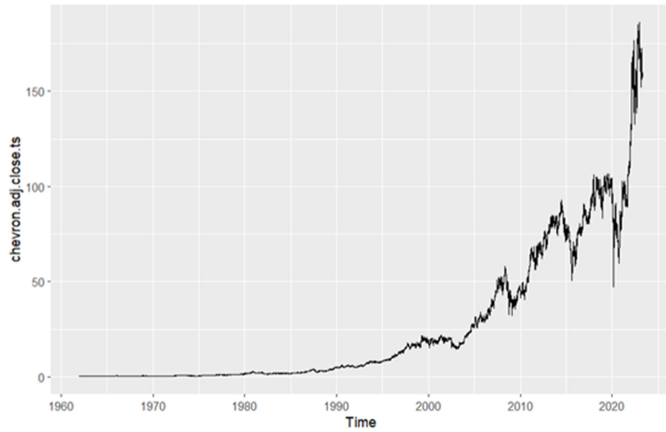
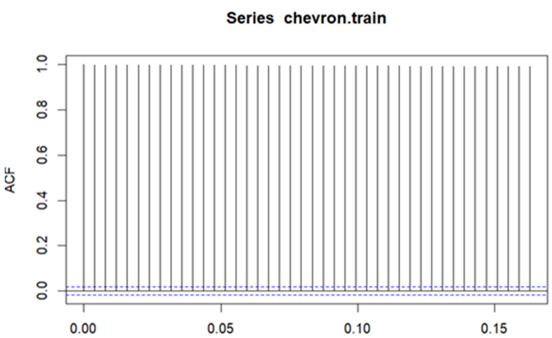
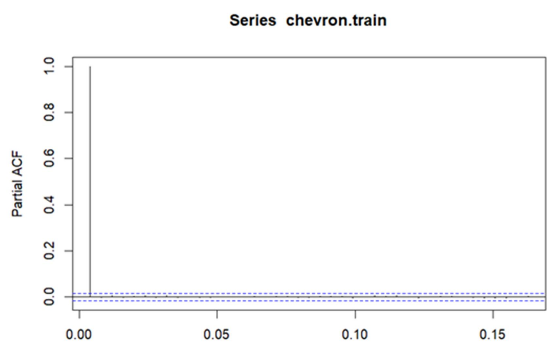
Chevron

Exploratory Analysis

As can be seen on the image below, on the left, the time series for the Chevron stocks is multiplicative, which required the log transform resulting in the image below, on the right. The decomposition of the log transformed time series showed a clear trend, but no seasonality.





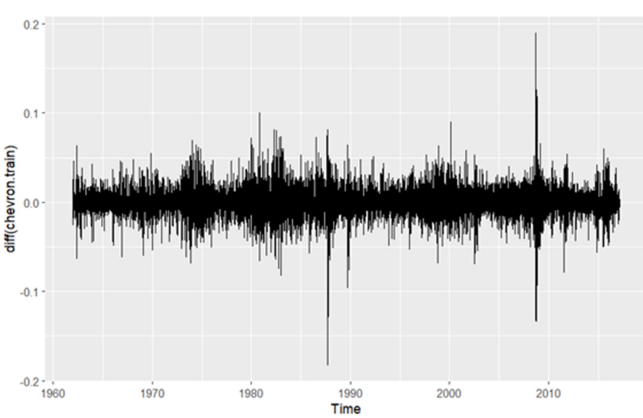



```
> adfTest(chevron.train, lags = 15, type = 'ct')

Title:
 Augmented Dickey-Fuller Test

Test Results:
  PARAMETER:
    Lag Order: 15
  STATISTIC:
    Dickey-Fuller: -3.3267
  P VALUE:
    0.06586
```

```
> eacf(chevron.train)
AR/MA
  0 1 2 3 4 5 6 7 8 9 10 11 12 13
0 x x x x x x x x x x x  x  x  x
1 o x o x o o x o o o o  o  o  o
2 x x o o o o x o o o o  o  o  o
3 x x o x o o x o o o o  o  o  o
4 x x x o o o o o o o o  o  o  o
5 x x x x o o o x o o o  o  o  o
6 x x x x x o o x o o o  o  o  o
7 x x x x x x o x o o o  o  o  o
```

