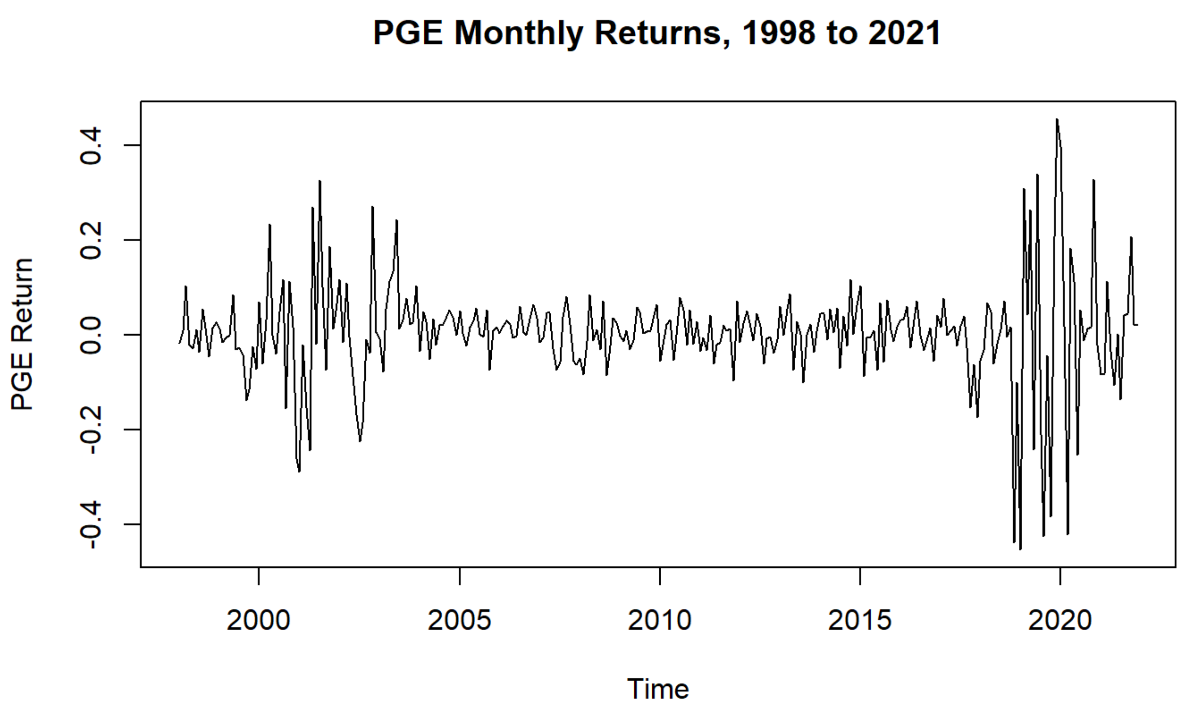
Bankruptcy of Pacific Gas and Electric

The company, Pacific Gas and Electric, 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.

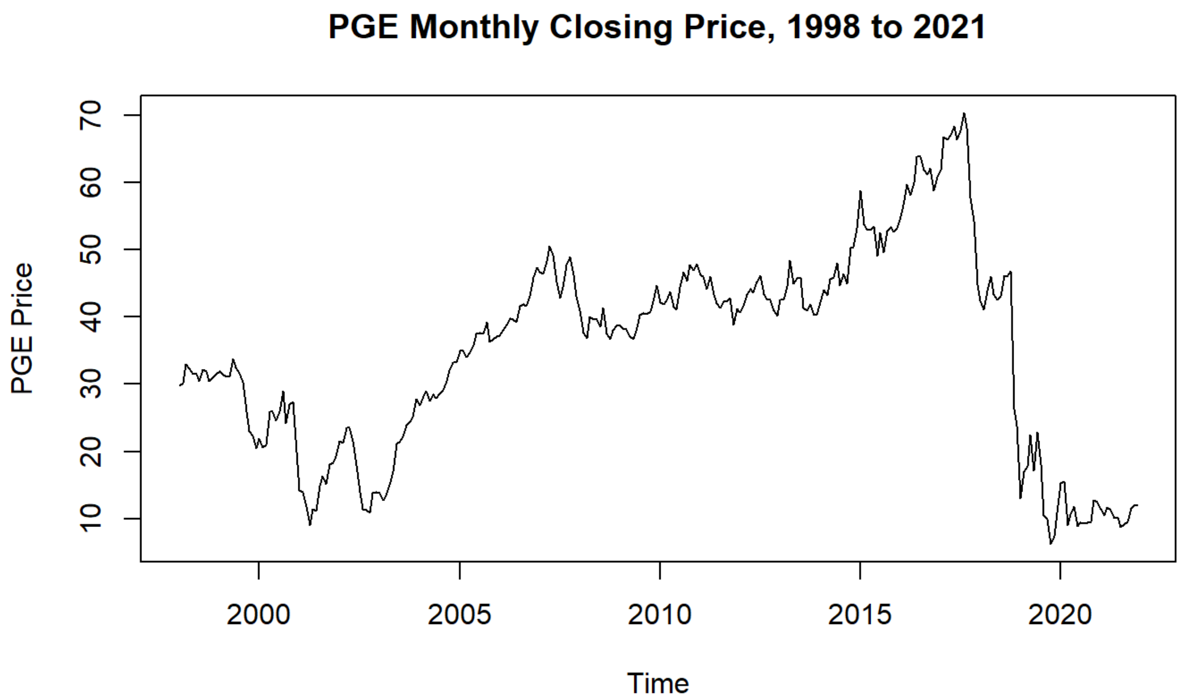
The dataset gives simple monthly returns for Pacific Gas and Electric common stock for the period 1998 through 2021.

