

# Time-Series Analysis and Forecasting of the S&P 500 Index

Please download the file "sp500\_full.csv". It provides the data on daily prices and returns (among other things) of the S&P 500 index from 1957-01-02 to 2021-12-31. The specific function implementations are hidden as the project mainly focuses on the overall methods.

## Time Series Modeling and Forecasting

The goal is to fit time series models like ARIMA, ARCH, GARCH, ARMA-GARCH, APARCH to S&P 500 data for inference and forecasting. Use the S&P 500 data from mid-1962 through end of 2021. Load data and useful packages:

```
options(warn = -1)
sp = read.csv("sp500_full.csv", header = T)
idx = which(is.na(sp$sprtrn)==F)      # remove null values
sp = sp[idx, ]
r = sp$sprtrn * 100
t = as.Date(as.character(sp$caldt), "%Y%m%d")
library("forecast");

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

library("tseries")
library("fGarch")

## NOTE: Packages 'fBasics', 'timeDate', and 'timeSeries' are no longer
## attached to the search() path when 'fGarch' is attached.
##
## If needed attach them yourself in your R script by e.g.,
##       require("timeSeries")
```

### 1. ARMA Model

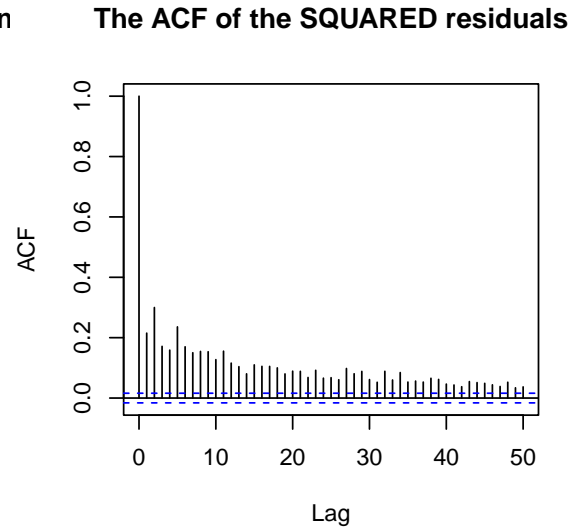
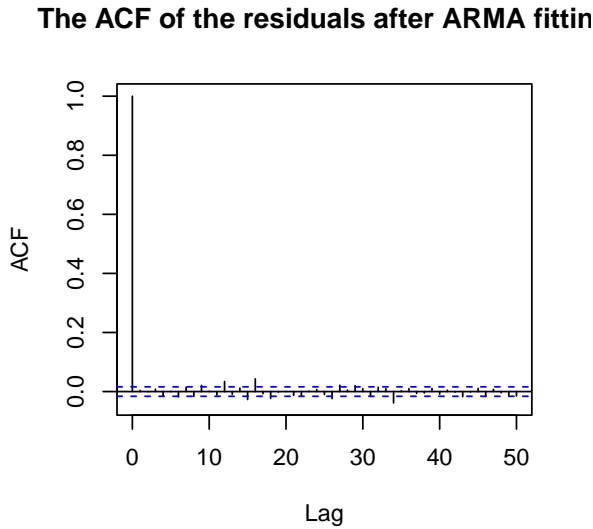
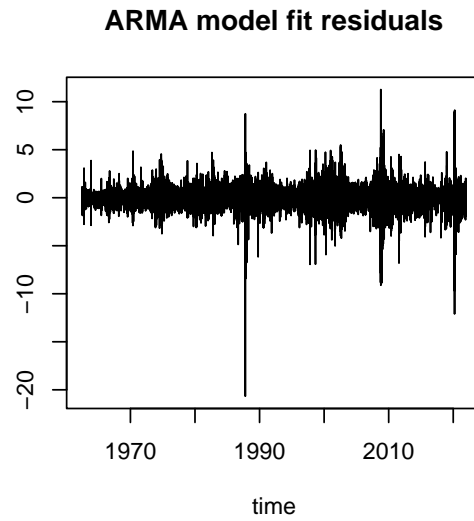
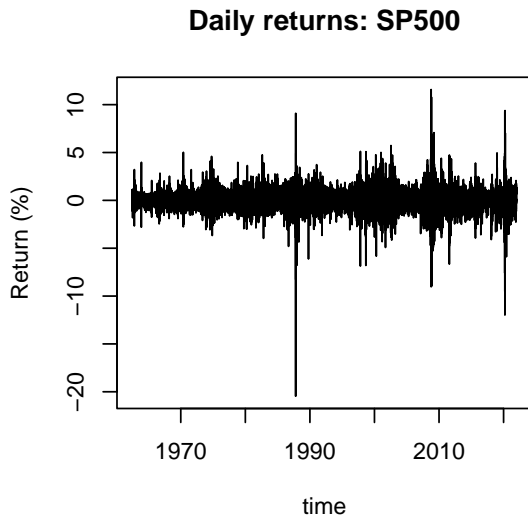
```
fit = auto.arima(r, d=0,max.p=50,max.q=50);
summary(fit)

## Series: r
## ARIMA(1,0,1) with non-zero mean
##
## Coefficients:
##          ar1          ma1          mean
##          0.8269    -0.8436    0.0351
## s.e.    0.0793     0.0759    0.0076
```

```
##
## sigma^2 = 1.06: log likelihood = -21684.76
## AIC=43377.52 AICc=43377.52 BIC=43407.98
##
## Training set error measures:
##               ME      RMSE      MAE MPE MAPE      MASE      ACF1
## Training set -0.0001202985 1.029255 0.6864911 NaN  Inf 0.7077847 0.003808404

par(mfrow=c(2,2));
plot(t,r,type="l",main="Daily returns: SP500",xlab="time",ylab="Return (%)")
plot(t,fit$residuals,type="l",
     main="ARMA model fit residuals",xlab="time",ylab="")

# ACF of the residuals and their squares
acf(fit$residuals,lag.max = 50,
    main="The ACF of the residuals after ARMA fitting")
acf(fit$residuals^2, lag.max = 50,
    main="The ACF of the SQUARED residuals")
```



