Group 5 ASSG2

2025-03-24

Importing Ford Motor Company stock statistics

```r
#This code does it.
getSymbols('F', src = 'yahoo', from = as.Date('2022-01-01'), to =
             as.Date('2025-03-20'))
```

```
## [1] "F"
```

Some Ford's stock closing prices

```
##            F.Close
## 2022-01-03   21.77
## 2022-01-04   24.31
## 2022-01-05   23.66
## 2022-01-06   24.46
## 2022-01-07   24.44
## 2022-01-10   23.85
```

Time series plot of Ford's Closing prices

-Ford Company's stock prices have been going down over the course of the 4 years. A sharp drop can be seen from the start of 2022 to the middle of the same year.

-Some seasonality can be seen from the middle of 2022 to the middle of 2023.

-We need to eliminate these components, so that the resulting time series can be easier to work with. Computing the log returns has the same effect as differencing the log of the time series. It can be shown that these returns exhibit stationarity from tests seen further below.

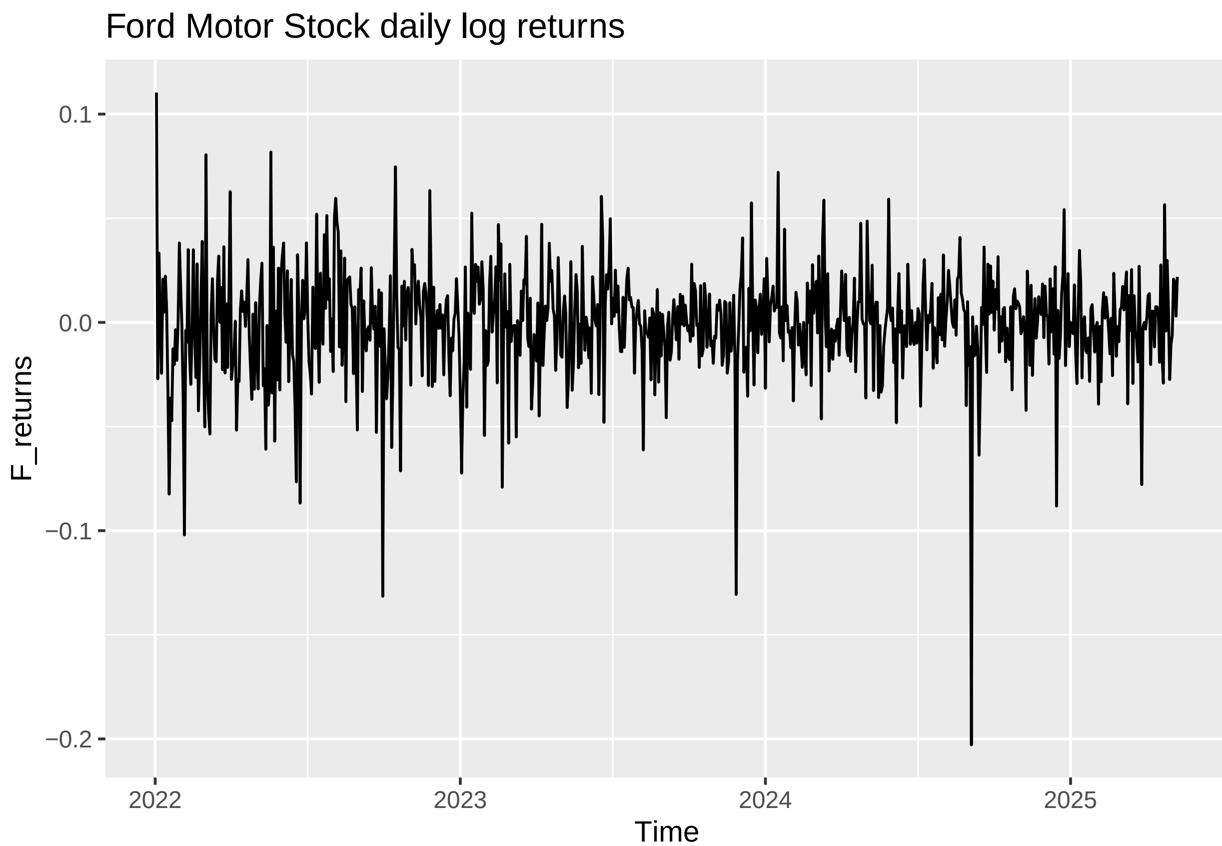
```
#This computes the daily log returns
F_returns <- diff(log(F_closing_ts))
```

