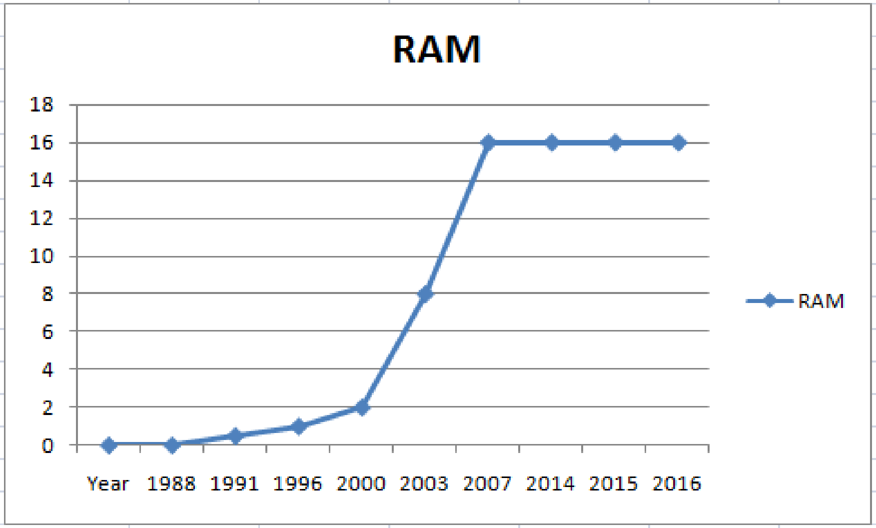
Final exam

Yuan Sun

hw1

Year	RAM
1988	0.002
1991	0.004
1996	0.5
2000	1
2003	2
2007	8
2014	16
2015	16
2016	16
2017	16



Logistic regression

Yuan Sun

Logistic regression is used in various fields, including machine learning, most medical fields, and social sciences. For example, the Trauma and Injury Severity Score (TRISS), which is widely used to predict mortality in injured patients, was originally developed by Boyd et al. using logistic regression.

- In economic it can be used to predict the likelihood of a person's choosing to be in the labor force, and a business application would be to predict the likelihood of a homeowner defaulting on a mortgage. Conditional random fields, an extension of logistic regression to sequential data, are used in natural language processing.

hw2

ex1 and ex2

- hw1.df = read.csv("hw1.csv",header = TRUE)
- plot(hw1.df$ram~hw1.df$year)

- splines.reg.l = smooth.spline(x = hw1.df$year, y = hw1.df$ram, spar = 0.2)
- splines.reg.2 = smooth.spline(x = hw1.df$year, y = hw1.df$ram, spar = 1)
- splines.reg.3= smooth.spline(x = hw1.df$year, y = hw1.df$ram, spar = 2)
- lines(splines.reg.1, col = "red", lwd = 2) # regression line with lambda = 0.2
- lines(splines.reg.2, col = "green", lwd = 2) # regression line with lambda = 1
- lines(splines.reg.3, col = "blue", lwd = 2) # regression line with lambda = 2

Hw2

Ex 3

```
x = 6
n = 1000
lambda = 2
p = lambda / n
dbinom (x,2*n,p) # binomial probability mass function

dpois (x, 2*lambda ) # Poisson probability mass function

dpois (0, 5 )
```

hw3

HW3-1

- install.packages("digest",repos='http://cran.us.r-project.org')
- library("digest")
- digest("I learn a lot from this class when I am proper listening to the professor","sha256")
- digest("I do not learn a lot from this class when i am absent and playing on my Iphone","sha256")

hw3

HW3-4

- install.packages("rjson",repos = "http://cran.us.r-project.org")
- library("rjson")
- json_file="http://crix.hu-berlin.de/data/crix.json"
- json_data=fromJSON(file=json_file)
- crix_data_frame=as.data.frame(json_data)

- crix_data_frame_t<-t(crix_data_frame)
- time<-crix_data_frame_t[seq(1,2350,by=2)]
- price<-crix_data_frame_t[seq(2,2350,by=2)]
- crix_data_frame<-cbind(time,price)
- time_series<-ts(data=price,start =c(2014,7,31),frequency = 365)
- plot(time_series)

- install.packages("tseries")
- library(tseries)
- adf.test(time_series)
- #Because p-value is greater than printed p-value, we can't reject the hypothesis#

Digital Signature Algorithms

Yuan Sun

The Digital Signature Algorithm (DSA) is a Federal Information Processing Standard for digital signatures. for the key generation, it has two phases. The first phase is a choice of algorithm parameters which may be shared between different users of the system, while the second phase computes public and private keys for a single user.