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.

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

  Year Month   Price    Return
1 1998     1 29.8125 -0.016495
2 1998     2 30.1250  0.010482
3 1998     3 33.0000  0.105394
4 1998     4 32.3750 -0.018939
5 1998     5 31.5000 -0.027027
6 1998     6 31.5625  0.011508

> plot(ts(Return,start=c(1998,1),freq=12),ylab="PGE Return", main="PGE
Monthly Returns, 1998 to 2021")
```



```
> plot(ts(Price,start=c(1998,1),freq=12),ylab="PGE Price", main="PGE Monthly
Closing Price, 1998 to 2021")
```



Comment:

In April 1998, Spot market for energy began operation. Soon after that, in May 2000, there was a significant rise in energy price. This led to the Western U.S. Energy Crisis of 2000 and 2021. The large volatility starting from 2000s lasted for almost 3 years.

The crisis was caused by market manipulations and illegal shutdowns of pipelines. This caused multiple large-scale rolling blackouts, which affected many businesses dependent upon a reliable supply of electricity and inconvenienced a large number of retail consumers, and then the states' largest energy companies collapsed.

Drought, delays in approval of new power plants, and market manipulation decreased supply. This caused 800% increase in wholesale prices from April 2000 to December 2000.

Federal Energy Regulatory Commission began investigation of Enron's involvement and the Enron Tapes scandal surfaced. In 2003, shortly before leaving office, Governor Davis officially brought the energy crisis to the end by issuing a proclamation ending the state of emergency.

After the emergency ended, there is constant steady dynamic seasonal structure associated with the returns over time up until 2018, and then the volatility of returns largely increased after 2019. Also, from the closing price plot, the price showed a steady increase up until 2018 to a high of $70 before dropping drastically to $8.

Because of heavy liabilities from multiple wildfires in the years 2015-2018, PGE began the process of filing for bankruptcy in 2019. They were accused of liabilities caused by their transmission lines leading to Tubbs Fire, Kincade Fire, etc. This is the reason for the high volatility and a second bankruptcy.

The fires collectively led to more than 100 deaths and burned over hundreds of thousands of acres. Claims for wildfire victims consisted of wrongful death, personal injuries, property loss, business losses, and other legal damages. PGE has obtained the financing needed to exit bankruptcy, but experts say the utility is still exposed to the wildfire risks that drove it into bankruptcy.

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.

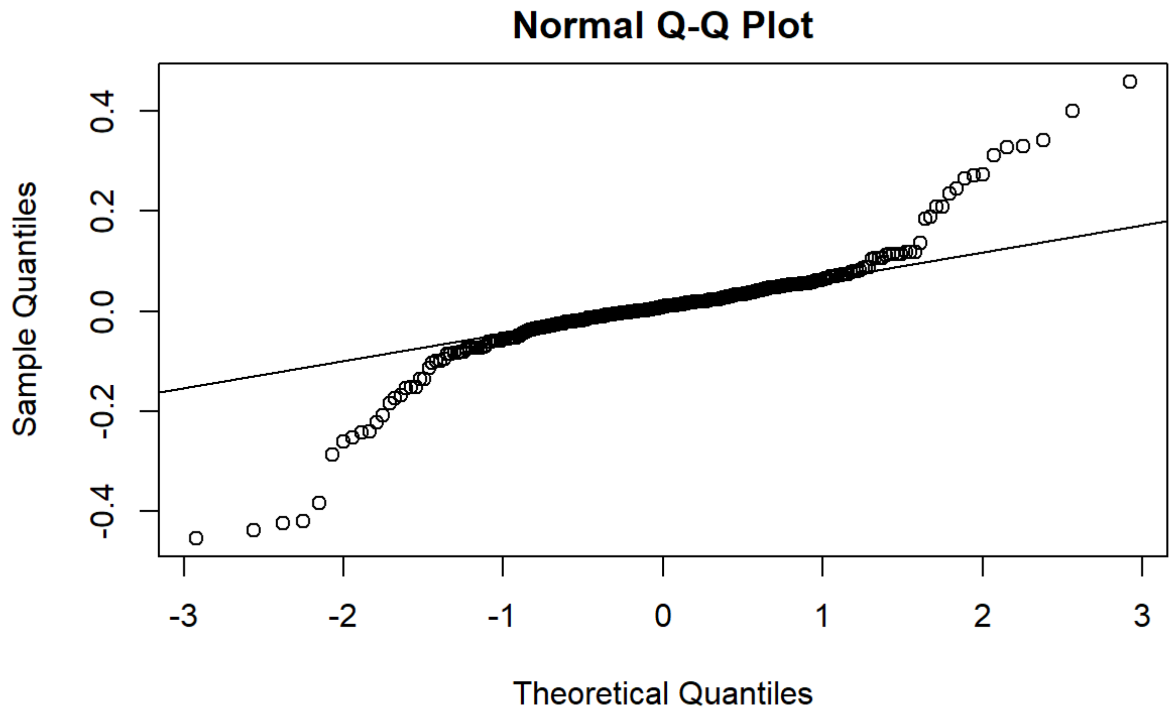
Let's begin by calculating the skewness and kurtosis for the return time series.

