

realtime-analysis

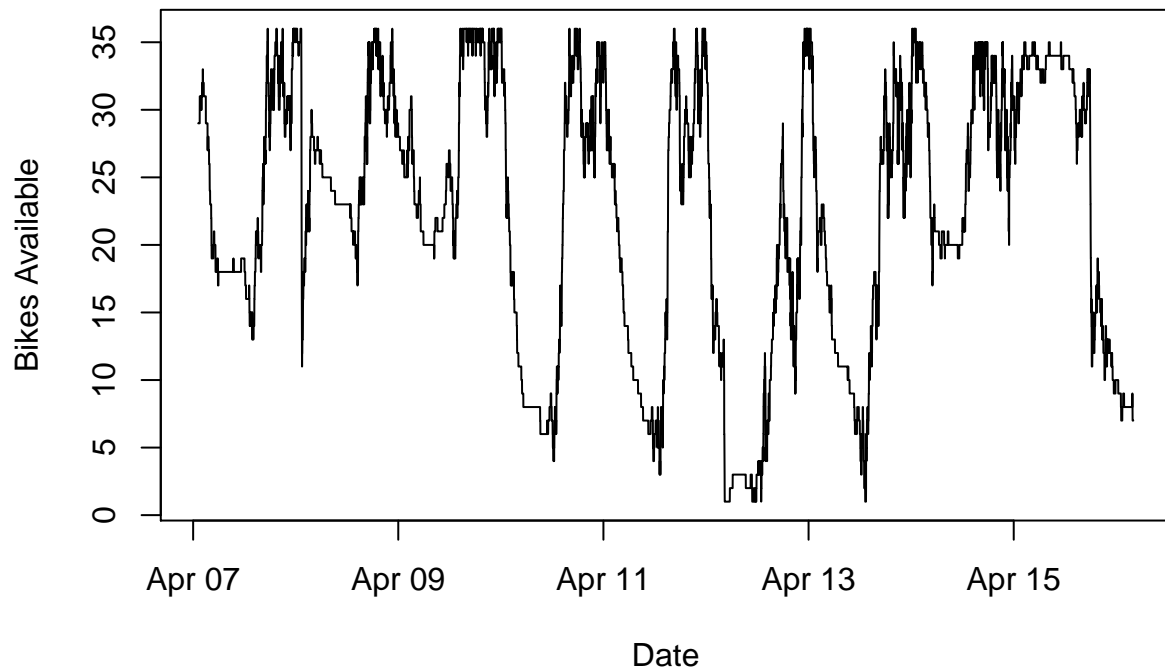
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4/10/2018

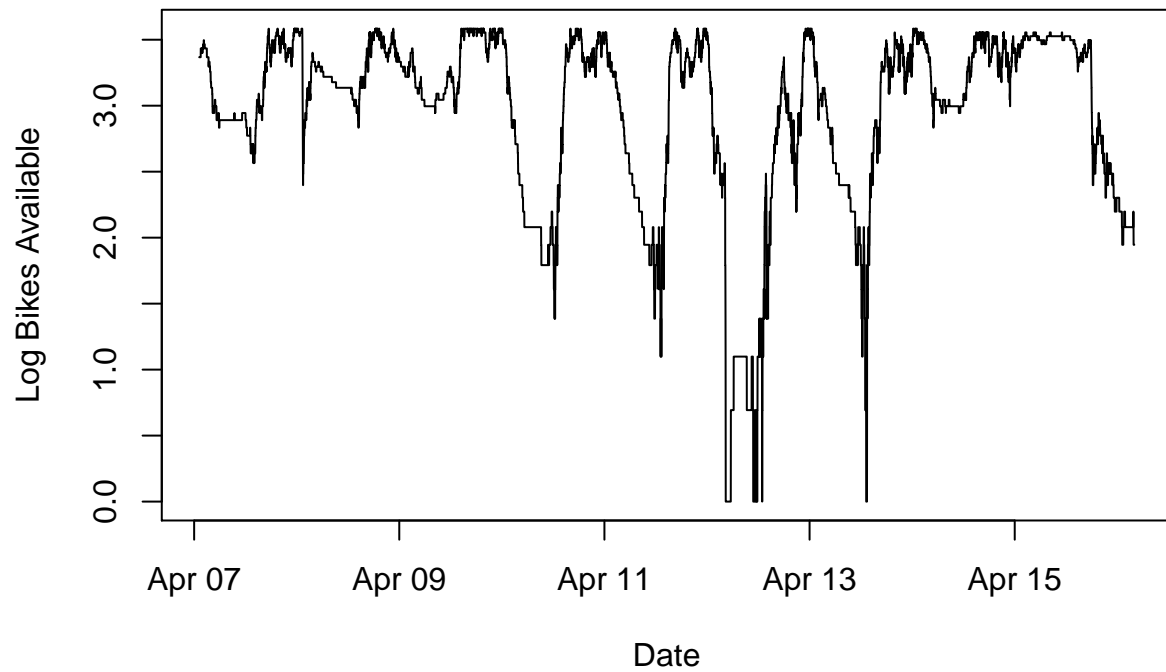
```
data <- read.csv("/Users/chuamelia/Google Drive/Forecasting Time Series/citi-bike/ts-realtime-analysis-1")
date <- as.POSIXlt(data$last_updated)
time <- 1:length(date)
status <- data$num_bikes_available + 1
```

```
log.status <- log(status)
diff.log.status <- c(NA, diff(log.status))
diff2.log.status <- c(NA, diff(diff.log.status))
```

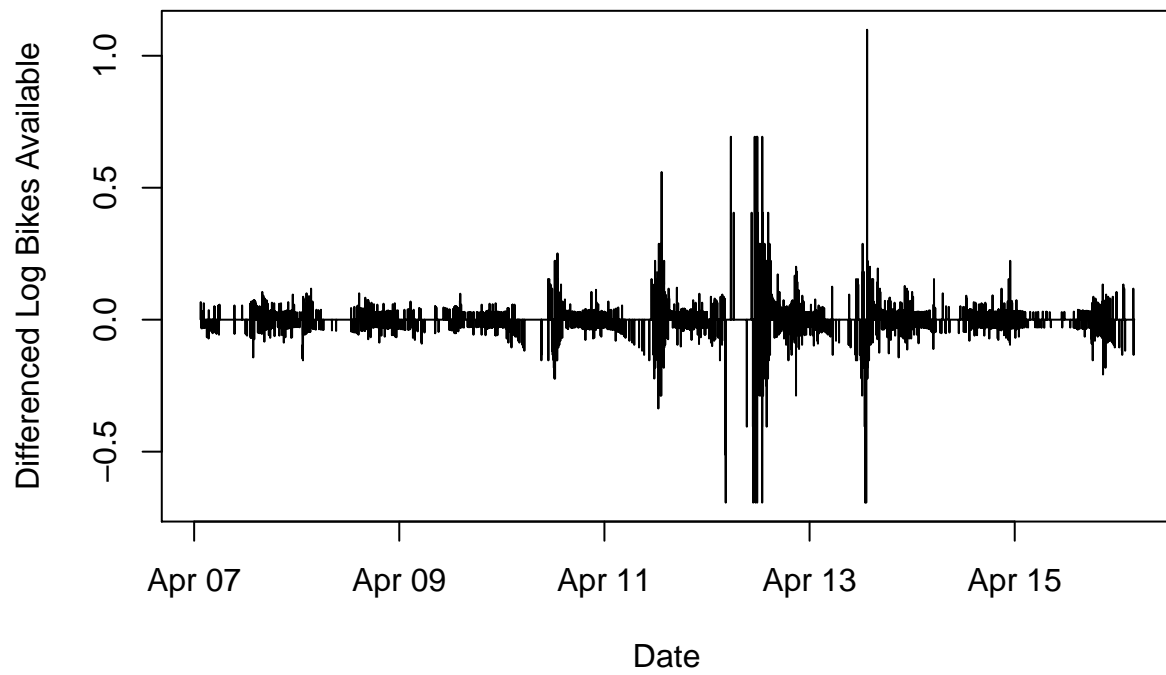
```
plot(date, status, type="l",
      xlab="Date", ylab="Bikes Available")
```



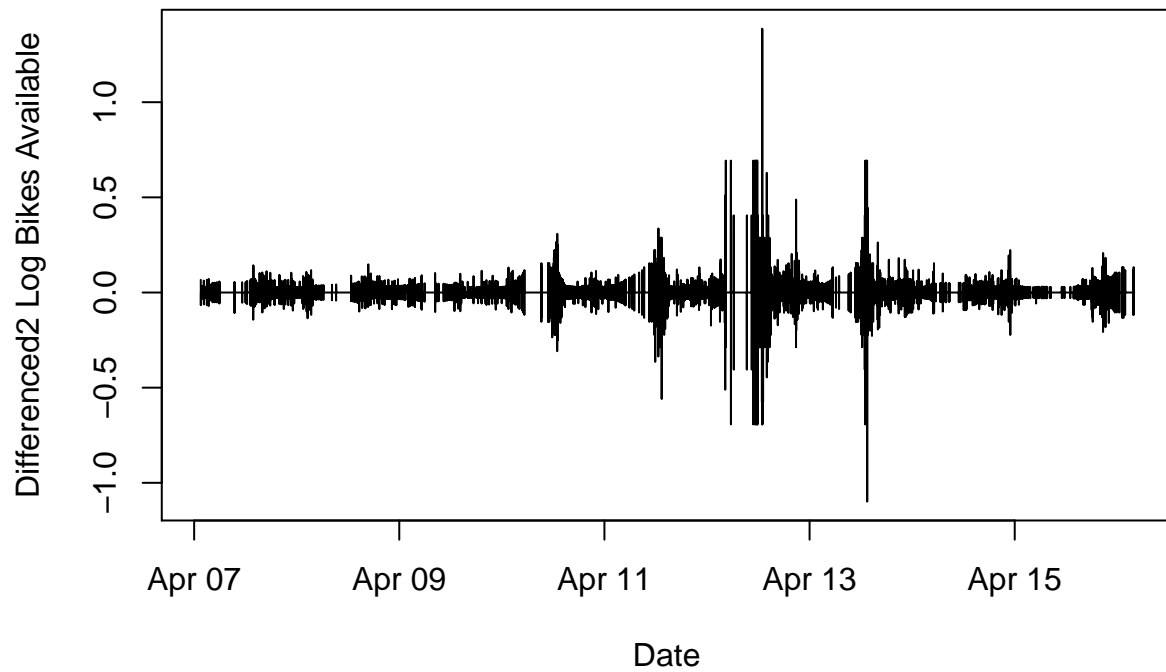
```
plot(date, log.status, type="l",
      xlab="Date", ylab="Log Bikes Available")
```