For the Parameter generation, the steps are: Choose an approved cryptographic hash function *H*; Decide on a key length L and N which is the primary measure of the cryptographic strength of the key; Choose an N-bit prime q; Choose an L-bit prime p such that p − 1 is a multiple of q; Choose g, a number whose multiplicative order modulo p is q.

The algorithm parameters (p, q, g) may be shared between different users of the system.

Per-user keys: Given a set of parameters, the second phase computes private and public keys for a single user.

Apart from these, we also need signing and verifying process, then check the Correctness of the algorithm

JSON DATA

Create a JSON data set

```
library(rjsonio)
Num <- [1:5]
Name <- c(“aaa”, ”bbb”, ”cccc”, “ddd”, “eee”)
data <- as.matrix(data.frame(Num,Name))
cat(toJSON(data))
```

Note: JSON data is a key-value pairs list.

2. Read the JSON data set

```
library("rjson")
json_data = fromJSON(file=data)
```

We can use function ‘fromJSON’ to read the JSON data set

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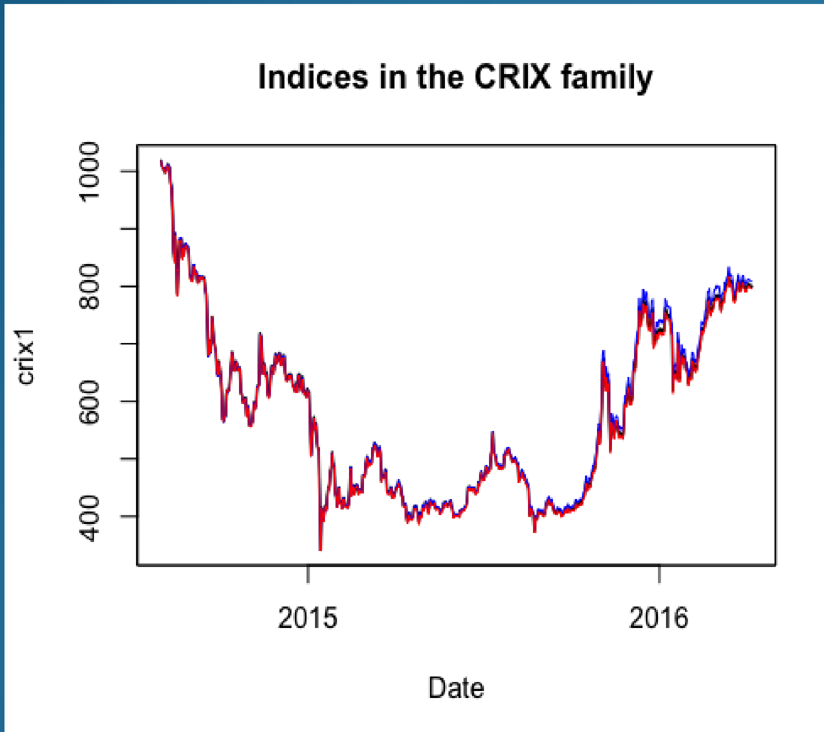
Homework 4

Yuan Sun

1. Improve the R quantlets on GH (from CRIX directory on quantlet.de) and make excellent graphics that follow Fig 3,4,5,6 of the ”Econometrics of CRIX“ paper.



