SAUDI ARABIA EXCHANGE PREDICTION USING TIME SERIES ANALYSIS TECHNIQUES

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Contents

Abstract Summary

This comprehensive study delivers an intricate analysis of the four most vibrant markets in Saudi Arabia as observed in 2022, and its primary ambition is to apply ARIMA and GARCH models to forecast the closing metrics for the forthcoming ten months. The methodology employed for this research entailed a meticulous review of the data, encompassing its purification, filtration, visualization, and a rigorous exploration leveraging descriptive statistics. In addition, we crafted model specifications, which were subsequently fitted and diagnosed utilizing sophisticated time series analysis techniques. The analytical process involved making three preliminary model selection decisions before arriving at the fourth and definitive choice. The resulting models have a forecasting scope of 10-15 future values. This constraint may be attributed to a combination of factors, including the limited availability of historical data, the inherent assumptions made by the ARIMA & GARCH models about the data, and most significantly, the volatility inherent in the data. This research did not exhaustively consider all the findings generated from the time series analysis. Consequently, to enhance the precision and reliability of these models, a more profound examination of the results is recommended in subsequent studies.

Introduction

The concept of the “stock market” encompasses various trading platforms where equities of publicly traded enterprises are purchased and exchanged. This marketplace facilitates the congregation and transaction of securities’ buyers and sellers. These markets function as an instrument for the price determination of corporate shares and operate as an economic indicator. Ensuring a fair pricing mechanism, optimal liquidity, and transparency, the market participants vie in an open and competitive environment (Murphy, 2023).

There exist numerous influences that contribute to the fluctuation in stock prices for companies listed on exchanges, extending beyond the basic principle of supply and demand. Indeed, a variety of factors coalesce to incite these oscillations in pricing. These factors include (Egan, 2023):

1- Corporate Operations: Numerous internal events within a firm may precipitate a rise or fall in its equity prices. For instance, the release of corporate reports can sway investor confidence in the company positively or negatively.

2- Economic Climate: The prevailing economic conditions wield substantial influence over the trajectory of stock prices.

3- Inflation: Inflation, characterized by the overall surge in costs of goods and services, compromises the purchasing power of both businesses and consumers.

4- Interest Rates: The role of interest rates is pivotal in determining the cost burden for companies to secure loans. Heightened interest rates can elevate corporate borrowing expenditures, potentially undermining corporate profits and, consequently, depressing overall stock prices.

5- Global Events: Geopolitical uncertainties, such as warfare and acts of terrorism, can not only trigger instability across nations but can also unsettle stock markets.

6- Significant Investors: As highlighted by Haigh, the investment activities executed by substantial institutional investors like mutual and hedge funds can instigate notable shifts in stock prices. The sizeable share portfolios held by these investors imply that their buying and selling behaviors can considerably influence stock valuations.

In the era predating machine learning, the formidable challenge of predicting stock market trends was amplified due to the extensive range of influencing factors. Today, however, the advent of machine learning has become integral in this domain. Financial institutions or individual investors can utilize machine learning to navigate stock trading in numerous ways, encompassing the prediction of market shifts, investigation of consumer patterns, and scrutiny of stock price movements. Conventional machine learning approaches encompass methodologies such as random forest, naive Bayesian, support vector machine, and K-nearest neighbor. Moreover, temporal sequence analysis, executed via the ARIMA (Autoregressive Integrated Moving Average) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH), can also serve to forecast stock market trajectories.

In this comprehensive analysis, we undertake an investigation of the four most active market values as per the Saudi Exchange's annual report published on December 31, 2022. The Saudi Exchange, being the sole authorized entity to function as the securities exchange within the Kingdom of Saudi Arabia, provides a reliable basis for our study. Our primary objective in this analysis is to project the values at the conclusion of a 10-month horizon, thereby providing potential insights for strategic decision-making processes (Gulen, 2023).

Data Overview

Libraries

```
packages =  c("ggplot2", "dplyr", "tidyr", "data.table", 'corrplot', 'gridExt
ra', 'forecast', 'tseries', 'TSA', 'tibble', 'TTR', 'xts', 'dygraphs', 'asser
tthat',"readxl","MASS","car","dplyr","fUnitRoots","lmtest","fGarch",'rugarch'
)

my.install <- function(pkg, ...){
  if (!(pkg %in% installed.packages()[,1])) {
    install.packages(pkg)
  }
  return (library(pkg, ...))
}

purrr::walk(packages, my.install, character.only = TRUE, warn.conflicts = FAL
SE)
```

Tail Observations

1- AlRajhi

```
## # A tibble: 6 × 10
##   Date                 Open  High   Low Close Change `% Change` `Volume
Traded`
##   <dttm>              <dbl> <dbl> <dbl> <dbl>  <dbl>      <dbl>
<dbl>
## 1 2023-06-01 00:00:00  71    72.6  70.9  72.3    1.6       2.26
4939287
## 2 2023-06-04 00:00:00  73    74.1  72.7  74.1    1.8       2.49
4431688
## 3 2023-06-05 00:00:00  74.3  74.3  73.3  73.3   -0.8      -1.08
4614427
## 4 2023-06-06 00:00:00  73.4  73.5  72.7  73.2   -0.1      -0.14
3348339
## 5 2023-06-07 00:00:00  73.3  73.4  73    73.1   -0.1      -0.14
4633466
## 6 2023-06-08 00:00:00  73.2  73.4  72.5  73.4    0.3       0.41
3869625
## # ℹ 2 more variables: `Value Traded (SAR)` <dbl>, `No. Of Trades` <dbl>
```

2- SNB

```
## # A tibble: 6 × 10
##   Date                Open   High  Low   Close Change `% Change` `Volume T
raded`
##   <dttm>              <chr>  <chr> <chr> <dbl>  <dbl>      <dbl> <chr>
## 1 2023-06-01 00:00:00 36.79… 37.15 36.4…  36.6  -0.25      -0.68 4068689
## 2 2023-06-04 00:00:00 37     37.2… 36.65  37.3   0.65       1.77 2861432
## 3 2023-06-05 00:00:00 37.29… 37.35 36.9   37.2  -0.15      -0.4  3892436
## 4 2023-06-06 00:00:00 37.20… 37.2… 36.7…  37    -0.15      -0.4  2761607
## 5 2023-06-07 00:00:00 37.15  37.85 37     37.8   0.85       2.3  5202836
## 6 2023-06-08 00:00:00 37.79… 37.9  37.4…  37.8  -0.05      -0.13 3762311
## # ℹ 2 more variables: `Value Traded (SAR)` <chr>, `No. Of Trades` <chr>
```

3- Alinma

```
## # A tibble: 6 × 10
##   Date                 Open  High   Low Close Change `% Change` `Volume Tr
aded`
##   <dttm>              <dbl> <dbl> <dbl> <dbl>  <dbl>      <dbl>
<dbl>
## 1 2023-06-01 00:00:00  32.2  32.6  32.0  32.0  -0.6       -1.84         27
89747
## 2 2023-06-04 00:00:00  32.2  32.8  32.2  32.6   0.6        1.87         30
92501
## 3 2023-06-05 00:00:00  32.6  33.4  32.6  33     0.35       1.07         69
21319
## 4 2023-06-06 00:00:00  32.8  33.6  32.8  33.2   0.25       0.76         58
59691
## 5 2023-06-07 00:00:00  33.4  34.5  33.4  33.6   0.4        1.2          55
64525
## 6 2023-06-08 00:00:00  33.8  34.4  33.6  33.7   0.05       0.15         31
26995
## # ℹ 2 more variables: `Value Traded (SAR)` <dbl>, `No. Of Trades` <dbl>
```

4- Sabic

```
## # A tibble: 6 × 10
##   Date                 Open  High   Low Close Change `% Change` `Volume Tr
aded`
##   <dttm>              <dbl> <dbl> <dbl> <dbl>  <dbl>      <dbl>
<dbl>
## 1 2023-06-01 00:00:00  126   126   124.  124    -1        -0.8           7
68112
## 2 2023-06-04 00:00:00  124.  126   124.  126.    1.8       1.45          4
25148
## 3 2023-06-05 00:00:00  126   128.  126.  128     2.2       1.75         10
68163
## 4 2023-06-06 00:00:00  129.  129   127.  127.   -0.8      -0.63          8
02860
## 5 2023-06-07 00:00:00  128.  128.  127.  128.    0.4       0.31          4
```

```
90493
## 6 2023-06-08 00:00:00  128.   128.   128.   128.    0.8       0.63          4
36306
## # ℹ 2 more variables: `Value Traded (SAR)` <dbl>, `No. Of Trades` <dbl>
```

Data Cleaning & Filtering

Filtering

Given that our objective is a thorough examination of these four markets, culminating in an informed assessment of the most viable investment opportunity, our focus is not on daily fluctuations, which are primarily relevant to day traders. Consequently, the data has been meticulously curated to incorporate only the end-of-month figures for each year under consideration.

```
# Function to filter data
filter_data <- function(df) {
  mydata_xts <- xts(df, order.by = as.Date(df$Date))
  eom_rows <- mydata_xts[endpoints(mydata_xts, "months")]
  eom_rows_df <- as.data.frame(eom_rows)

  return(eom_rows_df)
}

# Applying function to each dataset
eom_rows_AlRajhi <- filter_data(AlRajhi)
eom_rows_SNB <- filter_data(SNB)
eom_rows_Alinma <- filter_data(Alinma)
eom_rows_Sabic <- filter_data(Sabic)
```

Missing Values

```
# Checking missing values
any(is.na(eom_rows_AlRajhi))

## [1] FALSE

any(is.na(eom_rows_SNB))

## [1] FALSE

any(is.na(eom_rows_Alinma))

## [1] FALSE

any(is.na(eom_rows_Sabic))

## [1] FALSE
```