Some daily log returns

```
## Time Series:
## Start = c(2025, 80)
## End = c(2025, 85)
## Frequency = 240
##           F.Close
## [1,] -0.010373478
## [2,] -0.006276215
## [3,]  0.020769160
## [4,]  0.019339080
## [5,]  0.003019603
## [6,]  0.021869686
```

PART 1: EXPLORATORY DATA ANALYSIS

Log-returns ts plot



Summary statistics of the returns

```
##    vars   n mean   sd median trimmed  mad  min  max range skew kurtosis se
## X1    1 804    0 0.03      0       0 0.02 -0.2 0.11  0.31   -1     7.03  0
```

Ford Company's stock returns have a mean of zero and a variance of 1. This can imply stationarity since these statistics do not change over time, but further tests are needed to truly confirm this.

-Skewness measures asymmetry. This tells us whether there are extreme values on the left or on the right.

The negative skewness of -1 suggests the returns have a slightly longer left tail. Large losses are therefore more likely to occur.

-Kurtosis measures the tailedness of a distribution. This shows how often extreme values occur as compared to a normal distribution (Where kurtosis = 3).

Results show that returns have a high kurtosis (returns are leptokurtic). Losses (or gains) occur more frequently than normal. This implies higher risk involved with this stock.

ADF Stationarity test

-Null hypothesis: The Series is non-stationary

Fail to reject if P > [level of significance]

-Alternative hypothesis: The Series is stationary

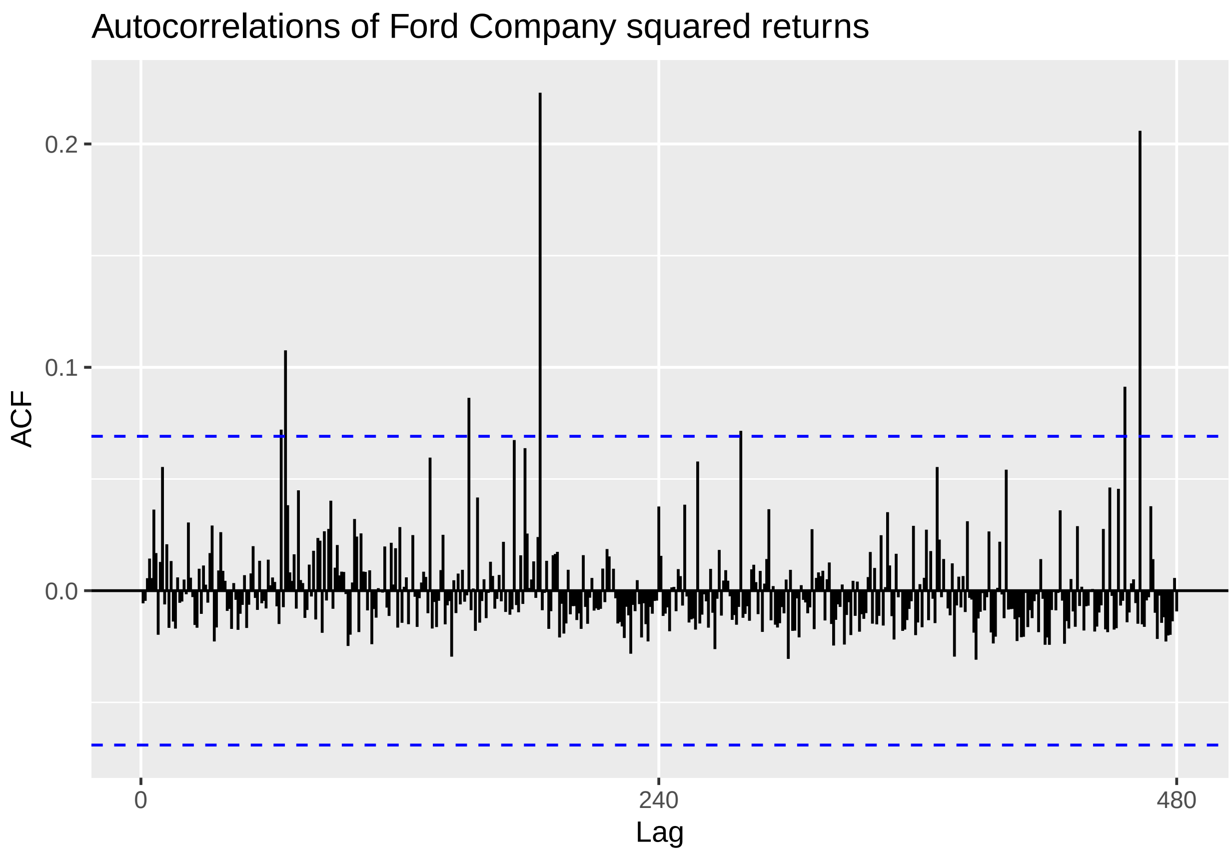
Reject Null in favour of the alternative if P < [level of significance]