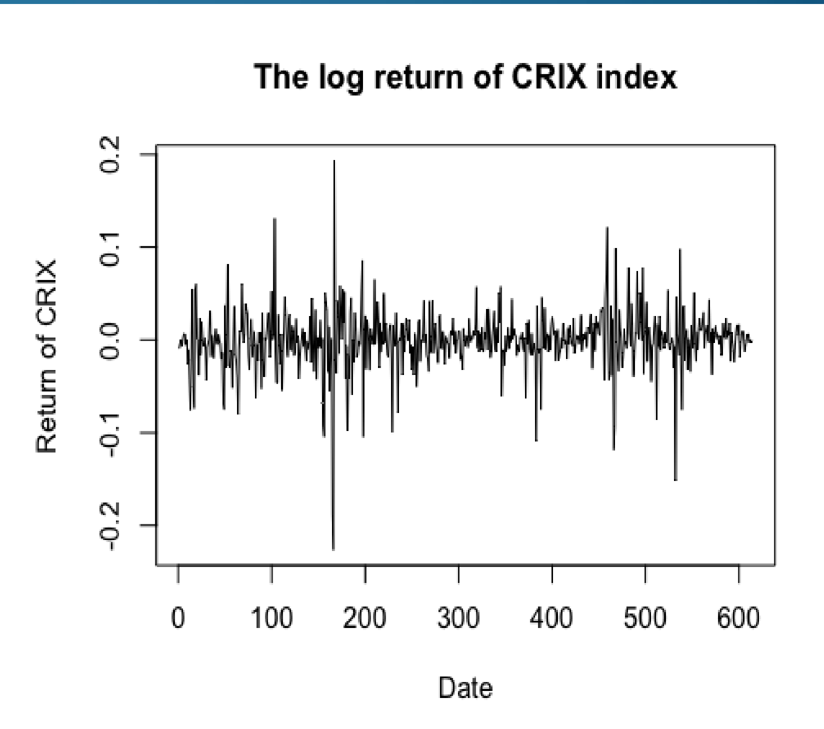


Figure 3: The daily value of indices in the CRIX family

Figure 4: The log returns of CRIX inde

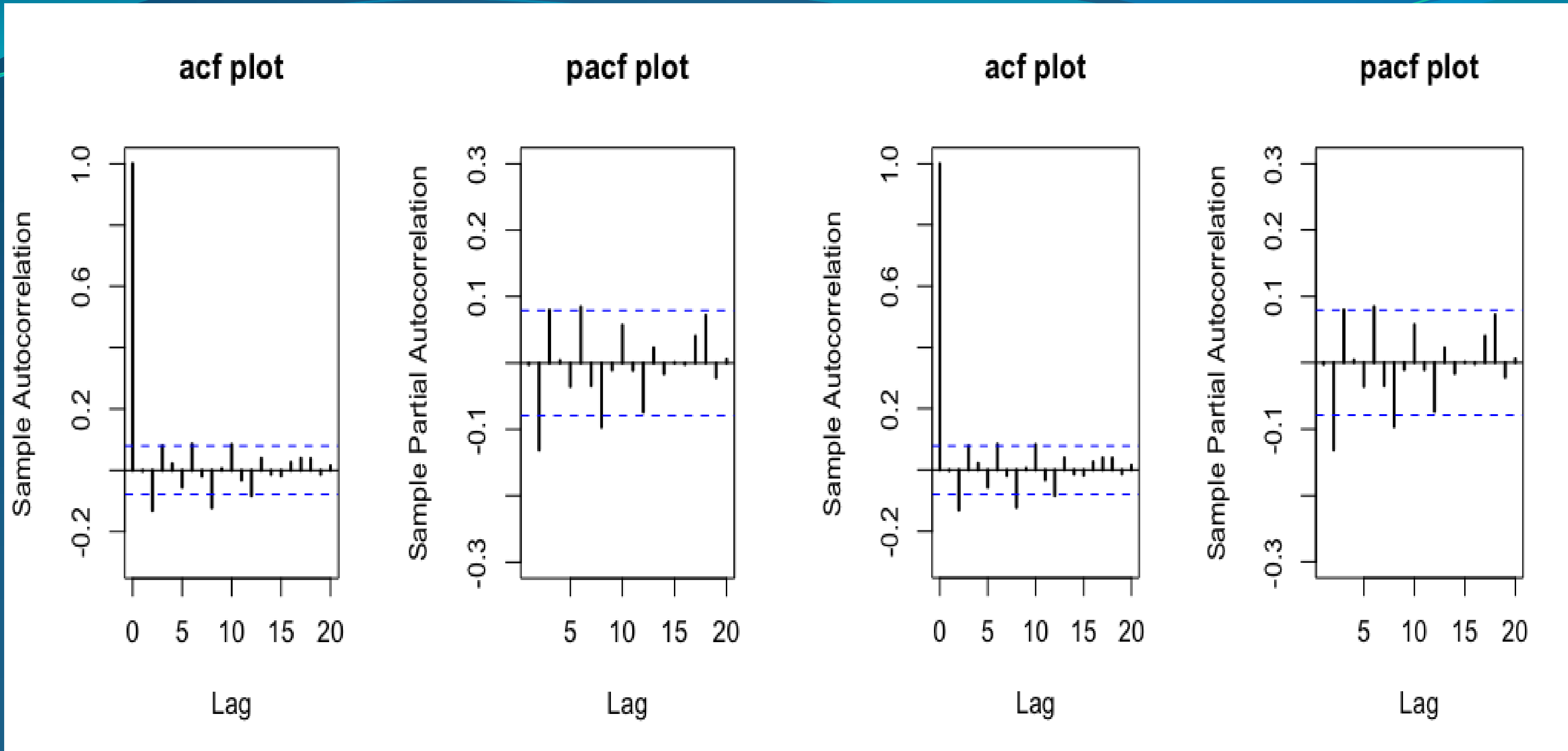


Figure 5: Histogram and QQ plot of CRIX returns

Figure 6: The sample ACF and PACF of CRIX r

```
rm(list = ls(all = TRUE))
graphics.off()
# install and load packages
libraries = c("zoo", "tseries", "xts","ccgarch")
lapply(libraries, function(x) if (!(x %in% installed.packages()))
{ install.packages(x)}
```

```r
lapply(libraries, library, quietly = TRUE, character.only = TRUE)

# load dataset
load(file.choose())
load(file.choose())
load(file.choose())

# three indices return
ecrix1 = zoo(ecrix, order.by = index(crix1))
efcrix1 = zoo(efcrix, order.by = index(crix1))

# plot with different x-axis scales with zoo
my.panel <- function(x, ...) {
  lines(x, ...)
  lines(ecrix1, col = "blue")
  lines(efcrix1, col = "red")
}
plot.zoo(crix1, plot.type = "multiple", type = "l", lwd = 1.5, panel = my.panel,
        main = "Indices in the CRIX family", xlab = "Date")
```

```
# plot of crix
# plot(as.xts(crix), type="l", auto.grid=FALSE, main = NA)
plot(crix1, ylab = "Price of CRIX", xlab = "Date")