```
> skewness(Return)
[1] -0.3794666
> kurtosis(Return)
[1] 8.548194
```

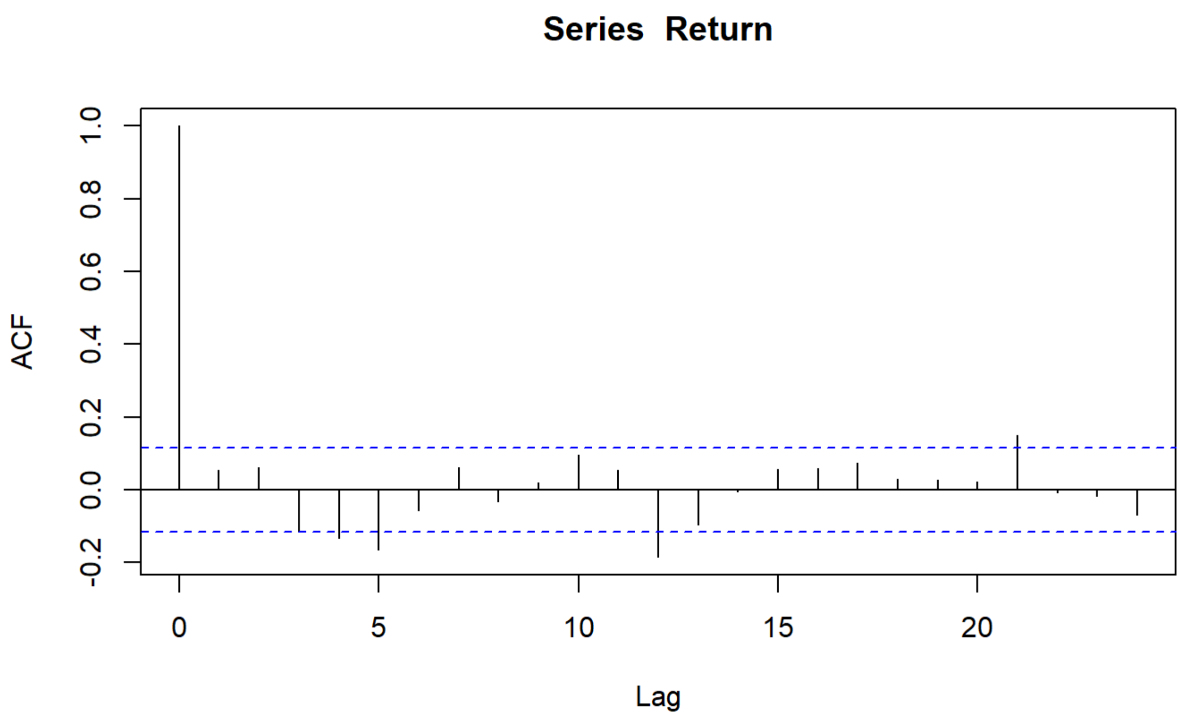
The kurtosis is estimated to be 8.55, and the skewness is mildly negative.

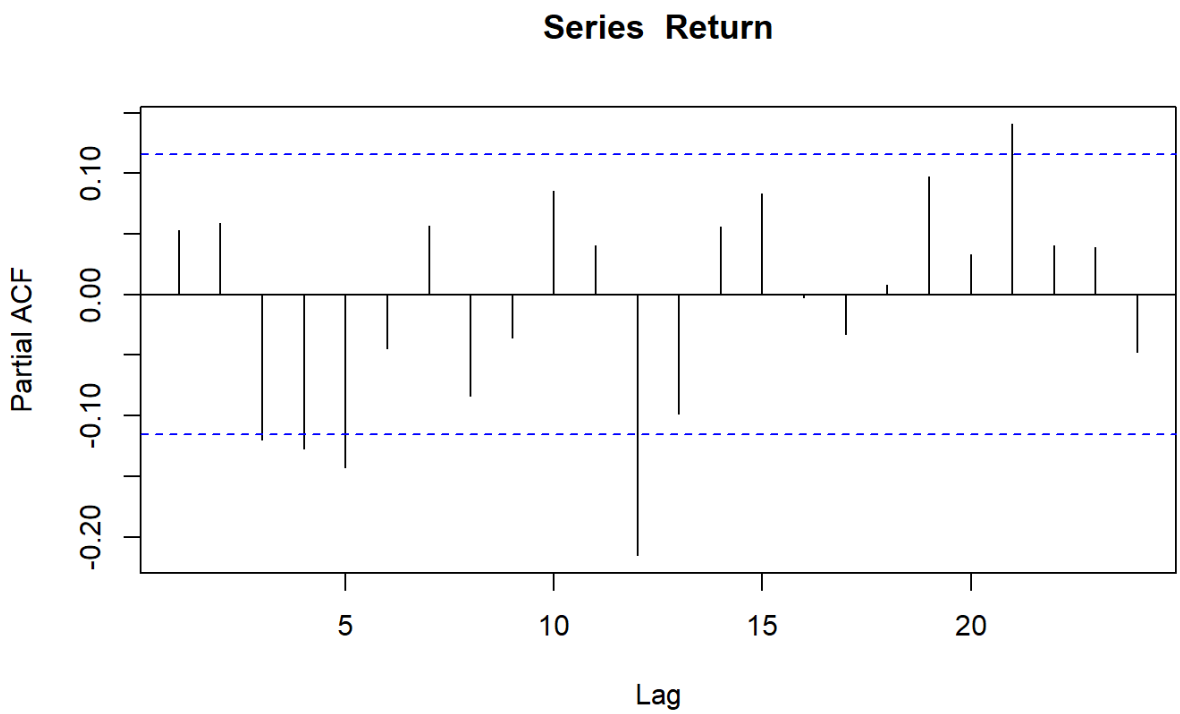
Let's begin by examining the autocorrelations and partial autocorrelations of the return series.

