  
irf6<-irf(var2,n.ahead=8,ortho=T,ci=0.95,impulse="s.nez",response="s.iip")  
plot(irf5)

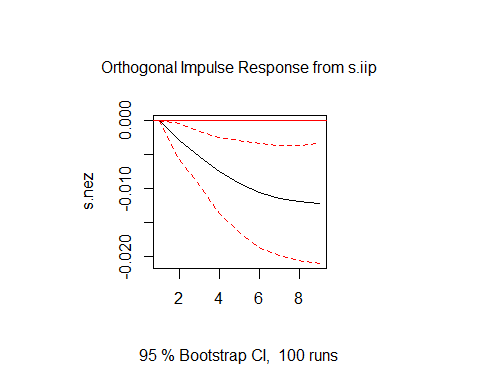


plot(irf6)



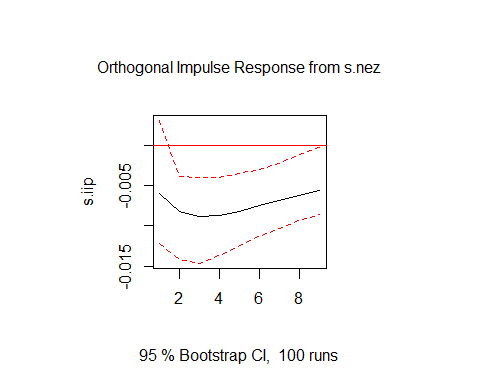
#### Slika 2.11. lijevi panel

plot(irf5)



#### Slika 2.11. desni panel

plot(irf6)



## Primjer 2.11

pod<-read.table("rh\_dinamicki.txt",sep="\t",header = T)  
iip<-ts(pod$hr\_iip,start=c(2001,1),frequency = 12)  
nez<-ts(pod$hr\_nez,start=c(2001,1),frequency = 12)  
iip<-iip/decompose(iip,type="multiplicative")$seasonal  
nez<-nez/decompose(nez,type="multiplicative")$seasonal  
s.iip<-diff(log(iip),12)  
s.nez<-diff(log(nez),12)  
library(vars)  
matrica<-cbind(s.iip,s.nez)  
m1<-VAR(matrica,p=1,type="const")

#### Slika 2.12.

fevd(m1,n.ahead = 4)

## $s.iip  
## s.iip s.nez  
## [1,] 1.0000000 0.000000000  
## [2,] 0.9975982 0.002401810  
## [3,] 0.9930467 0.006953344  
## [4,] 0.9873926 0.012607417  
##   
## $s.nez  
## s.iip s.nez  
## [1,] 0.03922820 0.9607718  
## [2,] 0.09755006 0.9024499  
## [3,] 0.13931147 0.8606885  
## [4,] 0.16751151 0.8324885

matrica<-cbind(s.nez,s.iip)  
m1<-VAR(matrica,p=1,type="const")

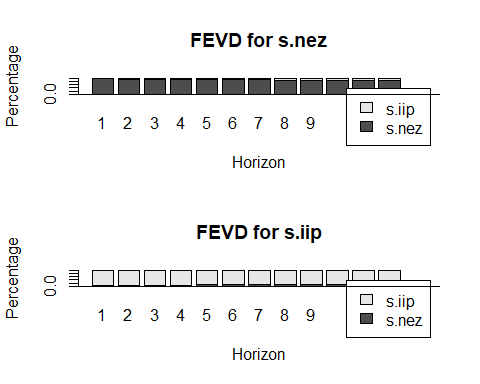
#### Slika 2.13.

fevd(m1,n.ahead = 4)

## $s.nez  
## s.nez s.iip  
## [1,] 1.0000000 0.00000000  
## [2,] 0.9792993 0.02070074  
## [3,] 0.9588250 0.04117500  
## [4,] 0.9435368 0.05646322  
##   
## $s.iip  
## s.nez s.iip  
## [1,] 0.03922820 0.9607718  
## [2,] 0.04961444 0.9503856  
## [3,] 0.05908382 0.9409162  
## [4,] 0.06762972 0.9323703

#### Slika 2.14.

plot(fevd(m1,n.ahead = 12))



## Primjer 2.12

pod<-read.table("rh\_dinamicki.txt",sep="\t",header = T)  
iip<-ts(pod$hr\_iip,start=c(2001,1),frequency = 12)  
nez<-ts(pod$hr\_nez,start=c(2001,1),frequency = 12)  
iip<-iip/decompose(iip,type="multiplicative")$seasonal  
nez<-nez/decompose(nez,type="multiplicative")$seasonal  
s.iip<-diff(log(iip),12)  
s.nez<-diff(log(nez),12)  
library(vars)  
matrica<-cbind(s.iip,s.nez)  
m1<-VAR(matrica,p=1,type="const")  
m2<-VAR(matrica,p=2,type="const")

#### Slika 2.15.

lr<-(length(s.iip)-2\*2+1)\*(log(det(summary(m1)$covres))-log(det(summary(m2)$covres)))  
lr

## [1] 105.0223

pchisq(lr,2^2\*(2+1),lower.tail = F)

## [1] 5.745193e-17

## Primjer 2.13

pod<-read.table("rh\_dinamicki.txt",sep="\t",header = T)  
iip<-ts(pod$hr\_iip,start=c(2001,1),frequency = 12)  
nez<-ts(pod$hr\_nez,start=c(2001,1),frequency = 12)  
iip<-iip/decompose(iip,type="multiplicative")$seasonal  
nez<-nez/decompose(nez,type="multiplicative")$seasonal  
s.iip<-diff(log(iip),12)  
s.nez<-diff(log(nez),12)  
library(vars)  
matrica<-cbind(s.iip,s.nez)

#### Slika 2.16.

VARselect(matrica,lag.max=12,type="const")$selection

## AIC(n) HQ(n) SC(n) FPE(n)   
## 5 5 3 5

## Primjer 2.14

pod<-read.table("rh\_dinamicki.txt",sep="\t",header = T)  
iip<-ts(pod$hr\_iip,start=c(2001,1),frequency = 12)  
nez<-ts(pod$hr\_nez,start=c(2001,1),frequency = 12)  
iip<-iip/decompose(iip,type="multiplicative")$seasonal  
nez<-nez/decompose(nez,type="multiplicative")$seasonal  
s.iip<-diff(log(iip),12)  
s.nez<-diff(log(nez),12)  
library(vars)  
matrica<-cbind(s.iip,s.nez)  
m1<-VAR(matrica,p=1,type="const")

#### Slika 2.16. i 2.17.

serial.test(m1, lags.pt=1, type="PT.asymptotic")

##   
## Portmanteau Test (asymptotic)  
##   
## data: Residuals of VAR object m1  
## Chi-squared = 69.771, df = 0, p-value < 2.2e-16

serial.test(m1, lags.pt=1, type="PT.adjusted")

##   
## Portmanteau Test (adjusted)  
##   
## data: Residuals of VAR object m1  
## Chi-squared = 70.068, df = 0, p-value < 2.2e-16

serial.test(m1, lags.bg=1, type="BG")

##   
## Breusch-Godfrey LM test  
##   
## data: Residuals of VAR object m1  
## Chi-squared = 87.651, df = 4, p-value < 2.2e-16

serial.test(m1, lags.bg=1, type="ES")

##   
## Edgerton-Shukur F test  
##   
## data: Residuals of VAR object m1  
## F statistic = 27.45, df1 = 4, df2 = 460, p-value < 2.2e-16

## Primjer 2.15

pod<-read.table("rh\_dinamicki.txt",sep="\t",header = T)  
iip<-ts(pod$hr\_iip,start=c(2001,1),frequency = 12)  
nez<-ts(pod$hr\_nez,start=c(2001,1),frequency = 12)  
iip<-iip/decompose(iip,type="multiplicative")$seasonal  
nez<-nez/decompose(nez,type="multiplicative")$seasonal  
s.iip<-diff(log(iip),12)  
s.nez<-diff(log(nez),12)  
library(vars)  
matrica<-cbind(s.iip,s.nez)  
m1<-VAR(matrica,p=1,type="const")

#### Slika 2.18.

arch.test(m1,lags.single=1,lags.multi=1,multivariate.only=F)

## $s.iip  
##   
## ARCH test (univariate)  
##   
## data: Residual of s.iip equation  
## Chi-squared = 0.29584, df = 1, p-value = 0.5865  
##   
##   
## $s.nez  
##   
## ARCH test (univariate)  
##   
## data: Residual of s.nez equation  
## Chi-squared = 40.322, df = 1, p-value = 2.154e-10  
##   
##   
##   
## ARCH (multivariate)  
##   
## data: Residuals of VAR object m1  
## Chi-squared = 54.974, df = 9, p-value = 1.232e-08

## Primjer 2.16

pod<-read.table("rh\_dinamicki.txt",sep="\t",header = T)  
iip<-ts(pod$hr\_iip,start=c(2001,1),frequency = 12)  
nez<-ts(pod$hr\_nez,start=c(2001,1),frequency = 12)  
iip<-iip/decompose(iip,type="multiplicative")$seasonal  
nez<-nez/decompose(nez,type="multiplicative")$seasonal  
s.iip<-diff(log(iip),12)  
s.nez<-diff(log(nez),12)  
library(vars)  
matrica<-cbind(s.iip,s.nez)  
m1<-VAR(matrica,p=1,type="const")

#### Slika 2.19.

normality.test(m1,multivariate.only=T)