# plot of crix return
ret   = diff(log(crix1))
# plot(as.xts(ret), type="l", auto.grid=FALSE, main = NA)
plot(ret, ylab = "Return of CRIX", xlab = "Date")

# stationary test
adf.test(ret, alternative = "stationary")
kpss.test(ret, null = "Trend")

par(mfrow = c(1, 2))
# histogram of returns
hist(ret, col = "grey", breaks = 20, freq = FALSE, ylim = c(0, 25), xlab = "Return of CRI
lines(density(ret), lwd = 2)
mu = mean(ret)
sigma = sd(ret)
x = seq(-4, 4, length = 100)
curve(dnorm(x, mean = mean(ret), sd = sd(ret)), add = TRUE, col = "red",
    lwd = 2)
```

```
# qq-plot
qqnorm(ret)
qqline(ret, col = "blue", lwd = 3)

# acf plot
autocorr = acf(ret, lag.max = 20, ylab = "Sample Autocorrelation", main = "acf plot",
          lwd = 2, ylim = c(-0.3, 1))

# pacf plot
autopcorr = pacf(ret, lag.max = 20, ylab = "Sample Partial Autocorrelation",
           main = "pacf plot", ylim = c(-0.3, 0.3), lwd = 2)
```

Q2. Make your R code perfect as in the R examples on quantlet.de i.e. m code is "time independent" by using actual dimensions of the data that from crix.hu-berlin.de Recreate Fig 7 from "Econometrics of CRIX".

