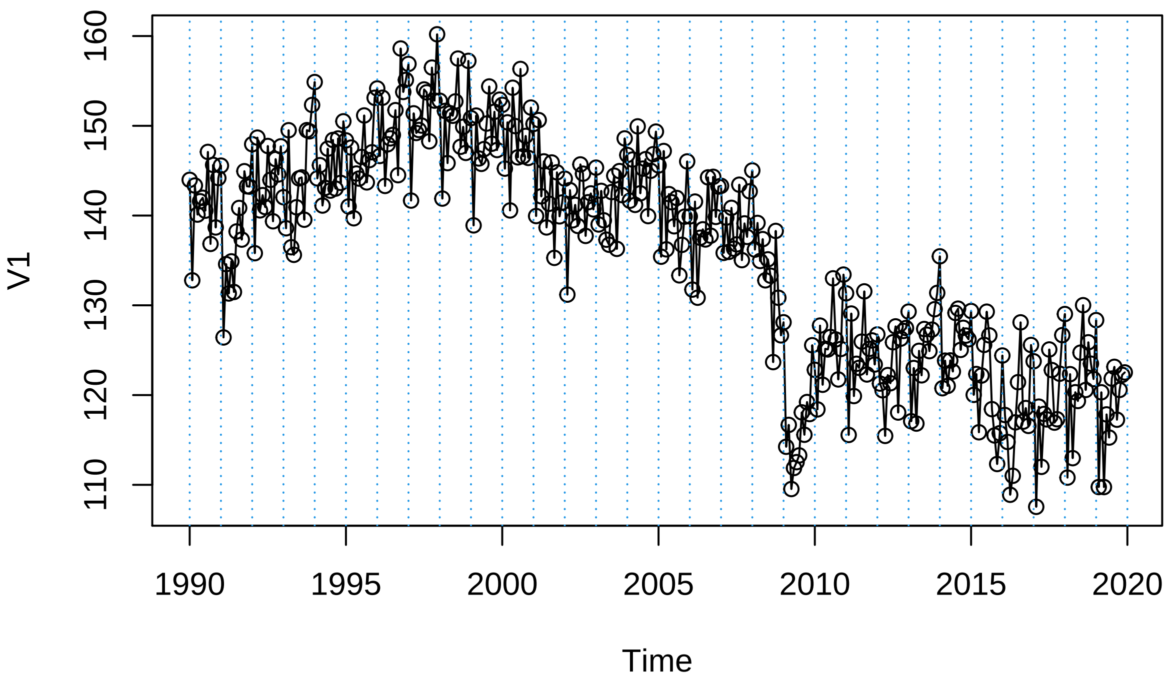
Project Time Series

Carolin Drenda, Silje Anfindsen, Jonathan Stålberg

3 5 2021

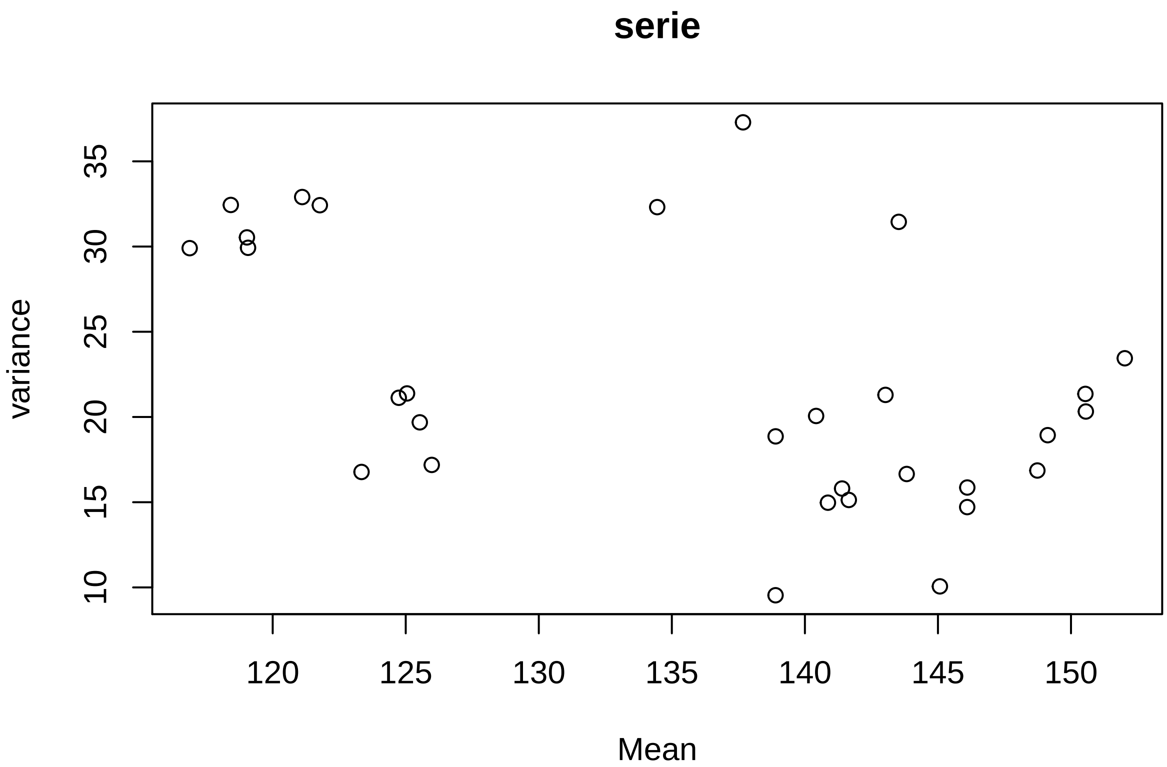
```
serie=ts(read.table("CO2IndUSA.dat"),start=1990,freq=12)
plot(serie, type = "o")
abline(v=1990:2020,col=4,lty=3)
```



Identification

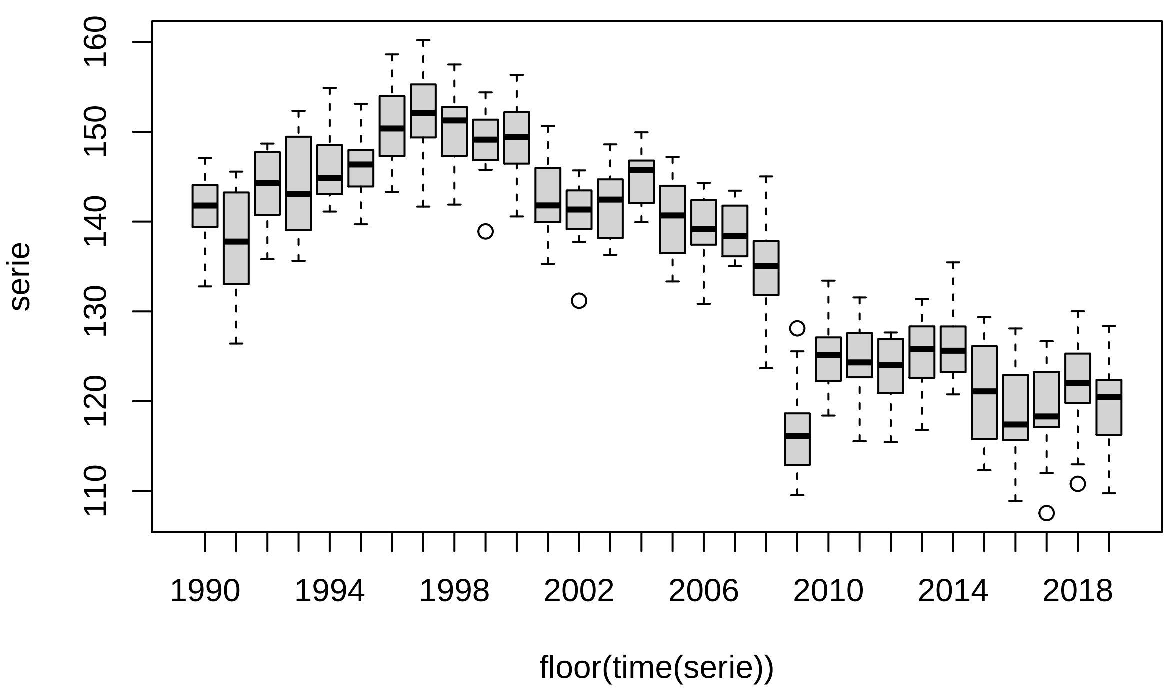
a)

```
m=apply(matrix(serie,nr=12),2,mean)
v=apply(matrix(serie,nr=12),2,var)
plot(m,v,xlab="Mean",ylab="variance",main="serie")
```

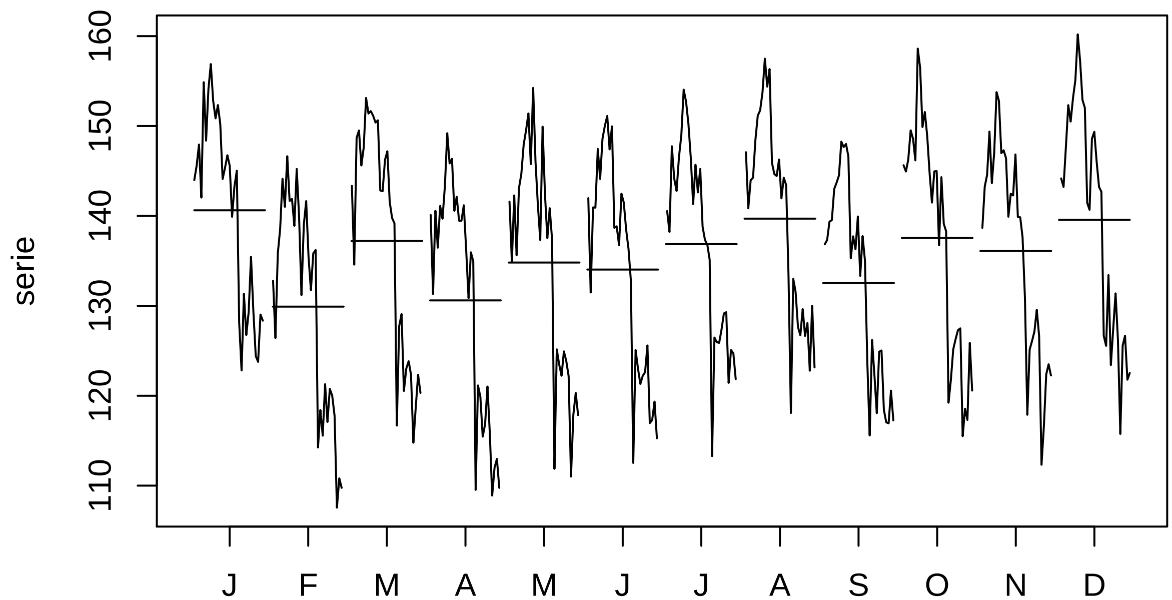



```
#abline(lm(v~m), col=2, lty=3,lwd=2)
```

```
boxplot(serie~floor(time(serie)))
```

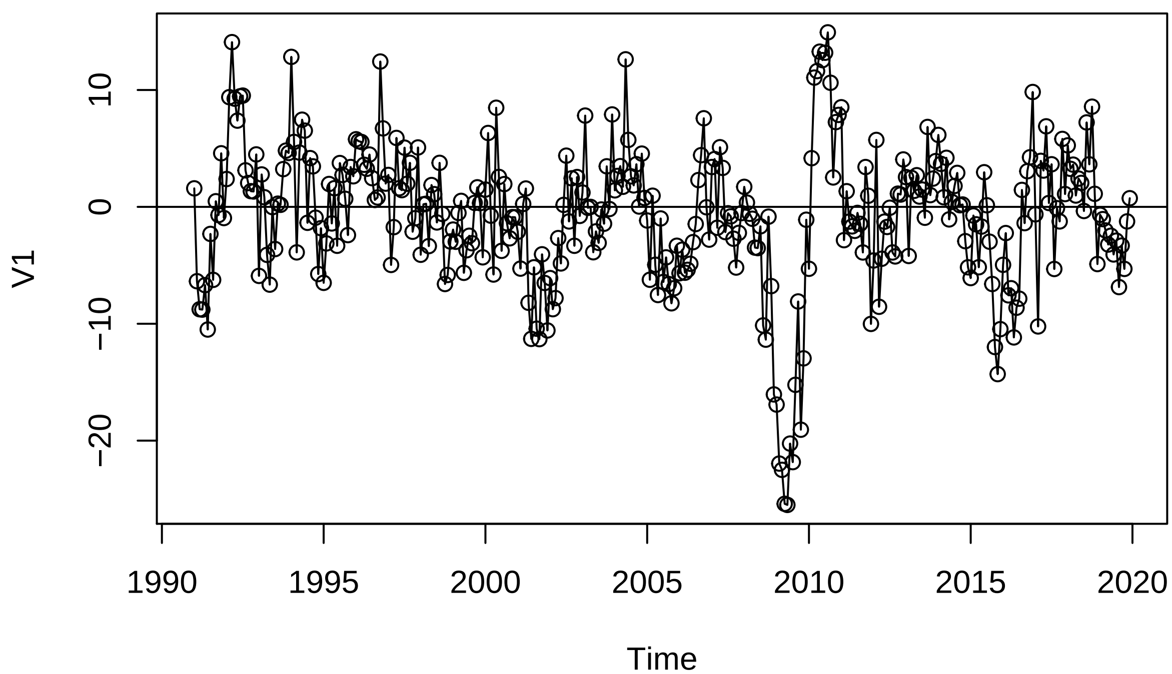



```
monthplot(serie)
```



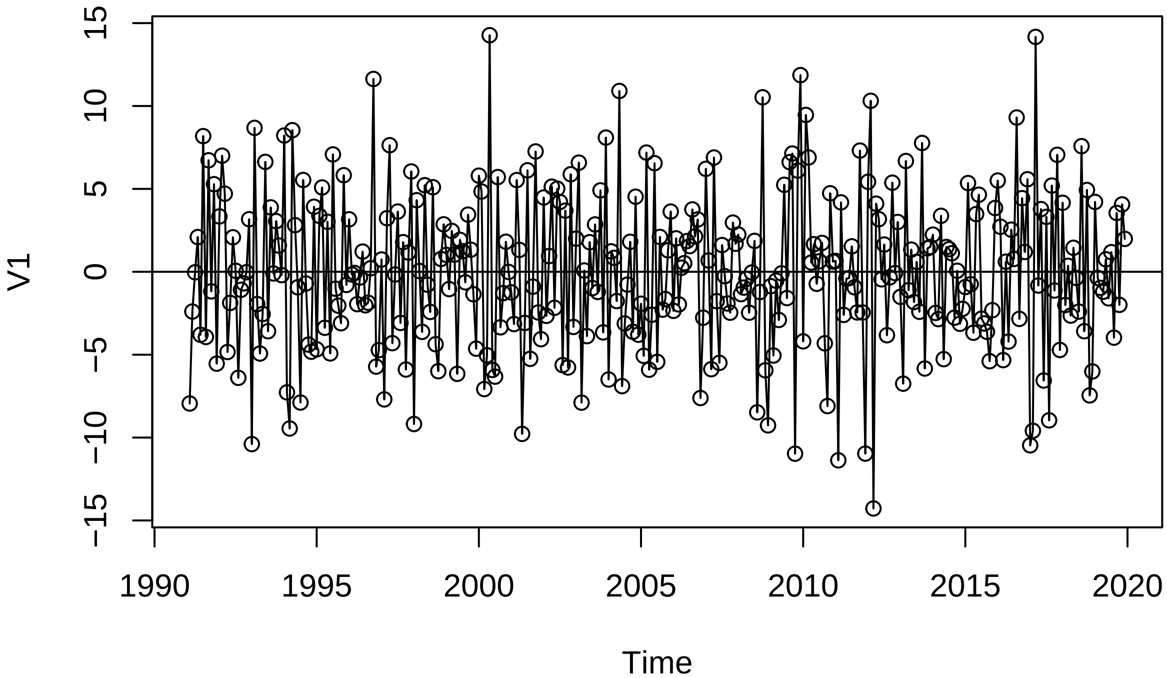

```r
d12serie <- diff(serie, 12)
```

```r
plot(d12serie, type = "o")
abline(h=0)
```




```r
d1d12serie <- diff(d12serie)
```

```r
plot(d1d12serie, type = "o")
abline(h=0)
```




```
var(serie)
```

```
##           V1
## V1 150.0063
```

```
var(d12serie)
```

```
##           V1
## V1 37.52583
```

```
var(d1d12serie)
```

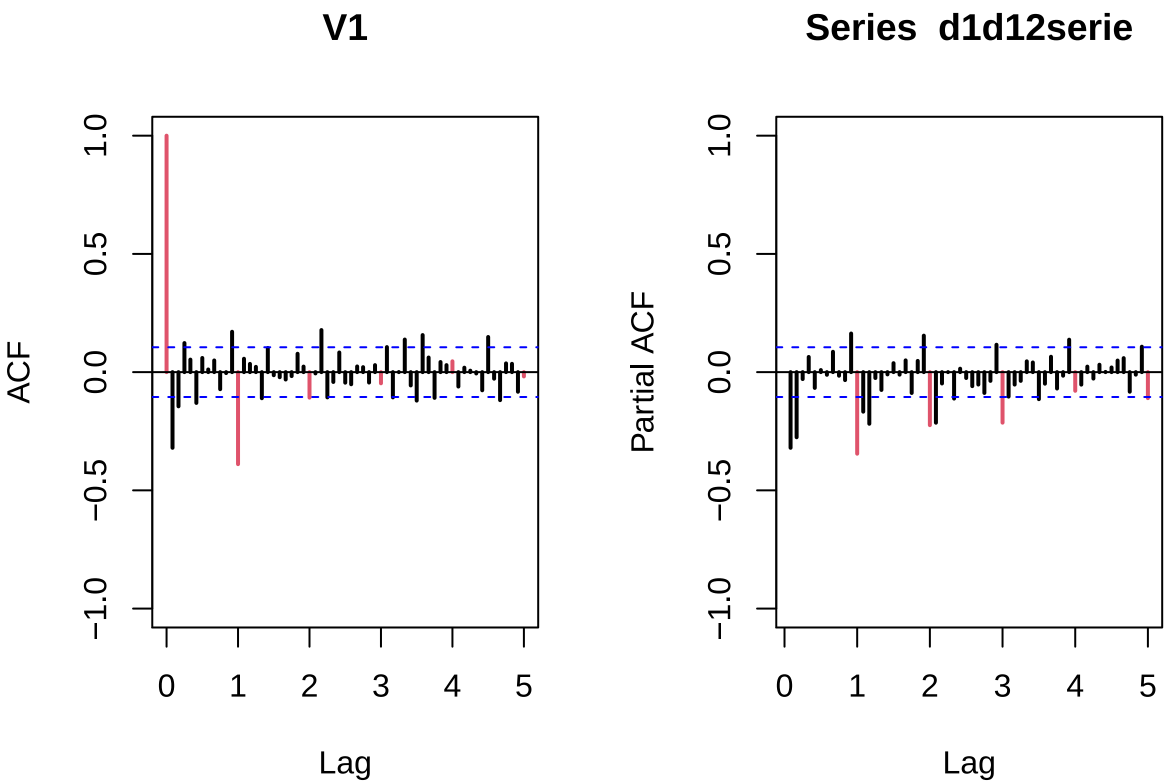
```
##           V1
## V1 22.08084
```

```
var(diff(d1d12serie)) # not needed
```

```
##           V1
## V1 58.26977
```

b)

```
par(mfrow = c(1,2))
acf(d1d12serie, ylim = c(-1,1), lag.max = 60, col = c(2,rep(1,11)), lwd = 2)
pacf(d1d12serie, ylim = c(-1,1), lag.max = 60, col = c(rep(1,11),2), lwd = 2)
```



Seasonal: MA(1),(AR(3)) Regular: ARMA(1,1), Ar(2), MA(1) (2,3)

Estimation

a)

Model 1

```
(mod=arima(d1d12serie, order=c(1,0,1),seasonal=list(order=c(0,0,1),period=12)))
```

```
##
## Call:
## arima(x = d1d12serie, order = c(1, 0, 1), seasonal = list(order = c(0, 0, 1),
##     period = 12))
##
## Coefficients:
##          ar1      ma1     sma1  intercept
##       0.0879  -0.5700  -0.8773    -0.0061
## s.e.  0.0969   0.0776   0.0350     0.0141
##
## sigma^2 estimated as 10.75:  log likelihood = -913.37,  aic = 1836.73
```

mean non-sign

```
# (mod1=arima(serie, order=c(1,1,1),seasonal=list(order=c(0,1,1),period=12)))
# ar 1 not sign
(mod1=arima(serie, order=c(0,1,1),seasonal=list(order=c(0,1,1),period=12)))
```

```
##
## Call:
## arima(x = serie, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1), period = 12))
```

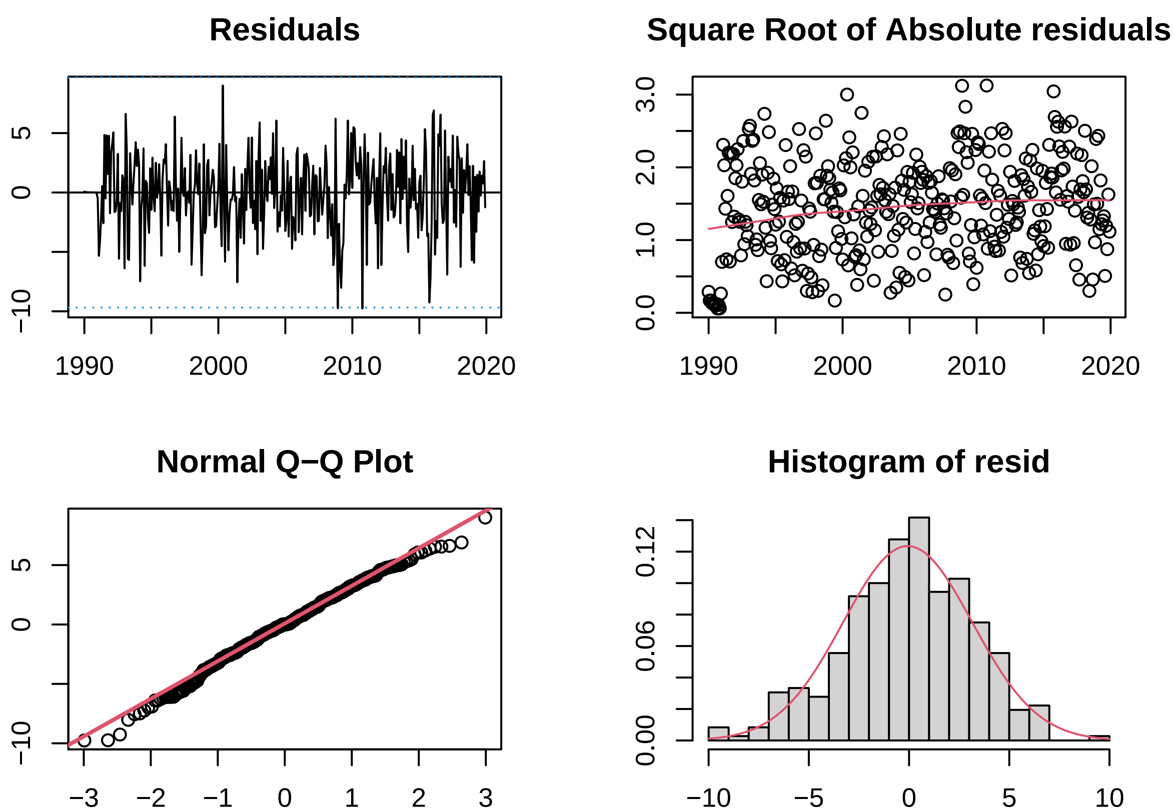
```
##
## Coefficients:
##           ma1     sma1
##       -0.5085  -0.8743
## s.e.   0.0467   0.0348
##
## sigma^2 estimated as 10.79:  log likelihood = -913.87,  aic = 1833.74
```

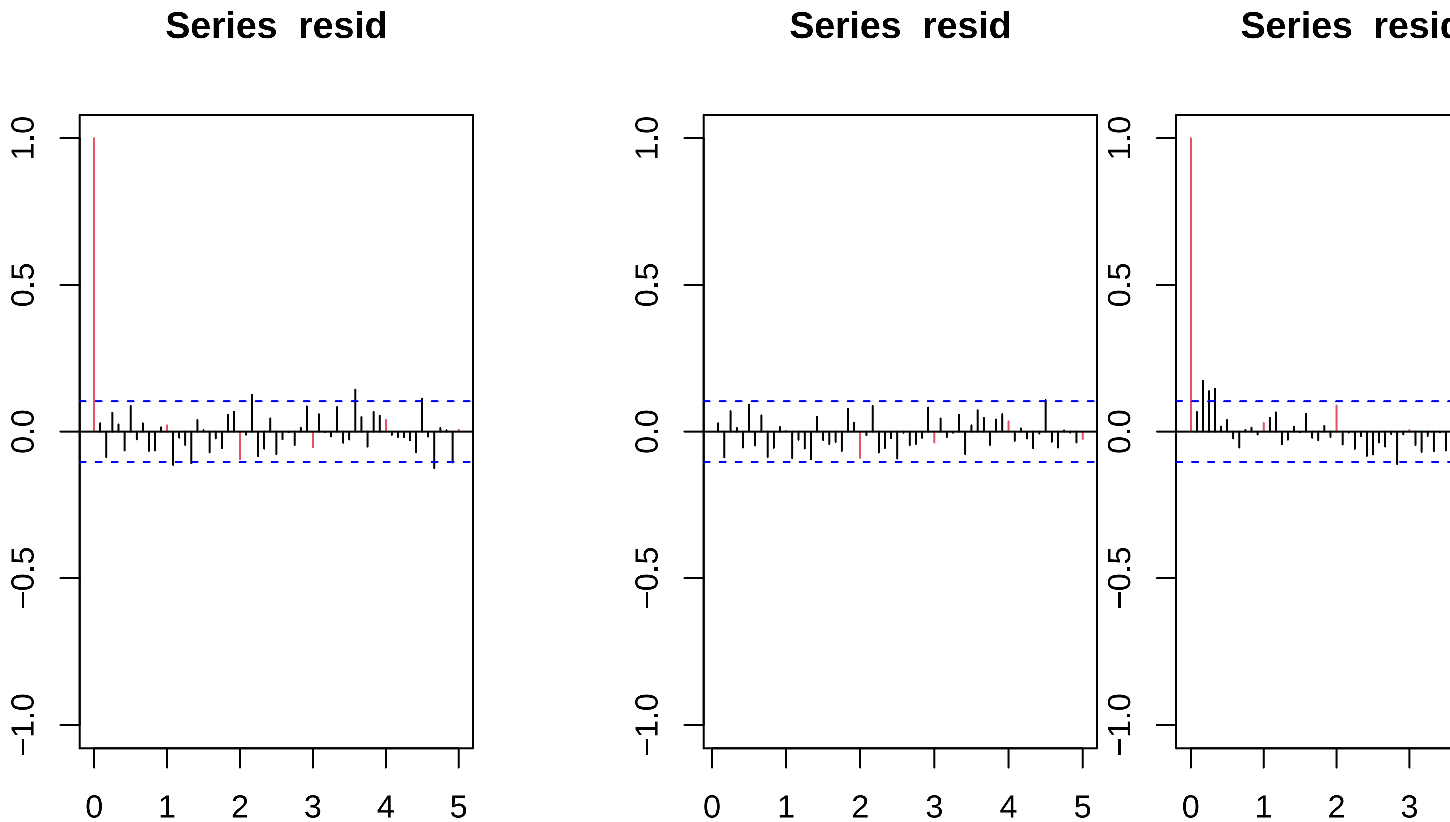
```
validation=function(model,dades){
  s=frequency(get(model$series))
  resid=model$residuals
  par(mfrow=c(2,2),mar=c(3,3,3,3))
  #Residuals plot
  plot(resid,main="Residuals")
  abline(h=0)
  abline(h=c(-3*sd(resid),3*sd(resid)),lty=3,col=4)
  #Square Root of absolute values of residuals (Homocedasticity)
  scatter.smooth(sqrt(abs(resid)),main="Square Root of Absolute residuals",
                 lpars=list(col=2))

  #Normal plot of residuals
  qqnorm(resid)
  qqline(resid,col=2,lwd=2)

  ##Histogram of residuals with normal curve
  hist(resid,breaks=20,freq=FALSE)
  curve(dnorm(x,mean=mean(resid),sd=sd(resid)),col=2,add=T)

  ## Individual Correlation Tests
  #ACF & PACF of residuals
  par(mfrow=c(1,2))
  acf(resid,ylim=c(-1,1),lag.max=60,col=c(2,rep(1,s-1)),lwd=1)
  pacf(resid,ylim=c(-1,1),lag.max=60,col=c(rep(1,s-1),2),lwd=1)
  par(mfrow=c(1,1))

  #ACF & PACF of square residuals
  par(mfrow=c(1,2))
  acf(resid^2,ylim=c(-1,1),lag.max=60,col=c(2,rep(1,s-1)),lwd=1)
  pacf(resid^2,ylim=c(-1,1),lag.max=60,col=c(rep(1,s-1),2),lwd=1)
  par(mfrow=c(1,1))

  #Global Correlation Test
  #Ljung-Box p-values
  par(mar=c(2,2,1,1))
  tsdiag(model,gof.lag=7*s)
  cat("\n--------------------------------------------------------------------\n")
  print(model)

  #Stationary and Invertible
  cat("\nModul of AR Characteristic polynomial Roots: ",
      Mod(polyroot(c(1,-model$model$phi))),"\n")
  cat("\nModul of MA Characteristic polynomial Roots: ",
      Mod(polyroot(c(1,model$model$theta))),"\n")
```