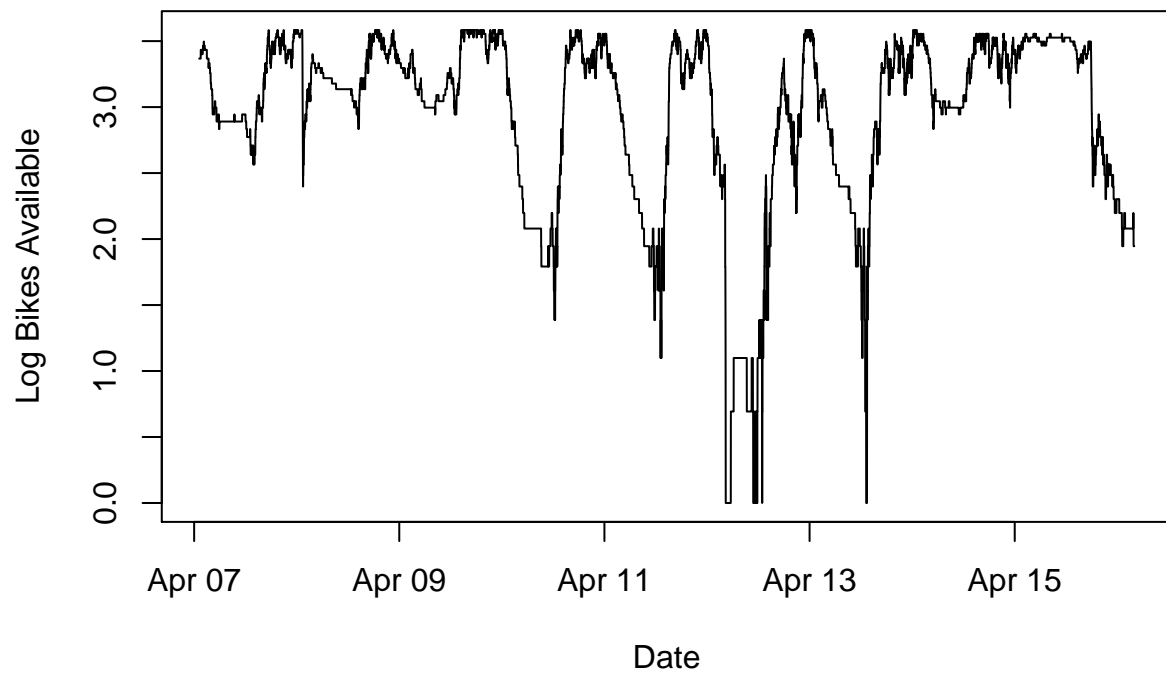
```
plot(date, diff.log.status, type="l",  
      xlab="Date", ylab="Differenced Log Bikes Available")
```



```
plot(date, diff2.log.status, type="l",  
      xlab="Date", ylab="Differenced2 Log Bikes Available")
```

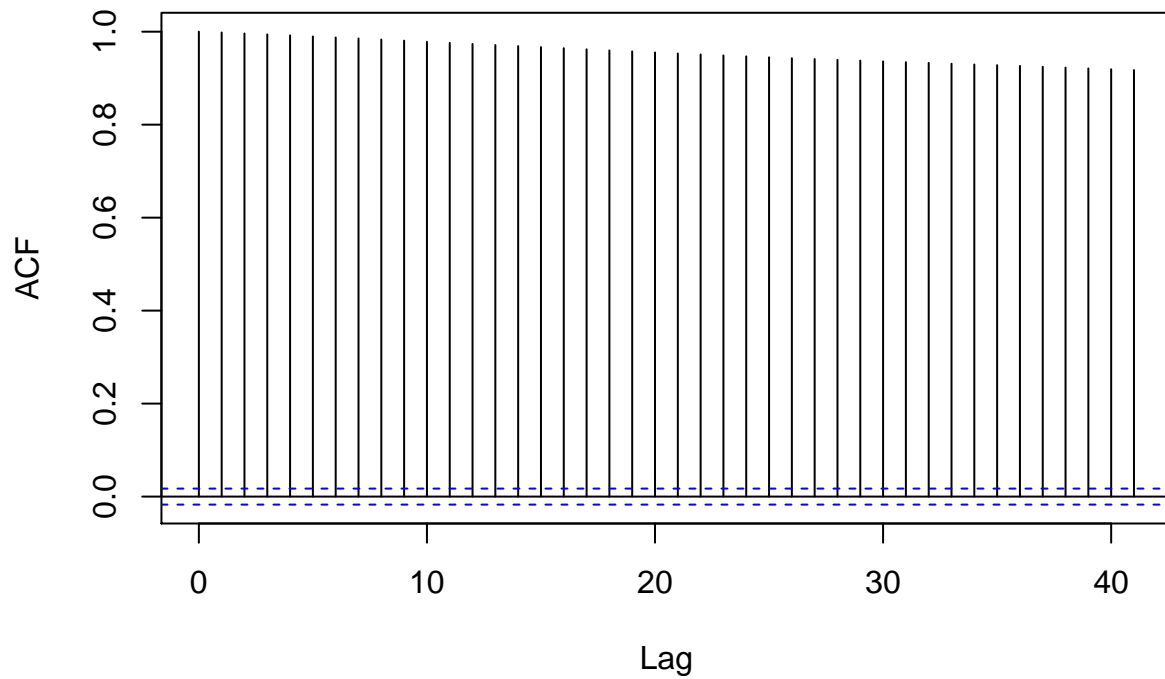


```
# Time series plot  
plot(date, log.status, type="l",  
      xlab="Date", ylab="Log Bikes Available")
```



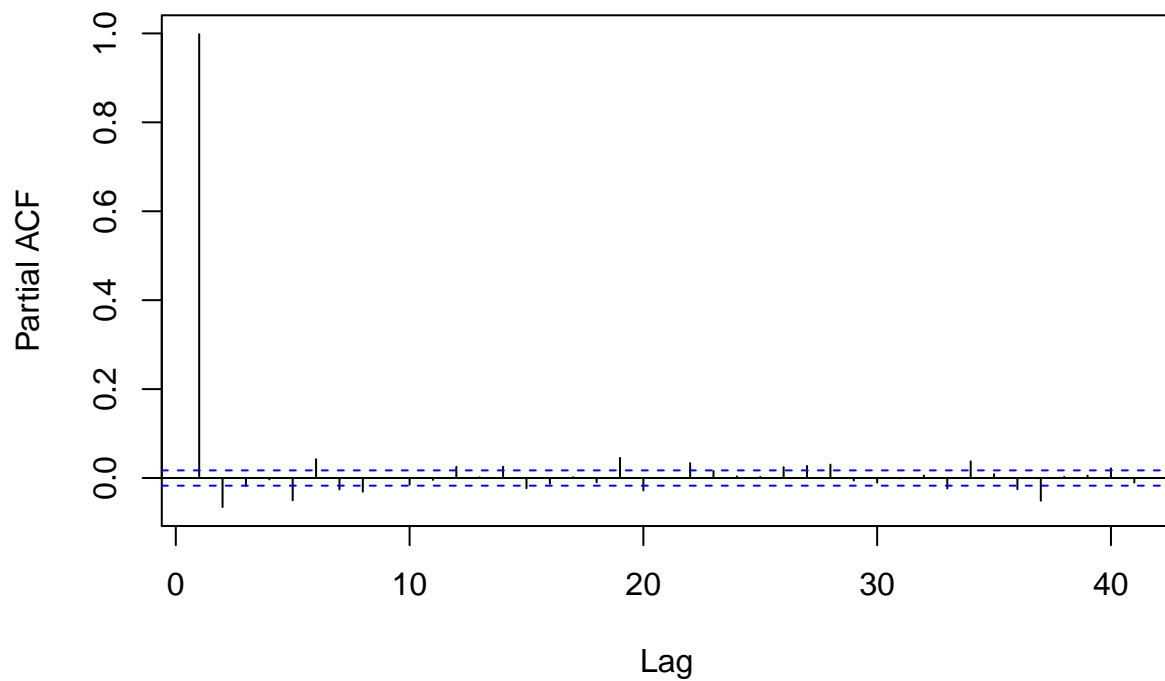
```
# ACF and PACF  
acf(log.status, na.action = na.pass)
```