From the above two plots, there are several observations:

- The empirical autocorrelation function(ACF) of the ARMA residuals for S&P500 seems to indicate a good fit. That is, the residuals are uncorrelated.
- The residuals from fitting the classic linear ARMA time series models appear non-stationary. A period of high-volatility persists for some time.
- The ACF of the squared residuals  $\hat{\epsilon}_t^2 = (r_t - \hat{r}_t)^2$  indicates that  $\{\hat{\epsilon}_t^2\}$  are correlated with non-linear dependence. Hence the residuals are dependent.

Thus the ARMA models are not capturing important dynamics in the returns.

## 2. ARCH(1) model

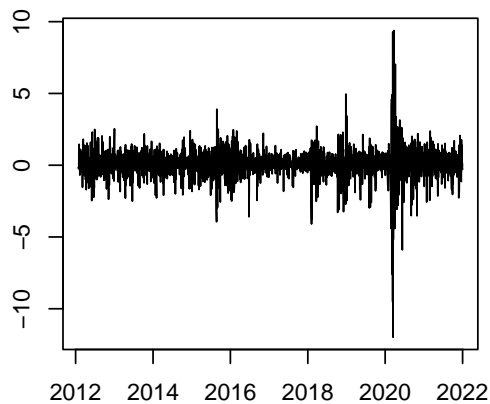
```

alpha0 = 0.001
alpha1 = 0.99
set.seed(123)
spec = garchSpec(model=
  list(omega = alpha0,alpha=alpha1,
       beta=0)); # beta = 0 means ARCH(1) not GARCH(1,1)
x = garchSim(spec,n=10*250); #Simulate ~ 10 years of trading days

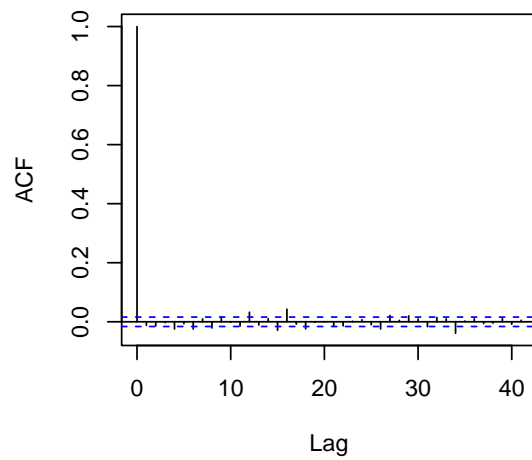
par(mfrow=c(2,2));
plot(tail(t,10*250), tail(r,10*250),type="l",
     xlab="",ylab="", main="Daily returns: SP500")
acf(r,main="ACF of SP500");
ts.plot(x, main="ARCH(1)")
acf(x, main="ACF of ARCH(1)")