```
> qqnorm(Return)
> qqline(Return)
```



The residual distribution is decidedly nonnormal, with long tails. It is approximately symmetric, though.



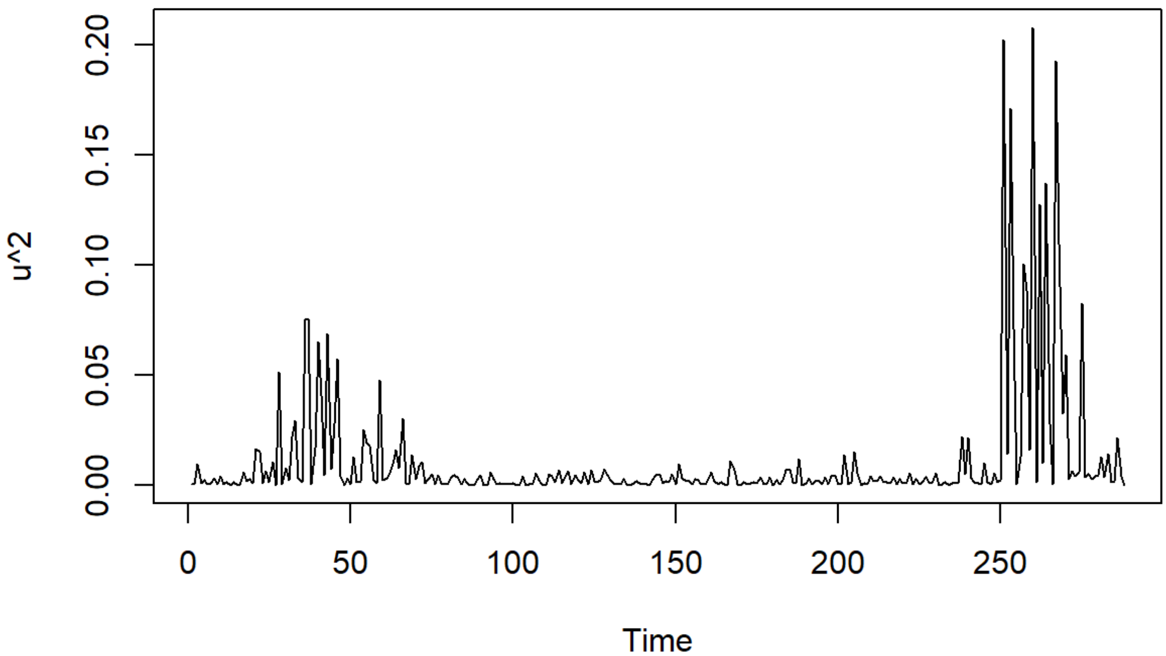


The acf plot suggests fitting an ARMA(0,0,5)(0,0,1)12 model and the pacf plot suggests an ARMA(5,0,0)(1,0,0)12 fit, if we ignore the mildly significant lag 21 estimates. Let's employ the former.

Fit the model ARMA$(\mathbf{0}, \mathbf{0}, \mathbf{5})(\mathbf{0}, \mathbf{0}, \mathbf{1})_{\mathbf{12}}$

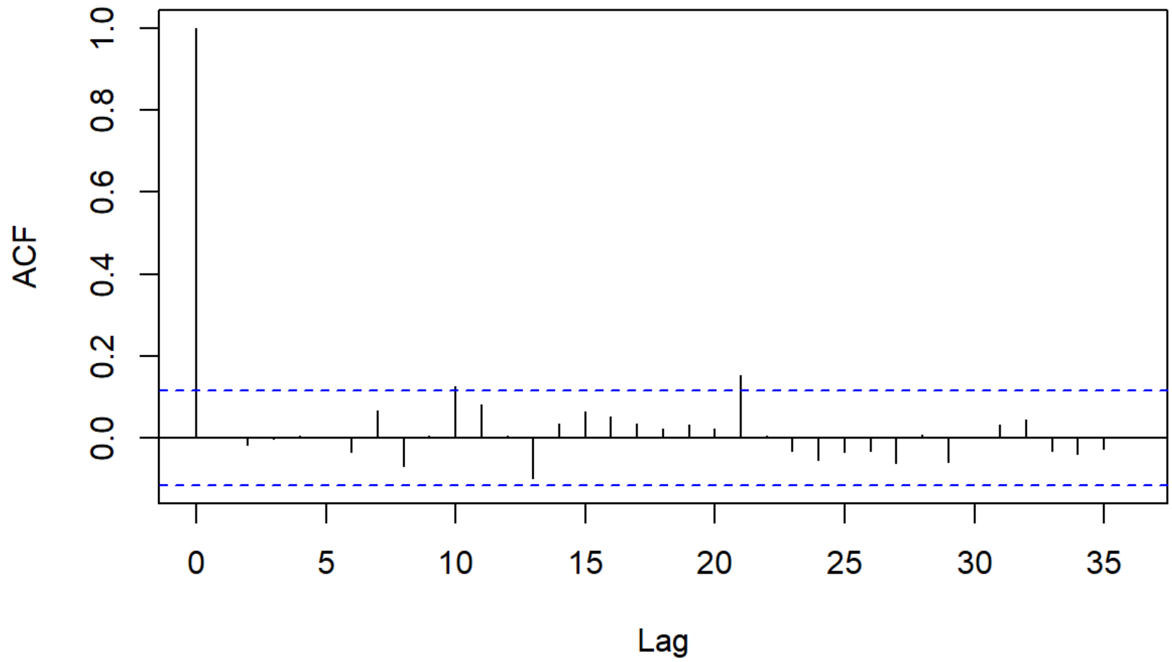
```
> modelma2<-
arima(ts(Return),order=c(0,0,5),seasonal=list(order=c(0,0,1),period=12))
> modelma2

