STAT 535 - HW 5

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The 27 April class notes analyze simple monthly returns of Pacific Gas and Electric common stock for the years 1975 through 2004. The company services northern California. During 2000 and 2001 the energy market in California experienced severe price increases which PG&E could not pass along to its customers, and the company was forced to file for bankruptcy. In early 2019 Pacific Gas and Electric again filed for bankruptcy.

The data for this assignment give simple monthly returns for Pacific Gas and Electric common stock for the period 1998 through 2021 and are in the file PGEmonthly9821.txt.

Problem 1

Plot the returns vs. time and comment in detail on the plot. Include a detailed discussion of factors responsible for the recent high volatility and second bankruptcy.

Discussion: The primary driving factor for the recent high volatility and second bankruptcy is PGE's liability in some of California's 2015-2018 wildfires such as Camp Fire and Tubbs Fire. The wildfires were caused by PGE's malfunctioning equipments, causing wrongful deaths, personal injuries, property loss, business losses, and other legal damages. The problem is compounded when PGE resorted to blackouts during seasons where risk of wildfire is highest, cutting both energy supplies and income, causing adverse reactions from stakeholders at all ends. Both the damage from wildfires and blackouts contribute to the volatility of PGE's stock prices which began in 2019.

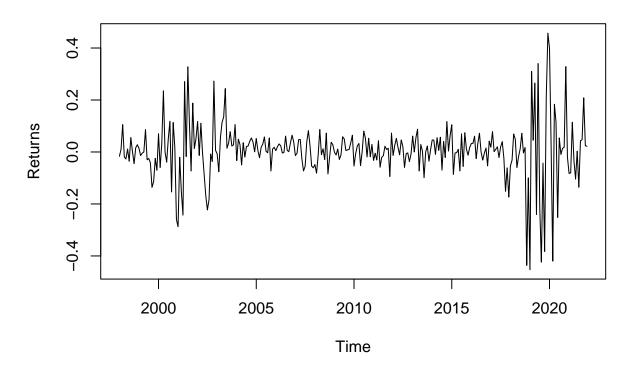
In 2019 PGE proposed to settle the wildfire victim claims for a total of \$13.5 billion. PGE also filed for bankruptcy protection in the same year, which was granted and lasted until June 2020. During this period PGE underwent restructuring. Both the financial liability and instability caused by the restructuring signals uncertain financial future for the company, leading to volatile stock prices and returns.

We do see that volatility seems to decline as PGE exits bankruptcy in June 2020. We see in the returns plot that volatility increased notably since the end of 2018, just two months before PGE filed for bankruptcy protection. We see signals of stabilization of the company's returns at towards the end of the plot (after June 2020), but definitively we cannot conclude that prices have stabilized to pre-2018 levels.

```
pge<-read.csv("PGEmonthly9821.txt")

return.ts<-ts(pge$Return,start=c(1998,1),freq=12)
plot(return.ts,xlab="Time",ylab="Returns",main="PGE Returns, 1998 to 2021")</pre>
```

PGE Returns, 1998 to 2021



Problem 2

Fit an ARMA–GARCH model to the returns, and carefully describe the results and the conclusions they allow you to reach. Use a GARCH(1,1) model to address the volatility. Use the 27 April class notes as a guide to indicate how to perform the fit and what issues to address in your analysis and discussion of the results. I recommend you form the ARMA model first and then fit the ARMA–GARCH model with the GARCH program.

Fitting ARMA model

Discussion:

Initial analysis of returns shows significant correlation and partial correlation structures, as well as non-normality in the distribution of data as indicated by kurtosis of 8.55 and the qqplot which shows bot tails relatively long to normality.