-The results are as shown:

```
##
##  Augmented Dickey-Fuller Test
##
## data:  F_returns
## Dickey-Fuller = -8.8182, Lag order = 9, p-value = 0.01
## alternative hypothesis: stationary
```

-Assuming the default significance level of 5% (0.05), The p-value shown is less than this. We therefore reject the null hypothesis in favour of the alternative one and conclude that Ford's returns are indeed stationary.

Checking for ARCH effects on squared returns



-Only 7 out of 480 lags exceed the confidence interval(~1.458% of lags). At 5% significance, 24 lags (480 * 5%) or more exceeding the confidence level would be regarded as statistically significant. We can therefore safely ignore all the lags appearing above the ci as there are statistically insignificant.

-The above plot therefore shows no significant autocorrelations seen from the squared returns; and therefore no volatility clustering. This means that volatility (squared returns) is homoscedastic (not heteroscedastic)… the variance, or volatility, is therefore constant. There are therefore no ARCH effects.

-ARCH effects can further be tested in depth using the Lagrange Multiplier (LM) test.

ARCH-LM test

-Null hypothesis: No ARCH effects (homoscedasticity)

-Alternative hypothesis: There is ARCH effects (heteroscedasticity)

Reject Null hypothesis if P < [level of significance]

```
##
##  ARCH LM-test; Null hypothesis: no ARCH effects
##
## data:  F_returns
## Chi-squared = 3.7086, df = 12, p-value = 0.9881
```

-The p-value (0.9881) is significantly more than 0.05. We therefore fail to reject the Null hypothesis and conclude that Ford Company's stock returns are homoscedastic; they exhibit no ARCH effects.

PART 2 ARCH

Estimating ARCH(p)