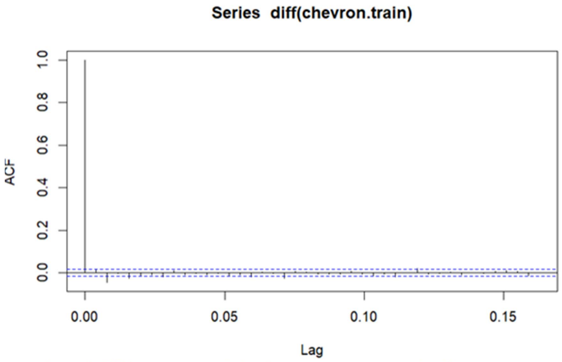
```
> kpss.test(chevron.train, null = 'Trend')

        KPSS Test for Trend Stationarity

data:  chevron.train
KPSS Trend = 8.4037, Truncation lag parameter = 13, p-value = 0.01
```

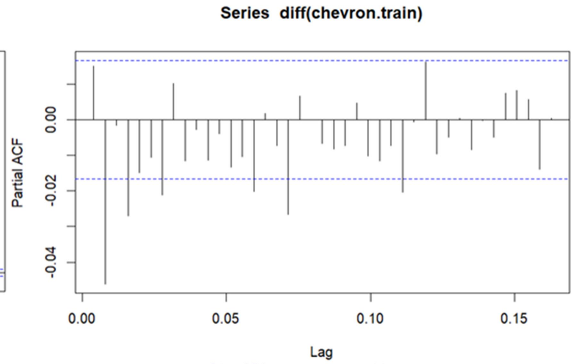
The incredibly slow decay of the auto correlation on the ACF, the auto correlation of one at lag 1 on the PACF and the first row filled with x on the EACF, as well as the ADF test failing to reject the null hypothesis of unit root and the KPSS test rejecting the null hypothesis of stationarity all indicate the series is a random walk.




```
> t.test(diff(chevron.log))

        One Sample t-test

data:  diff(chevron.log)
t = 3.0284, df = 15443, p-value = 0.002463
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 0.0001395019 0.0006514341
sample estimates:
  mean of x
0.000395468
```

By differencing the series we can see that it becomes stationary, and the T test rejects the null hypothesis of constant mean throughout the series, indicating a random walk with a drift.





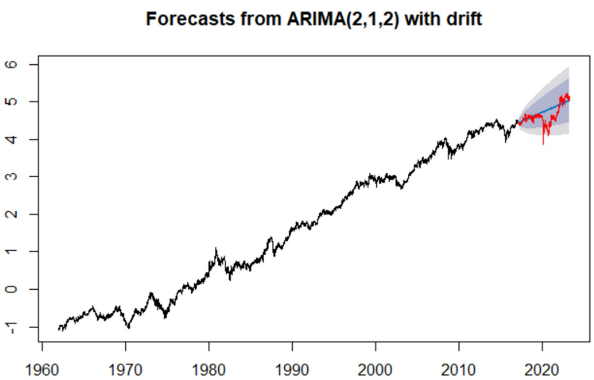

```
> adfTest(diff(chevron.train), lags = 15, type = 'nc')

Title:
 Augmented Dickey-Fuller Test

Test Results:
  PARAMETER:
    Lag Order: 15
  STATISTIC:
    Dickey-Fuller: -31.6217
  P VALUE:
    0.01
> kpss.test(diff(chevron.train), null = 'Level')

        KPSS Test for Level Stationarity

data:  diff(chevron.train)
KPSS Level = 0.037369, Truncation lag parameter = 13, p-value = 0.1
```

```
> eacf(diff(chevron.train))
AR/MA
  0 1 2 3 4 5 6 7 8 9 10 11 12 13
0 o x o x o o x o o o o  o  o  o
1 x x o o o o x o o o o  o  o  o
2 x x o x o o x o o o o  o  o  o
3 x x x o o o o o o o o  o  o  o
4 x x x x o o o x o o o  o  o  o
5 x x x x x o o x o o o  o  o  o
6 x x x x x x o x o o o  o  o  o
7 x x x x x x x x o o o  o  o  o
```