ACF Plot - significant autocorrelation structure at lags 4, 5, 12, and 21. The PACF plot also shows significant partial autocorrelation structure at lags 4, 5, 12, and 21. We will try three fits:

ARMA(5,0,0)(1,0,0)12 ARMA(0,0,5)(0,0,1)12 ARMA(5,0,5)(1,0,1)12

returns <- pge\$Return

skewness(returns)

- ## [1] -0.377492
- ## attr(,"method")
- ## [1] "moment"

```
kurtosis(returns)

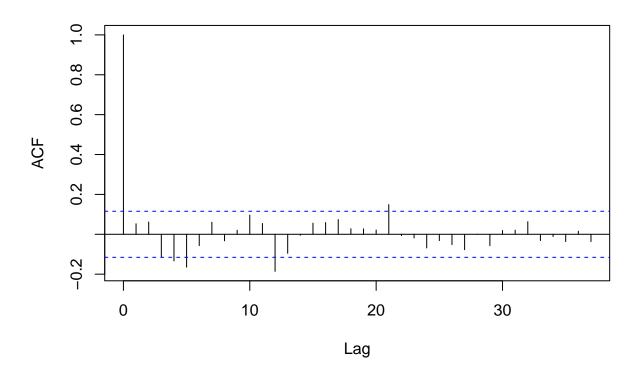
## [1] 5.488934

## attr(,"method")

## [1] "excess"

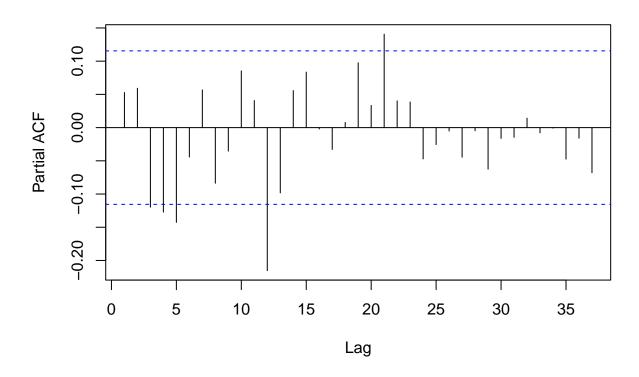
acf(ts(returns),37)
```

Series ts(returns)

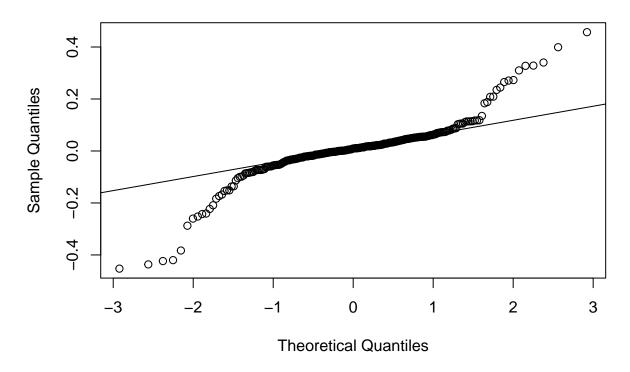


pacf(ts(returns),37)

Series ts(returns)



qqnorm(returns)
qqline(returns)



Discussion:

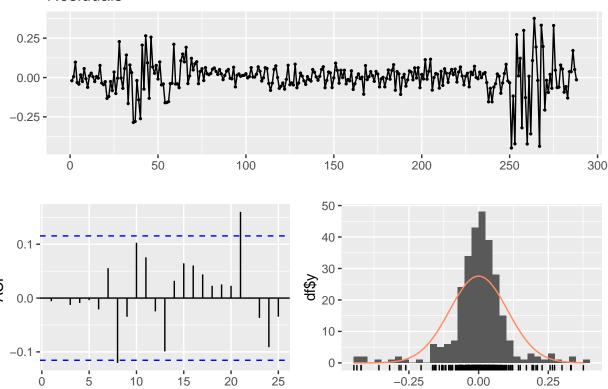
The ARMA(5,0,0)(1,0,0)12 model has an aic of -470.87. The ACF plot below shows significant autocorrelation structures at lags 8 and 21, the latter being more prominent than the other. The PACF plot also shows significance at lags 8 and 21, however in this plot both lags are only barely significant. Spectrum analysis and Bartlett's B test of residuals indicate that this model has been reduced to white noise (Spectrum shows that length between highest and lowest peaks are greater than twice the length of the upper half of the blue measurement line, and p-value for Bartlett's test is close to 1).

The residuals shows remaining non-normality. Kurtosis is 5.15, which is an improvement from previous 8.55 kurtosis of the original dataset. The Quantile plot shows that both tails are still relatively long to normality.

```
returns.ts <- ts(returns)
model1<-arima(returns.ts,order=c(5,0,0),seasonal=list(order=c(1,0,0),period=12))
checkresiduals(ts(resid(model1)))</pre>
```

Warning in modeldf.default(object): Could not find appropriate degrees of ## freedom for this model.