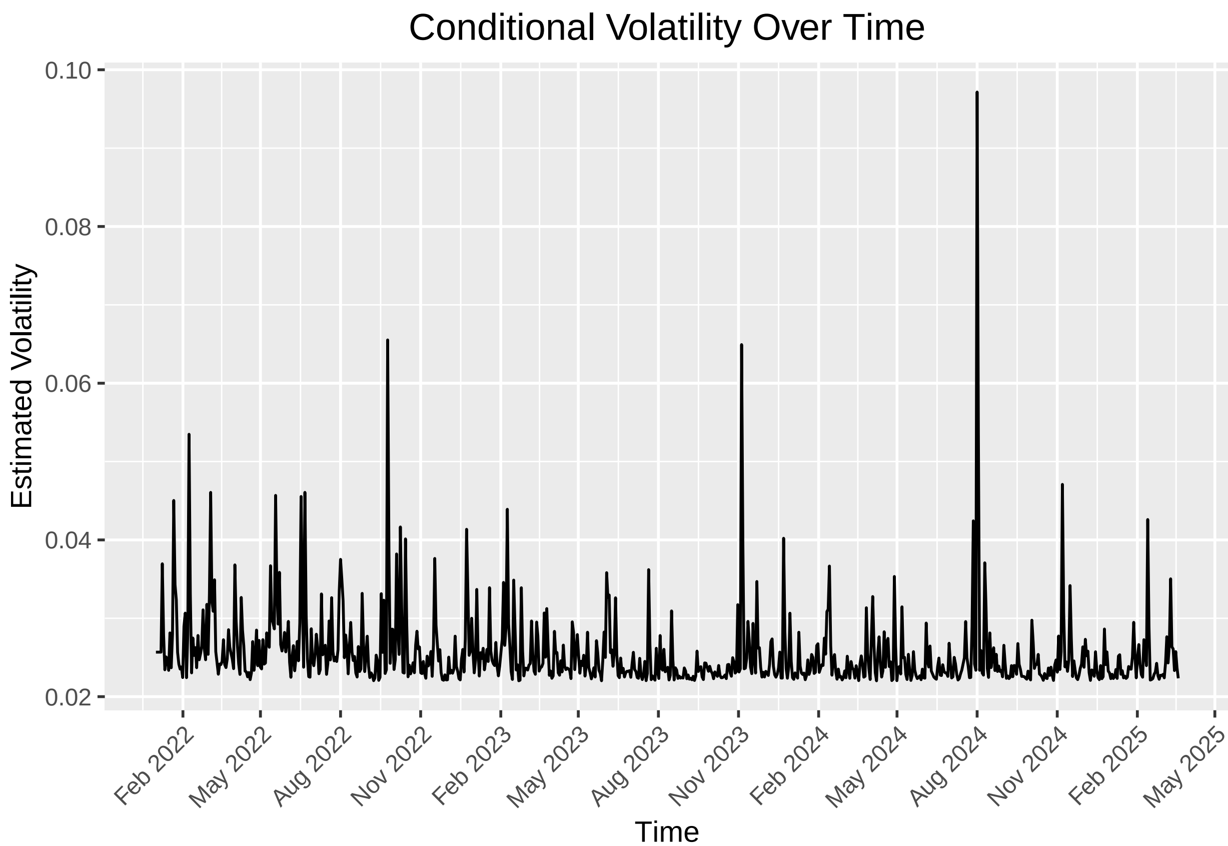
```r
# Initialize vectors to store AIC values and models
aic_values <- numeric(5)
models <- list()

# Loop over p from 1 to 5 to find best ARCH(p)
for (p in 1:5) {
  # Define ARCH(p) spec as sGARCH(p, 0) with zero-mean
  spec <- ugarchspec(
    variance.model = list(model = "sGARCH", garchOrder = c(p, 0)),
    mean.model = list(armaOrder = c(0, 0), include.mean = FALSE),  # Zero-mean model
    distribution.model = "norm"  # Normal distribution
  )

  # Fit the model to returns
  fit <- ugarchfit(spec = spec, data = F_returns)

  # Save AIC value
  aic_values[p] <- infocriteria(fit)[1]

  # Save model object
  models[[p]] <- fit

  # Print AIC for each p
  cat("ARCH(", p, ") AIC:", aic_values[p], "\n")
}
```

```
## ARCH( 1 ) AIC: -4.481548
## ARCH( 2 ) AIC: -4.479064
## ARCH( 3 ) AIC: -4.476895
## ARCH( 4 ) AIC: -4.485098
## ARCH( 5 ) AIC: -4.486936
```

-The best model has the lowest AIC which is an ARCH(5) model as shown:

```
##
## Best ARCH(p): p = 5 with AIC = -4.486936
```