```

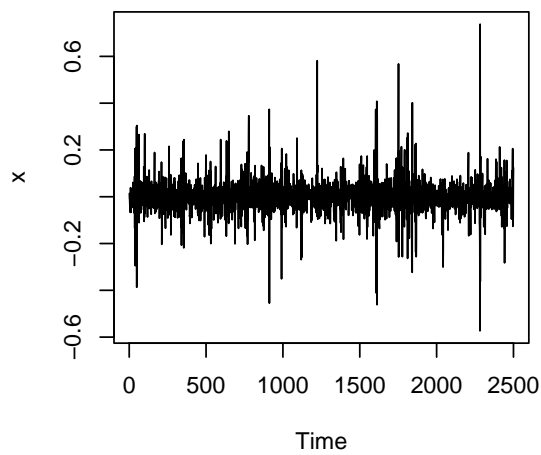
**Daily returns: SP500**



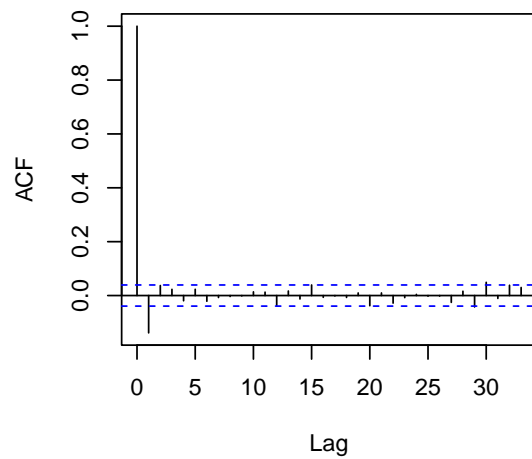
**ACF of SP500**



**ARCH(1)**

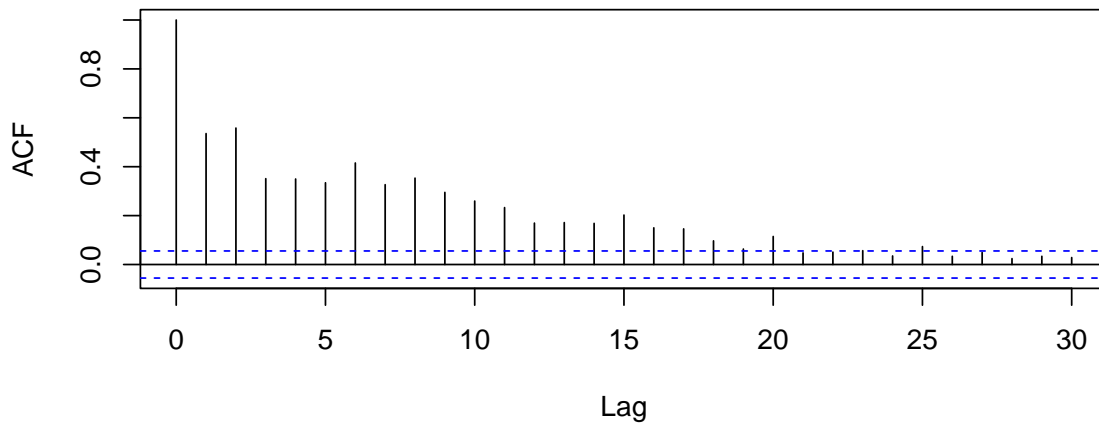


**ACF of ARCH(1)**

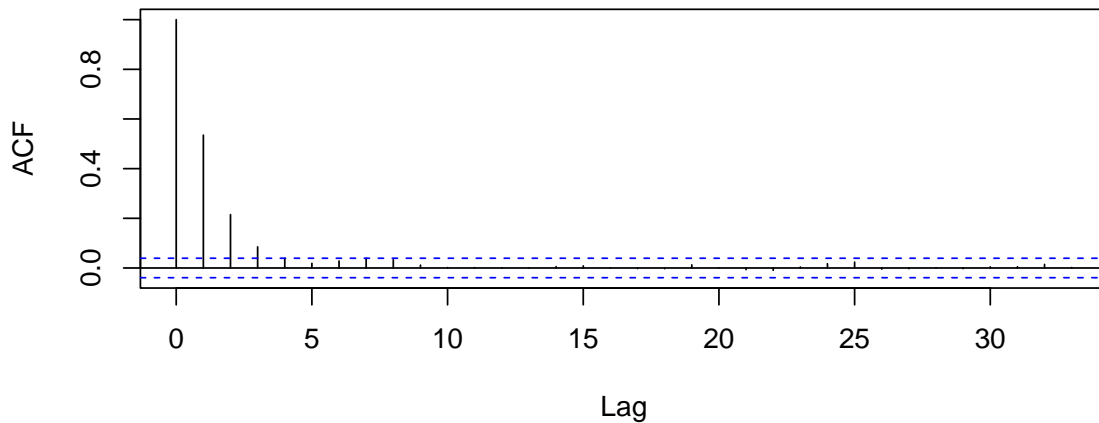


```
par(mfrow=c(2,1));  
acf(tail(r,5*250)^2,main="ACF of the SQUARE of the SP500 returns");  
acf(x^2,main="ACF of the SQUARE of the ARCH(1,1) time series");
```

### ACF of the SQUARE of the SP500 returns



### ACF of the SQUARE of the ARCH(1,1) time series



- ARCH(1) has the same phenomenon of uncorrelated returns as ARMA but different phenomenon correlated squared returns.
- The dependence in the market (S&P 500) squared returns is a lot more persistent, which experiences longer time lags.
- ARCH(1) still cannot interpret much information.