Residuals



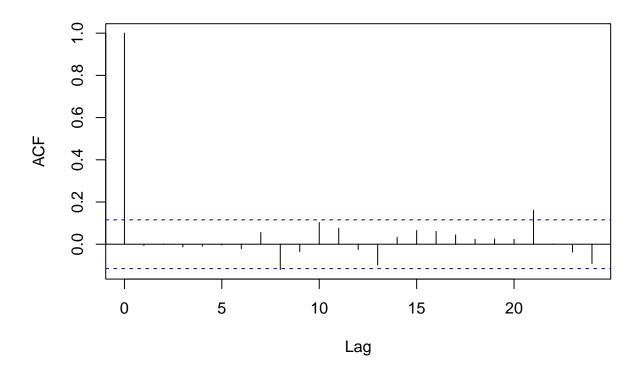
residuals

summary(model1)

Lag

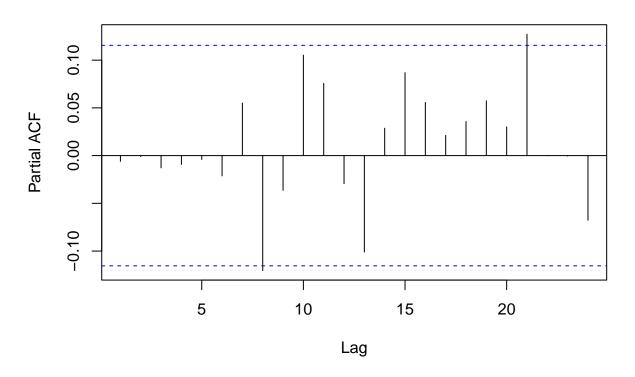
```
##
## Call:
## arima(x = returns.ts, order = c(5, 0, 0), seasonal = list(order = c(1, 0, 0),
       period = 12))
##
##
  Coefficients:
##
##
                                                              intercept
                    ar2
         0.0207 0.0852 -0.0949
                                 -0.1333
                                           -0.1262
                                                                 0.0050
##
                                                     -0.1867
   s.e. 0.0583 0.0586
                                   0.0581
                                             0.0587
                                                      0.0588
                          0.0581
                                                                 0.0042
##
##
## sigma^2 estimated as 0.01077: log likelihood = 243.43, aic = -470.87
##
## Training set error measures:
##
                          ME
                                  {\tt RMSE}
                                               MAE MPE MAPE
                                                                  MASE
                                                                               ACF1
## Training set 6.253954e-05 0.1037963 0.06631962 -Inf
                                                        Inf 0.6981863 -0.005965424
acf(ts(resid(model1)))
```

Series ts(resid(model1))



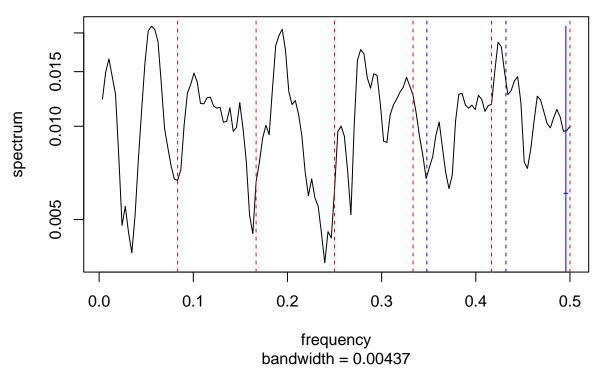
pacf(ts(resid(model1)))

Series ts(resid(model1))



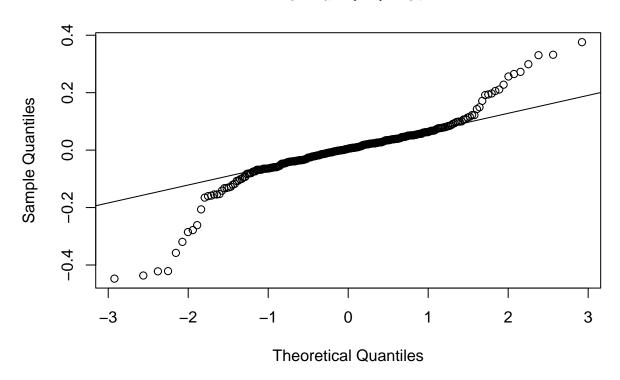
```
spectrum(resid(model1), span=5)
abline(v=c(1/12,2/12,3/12,4/12,5/12,6/12),col="red",lty=2)
abline(v=c(0.348,0.432),col="blue",lty=2)
```