Extract and plot the conditional volatility



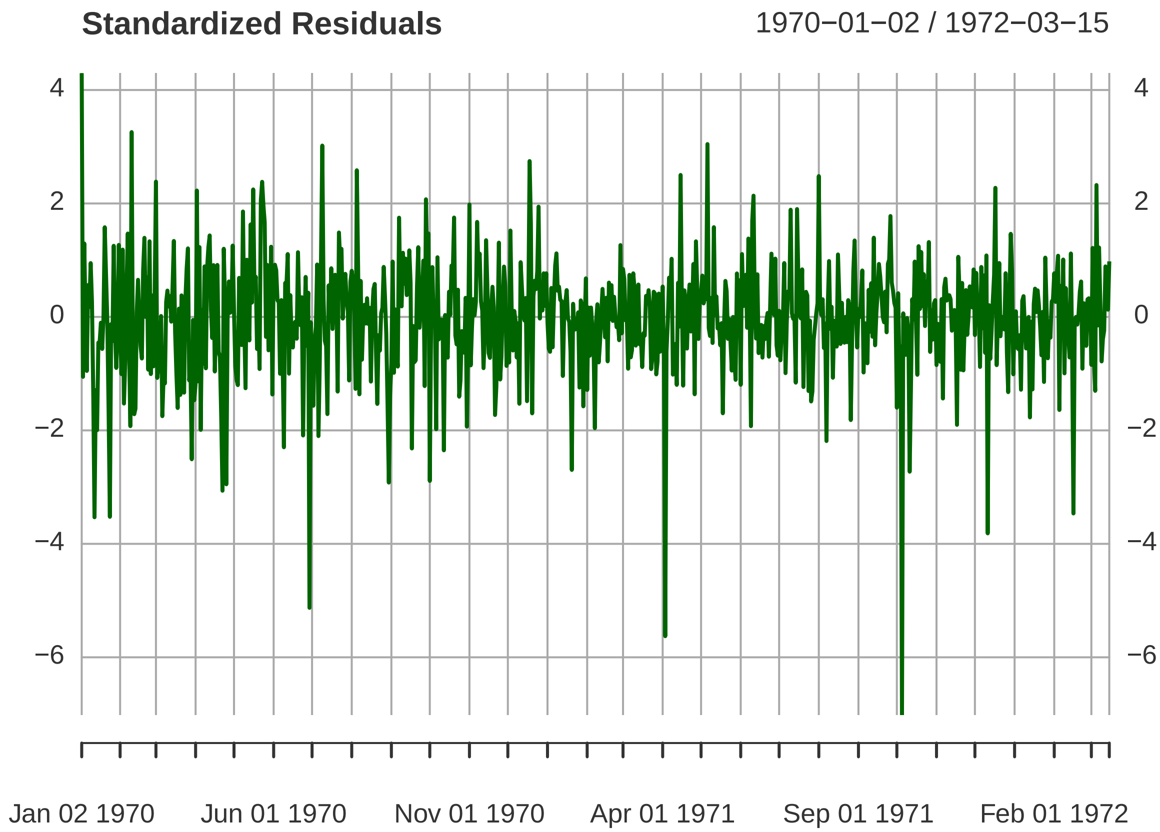
The extreme spikes around August 2024, November 2023,and around October show sudden market shocks or major financial events.

-This means that there is higher risk involved for investors at this time. Traders of Ford's stock should have expected either a huge loss or a huge gain at this point in time.

-Higher volatility is disadvantageous to investors due to a high uncertainty involved in this stock. However, this could be great for traders who profit from volatility such as option traders.