Call:
arima(x = ts(Return), order = c(0, 0, 5), seasonal = list(order = c(0, 0, 1),
    period = 12))

Coefficients:
         ma1     ma2      ma3      ma4      ma5     sma1  intercept
      0.0153  0.1149  -0.0925  -0.1483  -0.1568  -0.2161     0.0050
s.e.  0.0574  0.0614   0.0593   0.0655   0.0573   0.0635     0.0036

sigma^2 estimated as 0.01065:  log likelihood = 245.02,  aic = -474.05

> coeftest(modelma2)

z test of coefficients:

            Estimate Std. Error z value  Pr(>|z|)
ma1        0.0153321  0.0573720  0.2672 0.7892838
ma2        0.1148720  0.0614446  1.8695 0.0615505 .
ma3       -0.0924830  0.0593187 -1.5591 0.1189758
ma4       -0.1483482  0.0654653 -2.2661 0.0234478 *
```

```
ma5        -0.1568271  0.0573163 -2.7362 0.0062159 **
sma1       -0.2160686  0.0634778 -3.4038 0.0006644 ***
intercept   0.0050456  0.0035582  1.4180 0.1561804
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> u<-resid(modelma2)
```

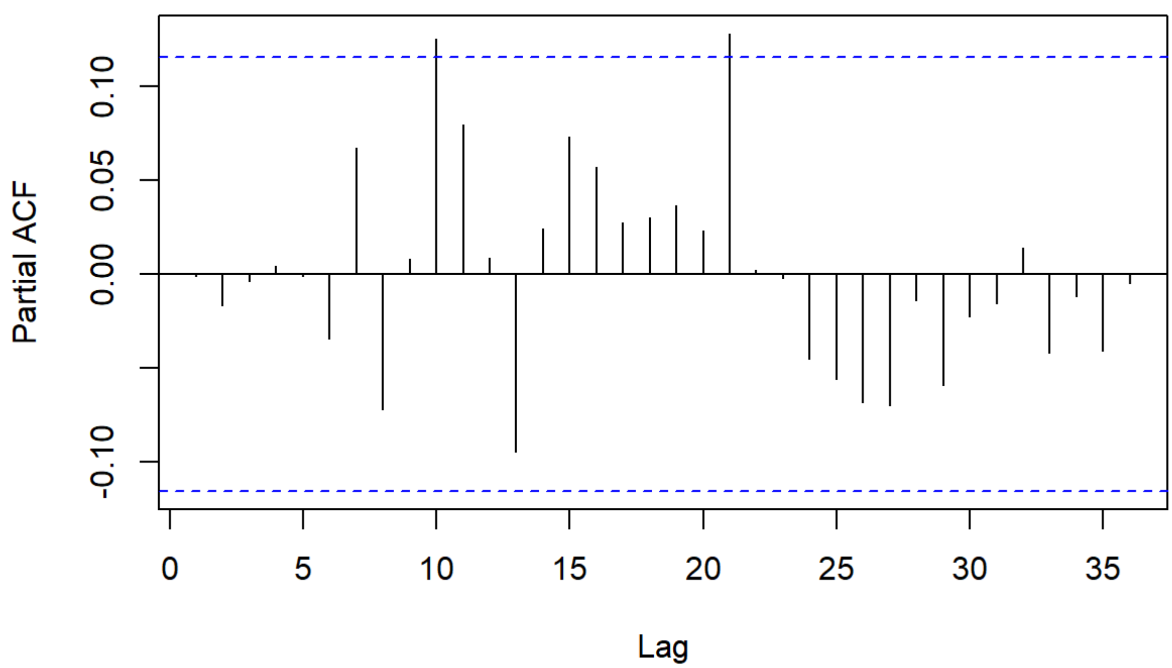


The residual plot closely resembles the plot of the return data. That is, the two periods of high volatility are still present—as we understand, the ARMA model has not addressed the volatility.