## $JB  
##   
## JB-Test (multivariate)  
##   
## data: Residuals of VAR object m1  
## Chi-squared = 6122.7, df = 4, p-value < 2.2e-16  
##   
##   
## $Skewness  
##   
## Skewness only (multivariate)  
##   
## data: Residuals of VAR object m1  
## Chi-squared = 396.39, df = 2, p-value < 2.2e-16  
##   
##   
## $Kurtosis  
##   
## Kurtosis only (multivariate)  
##   
## data: Residuals of VAR object m1  
## Chi-squared = 5726.3, df = 2, p-value < 2.2e-16

## 2.8. Primjer

nizevi<-read.table("var.txt",sep="\t",header = T)  
x<-ts(nizevi$x,start=c(2000,1),frequency = 12)  
y<-ts(nizevi$y,start=c(2000,1),frequency = 12)

#### Slika 2.20.

library(urca)  
summary(ur.df(x,type="drift",selectlags="BIC"))

##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -0.51008 -0.14848 -0.00402 0.15670 0.46363   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.52018 0.06153 8.454 3.00e-15 \*\*\*  
## z.lag.1 -0.62887 0.07277 -8.642 8.65e-16 \*\*\*  
## z.diff.lag 0.01040 0.06529 0.159 0.874   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.1974 on 235 degrees of freedom  
## Multiple R-squared: 0.3107, Adjusted R-squared: 0.3048   
## F-statistic: 52.96 on 2 and 235 DF, p-value: < 2.2e-16  
##   
## Value of test-statistic is: -8.6419 37.3416   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

summary(ur.df(y,type="drift",selectlags="BIC"))

##   
## Call:  
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -0.137550 -0.055996 0.008972 0.054913 0.136819   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.59153 0.05474 10.807 <2e-16 \*\*\*  
## z.lag.1 -0.94017 0.08661 -10.856 <2e-16 \*\*\*  
## z.diff.lag 0.03442 0.06195 0.556 0.579   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.07151 on 235 degrees of freedom  
## Multiple R-squared: 0.4544, Adjusted R-squared: 0.4497   
## F-statistic: 97.84 on 2 and 235 DF, p-value: < 2.2e-16  
##   
## Value of test-statistic is: -10.8558 58.9316   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

#### Slika 2.21.

library(vars)  
matrica<-cbind(x,y)  
var1<-VAR(matrica,1,type="const")  
summary(var1)

##   
## VAR Estimation Results:  
## =========================   
## Endogenous variables: x, y   
## Deterministic variables: const   
## Sample size: 239   
## Log Likelihood: 343.224   
## Roots of the characteristic polynomial:  
## 0.3799 0.06187  
## Call:  
## VAR(y = matrica, p = 1, type = "const")  
##   
##   
## Estimation results for equation x:   
## ==================================   
## x = x.l1 + y.l1 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## x.l1 0.38232 0.06057 6.312 1.35e-09 \*\*\*  
## y.l1 -0.07248 0.17050 -0.425 0.671   
## const 0.55726 0.11522 4.837 2.38e-06 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.1971 on 236 degrees of freedom  
## Multiple R-Squared: 0.1445, Adjusted R-squared: 0.1373   
## F-statistic: 19.93 on 2 and 236 DF, p-value: 1.004e-08   
##   
##   
## Estimation results for equation y:   
## ==================================   
## y = x.l1 + y.l1 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## x.l1 0.01075 0.02202 0.488 0.626   
## y.l1 0.05944 0.06199 0.959 0.339   
## const 0.58244 0.04189 13.904 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.07168 on 236 degrees of freedom  
## Multiple R-Squared: 0.005275, Adjusted R-squared: -0.003155   
## F-statistic: 0.6258 on 2 and 236 DF, p-value: 0.5357   
##   
##   
##   
## Covariance matrix of residuals:  
## x y  
## x 0.0388660 0.0008745  
## y 0.0008745 0.0051375  
##   
## Correlation matrix of residuals:  
## x y  
## x 1.00000 0.06189  
## y 0.06189 1.00000

#### Slika 2.22.

var2<-VAR(matrica,2,type="const")  
summary(var2)

##   
## VAR Estimation Results:  
## =========================   
## Endogenous variables: x, y   
## Deterministic variables: const   
## Sample size: 238   
## Log Likelihood: 344.486   
## Roots of the characteristic polynomial:  
## 0.4166 0.3172 0.3172 0.1469  
## Call:  
## VAR(y = matrica, p = 2, type = "const")  
##   
##   
## Estimation results for equation x:   
## ==================================   
## x = x.l1 + y.l1 + x.l2 + y.l2 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## x.l1 0.38863 0.06545 5.938 1.04e-08 \*\*\*  
## y.l1 -0.14594 0.18003 -0.811 0.4184   
## x.l2 -0.01965 0.06546 -0.300 0.7643   
## y.l2 0.26753 0.17144 1.560 0.1200   
## const 0.44515 0.15814 2.815 0.0053 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.197 on 233 degrees of freedom  
## Multiple R-Squared: 0.153, Adjusted R-squared: 0.1384   
## F-statistic: 10.52 on 4 and 233 DF, p-value: 7.503e-08   
##   
##   
## Estimation results for equation y:   
## ==================================   
## y = x.l1 + y.l1 + x.l2 + y.l2 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## x.l1 0.001635 0.023786 0.069 0.945   
## y.l1 0.091397 0.065425 1.397 0.164   
## x.l2 0.026013 0.023790 1.093 0.275   
## y.l2 -0.040774 0.062304 -0.654 0.513   
## const 0.574458 0.057469 9.996 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.07159 on 233 degrees of freedom  
## Multiple R-Squared: 0.01589, Adjusted R-squared: -0.001008   
## F-statistic: 0.9403 on 4 and 233 DF, p-value: 0.4413   
##   
##   
##   
## Covariance matrix of residuals:  
## x y  
## x 0.038808 0.001039  
## y 0.001039 0.005125  
##   
## Correlation matrix of residuals:  
## x y  
## x 1.00000 0.07369  
## y 0.07369 1.00000

#### Slika 2.23.

VARselect(matrica,lag.max = 12,type="const")$selection

## AIC(n) HQ(n) SC(n) FPE(n)   
## 1 1 1 1

library(lmtest)

#### Slika 2.24.

causality(var1,cause="x")$Granger

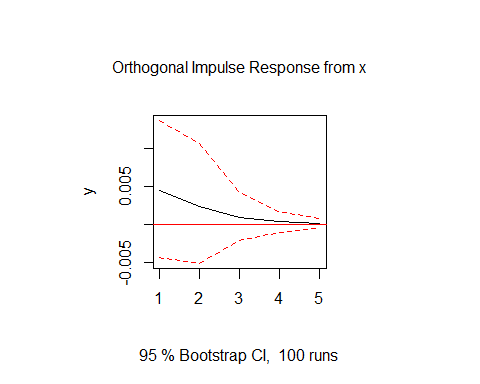
##   
## Granger causality H0: x do not Granger-cause y  
##   
## data: VAR object var1  
## F-Test = 0.23814, df1 = 1, df2 = 472, p-value = 0.6258

causality(var1,cause="y")$Granger

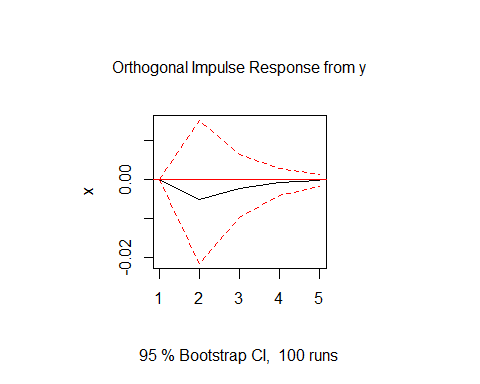
##   
## Granger causality H0: y do not Granger-cause x  
##   
## data: VAR object var1  
## F-Test = 0.18069, df1 = 1, df2 = 472, p-value = 0.671

#### Slika 2.25.

plot(irf(var1,n.ahead = 4,ortho=T,ci=.95,impulse="x",response="y"))



plot(irf(var1,n.ahead = 4,ortho=T,ci=.95,impulse="y",response="x"))



#### Slika 2.26.

fevd(var1,n.ahead=4)

## $x  
## x y  
## [1,] 1.0000000 0.0000000000  
## [2,] 0.9993962 0.0006037627  
## [3,] 0.9992914 0.0007085612  
## [4,] 0.9992759 0.0007241413  
##   
## $y  
## x y  
## [1,] 0.003829971 0.9961700  
## [2,] 0.004911857 0.9950881  
## [3,] 0.005085095 0.9949149  
## [4,] 0.005110467 0.9948895

#### Slika 2.27.

serial.test(var1, lags.pt=4, type="PT.asymptotic")

##   
## Portmanteau Test (asymptotic)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 15.964, df = 12, p-value = 0.1929

serial.test(var1, lags.pt=4, type="PT.adjusted")

##   
## Portmanteau Test (adjusted)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 16.152, df = 12, p-value = 0.1844

serial.test(var1, lags.bg=4, type="BG")

##   
## Breusch-Godfrey LM test  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 21.561, df = 16, p-value = 0.1579

serial.test(var1, lags.bg=4, type="ES")

##   
## Edgerton-Shukur F test  
##   
## data: Residuals of VAR object var1  
## F statistic = 1.3421, df1 = 16, df2 = 454, p-value = 0.1672

#### Slika 2.28.

arch.test(var1,lags.single=1,lags.multi=1,multivariate.only=F)

## $x  
##   
## ARCH test (univariate)  
##   
## data: Residual of x equation  
## Chi-squared = 0.39548, df = 1, p-value = 0.5294  
##   
##   
## $y  
##   
## ARCH test (univariate)  
##   
## data: Residual of y equation  
## Chi-squared = 1.1683, df = 1, p-value = 0.2798  
##   
##   
##   
## ARCH (multivariate)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 3.7906, df = 9, p-value = 0.9246