Series log.status

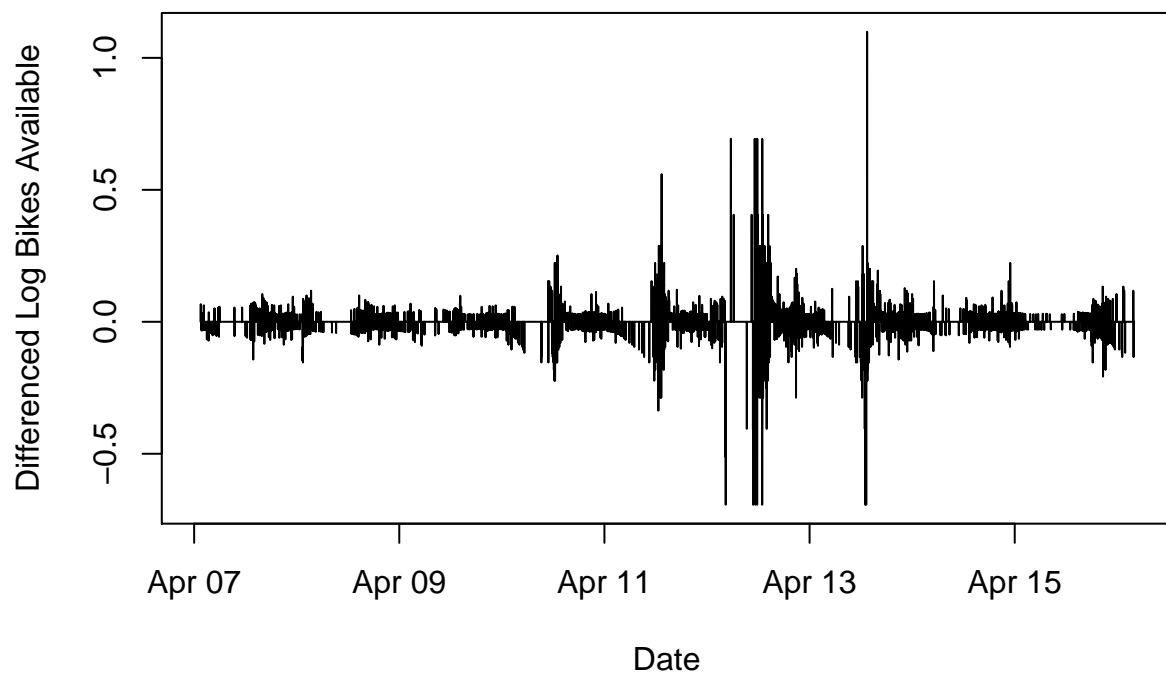


```
pacf(log.status, na.action = na.pass)
```

Series log.status

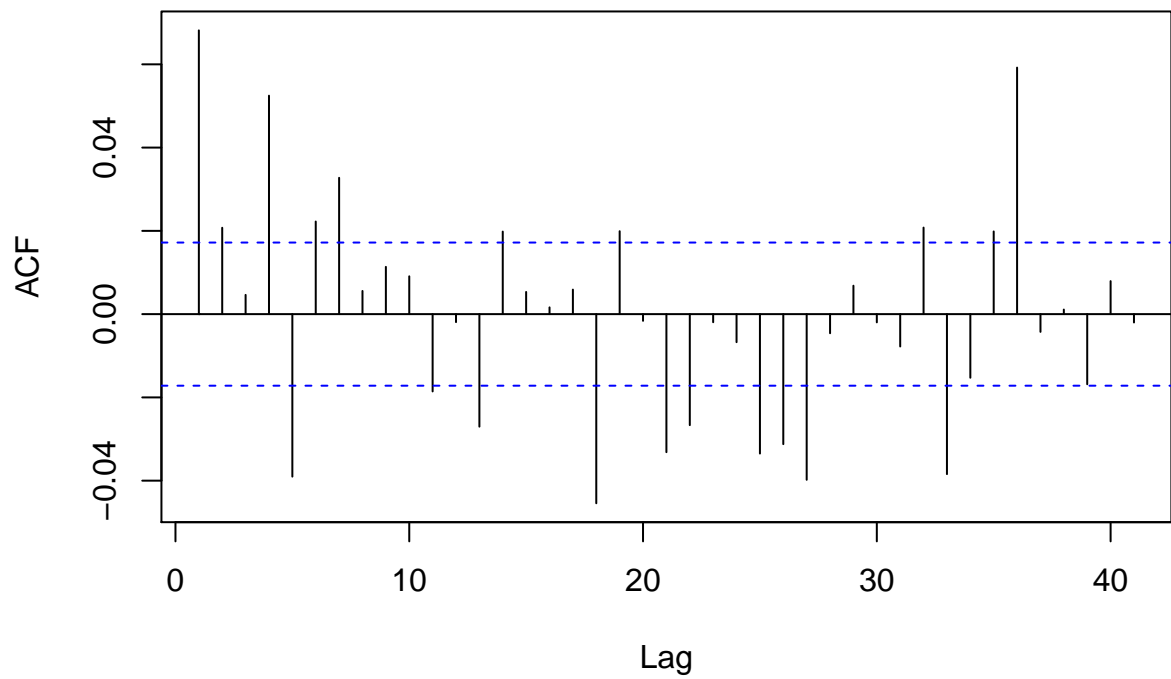


```
# Time series plot  
plot(date, diff.log.status, type="l",  
      xlab="Date", ylab="Differenced Log Bikes Available")
```



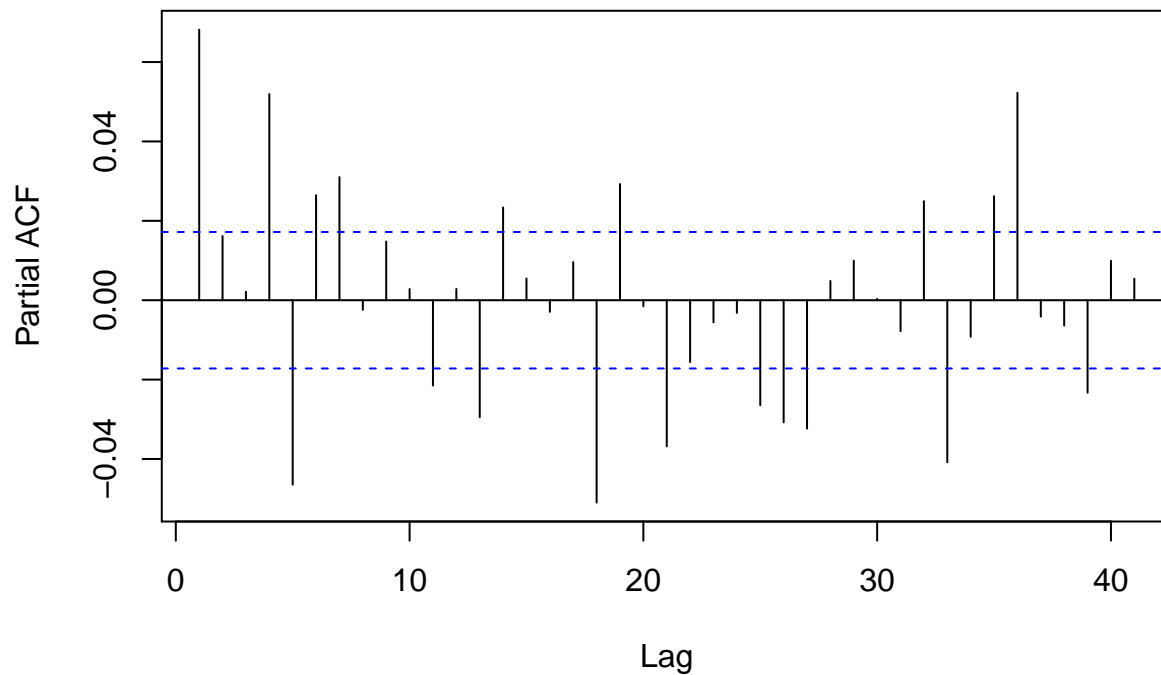
```
# ACF and PACF  
Acf(diff.log.status, na.action = na.pass)
```