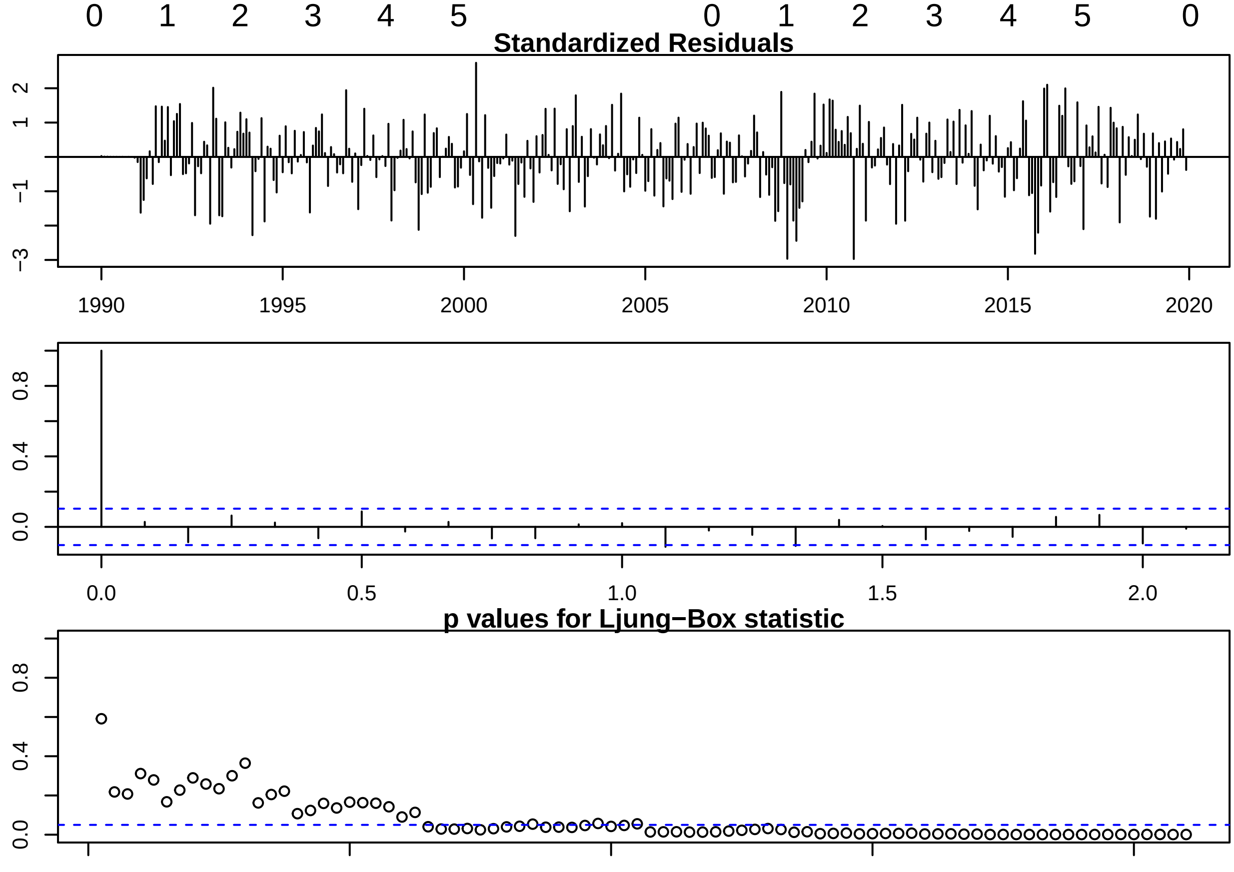
```r
  #Model expressed as an MA infinity (psi-weights)
  psis=ARMAtoMA(ar=model$model$phi,ma=model$model$theta,lag.max=72)
  names(psis)=paste("psi",1:72)
  cat("\nPsi-weights (MA(inf))\n")
  cat("\n--------------------\n")
  print(psis[1:20])

  plot(psis,type="h",main="Pesos Psis - MA infinito")

  #Model expressed as an AR infinity (pi-weights)
  pis=-ARMAtoMA(ar=-model$model$theta,ma=-model$model$phi,lag.max=72)
  names(pis)=paste("pi",1:72)
  cat("\nPi-weights (AR(inf))\n")
  cat("\n--------------------\n")
  print(pis[1:20])

  plot(pis,type="h",main="Pesos Pis - AR infinito")

#   #Some Complementary Tests
#   cat("\nNormality tests\n")
#   cat("\n--------------------\n")
#   ##Shapiro-Wilks Normality test
#   print(shapiro.test(resid(model)))
#
#   suppressMessages(require(nortest,quietly=TRUE,warn.conflicts=FALSE))
# ##Anderson-Darling test: Normality
#   print(ad.test(resid(model)))
#
#   suppressMessages(require(tseries,quietly=TRUE,warn.conflicts=FALSE))
#   ##Jarque-Bera test: Normality
#   print(jarque.bera.test(resid(model)))
#
#   cat("\nHomoscedasticity Test\n")
#   cat("\n--------------------\n")
#   suppressMessages(require(lmtest,quietly=TRUE,warn.conflicts=FALSE))
#   ##Breusch-Pagan test
#   obs=get(model$series)
#   print(bptest(resid(model)~I(obs-resid(model))))
#
#   cat("\nIndependence Tests\n")
#   cat("\n--------------------\n")
#
#   ##Durbin-Watson test
#   print(dwtest(resid(model)~I(1:length(resid(model)))))
#
  ##Ljung-Box test
  cat("\nLjung-Box test\n")
  print(t(apply(matrix(c(1:4,(1:4)*s)),1,function(el) {
    te=Box.test(resid(model),type="Ljung-Box",lag=el)
    c(lag=(te$parameter),statistic=te$statistic[[1]],p.value=te$p.value)})))


  #Sample ACF vs. Teoric ACF: similar?
```

```
  par(mfrow=c(2,2),mar=c(3,3,3,3))
  acf(dades, ylim=c(-1,1) ,lag.max=36,main="Sample ACF")

  plot(ARMAacf(model$model$phi,model$model$theta,lag.max=36),ylim=c(-1,1),
       type="h",xlab="Lag",  ylab="", main="ACF Teoric")
  abline(h=0)

  #Sample PACF vs. Teoric PACF
  pacf(dades, ylim=c(-1,1) ,lag.max=36,main="Sample PACF")

  plot(ARMAacf(model$model$phi,model$model$theta,lag.max=36, pacf=T),ylim=c(-1,1),
       type="h", xlab="Lag", ylab="", main="PACF Teoric")
  abline(h=0)
  par(mfrow=c(1,1))
}
```

```
validation(mod1, d1d12serie)
```

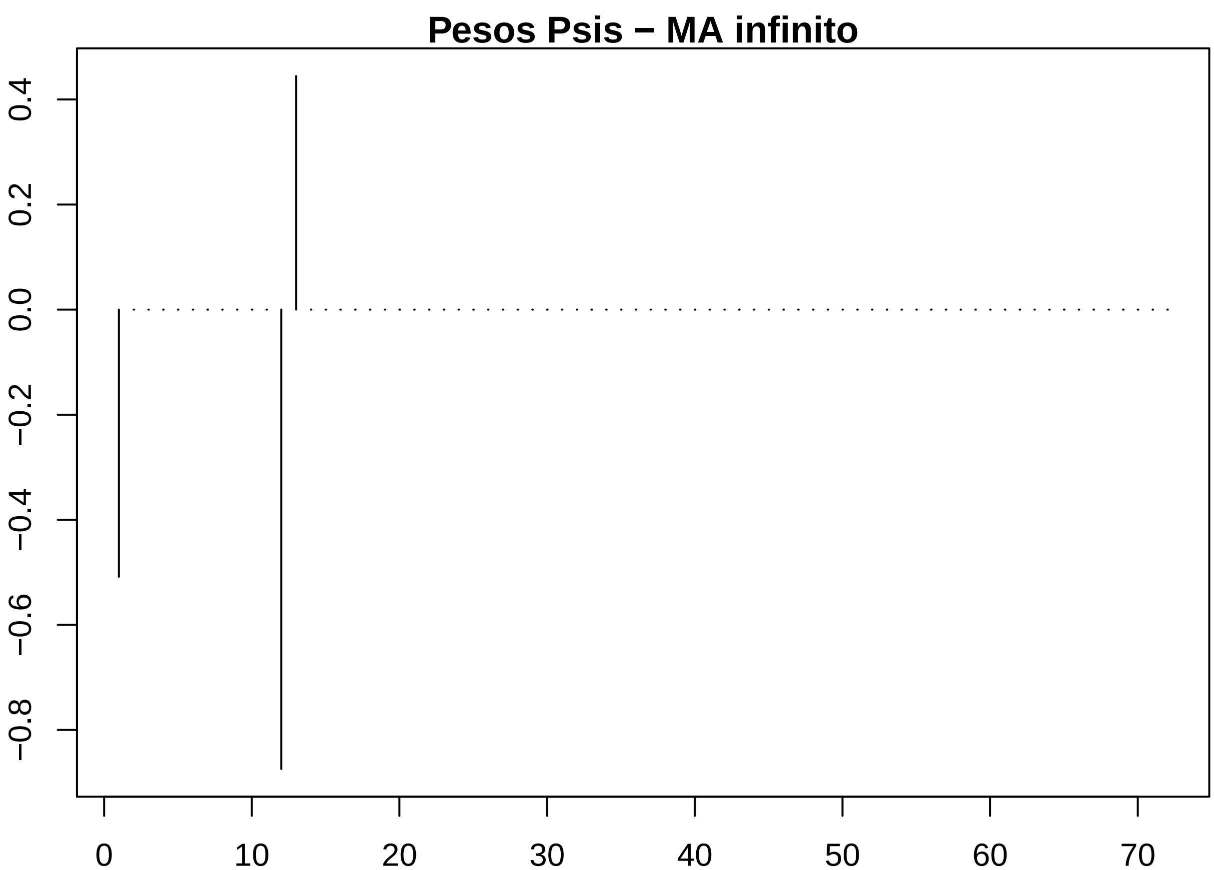



Series resid
Series resid
Series resid


Standardized Residuals
p values for Ljung−Box statistic

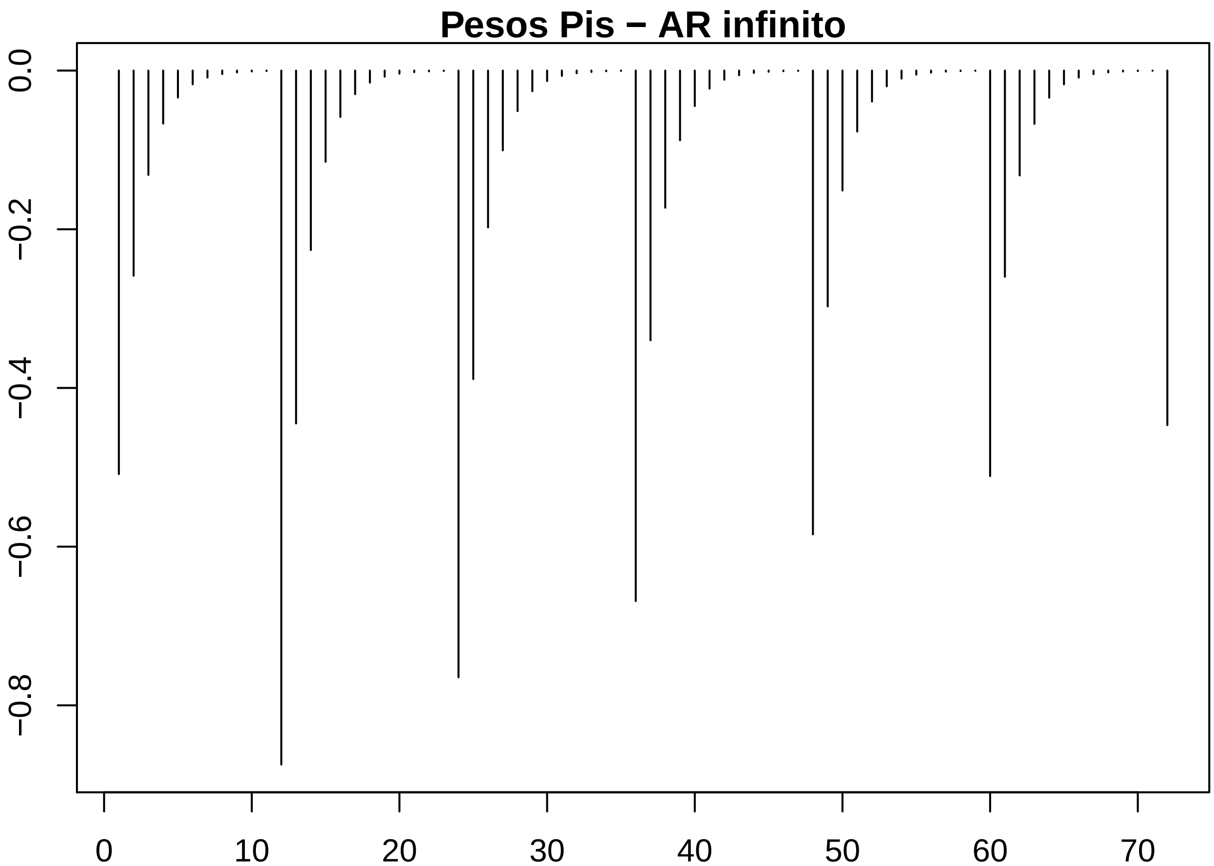
##

```
## -------------------------------------------------------------------
##
## Call:
## arima(x = serie, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1), period = 12))
##
## Coefficients:
##           ma1     sma1
##       -0.5085  -0.8743
## s.e.   0.0467   0.0348
##
## sigma^2 estimated as 10.79:  log likelihood = -913.87,  aic = 1833.74
##
## Modul of AR Characteristic polynomial Roots:
##
## Modul of MA Characteristic polynomial Roots:  1.011256 1.011256 1.011256 1.011256 1.011256 1.011256
##
## Psi-weights (MA(inf))
##
## --------------------
##      psi 1      psi 2      psi 3      psi 4      psi 5      psi 6      psi 7
## -0.5085041  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
##      psi 8      psi 9     psi 10     psi 11     psi 12     psi 13     psi 14
##  0.0000000  0.0000000  0.0000000  0.0000000 -0.8743122  0.4445913  0.0000000
##     psi 15     psi 16     psi 17     psi 18     psi 19     psi 20
##  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
```

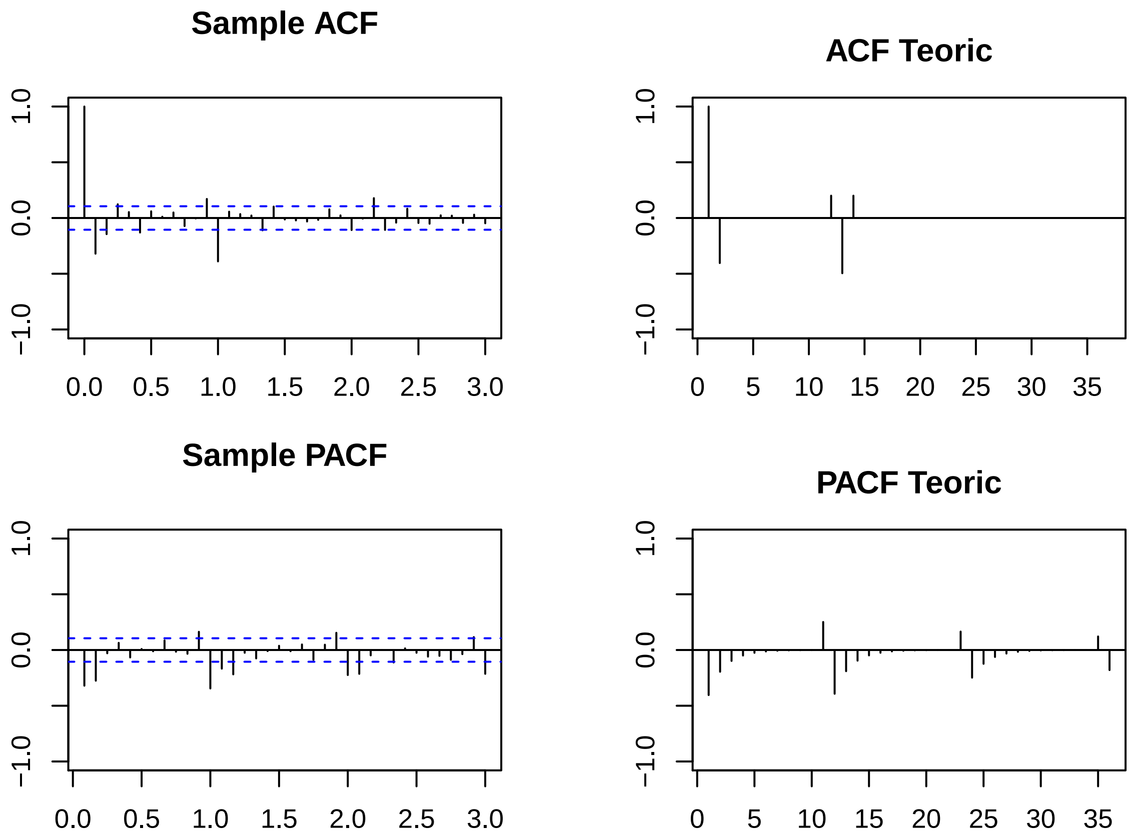



```
##
```

```
## Pi-weights (AR(inf))
##
## --------------------
##          pi 1          pi 2          pi 3          pi 4          pi 5
## -0.5085040680 -0.2585763871 -0.1314871447 -0.0668617480 -0.0339994708
##          pi 6          pi 7          pi 8          pi 9         pi 10
## -0.0172888692 -0.0087914603 -0.0044704933 -0.0022732641 -0.0011559640
##         pi 11         pi 12         pi 13         pi 14         pi 15
## -0.0005878124 -0.8746110823 -0.4447432932 -0.2261537738 -0.1150001140
##         pi 16         pi 17         pi 18         pi 19         pi 20
## -0.0584780258 -0.0297363140 -0.0151210366 -0.0076891086 -0.0039099430
```




```
##
## Ljung-Box test
##      lag.df  statistic    p.value
## [1,]      1  0.2888776 0.59094066
## [2,]      2  3.0474834 0.21789506
## [3,]      3  4.5539267 0.20753030
## [4,]      4  4.7724261 0.31145487
## [5,]     12 13.0621625 0.36453869
## [6,]     24 33.6975781 0.09018904
## [7,]     36 52.3320458 0.03847726
## [8,]     48 71.8636274 0.01443847
```



Ljung box is sign -> look for different model

```
(mod2 = arima(d1d12serie, order=c(2,0,0),seasonal=list(order=c(0,0,1),period=12)))
```

```
##
## Call:
## arima(x = d1d12serie, order = c(2, 0, 0), seasonal = list(order = c(0, 0, 1),
##     period = 12))
##
## Coefficients:
##           ar1      ar2     sma1  intercept
##       -0.4480  -0.2910  -0.8565    -0.0062
## s.e.   0.0513   0.0516   0.0351     0.0189
##
## sigma^2 estimated as 10.74:  log likelihood = -912.35,  aic = 1834.7
```

intercept not

```
#BEST MODEL:
(mod3 = arima(serie, order=c(2,1,0),seasonal=list(order=c(0,1,1),period=12)))
```

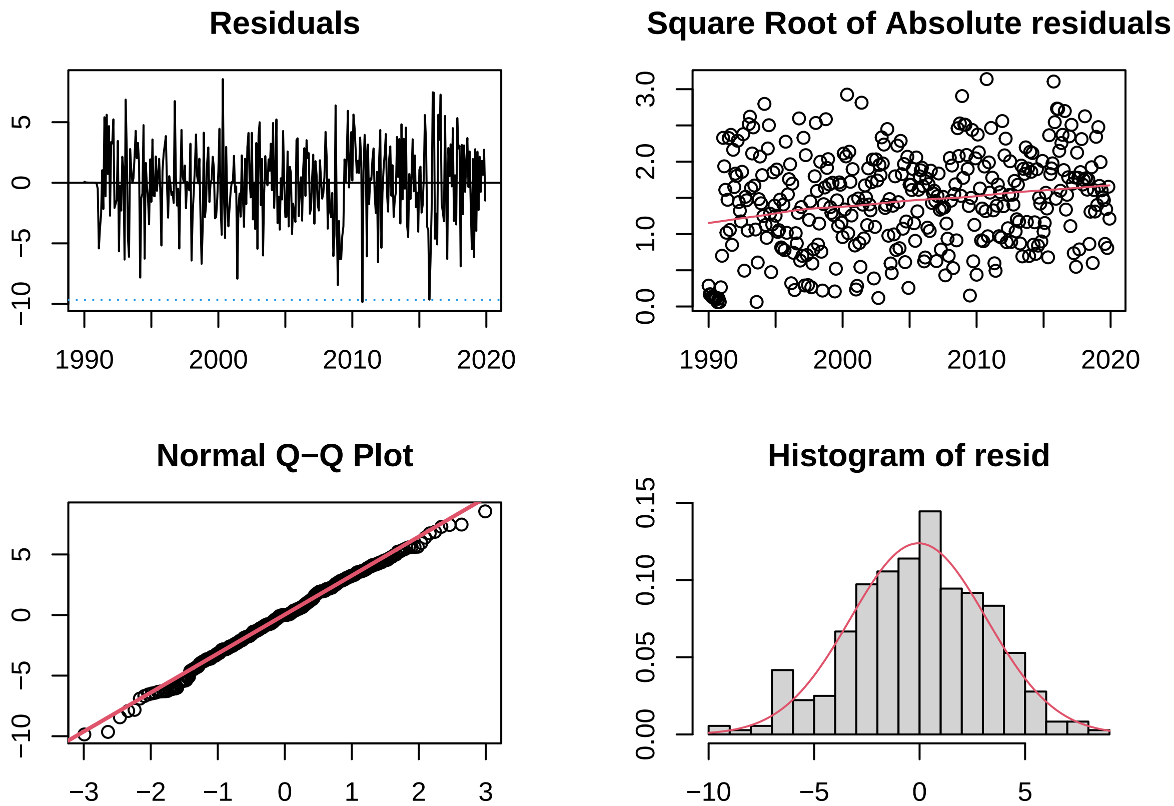
```
##
## Call:
## arima(x = serie, order = c(2, 1, 0), seasonal = list(order = c(0, 1, 1), period = 12))
##
## Coefficients:
##           ar1      ar2     sma1
##       -0.4478  -0.2909  -0.8557
## s.e.   0.0513   0.0516   0.0350
##
```