Converting

Our primary focus is on the 'High' attribute. Consequently, we have selectively converted this attribute to a numeric type and subsequently transformed it into a time series for further analysis.

```
# Converting Attributes Type
# AlRajhi
eom_rows_AlRajhi$High <- as.numeric(as.character(eom_rows_AlRajhi$High))

# SNB
eom_rows_SNB$High <- as.numeric(as.character(eom_rows_SNB$High))

# Alinma
eom_rows_Alinma$High <- as.numeric(as.character(eom_rows_Alinma$High))

# Sabic
eom_rows_Sabic$High <- as.numeric(as.character(eom_rows_Sabic$High))

eom_rows_AlRajhi$Date <- as.Date(eom_rows_AlRajhi$Date)
eom_rows_SNB$Date <- as.Date(eom_rows_SNB$Date)
eom_rows_Alinma$Date <- as.Date(eom_rows_Alinma$Date)
eom_rows_Sabic$Date <- as.Date(eom_rows_Sabic$Date)

# Convert 'High' column to a time series
AlRajhi_ts <- ts(eom_rows_AlRajhi$High)
SNB_ts <- ts(eom_rows_SNB$High)
Alinma_ts <- ts(eom_rows_Alinma$High)
Sabic_ts <- ts(eom_rows_Sabic$High)
```

Data Visualization & Descriptive Statistics

Summary Statistics & Series Investigations

```
summary(eom_rows_AlRajhi$High)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    6.46   24.59   28.26   34.46   38.58  112.40

summary(eom_rows_SNB$High)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   16.82   26.86   33.43   33.62   38.59   58.95

summary(eom_rows_Alinma$High)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    6.86    9.93   12.82   15.19   17.23   41.80

summary(eom_rows_Sabic$High)
```

```
##     Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    10.95   64.00   81.90   86.02  117.00  186.40
```

```r
# Set up the layout for 4 plots
par(mfrow = c(2, 2))

# Create the 4 plots
plot(AlRajhi_ts, main = "AlRajhi", ylab = "High")
plot(SNB_ts, main = "SNB", ylab = "High")
plot(Alinma_ts, main = "Alinma", ylab = "High")
plot(Sabic_ts, main = "Sabic", ylab = "High")
```

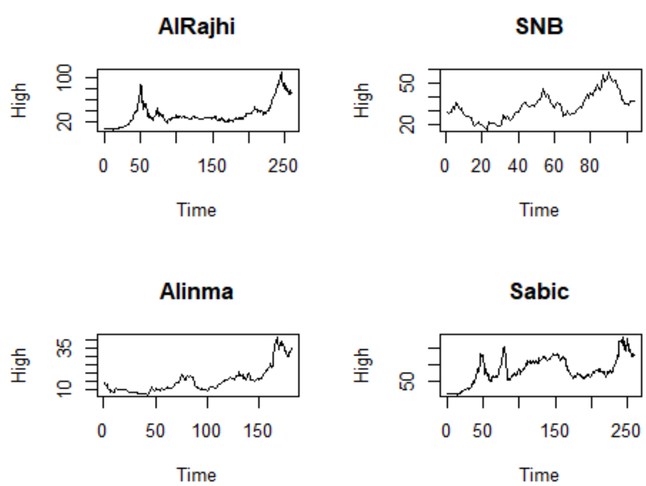


Figure 1. Markets Time Series

The observed patterns in the stock prices of AlRajhi and Alinma indicate notable instances of significant upsurges, which may frequently be attributable to speculative trading practices. However, a subsequent regression to levels more congruent with the companies' inherent value is also discernible. This dynamic volatility, characterized by substantial price fluctuations, is manifest in the higher occurrence of outliers in their respective data sets.

Key Features Assumptions About The Time Serieses

Market	Trend	Seasonality	Fluctuations	Behavior	Turning_Points
AlRajhi	Positive	Unknown	Yes	AR/MR	No
SNB	Positive	Unknown	Yes	AR/MR	Yes
Alinma	Positive	Unknown	Yes	AR/MR	Maybe
Sabic	Positive	Unknown	Yes	AR/MR	Yes

Distributions

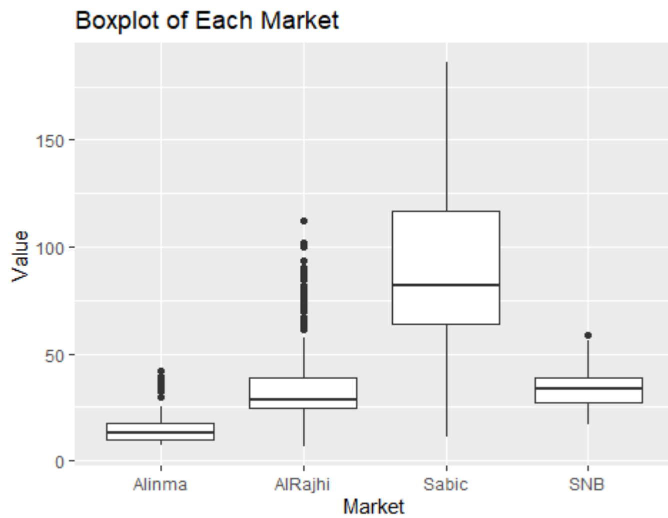


Figure 2. Markets Boxplot

Sabic, from our observations, presents itself as the steadiest market with an absence of outliers, a stark contrast to Alinma and AlRajhi. Noteworthy fluctuations such as these outliers could be indicative of a market boom or a downturn, often precipitated by company-specific events such as the announcement of pivotal decisions. Conversely, while Saudi National Bank (SNB) does not showcase outliers, its median value is noticeably lower compared to Sabic. This suggests different market dynamics and performance metrics when comparing SNB to Sabic.

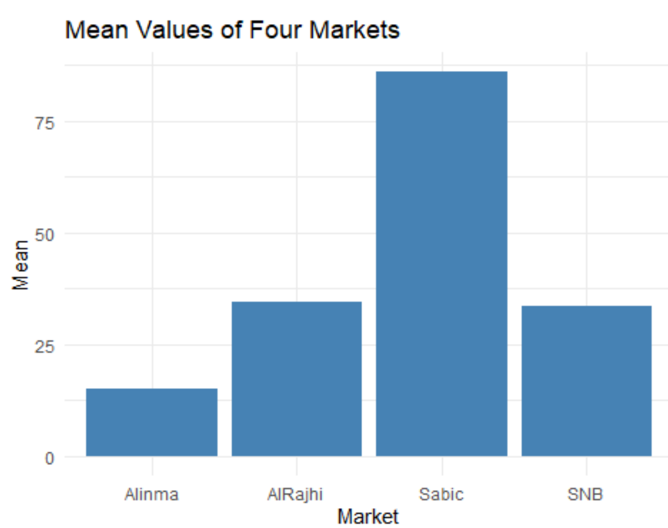


Figure 3. Markets Mean Values

Despite the pronounced presence of outliers in Alinma and AlRajhi, indicative of significant market fluctuations, they still register a mean value that is inferior to Sabic. This underscores that even amidst their periods of market buoyancy, they remain unable to surpass Sabic's performance levels.

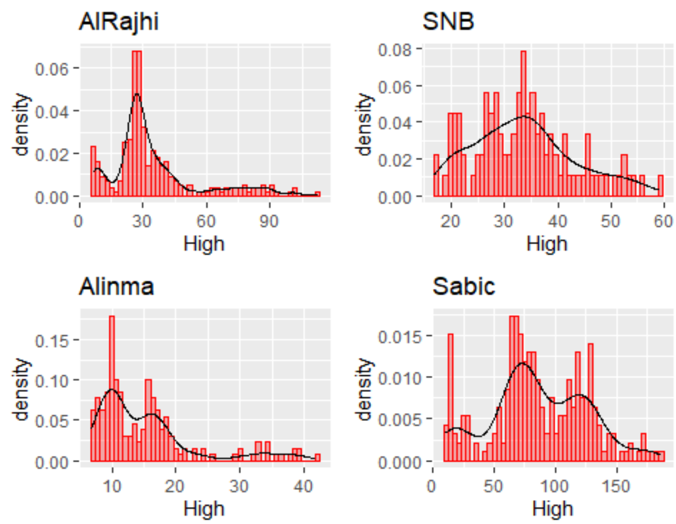


Figure 4. Markets Distribution

The data distributions for AlRajhi and Alinma demonstrate a pronounced skew towards particular values, suggestive of a distinct central tendency within these datasets. In contrast, the data for SNB and Sabic exhibit a more expansive dispersion, indicative of a higher degree of variability.

Normality

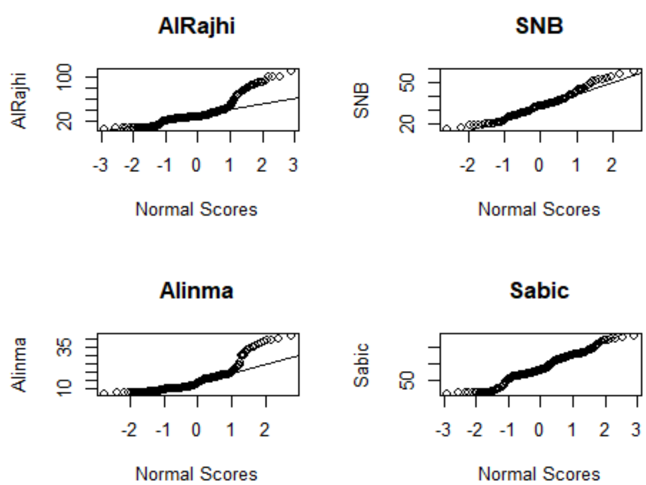


Figure 5. Markets Normality

Examination of the Normality plots can provide further confirmation of the underlying data distributions. Upon closer inspection, it is evident that Alinma and AlRajhi demonstrate a greater frequency of data points deviating from the line of normality. This suggests a lesser degree of normal distribution within their datasets. Conversely, the distributions of SNB and Sabic, characterized by a higher degree of alignment with the normality line, suggest a stronger adherence to normal distribution within their respective datasets.

```
## AlRajhi:
##  Shapiro-Wilk normality test
##
## data:  AlRajhi_ts
## W = 0.8347, p-value = 6.32e-16

## SNB:
##  Shapiro-Wilk normality test
##
## data:  SNB_ts
## W = 0.97033, p-value = 0.01948

##  Alinma:
##  Shapiro-Wilk normality test
##
## data:  Alinma_ts
## W = 0.8086, p-value = 3.876e-14

##  Sabic:
##  Shapiro-Wilk normality test
##
## data:  Sabic_ts
## W = 0.97602, p-value = 0.0002338
```

The results from the Shapiro-Wilk test offer insights into the normality of our series. It is evident that all the series could benefit from enhancing their alignment with normal distribution. However, it is noteworthy that the data from SNB and Sabic exhibit a closer adherence to a normal distribution when compared to AlRajhi and AlInma which confirm the previous analyses. This is demonstrated by their p-values being proximate to exceeding the 0.05 threshold, which signifies an alignment with normality. This offers a constructive direction for further investigation and potential data transformations.