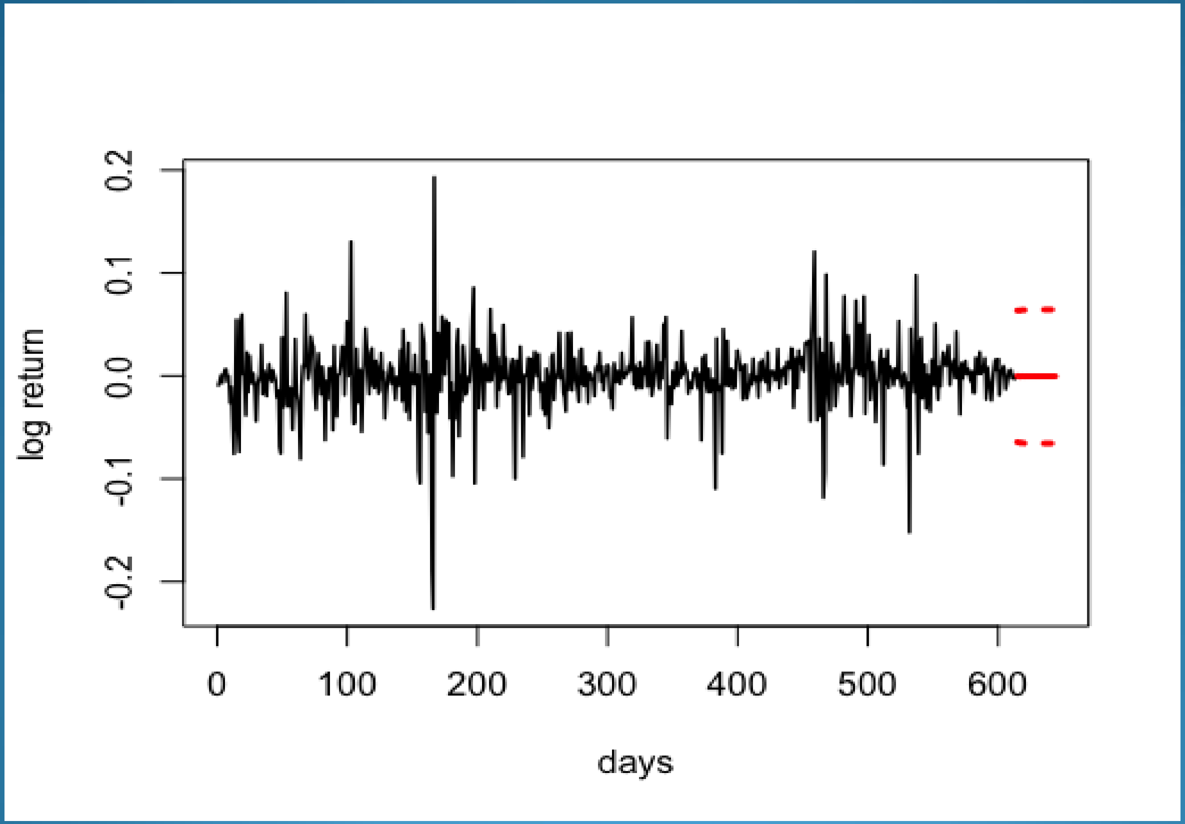


Figure 7: CRIX returns and predicted values.

Codes:

```
# arima model
par(mfrow = c(1, 1))
fit1 = arima(ret, order = c(1, 0,
1))
tsdiag(fit1)
Box.test(fit1$residuals, lag = 1)

# aic
aic = matrix(NA, 6, 6)
for (p in 0:4) {
  for (q in 0:3) {
    a.p.q = arima(ret, order =
c(p, 0, q))
    aic.p.q = a.p.q$aic
    aic[p + 1, q + 1] = aic.p.q
  }
}

# bic
bic = matrix(NA, 6, 6)
for (p in 0:4) {
  for (q in 0:3) {
    b.p.q = arima(ret, order
= c(p, 0, q))
    bic.p.q = AIC(b.p.q, k =
log(length(ret)))
    bic[p + 1, q + 1] = bic.p.q
  }
}

# select p and q order of
ARIMA model
fit4 = arima(ret, order =
c(2, 0, 3))
tsdiag(fit4)
Box.test(fit4$residuals,
lag = 1)

fitr4 = arima(ret, order =
c(2, 1, 3))
```

```
# to conclude, 202 is better than 213
fit202 = arima(ret, order = c(2, 0, 2))

AIC(fit202, k = log(length(ret)))
AIC(fit4, k = log(length(ret)))
AIC(fitr4, k = log(length(ret)))
fit202$aic
fit4$aic
fitr4$aic

# arima202 predict
predict_num = 30
fit202 = arima(ret, order = c(2, 0, 2))
crpre = predict(fit202, n.ahead = predict_num)

dates = seq(as.Date("02/08/2014", format = "%d/%m/%Y"), by = "days", length = lengt
plot(ret, type = "l", xlim = c(0, length(ret)+predict_num), ylab = "log return", xlab = "d
    lwd = 1.5, col = "black")
lines(crpre$pred, col = "red", lwd = 3)
lines(crpre$pred + 2 * crpre$se, col = "red", lty = 3, lwd = 3)
lines(crpre$pred - 2 * crpre$se, col = "red", lty = 3, lwd = 3)
```

Q3. Redo as many figures as you can.

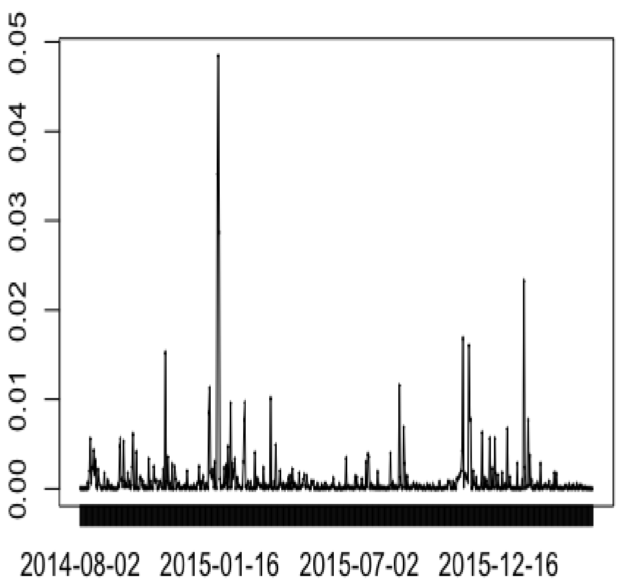


Figure 8: The squared ARIMA(2,0,2) residuals of CRIX returns.