```
> acf(resid(modelma2),36)
```

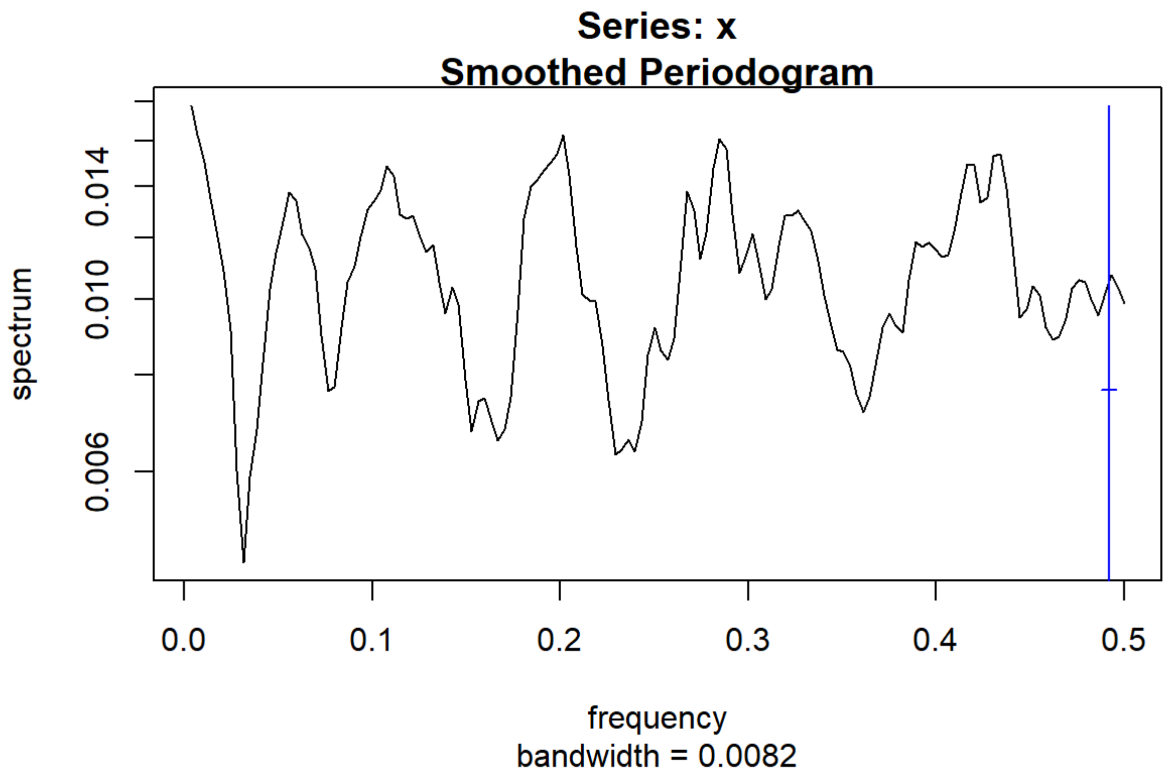


> pacf(resid(modelma2),36)



The residual acf and pacf plots show mildly significant results at lags 10 and 21. Otherwise none of the other estimates indicates significance. The residual spectral plot and Bartlett's test follow.

> spectrum(resid(modelma2),span=8)




```
> bartlettB.test(resid(modelma2))

      Bartlett B Test for white noise

data:
= 0.38241, p-value = 0.9986
```

The residual spectrum is essentially flat, and the plot and Bartlett's test strongly assert the ARMA model has produced reduction to white noise.