Stationarity

```
## AlRajhi:
##  Augmented Dickey-Fuller Test
##
## data:  AlRajhi_ts
## Dickey-Fuller = -2.2084, Lag order = 6, p-value = 0.4881
## alternative hypothesis: stationary

## SNB:
##  Augmented Dickey-Fuller Test
##
## data:  SNB_ts
## Dickey-Fuller = -2.8447, Lag order = 4, p-value = 0.2264
## alternative hypothesis: stationary
```

```
## Alinma:
##  Augmented Dickey-Fuller Test
##
## data:  Alinma_ts
## Dickey-Fuller = -1.8713, Lag order = 5, p-value = 0.63
## alternative hypothesis: stationary
```

```
##  Sabic:
##  Augmented Dickey-Fuller Test
##
## data:  Sabic_ts
## Dickey-Fuller = -2.8575, Lag order = 6, p-value = 0.2148
## alternative hypothesis: stationary
```

All p-values are higher than 0.05 which indicate that the series is non-stationary. Hence, it contains Trend.

Variance

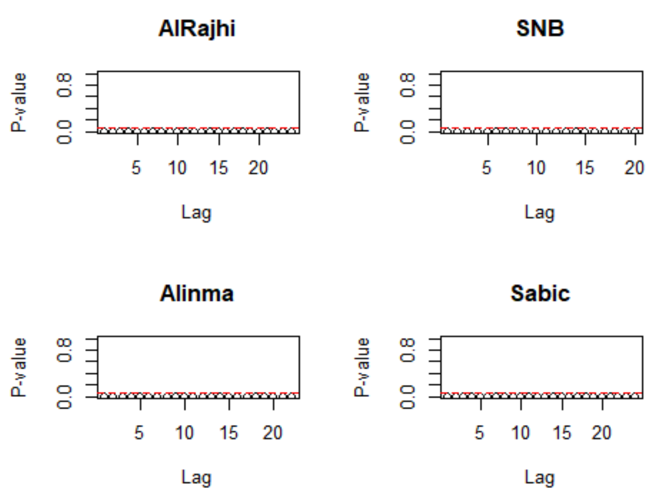


Figure 6. Markets Variance Test

The results of the McLeod-Li test indicate the presence of changing variance across all assessed series. This suggests that the assumption of constant variance, which is required by traditional models such as ARIMA, may not hold. The detection of heteroscedasticity highlights the need to employ more advanced modeling techniques that can account for varying volatility.

In this context, the use of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models becomes particularly relevant. GARCH models are specifically designed to capture and model time-varying volatility, making them suitable for addressing the observed heteroscedasticity in the data. By incorporating GARCH models into the analysis, we can better account for and forecast the changing variance patterns, leading to improved modeling accuracy and performance.

Therefore, based on the evidence of changing variance, it is recommended to utilize GARCH models to adequately capture the volatility dynamics in the data and enhance the reliability of predictions.

Differencing

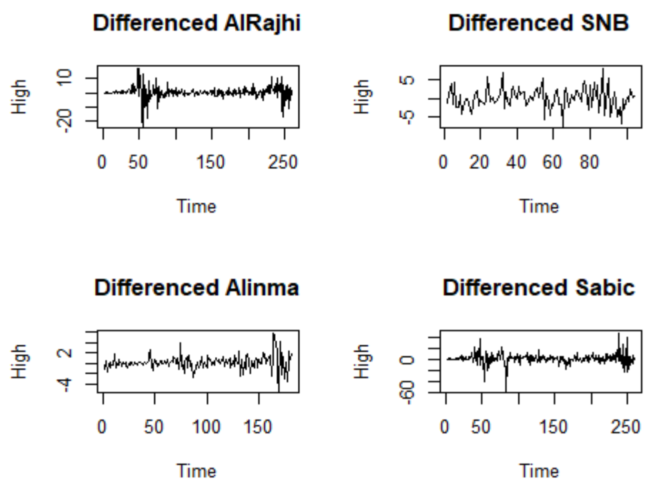


Figure 7. Markets Differenced Series

Stationarity Confirmation

```
## AlRajhi:
##  Augmented Dickey-Fuller Test
##
## data:  diff_AlRajhi
## Dickey-Fuller = -5.0384, Lag order = 6, p-value = 0.01
## alternative hypothesis: stationary

## SNB:
##  Augmented Dickey-Fuller Test
##
## data:  diff_SNB
## Dickey-Fuller = -4.0253, Lag order = 4, p-value = 0.01068
## alternative hypothesis: stationary

## Alinma:
##  Augmented Dickey-Fuller Test
##
## data:  diff_Alinma
## Dickey-Fuller = -4.6367, Lag order = 5, p-value = 0.01
## alternative hypothesis: stationary

## Sabic:
##  Augmented Dickey-Fuller Test
##
```

```
## data:  diff_Sabic
## Dickey-Fuller = -6.2585, Lag order = 6, p-value = 0.01
## alternative hypothesis: stationary
```

The series is stationary now.

Variance After Differencing

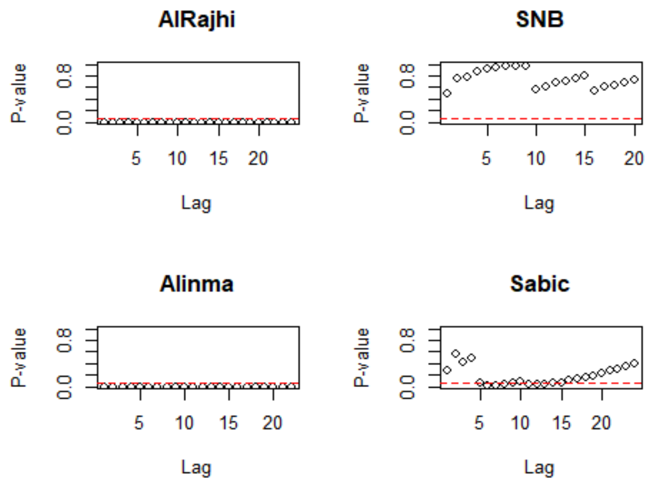


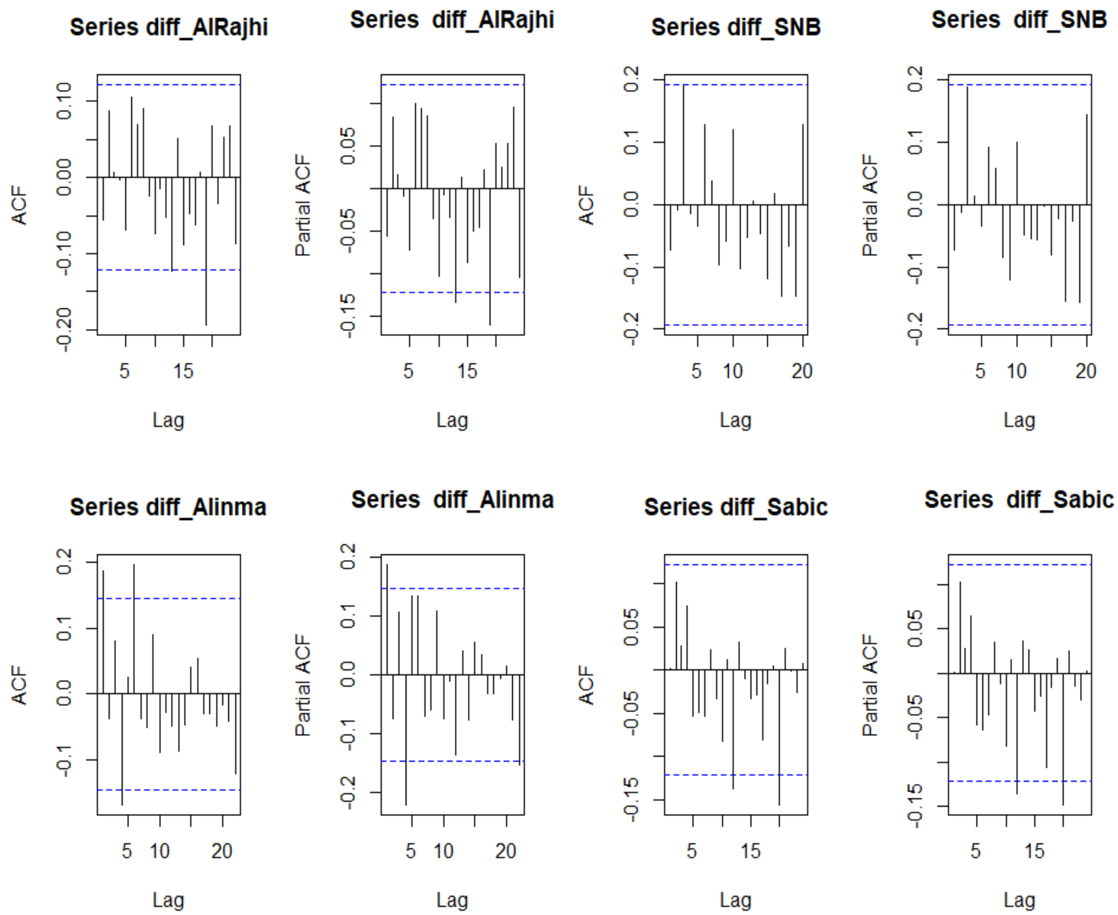
Figure 8. Markets Variance After Differencing

After applying differencing, the analysis suggests that the SNB and Sabic series exhibit a relatively constant variance.

There are several potential reasons why these series might demonstrate a more stable variance after differencing. Firstly, differencing can help remove or reduce any trend or seasonality present in the data, thereby resulting in a more stationary and constant variance process. Additionally, differencing can eliminate any long-term dependencies or memory effects in the time series, leading to a more consistent and predictable behavior in terms of variance.