After differencing it, ACF, PACF and EACF as well as ADF and KPSS tests all corroborated a stationary behavior. ACF of the differenced series indicates an MA behavior and the significant auto correlation at lag 2 indicates it might be of second order. The PACF shows more clearly some significant auto correlation at lags 2 and 3, aside from other ones at much higher orders. EACF indicates many possible models, and of the many tried, the one with the best performance and most conforming residuals was an ARIMA(2, 1, 2) with drift.

Model Building

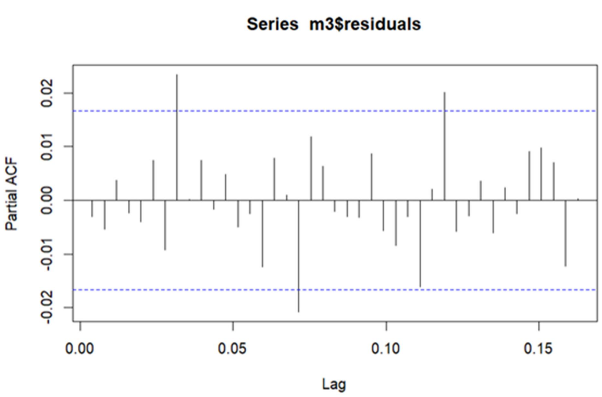
The model chosen has very significant coefficients, with very low RMSFE and MAPE, at .22 and 3.5%, respectively, as well as incredibly low AIC and BIC values, at -76244.66 and -76199.42. The performance of the model can be visually analyzed on the chart on the left, where the blue line represents the predictions produced and the red line represents the true values for the period.




```
> m3
Series: chevron.train
ARIMA(2,1,2) with drift

Coefficients:
         ar1     ar2      ma1      ma2  drift
      0.3876  0.4802  -0.3708  -0.5300  4e-04
s.e.  0.0924  0.0889   0.0896   0.0869  1e-04

sigma^2 = 0.0002426:  log likelihood = 38128.33
AIC=-76244.66   AICc=-76244.65   BIC=-76199.42
> coeftest(m3)

z test of coefficients:

        Estimate  Std. Error z value  Pr(>|z|)
ar1   3.8758e-01  9.2424e-02  4.1935 2.747e-05 ***
ar2   4.8019e-01  8.8898e-02  5.4016 6.606e-08 ***
ma1  -3.7079e-01  8.9564e-02 -4.1400 3.473e-05 ***
ma2  -5.3003e-01  8.6914e-02 -6.0983 1.072e-09 ***
drift 3.8899e-04  9.9472e-05  3.9106 9.208e-05 ***
```