```
> skewness(resid(modelma2))
[1] -0.8650817
> kurtosis(resid(modelma2))
[1] 8.404032
```

The kurtosis of the ARMA residuals is very slightly lower than that of the return series, at 8.40 in comparison to 8.55 originally, and the skewness is more negative than previously.

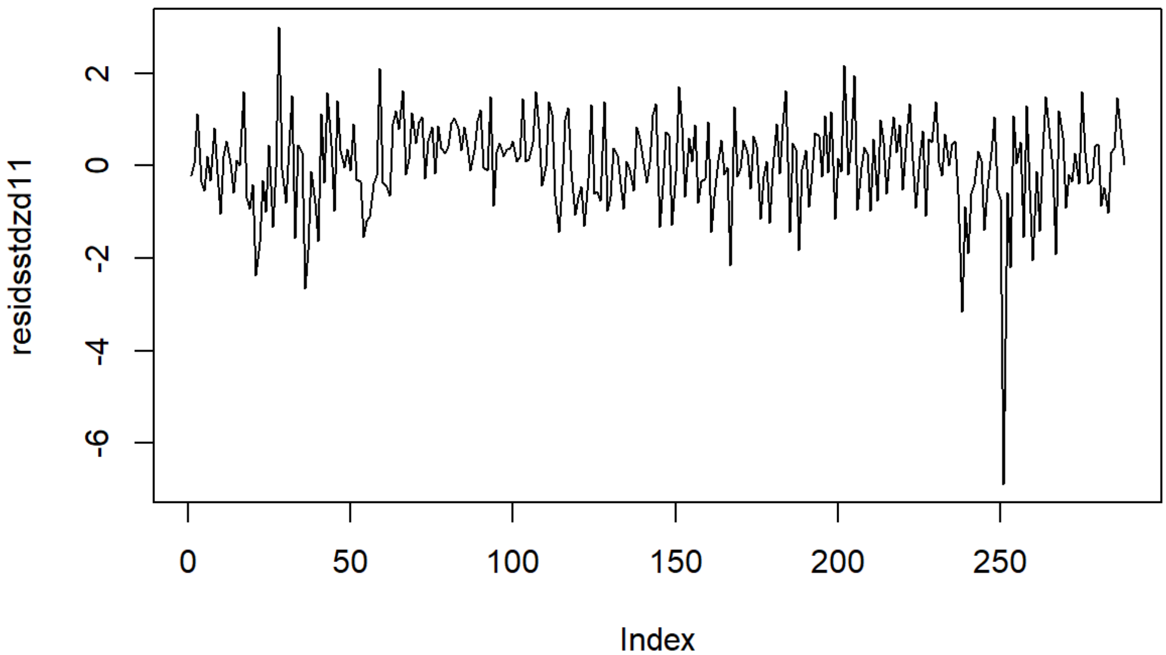
Next, we fit a GARCH(1,1) model to the ARMA residuals.

```
> u.ts<-ts(resid(modelma2))
> modelgarch11<-garchFit(~garch(1,1),data=u.ts,trace=FALSE)
> summary(modelgarch11)

Title:
 GARCH Modelling
```

```
Call:
 garchFit(formula = ~garch(1, 1), data = u.ts, trace = FALSE)

Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x000001e267260c30>
 [data = u.ts]

Conditional Distribution:
 norm

Coefficient(s):
        mu       omega      alpha1       beta1
0.00049893  0.00026532  0.18456677  0.80041442

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     0.0004989   0.0041871    0.119   0.9052
omega  0.0002653   0.0001222    2.172   0.0299 *
alpha1 0.1845668   0.0457246    4.036 5.43e-05 ***
beta1  0.8004144   0.0399069   20.057  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 326.3163    normalized:  1.133043

Description:
 Tue May 10 21:39:01 2022 by user: zhang


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  759.8523  0
 Shapiro-Wilk Test  R    W      0.9337786 4.799393e-10
 Ljung-Box Test     R    Q(10)  8.81715   0.5495404
 Ljung-Box Test     R    Q(15)  22.38016  0.09821653
 Ljung-Box Test     R    Q(20)  25.448    0.1848261
 Ljung-Box Test     R^2  Q(10)  2.503192  0.9908291
 Ljung-Box Test     R^2  Q(15)  13.34171  0.5759227
 Ljung-Box Test     R^2  Q(20)  14.36227  0.8116635
 LM Arch Test       R    TR^2   3.81229   0.9865902

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-2.238307 -2.187433 -2.238686 -2.217920
```

The estimated parameters alpha1 and beta1 add to less than 1, as required. A plot of the standardized residuals follows.