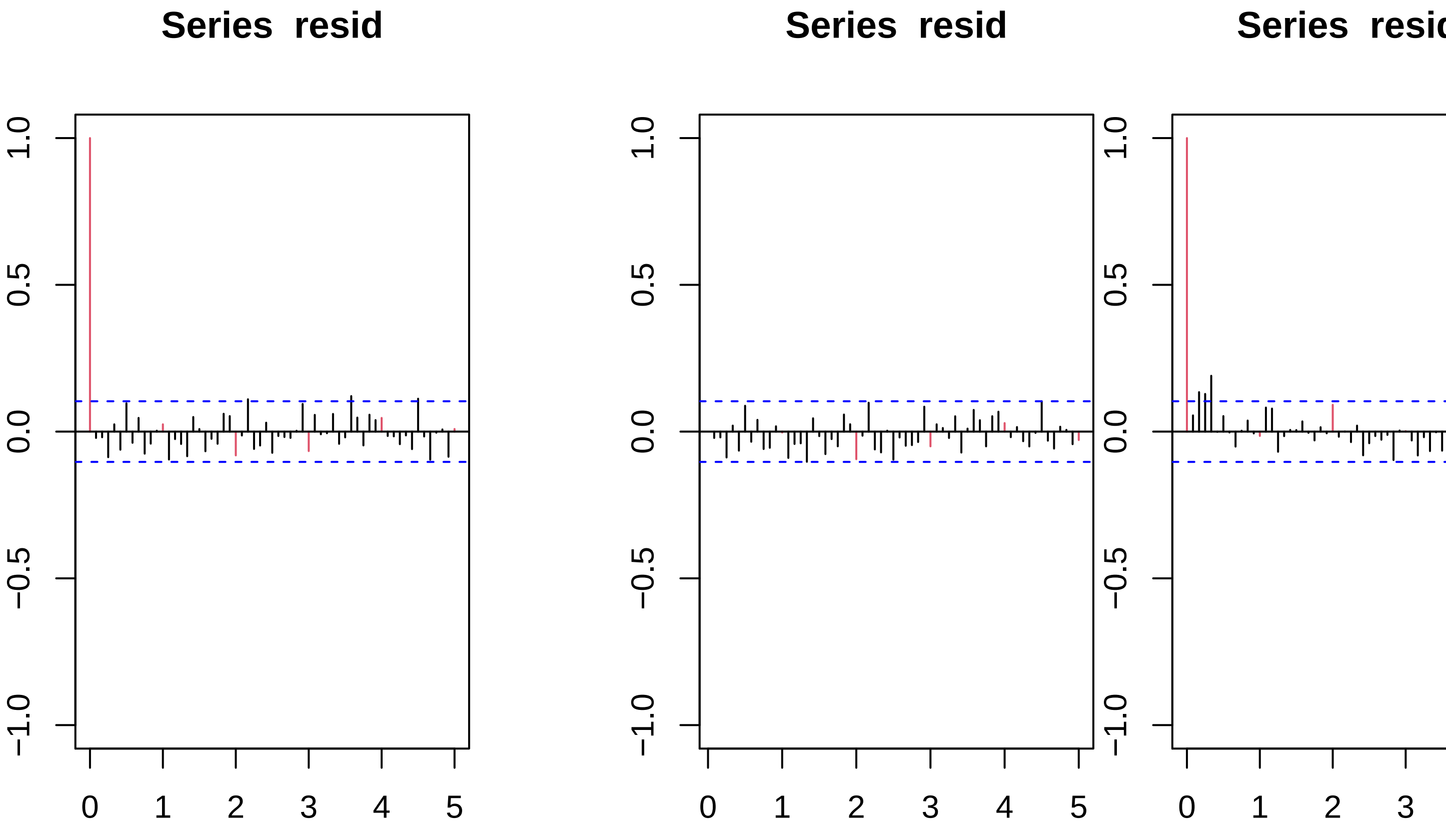
```
## sigma^2 estimated as 10.75:  log likelihood = -912.4,  aic = 1832.81
```

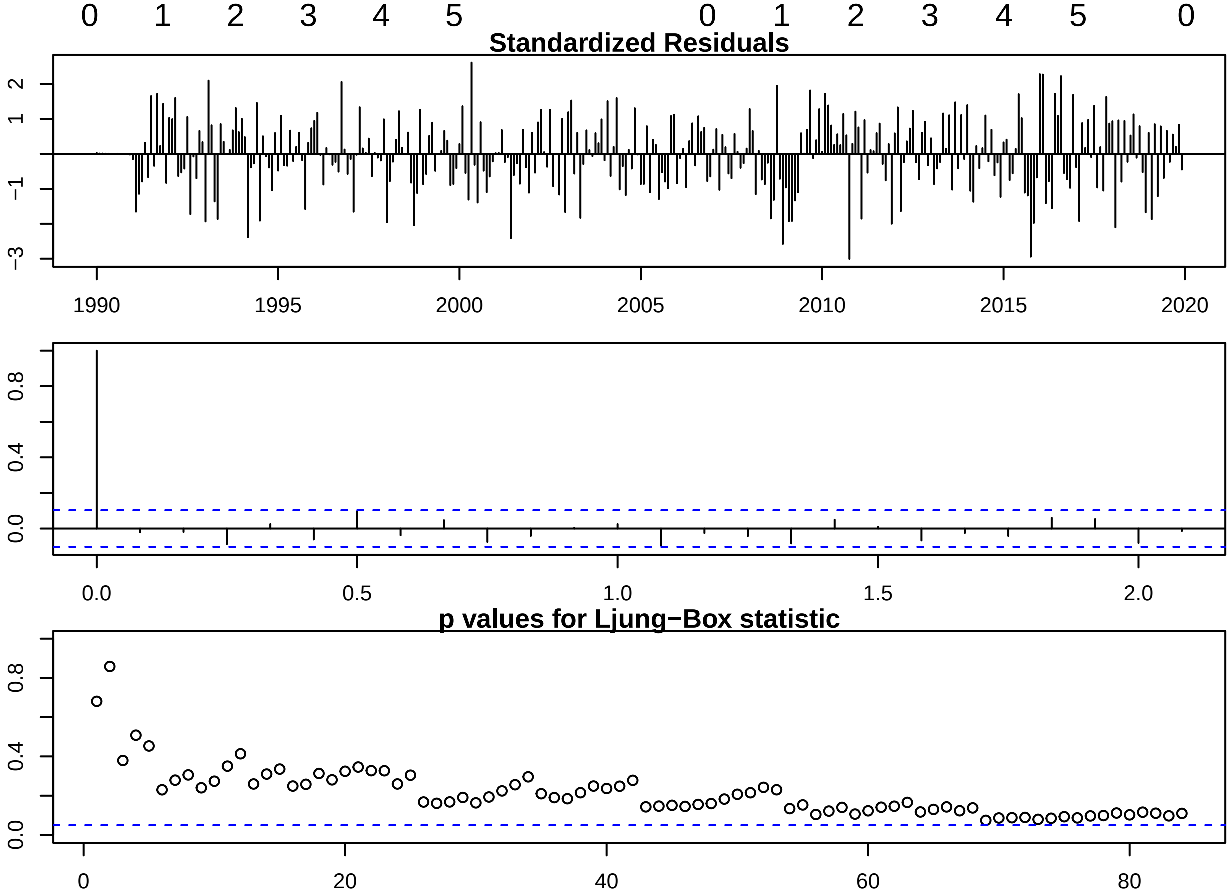
Validation

a,b,d)

```
validation(mod3,d1d12serie)
```

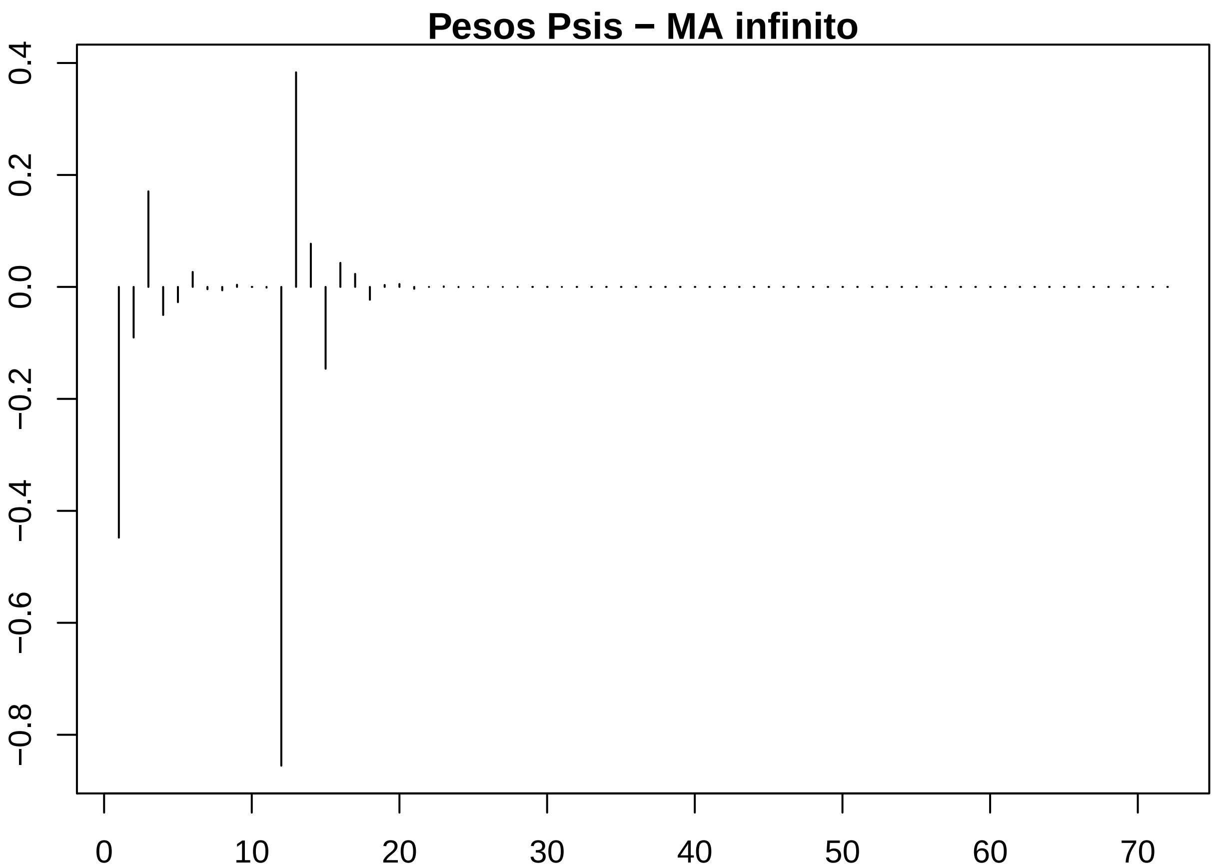



Series resid
Series resid

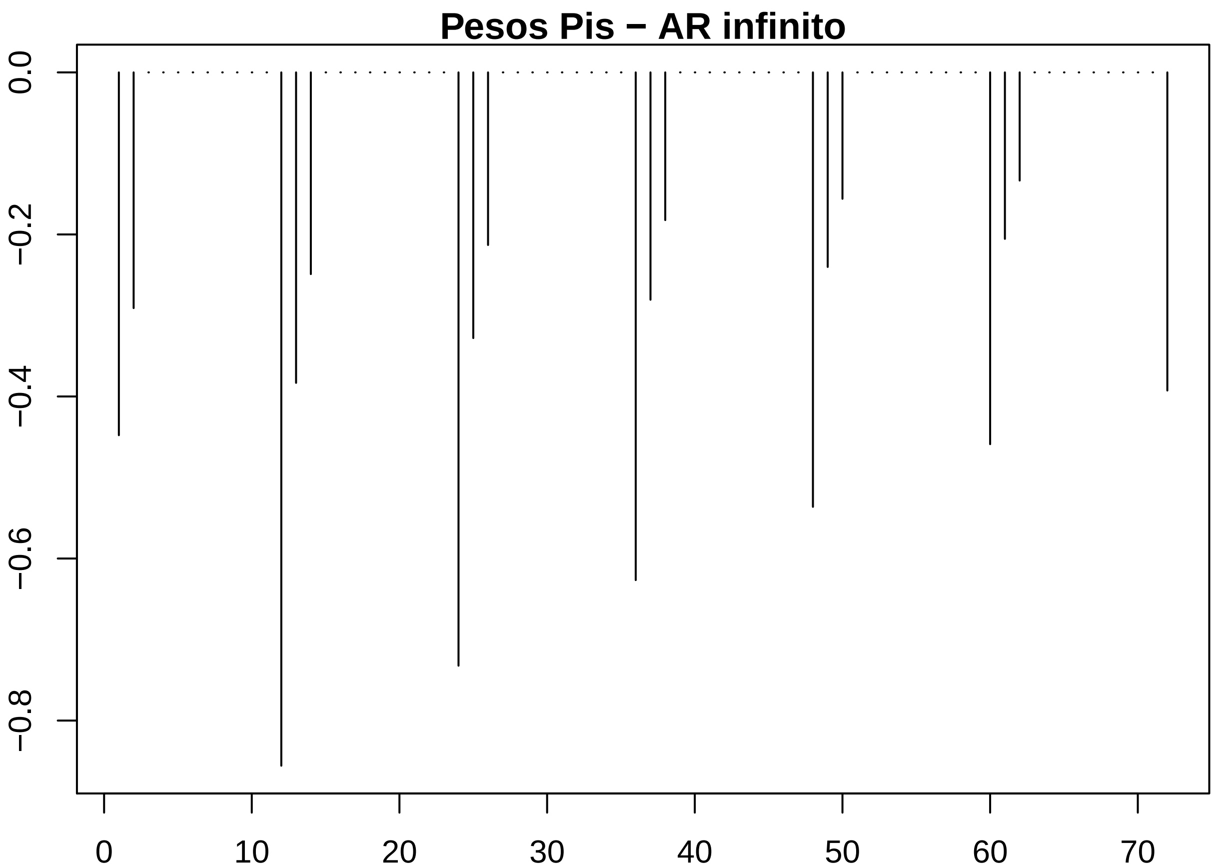

Standardized Residuals
p values for Ljung−Box statistic

##

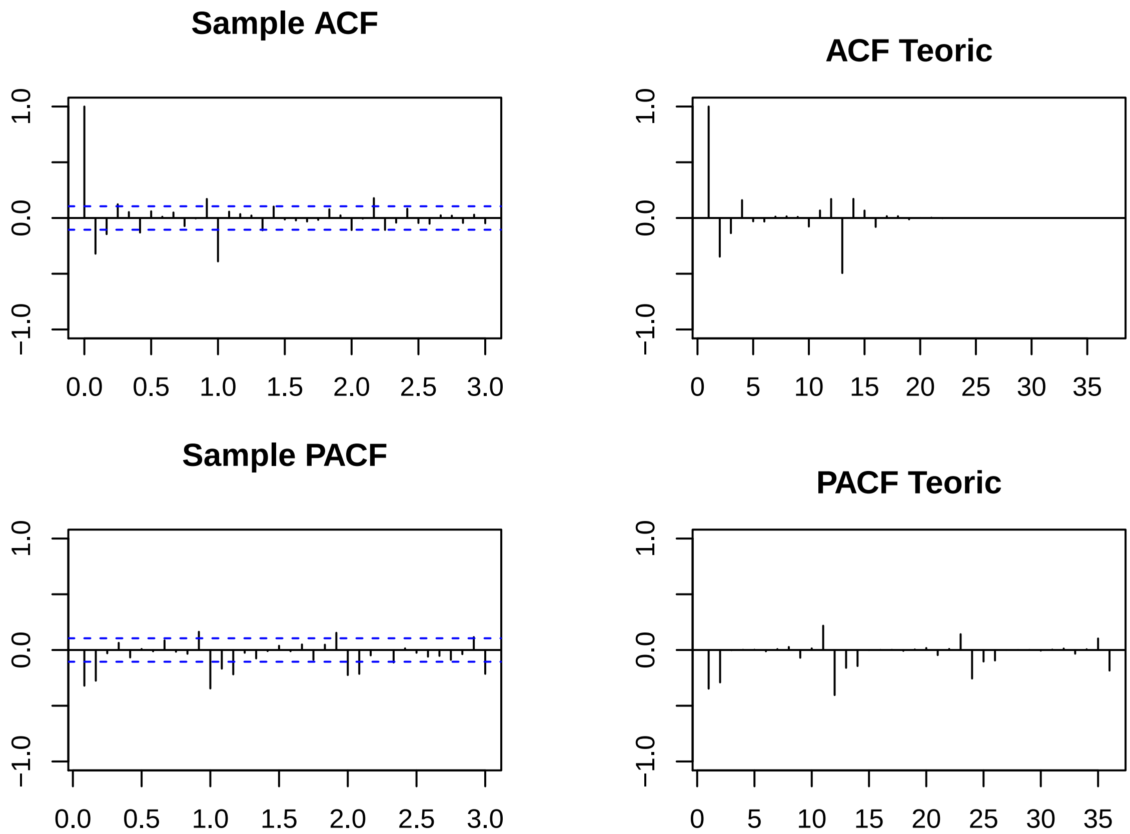
```
## --------------------------------------------------------------------
##
## Call:
## arima(x = serie, order = c(2, 1, 0), seasonal = list(order = c(0, 1, 1), period = 12))
##
## Coefficients:
##           ar1      ar2     sma1
##       -0.4478  -0.2909  -0.8557
## s.e.   0.0513   0.0516   0.0350
##
## sigma^2 estimated as 10.75:  log likelihood = -912.4,  aic = 1832.81
##
## Modul of AR Characteristic polynomial Roots:  1.854004 1.854004
##
## Modul of MA Characteristic polynomial Roots:  1.013068 1.013068 1.013068 1.013068 1.013068 1.013068
##
## Psi-weights (MA(inf))
##
## --------------------
##         psi 1         psi 2         psi 3         psi 4         psi 5
## -4.477948e-01 -9.040313e-02  1.707560e-01 -5.016326e-02 -2.721404e-02
##         psi 6         psi 7         psi 8         psi 9        psi 10
##  2.677997e-02 -4.074730e-03 -5.966273e-03  3.857100e-03  8.538685e-06
##        psi 11        psi 12        psi 13        psi 14        psi 15
## -1.125944e-03 -8.552243e-01  3.832925e-01  7.716827e-02 -1.460643e-01
##        psi 16        psi 17        psi 18        psi 19        psi 20
##  4.295677e-02  2.325768e-02 -2.291179e-02  3.493580e-03  5.101167e-03
```



```
##
## Pi-weights (AR(inf))
##
## --------------------
##       pi 1       pi 2       pi 3       pi 4       pi 5       pi 6       pi 7
## -0.4477948 -0.2909233  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
##       pi 8       pi 9      pi 10      pi 11      pi 12      pi 13      pi 14
##  0.0000000  0.0000000  0.0000000  0.0000000 -0.8557260 -0.3831896 -0.2489506
##      pi 15      pi 16      pi 17      pi 18      pi 19      pi 20
##  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
```




```
##
## Ljung-Box test
##      lag.df  statistic   p.value
## [1,]      1  0.1695331 0.6805271
## [2,]      2  0.3058078 0.8582122
## [3,]      3  3.0820338 0.3791493
## [4,]      4  3.3053343 0.5080875
## [5,]     12 12.4093335 0.4133903
## [6,]     24 28.0117983 0.2595426
## [7,]     36 43.2220957 0.1901054
## [8,]     48 57.6881908 0.1595803
```



c)Stability

```
ultim = c(2018,12)
#pdq = c(2,1,0)
#PDQ = c(0,1,1)
serie1=window(serie)
serie2=window(serie,end=ultim)
```

```
(mod31= arima(serie1, order=c(2,1,0),seasonal=list(order=c(0,1,1),period=12)))
```

```
##
## Call:
## arima(x = serie1, order = c(2, 1, 0), seasonal = list(order = c(0, 1, 1), period = 12))
##
## Coefficients:
##           ar1      ar2     sma1
##       -0.4478  -0.2909  -0.8557
## s.e.   0.0513   0.0516   0.0350
##
## sigma^2 estimated as 10.75:  log likelihood = -912.4,  aic = 1832.81
```

```
(mod32= arima(serie2, order=c(2,1,0),seasonal=list(order=c(0,1,1),period=12)))
```

```
##
## Call:
## arima(x = serie2, order = c(2, 1, 0), seasonal = list(order = c(0, 1, 1), period = 12))
##
```

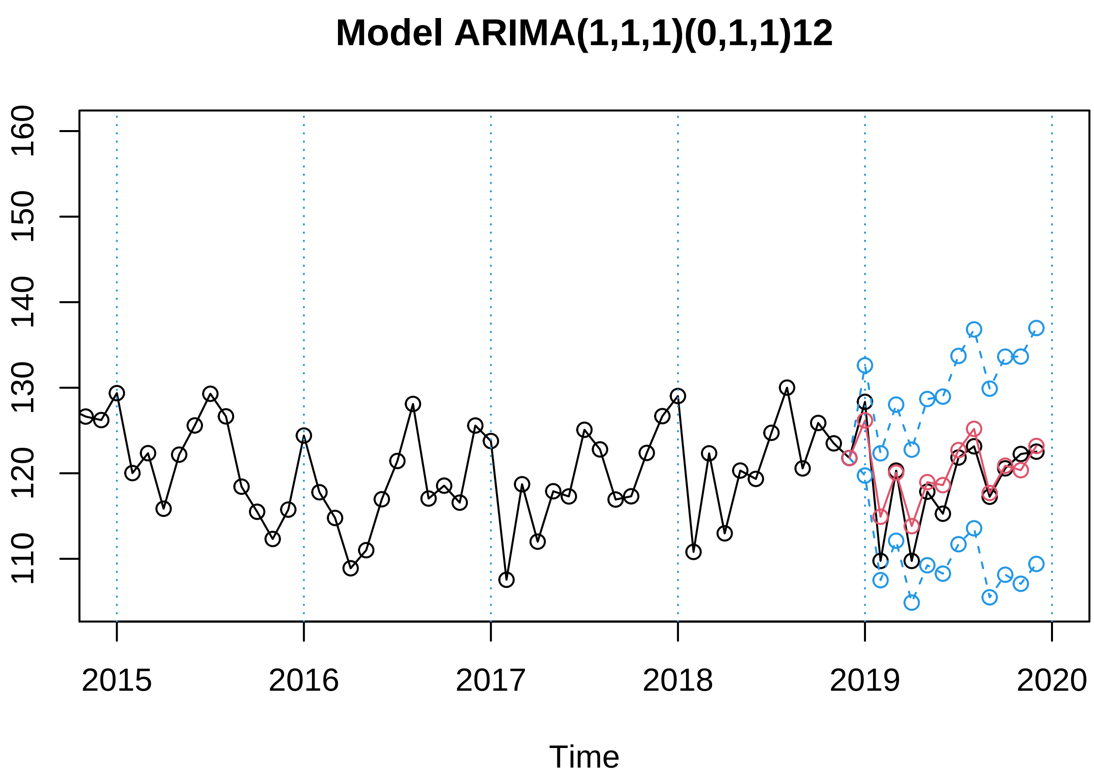
```
## Coefficients:
##           ar1      ar2     sma1
##       -0.4292  -0.3068  -0.8673
## s.e.   0.0523   0.0524   0.0356
##
## sigma^2 estimated as 10.8:  log likelihood = -882.47,  aic = 1772.95
```

Problem: shorter TS has lower aic

Prediction

a)

```
pred=predict(mod32,n.ahead=12)
pr<-ts(c(tail(serie2,1),pred$pred),start=ultim,freq=12)

se<-ts(c(0,pred$se),start=ultim,freq=12)

#Intervals
tl<-ts(pr-1.96*se,start=ultim,freq=12)
tu<-ts(pr+1.96*se,start=ultim,freq=12)
pr<-ts(pr,start=ultim,freq=12)


ts.plot(serie,tl,tu,pr,lty=c(1,2,2,1),col=c(1,4,4,2),xlim=ultim[1]+c(-3,+2),type="o",main="Model ARIMA(
abline(v=(ultim[1]-3):(ultim[1]+2),lty=3,col=4)
```



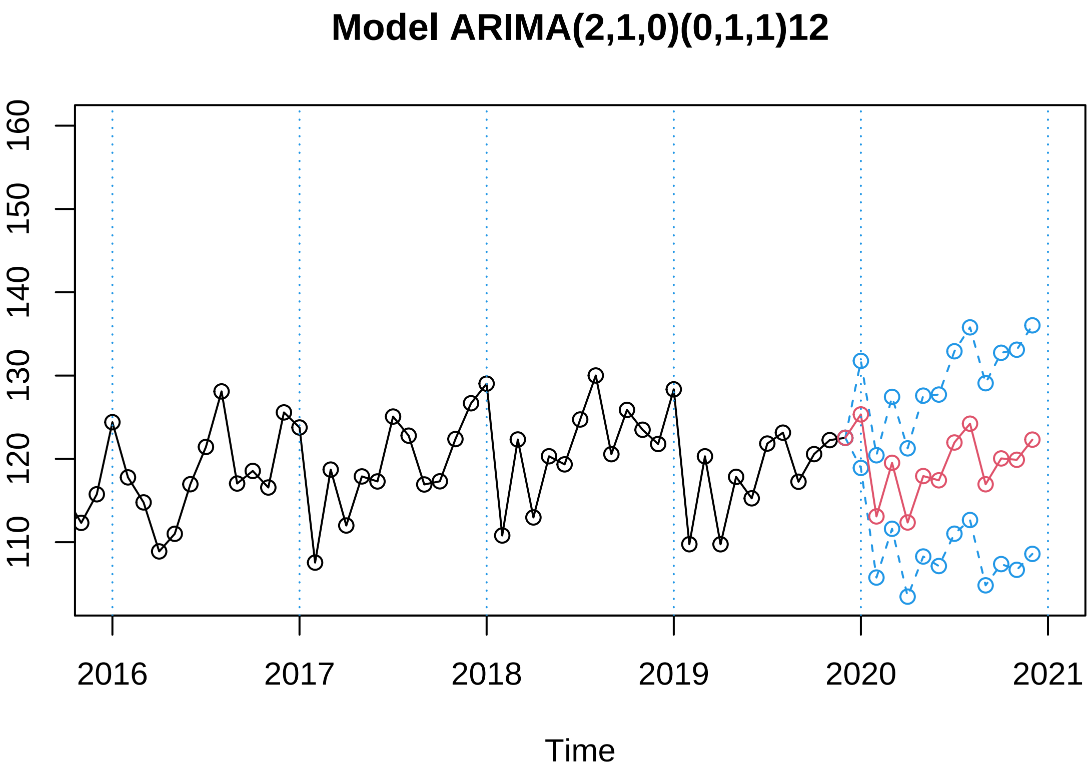

```
obs=window(serie,start=ultim)
(mod.EQM1=sqrt(sum(((obs-pr)/obs)^2)/12))
```

```
## [1] 0.02125953
```

```
(mod.EAM1=sum(abs(obs-pr)/obs)/12)
```

```
## [1] 0.01604008
```

```
pred <- predict(mod31,n.ahead=12)
pr<-ts(c(tail(serie1,1),pred$pred),start=ultim + c(1,0),freq=12)
se<-ts(c(0,pred$se),start=ultim + c(1,0),freq=12)

#Intervals
tl1<-ts(pr-1.96*se,start=ultim + c(1,0),freq=12)
tu1<-ts(pr+1.96*se,start=ultim + c(1,0),freq=12)
pr1<-ts(pr,start=ultim + c(1,0),freq=12)

ts.plot(serie,tl1,tu1,pr1,lty=c(1,2,2,1),col=c(1,4,4,2),xlim=c(ultim[1]-2,ultim[1]+3),type="o",main="Mod
abline(v=(ultim[1]-2):(ultim[1]+3),lty=3,col=4)
```




```
previs1=window(cbind(tl1,pr1,tu1),start=ultim+c(1,0))
```