### 3. GARCH(1,1) model

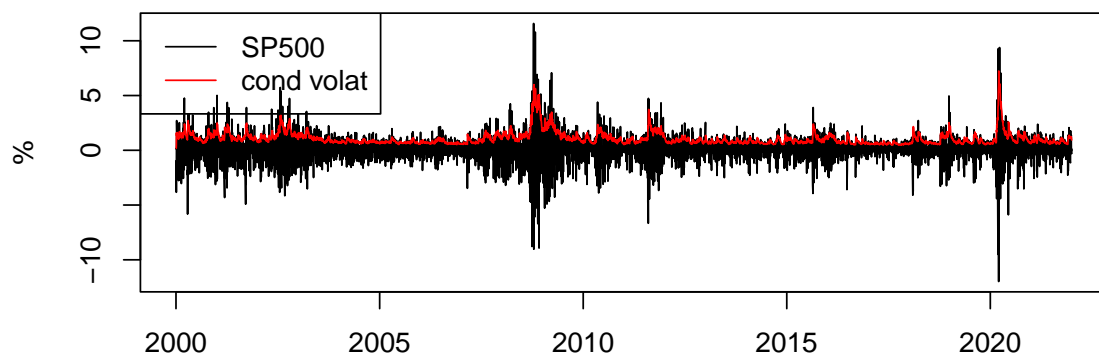
```
idx = which (t>=as.Date("2000-01-01"))  
mu.r = mean(r[idx])  
fit.garch = fit_simple_garch(data = r[idx]-mu.r)
```

```

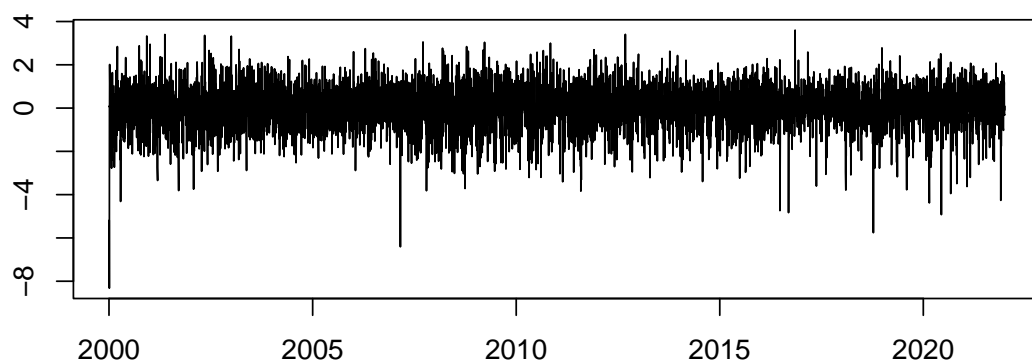
par(mfrow=c(2,1));
plot(t[idx],r[idx],main="Daily SP500 returns",
     ylab="%",type="l",xlab="");
lines(t[idx],fit.garch$sigma.t,col="red");
legend("topleft",
      legend = c("SP500","cond volat"),
      col=c("black","red"),lwd=c(1,1))
plot(t[idx],fit.garch$residuals,main="GARCH(1,1) residuals",
     ylab="",type="l",xlab="")