#### Slika 2.29.

normality.test(var1,multivariate.only = T)

## $JB  
##   
## JB-Test (multivariate)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 14.581, df = 4, p-value = 0.005654  
##   
##   
## $Skewness  
##   
## Skewness only (multivariate)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 0.038716, df = 2, p-value = 0.9808  
##   
##   
## $Kurtosis  
##   
## Kurtosis only (multivariate)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 14.542, df = 2, p-value = 0.0006953

#### 2.9. pitanja za ponavljanje, zadatak 25:

nizevi<-read.table("var.txt",sep="\t",header = T)  
z<-ts(nizevi$z,start=c(2000,1),frequency = 12)  
w<-ts(nizevi$w,start=c(2000,1),frequency = 12)  
  
library(urca)  
summary(ur.df(z,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # 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   
## -0.47488 -0.14789 0.01018 0.15145 0.50318   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.51073 0.06420 7.955 7.54e-14 \*\*\*  
## z.lag.1 -0.59539 0.07313 -8.142 2.29e-14 \*\*\*  
## z.diff.lag -0.05164 0.06527 -0.791 0.43   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.2011 on 235 degrees of freedom  
## Multiple R-squared: 0.3156, Adjusted R-squared: 0.3098   
## F-statistic: 54.19 on 2 and 235 DF, p-value: < 2.2e-16  
##   
##   
## Value of test-statistic is: -8.1415 33.1455   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

summary(ur.df(w,type="drift",selectlags="BIC"))

##   
## ###############################################   
## # 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   
## -0.3903 -0.1295 -0.0065 0.1373 0.3076   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.38134 0.05379 7.090 1.56e-11 \*\*\*  
## z.lag.1 -0.47791 0.06614 -7.226 6.92e-12 \*\*\*  
## z.diff.lag -0.07828 0.06461 -1.212 0.227   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.1628 on 235 degrees of freedom  
## Multiple R-squared: 0.2648, Adjusted R-squared: 0.2585   
## F-statistic: 42.31 on 2 and 235 DF, p-value: < 2.2e-16  
##   
##   
## Value of test-statistic is: -7.2258 26.1062   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

library(vars)  
matrica<-cbind(z,w)  
var1<-VAR(matrica,1,type="const")  
summary(var1)

##   
## VAR Estimation Results:  
## =========================   
## Endogenous variables: z, w   
## Deterministic variables: const   
## Sample size: 239   
## Log Likelihood: 142.311   
## Roots of the characteristic polynomial:  
## 0.4557 0.3906  
## Call:  
## VAR(y = matrica, p = 1, type = "const")  
##   
##   
## Estimation results for equation z:   
## ==================================   
## z = z.l1 + w.l1 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## z.l1 0.37211 0.06000 6.202 2.48e-09 \*\*\*  
## w.l1 0.12247 0.06957 1.760 0.0796 .   
## const 0.44089 0.07697 5.728 3.08e-08 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.1996 on 236 degrees of freedom  
## Multiple R-Squared: 0.1495, Adjusted R-squared: 0.1423   
## F-statistic: 20.75 on 2 and 236 DF, p-value: 5.001e-09   
##   
##   
## Estimation results for equation w:   
## ==================================   
## w = z.l1 + w.l1 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## z.l1 -0.01259 0.04930 -0.255 0.799   
## w.l1 0.47412 0.05717 8.294 8.39e-15 \*\*\*  
## const 0.42923 0.06325 6.786 9.21e-11 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.164 on 236 degrees of freedom  
## Multiple R-Squared: 0.2259, Adjusted R-squared: 0.2193   
## F-statistic: 34.43 on 2 and 236 DF, p-value: 7.558e-14   
##   
##   
##   
## Covariance matrix of residuals:  
## z w  
## z 0.039855 -0.001989  
## w -0.001989 0.026912  
##   
## Correlation matrix of residuals:  
## z w  
## z 1.00000 -0.06073  
## w -0.06073 1.00000

var2<-VAR(matrica,2,type="const")  
summary(var2)

##   
## VAR Estimation Results:  
## =========================   
## Endogenous variables: z, w   
## Deterministic variables: const   
## Sample size: 238   
## Log Likelihood: 144.178   
## Roots of the characteristic polynomial:  
## 0.6209 0.414 0.1211 0.1211  
## Call:  
## VAR(y = matrica, p = 2, type = "const")  
##   
##   
## Estimation results for equation z:   
## ==================================   
## z = z.l1 + w.l1 + z.l2 + w.l2 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## z.l1 0.35150 0.06553 5.364 1.96e-07 \*\*\*  
## w.l1 0.11859 0.07990 1.484 0.139   
## z.l2 0.05411 0.06517 0.830 0.407   
## w.l2 0.01279 0.08026 0.159 0.873   
## const 0.40513 0.09018 4.492 1.11e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.2006 on 233 degrees of freedom  
## Multiple R-Squared: 0.1523, Adjusted R-squared: 0.1377   
## F-statistic: 10.46 on 4 and 233 DF, p-value: 8.228e-08   
##   
##   
## Estimation results for equation w:   
## ==================================   
## w = z.l1 + w.l1 + z.l2 + w.l2 + const   
##   
## Estimate Std. Error t value Pr(>|t|)   
## z.l1 -0.03889 0.05327 -0.730 0.466   
## w.l1 0.44219 0.06495 6.808 8.30e-11 \*\*\*  
## z.l2 0.05969 0.05298 1.127 0.261   
## w.l2 0.08383 0.06525 1.285 0.200   
## const 0.36025 0.07331 4.914 1.68e-06 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
##   
## Residual standard error: 0.1631 on 233 degrees of freedom  
## Multiple R-Squared: 0.2416, Adjusted R-squared: 0.2285   
## F-statistic: 18.55 on 4 and 233 DF, p-value: 2.985e-13   
##   
##   
##   
## Covariance matrix of residuals:  
## z w  
## z 0.040236 -0.002228  
## w -0.002228 0.026589  
##   
## Correlation matrix of residuals:  
## z w  
## z 1.0000 -0.0681  
## w -0.0681 1.0000

VARselect(matrica,lag.max = 12,type="const")$selection

## AIC(n) HQ(n) SC(n) FPE(n)   
## 1 1 1 1

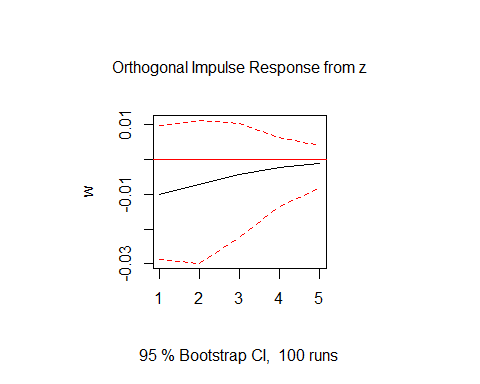
library(lmtest)  
  
causality(var1,cause="z")$Granger

##   
## Granger causality H0: z do not Granger-cause w  
##   
## data: VAR object var1  
## F-Test = 0.065192, df1 = 1, df2 = 472, p-value = 0.7986

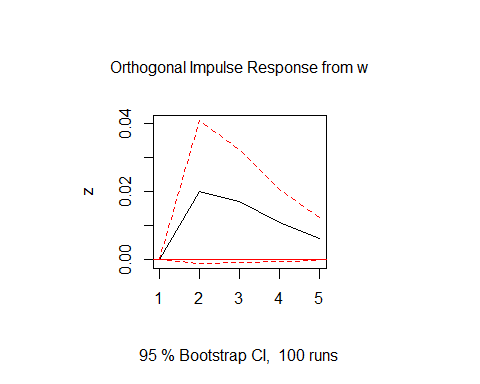
causality(var1,cause="w")$Granger

##   
## Granger causality H0: w do not Granger-cause z  
##   
## data: VAR object var1  
## F-Test = 3.0991, df1 = 1, df2 = 472, p-value = 0.07898

plot(irf(var1,n.ahead = 4,ortho=T,ci=.95,impulse="z",response="w"))



plot(irf(var1,n.ahead = 4,ortho=T,ci=.95,impulse="w",response="z"))



fevd(var1,n.ahead=4)

## $z  
## z w  
## [1,] 1.0000000 0.000000000  
## [2,] 0.9911803 0.008819668  
## [3,] 0.9851829 0.014817084  
## [4,] 0.9827573 0.017242655  
##   
## $w  
## z w  
## [1,] 0.003687650 0.9963124  
## [2,] 0.004595303 0.9954047  
## [3,] 0.004965078 0.9950349  
## [4,] 0.005087667 0.9949123

serial.test(var1, lags.pt=4, type="PT.asymptotic")

##   
## Portmanteau Test (asymptotic)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 10.086, df = 12, p-value = 0.6084

serial.test(var1, lags.pt=4, type="PT.adjusted")

##   
## Portmanteau Test (adjusted)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 10.202, df = 12, p-value = 0.5983

serial.test(var1, lags.bg=4, type="BG")

##   
## Breusch-Godfrey LM test  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 12.609, df = 16, p-value = 0.7011

serial.test(var1, lags.bg=4, type="ES")

##   
## Edgerton-Shukur F test  
##   
## data: Residuals of VAR object var1  
## F statistic = 0.7724, df1 = 16, df2 = 454, p-value = 0.7174

arch.test(var1,lags.single=1,lags.multi=1,multivariate.only=F)

## $z  
##   
## ARCH test (univariate)  
##   
## data: Residual of z equation  
## Chi-squared = 1.4643, df = 1, p-value = 0.2262  
##   
##   
## $w  
##   
## ARCH test (univariate)  
##   
## data: Residual of w equation  
## Chi-squared = 0.065674, df = 1, p-value = 0.7977  
##   
##   
##   
## ARCH (multivariate)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 7.7129, df = 9, p-value = 0.5633

normality.test(var1,multivariate.only = T)