Outlier treatment

```
source("CalendarEffects.r")
source("atipics2.r")
```

a) Calendar effect:

```
data=c(start(serie)[1],start(serie)[2], length(serie)) #starting year, month, series size
(wTradDays=Wtrad(data)) #creates auxiliary variable for trading days configurations (5/2 the ideal prop
```

```
##       Jan  Feb  Mar  Apr  May  Jun  Jul  Aug  Sep  Oct  Nov  Dec
## 1990  3.0  0.0 -0.5 -1.5  3.0 -1.5 -0.5  3.0 -5.0  3.0  2.0 -4.0
## 1991  3.0  0.0 -4.0  2.0  3.0 -5.0  3.0 -0.5 -1.5  3.0 -1.5 -0.5
## 1992  3.0 -2.5 -0.5  2.0 -4.0  2.0  3.0 -4.0  2.0 -0.5 -1.5  3.0
## 1993 -4.0  0.0  3.0  2.0 -4.0  2.0 -0.5 -0.5  2.0 -4.0  2.0  3.0
## 1994 -4.0  0.0  3.0 -1.5 -0.5  2.0 -4.0  3.0  2.0 -4.0  2.0 -0.5
## 1995 -0.5  0.0  3.0 -5.0  3.0  2.0 -4.0  3.0 -1.5 -0.5  2.0 -4.0
## 1996  3.0  1.0 -4.0  2.0  3.0 -5.0  3.0 -0.5 -1.5  3.0 -1.5 -0.5
## 1997  3.0  0.0 -4.0  2.0 -0.5 -1.5  3.0 -4.0  2.0  3.0 -5.0  3.0
## 1998 -0.5  0.0 -0.5  2.0 -4.0  2.0  3.0 -4.0  2.0 -0.5 -1.5  3.0
## 1999 -4.0  0.0  3.0  2.0 -4.0  2.0 -0.5 -0.5  2.0 -4.0  2.0  3.0
## 2000 -4.0  1.0  3.0 -5.0  3.0  2.0 -4.0  3.0 -1.5 -0.5  2.0 -4.0
## 2001  3.0  0.0 -0.5 -1.5  3.0 -1.5 -0.5  3.0 -5.0  3.0  2.0 -4.0
## 2002  3.0  0.0 -4.0  2.0  3.0 -5.0  3.0 -0.5 -1.5  3.0 -1.5 -0.5
## 2003  3.0  0.0 -4.0  2.0 -0.5 -1.5  3.0 -4.0  2.0  3.0 -5.0  3.0
## 2004 -0.5 -2.5  3.0  2.0 -4.0  2.0 -0.5 -0.5  2.0 -4.0  2.0  3.0
## 2005 -4.0  0.0  3.0 -1.5 -0.5  2.0 -4.0  3.0  2.0 -4.0  2.0 -0.5
## 2006 -0.5  0.0  3.0 -5.0  3.0  2.0 -4.0  3.0 -1.5 -0.5  2.0 -4.0
## 2007  3.0  0.0 -0.5 -1.5  3.0 -1.5 -0.5  3.0 -5.0  3.0  2.0 -4.0
## 2008  3.0  1.0 -4.0  2.0 -0.5 -1.5  3.0 -4.0  2.0  3.0 -5.0  3.0
## 2009 -0.5  0.0 -0.5  2.0 -4.0  2.0  3.0 -4.0  2.0 -0.5 -1.5  3.0
## 2010 -4.0  0.0  3.0  2.0 -4.0  2.0 -0.5 -0.5  2.0 -4.0  2.0  3.0
## 2011 -4.0  0.0  3.0 -1.5 -0.5  2.0 -4.0  3.0  2.0 -4.0  2.0 -0.5
## 2012 -0.5  1.0 -0.5 -1.5  3.0 -1.5 -0.5  3.0 -5.0  3.0  2.0 -4.0
## 2013  3.0  0.0 -4.0  2.0  3.0 -5.0  3.0 -0.5 -1.5  3.0 -1.5 -0.5
## 2014  3.0  0.0 -4.0  2.0 -0.5 -1.5  3.0 -4.0  2.0  3.0 -5.0  3.0
## 2015 -0.5  0.0 -0.5  2.0 -4.0  2.0  3.0 -4.0  2.0 -0.5 -1.5  3.0
## 2016 -4.0  1.0  3.0 -1.5 -0.5  2.0 -4.0  3.0  2.0 -4.0  2.0 -0.5
## 2017 -0.5  0.0  3.0 -5.0  3.0  2.0 -4.0  3.0 -1.5 -0.5  2.0 -4.0
## 2018  3.0  0.0 -0.5 -1.5  3.0 -1.5 -0.5  3.0 -5.0  3.0  2.0 -4.0
## 2019  3.0  0.0 -4.0  2.0  3.0 -5.0  3.0 -0.5 -1.5  3.0 -1.5 -0.5
```

```
(wEast=Weaster(data))
```

```
##             Jan        Feb        Mar        Apr        May        Jun
## 1990  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 1991  0.0000000  0.0000000  0.5000000 -0.5000000  0.0000000  0.0000000
## 1992  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 1993  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 1994  0.0000000  0.0000000  0.1666667 -0.1666667  0.0000000  0.0000000
## 1995  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 1996  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 1997  0.0000000  0.0000000  0.5000000 -0.5000000  0.0000000  0.0000000
## 1998  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 1999  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2000  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 2001  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 2002  0.0000000  0.0000000  0.5000000 -0.5000000  0.0000000  0.0000000
## 2003  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 2004  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 2005  0.0000000  0.0000000  0.5000000 -0.5000000  0.0000000  0.0000000
## 2006  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 2007  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 2008  0.0000000  0.0000000  0.5000000 -0.5000000  0.0000000  0.0000000
## 2009  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
```

```
## 2010  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2011  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 2012  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 2013  0.0000000  0.0000000  0.5000000 -0.5000000  0.0000000  0.0000000
## 2014  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 2015  0.0000000  0.0000000 -0.1666667  0.1666667  0.0000000  0.0000000
## 2016  0.0000000  0.0000000  0.5000000 -0.5000000  0.0000000  0.0000000
## 2017  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
## 2018  0.0000000  0.0000000  0.5000000 -0.5000000  0.0000000  0.0000000
## 2019  0.0000000  0.0000000 -0.5000000  0.5000000  0.0000000  0.0000000
##             Jul        Aug        Sep        Oct        Nov        Dec
## 1990  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 1991  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 1992  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 1993  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 1994  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 1995  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 1996  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 1997  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 1998  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 1999  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2001  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2002  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2003  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2004  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2005  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2006  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2007  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2008  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2009  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2010  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2011  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2012  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2013  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2014  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2015  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2016  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2017  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2018  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
## 2019  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
```

```
(mod3EC=arima(serie,order=c(2,1,0),seasonal=list(order=c(1,1,0),period=12),xreg=data.frame(wTradDays,wE
```

```
##
## Call:
## arima(x = serie, order = c(2, 1, 0), seasonal = list(order = c(1, 1, 0), period = 12),
##     xreg = data.frame(wTradDays, wEast))
##
## Coefficients:
##           ar1      ar2     sar1  wTradDays    wEast
##       -0.3804  -0.3156  -0.4787     0.2429  -0.3014
## s.e.   0.0510   0.0512   0.0474     0.0424   0.5557
##
## sigma^2 estimated as 13.35:  log likelihood = -943.76,  aic = 1899.52
```

```
(mod3Ea=arima(serie,order=c(2,1,0),seasonal=list(order=c(1,1,0),period=12),xreg=data.frame(wEast)))
```

```
##
## Call:
## arima(x = serie, order = c(2, 1, 0), seasonal = list(order = c(1, 1, 0), period = 12),
##     xreg = data.frame(wEast))
##
## Coefficients:
##           ar1      ar2     sar1    wEast
##       -0.4416  -0.3382  -0.4473  -0.5613
## s.e.   0.0507   0.0511   0.0487   0.5946
##
## sigma^2 estimated as 14.55:  log likelihood = -958.41,  aic = 1926.82
```

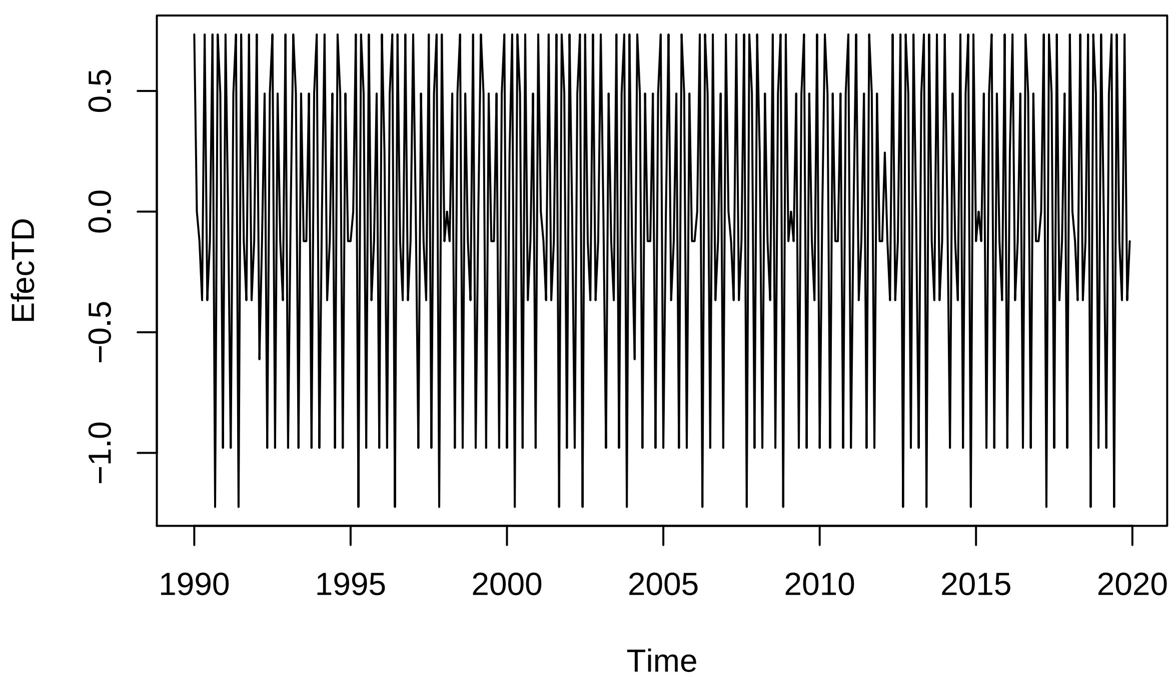
```
(mod3TD=arima(serie,order=c(2,1,0),seasonal=list(order=c(1,1,0),period=12),xreg=data.frame(wTradDays)))
```

```
##
## Call:
## arima(x = serie, order = c(2, 1, 0), seasonal = list(order = c(1, 1, 0), period = 12),
##     xreg = data.frame(wTradDays))
##
## Coefficients:
##           ar1      ar2     sar1  wTradDays
##       -0.3802  -0.3174  -0.4786     0.2448
## s.e.   0.0510   0.0511   0.0474     0.0423
##
## sigma^2 estimated as 13.37:  log likelihood = -943.91,  aic = 1897.81
```

Only use trading days not easter, because lowest aic and other parameters are not significant

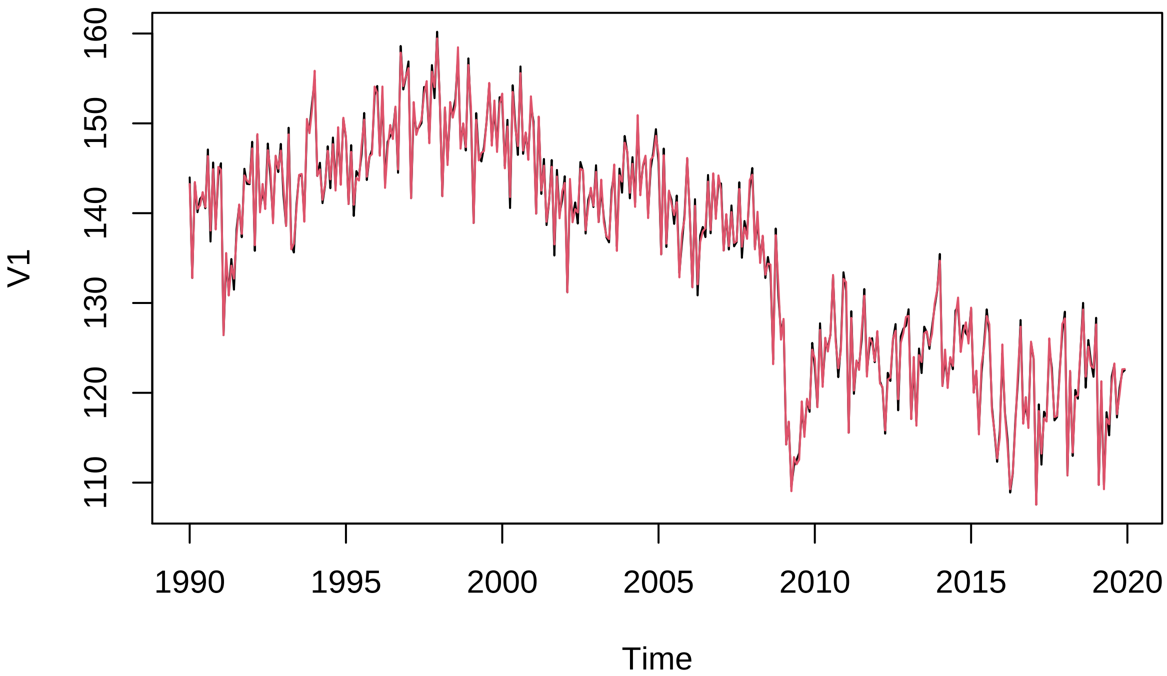
Calculate Trading day effect:

```
EfecTD=coef(mod3TD)["wTradDays"]*wTradDays
plot(EfecTD)
```



corrected series for trading day effect and compare with original serie:

```
serieTD=serie-EfecTD
plot(serie)
lines(serieTD,col=2)
```



Transform into stationarity:

```
d12serieTD <- diff(serieTD, 12)
d1d12serieTD <- diff(d12serieTD)
```

Variance

```
var(serieTD)
```

```
##          serie
## serie 149.4372
```

```
var(d12serieTD)
```

```
##          serie
## serie 37.02932
```

```
var(d1d12serieTD)
```

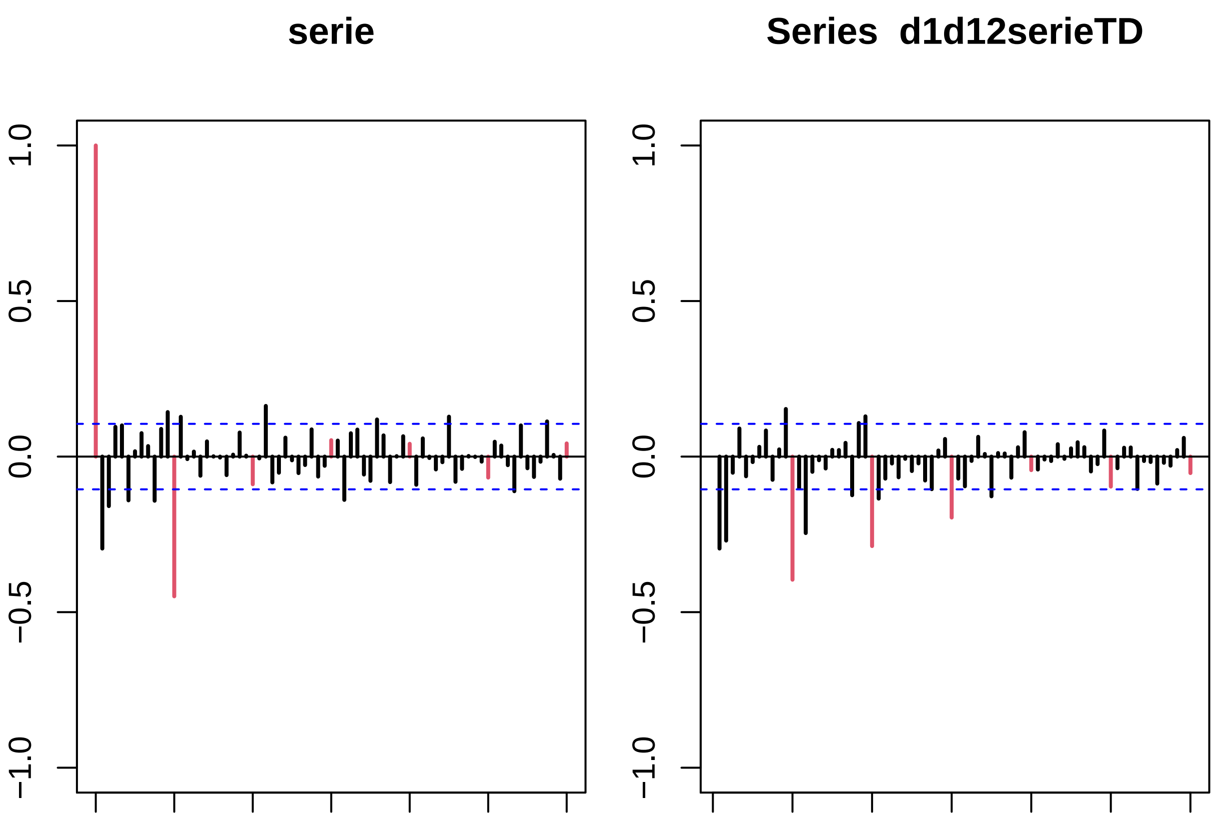
```
##          serie
## serie 20.63326
```

```
var(diff(d1d12serieTD)) # not necessary
```

```
##          serie
## serie 53.43205
```

Same Transformation as before.

```
par(mfrow=c(1,2), mar =c(1,2,4,1))
acf(d1d12serieTD,ylim=c(-1,1),lag.max=72,col=c(2,rep(1,11)),lwd=2)
pacf(d1d12serieTD,ylim=c(-1,1),lag.max=72,col=c(rep(1,11),2),lwd=2)
```



Modelidentification: seasonal: MA(1) (AR(3)) Regular: MA(2), AR(2)

Mdoel estimation

```
#(modec <- arima(serie, order=c(0,1,1),seasonal=list(order=c(0,1,2),period=12), xreg=data.frame(wTradDa
# sma 2 not sign
(modec <- arima(serie, order=c(0,1,1),seasonal=list(order=c(0,1,1),period=12), xreg=data.frame(wTradDays
```

```
##
## Call:
## arima(x = serie, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1), period = 12),
##     xreg = data.frame(wTradDays))
##
## Coefficients:
##           ma1     sma1  wTradDays
##       -0.4677  -0.8652     0.2530
## s.e.   0.0502   0.0343     0.0438
##
## sigma^2 estimated as 9.889:  log likelihood = -898.33,  aic = 1804.66
```

```
# same parameters as before
(modec2 <- arima(serie, order=c(2,1,0),seasonal=list(order=c(1,1,0),period=12), xreg=data.frame(wTradDa
```

```
##
## Call:
## arima(x = serie, order = c(2, 1, 0), seasonal = list(order = c(1, 1, 0), period = 12),
##     xreg = data.frame(wTradDays))
##
## Coefficients:
##           ar1      ar2     sar1  wTradDays
##       -0.3802  -0.3174  -0.4786     0.2448
```

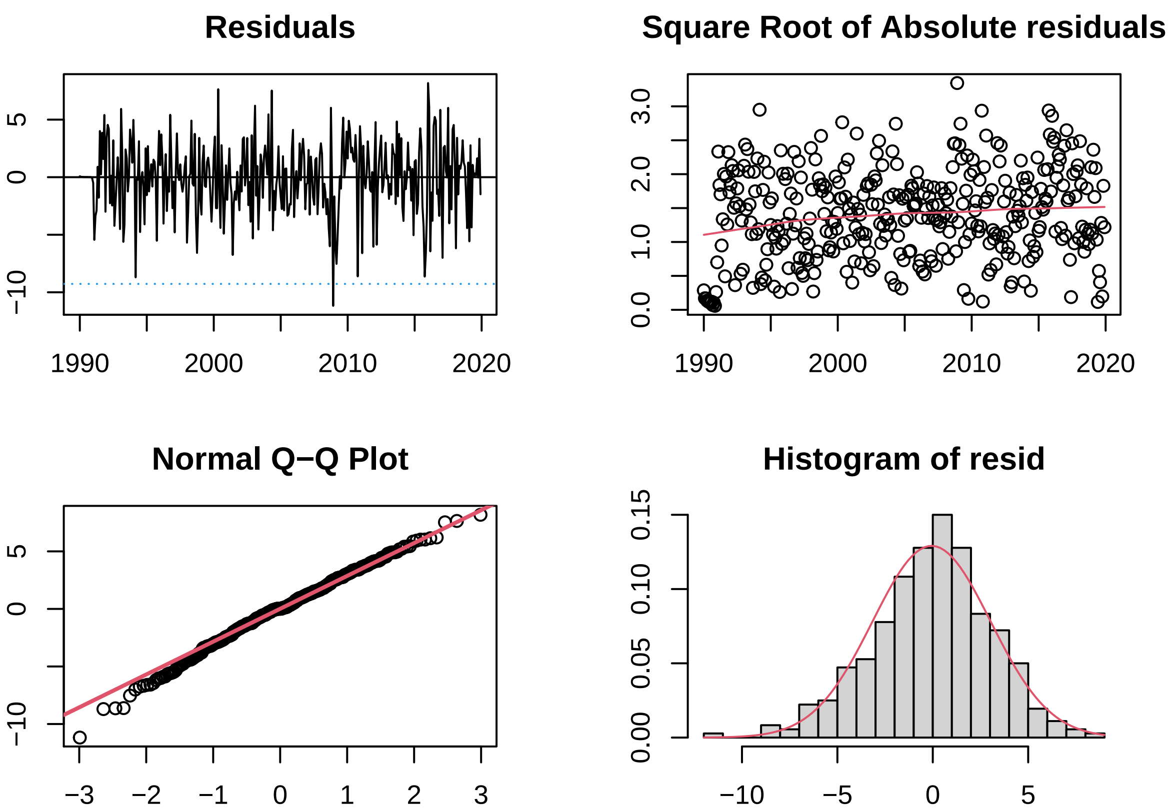
```
## s.e.    0.0510   0.0511   0.0474     0.0423
##
## sigma^2 estimated as 13.37:  log likelihood = -943.91,  aic = 1897.81
```

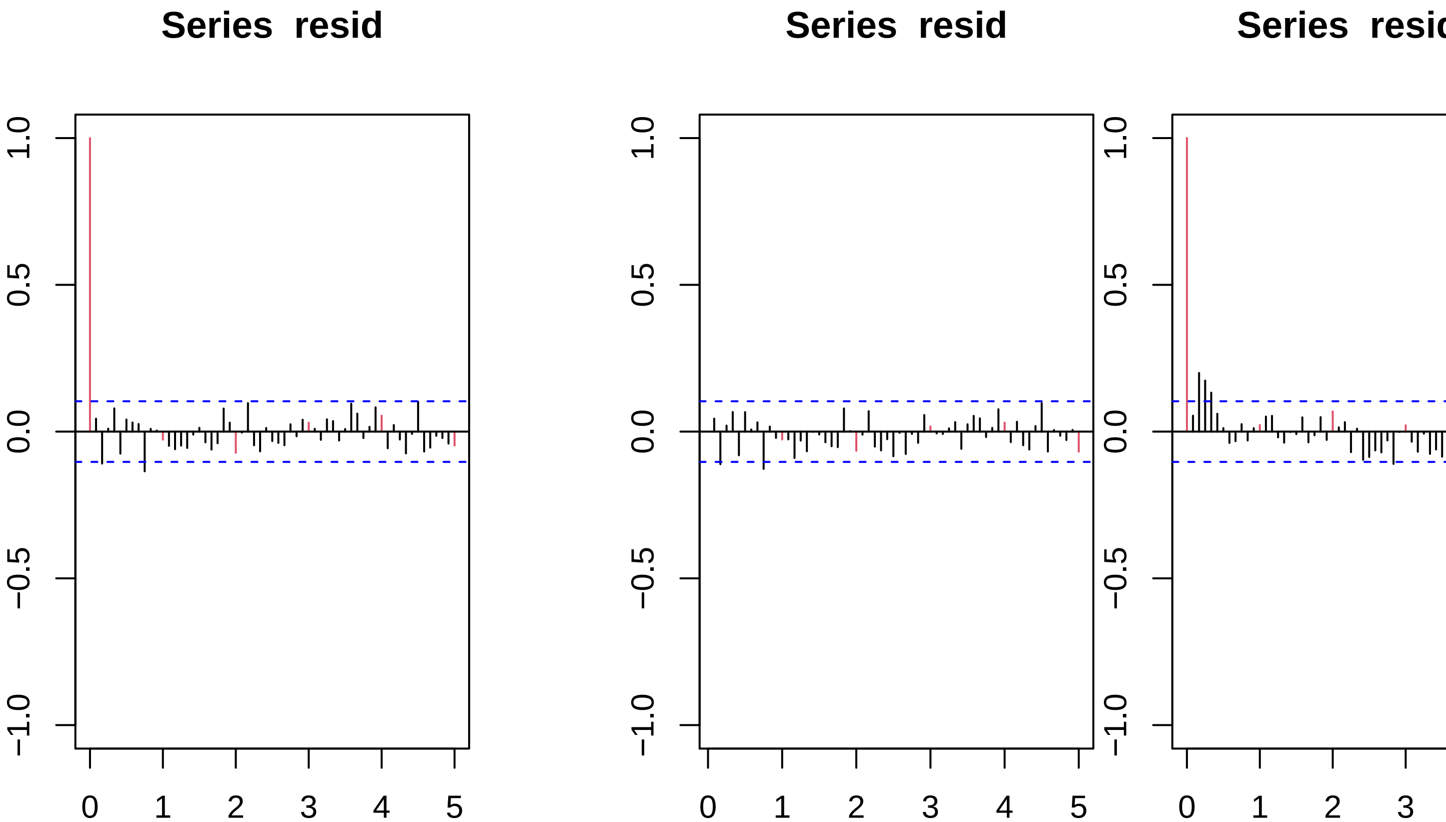
```
(modec3 <- arima(serie, order=c(2,1,0),seasonal=list(order=c(0,1,1),period=12), xreg=data.frame(wTradDa
```