Model Specifications

ACF & PACF



AlRajhi	ARMA(0,0)
SNB	ARMA(0,0)
Alinma	ARMA(1,1)
Sabic	ARMA(0,0)

Figure 9. Markets ACF & PACF

EACF

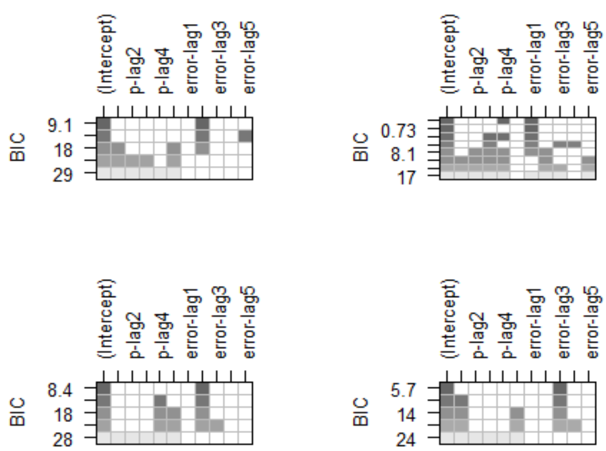
```
## AlRajhi:

AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 o o o o o o o o o o o  o  o  o
## 1 x o o o o o o o o o o  o  o  o
## 2 x o o o o o o o o o o  o  o  o
## 3 x o x o o o o o o o o  o  o  o
## 4 o x o x o o o o o o o  o  o  o
## 5 x x o x o o o o o o o  o  o  o
## 6 x o x o x x o o o o o  o  o  o
## 7 x o x o x x x o o o o  o  o  o

## SNB:

AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 o o o o o o o o o o o  o  o  o
## 1 o o o o o o o o o o o  o  o  o
## 2 o x o o o o o o o o o  o  o  o
## 3 o o x o o o o o o o o  o  o  o
## 4 x o x o o o o o o o o  o  o  o
## 5 x o x o o o o o o o o  o  o  o
## 6 x x o o o x o o o o o  o  o  o
## 7 x x x o o o o o o o o  o  o  o

## Alinma:

AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 x o o x o x o o o o o  o  o  o
## 1 x o o o o x o o o o o  o  o  o
## 2 x o o o o o o 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 o x o o o o o o  o  o  o
## 5 x x x o x o o o o o o  o  o  o
## 6 x x x o x o o o o o o  o  o  o
## 7 x x o o x o x o o o o  o  o  o

## Sabic:

AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 o o o o o o o o o o o  x  o  o
## 1 o o o o o o o o o o o  o  o  o
## 2 x x o o o o o 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 o o o o o o o o  o  o  o
```

```
## 5 x o x o x o o o o o o  o  o  o
## 6 x o x x o o o o o o o  o  o  o
## 7 x o x o x o o o o o o  o  o  o
```

AlRajhi	ARMA(0,0), ARMA(0,1), ARMA(1,1)
SNB	ARMA(0,0), ARMA(0,1), ARMA(1,1)
Alinma	ARMA(0,1), ARMA(1,1), ARMA(1,2), ARMA(0,2)
Sabic	ARMA(0,0), ARMA(0,1), ARMA(1,1)

Figure 10. Markets EACF

BIC



AlRajhi (Top Left)	ARMA(0,2), ARMA(0,5)
Alinma (Top Right)	ARMA(4,1), ARMA(0,1)
SNB (Bottom Left)	ARMA(0,2), ARMA(4,2)
Sabic (Bottom Right)	ARMA(0,3), ARMA(1,3)

Figure 11. Markets BIC

Models Decision 1

AlRajhi	ARMA(0,0), ARMA(0,1), ARMA(1,1), ARMA(0,2), ARMA(0,5)
Alinma	ARMA(1,1), ARMA(0,1), ARMA(1,2), ARMA(0,2), ARMA(4,1)
SNB	ARMA(0,0), ARMA(0,1), ARMA(1,1), ARMA(0,2), ARMA(4,2)
Sabic	ARMA(0,0), ARMA(0,1), ARMA(1,1), ARMA(0,3)

Figure 12. Models Decision 1

Model Fitting

The functions detailed below have been meticulously employed to generate all respective models, utilizing both Maximum Likelihood (ML) and Conditional Sum of Squares (CSS) methods.

```
# a function that makes a variable named with the order p,d,q and a model wit
h p,d,q based on parameter estimation method: ML
fit_arima_ML <- function(p,q,data_set) {
  var_name <- paste0("arima_ML_", p, 1, q)
  assign(var_name, arima(data_set, order = c(p, 0, q), method='ML'), envir =
.GlobalEnv)
  return(get(var_name))
}

# a function that makes a variable named with the order p,d,q and a model wit
h p,d,q based on parameter estimation method: CSS

fit_arima_CSS <- function(p,q,dataset) {
  var_name <- paste0("arima_CSS_", p, 1, q)
  assign(var_name, arima(data_set, order = c(p, 0, q), method='CSS'), envir =
.GlobalEnv)
  return(get(var_name))
}



## AIC & BIC of AlRajhi:

            Model      AIC      BIC
## 1  arima_CSS_010 1494.364 1501.470
## 6   arima_ML_111 1494.364 1501.470
```

```
## 3  arima_CSS_011 1495.492 1509.704
## 8   arima_ML_012 1495.492 1509.704
## 4   arima_ML_011 1495.577 1509.789
## 9  arima_CSS_015 1495.577 1509.789
## 2   arima_ML_010 1495.694 1506.353
## 7  arima_CSS_012 1495.694 1506.353
## 5  arima_CSS_111 1499.195 1524.066
## 10  arima_ML_015 1499.195 1524.066
```

The best Model for AlRajhi based on AIC & BIC is arima_CSS_010.

```
## AIC & BIC of Alinma:

            Model      AIC      BIC
## 1  arima_CSS_111 611.0514 623.8232
## 6   arima_ML_112 611.0514 623.8232
## 5  arima_CSS_112 611.9218 634.2725
## 10  arima_ML_411 611.9218 634.2725
## 3  arima_CSS_011 612.8744 628.8392
## 8   arima_ML_012 612.8744 628.8392
## 4   arima_ML_011 615.5200 628.2919
## 9  arima_CSS_411 615.5200 628.2919
## 2   arima_ML_111 616.5552 626.1341
## 7  arima_CSS_012 616.5552 626.1341
```

The best models for Alinma based on AIC & BIC is arima_CSS_111

```
## AIC & BIC of SNB:

            Model      AIC      BIC
## 1  arima_CSS_010 510.1410 515.4104
## 6   arima_ML_111 510.1410 515.4104
## 2   arima_ML_010 511.5994 519.5035
## 7  arima_CSS_012 511.5994 519.5035
## 4   arima_ML_011 513.5525 524.0914
## 9  arima_CSS_412 513.5525 524.0914
## 3  arima_CSS_011 513.5931 524.1320
## 8   arima_ML_012 513.5931 524.1320
## 5  arima_CSS_111 514.8021 535.8799
## 10  arima_ML_412 514.8021 535.8799
```

The best models for SNB based on AIC & BIC is arima_CSS_010

```
##  AIC & BIC of Sabic:

          Model      AIC      BIC
## 1  arima_CSS_010 1886.689 1893.795
## 6   arima_ML_111 1886.689 1893.795
## 2   arima_ML_010 1888.688 1899.347
## 7  arima_CSS_013 1888.688 1899.347
## 4   arima_ML_011 1889.946 1907.710
## 9  arima_CSS_113 1889.946 1907.710
```

```
## 3  arima_CSS_011 1890.688 1904.900
## 8   arima_ML_013 1890.688 1904.900
## 5  arima_CSS_111 1891.460 1912.778
## 10  arima_ML_113 1891.460 1912.778
```

The best model for Sabic based on AIC & BIC is arima_ML_113.

Coefficients Test

AlRajhi:

```
coeftest(AlRajhi_Model)

## 
## z test of coefficients:
## 
##           Estimate Std. Error z value Pr(>|z|)
## intercept  0.25391    0.27060  0.9383   0.3481
```

Considering the derived coefficients, the AlRajhi Model has been judiciously revised and updated.

```
updated_AlRajhi = arima(diff_AlRajhi, order = c(2, 0, 2), method='ML')

coeftest(updated_AlRajhi)

## 
## z test of coefficients:
## 
##            Estimate Std. Error  z value Pr(>|z|)    
## ar1        0.436721   0.048766   8.9555   <2e-16 ***
## ar2       -0.875150   0.053193 -16.4522   <2e-16 ***
## ma1       -0.474111   0.024651 -19.2331   <2e-16 ***
## ma2        0.979051   0.034042  28.7605   <2e-16 ***
## intercept  0.258216   0.276566   0.9336   0.3505    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Alinma:

```
coeftest(Alinma_Model)

## 
## z test of coefficients:
## 
##            Estimate Std. Error z value  Pr(>|z|)    
## ar1       -0.510602   0.120829 -4.2258 2.381e-05 ***
## ma1        0.772109   0.095707  8.0675 7.178e-16 ***
## intercept  0.115057   0.112701  1.0209    0.3073    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Considering the derived coefficients, the Alinma Model has been judiciously revised and updated.

```
updated_Alinma  = arima(diff_Alinma, order = c(4, 0, 2), method='ML')

coeftest(updated_Alinma)

##
## z test of coefficients:
##
##             Estimate Std. Error z value  Pr(>|z|)
## ar1       -0.218891   0.178121 -1.2289  0.219114
## ar2       -0.558191   0.134628 -4.1462 3.381e-05 ***
## ar3        0.217888   0.075914  2.8702  0.004102 **
## ar4       -0.257691   0.085359 -3.0189  0.002537 **
## ma1        0.480474   0.182220  2.6368  0.008370 **
## ma2        0.595076   0.136361  4.3640 1.277e-05 ***
## intercept  0.114318   0.106192  1.0765  0.281695
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

SNB:

```
coeftest(SNB_Model)

##
## z test of coefficients:
##
##           Estimate Std. Error z value Pr(>|z|)
## intercept  0.08068    0.27823    0.29   0.7718
```

Considering the derived coefficients, the SNB Model has been judiciously revised and updated.