Series diff.log.status



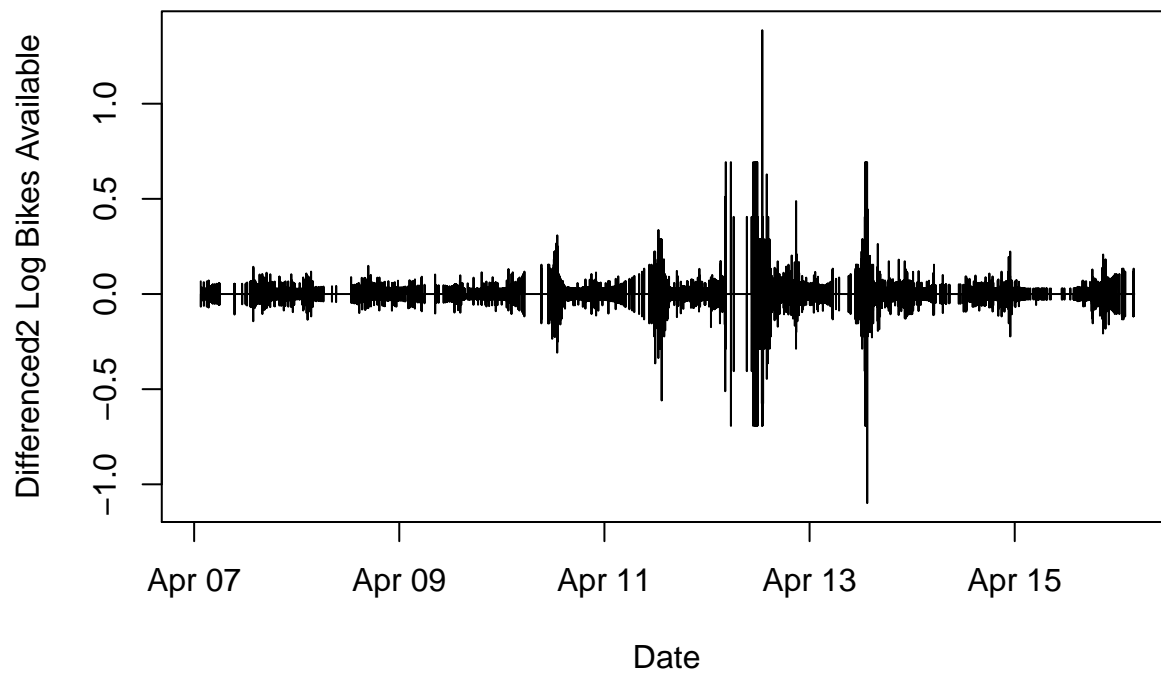
```
pacf(diff.log.status, na.action = na.pass)
```

Series diff.log.status



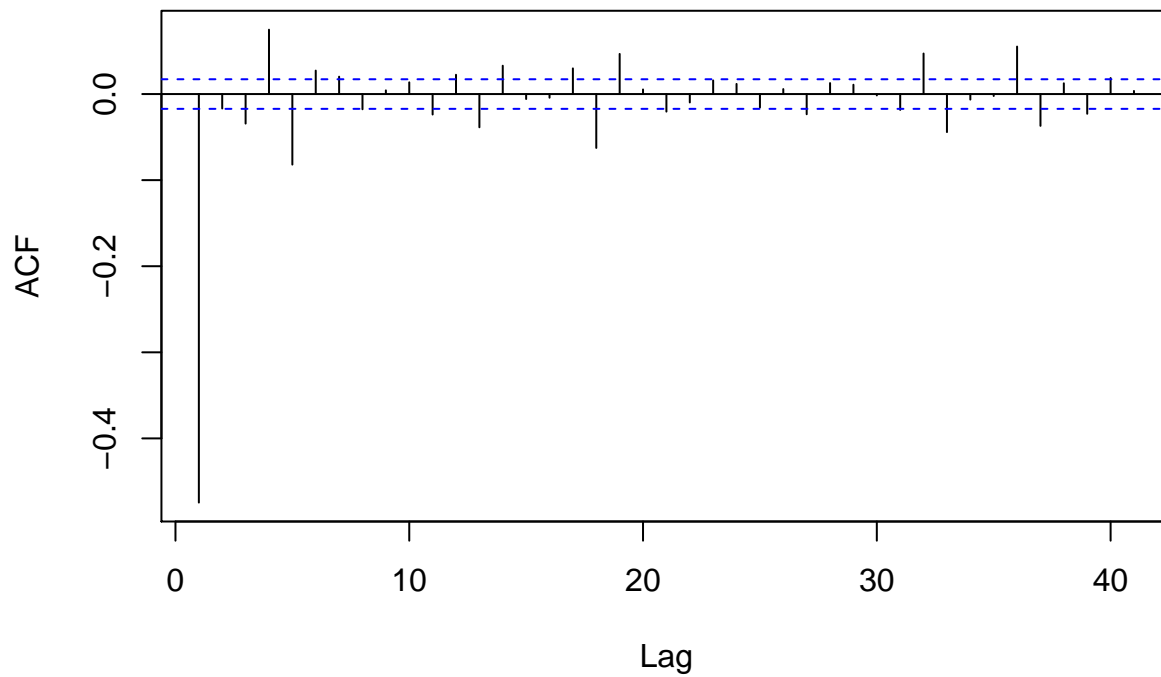
```
## Add code to compute the second difference and make the plots.
```

```
# Time series plot  
plot(date, diff2.log.status, type="l",  
      xlab="Date", ylab="Differenced2 Log Bikes Available")
```



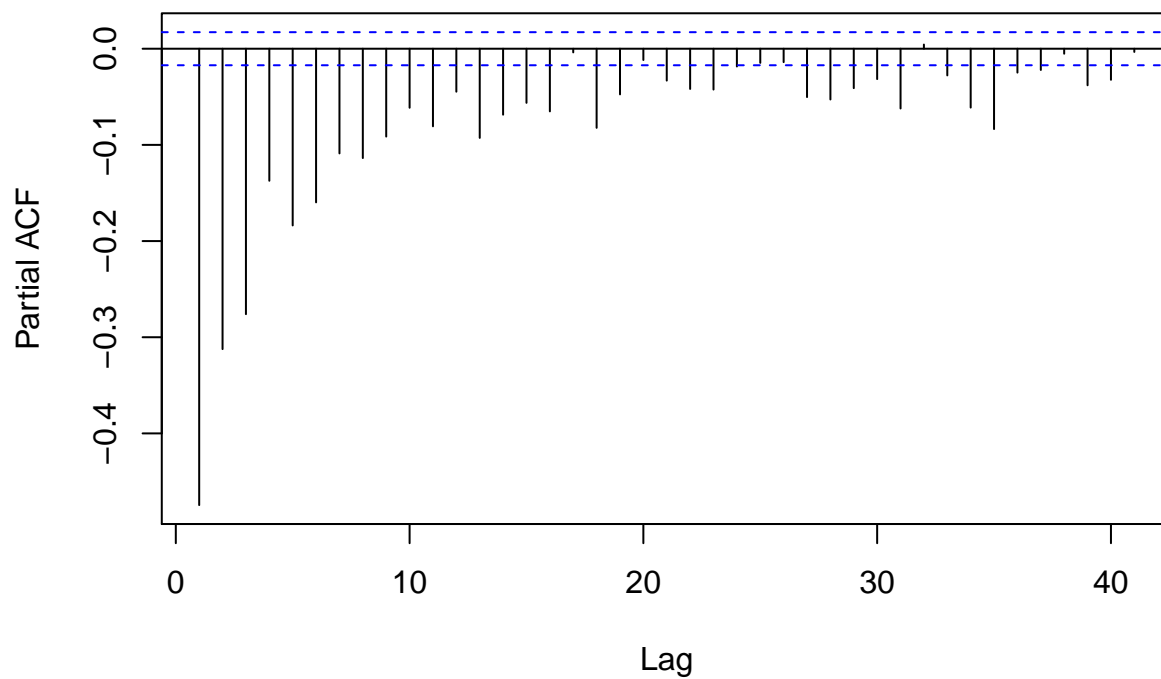
```
# ACF and PACF  
Acf(diff2.log.status, na.action = na.pass)
```

Series diff2.log.status



```
pacf(diff2.log.status, na.action = na.pass)
```

Series diff2.log.status



```
# Add code to compute the AICc values. You can modify the code from  
# http://ptrckprry.com/course/forecasting/lecture/nasdaq-arch.html  
# if you don't want to do this by hand.
```

```

d <- 1

# choose p, q with AICc
for (include.constant in c(FALSE, TRUE)) {
  for (p in 0:4) {
    for (q in 0:4) {
      # work-around bug in R by manually differencing
      fit <- Arima(diff(log.status), c(p,0,q),
                  include.constant=include.constant, method="ML")
      cat("ARIMA",
          "(", p, ",", d, ",", q, ")",
          "(constant=", include.constant, ")",
          " : ", fit$aicc, "\n", sep="")
      #cat( p, ":", d, ":", q, ":",
      #     ":", include.constant, ":",
      #     " : ", fit$aicc, "\n", sep="")
    }
  }
}

```

```

## ARIMA(0,1,0)(constant=FALSE) : -46902
## ARIMA(0,1,1)(constant=FALSE) : -46958.35
## ARIMA(0,1,2)(constant=FALSE) : -46961.45
## ARIMA(0,1,3)(constant=FALSE) : -46959.47
## ARIMA(0,1,4)(constant=FALSE) : -47001.25
## ARIMA(1,1,0)(constant=FALSE) : -46960.51
## ARIMA(1,1,1)(constant=FALSE) : -46963.24
## ARIMA(1,1,2)(constant=FALSE) : -46959.45
## ARIMA(1,1,3)(constant=FALSE) : -46957.45
## ARIMA(1,1,4)(constant=FALSE) : -47018.71
## ARIMA(2,1,0)(constant=FALSE) : -46961.91
## ARIMA(2,1,1)(constant=FALSE) : -46959.9
## ARIMA(2,1,2)(constant=FALSE) : -46959.72
## ARIMA(2,1,3)(constant=FALSE) : -46986.12
## ARIMA(2,1,4)(constant=FALSE) : -47039.36
## ARIMA(3,1,0)(constant=FALSE) : -46959.97
## ARIMA(3,1,1)(constant=FALSE) : -46957.91
## ARIMA(3,1,2)(constant=FALSE) : -46982.99
## ARIMA(3,1,3)(constant=FALSE) : -47052.78
## ARIMA(3,1,4)(constant=FALSE) : -47051.17
## ARIMA(4,1,0)(constant=FALSE) : -46993.07
## ARIMA(4,1,1)(constant=FALSE) : -47014.74
## ARIMA(4,1,2)(constant=FALSE) : -47043.02
## ARIMA(4,1,3)(constant=FALSE) : -47050.91
## ARIMA(4,1,4)(constant=FALSE) : -47049.37
## ARIMA(0,1,0)(constant=TRUE) : -46900.09
## ARIMA(0,1,1)(constant=TRUE) : -46956.43
## ARIMA(0,1,2)(constant=TRUE) : -46959.53
## ARIMA(0,1,3)(constant=TRUE) : -46957.55
## ARIMA(0,1,4)(constant=TRUE) : -46999.32
## ARIMA(1,1,0)(constant=TRUE) : -46958.59
## ARIMA(1,1,1)(constant=TRUE) : -46961.76
## ARIMA(1,1,2)(constant=TRUE) : -46957.53