```

**Daily SP500 returns**



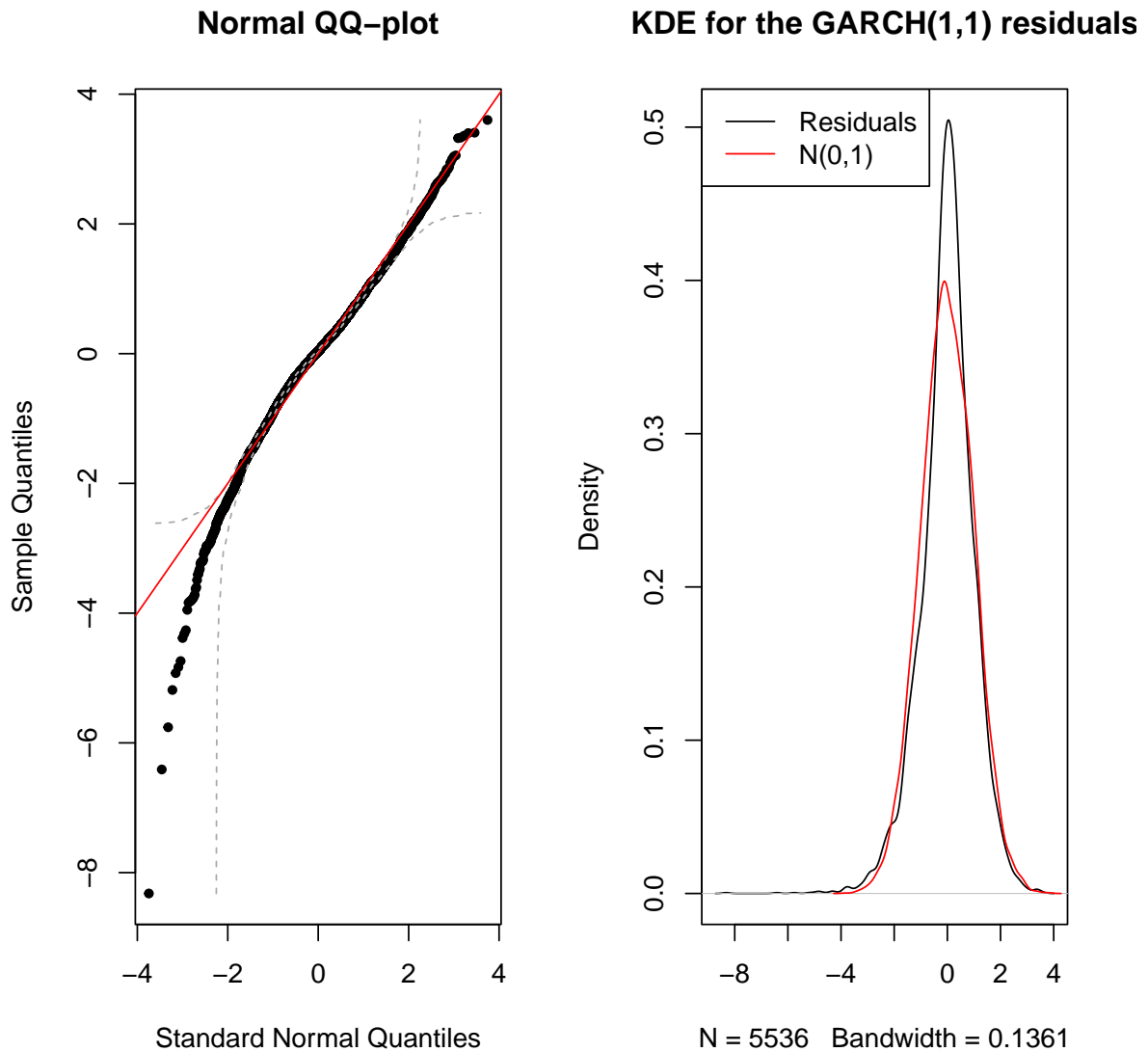
**GARCH(1,1) residuals**



```

par(mfrow=c(1,2));
extRemes::qqnorm(fit.garch$residuals,main="Normal QQ-plot")
abline(a=0,b=1,col="red")
plot(density(fit.garch$residuals),main="KDE for the GARCH(1,1) residuals")
lines(density(rnorm(1e4)),col="red");
legend("topleft",legend=c("Residuals","N(0,1)"),
      col=c("black","red"),lwd=c(1,1))

```



- From the normal QQ-plot, GARCH(1,1) residuals have a heavier left tail than Gaussian. That is, the losses have heavier tails than the gains. Therefore, extreme losses have greater effect on increasing the volatility than extreme gains.



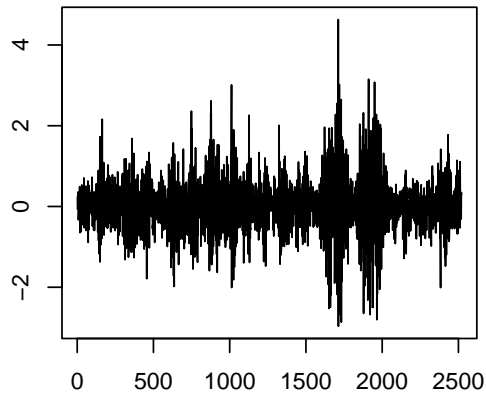
- In practice, extreme losses have greater effect on increasing the volatility than extreme gains.
- This [asymmetry phenomenon](#) is not reflected in the simple GARCH(1,1).