```
> residsstdzd11<-residuals(modelgarch11,standard=TRUE)
> plot(residsstdzd11,type='l')
```



The plot shows that, save for several points, the GARCH model has done an excellent job of accounting for the changing volatility. The problematic points correspond to the downturn of the returns in late 2017 and the onset of high volatility beginning in late 2018. The November 2018 point (point 251) is the prominent outlier. In that month Pacific Gas and Electric and its parent company were sued by victims of the Camp Fire.

Calculation of skewness and kurtosis for the standardized residuals follows.

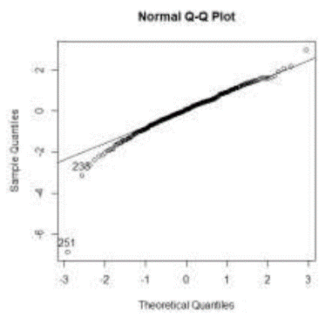
```
> skewness(residsstdzd)
[1] -1.313831
attr(,"method")
[1] "moment"
> kurtosis(residsstdzd)
[1] 7.43343
attr(,"method")
[1] "excess"
```

The skewness is more negative than for the ARMA residuals, and the kurtosis, now 10.43, is even greater than that of the ARMA residuals, which was 8.40. Kurtosis is very sensitive to the presence of large outliers, and the difficulty here is caused by point 251. Given that the standardized residual plot shows that the GARCH model has done an excellent job of controlling volatility, except for late 2018, let' s calculate skewness and kurtosis with omission of point 251.

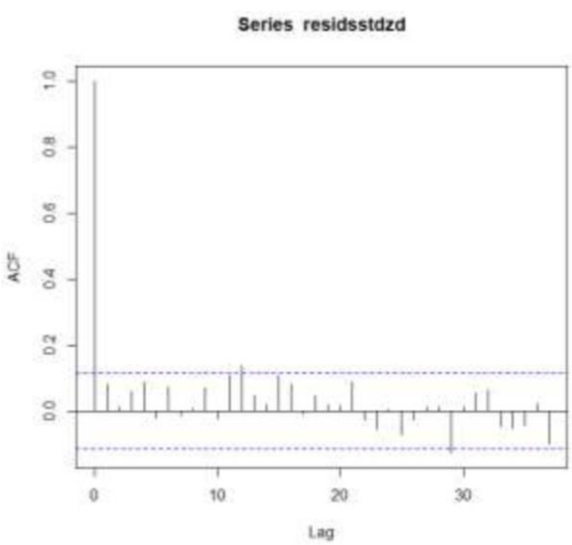
```
> skewness(residsstdzd[-251])
[1] -0.2798312
attr(,"method")
[1] "moment"
```

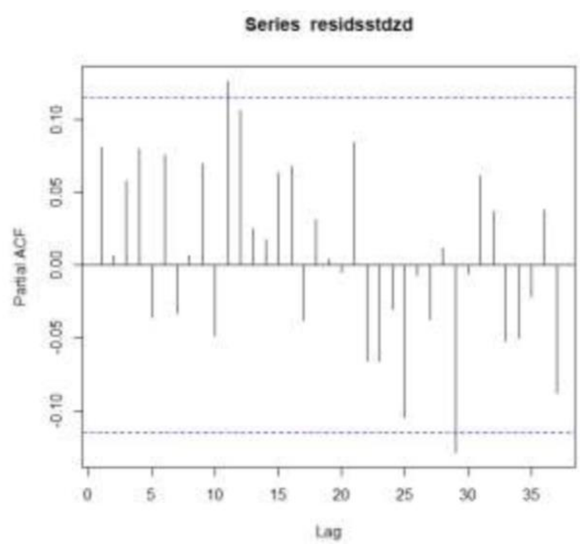
```
> kurtosis(residsstdzd[-251])
[1] 0.4430673
attr(,"method")
[1] "excess"
```

With omission of the November 2018 data point skewness for the standardized residuals is now close to 0, and the kurtosis is 3.44, not far from the value 3 corresponding to normal data. GARCH models do not immediately adjust to sudden data changes, and the November 2018 data point is in this category. As mentioned above, kurtosis is very sensitive to outlier values. Also, here the skewness moved closer to zero because point 251 caused asymmetry of the distribution. To finish this discussion let's examine the standardized residuals to determine if they correspond to normality and a white noise sequence.

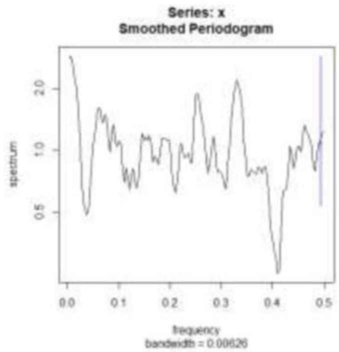


The distribution of the standardized residuals is clearly nonnormal because of the long lower tail, and we can see how extreme the November 2018 data point is.





There is very modest significance in the acf plot at lags 12 and 29 and in the pacf plot at lags 11 and 29. But, nonetheless, the plots are suggestive of white noise structure for the standardized residuals.




```
> bartlettB.test(residsstdzd)

      Bartlett B Test for white noise

data:
= 0.82641, p-value = 0.5018
```

The spectral plot suggests a slight bit of trending of the standardized residuals and is not as flat as we would like to see. However, Bartlett's test judges there is white noise structure.

To conclude, we have to say that ARMA and GARCH have done an excellent job of estimating volatility structure of Pacific Gas and Electric time series.