```
updated_SNB = arima(diff_SNB, order = c(2, 0, 3), method='ML')

coeftest(updated_SNB)

##
## z test of coefficients:
##
##              Estimate  Std. Error  z value  Pr(>|z|)
## ar1       -0.63482421 0.03393719 -18.7059 < 2.2e-16 ***
## ar2       -0.98203447 0.03912995 -25.0967 < 2.2e-16 ***
## ma1        0.58128683 0.10064855   5.7754 7.676e-09 ***
## ma2        0.95915506 0.09988284   9.6028 < 2.2e-16 ***
## ma3        0.00038769 0.09644966   0.0040    0.9968
## intercept  0.08305400 0.25944139   0.3201    0.7489
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Sabic:

```
coeftest(Sabic_Model)

##
## z test of coefficients:
##
##            Estimate Std. Error z value Pr(>|z|)
## ar1        0.358452   0.428578  0.8364   0.4029
## ma1       -0.364327   0.426423 -0.8544   0.3929
## ma2        0.099379   0.062823  1.5819   0.1137
## ma3        0.025317   0.081337  0.3113   0.7556
## intercept  0.433775   0.680526  0.6374   0.5239
```

Considering the derived coefficients, the Sabic Model has been judiciously revised and updated.

```
updated_Sabic = arima(diff_Sabic, order = c(4, 0, 2), method='ML')

coeftest(updated_Sabic)

##
## z test of coefficients:
##
##            Estimate Std. Error z value  Pr(>|z|)
## ar1        0.567984   0.132668  4.2812 1.859e-05 ***
## ar2       -0.819457   0.116589 -7.0286 2.087e-12 ***
## ar3       -0.011133   0.074452 -0.1495    0.8811
## ar4        0.107798   0.071909  1.4991    0.1339
## ma1       -0.578242   0.117687 -4.9134 8.952e-07 ***
## ma2        0.938187   0.099428  9.4359 < 2.2e-16 ***
## intercept  0.433961   0.670365  0.6473    0.5174
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Models Decision 2

AlRajhi	arima(diff_AlRajhi, order = c(2, 0, 2), method='ML')
Alinma	arima(diff_Alinma, order = c(4, 0, 2), method='ML')
SNB	arima(diff_SNB, order = c(2, 0, 3), method='ML')
Sabic	updated_Sabic = arima(diff_Sabic, order = c(4, 0, 2), method='ML')

Figure 13. Models Decision 2

ARIMA Models Diagnostic

```
residual.analysis <- function(model, std = TRUE,start = 2, class = c("ARIMA",
"GARCH","ARMA-GARCH", "garch", "fGARCH")[1]){
  library(TSA)
  if (class == "ARIMA"){
    if (std == TRUE){
      res.model = rstandard(model)
    }else{
      res.model = residuals(model)
    }
  }else if (class == "GARCH"){
    res.model = model$residuals[start:model$n.used]
  }else if (class == "garch"){
    res.model = model$residuals[start:model$n.used]
  }else if (class == "ARMA-GARCH"){
    res.model = model@fit$residuals
  }else if (class == "fGARCH"){
    res.model = model@residuals
  }else {
    stop("The argument 'class' must be either 'ARIMA' or 'GARCH' ")
  }
  par(mfrow=c(2,2))
  plot(res.model,type='o',ylab='Standardised residuals', main="Standardised r
esiduals")
  abline(h=0)
  hist(res.model,main="Histogram")
  qqnorm(res.model,main="QQ plot")
  qqline(res.model, col = 2)
  acf(res.model,main="ACF")
  k=0
}
```

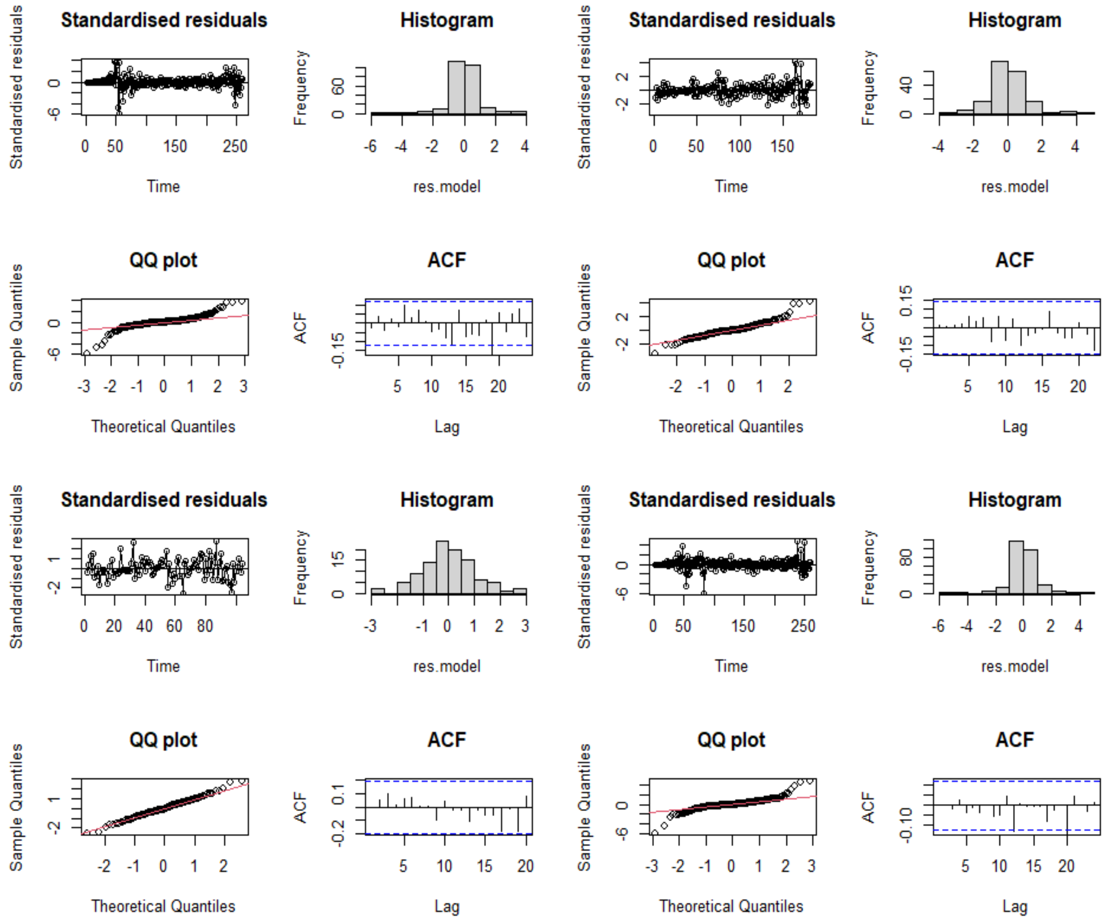


Figure 14. Markets ARIMA Models Diagnostic: AlRajhi (Top Right), Alinma (Top Left), SNB (Bottom Left) & Sabic (Bottom Right)

GARCH Models

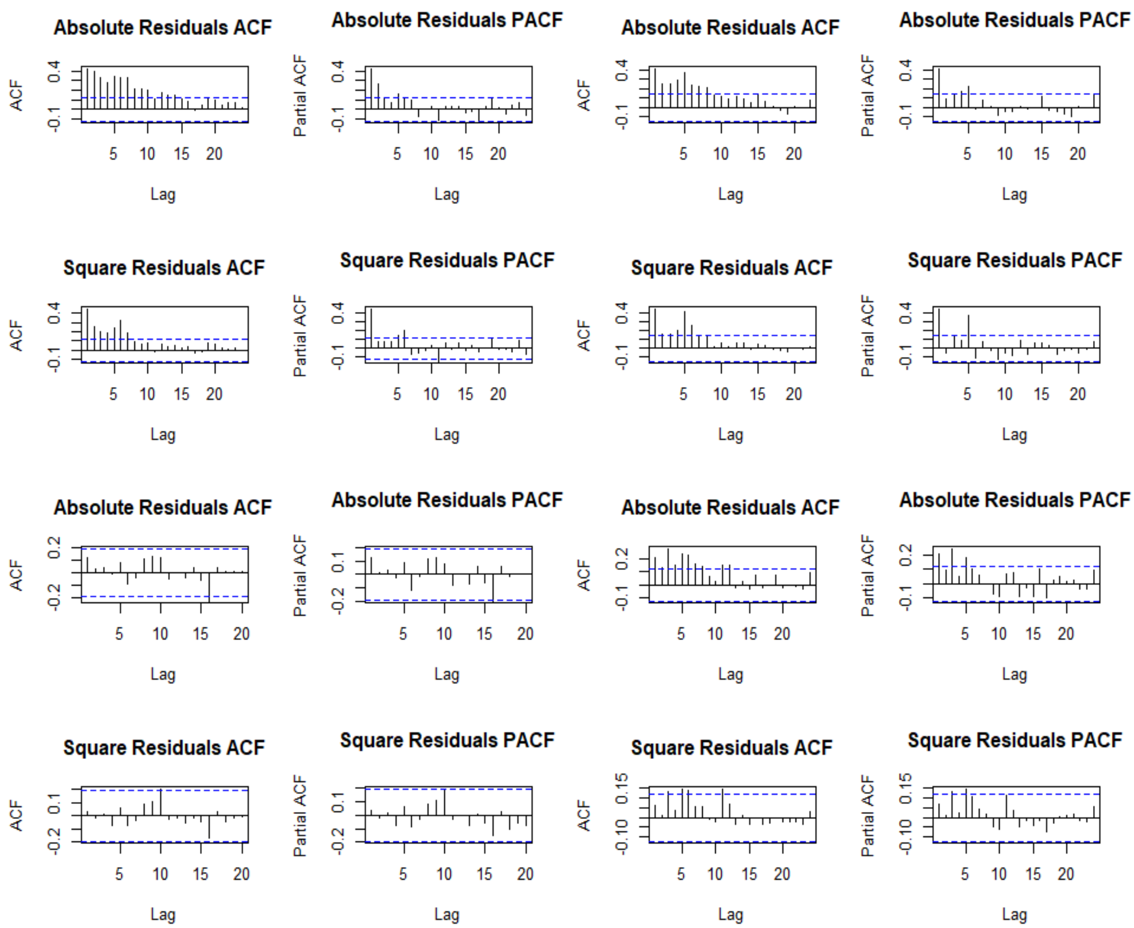
The following points provide compelling evidence that all three markets except SNB under examination necessitate the implementation of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models:

1- Both the Shapiro-Wilk test and the Quantile-Quantile (QQ) plot indicate a deviation from normal distribution across the data from all four markets. This suggests that the features of the datasets are not being fully encapsulated by the Autoregressive Integrated Moving Average (ARIMA) models currently employed.

2- Despite the lack of normality in the residuals, the employed ARIMA models have been successful in capturing the autocorrelation within the datasets. This is evidenced by the absence of significant lags in the residuals.

3- A considerable proportion of the model coefficients have exhibited high p-values, indicating that they are not statistically significant, and their true values may be zero. This lack of statistical significance suggests that these coefficients are not meaningfully contributing to the predictive capacity of the models.

ACF & PACF



AlRajhi	From abs: max(p,q) = 4, q = 0 ==> max(p,q = 0) = 4 ==> p can only be 4. - GARCH(4,0) From sqrt: max(p,q) = 3, q = 0 ==> max(p,q = 0) = 3 ==> p can only be 3 - GARCH(3,0)

Alinma	From abs: max(p,q) = 3, q = 0, p can only be 3 - GARCH(3,0) From sqrt: max(p,q) = 2, q = 0, p can only be 2 - GARCH(2,2)
SNB	Based on the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analysis of the residuals from the Swiss National Bank (SNB), we can determine that the application of a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model may not be necessary. The absence of statistically significant lags in the ACF and PACF provides evidence to suggest that no autoregressive conditional heteroscedasticity is present in the residuals, negating the requirement for a GARCH model.
Sabic	From sqrt: max(p,q) = 3, q = 0, p can only be 3 - GARCH(3,0) From abs: p = 2 and q = 4 because no decaying patterns - GARCH (2,4)

Figure 15. ACF & PACF of Absolut & Square Values of Chosen ARIMA Models to Identify GARCH Orders: AlRajhi (Top Right), Alinma (Top Left), SNB (Bottom Left) & Sabic (Bottom Right)

EACF