```



```
## ARIMA(1,1,3)(constant=TRUE) : -46955.53
## ARIMA(1,1,4)(constant=TRUE) : -47016.79
## ARIMA(2,1,0)(constant=TRUE) : -46959.99
## ARIMA(2,1,1)(constant=TRUE) : -46957.98
## ARIMA(2,1,2)(constant=TRUE) : -46957.81
## ARIMA(2,1,3)(constant=TRUE) : -46984.2
## ARIMA(2,1,4)(constant=TRUE) : -47035.25
## ARIMA(3,1,0)(constant=TRUE) : -46958.05
## ARIMA(3,1,1)(constant=TRUE) : -46955.99
## ARIMA(3,1,2)(constant=TRUE) : -46980.94
## ARIMA(3,1,3)(constant=TRUE) : -47050.73
## ARIMA(3,1,4)(constant=TRUE) : -47049.09
## ARIMA(4,1,0)(constant=TRUE) : -46991.14
## ARIMA(4,1,1)(constant=TRUE) : -47012.81
## ARIMA(4,1,2)(constant=TRUE) : -47041.1
## ARIMA(4,1,3)(constant=TRUE) : -47048.97
## ARIMA(4,1,4)(constant=TRUE) : -47047.36
```

Here is code to fit the model, then compute residuals and the fitted values:

```
# Add code to fit the ARIMA model.
fit.mean <- Arima(log.status, c(3, 1, 3), include.constant=FALSE)
```

```
summary(fit.mean)
```

```
## Series: log.status
## ARIMA(3,1,3)
##
## Coefficients:
##          ar1          ar2          ar3          ma1          ma2          ma3
##      -0.6394  0.1644  0.5990  0.7143  -0.0968  -0.6067
## s.e.    0.0984  0.1237  0.0723  0.1001   0.1331   0.0804
##
## sigma^2 estimated as 0.001565:  log likelihood=23533.36
## AIC=-47052.71  AICc=-47052.7  BIC=-47000.41
##
## Training set error measures:
##              ME              RMSE              MAE MPE MAPE      MASE
## Training set -9.475436e-05 0.03955459 0.01217285 NaN  Inf 1.167503
##              ACF1
## Training set -0.003174141
```

```
Box.test(diff.log.status, lag = 12, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
```

```
##
## Box-Pierce test
##
## data:  diff.log.status
## X-squared = 149.85, df = 12, p-value < 2.2e-16
```

```
Box.test(diff.log.status, lag = 24, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
```

```
##
## Box-Pierce test
##
## data:  diff.log.status
## X-squared = 221.48, df = 24, p-value < 2.2e-16
```

```
Box.test(diff.log.status, lag = 36, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
```

```
##  
## Box-Pierce test  
##  
## data: diff.log.status  
## X-squared = 349.56, df = 36, p-value < 2.2e-16
```

```
Box.test(diff.log.status, lag = 48, type = c("Box-Pierce", "Ljung-Box"), fitdf = 0)
```

```
##  
## Box-Pierce test  
##  
## data: diff.log.status  
## X-squared = 365.1, df = 48, p-value < 2.2e-16
```

Here are the residuals, with the last 10 residuals printed out:

```
# Uncomment:  
resid <- residuals(fit.mean)  
tail(resid, n=10)
```

```
## Time Series:  
## Start = 12986  
## End = 12995  
## Frequency = 1  
## [1] 0.015334141 -0.001851248 0.003245700 0.006805391 -0.005669778  
## [6] 0.006677641 -0.001189804 -0.001943458 0.005324153 -0.004712837
```

Here are the fitted values, with the last 10 fitted values printed out:

```
f <- fitted.values(fit.mean)  
tail(f, n=10)
```

```
## Time Series:  
## Start = 12986  
## End = 12995  
## Frequency = 1  
## [1] 1.930576 1.947761 1.942664 1.939105 1.951580 1.939233 1.947100  
## [8] 1.947854 1.940586 1.950623
```

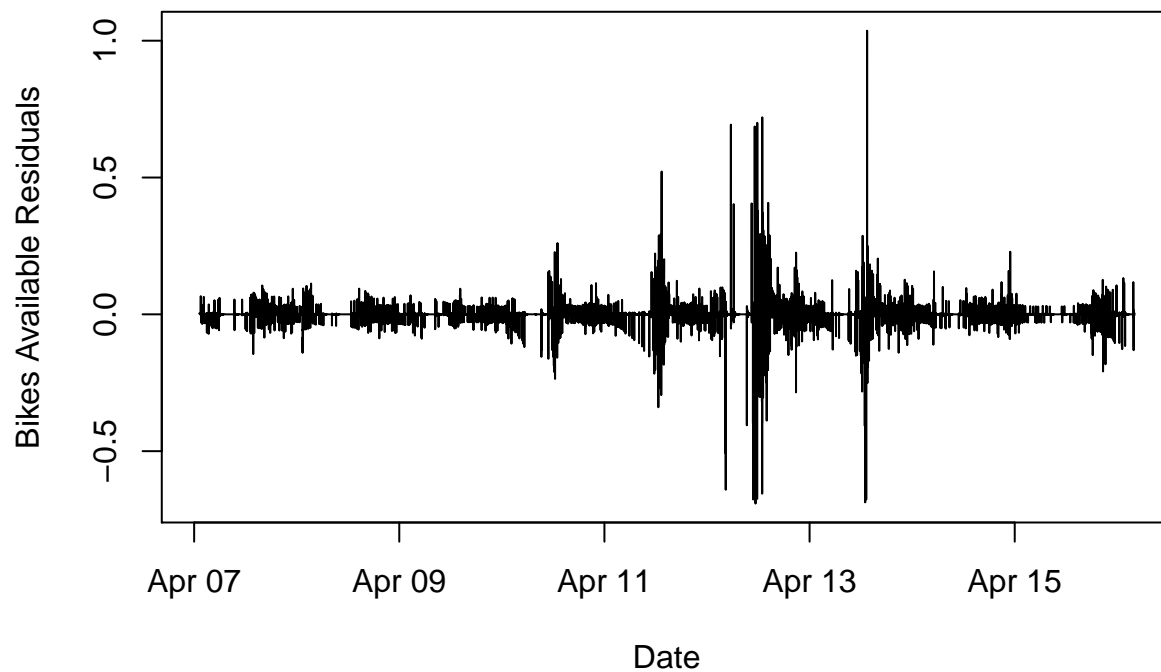
Here is the one step ahead forecast and 95% forecast interval:

```
forecast(fit.mean, h=1, level = 95)
```

```
##      Point Forecast    Lo 95    Hi 95  
## 12996      1.943208 1.865661 2.020754
```

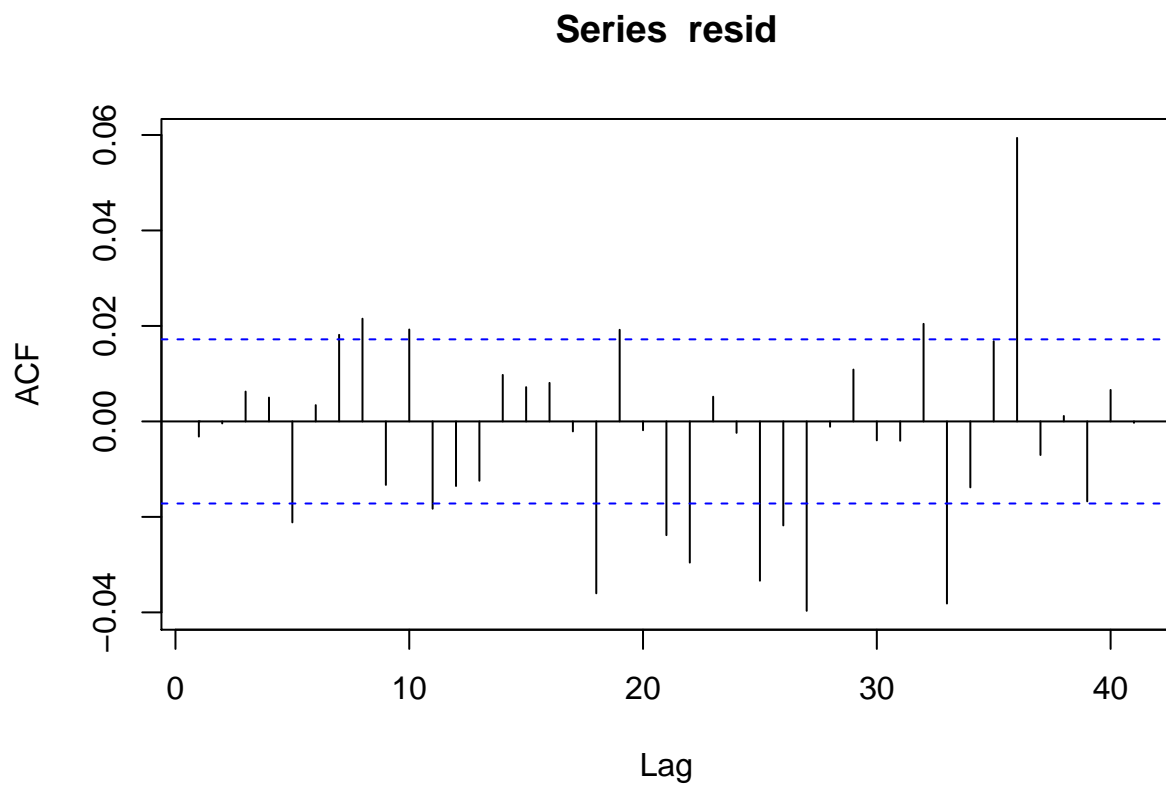
Here is a plot of the residuals:

```
plot(date, resid, type="l",  
      xlab="Date", ylab="Bikes Available Residuals")
```