Series: x Smoothed Periodogram



```
bartlettB.test(resid(model1))
```

```
##
## Bartlett B Test for white noise
##
## data:
## = 0.37532, p-value = 0.999
qqnorm(resid(model1))
qqline(resid(model1))
```



kurtosis(resid(model1))

[1] 5.151809

attr(,"method")

[1] "excess"

Discussion:

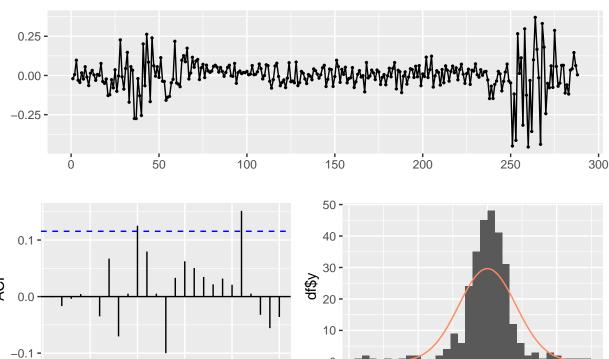
The ARMA(0,0,5)(0,0,1)12 model has an aic of -474.87, better than our previous model. The ACF plot below shows significant autocorrelation structures at lags 10 and 21. The PACF plot also shows significance at lags 10 and 21, however in this plot both lags are only barely significant. Spectrum analysis and Bartlett's B test of residuals indicate that this model has been reduced to white noise (Spectrum shows that length between highest and lowest peaks are greater than twice the length of the upper half of the blue measurement line, and p-value for Bartlett's test is close to 1).

The residuals shows remaining non-normality. Kurtosis is 5.345, which is roughly the same as model1. The Quantile plot shows that both tails are still relatively long to normality.

```
model2<-arima(returns.ts,order=c(0,0,5),seasonal=list(order=c(0,0,1),period=12))
checkresiduals(ts(resid(model2)))</pre>
```

Warning in modeldf.default(object): Could not find appropriate degrees of ## freedom for this model.





-0.50

-0.25

0.00

residuals

11 1 11 1 11 1, 1 11 1

0.25

summary(model2)