RMSFE: 0.22,
MAPE: 3.5%

Residual Analysis



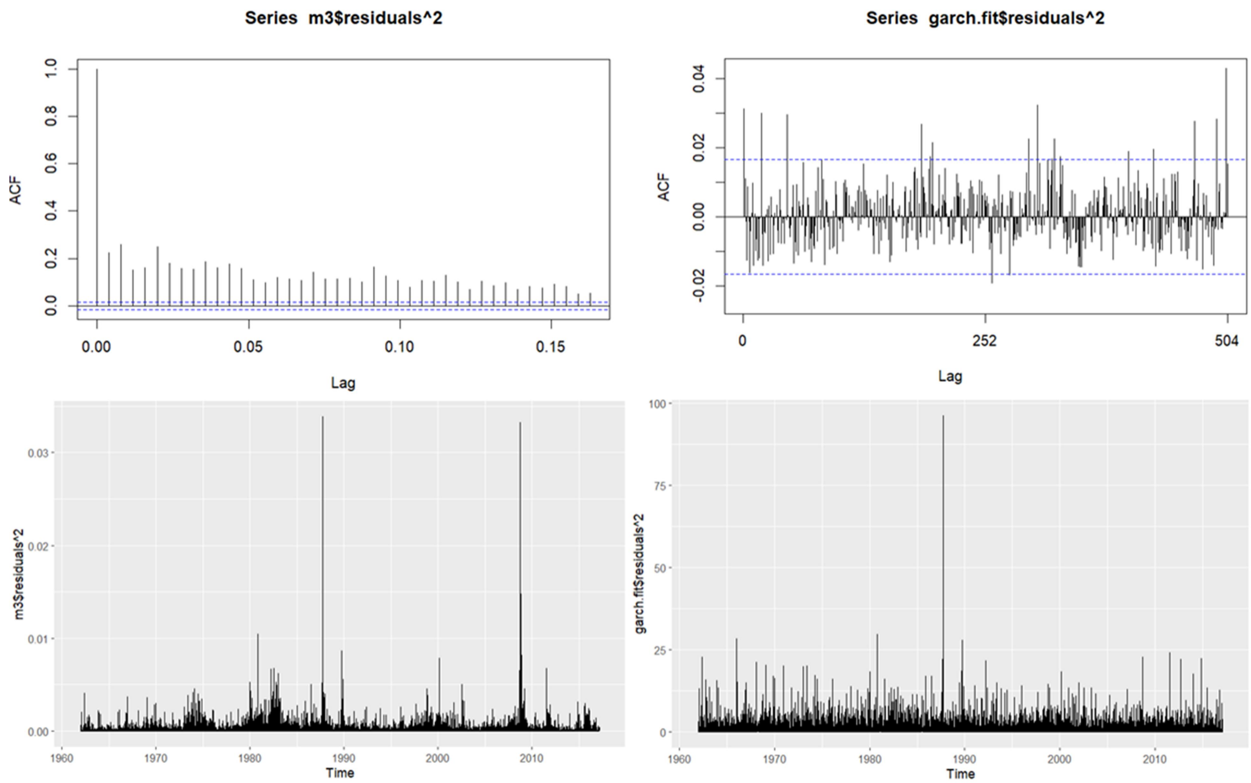

```
> Box.test(m3$residuals, lag = 10, type = 'Ljung')

        Box-Ljung test

data:  m3$residuals
X-squared = 11.313, df = 10, p-value = 0.3337
```

The residuals, as can be seen on the PACF on the left, look very good, with only a few auto correlations that are barely significant, and the Ljung Box test fails to reject the null hypothesis of independence.

Even though the residuals for the model look independent, there is still some volatility to it, which can be seen on the ACF and time plot, on the left middle and bottom corner of the image below, respectively. By running a first GARCH (1, 1) model the volatility of the model reduced significantly, as can be seen on the ACF and time plot for the squared residuals, on the right middle and bottom corner of the image below. The coefficients for the first GARCH model were all very significant as can be seen on the left upper corner, and the Ljung box test came close to failing to reject the null hypothesis of independence at p-value of 0.0002. These results motivated the integration of the ARIMA and GARCH models into an ARMA(2, 2) GARCH(1, 1) model.

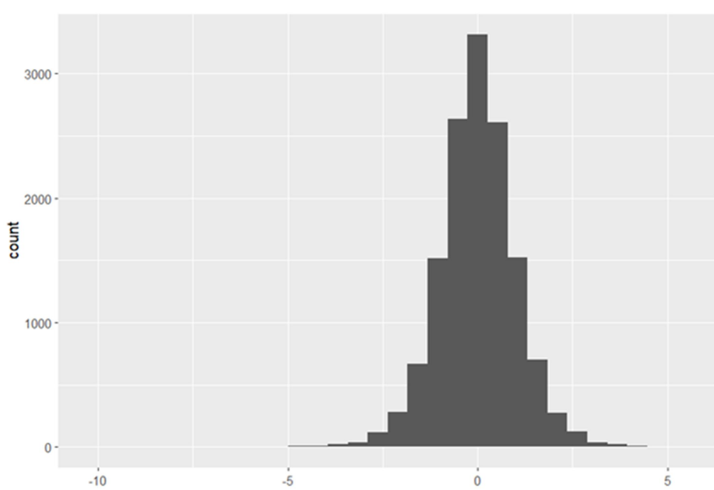
```
> coeftest(garch.fit)

z test of coefficients:

    Estimate Std. Error z value  Pr(>|z|)
a0 2.5854e-06 2.2796e-07  11.342 < 2.2e-16 ***
a1 6.0380e-02 2.4737e-03  24.408 < 2.2e-16 ***
b1 9.2934e-01 2.8817e-03 322.492 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
> Box.test(garch.fit$residuals^2, type = 'Ljung')

        Box-Ljung test

data:  garch.fit$residuals^2
X-squared = 13.591, df = 1, p-value = 0.0002273
```




```
        Box-Ljung test

data:  gfit4res^2
X-squared = 25.625, df = 15, p-value = 0.04216
```