## $JB  
##   
## JB-Test (multivariate)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 11.879, df = 4, p-value = 0.01827  
##   
##   
## $Skewness  
##   
## Skewness only (multivariate)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 0.538, df = 2, p-value = 0.7641  
##   
##   
## $Kurtosis  
##   
## Kurtosis only (multivariate)  
##   
## data: Residuals of VAR object var1  
## Chi-squared = 11.341, df = 2, p-value = 0.003446

# POGLAVLJE 3

## Primjer 3.1.

#### Slika 3.1.

vec<-read.table("vec.txt",header = T, sep="\t")  
y1<-ts(vec$y1,start=c(2002,1),frequency = 12)  
y2<-ts(vec$y2,start=c(2002,1),frequency = 12)  
y3<-ts(vec$y3,start=c(2002,1),frequency = 12)  
y4<-ts(vec$y4,start=c(2002,1),frequency = 12)  
library(urca)  
summary(ur.df(y1,type="drift",selectlags="BIC"))@teststat[1,1];

## [1] -2.758782

summary(ur.df(y2,type="drift",selectlags="BIC"))@teststat[1,1];

## [1] 1.081476

summary(ur.df(y3,type="drift",selectlags="BIC"))@teststat[1,1];

## [1] -2.390705

summary(ur.df(y4,type="drift",selectlags="BIC"))@teststat[1,1]

## [1] -2.477187

library(vars)  
library(tsDyn)

## Warning: package 'tsDyn' was built under R version 4.2.2

#### Slika 3.2.

m1<-cbind(y1,y4)  
VARselect(m1,12,type="none")$selection

## AIC(n) HQ(n) SC(n) FPE(n)   
## 1 1 1 1

vec1<-VECM(m1,lag=0,include="none",LRinclude="none",estim="ML")

summary(rank.test(vec1))

## r trace trace\_pval trace\_pval\_T eigen eigen\_pval  
## 1 0 11.39036655 0.07075 0.07227 11.33785471 0.04653  
## 2 1 0.05251183 0.87588 0.86742 0.05251183 0.86785

#### Slika 3.3.

m2<-cbind(y2,y4)  
VARselect(m2,12,type="none")$selection

## AIC(n) HQ(n) SC(n) FPE(n)   
## 1 1 1 1

vec2<-VECM(m2,lag=0,include="none",LRinclude="none",estim="ML")

## Warning in lineVar(data, lag, r = r, include = include, model = "VECM", : Lag=0  
## not fully implemented, methods not expected to work: fevd, predict, irf,...

summary(rank.test(vec2))

## r trace trace\_pval trace\_pval\_T eigen eigen\_pval  
## 1 0 21.6002427 <0.001 <0.001 20.7344632 <0.001  
## 2 1 0.8657795 0.4085 0.404 0.8657795 0.4042

#### Slika 3.4.

m3<-cbind(y3,y1)  
VARselect(m3,12,type="none")$selection

## AIC(n) HQ(n) SC(n) FPE(n)   
## 1 1 1 1

vec3<-VECM(m3,lag=0,include="none",LRinclude="none",estim="ML")

## Warning in lineVar(data, lag, r = r, include = include, model = "VECM", : Lag=0  
## not fully implemented, methods not expected to work: fevd, predict, irf,...

summary(rank.test(vec3))

## r trace trace\_pval trace\_pval\_T eigen eigen\_pval  
## 1 0 9.89331842 0.1238 0.1266 9.82016071 0.08757  
## 2 1 0.07315771 0.8485 0.8395 0.07315771 0.83994

#### Slika 3.5.

summary(vec2)

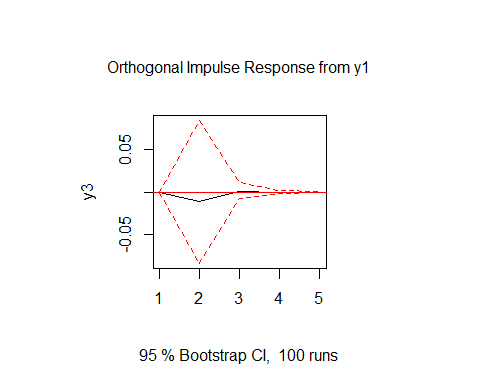
## #############  
## ###Model VECM   
## #############  
## Full sample size: 220 End sample size: 219  
## Number of variables: 2 Number of estimated slope parameters 2  
## AIC 150.8868 BIC 161.0541 SSR 868.1138  
## Cointegrating vector (estimated by ML):  
## y2 y4  
## r1 1 48.15125  
##   
##   
## ECT   
## Equation y2 0.0012(0.0003)\*\*\*   
## Equation y4 2.7e-05(0.0001)

summary(vec2)$coefMat

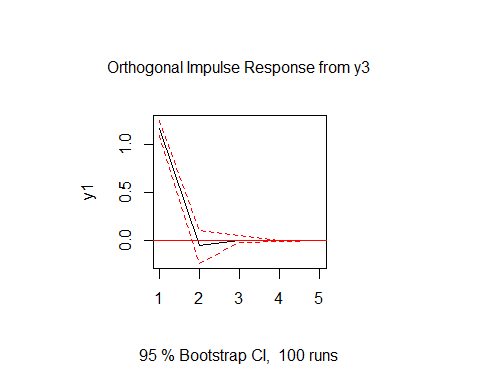
## Estimate Std. Error t value Pr(>|t|)  
## y2:ECT 1.190482e-03 0.0002568956 4.634106 6.167974e-06  
## y4:ECT 2.694515e-05 0.0001054931 0.255421 7.986388e-01

#### Slika 3.6.

var<-VAR(diff(m3),p=1,type="none")  
plot(irf(var,impulse="y1",response="y3",ci=0.95,n.ahead=4,ortho=T))

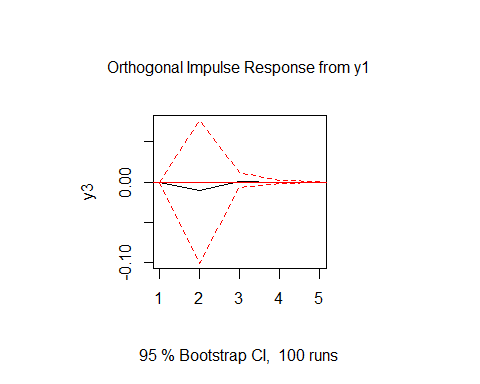


plot(irf(var,impulse="y3",response="y1",ci=0.95,n.ahead=4,ortho=T))



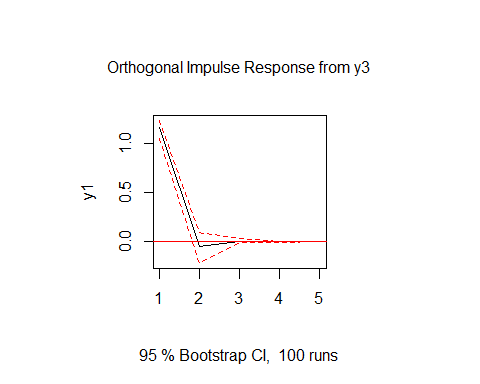
#### Slika 3.7 lijevi panel

plot(irf(var,impulse="y1",response="y3",ci=0.95,n.ahead=4,ortho=T))



#### Slika 3.7. desni panel

plot(irf(var,impulse="y3",response="y1",ci=0.95,n.ahead=4,ortho=T))



#### Slika 3.8.

m4<-cbind(y1,y2,y3)  
vec4<-VECM(m4,lag=1,r=2,include="none",LRinclude="none",estim="ML")  
summary(vec4)

## #############  
## ###Model VECM   
## #############  
## Full sample size: 220 End sample size: 218  
## Number of variables: 3 Number of estimated slope parameters 15  
## AIC -1220.924 BIC -1163.388 SSR 1102.6  
## Cointegrating vector (estimated by ML):  
## y1 y2 y3  
## r1 1 5.20417e-18 -2.779373  
## r2 0 1.00000e+00 50.364341  
##   
##   
## ECT1 ECT2 y1 -1   
## Equation y1 1.9039(0.6537)\*\* 0.0369(0.0126)\*\* -2.2353(1.6519)   
## Equation y2 -0.8194(1.0531) -0.0146(0.0203) -1.4975(2.6610)   
## Equation y3 1.0944(0.3665)\*\* 0.0212(0.0071)\*\* -1.2550(0.9259)   
## y2 -1 y3 -1   
## Equation y1 -0.0646(0.0494) 3.8852(2.9418)   
## Equation y2 -0.1140(0.0796) 2.5234(4.7389)   
## Equation y3 -0.0368(0.0277) 2.1778(1.6490)