10

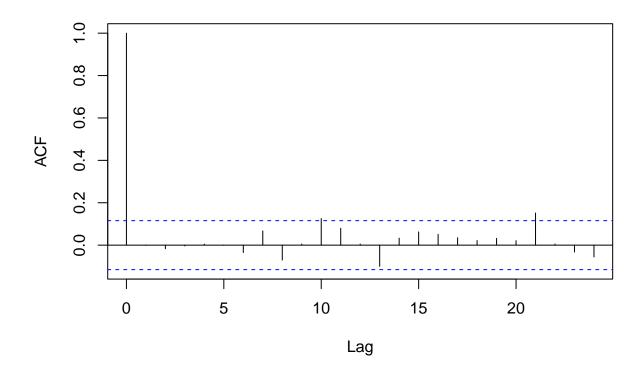
15

Lag

20

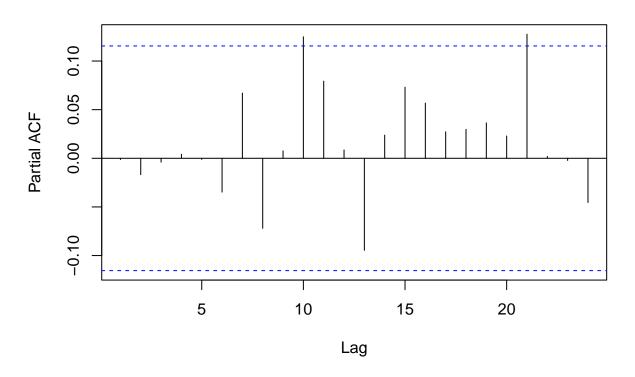
```
##
## Call:
## arima(x = returns.ts, order = c(0, 0, 5), seasonal = list(order = c(0, 0, 1),
      period = 12))
##
##
  Coefficients:
##
##
                                                              intercept
            ma1
                    ma2
                             ma3
                                      ma4
                                                        sma1
         0.0153 0.1149 -0.0925
                                 -0.1483
                                           -0.1568
                                                                 0.0050
##
                                                    -0.2161
   s.e. 0.0574 0.0614
                                  0.0655
                                            0.0573
                                                     0.0635
                                                                 0.0036
                          0.0593
##
##
## sigma^2 estimated as 0.01065: log likelihood = 245.02, aic = -474.05
##
## Training set error measures:
##
                           ME
                                   RMSE
                                               MAE MPE MAPE
                                                                 MASE
                                                                               ACF1
## Training set -4.989301e-05 0.1031883 0.06683834 NaN Inf 0.7036471 -0.001291452
acf(ts(resid(model2)))
```

Series ts(resid(model2))



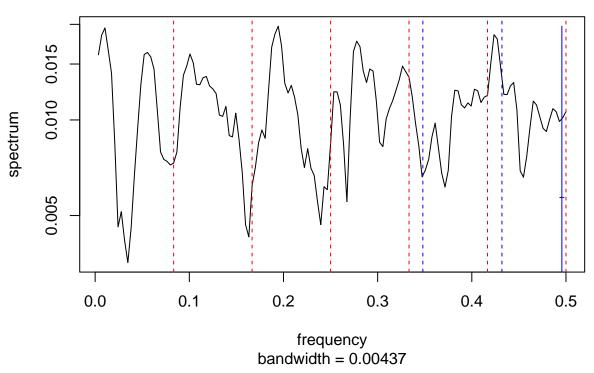
pacf(ts(resid(model2)))

Series ts(resid(model2))



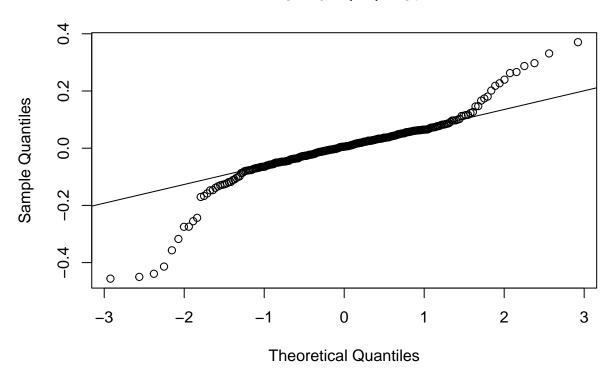
```
spectrum(resid(model2), span=5)
abline(v=c(1/12,2/12,3/12,4/12,5/12,6/12),col="red",lty=2)
abline(v=c(0.348,0.432),col="blue",lty=2)
```

Series: x Smoothed Periodogram



bartlettB.test(resid(model2))

```
##
## Bartlett B Test for white noise
##
## data:
## = 0.38241, p-value = 0.9986
qqnorm(resid(model2))
qqline(resid(model2))
```



kurtosis(resid(model2))

[1] 5.345772

attr(,"method")

[1] "excess"

Discussion:

The ARMA(5,0,5)(1,0,1)12 model has an aic of -469.98, worse than our previous two models and an indication that it may be overfit. The ACF and PACF plots do not indicate significant improvement from the previous models. We go with the ARMA(0,0,5)(0,0,1)12 model, which has the best AIC.

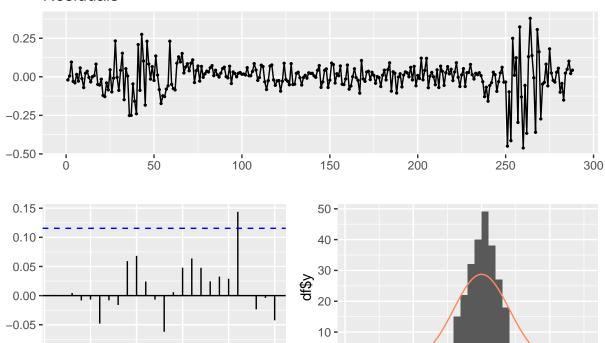
The residuals shows remaining non-normality. Kurtosis is 5.04, which is roughly the same as model1. The Quantile plot shows that both tails are still relatively long to normality.

```
model3<-arima(returns.ts,order=c(5,0,5),seasonal=list(order=c(1,0,1),period=12))</pre>
```

checkresiduals(ts(resid(model3)))

Warning in modeldf.default(object): Could not find appropriate degrees of ## freedom for this model.