Skewness: -0.15
Kurtosis: 2.19

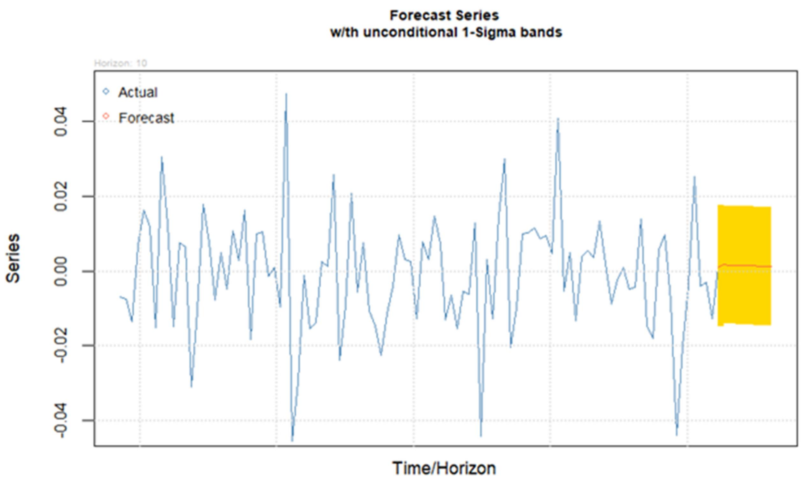



```
> jarque.bera.test(na.omit(gfit4res)) # rejects normality

        Jarque Bera Test

data:  na.omit(gfit4res)
X-squared = 3149.3, df = 2, p-value < 2.2e-16
```

As expected, all coefficients for the integrated model were significant and the volatility was kept at a very low level, just like on the first ARIMA(2, 1, 2) and GARCH(1, 1) models. Even though the differences for the squared residuals between the first GARCH model and the integrated model were visually imperceptible, the Ljung box test for the ARMA(2, 2), GARCH(1, 1) model returned a p-value of .04, on the edge of failing to reject the null hypothesis of independence, indicating the integrated model has extremely well behaved residuals. The residuals presented a somewhat normal behavior, as can be seen on the histogram to the left, with a skewness of -0.15 and a Kurtosis of 2.19, but not enough for the Jarque Bera test to fail to reject the null hypothesis of normality.

Forecast Analysis

The forecasts from the ARMA(2, 2) GARCH(1, 1) model can be seen below, with really low MSE and MAE. The integrated model has equal contributions from auto regressive and moving average processes, seeing that AR 1 and 2, MA 1 and 2, Alpha 1 and Beta 1 are all very significant.




```
> report(gfit4.rolltest, type = 'fpm')

GARCH Roll Mean Forecast Performance Measures
---------------------------------------------
Model           : sGARCH
No.Refits       : 27
No.Forecasts: 13444

        Stats
MSE 0.0002834
MAE 0.0119000
DAC 0.4953000

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000571    0.000076   7.5404  0.00000
ar1     0.877407    0.008244 106.4320  0.00000
ar2     0.050740    0.003890  13.0446  0.00000
ma1    -0.843608    0.002508 -336.3150 0.00000
ma2    -0.103779    0.008259 -12.5660  0.00000
omega   0.000003    0.000001   2.7511  0.00594
alpha1  0.064495    0.008041   8.0210  0.00000
beta1   0.924647    0.009772  94.6232  0.00000
```