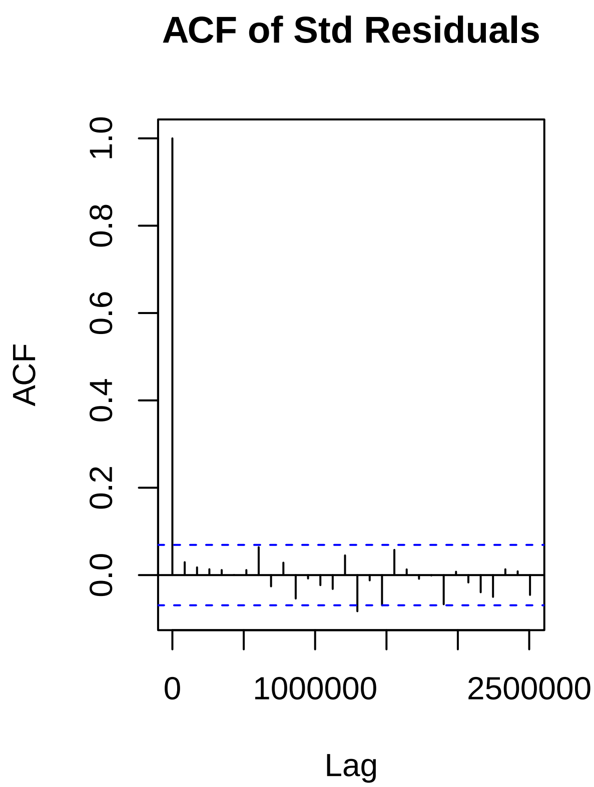
-Some seasonality can be seen here. This proves that there is conditional heteroscedasticity or volatility clustering; Periods of low volatility following periods of high volatility.

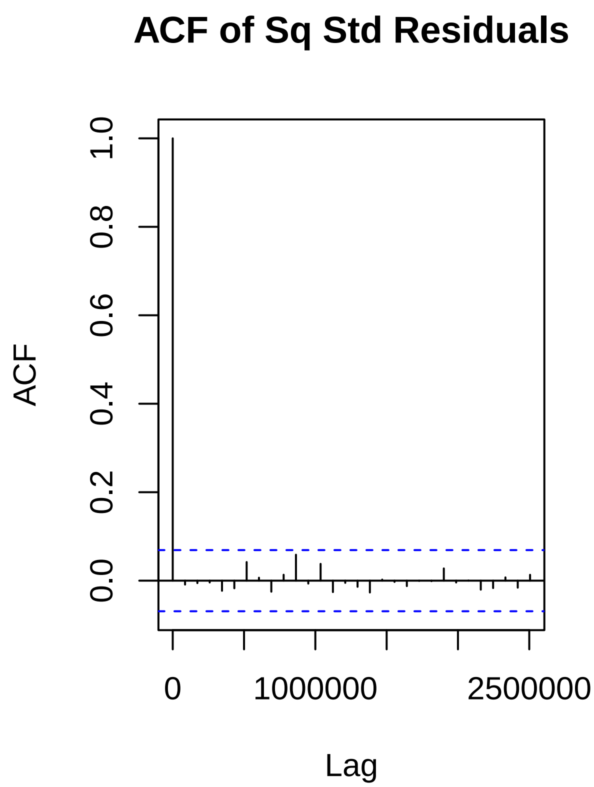
Check the standardized residuals for autocorrelation




```
##
##  Box-Ljung test
##
## data:  std_residuals
## X-squared = 8.1854, df = 10, p-value = 0.6107
```

```
##
##  Box-Ljung test
##
## data:  std_residuals^2
## X-squared = 5.7009, df = 10, p-value = 0.8397
```


ACF of Std Residuals
ACF
1.0
0.8
0.6
0.4
0.2
0.0
0
1000000
2500000
Lag


ACF of Sq Std Residuals
ACF
1.0
0.8
0.6
0.4
0.2
0.0
0
1000000
2500000
Lag

Discussion: Why ARCH(p) May Be Insufficient for Financial Volatility

#Captures short-term volatility clustering poorly.

ARCH models require high orders (large p) to capture persistent volatility, which can lead to overfitting and inefficient estimation.

#Volatility persistence is not well-modeled.

Financial returns show long memory in volatility. ARCH models do not allow for volatility to decay slowly over time like GARCH models do.

#Cannot model asymmetry (leverage effect).

Financial markets often exhibit asymmetric volatility (negative shocks increase volatility more than positive shocks). ARCH ignores this.

#Residual diagnostics may show remaining ARCH effects.

Even after fitting ARCH, squared standardized residuals may still show autocorrelation, indicating that the model hasn't captured all dynamics.