Residuals



-0.50

-0.25

0.00

residuals

0.25

summary(model3)

0

5

10

-0.10 **-**

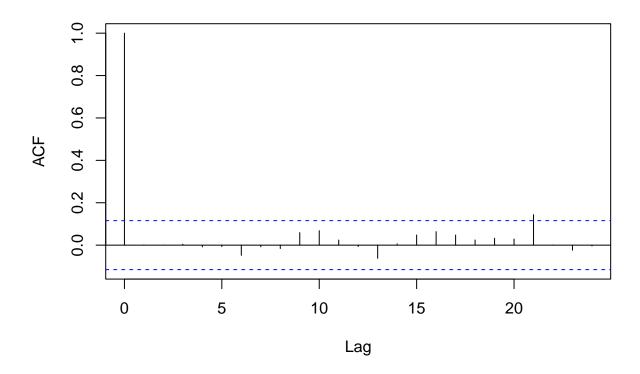
```
##
## Call:
## arima(x = returns.ts, order = c(5, 0, 5), seasonal = list(order = c(1, 0, 1),
       period = 12))
##
##
  Coefficients:
##
##
            ar1
                     ar2
                              ar3
                                       ar4
                                               ar5
                                                                 ma2
                                                                         ma3
         0.2274
                 -0.6704
                          0.3029
                                                              0.7716
                                                                      -0.425
##
                                  -0.0537
                                            0.0556
                                                    -0.2175
         0.3498
                  0.3462
                          0.3732
                                    0.2849
                                            0.2228
                                                     0.3418
                                                              0.3353
                                                                       0.377
##
##
                      {\tt ma5}
                              sar1
                                             intercept
             ma4
                                       sma1
         -0.0070
                                                0.0053
##
                  -0.2853
                            0.4708
                                    -0.6333
## s.e.
        0.3025
                   0.2484
                           0.2780
                                     0.2486
                                                0.0032
##
## sigma^2 estimated as 0.01034: log likelihood = 248.99, aic = -469.98
## Training set error measures:
                                    RMSE
                                                MAE MPE MAPE
                                                                   MASE
                                                                                ACF1
## Training set -0.0002399165 0.1016899 0.06697305 NaN Inf 0.7050654 0.001212317
acf(ts(resid(model3)))
```

20

15

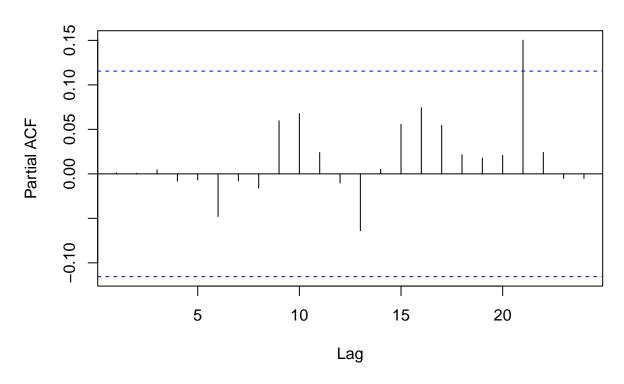
Lag

Series ts(resid(model3))



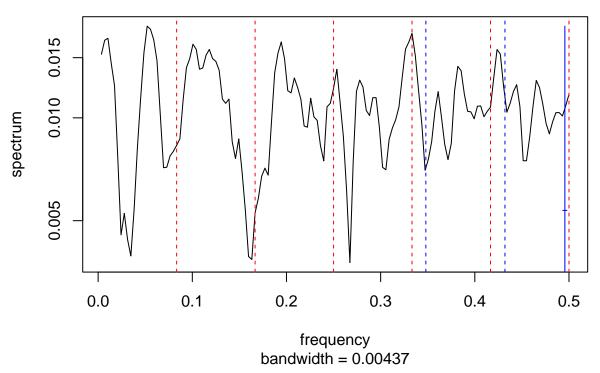
pacf(ts(resid(model3)))