```
## AlRajhi EACF of Absolute:

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 o  x  x  x
## 1 x o o o o o x o o o o  o  o  o
## 2 x o o x o o o o o o o  o  o  o
## 3 x o x x o o x o o o o  o  o  o
## 4 x x x x o o x o o o x  o  o  o
## 5 x o x x x o o o o o x  o  o  o
## 6 x o x x o x o o o o o  o  o  o
## 7 x x o x x o x o o o o  o  o  o

## AlRajhi EACF of Square:

AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
```

```
## 0 x x x x x x x o o o o  o  o  o
## 1 x o o o o x o o o o o  o  o  o
## 2 x o o o o x x o o o o  o  o  o
## 3 x x o o o x o o o o o  o  o  o
## 4 x x x o o x o o o o o  o  o  o
## 5 x o x o x x o o o o x  o  o  o
## 6 x x x o x o o o o x o  o  o  o
## 7 x o x o x o o o o x o  o  o  o
```

```
## Alinma EACF of Absolute:

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 o o o  o  o  o
## 1 x o o o x o o o o o o  o  o  o
## 2 x o o o x o o o o o o  o  o  o
## 3 x x o o x o o o o o o  o  o  o
## 4 x o o x x o o o o o o  o  o  o
## 5 o x o x x o o o o o o  o  o  o
## 6 x x o x o o o o o o o  o  o  o
## 7 x x o x o x o o o o o  o  o  o

## Alinma EACF of Square:

AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 x x x x x x o o o o o  o  o  o
## 1 o x o o x o o o o o o  o  o  o
## 2 x x o o x o o o o o o  o  o  o
## 3 x x o o x x o o o o o  o  o  o
## 4 x x x x x x o o o o o  o  o  o
## 5 x o o x x x o o o o o  o  o  o
## 6 x x o x o o o o o o o  o  o  o
## 7 x o o x o x o o o o o  o  o  o
```

```
## Sabic EACF of Absolute:

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 o o x  x  o  o
## 1 x o x o o o o o o o o  x  o  o
## 2 x x o o o o o o o o o  x  o  o
## 3 x x x o x o o o o o o  x  o  o
## 4 x x x o o o o o o o o  o  o  o
## 5 x o o o o o o o o o o  o  o  o
## 6 x o o x o o o o o o o  x  o  o
## 7 o x o o o o o o o o o  o  o  o
```

```
## Sabic EACF of Square:

AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 o o x o x x o o o o x  o  o  o
## 1 o o o o o o o o o o x  o  o  o
## 2 o x o o o o o 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 o o o o o o o o  o  o  o
## 5 x x o x o o o o o o o  o  o  o
## 6 x o o x o x o o o o o  o  o  o
## 7 x o x o o x x o o o o  x  o  o
```

AlRajhi	From abs: max(p,q) = 1, q = 1 ==> max(p,q = 1) ==> p can only be 0 - GARCH(0,1) From sqrt: max(p,q) = 1, q = 6 ==> No Models
Alinma	From abs: max(p,q) = 6, q = 4 ==> max(p,q = 4) ==> p can only be 6 - GARCH(6,4) From sqrt: max(p,q) = 6, q = 4 ==> max(p,q = 4) ==> p can only be 6 - Same
Sabic	From abs: max(p,q) = 2, q = 2, p can only be 2 - GARCH(2,2) From sqrt: max(p,q) = 1, q = 1, p can only be 1 - GARCH(1,1)

Figure 16. EACF Results

Models Decision 3

AlRajhi ARIMA(2,0,2) +	GARCH(4,0), GARCH(3,0), GARCH(0,1)
Alinma ARIMA(4,0,2) +	GARCH(3,0), GARCH(2,2), GARCH(6,4)
Sabic ARIMA(4,0,2) +	GARCH(3,0), GARCH (2,4), GARCH(2,2), GARCH(1,1)

Figure 17. Models Decision 3

GARICH + ARIMA Models Diagnostic

Residuals Analysis

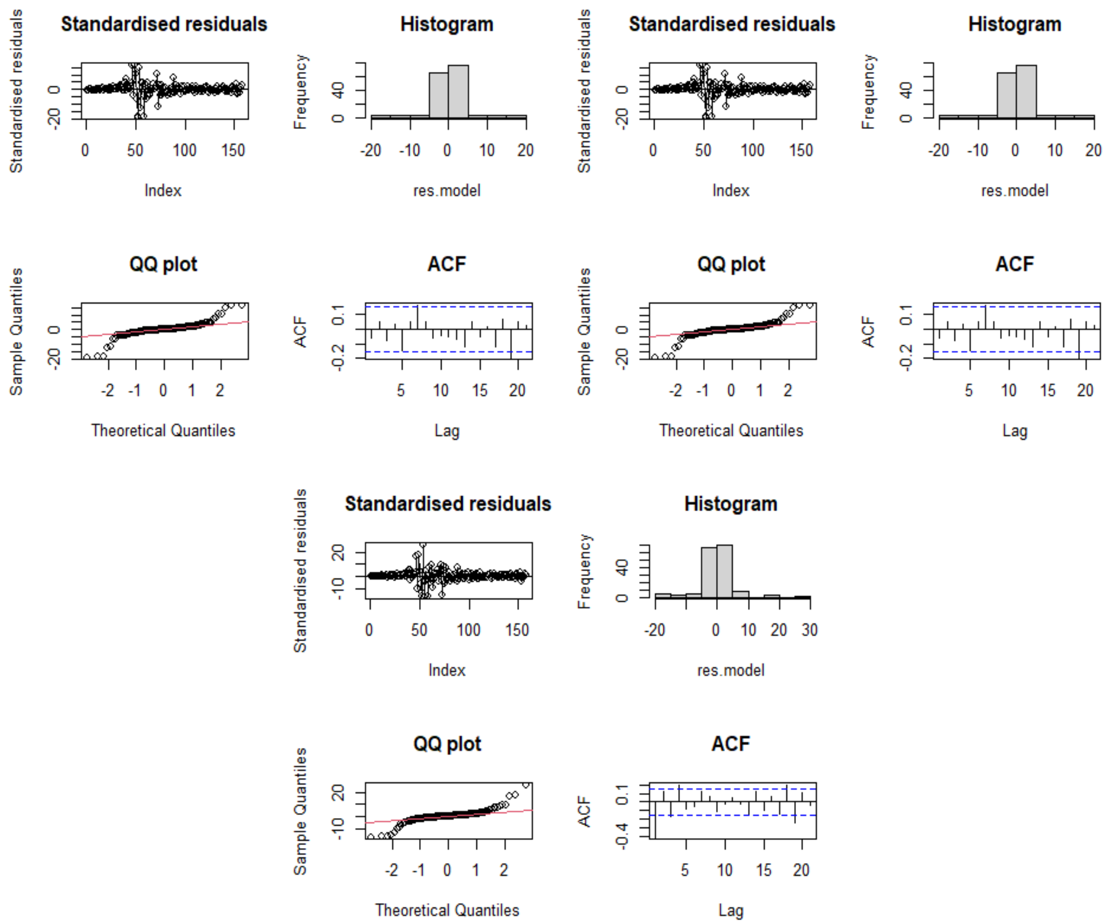


Figure 18. AlRajhi ARIMA(2,1,2) + GARCH Model Residuals Analysis: GARCH(4,0) (Top Left), GARCH(3,0) (Top Right) & GARCH(0,1) (Bottom)

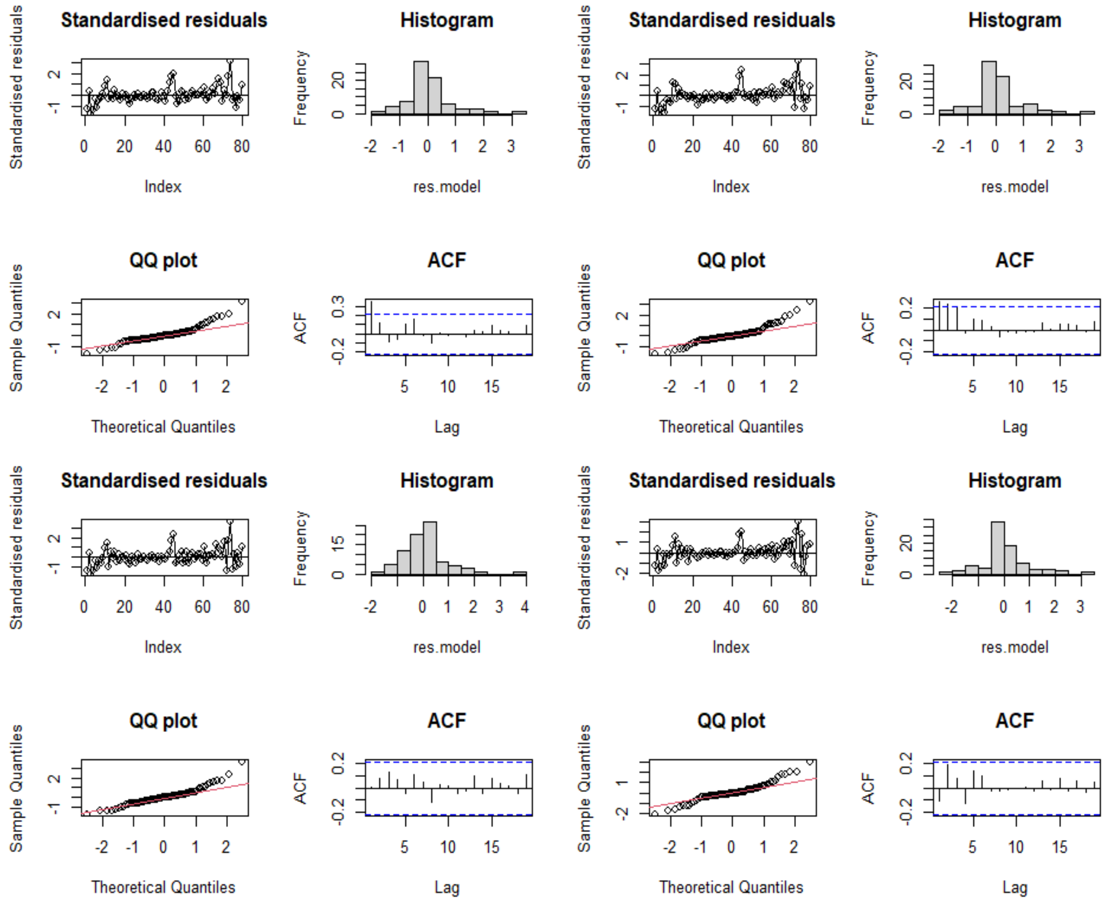


Figure 19. Alinma ARIMA(4,1,2) + GARCH Model Residuals Analysis: GARCH(3,0) (Top Left), GARCH(2,2) (Top Right), GARCH(6,4) (Bottom Left) & New Guessed Order GARCH(0,2)

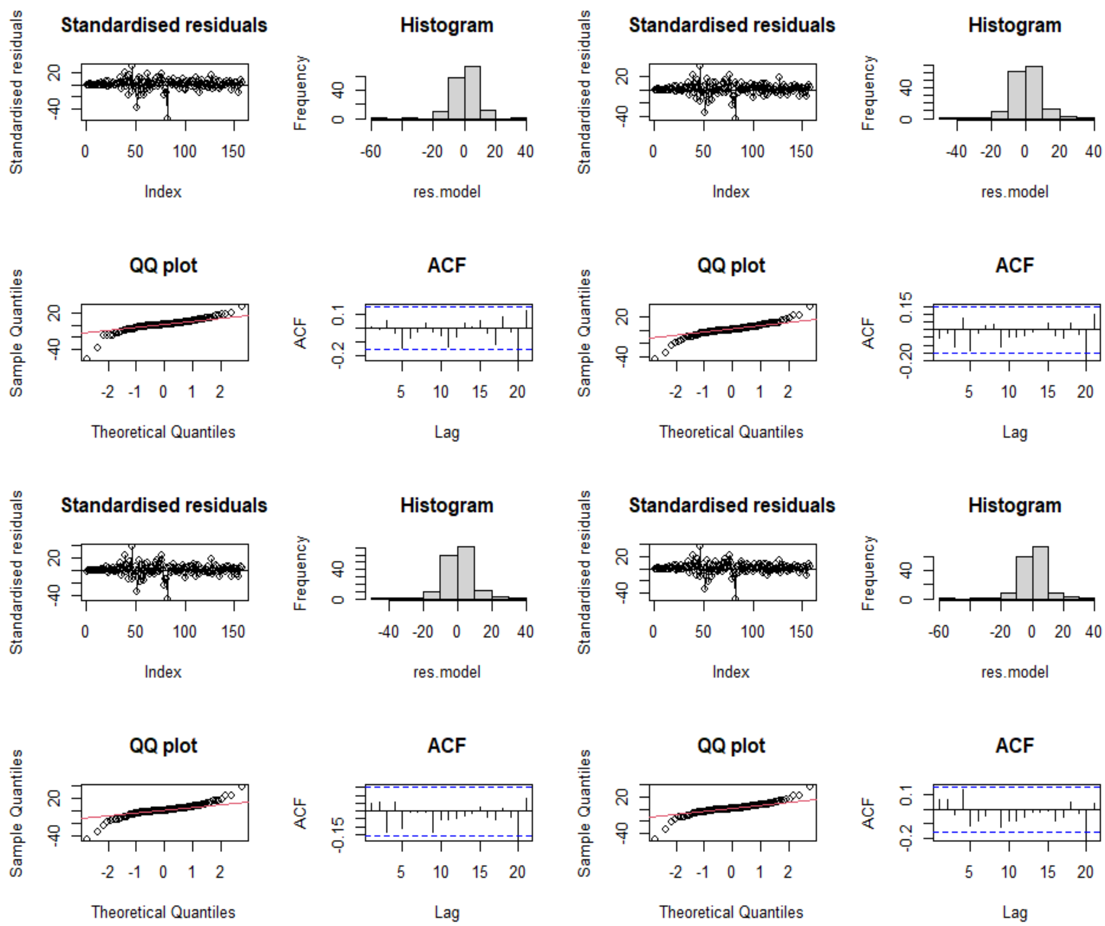


Figure 20. Sabic ARIMA(4,1,2) + GARCH Model Residuals Analysis: GARCH(3,0) (Top Left), GARCH(2,4) (Top Right), GARCH(1,1) (Bottom Left) & GARCH(2,2)

Coefficients Diagnosis

AlRajhi: 3 Models

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(0,4)
Mean Model      : ARFIMA(2,0,2)
Distribution    : snorm

Optimal Parameters
------------------------------------
        Estimate  Std. Error     t value Pr(>|t|)
ar1    -0.725675    0.097107   -7.472919        0
ar2    -0.723148    0.123476   -5.856586        0
ma1     0.807988    0.058159   13.892860        0
ma2     0.904949    0.079857   11.332090        0
omega   0.000000    0.000519    0.000002        1
beta1   0.995162    0.000196 5086.834790        0
```

```
beta2  0.000005    4.580158    0.000001         1
beta3  0.000002    8.839766    0.000000         1
beta4  0.000001    4.261748    0.000000         1
skew   0.945528    0.048777   19.384592         0
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(0,3)
Mean Model      : ARFIMA(2,0,2)
Distribution    : snorm

Optimal Parameters
------------------------------------
       Estimate  Std. Error     t value Pr(>|t|)
ar1   -0.725499    0.097402 -7.4485e+00  0.00000
ar2   -0.722827    0.123921 -5.8329e+00  0.00000
ma1    0.808143    0.058434  1.3830e+01  0.00000
ma2    0.904944    0.080100  1.1298e+01  0.00000
omega  0.000000    0.000525  0.0000e+00  1.00000
beta1  0.995239    0.000066  1.5047e+04  0.00000
beta2  0.000065    0.134779  4.8500e-04  0.99961
beta3  0.000001    0.132720  8.0000e-06  0.99999
skew   0.945620    0.048821  1.9369e+01  0.00000
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,0)
Mean Model      : ARFIMA(2,0,2)
Distribution    : snorm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ar1      0.99528    0.000299   3331.8        0
ar2     -0.50384    0.000151  -3335.2        0
ma1     -0.55022    0.000164  -3348.6        0
ma2      0.32539    0.000095   3412.1        0
omega    0.13452    0.000039   3423.4        0
alpha1   0.42884    0.000125   3421.4        0
skew     1.19168    0.000354   3364.1        0
```

Alinma: 4 Models

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(0,3)
Mean Model      : ARFIMA(4,0,2)
Distribution    : snorm

Optimal Parameters
------------------------------------
       Estimate  Std. Error     t value Pr(>|t|)
ar1   -0.214367    0.000032 -6.6139e+03  0.00000
ar2   -1.143864    0.000016 -7.1941e+04  0.00000
```

```
ar3    -0.243228    0.000011 -2.2159e+04  0.00000
ar4    -0.163913    0.000026 -6.2755e+03  0.00000
ma1    -0.048083    0.000003 -1.8407e+04  0.00000
ma2     1.332195    0.000201  6.6283e+03  0.00000
omega   0.271618    0.223693  1.2142e+00  0.22465
beta1   0.000000    1.919842  0.0000e+00  1.00000
beta2   0.344541    1.245852  2.7655e-01  0.78212
beta3   0.000003    1.139031  2.0000e-06  1.00000
skew    1.420861    0.007727  1.8389e+02  0.00000
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(2,2)
Mean Model      : ARFIMA(4,0,2)
Distribution    : snorm