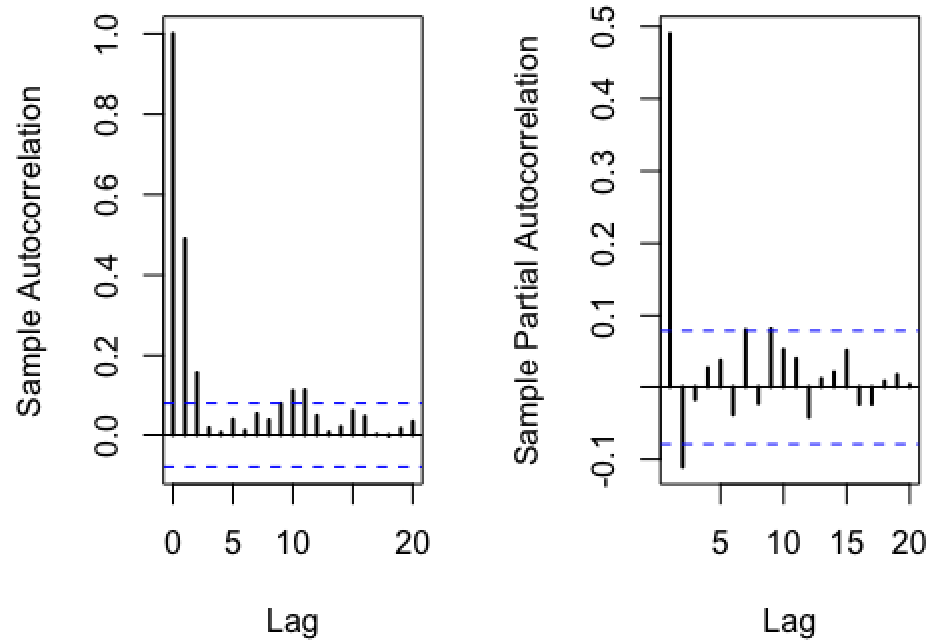


Figure 9: The ACF and PACF of squared ARIMA(2,0,2) residuals

Codes:

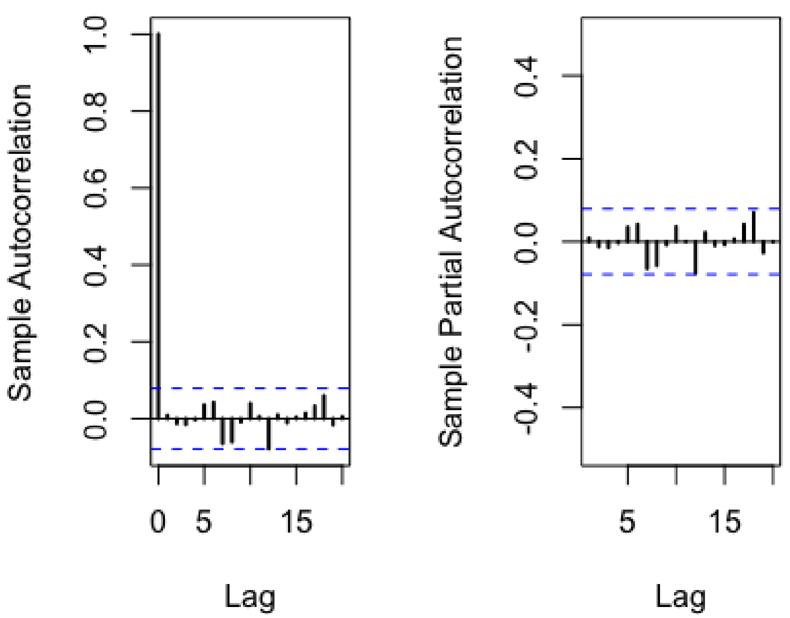
```
rm(list = ls(all = TRUE))
graphics.off()

# install and load packages
libraries = c("tseries")
lapply(libraries, function(x) if (!(x %in%
installed.packages())) {
  install.packages(x)
})
lapply(libraries, library, quietly = TRUE,
character.only = TRUE)

# please change your working directory
setwd()
load(file.choose())
Pr = as.numeric(crix)
Da = factor(date1)
crx = data.frame(Da, Pr)
# plot of crix return
ret = diff(log(crx$Pr))
Dare = factor(date1[-1])
retts = data.frame(Dare, ret)
# arima202 predict
```

```
# vola cluster
par(mfrow = c(1, 1))
res = fit202$residuals
res2 =
fit202$residuals^2
tsres202 =
data.frame(Dare, res2)
plot(tsres202$Dare,
tsres202$res2, type =
"o", ylab = NA)
lines(tsres202$res2)

# plot(res2,
ylab='Squared
residuals', main=NA)
par(mfrow = c(1, 2))
acfres2 = acf(res2, main
= NA, lag.max = 20,
ylab = "Sample
Autocorrelation", lwd =
2)
pacfres2 = pacf(res2,
```