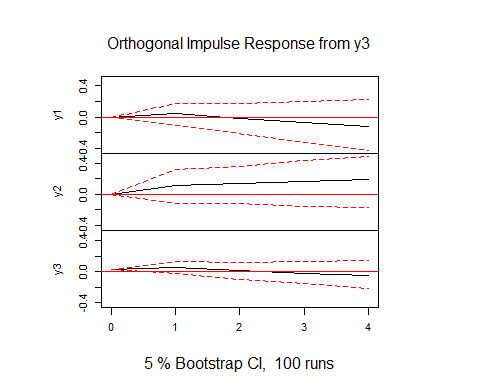
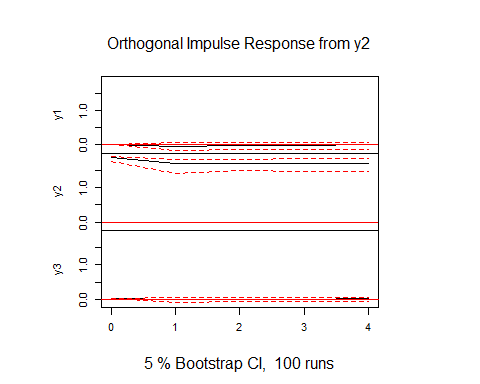
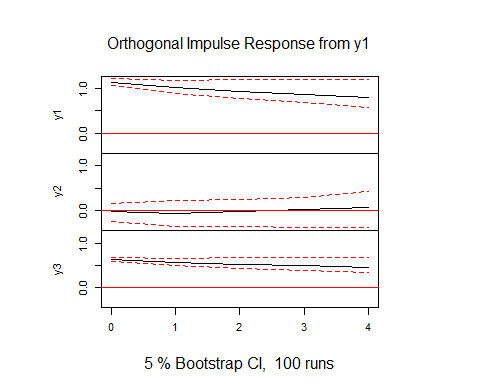
#### Slika 3.9.

m4<-cbind(y1,y2,y3)  
vec4<-VECM(m4,lag=1,r=2,include="const",LRinclude="none",estim="ML")  
summary(vec4)

## #############  
## ###Model VECM   
## #############  
## Full sample size: 220 End sample size: 218  
## Number of variables: 3 Number of estimated slope parameters 18  
## AIC -1230.322 BIC -1162.632 SSR 1096.422  
## Cointegrating vector (estimated by ML):  
## y1 y2 y3  
## r1 1 1.387779e-17 -1.141363  
## r2 0 1.000000e+00 -34.561214  
##   
##   
## ECT1 ECT2 Intercept   
## Equation y1 1.1378(0.7244) 0.0253(0.0133). 0.9702(0.4090)\*   
## Equation y2 -0.9386(1.1841) -0.0194(0.0218) 0.2403(0.6685)   
## Equation y3 0.6890(0.4066). 0.0150(0.0075)\* 0.5148(0.2296)\*   
## y1 -1 y2 -1 y3 -1   
## Equation y1 -2.2801(1.6348) -0.0670(0.0488) 4.0208(2.9118)   
## Equation y2 -1.5436(2.6724) -0.1076(0.0797) 2.6075(4.7598)   
## Equation y3 -1.2793(0.9177) -0.0380(0.0274) 2.2506(1.6346)

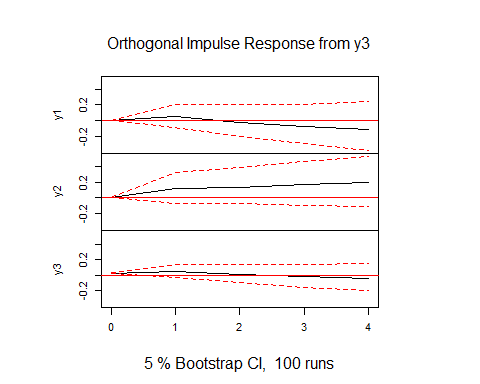
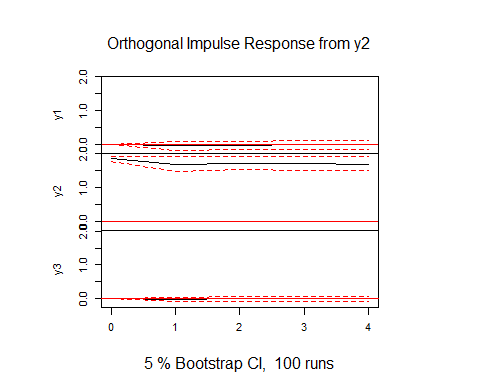
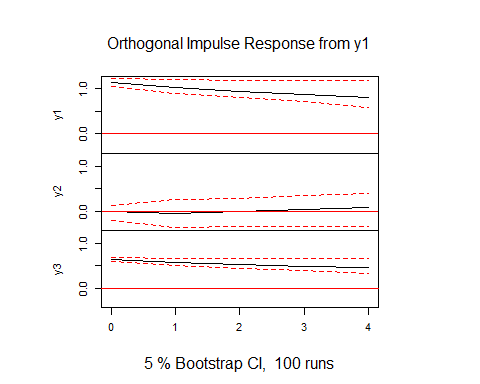
#### Slika 3.10. prvi red prvi stupac

plot(irf(vec4,impulse="y1",response="y2",ci=0.95,n.ahead=4,ortho=T))



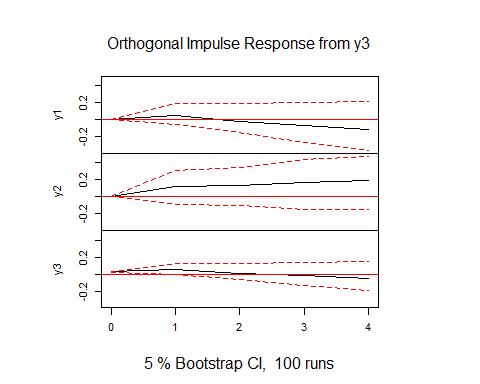
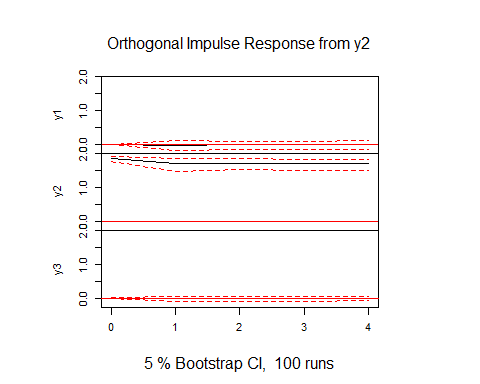
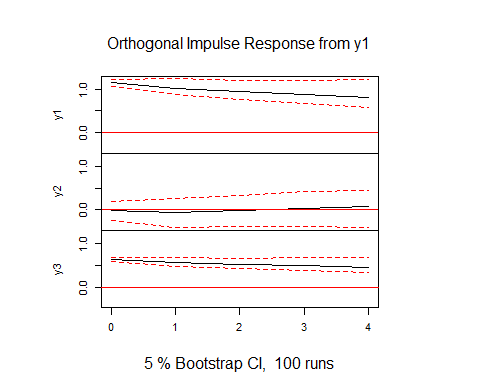
#### Slika 3.10. prvi red drugi stupac

plot(irf(vec4,impulse="y1",response="y3",ci=0.95,n.ahead=4,ortho=T))



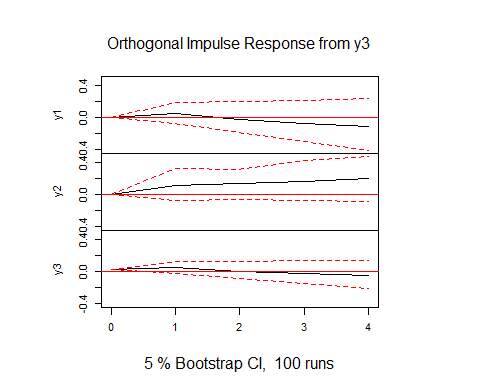
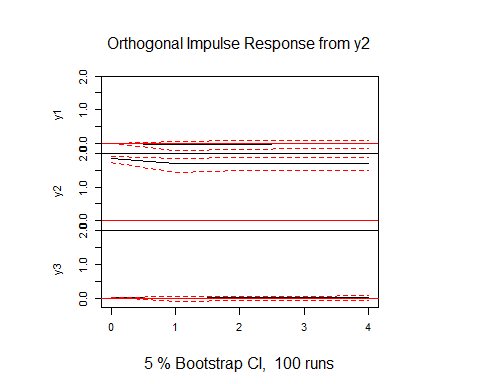
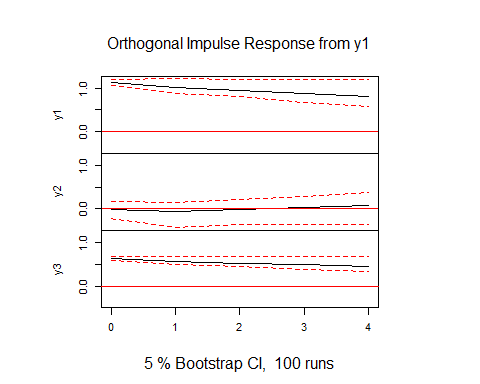
#### Slika 3.10. drugi red prvi stupac

plot(irf(vec4,impulse="y2",response="y1",ci=0.95,n.ahead=4,ortho=T))



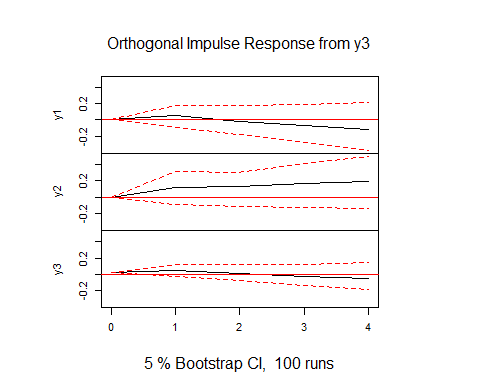
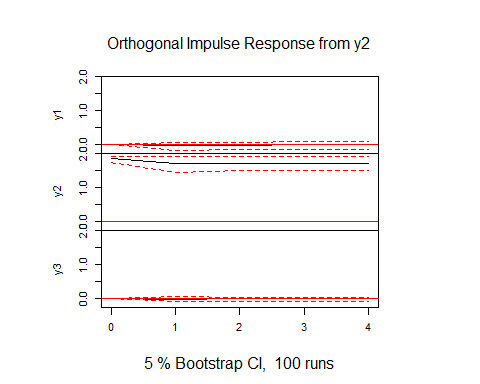
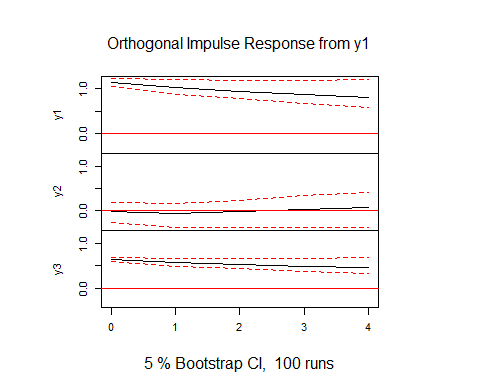
#### Slika 3.10. drugi red drugi stupac

plot(irf(vec4,impulse="y2",response="y3",ci=0.95,n.ahead=4,ortho=T))