#### 4. APARCH model

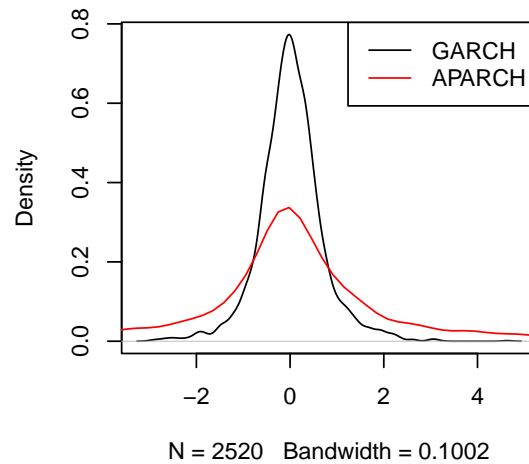
```
# the implementation of a simple APARCH(1,1) model
sim_simple_APARCH <- function(n, s0=0.00001, x0=0.00001,
                              a0=0.01, a=0.2, b=0.79,
                              delta=2, gamma=0.7){
  s.delta = abs(s0)^delta;
  x = x0;
  for (t in c(2:(n+1))) {
    s.delta = a0+a*abs((abs(x[t-1])-gamma*x[t-1]))^delta + b*s.delta;
    x = c(x,s.delta^(1/delta)*rnorm(1));
  }
  return(x[-1])}

set.seed(123)
x.garch = sim_simple_APARCH(n=2520, gamma=0);
set.seed(123)
x.aparch = sim_simple_APARCH(n=2520, gamma= 0.7);
par(mfrow=c(2,2));
plot(x.garch,xlab="",ylab="",type="l",
     main="Simple GARCH(1,1)");
plot(density(x.garch),main="GARCH(1,1): KDE")
lines(density(x.aparch),col="red");
legend("topright",legend=c("GARCH","APARCH"),
     col=c("black","red"),lwd=c(1,1))
plot(x.aparch,xlab="",ylab="",type="l",
     main="Simple APARCH(1,1), gamma=0.7");
stats::qqplot(x.garch,
              x.aparch,main="QQ plot");
abline(a=0,b=sd(x.aparch)/sd(x.garch),col="red")
```

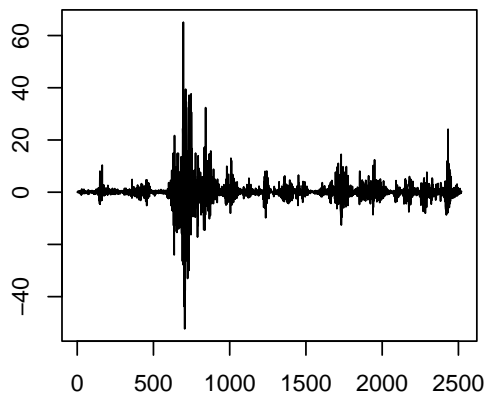
Simple GARCH(1,1)