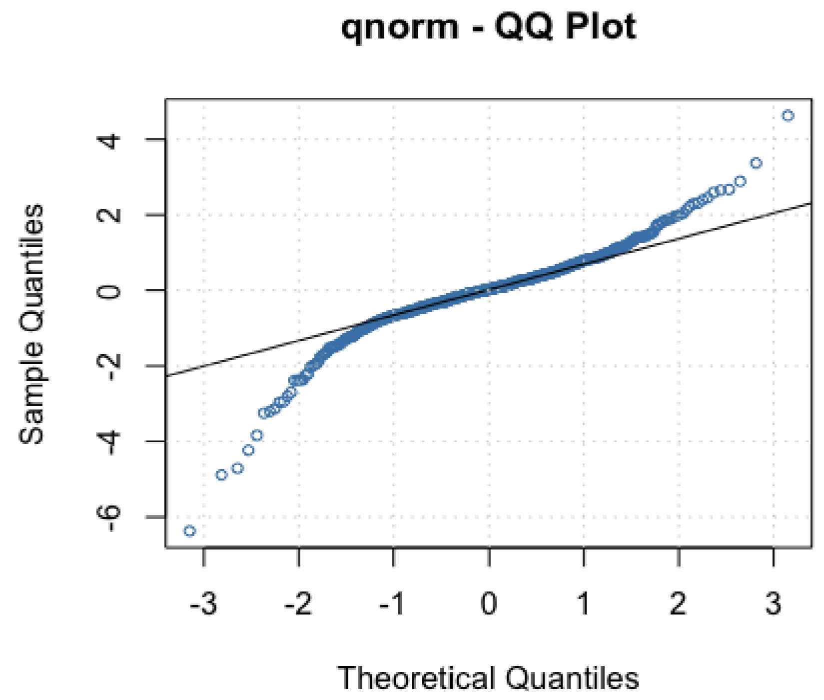


Figure 10: The ACF and PACF of squared ARIMA(2,0,2) residuals

Figure 11: The QQ plots of model residuals of ARIMA-GARCH process.

Codes:

```
rm(list = ls(all = TRUE))
graphics.off()

# install and load packages
libraries = c("forecast", "fGarch")
lapply(libraries, function(x) if (!(x %in%
installed.packages())) {
  install.packages(x)
})
lapply(libraries, library, quietly = TRUE,
character.only = TRUE)

# load dataset
load(file.choose())
ret = diff(log(crix1))

# vol cluster
fit202 = arima(ret, order = c(2, 0, 2))
par(mfrow = c(1, 1))
res = fit202$residuals
res2 = fit202$residuals^2

# different garch model
fg11 = garchFit(data = res, data ~
garch(1, 1))
summary(fg11)
fg12 = garchFit(data = res, data ~
garch(1, 2))
summary(fg12)
fg21 = garchFit(data = res, data ~
garch(2, 1))
summary(fg21)
fg22 = garchFit(data = res, data ~
garch(2, 2))
summary(fg22)

# residual plot
reszo = zoo(fg11@residuals,
order.by = index(crix1))
plot(reszo, ylab = NA, lwd = 2)
```

```
par(mfrow = c(1, 2))
fg11res2 = fg11@residuals
acfres2  = acf(fg11res2, lag.max = 20, ylab = "Sample Autocorrelation",
               main = NA, lwd = 2)
pacfres2 = pacf(fg11res2, lag.max = 20, ylab = "Sample Partial Autocorrelation",
                main = NA, lwd = 2, ylim = c(-0.5, 0.5))

fg12res2 = fg12@residuals
acfres2  = acf(fg12res2, lag.max = 20, ylab = "Sample Autocorrelation",
               main = NA, lwd = 2)
pacfres2 = pacf(fg12res2, lag.max = 20, ylab = "Sample Partial Autocorrelation",
                main = NA, lwd = 2, ylim = c(-0.5, 0.5))

# qq plot
par(mfrow = c(1, 1))
plot(fg11, which = 13)  #9,10,11,13
```