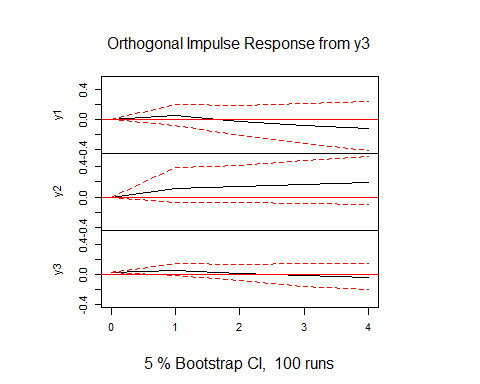
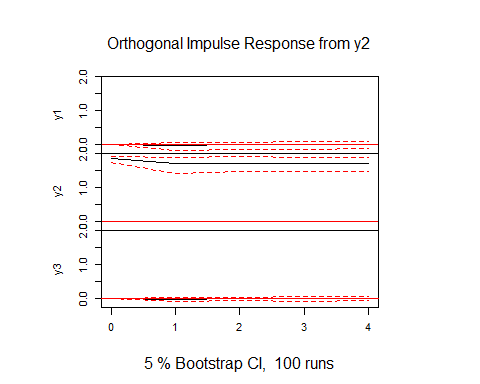
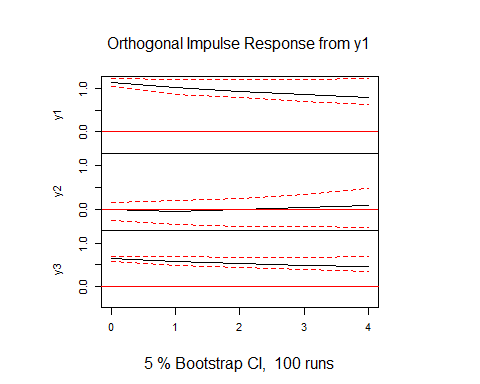
#### Slika 3.10. treći red prvi stupac

plot(irf(vec4,impulse="y3",response="y1",ci=0.95,n.ahead=4,ortho=T))



#### Slika 3.10. trećii red drugi stupac

plot(irf(vec4,impulse="y3",response="y2",ci=0.95,n.ahead=4,ortho=T))



## Primjer 3.2

vec<-read.table("vec.txt",header = T, sep="\t")  
y1<-ts(vec$y1,start=c(2002,1),frequency = 12)  
y2<-ts(vec$y2,start=c(2002,1),frequency = 12)  
y3<-ts(vec$y3,start=c(2002,1),frequency = 12)  
y4<-ts(vec$y4,start=c(2002,1),frequency = 12)  
  
library(tsDyn)  
m2<-cbind(y2,y4)

#### Slika 3.11.

vec6<-VECM(m2,lag=0,include="const",LRinclude="none",estim="ML")

## Warning in lineVar(data, lag, r = r, include = include, model = "VECM", : Lag=0  
## not fully implemented, methods not expected to work: fevd, predict, irf,...

summary(vec6)

## #############  
## ###Model VECM   
## #############  
## Full sample size: 220 End sample size: 219  
## Number of variables: 2 Number of estimated slope parameters 4  
## AIC 143.8678 BIC 157.4241 SSR 864.8431  
## Cointegrating vector (estimated by ML):  
## y2 y4  
## r1 1 -40.11634  
##   
##   
## ECT Intercept   
## Equation y2 -0.0018(0.0016) 0.0130(0.4772)   
## Equation y4 0.0019(0.0006)\*\* 0.6017(0.1914)\*\*

## 3.4. Primjer

#### Slika 3.12.

vec<-read.table("vec\_primjer.txt",header = T, sep="\t")  
x<-ts(vec$x,start=c(2003,1),frequency = 12)  
y1<-ts(vec$y1,start=c(2003,1),frequency = 12)  
y2<-ts(vec$y2,start=c(2003,1),frequency = 12)  
  
library(urca)  
summary(ur.df(x,type="drift",selectlags = "BIC"))

##   
## ###############################################   
## # 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   
## -3.04816 -0.68731 0.00905 0.77294 2.13634   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -0.16629 0.10376 -1.603 0.1106   
## z.lag.1 -0.03301 0.01755 -1.881 0.0615 .  
## z.diff.lag 0.01788 0.07192 0.249 0.8039   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1.015 on 195 degrees of freedom  
## Multiple R-squared: 0.01781, Adjusted R-squared: 0.00774   
## F-statistic: 1.768 on 2 and 195 DF, p-value: 0.1733  
##   
##   
## Value of test-statistic is: -1.8805 1.8333   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

summary(ur.df(y1,type="drift",selectlags = "BIC"))

##   
## ###############################################   
## # 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   
## -2.39257 -0.69635 -0.01544 0.66751 2.67981   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -0.38745 0.15881 -2.440 0.0156 \*  
## z.lag.1 -0.05822 0.02322 -2.507 0.0130 \*  
## z.diff.lag 0.02898 0.07149 0.405 0.6857   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1.01 on 195 degrees of freedom  
## Multiple R-squared: 0.03122, Adjusted R-squared: 0.02128   
## F-statistic: 3.142 on 2 and 195 DF, p-value: 0.0454  
##   
##   
## Value of test-statistic is: -2.5067 3.2435   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

summary(ur.df(y2,type="drift",selectlags = "BIC"))

##   
## ###############################################   
## # 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   
## -4.7055 -1.0340 0.1154 1.1284 3.4861   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -0.29062 0.14518 -2.002 0.0467 \*   
## z.lag.1 -0.07536 0.03056 -2.466 0.0145 \*   
## z.diff.lag -0.28407 0.06748 -4.210 3.9e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1.442 on 195 degrees of freedom  
## Multiple R-squared: 0.1337, Adjusted R-squared: 0.1249   
## F-statistic: 15.05 on 2 and 195 DF, p-value: 8.33e-07  
##   
##   
## Value of test-statistic is: -2.4659 3.106   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

library(vars)  
library(tsDyn)

#### Slika 3.13

m1<-cbind(x,y1)  
VARselect(m1,12,type="none")$selection

## AIC(n) HQ(n) SC(n) FPE(n)   
## 1 1 1 1

vec1<-VECM(m1,lag=0,include="none",LRinclude="none",estim="ML")

## Warning in lineVar(data, lag, r = r, include = include, model = "VECM", : Lag=0  
## not fully implemented, methods not expected to work: fevd, predict, irf,...

summary(rank.test(vec1))

## r trace trace\_pval trace\_pval\_T eigen eigen\_pval  
## 1 0 3.5299544 0.7674 0.7766 3.1534852 0.7593  
## 2 1 0.3764692 0.6107 0.6021 0.3764692 0.6024

#### Slika 3.14.

m2<-cbind(x,y2)  
VARselect(m2,12,type="none")$selection

## AIC(n) HQ(n) SC(n) FPE(n)   
## 1 1 1 1

vec2<-VECM(m2,lag=0,include="none",LRinclude="none",estim="ML")

## Warning in lineVar(data, lag, r = r, include = include, model = "VECM", : Lag=0  
## not fully implemented, methods not expected to work: fevd, predict, irf,...

summary(rank.test(vec2))

## r trace trace\_pval trace\_pval\_T eigen eigen\_pval  
## 1 0 147.590311 <0.001 <0.001 146.476284 <0.001  
## 2 1 1.114027 0.3398 0.3369 1.114027 0.337

#### Slika 3.15.

summary(vec2)

## #############  
## ###Model VECM   
## #############  
## Full sample size: 200 End sample size: 199  
## Number of variables: 2 Number of estimated slope parameters 2  
## AIC 4.860005 BIC 14.73992 SSR 525.1199  
## Cointegrating vector (estimated by ML):  
## x y2  
## r1 1 -1.256386  
##   
##   
## ECT   
## Equation x -0.1304(0.0570)\*   
## Equation y2 0.7132(0.0725)\*\*\*

coefA(vec2); coefB(vec2);coefPI(vec2)

## ECT  
## Equation x -0.1304307  
## Equation y2 0.7132276

## r1  
## x 1.000000  
## y2 -1.256386

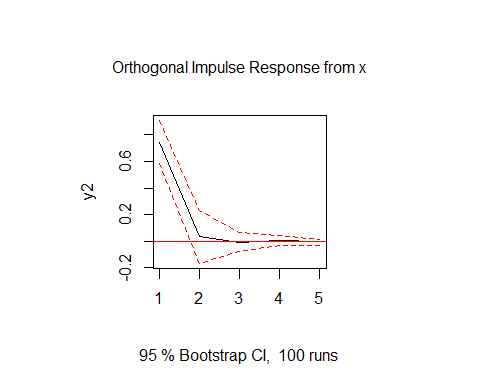
## x y2  
## Equation x -0.1304307 0.1638712  
## Equation y2 0.7132276 -0.8960889

vec2

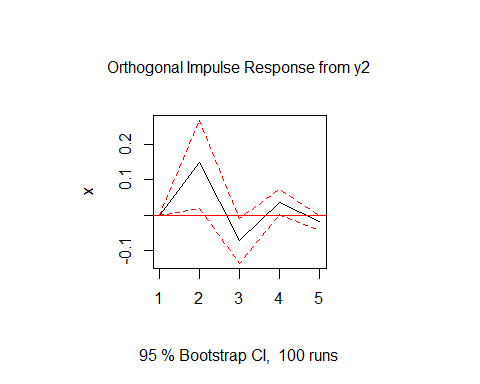
## ECT  
## Equation x -0.1304307  
## Equation y2 0.7132276