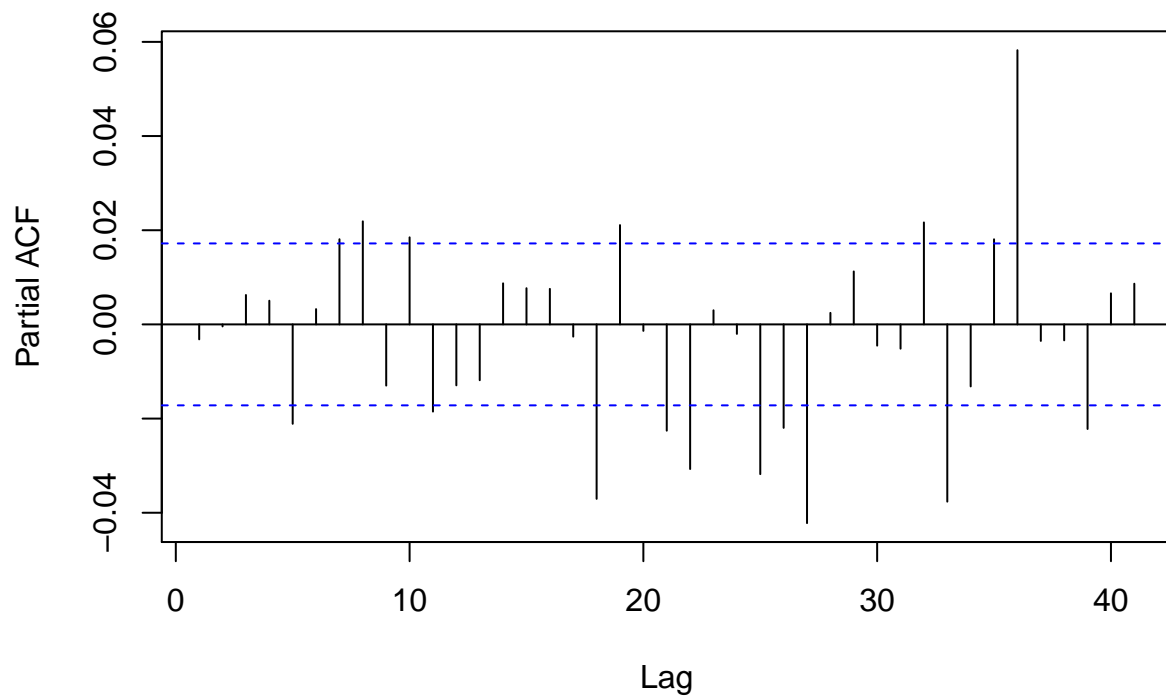
Here are an ACF and PACF of the residuals:

```
# Add ACF, PACF of residuals.
# ACF and PACF
Acf(resid, na.action = na.pass)
```



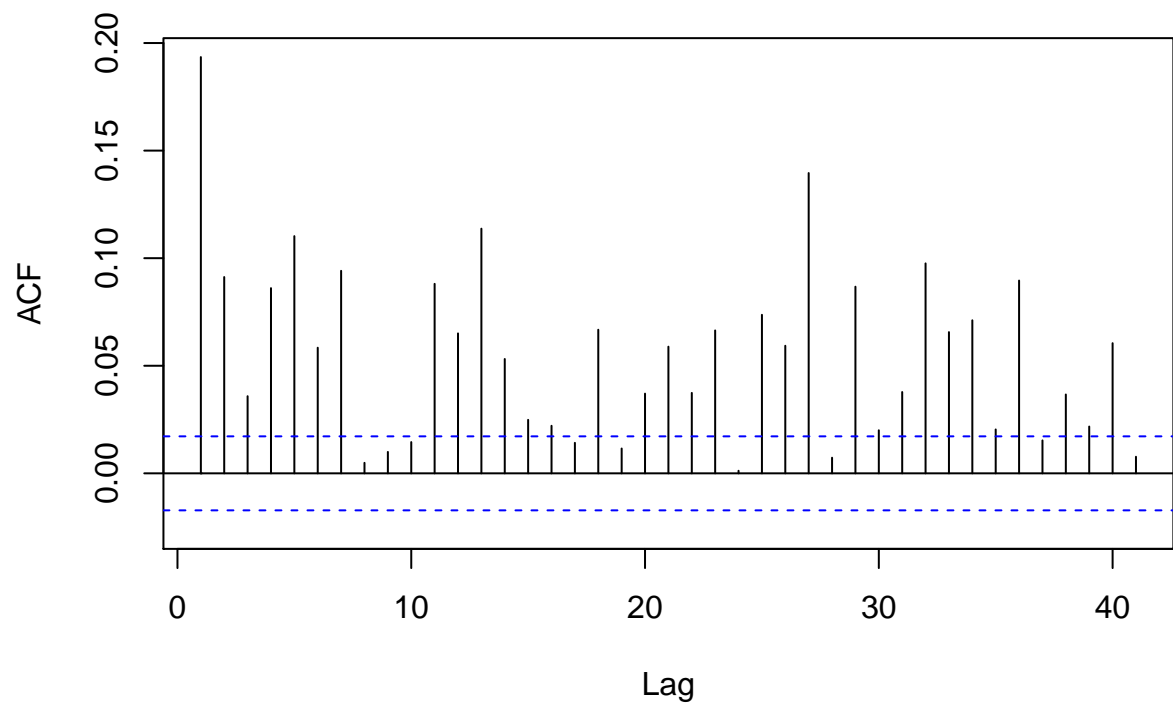
```
Pacf(resid, na.action = na.pass)
```

Series resid

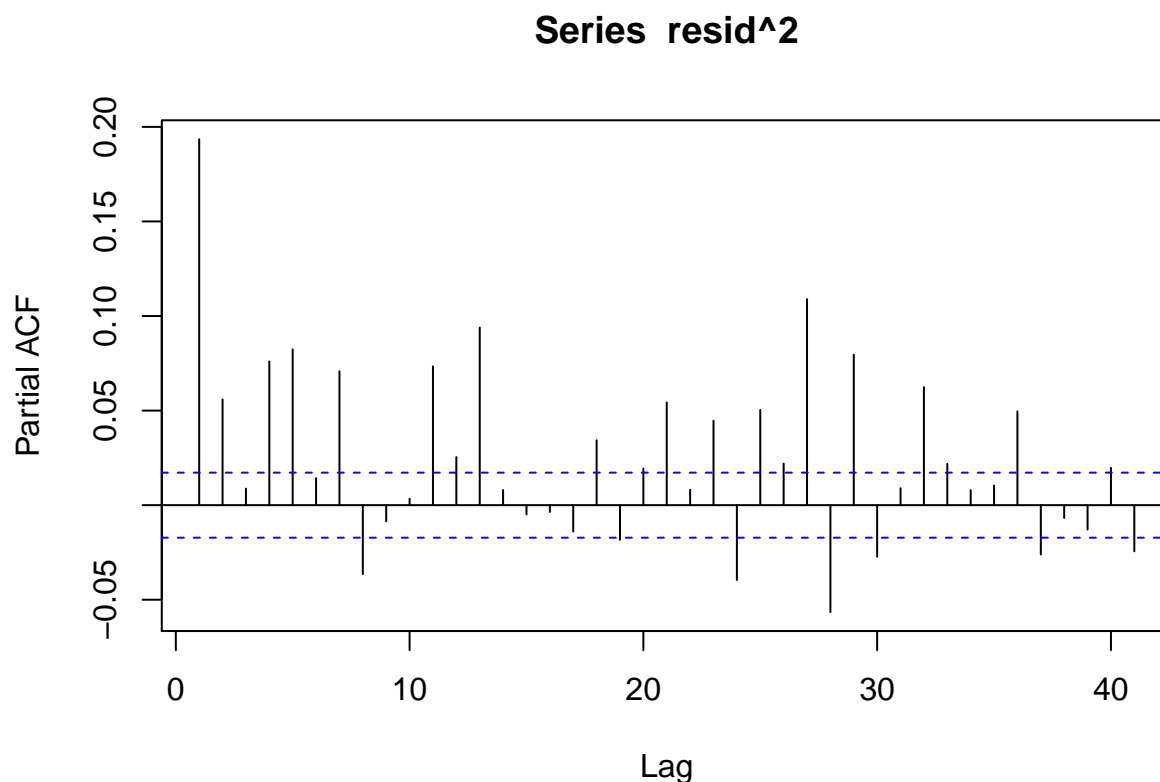


```
# Add ACF, PACF of squared residuals.  
Acf(resid^2, na.action = na.pass)
```