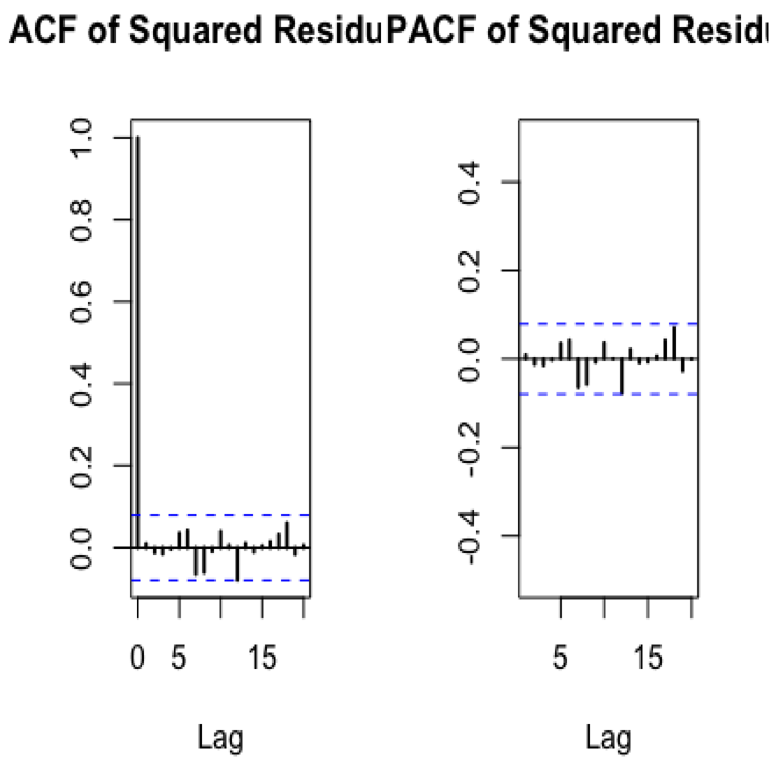


Figure 12: The ACF and PACF plots for model residuals of ARIMA(2,0,2)- t-GARCH(1,1) process.

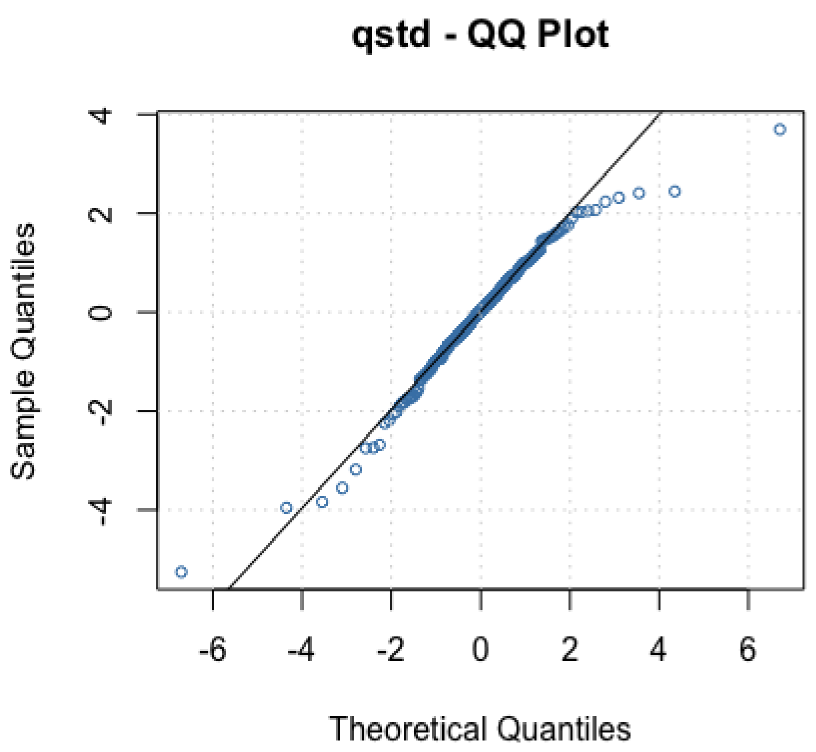


Figure 13: The QQ plots of model residuals of ARIMA-t-GARCH process.

Codes:

```
fg11stu = garchFit(data = res, data ~ garch(1, 1), cond.dist = "std")

# different forecast with t-garch
# fg11stufore = predict(fg11stu, n.ahead = 30, plot=TRUE, mse='uncond', auto.grid=FAl
fg11stufore = predict(fg11stu, n.ahead = 30, plot = TRUE, cond.dist = "QMLE",
                      auto.grid = FALSE)

par(mfrow = c(1, 2))
stu.fg11res2 = fg11stu@residuals

# acf and pacf for t-garch
stu.acfres2 = acf(stu.fg11res2, ylab = NA, lag.max = 20, main = "ACF of Squared Residu
                  lwd = 2)
stu.pacfres2 = pacf(stu.fg11res2, lag.max = 20, main = "PACF of Squared Residuals",
                    lwd = 2, ylab = NA, ylim = c(-0.5, 0.5))

# ARIMA-t-GARCH qq plot
par(mfrow = c(1, 1))
plot(fg11stu, which = 13)
```