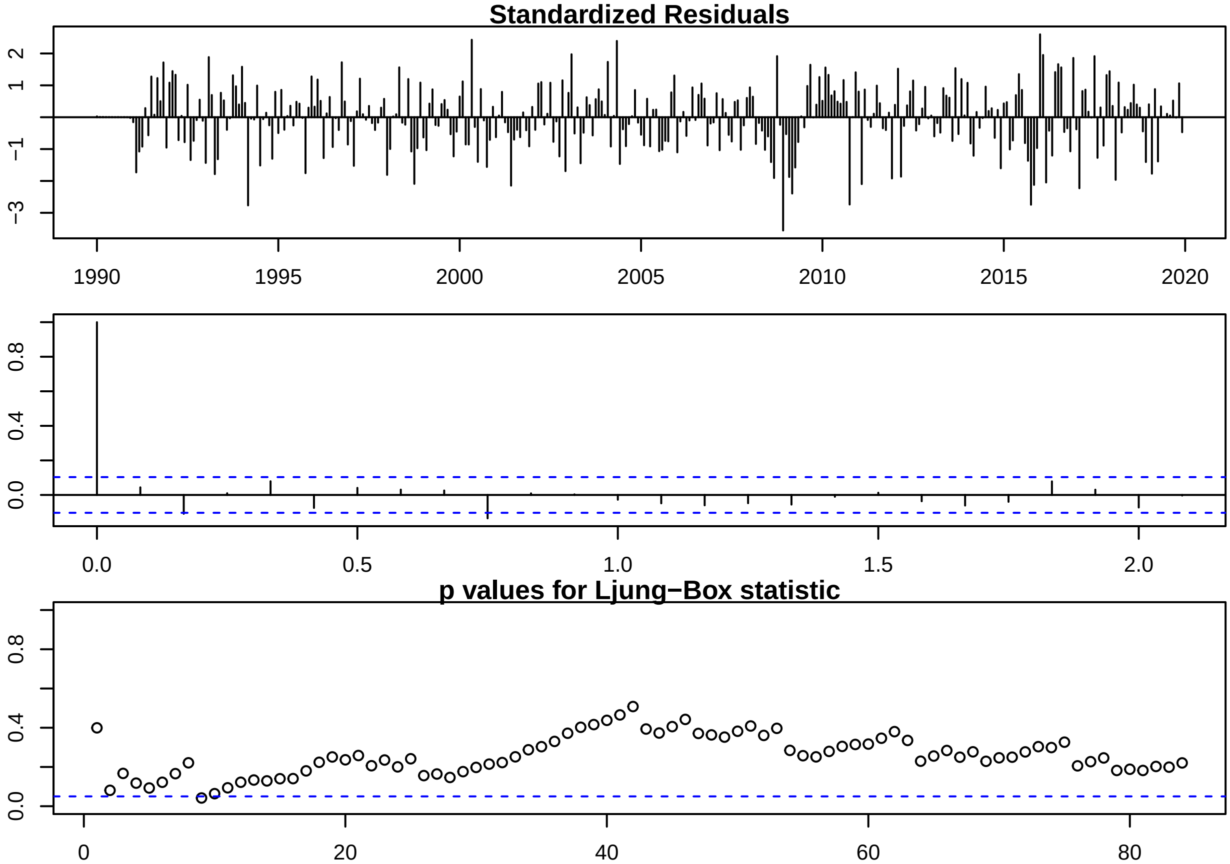
```
##
## Call:
## arima(x = serie, order = c(2, 1, 0), seasonal = list(order = c(0, 1, 1), period = 12),
##     xreg = data.frame(wTradDays))
##
## Coefficients:
##           ar1      ar2     sma1  wTradDays
##       -0.3850  -0.2614  -0.8494     0.2556
## s.e.   0.0518   0.0521   0.0344     0.0445
##
## sigma^2 estimated as 9.872:  log likelihood = -897.43,  aic = 1804.86
```

Prefer modec ARIMA(0,1,1)(0,1,1)_12 + wTradDays since aic is smaller, modec3 with ARIMA(2,1,0)(0,1,1)_12 + wTradDays also possible

```
dades=d1d12serieTD
model=modec
validation(model,dades)
```

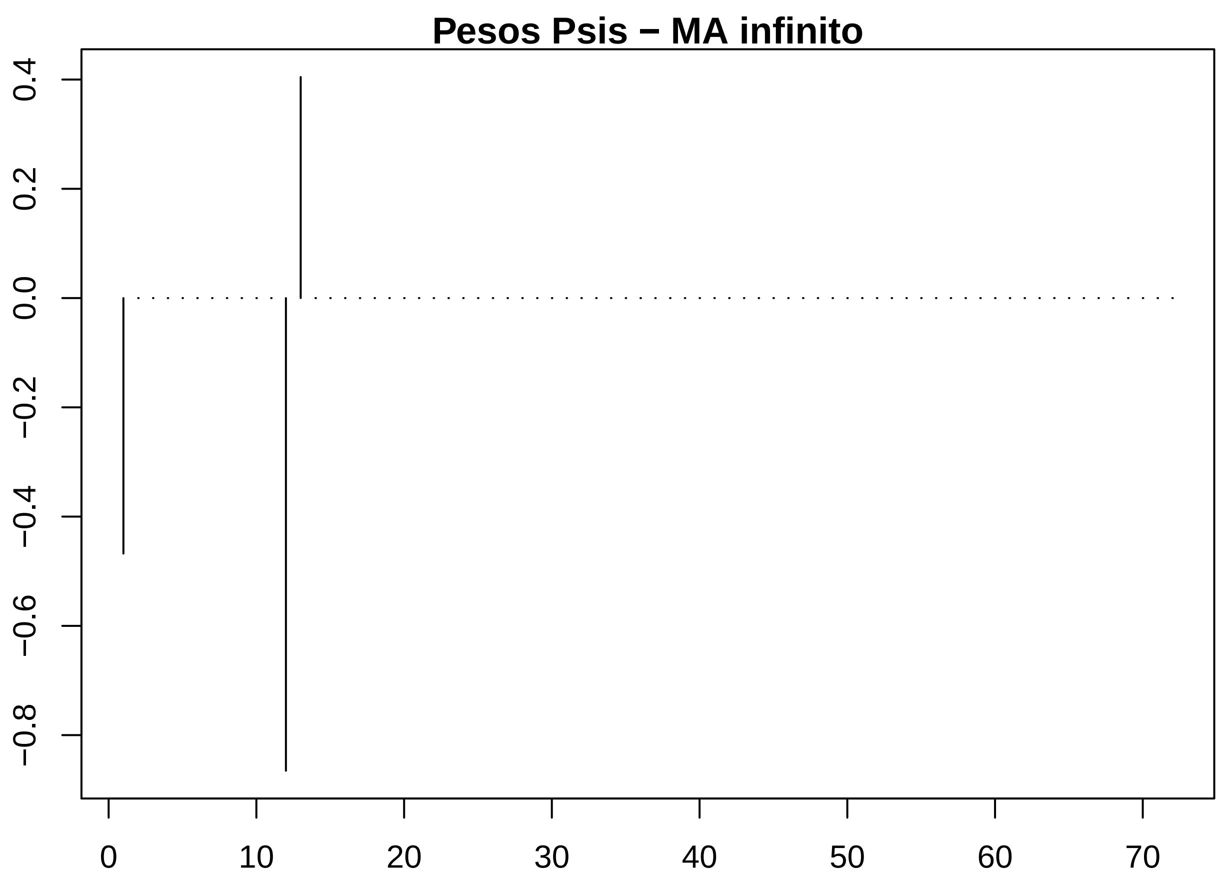



Series resid
Series resid

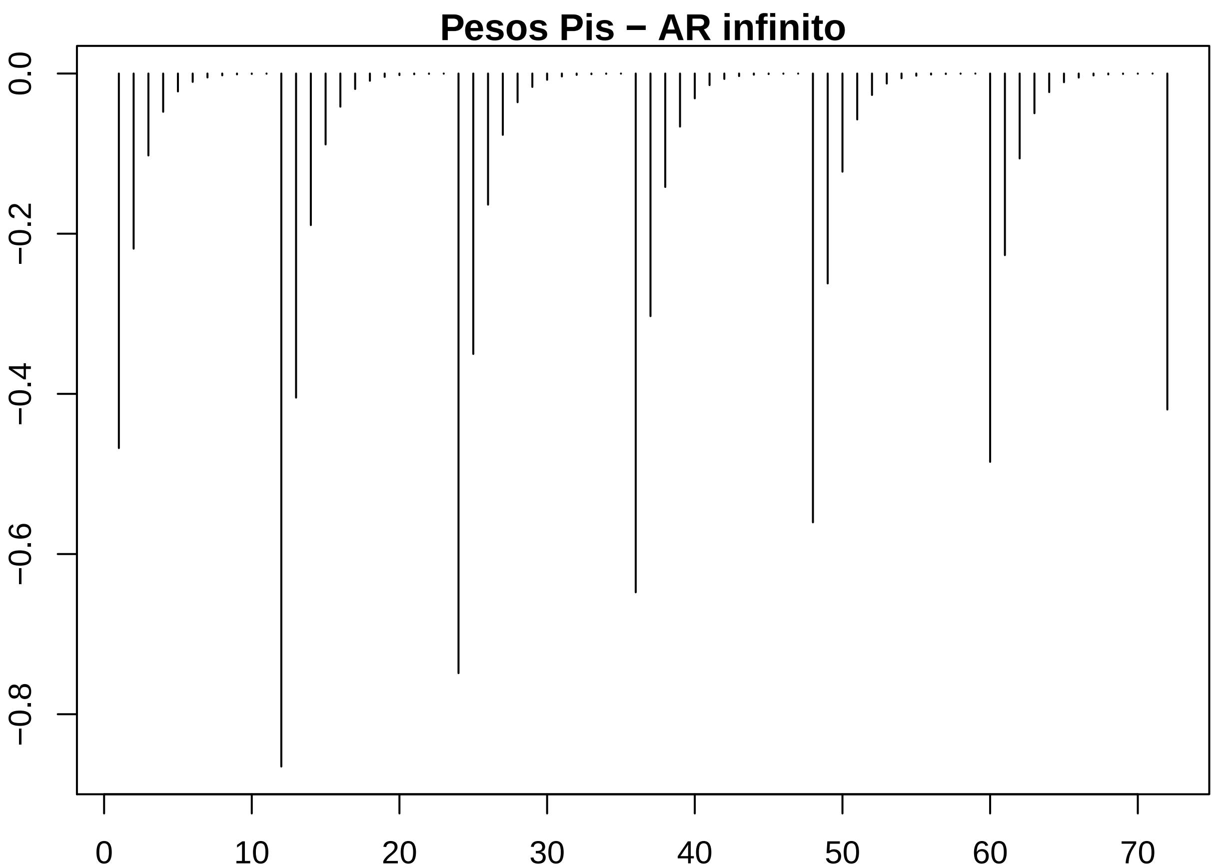

Standardized Residuals
p values for Ljung−Box statistic

##

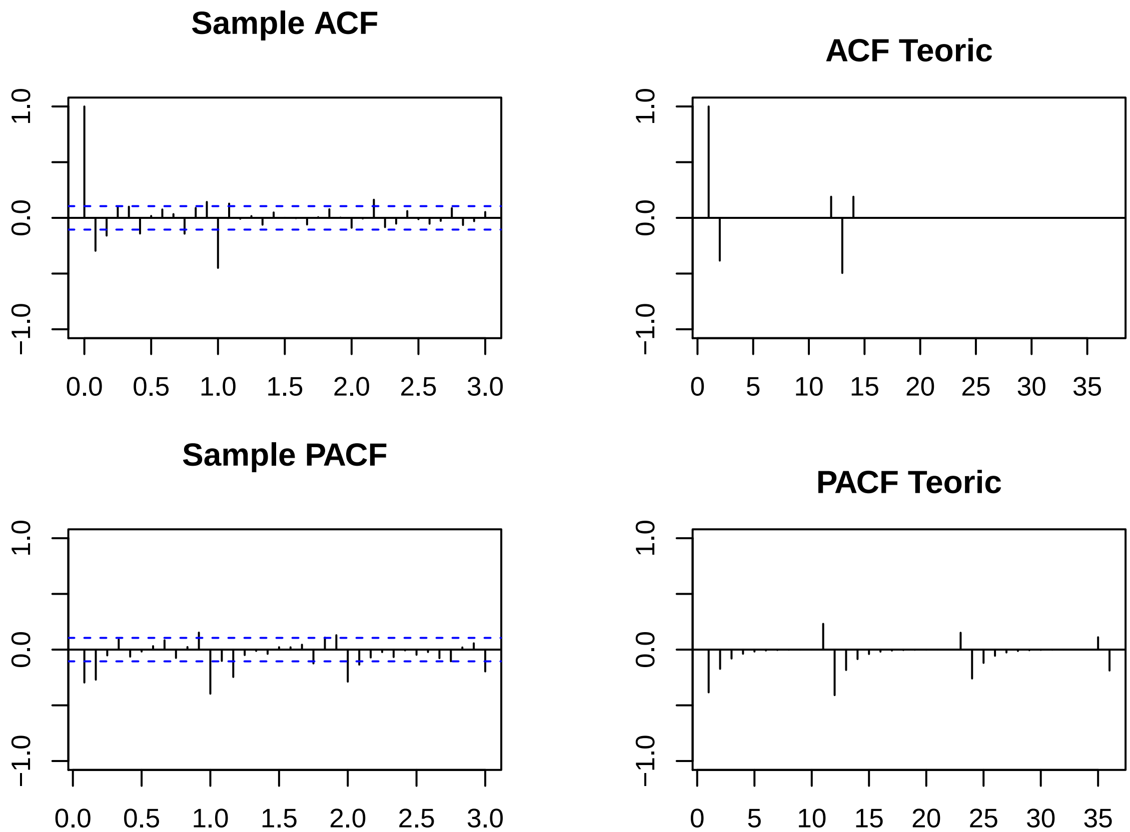
```
## -------------------------------------------------------------------
##
## Call:
## arima(x = serie, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1), period = 12),
##     xreg = data.frame(wTradDays))
##
## Coefficients:
##           ma1     sma1  wTradDays
##       -0.4677  -0.8652     0.2530
## s.e.   0.0502   0.0343     0.0438
##
## sigma^2 estimated as 9.889:  log likelihood = -898.33,  aic = 1804.66
##
## Modul of AR Characteristic polynomial Roots:
##
## Modul of MA Characteristic polynomial Roots:  1.012139 1.012139 1.012139 1.012139 1.012139 1.012139
##
## Psi-weights (MA(inf))
##
## --------------------
##      psi 1      psi 2      psi 3      psi 4      psi 5      psi 6      psi 7
## -0.4676774  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
##      psi 8      psi 9     psi 10     psi 11     psi 12     psi 13     psi 14
##  0.0000000  0.0000000  0.0000000  0.0000000 -0.8652049  0.4046368  0.0000000
##     psi 15     psi 16     psi 17     psi 18     psi 19     psi 20
##  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
```



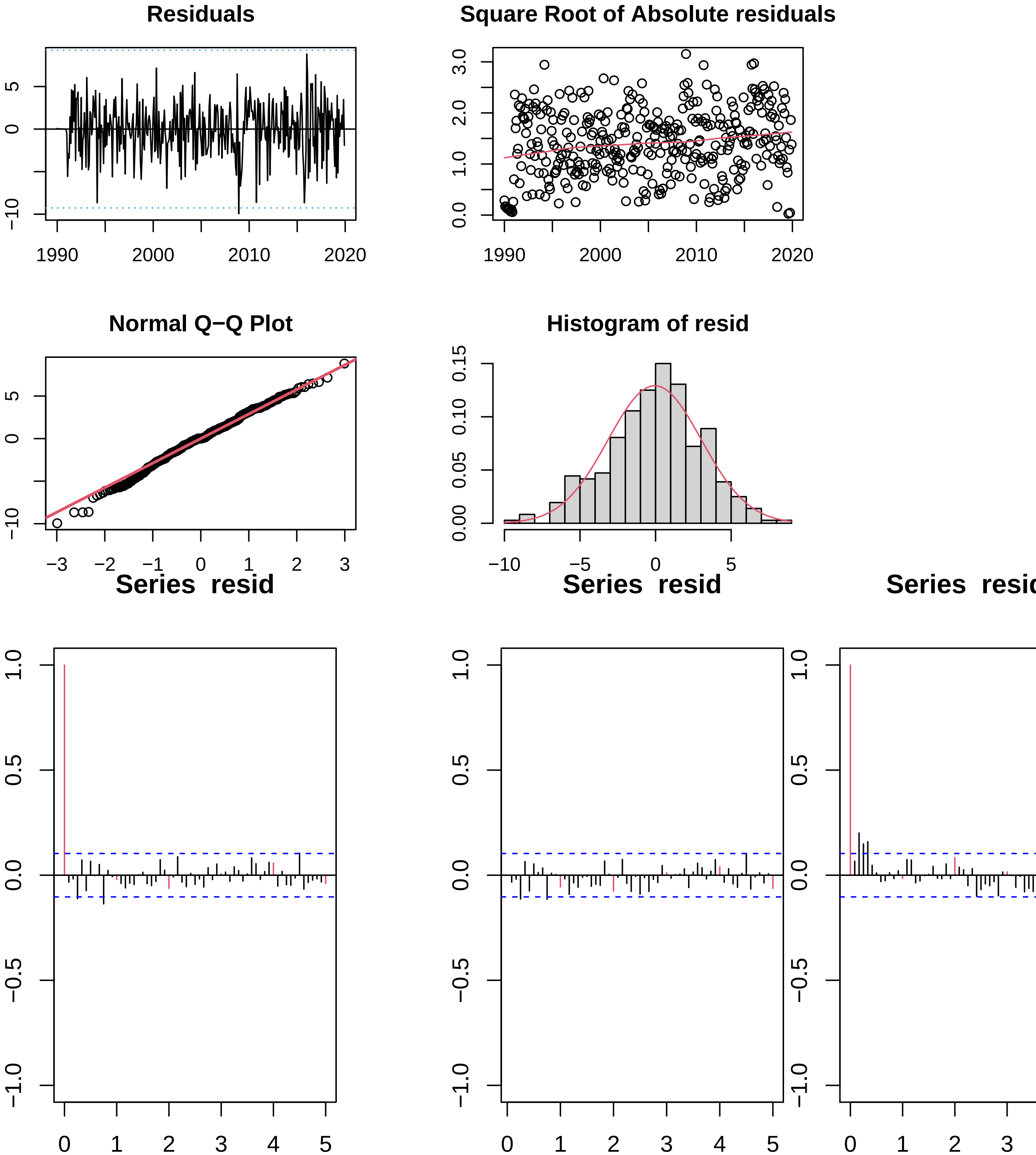
```
##
## Pi-weights (AR(inf))
##
## --------------------
##          pi 1          pi 2          pi 3          pi 4          pi 5
## -0.4676774094 -0.2187221593 -0.1022914128 -0.0478393830 -0.0223733987
##          pi 6          pi 7          pi 8          pi 9         pi 10
## -0.0104635331 -0.0048935581 -0.0022886066 -0.0010703296 -0.0005005690
##         pi 11         pi 12         pi 13         pi 14         pi 15
## -0.0002341048 -0.8653143873 -0.4046879910 -0.1892634313 -0.0885142312
##         pi 16         pi 17         pi 18         pi 19         pi 20
## -0.0413961064 -0.0193600238 -0.0090542458 -0.0042344662 -0.0019803642
```

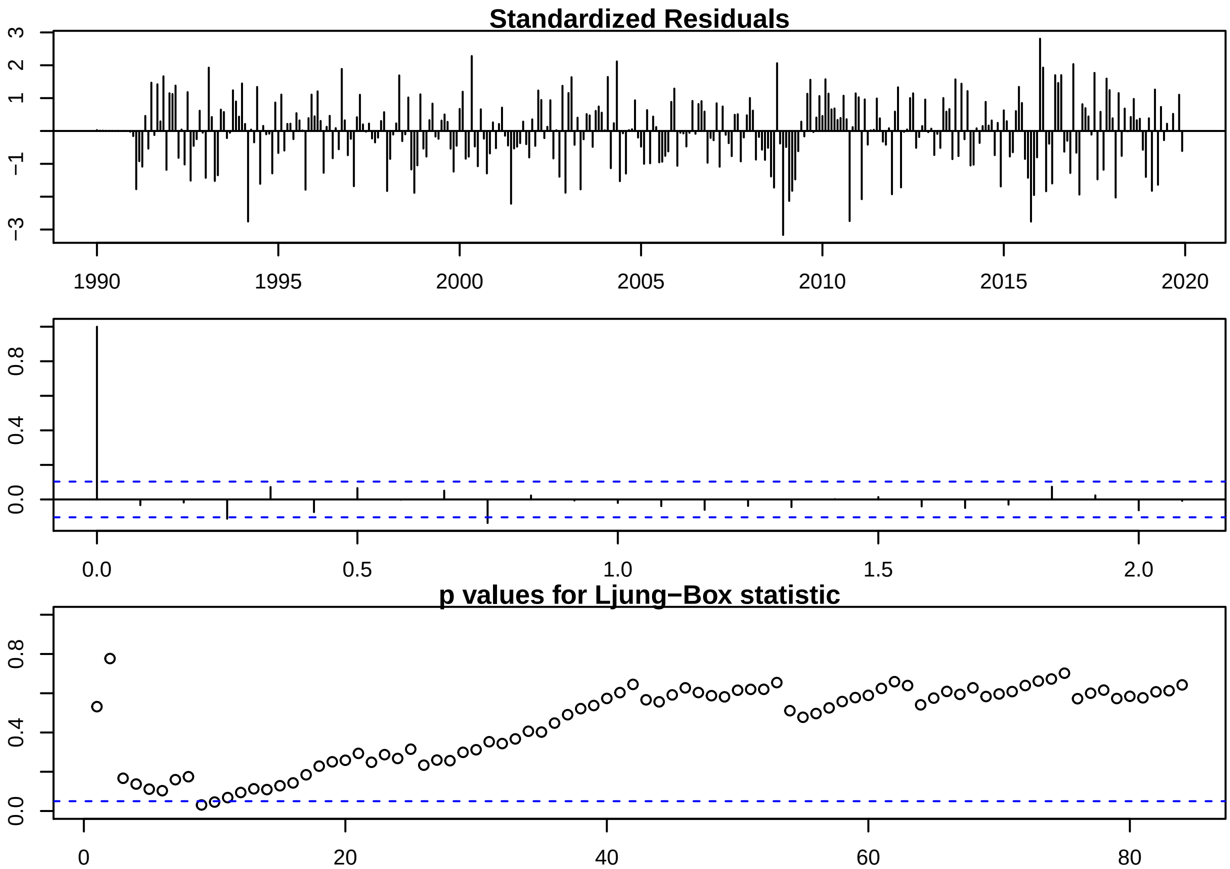



```
##
## Ljung-Box test
##      lag.df  statistic    p.value
## [1,]      1  0.7099452 0.39946200
## [2,]      2  5.0290265 0.08090228
## [3,]      3  5.0653621 0.16707310
## [4,]      4  7.3680593 0.11767004
## [5,]     12 17.7926561 0.12213277
## [6,]     24 29.5411654 0.20042721
## [7,]     36 39.1538578 0.33016082
## [8,]     48 50.8110983 0.36344213
```



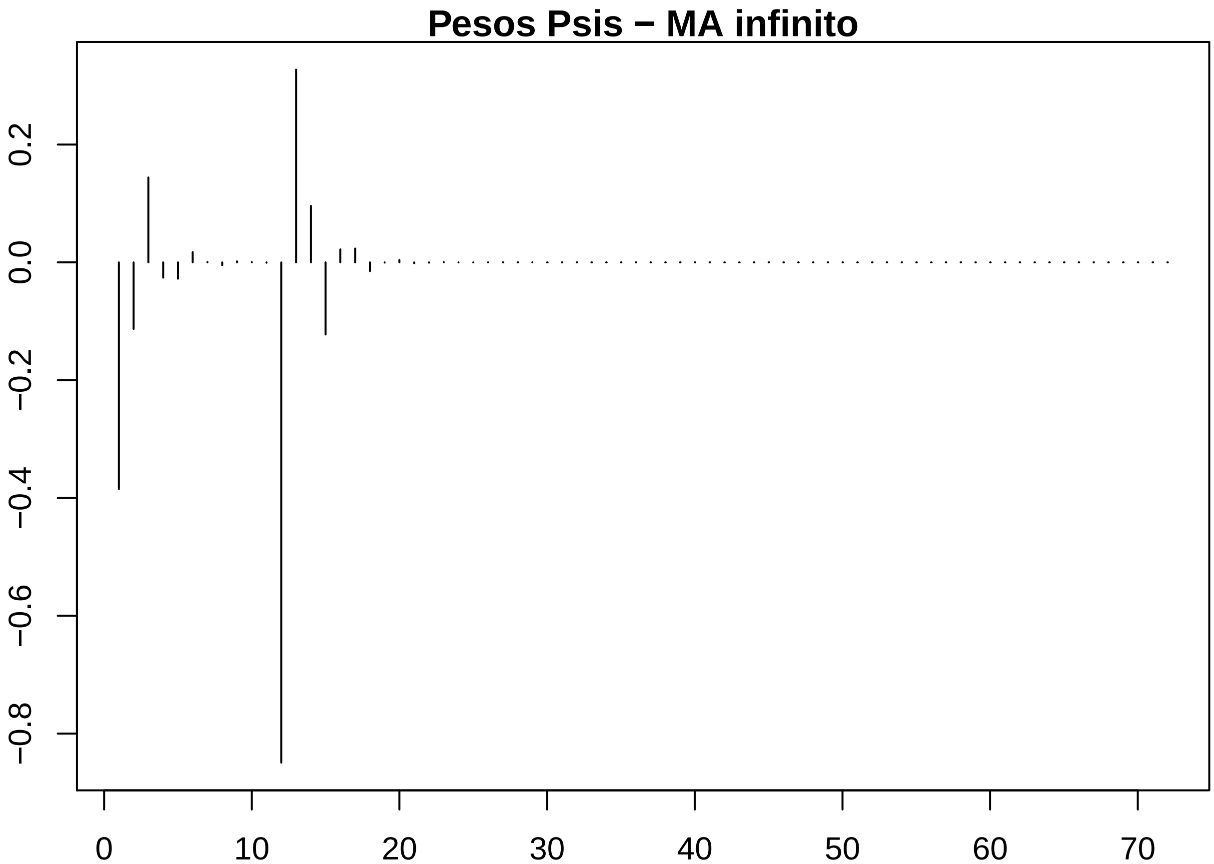

```
dades=d1d12serieTD
model=modec3
validation(model,dades)
```


Residuals
Square Root of Absolute residuals
Normal Q−Q Plot
Histogram of resid
Series resid
Series resid
Series resid