#### Slika 3.16.

var2<-VAR(diff(m2),type="none",p=1)  
plot(irf(var2,impulse = "x",response = "y2",ci=.95,n.ahead=4,ortho = T))



plot(irf(var2,impulse = "y2",response = "x",ci=.95,n.ahead=4,ortho = T))



#### Slika 3.17.

vec3<-VECM(m2,lag=0,include="const",LRinclude="none",estim="ML")

summary(vec3)

## #############  
## ###Model VECM   
## #############  
## Full sample size: 200 End sample size: 199  
## Number of variables: 2 Number of estimated slope parameters 4  
## AIC 6.550309 BIC 19.72353 SSR 525.7622  
## Cointegrating vector (estimated by ML):  
## x y2  
## r1 1 -1.247197  
##   
##   
## ECT Intercept   
## Equation x -0.1341(0.0575)\* -0.0268(0.0715)   
## Equation y2 0.7161(0.0733)\*\*\* 0.0246(0.0912)

coefA(vec3); coefB(vec3); coefPI(vec3)

## ECT  
## Equation x -0.1341477  
## Equation y2 0.7161387

## r1  
## x 1.000000  
## y2 -1.247197

## x y2  
## Equation x -0.1341477 0.1673086  
## Equation y2 0.7161387 -0.8931657

#### Slika 3.18.

vec4<-VECM(m2,lag=1,include="const",LRinclude="none",estim="ML")  
summary(vec4)

## #############  
## ###Model VECM   
## #############  
## Full sample size: 200 End sample size: 198  
## Number of variables: 2 Number of estimated slope parameters 8  
## AIC 11.52204 BIC 41.11644 SSR 511.9875  
## Cointegrating vector (estimated by ML):  
## x y2  
## r1 1 -1.256319  
##   
##   
## ECT Intercept x -1   
## Equation x -0.0793(0.0827) -0.0284(0.0718) -0.0443(0.0848)   
## Equation y2 0.7549(0.1043)\*\*\* -0.0084(0.0906) 0.0338(0.1070)   
## y2 -1   
## Equation x 0.0706(0.0728)   
## Equation y2 0.0662(0.0918)

coefA(vec4); coefB(vec4); coefPI(vec4)

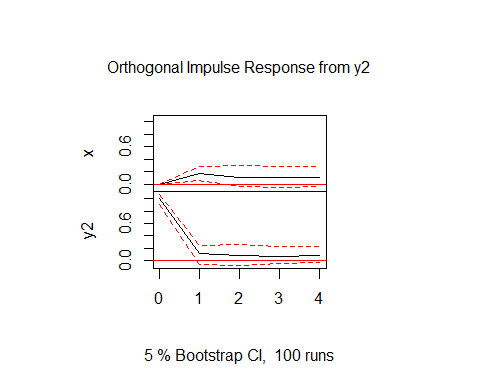
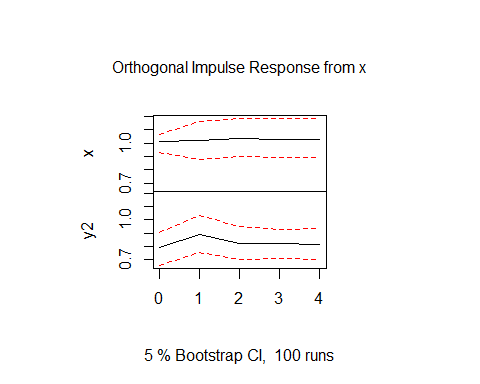
## ECT  
## Equation x -0.07933001  
## Equation y2 0.75489259

## r1  
## x 1.000000  
## y2 -1.256319

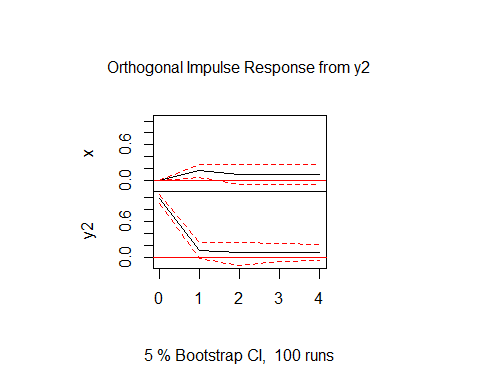
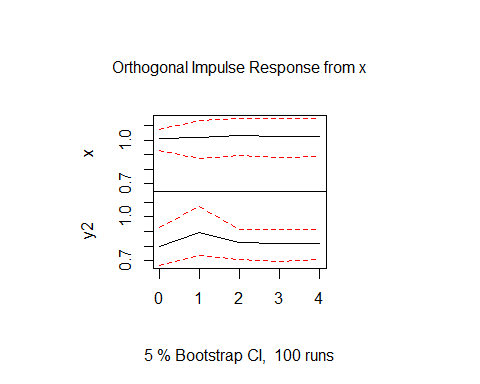
## x y2  
## Equation x -0.07933001 0.09966379  
## Equation y2 0.75489259 -0.94838577

#### Slika 3.19.

plot(irf(vec4,impulse="x",response="y2",ci=0.95,n.ahead=4,ortho=T))



plot(irf(vec4,impulse="y2",response="x",ci=0.95,n.ahead=4,ortho=T))



#### Slika 3.20.

m3<-cbind(x,y1,y2)  
vec5<-VECM(m3,lag=0,r=2,include="none",LRinclude="const",estim="ML")

## Warning in lineVar(data, lag, r = r, include = include, model = "VECM", : Lag=0  
## not fully implemented, methods not expected to work: fevd, predict, irf,...

summary(vec5)

## #############  
## ###Model VECM   
## #############  
## Full sample size: 200 End sample size: 199  
## Number of variables: 3 Number of estimated slope parameters 6  
## AIC 8.848515 BIC 35.19495 SSR 720.2231  
## Cointegrating vector (estimated by ML):  
## x y1 y2 const  
## r1 1 -3.469447e-18 -1.2398906 0.09203653  
## r2 0 1.000000e+00 0.3386793 7.81256533  
##   
##   
## ECT1 ECT2   
## Equation x -0.1395(0.0576)\* -0.0294(0.0215)   
## Equation y1 0.0692(0.0576) -0.0514(0.0215)\*   
## Equation y2 0.7142(0.0735)\*\*\* -0.0397(0.0274)

coefA(vec5);coefB(vec5);coefPI(vec5)

## ECT1 ECT2  
## Equation x -0.13951360 -0.02937913  
## Equation y1 0.06924198 -0.05137222  
## Equation y2 0.71416599 -0.03969189

## r1 r2  
## x 1.000000e+00 0.0000000  
## y1 -3.469447e-18 1.0000000  
## y2 -1.239891e+00 0.3386793  
## const 9.203653e-02 7.8125653

## x y1 y2 const  
## Equation x -0.13951360 -0.02937913 0.1630315 -0.2423667  
## Equation y1 0.06924198 -0.05137222 -0.1032512 -0.3949760  
## Equation y2 0.71416599 -0.03969189 -0.8989305 -0.2443661

#### 3.5. pitanja za ponavljanje, zadatak 6

data<-read.table("vec\_vjezba.txt",sep="\t",header=T)  
x<-ts(data$x,start=c(2003,1),frequency = 12)  
y1<-ts(data$y1,start=c(2003,1),frequency = 12)  
y2<-ts(data$y2,start=c(2003,1),frequency = 12)  
  
library(urca)  
summary(ur.df(x,type="drift",selectlags = "BIC"))

##   
## ###############################################   
## # 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   
## -0.033399 -0.007162 0.000106 0.008231 0.023410   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.15103 0.08032 1.880 0.0615 .  
## z.lag.1 -0.03317 0.01761 -1.884 0.0611 .  
## z.diff.lag 0.01591 0.07196 0.221 0.8253   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.01064 on 195 degrees of freedom  
## Multiple R-squared: 0.01788, Adjusted R-squared: 0.007802   
## F-statistic: 1.775 on 2 and 195 DF, p-value: 0.1723  
##   
##   
## Value of test-statistic is: -1.8839 1.8374   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

summary(ur.df(y1,type="drift",selectlags = "BIC"))

##   
## ###############################################   
## # 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   
## -0.0263037 -0.0074288 -0.0000104 0.0069892 0.0269193   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.26555 0.10586 2.508 0.0129 \*  
## z.lag.1 -0.05854 0.02331 -2.512 0.0128 \*  
## z.diff.lag 0.02884 0.07152 0.403 0.6872   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.01077 on 195 degrees of freedom  
## Multiple R-squared: 0.03134, Adjusted R-squared: 0.0214   
## F-statistic: 3.154 on 2 and 195 DF, p-value: 0.04485  
##   
##   
## Value of test-statistic is: -2.5118 3.2538   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

summary(ur.df(y2,type="drift",selectlags = "BIC"))