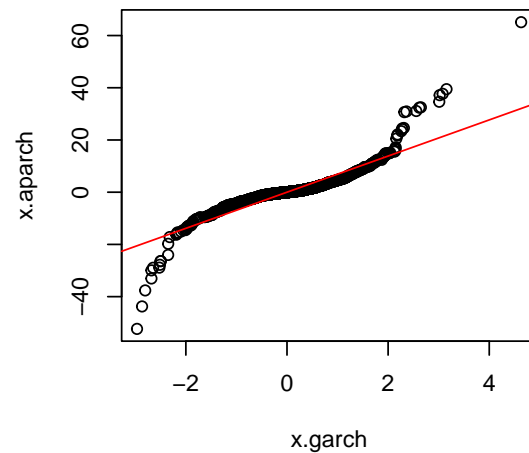
GARCH(1,1): KDE



Simple APARCH(1,1), gamma=0.7



QQ plot



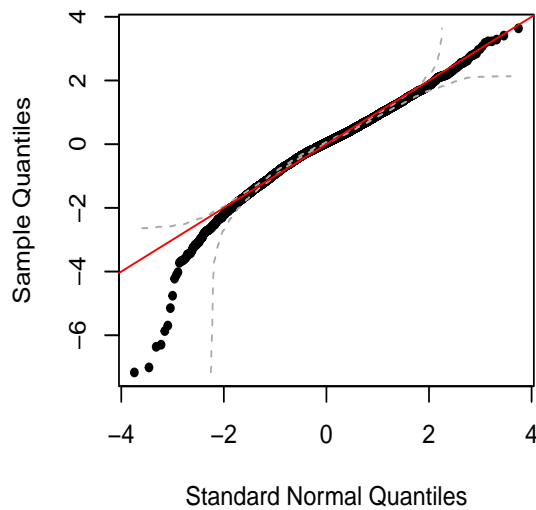
Test/validation...

```
fit.aparch = fit_simple_APARCH(data = r[idx]-mu.r)
par(mfrow=c(2,2));
extRemes::qqnorm(fit.aparch$residuals,main="Normal QQ-plot")
abline(a=0,b=1,col="red")
plot(density(fit.aparch$residuals),main="KDE for the APARCH(1,1) residuals")
lines(density(rnorm(1e4)),col="red");
legend("topleft",legend=c("APARCH","N(0,1)"),
      col=c("black","red"),lwd=c(1,1))

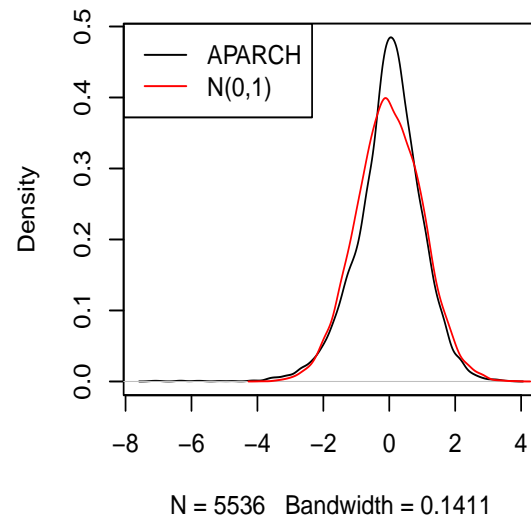
extRemes::qqnorm(fit.garch$residuals,main="Normal QQ-plot")
abline(a=0,b=1,col="red")
```

```
plot(density(fit.garch$residuals),main="KDE for the GARCH(1,1) residuals")
lines(density(rnorm(1e4)),col="red");
legend("topleft",legend=c("GARCH","N(0,1)"),
      col=c("black","red"),lwd=c(1,1))
```

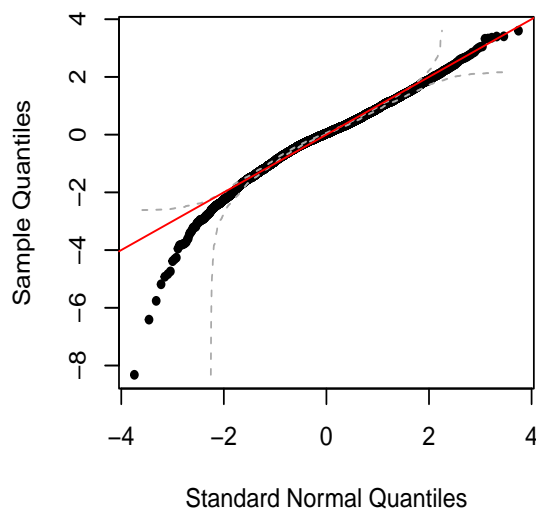
**Normal QQ-plot**



**KDE for the APARCH(1,1) residuals**



**Normal QQ-plot**



**KDE for the GARCH(1,1) residuals**