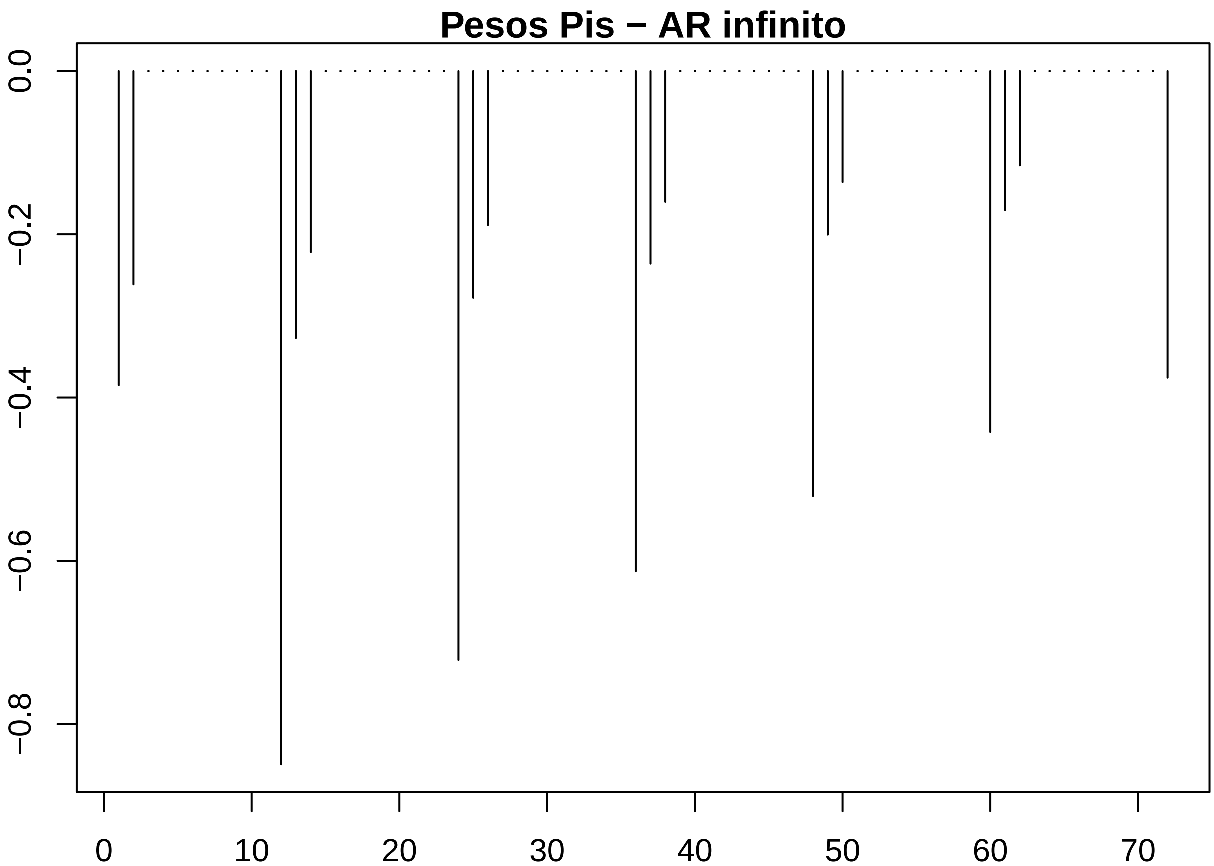



```
##
## ------------------------------------------------------------------
##
## Call:
## arima(x = serie, order = c(2, 1, 0), seasonal = list(order = c(0, 1, 1), period = 12),
##     xreg = data.frame(wTradDays))
##
## Coefficients:
##           ar1      ar2     sma1  wTradDays
##       -0.3850  -0.2614  -0.8494     0.2556
## s.e.   0.0518   0.0521   0.0344     0.0445
##
## sigma^2 estimated as 9.872:  log likelihood = -897.43,  aic = 1804.86
##
## Modul of AR Characteristic polynomial Roots:  1.955997 1.955997
##
## Modul of MA Characteristic polynomial Roots:  1.013692 1.013692 1.013692 1.013692 1.013692 1.013692
##
## Psi-weights (MA(inf))
##
## --------------------
##         psi 1         psi 2         psi 3         psi 4         psi 5
## -0.3849552064 -0.1131843451  0.1441885146 -0.0259225775 -0.0277082211
##         psi 6         psi 7         psi 8         psi 9        psi 10
##  0.0174419339  0.0005278690 -0.0047620889  0.0016952192  0.0005921068
##        psi 11        psi 12        psi 13        psi 14        psi 15
```

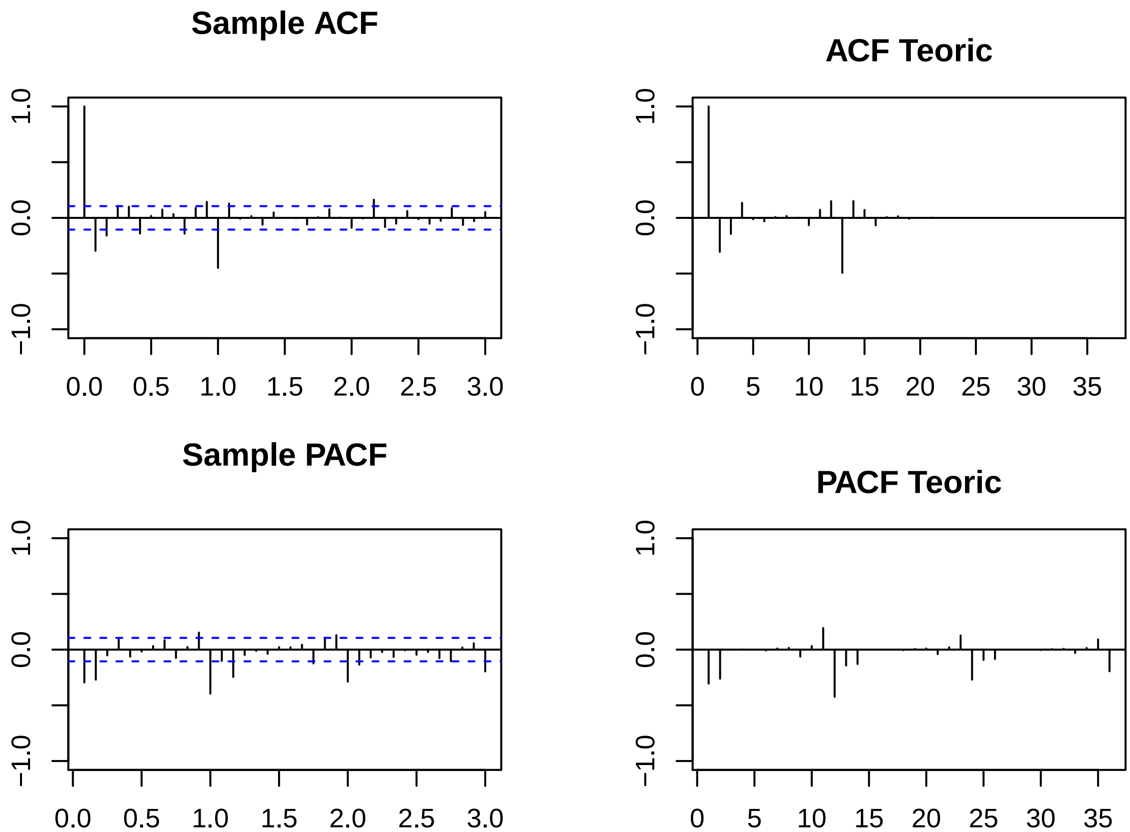
```
## -0.0006710223 -0.8493274127  0.3271283978  0.0960630503 -0.1224831093
##        psi 16        psi 17        psi 18        psi 19        psi 20
##  0.0220420447  0.0235288052 -0.0148187723 -0.0004452745  0.0040446652
```




```
##
## Pi-weights (AR(inf))
##
## --------------------
##       pi 1       pi 2       pi 3       pi 4       pi 5       pi 6       pi 7
## -0.3849552 -0.2613749  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
##       pi 8       pi 9      pi 10      pi 11      pi 12      pi 13      pi 14
##  0.0000000  0.0000000  0.0000000  0.0000000 -0.8494310 -0.3269929 -0.2220199
##      pi 15      pi 16      pi 17      pi 18      pi 19      pi 20
##  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
```




```
##
## Ljung-Box test
##      lag.df  statistic    p.value
## [1,]      1  0.3911560 0.53169239
## [2,]      2  0.5053738 0.77671102
## [3,]      3  5.0697845 0.16675792
## [4,]      4  6.9728113 0.13733202
## [5,]     12 18.7677730 0.09428901
## [6,]     24 27.8216525 0.26763427
## [7,]     36 36.4468952 0.44787184
## [8,]     48 45.2163861 0.58758822
```

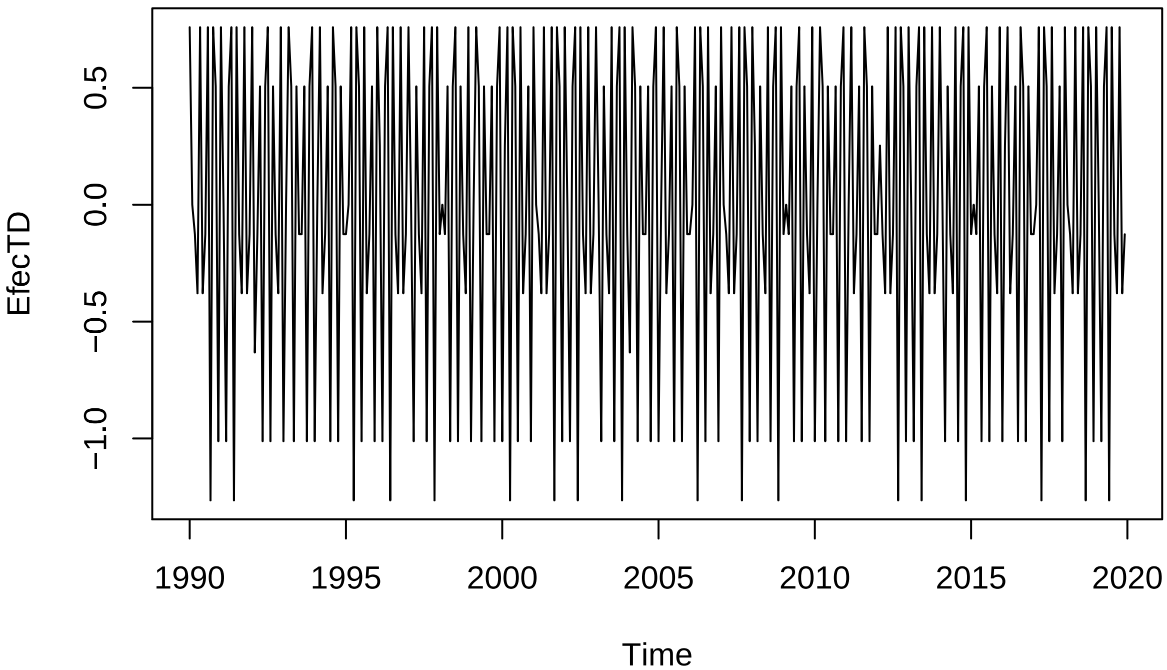


Prefer modec3 (arima(2,1,0)(0,1,1)) because there are only 2 sign Ljung Box

Maybe change model and use modec instead of modec3

Effect of trading days:

```
EfecTD=coef(modec)["wTradDays"]*wTradDays
plot(EfecTD)
```



b) Outlier

(session 5:)

```
# automatic detection of outliers
mod.atip=outdetec(modec,dif=c(1,12),crit=2.8,LS=T)

# estimated variance after outlier detection and treatment
mod.atip$sigma2
```

```
## [1] 6.530993
```

```
modec$sigma2
```

```
## [1] 9.888563
```

Variance after detection is smaller

```
#Table with detected outliers, their types, magnitud, statistic values and chronology
atipics=mod.atip$atip[order(mod.atip$atip[,1]),]

meses=c("Jan","Feb","Mar","Apr","May","Jun","Jul","Aug","Sep","Oct","Nov","Dec")

data.frame(atipics,Fecha=paste(meses[(atipics[,1]-1)%%12+1],start(serie)[1]+((atipics[,1]-1)%/%12)))
```

```
##    Obs type_detected    W_coeff ABS_L_Ratio    Fecha
## 9   14            TC  -6.867291    2.869206 Feb 1991
## 13  40            TC  -6.658615    2.913762 Apr 1993
## 12  51            LS  -6.464667    2.895178 Mar 1994
## 14  82            TC   6.577298    2.911797 Oct 1996
## 6  125            TC   7.149050    2.886624 May 2000
## 4  173            AO   7.442664    3.131095 May 2004
## 5  225            AO  -7.331548    3.122850 Sep 2008
## 1  228            LS -11.060704    4.296762 Dec 2008
## 10 231            LS  -6.587483    2.877064 Mar 2009
```

```
## 7  242            LS   6.881041    2.903492 Feb 2010
## 8  266            AO   6.485825    2.849909 Feb 2012
## 3  310            LS  -8.688132    3.459232 Oct 2015
## 11 313            AO   6.495974    2.925275 Jan 2016
## 2  314            AO   8.895463    3.582324 Feb 2016
```

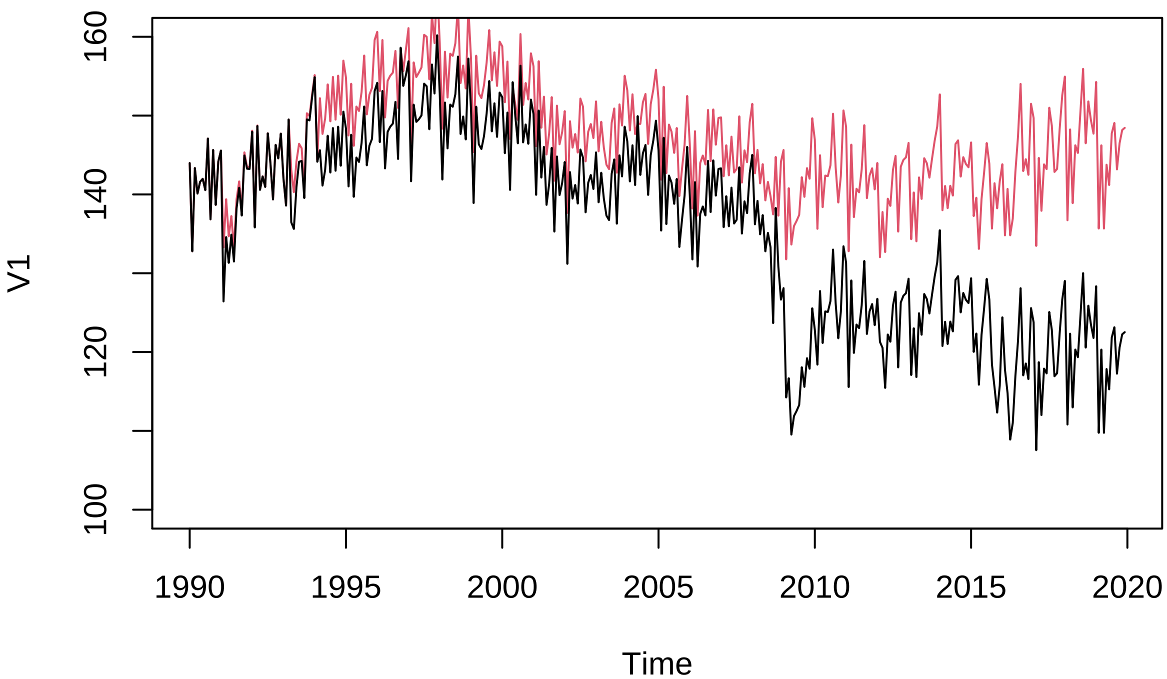
```
#additional column: percentage variation
data.frame(atipics,Fecha=paste(meses[(atipics[,1]-1)%%12+1],start(serie)[1]+((atipics[,1]-1)%/%12)),perc
```

```
##     Obs type_detected    W_coeff ABS_L_Ratio    Fecha      perc.Obs
## 9    14            TC  -6.867291    2.869206 Feb 1991 1.041294e-01
## 13   40            TC  -6.658615    2.913762 Apr 1993 1.282921e-01
## 12   51            LS  -6.464667    2.895178 Mar 1994 1.557510e-01
## 14   82            TC   6.577298    2.911797 Oct 1996 7.185952e+04
## 6  125            TC   7.149050    2.886624 May 2000 1.272897e+05
## 4  173            AO   7.442664    3.131095 May 2004 1.707293e+05
## 5  225            AO  -7.331548    3.122850 Sep 2008 6.545593e-02
## 1  228            LS -11.060704    4.296762 Dec 2008 1.571801e-03
## 10 231            LS  -6.587483    2.877064 Mar 2009 1.377503e-01
## 7  242            LS   6.881041    2.903492 Feb 2010 9.736395e+04
## 8  266            AO   6.485825    2.849909 Feb 2012 6.557794e+04
## 3  310            LS  -8.688132    3.459232 Oct 2015 1.685746e-02
## 11 313            AO   6.495974    2.925275 Jan 2016 6.624693e+04
## 2  314            AO   8.895463    3.582324 Feb 2016 7.298785e+05
```

Linearize serie, (without outliers)

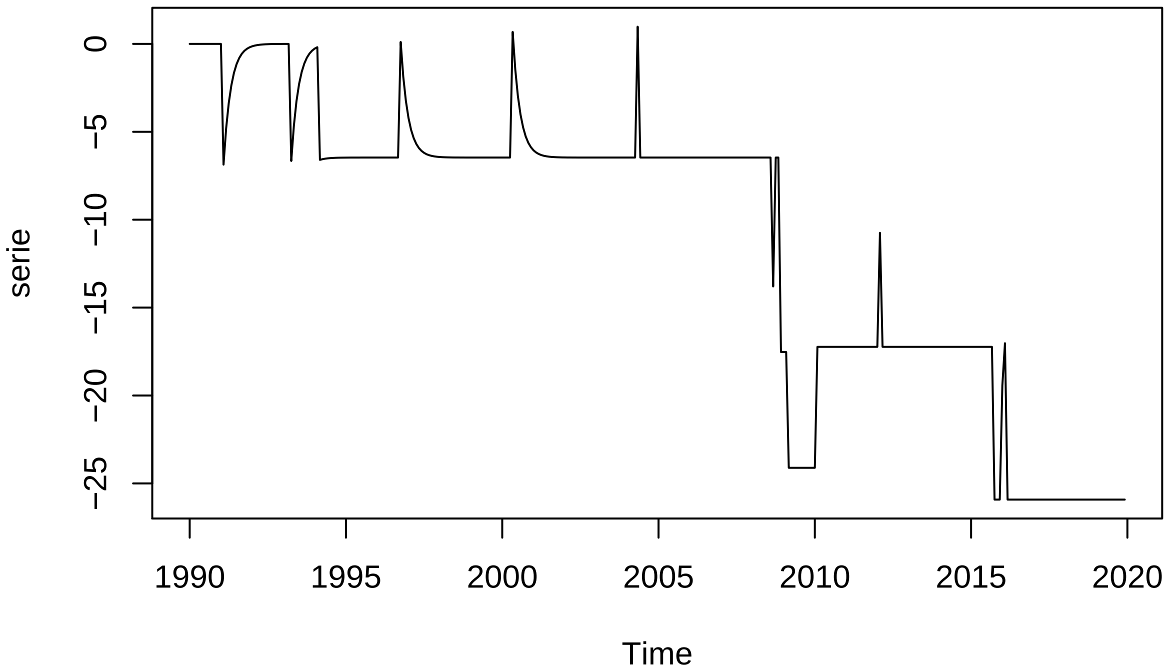
```
serie.lin=lineal(serie,mod.atip$atip)
#serieEC.lin=serie.lin-EfecTD
```

```
plot(serie.lin,col=2, ylim = c(100,160))
lines(serie)
```

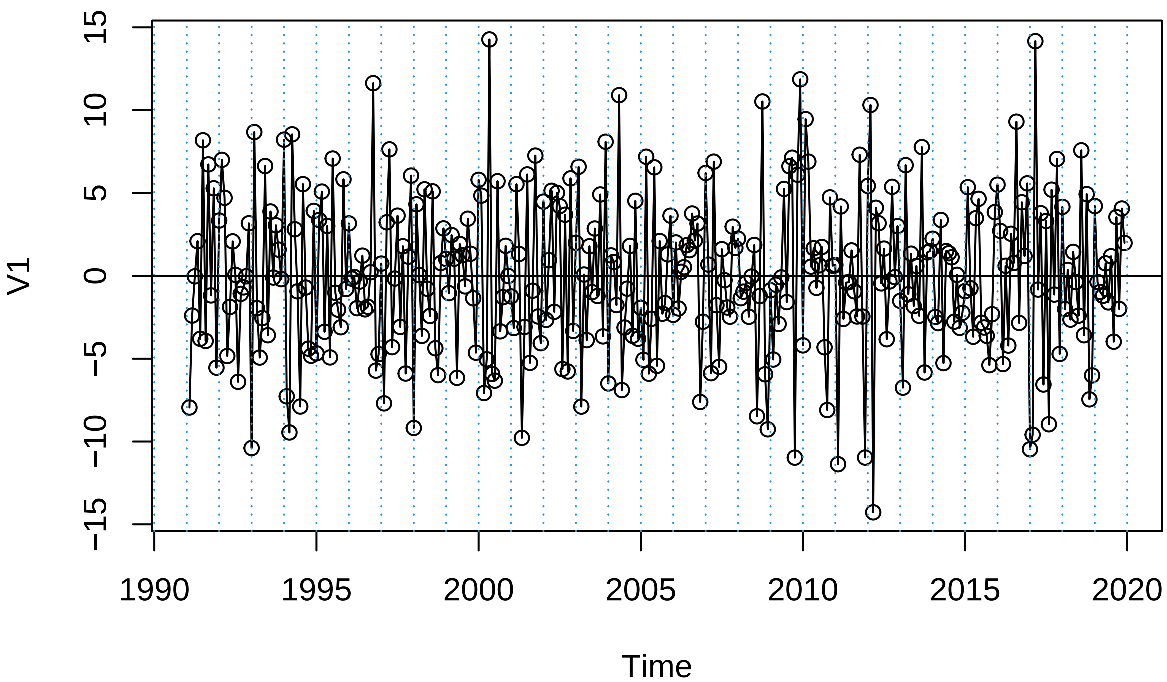


Plot of outlier profile

```
plot(serie-serie.lin)
```



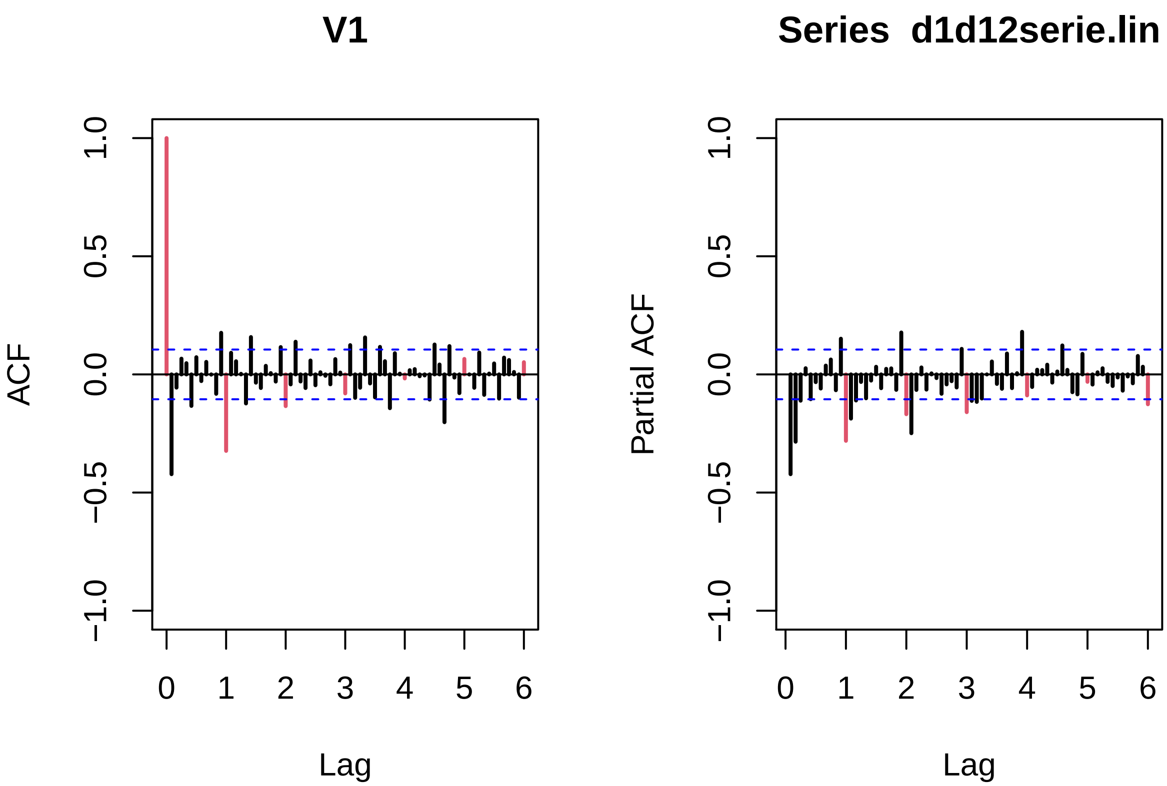

```
d12serie.lin=diff(serie.lin,12)
d1d12serie.lin=diff(d12serie.lin)
plot(d1d12serie,col=1,type="o")
abline(v=1990:2020,lty=3,col=4)
abline(h=0)
```



Identify model:

```
par(mfrow=c(1,2))
acf(d1d12serie.lin,ylim=c(-1,1),lag.max=72,col=c(2,rep(1,11)),lwd=2)
```

```
pacf(d1d12serie.lin,ylim=c(-1,1),lag.max=72,col=c(rep(1,11),2),lwd=2)
```



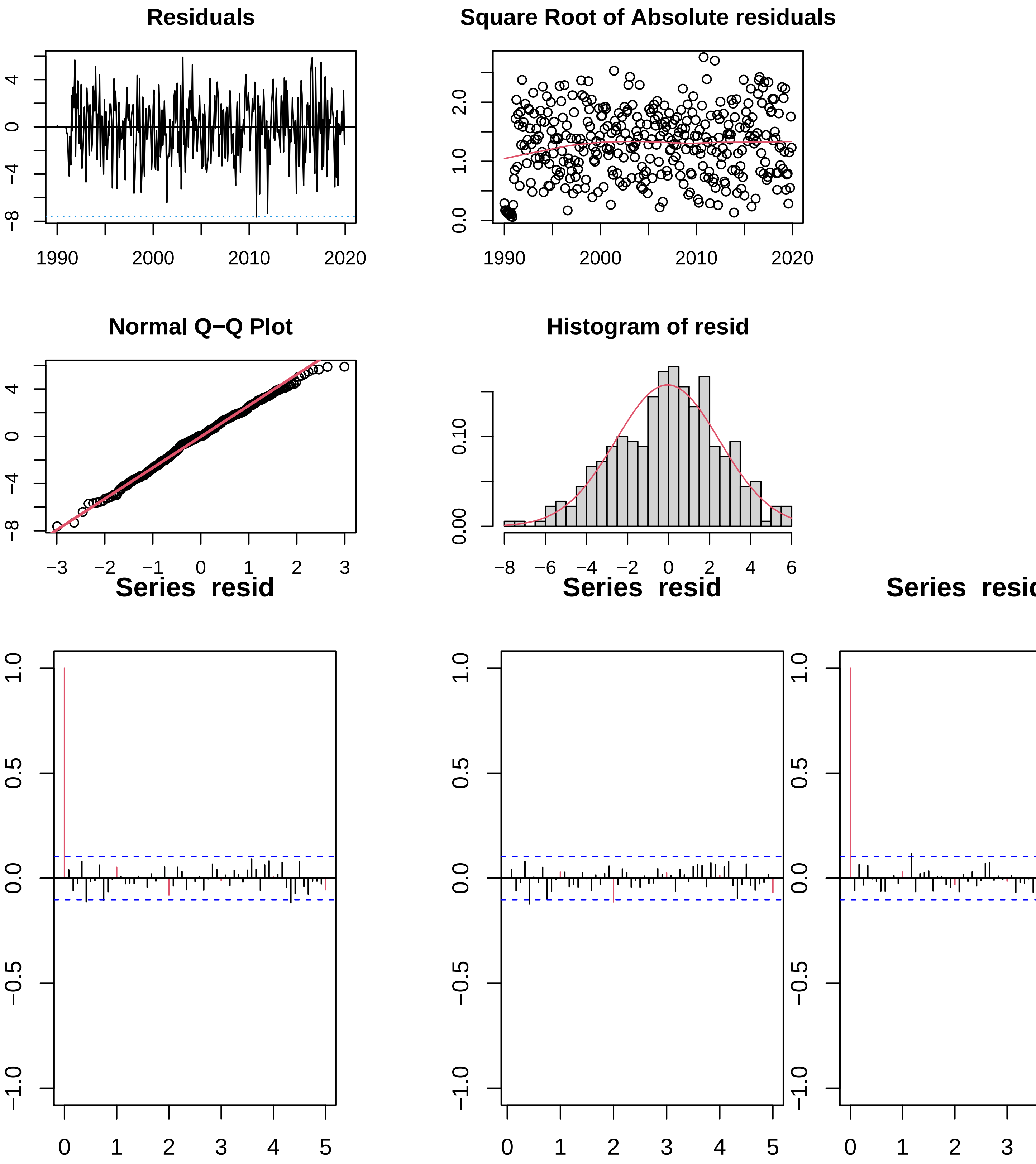
Seasonal: MA(1) MA(2) (AR(3)) Regular: AR(1), AR(2), MA(1)