Series ts(resid(model3))



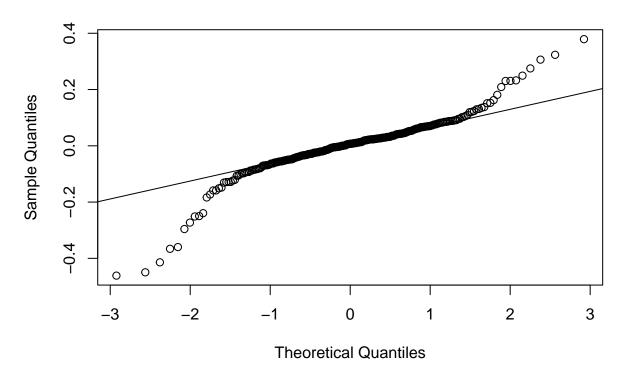
```
spectrum(resid(model3), span=5)
abline(v=c(1/12,2/12,3/12,4/12,5/12,6/12),col="red",lty=2)
abline(v=c(0.348,0.432),col="blue",lty=2)
```

Series: x Smoothed Periodogram



```
bartlettB.test(resid(model3))
```

```
##
## Bartlett B Test for white noise
##
## data:
## = 0.27864, p-value = 1
qqnorm(resid(model3))
qqline(resid(model3))
```



kurtosis(resid(model3))

```
## [1] 5.035533
## attr(,"method")
## [1] "excess"
```

Fitting ARMA-GARCH model using ARMA(0,0,5)(0,0,1)12 (model2).

Discussion: We can immediately see from the standardized residuals plot of ARMA(0,0,5)(0,0,1)12 - GARCH(1,1) model that there is an outlier residuals at time 251 or month of November 2018. The quantile plot also shows the same outlying residual in the left bottom corner of the plot, the observation which stands furthest from the normal line. With this residual included, the first analysis shows an excess kurtosis of 8.41, very high and clearly indicates non-normality. However when the residual at time 251 is excluded we see a dramatic improvement in excess kurtosis, down to 0.157, which indicates that we are far closer to normality than before.

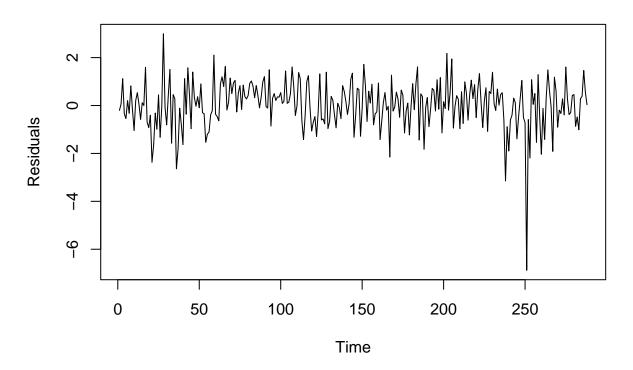
The quantile plot also shows that normality has been achieved, as indicated by the residuals falling mostly on or close to the normal line. A look at the spectal density plot and bartlett's test also shows that the model has been largely reduced to white noise (spectrum shows that length between highest and lowest peaks are greater than twice the length of the upper half of the blue measurement line, and p-value for Bartlett's test is .552).

```
u.ts<-ts(resid(model2))
modelgarch11<-garchFit( ~garch(1,1),data=u.ts,trace=FALSE)</pre>
```

Warning: Using formula(x) is deprecated when x is a character vector of length > 1.

```
## Consider formula(paste(x, collapse = " ")) instead.
residsstdzd11<-residuals(modelgarch11,standard=TRUE)
plot(ts(residsstdzd11), type='1', xlab="Time",ylab="Residuals",main="Residuals of ARMA(0,0,5)(0,0,1)12</pre>
```

Residuals of ARMA(0,0,5)(0,0,1)12 - GARCH(1,1)



kurtosis(residsstdzd11)