##   
## ###############################################   
## # 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   
## -0.050505 -0.010707 0.001342 0.011714 0.034205   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.34668 0.14030 2.471 0.0143 \*   
## z.lag.1 -0.07594 0.03070 -2.474 0.0142 \*   
## z.diff.lag -0.28417 0.06755 -4.206 3.95e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.01501 on 195 degrees of freedom  
## Multiple R-squared: 0.1339, Adjusted R-squared: 0.125   
## F-statistic: 15.08 on 2 and 195 DF, p-value: 8.172e-07  
##   
##   
## Value of test-statistic is: -2.4737 3.1226   
##   
## Critical values for test statistics:   
## 1pct 5pct 10pct  
## tau2 -3.46 -2.88 -2.57  
## phi1 6.52 4.63 3.81

library(vars)  
library(tsDyn)  
m1<-cbind(x,y1)  
VARselect(m1,12,type="none")$selection

## AIC(n) HQ(n) SC(n) FPE(n)   
## 1 1 1 1

vec1<-VECM(m1,lag=0,include="none",LRinclude="none",estim="ML")

## Warning in lineVar(data, lag, r = r, include = include, model = "VECM", : Lag=0  
## not fully implemented, methods not expected to work: fevd, predict, irf,...

summary(rank.test(vec1))

## r trace trace\_pval trace\_pval\_T eigen eigen\_pval  
## 1 0 3.6812859 0.7470 0.7564 3.5098505 0.7057  
## 2 1 0.1714354 0.7497 0.7400 0.1714354 0.7403

m2<-cbind(x,y2)  
VARselect(m2,12,type="none")$selection

## AIC(n) HQ(n) SC(n) FPE(n)   
## 8 3 1 8

vec2<-VECM(m2,lag=0,include="none",LRinclude="none",estim="ML")

## Warning in lineVar(data, lag, r = r, include = include, model = "VECM", : Lag=0  
## not fully implemented, methods not expected to work: fevd, predict, irf,...

summary(rank.test(vec2))

## r trace trace\_pval trace\_pval\_T eigen eigen\_pval  
## 1 0 74.44295028 <0.001 <0.001 74.37110487 <0.001  
## 2 1 0.07184542 0.8502 0.8412 0.07184542 0.8416

summary(vec2)

## #############  
## ###Model VECM   
## #############  
## Full sample size: 200 End sample size: 199  
## Number of variables: 2 Number of estimated slope parameters 2  
## AIC -3553.94 BIC -3544.06 SSR 0.06614567  
## Cointegrating vector (estimated by ML):  
## x y2  
## r1 1 -0.9979015  
##   
##   
## ECT   
## Equation x -0.1616(0.0536)\*\*   
## Equation y2 0.4497(0.0768)\*\*\*

coefA(vec2); coefB(vec2);coefPI(vec2)

## ECT  
## Equation x -0.1615954  
## Equation y2 0.4497499

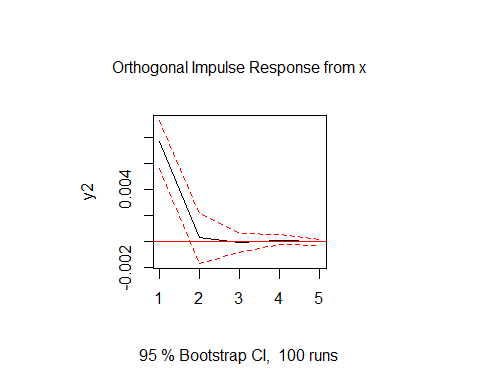
## r1  
## x 1.0000000  
## y2 -0.9979015

## x y2  
## Equation x -0.1615954 0.1612563  
## Equation y2 0.4497499 -0.4488061

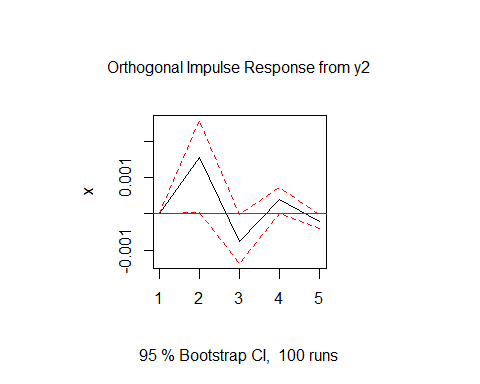
vec2

## ECT  
## Equation x -0.1615954  
## Equation y2 0.4497499

var2<-VAR(diff(m2),type="none",p=1)  
plot(irf(var2,impulse = "x",response = "y2",ci=.95,n.ahead=4,ortho = T))



plot(irf(var2,impulse = "y2",response = "x",ci=.95,n.ahead=4,ortho = T))



vec3<-VECM(m2,lag=0,include="const",LRinclude="none",estim="ML")

## Warning in lineVar(data, lag, r = r, include = include, model = "VECM", : Lag=0  
## not fully implemented, methods not expected to work: fevd, predict, irf,...

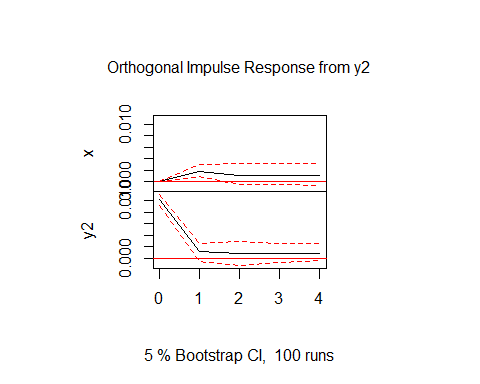
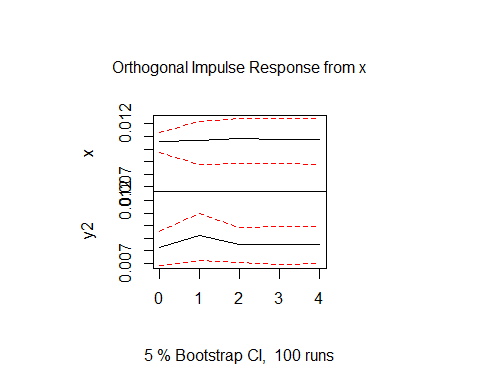
summary(rank.test(vec3))

## r trace trace\_pval trace\_pval\_T eigen eigen\_pval  
## 1 0 151.192991 < 0.001 < 0.001 147.940980 < 0.001  
## 2 1 3.252011 0.07134 0.07296 3.252011 0.07133

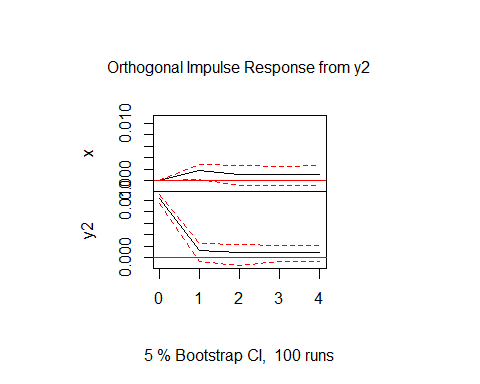
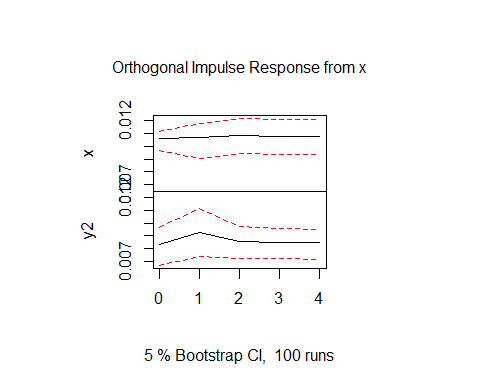
vec4<-VECM(m2,lag=1,include="const",LRinclude="none",estim="ML")  
summary(rank.test(vec4))

## r trace trace\_pval trace\_pval\_T eigen eigen\_pval  
## 1 0 88.394001 < 0.001 < 0.001 84.709425 < 0.001  
## 2 1 3.684576 0.05492 0.05632 3.684576 0.05492

plot(irf(vec4,impulse="x",response="y2",ci=0.95,n.ahead=4,ortho=T))



plot(irf(vec4,impulse="y2",response="x",ci=0.95,n.ahead=4,ortho=T))



m3<-cbind(x,y1,y2)  
vec5<-VECM(m3,lag=0,r=2,include="none",LRinclude="const",estim="ML")

## Warning in lineVar(data, lag, r = r, include = include, model = "VECM", : Lag=0  
## not fully implemented, methods not expected to work: fevd, predict, irf,...

summary(vec5)

## #############  
## ###Model VECM   
## #############  
## Full sample size: 200 End sample size: 199  
## Number of variables: 3 Number of estimated slope parameters 6  
## AIC -5430.715 BIC -5404.369 SSR 0.07930191  
## Cointegrating vector (estimated by ML):  
## x y1 y2 const  
## r1 1 0 -1.2515825 1.159443  
## r2 0 1 0.3501204 -6.135848  
##   
##   
## ECT1 ECT2   
## Equation x -0.1447(0.0575)\* -0.0299(0.0212)   
## Equation y1 0.0723(0.0586) -0.0515(0.0216)\*   
## Equation y2 0.7071(0.0729)\*\*\* -0.0383(0.0269)

coefA(vec5);coefB(vec5);coefPI(vec5)

## ECT1 ECT2  
## Equation x -0.14469932 -0.02994260  
## Equation y1 0.07226396 -0.05148972  
## Equation y2 0.70705711 -0.03826133

## r1 r2  
## x 1.000000 0.0000000  
## y1 0.000000 1.0000000  
## y2 -1.251582 0.3501204  
## const 1.159443 -6.1358477

## x y1 y2 const  
## Equation x -0.14469932 -0.02994260 0.1706196 0.01595253  
## Equation y1 0.07226396 -0.05148972 -0.1084719 0.39971905  
## Equation y2 0.70705711 -0.03826133 -0.8983364 1.05455845