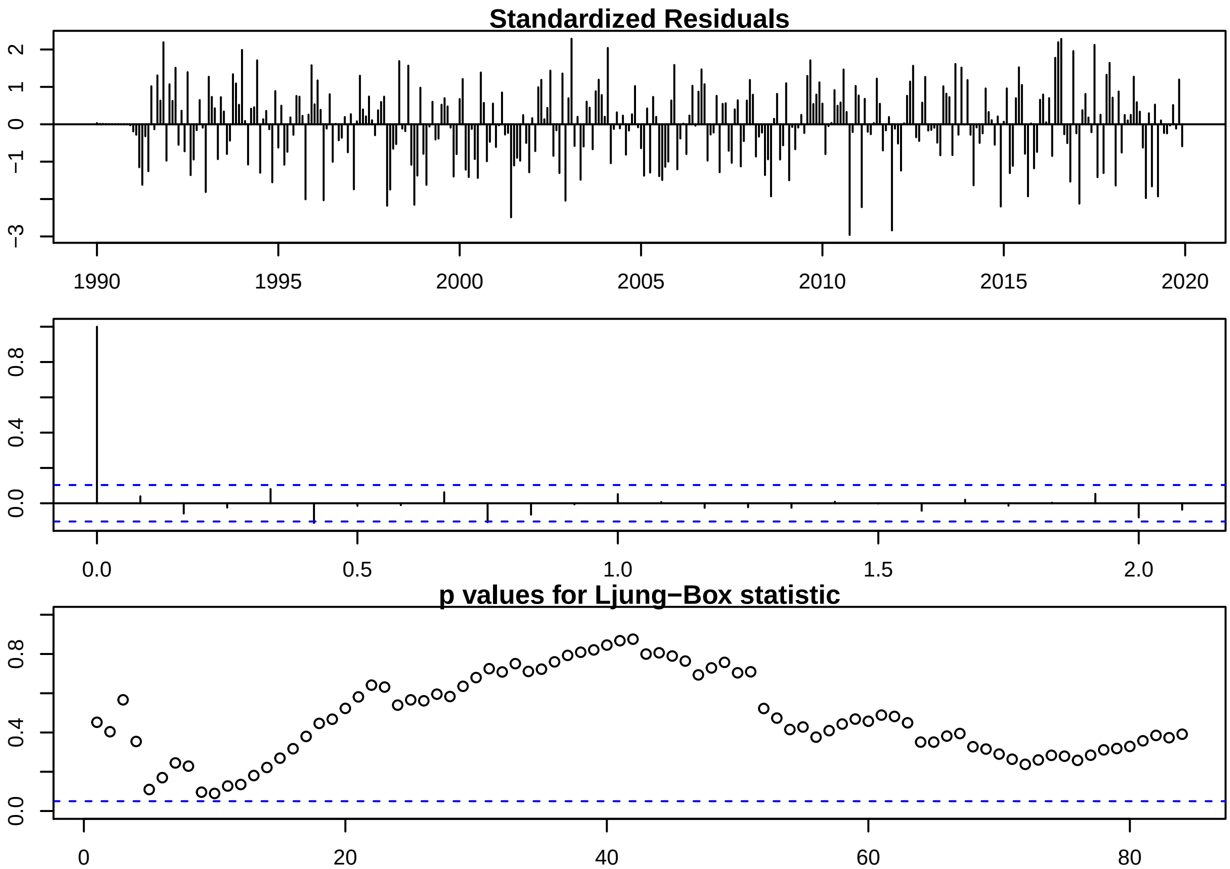
```
#(mod.lin2=arima(serie.lin,order=c(2,1,0),seasonal=list(order=c(0,1,2),period=12),xreg=data.frame(wTrad
#ma 2 not sign
(mod.lin2=arima(serie.lin,order=c(0,1,1),seasonal=list(order=c(0,1,1),period=12),xreg=data.frame(wTradD
```

```
##
## Call:
## arima(x = serie.lin, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1),
##     period = 12), xreg = data.frame(wTradDays))
##
## Coefficients:
##           ma1     sma1  wTradDays
##       -0.5794  -0.8232     0.2667
## s.e.   0.0474   0.0366     0.0377
##
## sigma^2 estimated as 6.641:  log likelihood = -827.85,  aic = 1663.69
```

Looks okay:

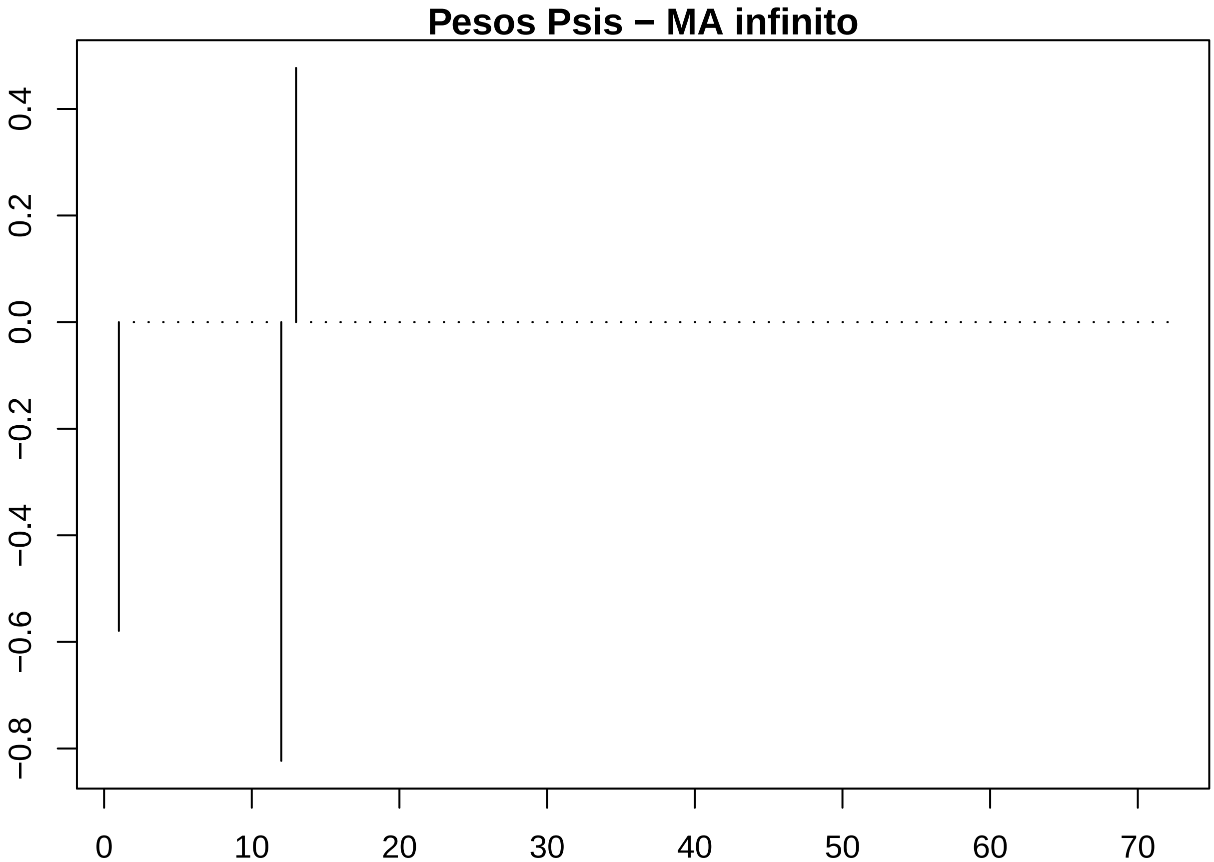
```
dades=d1d12serie.lin
model=mod.lin2
validation(model,dades)
```


Residuals
Square Root of Absolute residuals
Normal Q−Q Plot
Histogram of resid
Series resid
Series resid
Series resid

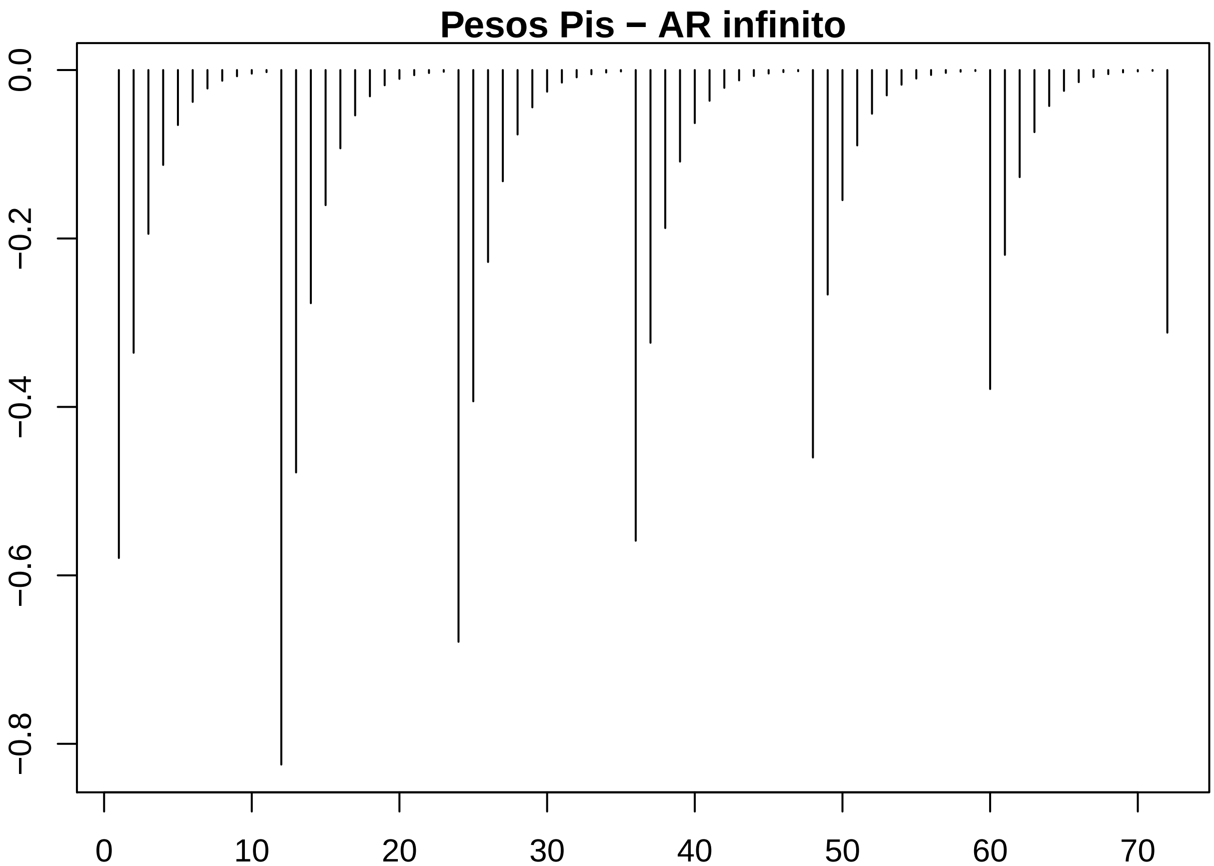



```
##
## ------------------------------------------------------------------
##
## Call:
## arima(x = serie.lin, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1),
##     period = 12), xreg = data.frame(wTradDays))
##
## Coefficients:
##           ma1     sma1  wTradDays
##       -0.5794  -0.8232     0.2667
## s.e.   0.0474   0.0366     0.0377
##
## sigma^2 estimated as 6.641:  log likelihood = -827.85,  aic = 1663.69
##
## Modul of AR Characteristic polynomial Roots:
##
## Modul of MA Characteristic polynomial Roots:  1.016343 1.016343 1.016343 1.016343 1.016343 1.016343 1
##
## Psi-weights (MA(inf))
##
## --------------------
##      psi 1      psi 2      psi 3      psi 4      psi 5      psi 6      psi 7
## -0.5793860  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
##      psi 8      psi 9     psi 10     psi 11     psi 12     psi 13     psi 14
##  0.0000000  0.0000000  0.0000000  0.0000000 -0.8232220  0.4769633  0.0000000
##     psi 15     psi 16     psi 17     psi 18     psi 19     psi 20
```

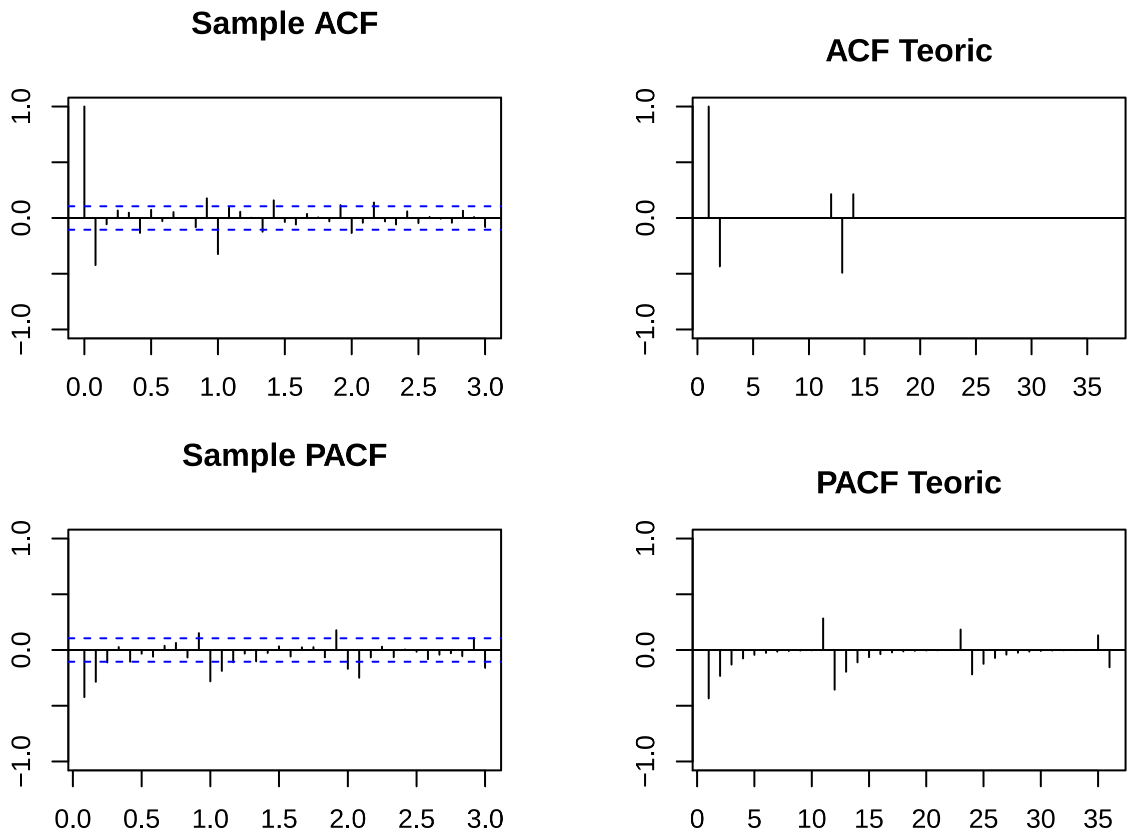
```
##  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
```




```
##
## Pi-weights (AR(inf))
##
## --------------------
##         pi 1         pi 2         pi 3         pi 4         pi 5         pi 6
## -0.579386033 -0.335688175 -0.194493040 -0.112686551 -0.065289014 -0.037827543
##         pi 7         pi 8         pi 9        pi 10        pi 11        pi 12
## -0.021916750 -0.012698259 -0.007357194 -0.004262655 -0.002469723 -0.824652922
##        pi 13        pi 14        pi 15        pi 16        pi 17        pi 18
## -0.477792385 -0.276826234 -0.160389254 -0.092927293 -0.053840776 -0.031194594
##        pi 19        pi 20
## -0.018073712 -0.010471656
```



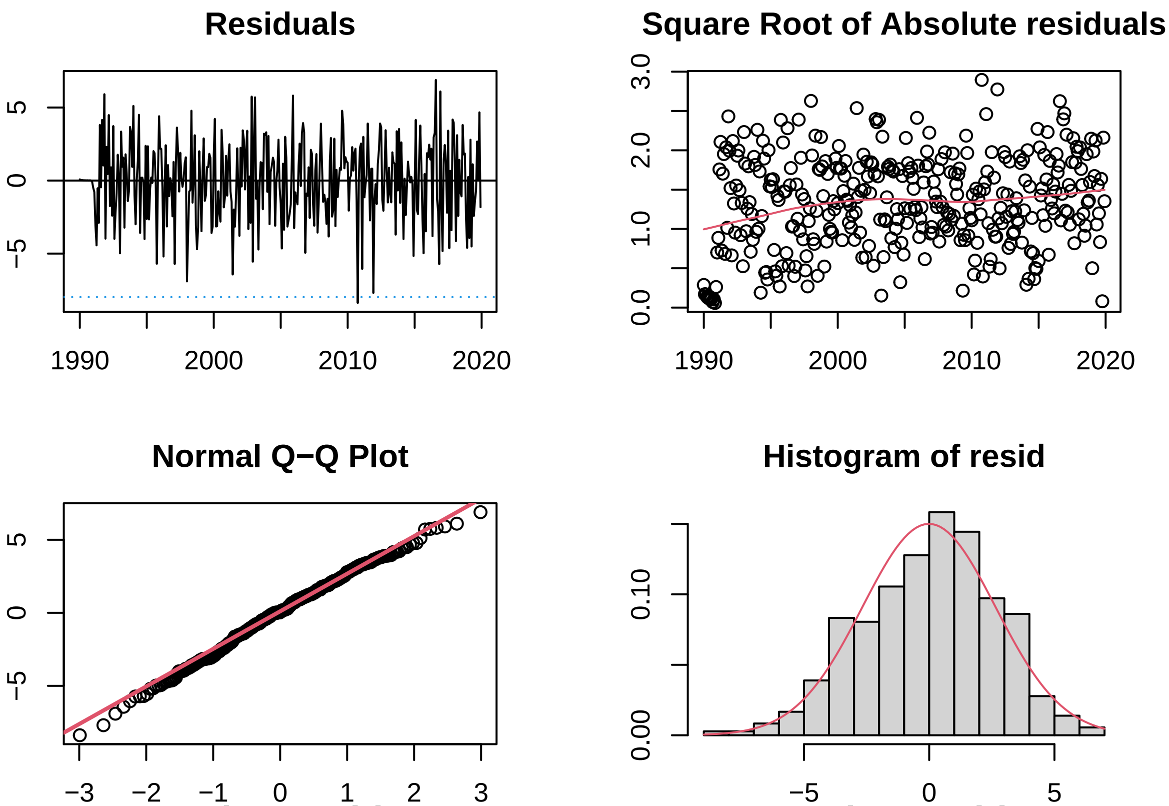

```
##
## Ljung-Box test
##      lag.df  statistic   p.value
## [1,]      1  0.5656864 0.4519781
## [2,]      2  1.8129189 0.4039519
## [3,]      3  2.0289656 0.5664166
## [4,]      4  4.4028800 0.3542192
## [5,]     12 17.4040374 0.1350204
## [6,]     24 22.6682688 0.5394448
## [7,]     36 29.7382710 0.7598491
## [8,]     48 41.6542403 0.7289835
```

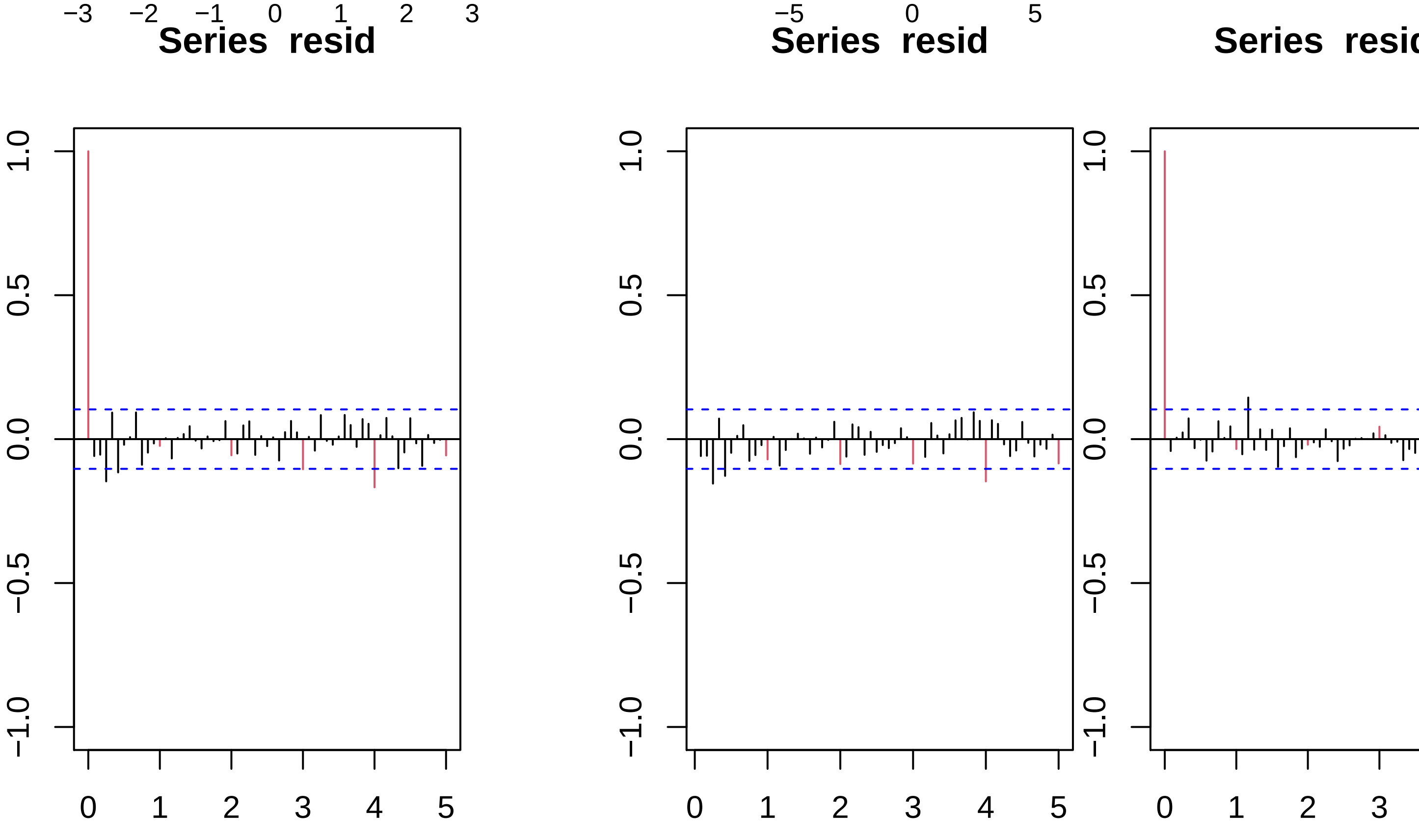


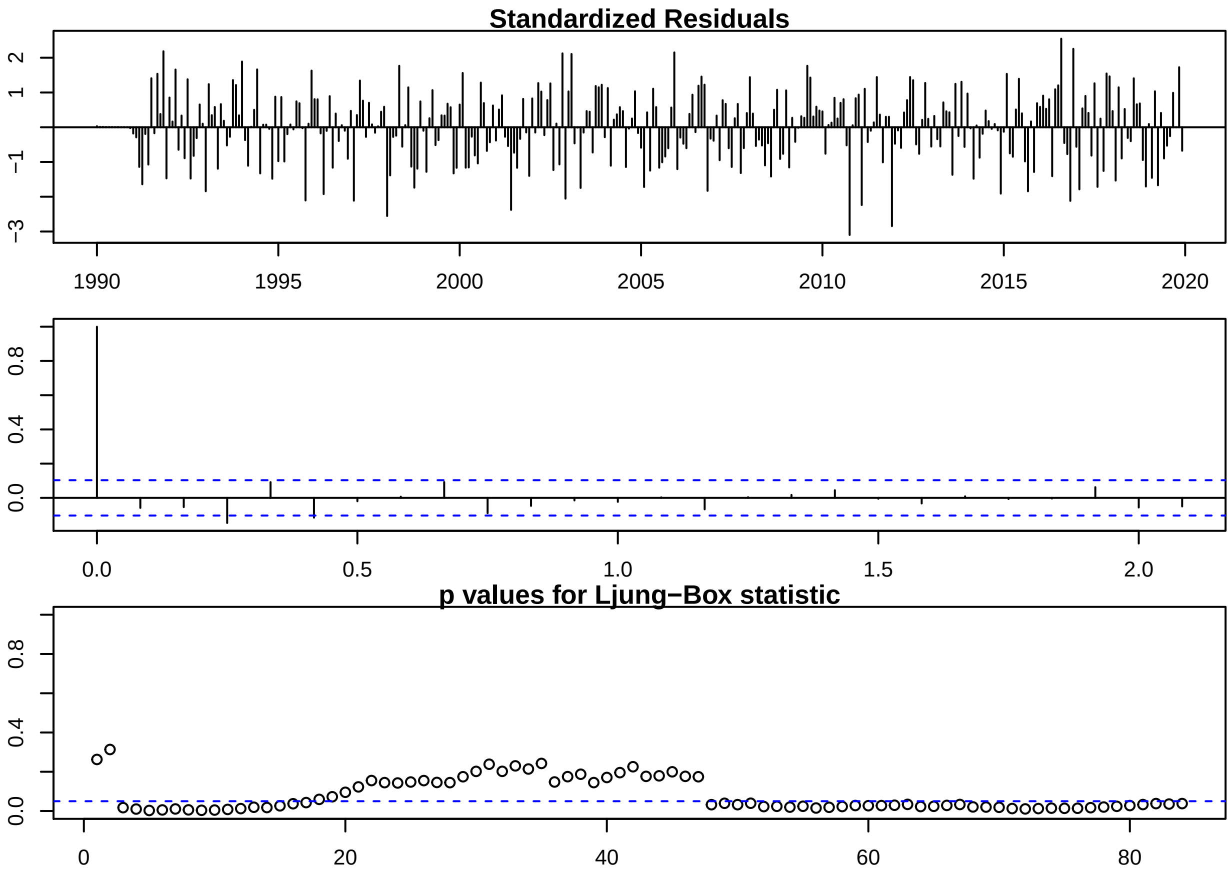

```
(mod.lin=arima(serie.lin,order=c(2,1,0),seasonal=list(order=c(3,1,0),period=12),xreg=data.frame(wTradDay
```

```
##
## Call:
## arima(x = serie.lin, order = c(2, 1, 0), seasonal = list(order = c(3, 1, 0),
##     period = 12), xreg = data.frame(wTradDays))
##
## Coefficients:
##           ar1      ar2     sar1     sar2     sar3  wTradDays
##       -0.4922  -0.2882  -0.6502  -0.5021  -0.2731     0.2706
## s.e.   0.0515   0.0520   0.0539   0.0586   0.0565     0.0371
##
## sigma^2 estimated as 7.312:  log likelihood = -841.8,  aic = 1697.6
```

```
dades=d1d12serie.lin
model=mod.lin
validation(model,dades)
```