Series resid^2



```
Pacf(resid^2, na.action = na.pass)
```



Here are the AICc values for the ARCH(q):

```
q <- 0:10
loglik <- rep(NA, length(q))
N <- length(resid)

for (i in 1:length(q)) {
  if (q[i] == 0) {
    loglik[i] <- -0.5 * N * (1 + log(2 * pi * mean(resid^2)))
  } else {
    fit <- garch(resid, c(0,q[i]), trace=FALSE)
    loglik[i] <- logLik(fit)
  }
}

k <- q + 1
aicc <- -2 * loglik + 2 * k * N / (N - k - 1)

print(data.frame(q, loglik, aicc))
```

```
##      q  loglik    aicc
## 1    0 23535.70 -47069.40
## 2    1 24599.58 -49195.17
## 3    2 25231.45 -50456.89
## 4    3 25396.27 -50784.55
## 5    4 26038.83 -52067.66
## 6    5 26197.94 -52383.88
## 7    6 26462.68 -52911.36
```

```
## 8 7 26718.38 -53420.74
## 9 8 26727.14 -53436.26
## 10 9 26844.89 -53669.76
## 11 10 26909.97 -53797.91
```

Here is the AICc for the GARCH(1,1):

```
fit <- garch(resid, c(1,1), trace=FALSE)
```

```
## Warning in sqrt(pred$e): NaNs produced
```

```
loglik <- logLik(fit)
```

```
k <- 2
```

```
aicc <- -2 * loglik + 2 * k * N / (N - k - 1)
```

```
print(data.frame(loglik, aicc))
```

```
##      loglik      aicc
```

```
## 1 30774.76 -61545.52
```

Here are the summary and log likelihood of the selected model:

```
fit.var <- garch(resid, c(1,1), trace=FALSE)
```

```
## Warning in sqrt(pred$e): NaNs produced
```

```
summary(fit.var)
```

```
##
```

```
## Call:
```

```
## garch(x = resid, order = c(1, 1), trace = FALSE)
```

```
##
```

```
## Model:
```

```
## GARCH(1,1)
```

```
##
```

```
## Residuals:
```

```
##      Min      1Q      Median      3Q      Max
## -2.175e+01 -6.514e-02  3.249e-06  6.761e-02  2.435e+01
```

```
##
```

```
## Coefficient(s):
```

```
##      Estimate Std. Error  t value Pr(>|t|)
## a0 5.255e-07  7.191e-09   73.08  <2e-16 ***
## a1 2.037e-02  1.232e-04  165.27  <2e-16 ***
## b1 9.812e-01  3.577e-05 27431.44  <2e-16 ***
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## Diagnostic Tests:
```

```
## Jarque Bera Test
```

```
##
```

```
## data: Residuals
```

```
## X-squared = 2116700, df = 2, p-value < 2.2e-16
```

```
##
```

```
##
```

```
## Box-Ljung test
```

```
##
```

```
## data: Squared.Residuals
```

```
## X-squared = 1.489, df = 1, p-value = 0.2224
```

```

logLik(fit.var)

## 'log Lik.' 30774.76 (df=3)
a0 <- 5.255e-07
a1 <- 2.037e-02
b1 <- 9.812e-01
f1 <- 1.943208
h1<- a0 + a1*(tail(fit.mean$residuals,1)^2) +b1 * tail(fit.var$fit[,1],1)

# conditional variance:
#h1 <- fit.var$fit[,1]^2

# Finally, we compute the 95% forecast interval:
f1 + -1 * 1.96 * sqrt(h1)

## Time Series:
## Start = 12995
## End = 12995
## Frequency = 1
## a0 + a1 * (tail(fit.mean$residuals, 1)^2)
##                                     1.608771
f1 + 1 * 1.96 * sqrt(h1)

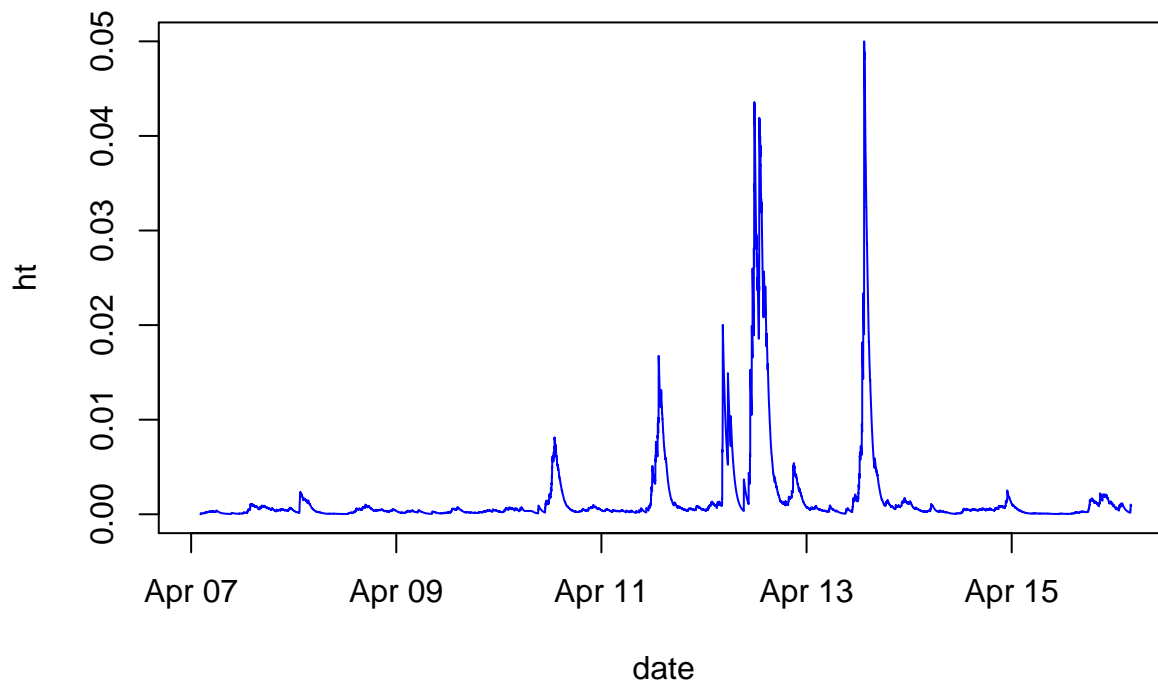
## Time Series:
## Start = 12995
## End = 12995
## Frequency = 1
## a0 + a1 * (tail(fit.mean$residuals, 1)^2)
##                                     2.277645

Here are the conditional variances, with the last 10 values printed out:
ht <- fit.var$fit[,1]^2
tail(ht, n=10)

## Time Series:
## Start = 12986
## End = 12995
## Frequency = 1
## [1] 0.0010309162 0.0010168000 0.0009982306 0.0009801559 0.0009631506
## [6] 0.0009461772 0.0009297773 0.0009128071 0.0008962048 0.0008804159

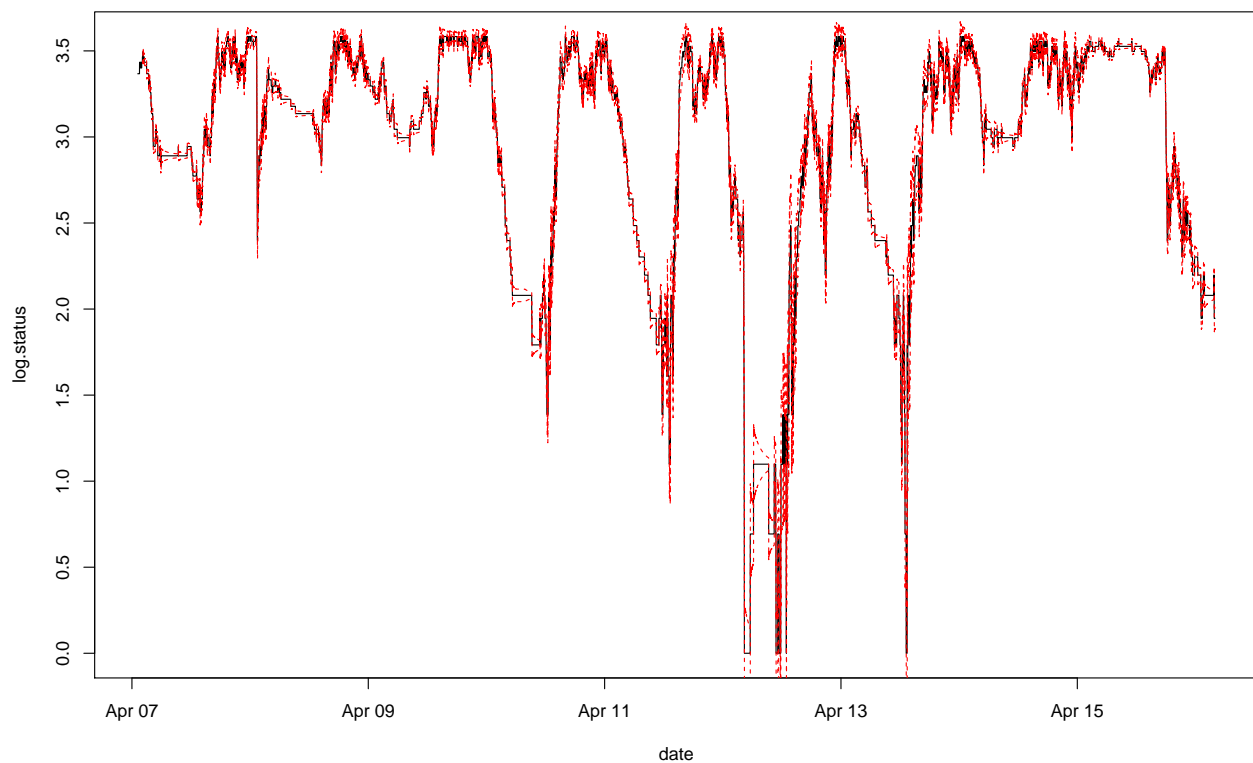
Here is a plot of the conditional variances:
# Add plot of the conditional variances
plot(date, ht, type="l", col=4)