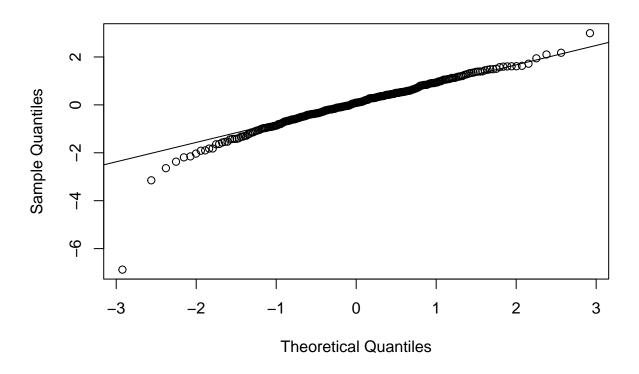
[1] 7.43343

attr(,"method")

[1] "excess"

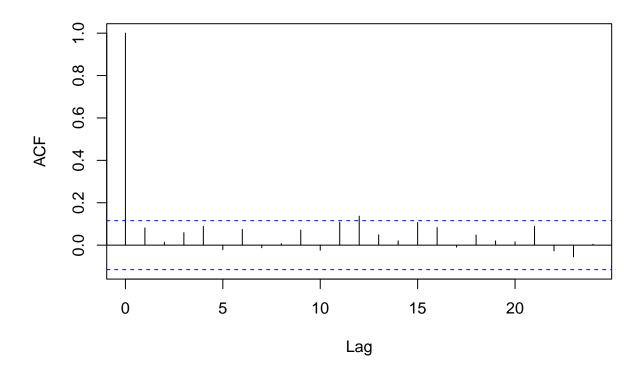
qqnorm(residsstdzd11)
qqline(residsstdzd11)

Normal Q-Q Plot



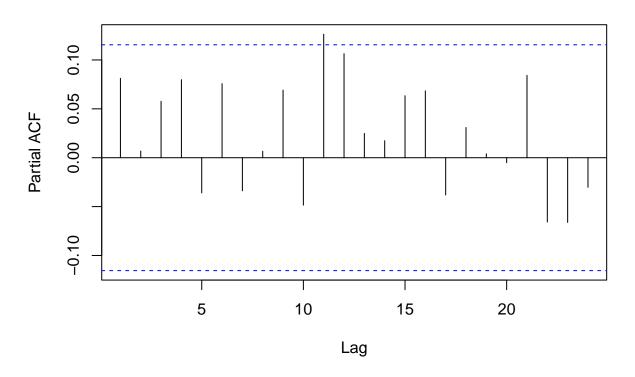
acf(ts(residsstdzd11))

Series ts(residsstdzd11)



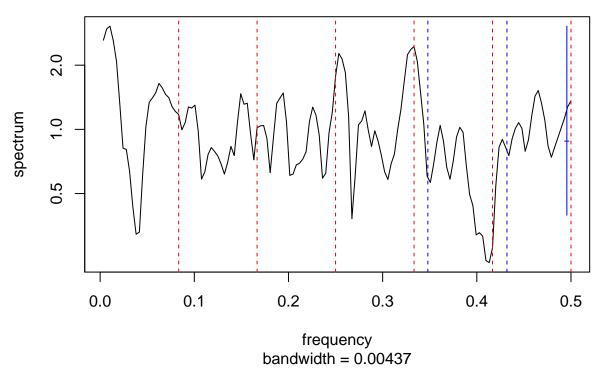
pacf(ts(residsstdzd11))

Series ts(residsstdzd11)



```
spectrum(residsstdzd11, span=5)
abline(v=c(1/12,2/12,3/12,4/12,5/12,6/12),col="red",lty=2)
abline(v=c(0.348,0.432),col="blue",lty=2)
```

Series: x Smoothed Periodogram



```
bartlettB.test(residsstdzd11)
```

```
##
## Bartlett B Test for white noise
##
## data:
## = 0.82641, p-value = 0.5018
```

Residuals analysis of garch (1,1) model without outlier at time 251

```
residsstdzd11[250:252]

## [1] -0.7156127 -6.8777044 -0.5845295

residsstdzd11.partial <- c(residsstdzd11[1:250],residsstdzd11[252:288])
kurtosis(residsstdzd11.partial)

## [1] 0.4430673
## attr(,"method")
## [1] "excess"

qqnorm(residsstdzd11.partial)
qqline(residsstdzd11.partial)</pre>
```