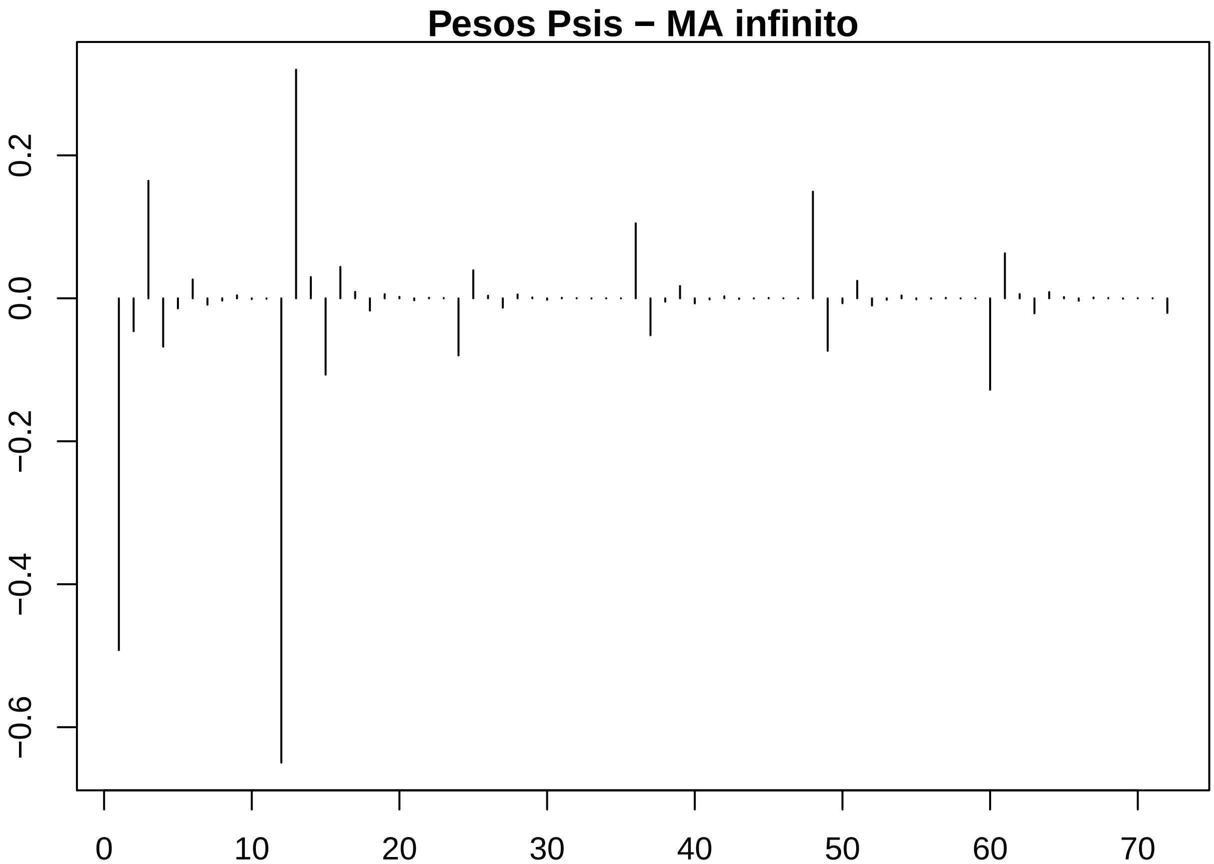

Residuals
Square Root of Absolute residuals
Normal Q−Q Plot
Histogram of resid


Series resid
Series resid
Series resid

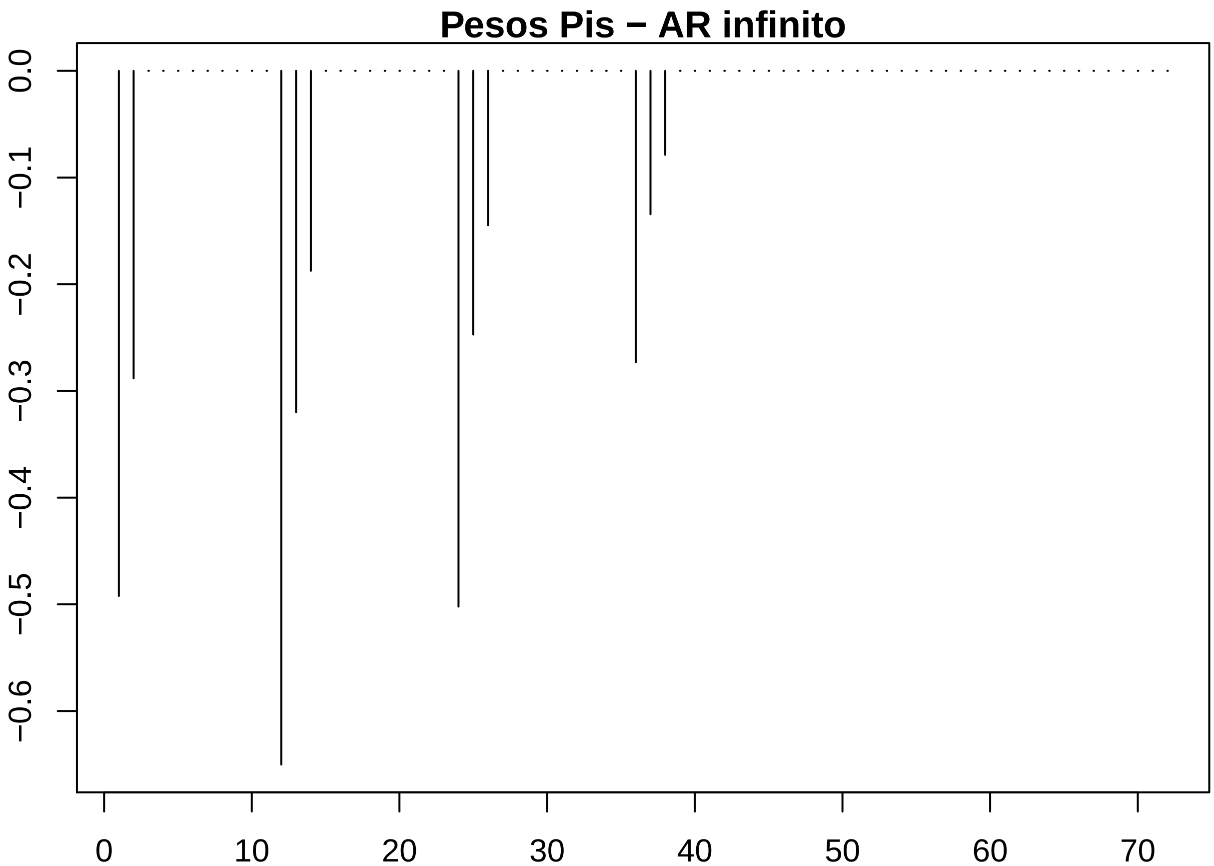



```
##
## ------------------------------------------------------------------
##
## Call:
## arima(x = serie.lin, order = c(2, 1, 0), seasonal = list(order = c(3, 1, 0),
##     period = 12), xreg = data.frame(wTradDays))
##
## Coefficients:
##           ar1      ar2     sar1     sar2     sar3  wTradDays
##       -0.4922  -0.2882  -0.6502  -0.5021  -0.2731     0.2706
## s.e.   0.0515   0.0520   0.0539   0.0586   0.0565     0.0371
##
## sigma^2 estimated as 7.312:  log likelihood = -841.8,  aic = 1697.6
##
## Modul of AR Characteristic polynomial Roots:  1.032404 1.032404 1.032404 1.032404 1.032404 1.032404
##
## Modul of MA Characteristic polynomial Roots:
##
## Psi-weights (MA(inf))
##
## --------------------
##         psi 1         psi 2         psi 3         psi 4         psi 5
## -0.4921530242 -0.0460053020  0.1644899445 -0.0676945800 -0.0140931833
##         psi 6         psi 7         psi 8         psi 9        psi 10
##  0.0264469279 -0.0089539997 -0.0032157929  0.0041633831 -0.0011221661
##        psi 11        psi 12        psi 13        psi 14        psi 15
```

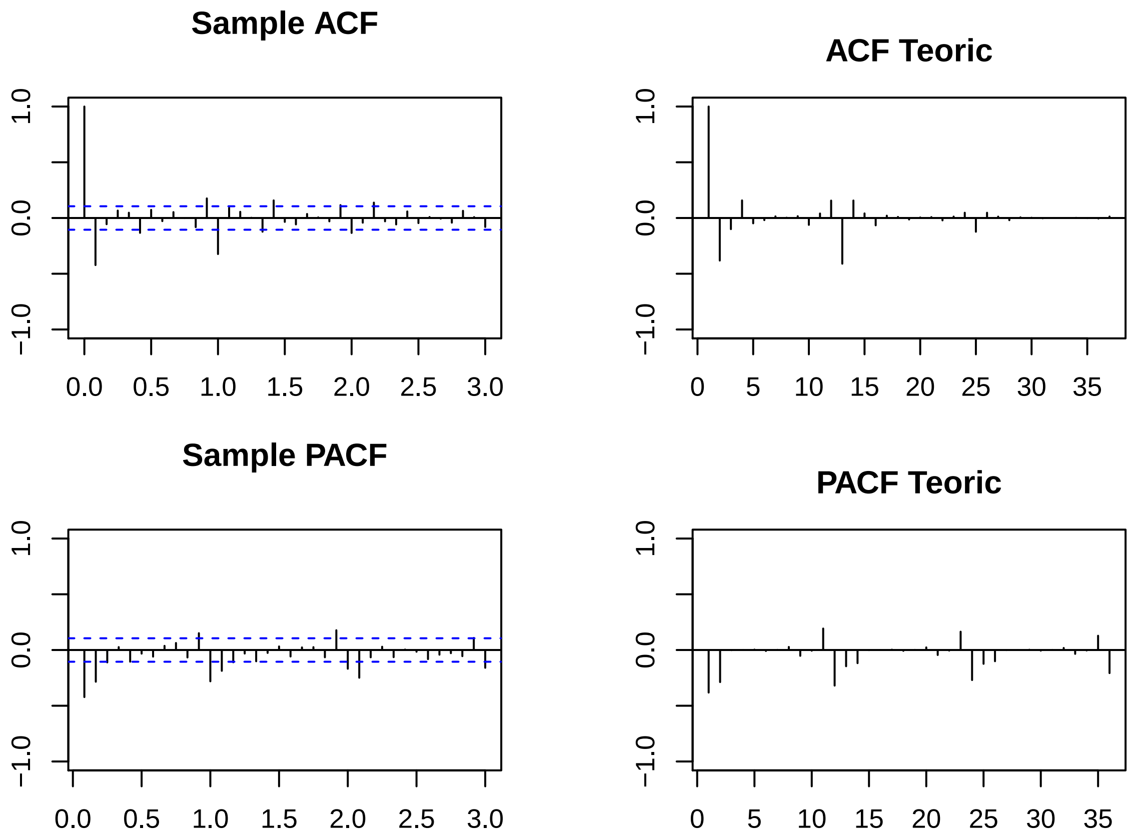
```
## -0.0006476924 -0.6495356030  0.3198575892  0.0297902075 -0.1068506634
##        psi 16        psi 17        psi 18        psi 19        psi 20
##  0.0440007465  0.0091413872 -0.0171808522  0.0058208786  0.0020871005
```




```
##
## Pi-weights (AR(inf))
##
## --------------------
##       pi 1       pi 2       pi 3       pi 4       pi 5       pi 6       pi 7
## -0.4921530 -0.2882199  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
##       pi 8       pi 9      pi 10      pi 11      pi 12      pi 13      pi 14
##  0.0000000  0.0000000  0.0000000  0.0000000 -0.6501778 -0.3199870 -0.1873942
##      pi 15      pi 16      pi 17      pi 18      pi 19      pi 20
##  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000  0.0000000
```




```
##
## Ljung-Box test
##      lag.df statistic     p.value
## [1,]      1  1.255102 0.262580229
## [2,]      2  2.320745 0.313369490
## [3,]      3 10.180004 0.017096401
## [4,]      4 13.298904 0.009903984
## [5,]     12 25.597919 0.012230271
## [6,]     24 31.393390 0.142760822
## [7,]     36 44.855073 0.147849733
## [8,]     48 67.650740 0.032223555
```



This model does not look goof

Stability

```r
ultim=c(2018,12)
pdq=c(0,1,1)
PDQ=c(0,1,1)

serie1=window(serie.lin,end=ultim+c(1,0))
serie2=window(serie.lin,end=ultim)

wTradDays2=window(wTradDays,end=ultim)


(mod=arima(serie1,order=pdq,seasonal=list(order=PDQ,period=12),xreg=data.frame(wTradDays)))
```

```
##
## Call:
## arima(x = serie1, order = pdq, seasonal = list(order = PDQ, period = 12), xreg = data.frame(wTradDay
##
## Coefficients:
##           ma1     sma1  wTradDays
##       -0.5794  -0.8232     0.2667
## s.e.   0.0474   0.0366     0.0377
##
## sigma^2 estimated as 6.641:  log likelihood = -827.85,  aic = 1663.69
```

```r
(mod2=arima(serie2,order=pdq,seasonal=list(order=PDQ,period=12),xreg=data.frame(wTradDays2)))
```

```
##
```

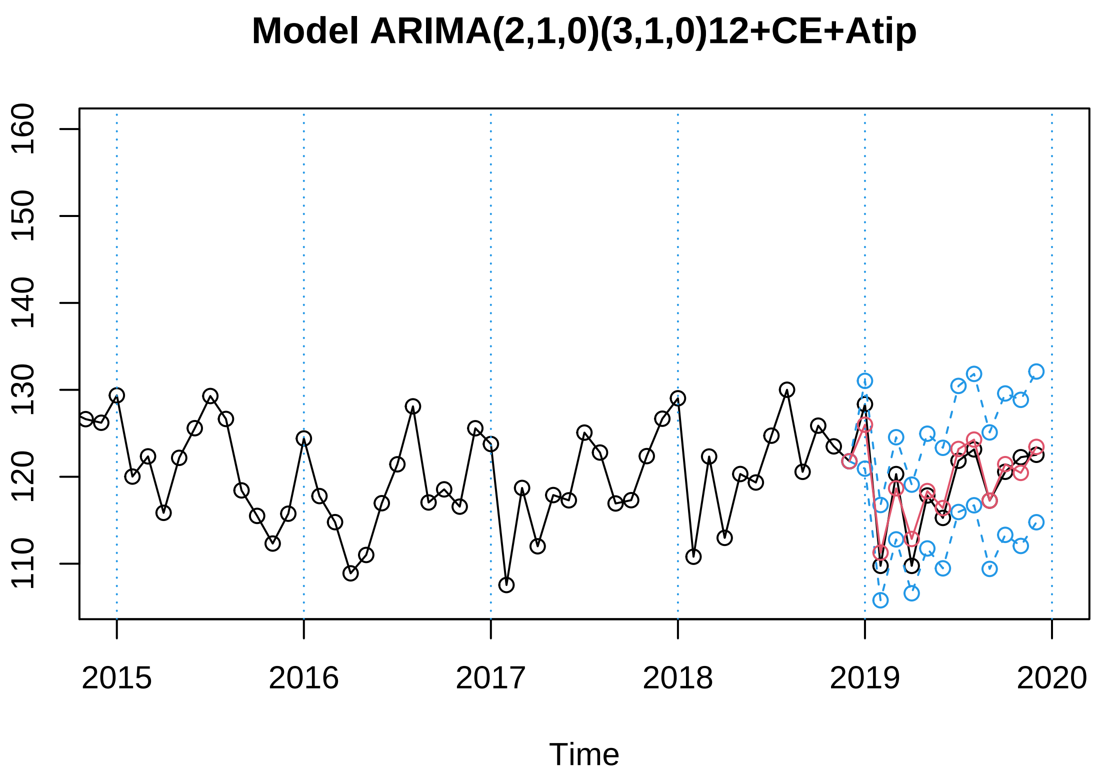
```
## Call:
## arima(x = serie2, order = pdq, seasonal = list(order = PDQ, period = 12), xreg = data.frame(wTradDays
##
## Coefficients:
##           ma1     sma1  wTradDays2
##       -0.5798  -0.8323      0.2736
## s.e.   0.0496   0.0383      0.0386
##
## sigma^2 estimated as 6.687:  log likelihood = -800.9,  aic = 1609.8
```

model is stable

Forecast:

Insample prediction: (not in assignment?)

```
pred=predict(mod.lin2,n.ahead=12,newxreg=window(wTradDays,start=c(ultim[1]+1,1)))
predic=pred$pr

wLS=sum(mod.atip$atip[mod.atip$atip$type_detected=="LS" & mod.atip$atip$Obs<=length(serie)-12,3])
pr<-ts(c(tail(serie2,1),predic)+wLS,start=ultim,freq=12)


se<-ts(c(0,pred$se),start=ultim,freq=12)

#Intervals
tl<-ts(pr-1.96*se,start=ultim,freq=12)
tu<-ts(pr+1.96*se,start=ultim,freq=12)
pr<-ts(pr,start=ultim,freq=12)


ts.plot(serie,tl,tu,pr,lty=c(1,2,2,1),col=c(1,4,4,2),xlim=ultim[1]+c(-3,2),type="o",main="Model ARIMA(2
abline(v=(ultim[1]-3):(ultim[1]+2),lty=3,col=4)
```



red obs in

2019 is weird, besides that: looks good,

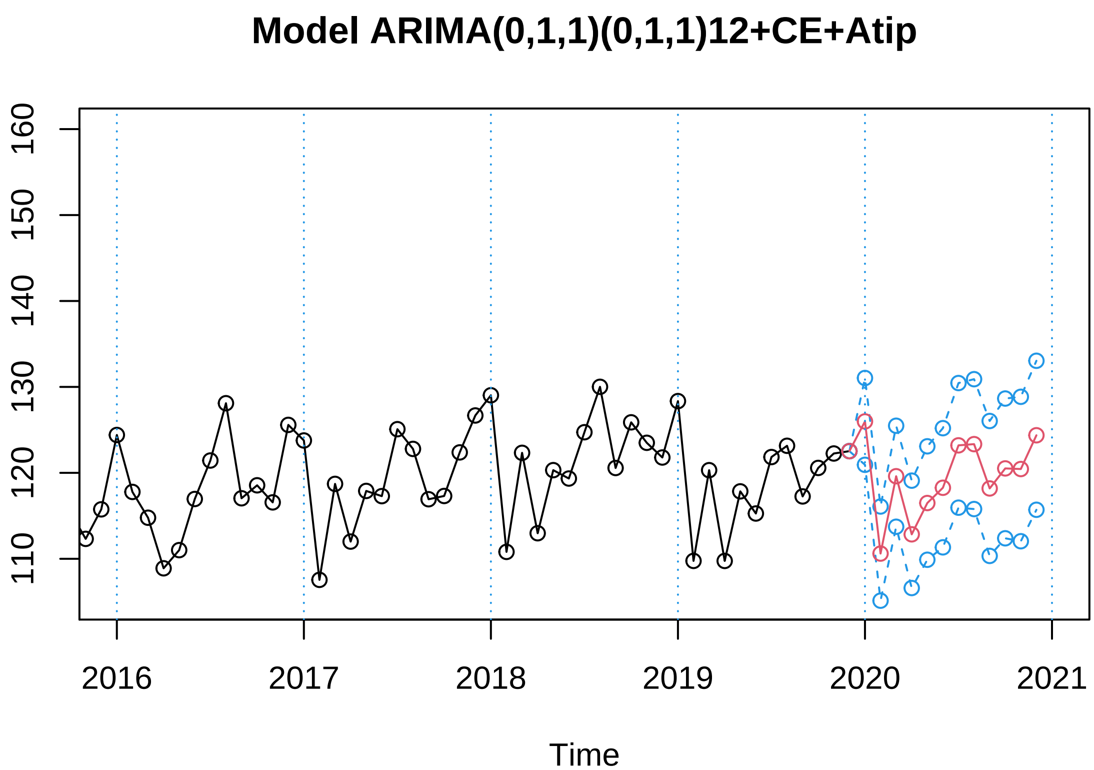
```
obs=window(serie,start=ultim)
(mod.EQM3=sqrt(sum(((obs-pr)/obs)^2)/12))
```

```
## [1] 0.01342432
```

```
(mod.EAM3=sum(abs(obs-pr)/obs)/12)
```

```
## [1] 0.01150628
```

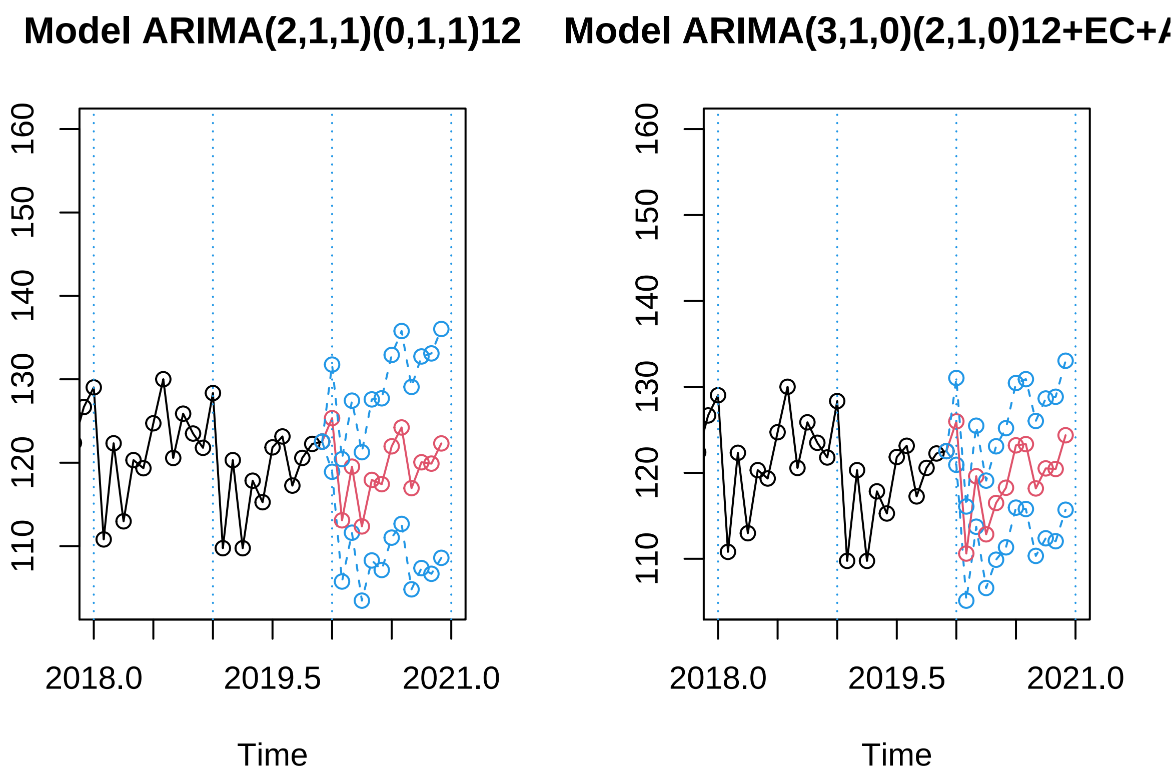
```
data3=c(ultim[1]+2, 1, 12)

wTradDays3=Wtrad(data3)

pred=predict(mod.lin2,n.ahead=12,newxreg=data.frame(wTradDays3)) ##wEast3))
predic=pred$pr
wLS=sum(mod.atip$atip[mod.atip$atip$type_detected=="LS",3])
pr<-ts(c(serie[length(serie)],predic+wLS),start=ultim+c(1,0),freq=12)
se<-ts(c(0,pred$se),start=ultim+c(1,0),freq=12)

#Intervals
tl3<-ts(pr-1.96*se,start=ultim+c(1,0),freq=12)
tu3<-ts(pr+1.96*se,start=ultim+c(1,0),freq=12)
pr3<-ts(pr,start=ultim+c(1,0),freq=12)

ts.plot(serie,tl3,tu3,pr3,lty=c(1,2,2,1),col=c(1,4,4,2),xlim=ultim[1]+c(-2,3),type="o",main="Model ARIMA
abline(v=(ultim[1]-2):(ultim[1]+3),lty=3,col=4)
```




```
previs3=window(cbind(tl3,pr3,tu3),start=ultim+c(1,0))
```

Compare models

```
par(mfrow = c(1,2))
ts.plot(serie,previs1,lty=c(1,2,1,2),col=c(1,4,2,4),xlim=c(2018,2021),type="o",main="Model ARIMA(2,1,1)
abline(v=2016:2021,lty=3,col=4,ylim=c(15,280))
ts.plot(serie,previs3,lty=c(1,2,1,2),col=c(1,4,2,4),xlim=c(2018,2021),type="o",main="Model ARIMA(3,1,0)
abline(v=2016:2021,lty=3,col=4,ylim=c(15,280))
```




```
resul=data.frame(
  par=c(length(coef(mod3)),length(coef(mod.lin2))+nrow(mod.atip$atip)),

  Sigma2Z=c(mod3$sigma2, mod.lin2$sigma2),
  AIC=c(AIC(mod3), AIC(mod.lin2) + 2 * nrow(mod.atip$atip)),
  BIC=c(BIC(mod3), BIC(mod.lin2) + log(length(serie)-13) * nrow(mod.atip$atip)),
  RMSPE=c(mod.EQM1,mod.EQM3),
  MAPE=c(mod.EAM1,mod.EAM3),
  meanLength=c(sum(previs1[,3]-previs1[,1]),sum(previs3[,3]-previs3[,1]))/12)
row.names(resul)=c("ARIMA(2,1,0)(0,1,1)12","ARIMA(0,1,1)(0,1,1)12+EC+IA+Atip")


resul
```

```
##                                  par    Sigma2Z      AIC      BIC      RMSPE
## ARIMA(2,1,0)(0,1,1)12              3 10.745501 1832.807 1848.204 0.02125953
## ARIMA(0,1,1)(0,1,1)12+EC+IA+Atip  17  6.640788 1691.693 1760.981 0.01342432
##                                        MAPE meanLength
## ARIMA(2,1,0)(0,1,1)12            0.01604008   20.79713
## ARIMA(0,1,1)(0,1,1)12+EC+IA+Atip 0.01150628   14.00928
```