```



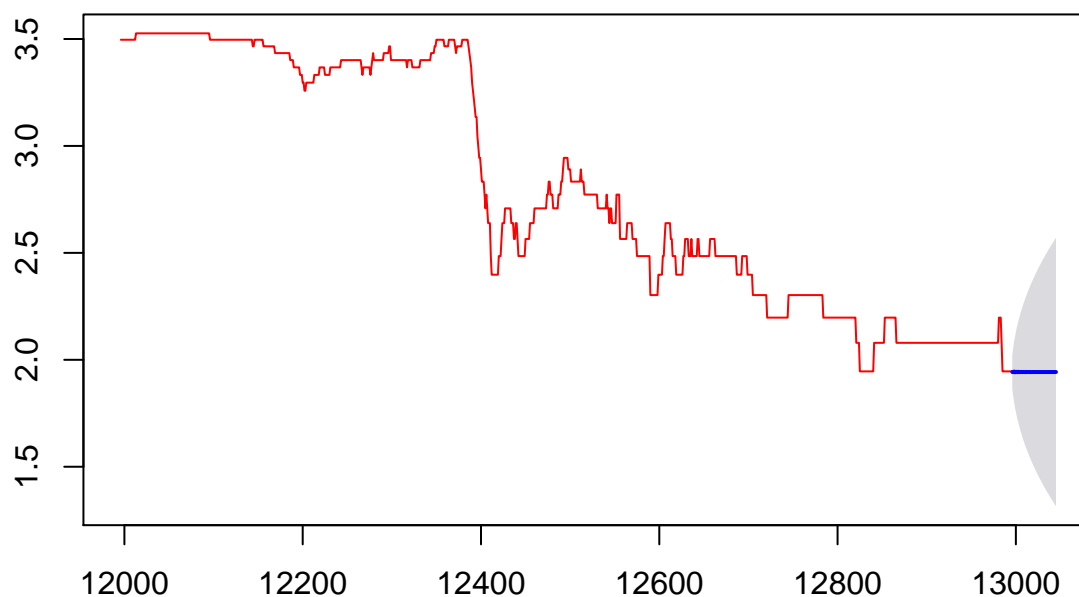
Here is a time series plot which simultaneously shows the log exchange rates, together with the ARIMA-ARCH one-step-ahead 95% forecast intervals based on information available in the previous day:

```
plot(date, log.status, type="l")
lines(date, f + 1.96 * sqrt(ht), lty=2, col=2)
lines(date, f - 1.96 * sqrt(ht), lty=2, col=2)
```



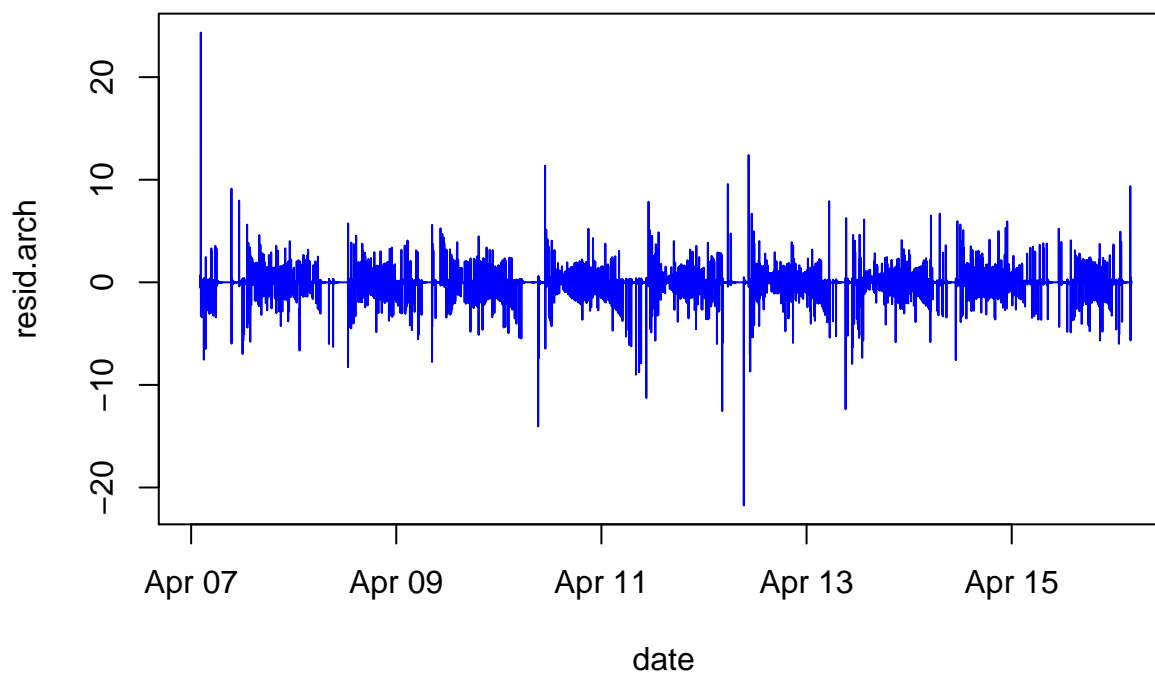
```
plot(forecast(fit.mean, h=50, level=95), include = 1000, col=2)
```


Forecasts from ARIMA(3,1,3)



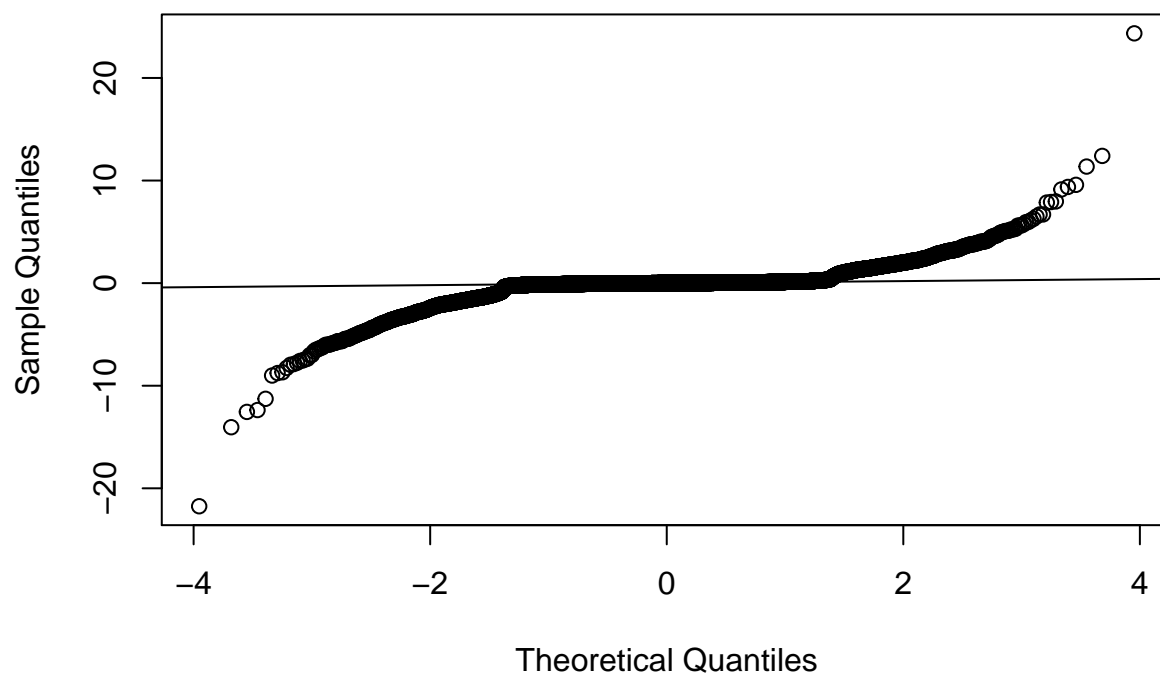
Here is a normal probability plot of the ARCH residuals.

```
library("e1071")  
# Add code to compute the arch residuals:  
# resid.arch <- ?????  
resid.arch <- resid / sqrt(ht)  
plot(date, resid.arch, col=4, type="l")
```



```
# Now, add code to make a normal probability plot (with the qqnorm command)  
qqnorm(resid.arch)  
qqline(resid.arch)
```

Normal Q-Q Plot



```
kurtosis(resid.arch, na.rm=TRUE)
```

```
## [1] 62.59582
```

Here is a count of how many prediction interval failures there were:

```
# Count the number of times the prediciton  
# interval failed:
```

```
sum(abs(resid.arch) > 1.96, na.rm=TRUE)
```

```
## [1] 738
```

The number of prediction intervals is:

```
sum(!is.na(resid.arch))
```

```
## [1] 12955
```