Optimal Parameters
------------------------------------
        Estimate  Std. Error     t value Pr(>|t|)
ar1    -1.189852    0.000443 -2.6860e+03 0.000000
ar2    -0.507600    0.000124 -4.0835e+03 0.000000
ar3    -0.663411    0.000340 -1.9507e+03 0.000000
ar4    -0.349359    0.000142 -2.4590e+03 0.000000
ma1     1.298073    0.000493  2.6318e+03 0.000000
ma2     0.184090    0.000233  7.8952e+02 0.000000
omega   0.098495    0.050017  1.9692e+00 0.048927
alpha1  0.749784    0.259822  2.8858e+00 0.003905
alpha2  0.001045    0.225736  4.6300e-03 0.996306
beta1   0.081543    0.270973  3.0093e-01 0.763470
beta2   0.002305    0.062472  3.6891e-02 0.970572
skew    1.444969    0.210533  6.8634e+00 0.000000
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(4,6)
Mean Model      : ARFIMA(4,0,2)
Distribution    : snorm

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
ar1    -0.368340    0.639168 -0.576281 0.564425
ar2    -0.663852    0.085887 -7.729381 0.000000
ar3    -0.183327    0.361851 -0.506638 0.612409
ar4    -0.298002    0.237375 -1.255404 0.209332
ma1     0.565849    0.413386  1.368813 0.171058
ma2     0.602403    0.296205  2.033737 0.041978
omega   0.000000    0.000450  0.000001 0.999999
alpha1  0.485548    0.144034  3.371059 0.000749
alpha2  0.000000    0.157230  0.000000 1.000000
alpha3  0.000000    0.061918  0.000001 1.000000
alpha4  0.000002    0.066999  0.000032 0.999974
beta1   0.000000    0.589448  0.000000 1.000000
beta2   0.000000    0.032273  0.000000 1.000000
beta3   0.000000    0.058988  0.000000 1.000000
```

```
beta4    0.000000    0.049507  0.000000 1.000000
beta5    0.513449    0.086710  5.921468 0.000000
beta6    0.000000    0.401071  0.000000 1.000000
skew     1.604199    0.340918  4.705531 0.000003
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(2,0)
Mean Model      : ARFIMA(4,0,2)
Distribution    : snorm

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
ar1    -0.715024    0.033115  -21.5921 0.000000
ar2    -1.086757    0.002356 -461.3085 0.000000
ar3    -0.195360    0.011794  -16.5649 0.000000
ar4    -0.334027    0.021363  -15.6360 0.000000
ma1     1.083253    0.005724  189.2618 0.000000
ma2     1.067045    0.000900 1185.8840 0.000000
omega   0.063115    0.032698    1.9303 0.053572
alpha1  0.773907    0.264938    2.9211 0.003488
alpha2  0.225093    0.105029    2.1432 0.032101
skew    1.381554    0.203182    6.7996 0.000000
```

Sabic: 4 Models

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(0,3)
Mean Model      : ARFIMA(4,0,2)
Distribution    : snorm

Optimal Parameters
------------------------------------
       Estimate  Std. Error   t value Pr(>|t|)
ar1   -0.288662    0.349405 -0.826154 0.408717
ar2   -0.317991    0.292568 -1.086895 0.277083
ar3    0.053835    0.093217  0.577521 0.563587
ar4    0.204578    0.081866  2.498955 0.012456
ma1    0.417183    0.354712  1.176118 0.239548
ma2    0.474966    0.284953  1.666821 0.095550
omega  0.000000    0.004107  0.000067 0.999947
beta1  0.000000    0.091011  0.000001 0.999999
beta2  0.000000    0.063617  0.000001 0.999999
beta3  0.994210    0.077501 12.828304 0.000000
skew   0.805602    0.061267 13.148940 0.000000
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(4,2)
Mean Model      : ARFIMA(4,0,2)
Distribution    : snorm
```

```
Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
ar1     0.934540    0.050694  18.434928 0.000000
ar2    -0.916875    0.065765 -13.941729 0.000000
ar3     0.191185    0.099057   1.930063 0.053599
ar4     0.062331    0.085643   0.727800 0.466736
ma1    -0.779141    0.017519 -44.475100 0.000000
ma2     0.952108    0.015112  63.004448 0.000000
omega   8.095840    3.745563   2.161448 0.030661
alpha1  0.062057    0.042846   1.448380 0.147511
alpha2  0.029276    0.029618   0.988456 0.322930
alpha3  0.445824    0.122162   3.649452 0.000263
alpha4  0.376412    0.681911   0.551995 0.580952
beta1   0.085430    0.819668   0.104225 0.916991
beta2   0.000001    0.187322   0.000007 0.999995
skew    1.011020    0.045942  22.006620 0.000000
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(2,2)
Mean Model      : ARFIMA(4,0,2)
Distribution    : snorm

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
ar1     0.827839    0.081317  10.18037 0.000000
ar2    -0.899490    0.133946  -6.71532 0.000000
ar3     0.183613    0.120648   1.52189 0.128036
ar4    -0.027983    0.108541  -0.25782 0.796550
ma1    -0.785512    0.026437 -29.71289 0.000000
ma2     0.944296    0.024255  38.93185 0.000000
omega   3.607247    1.967766   1.83317 0.066777
alpha1  0.027498    0.054949   0.50043 0.616774
alpha2  0.447158    0.120453   3.71231 0.000205
beta1   0.524344    0.220654   2.37632 0.017486
beta2   0.000000    0.170323   0.00000 1.000000
skew    1.080879    0.103263  10.46727 0.000000
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(4,0,2)
Distribution    : snorm

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
ar1     0.949004    0.108417   8.75329 0.000000
ar2    -0.946152    0.156659  -6.03956 0.000000
ar3     0.082609    0.149735   0.55170 0.581153
ar4    -0.050068    0.110048  -0.45497 0.649134
ma1    -0.928093    0.017614 -52.68988 0.000000
ma2     1.000502    0.017336  57.71113 0.000000
```

	omega	3.505002	2.339703	1.49805	0.134119
	alpha1	0.375379	0.103608	3.62306	0.000291
	beta1	0.623621	0.064267	9.70353	0.000000
	skew	1.042260	0.114315	9.11746	0.000000

Figure 21. All Possible Models Coefficient Diagnosis

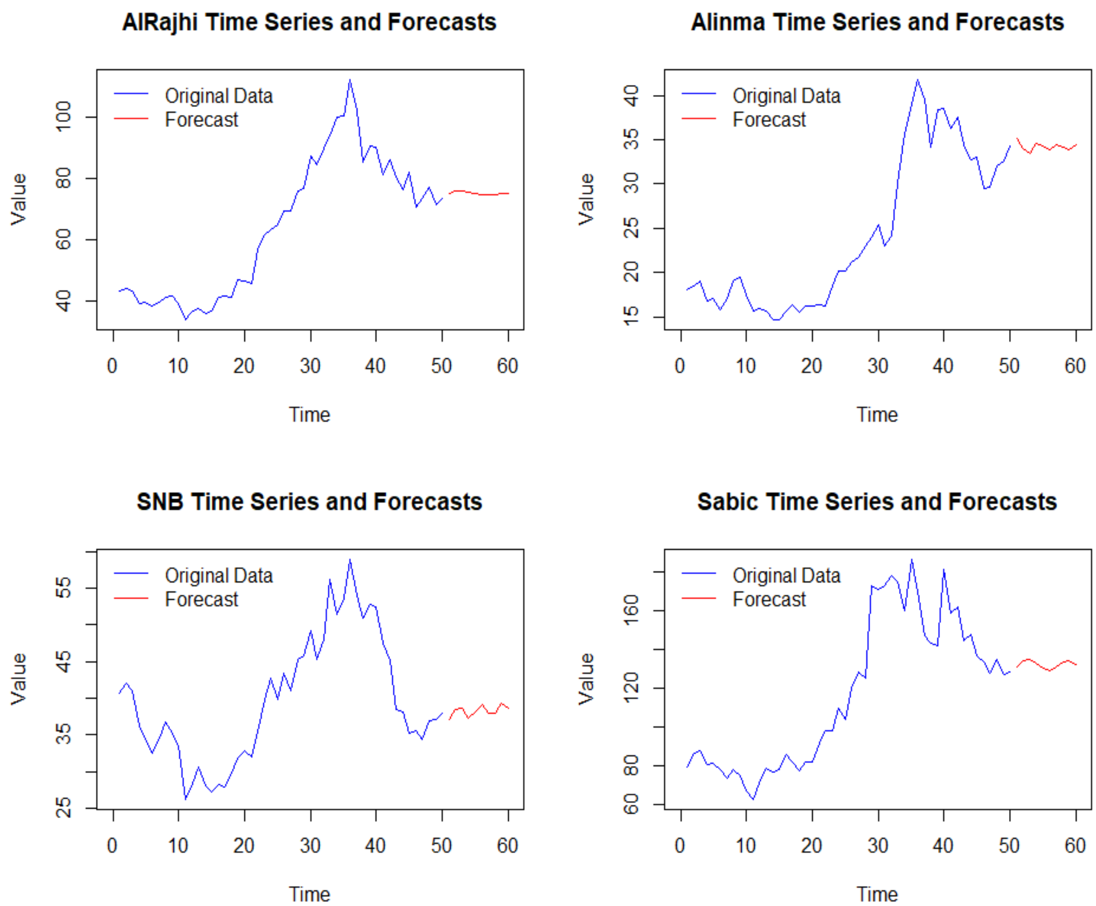
Models Decision 4: Final

The model selection process was guided primarily by the p-values associated with the model's parameters. Emphasis was placed on selecting models characterized by the highest number of coefficients exhibiting p-values less than the established threshold. This stringent selection criterion ensured that chosen models included only those parameters that significantly diverge from zero, thereby implying that these parameters exert a measurable influence on the model's output. This approach facilitates the inclusion of impactful variables while excluding those that do not contribute significantly to the explanation of the dependent variable's variance, thereby enhancing the model's overall predictive capability and efficiency.

AlRajhi	ARIMA(2,1,2)+GARCH (0,1)
Alinma	ARIMA(4,1,2)+GARCH(0,2)
SNB	ARIMA(2,1,3)
Sabic	ARIMA(4,1,2)+GARCH(1,1)

Figure 22. Models Decision 4: Final

Forecasting



	1	2	3	4	5	6	7	8	9	10
AlRajhi	74.98420	75.80064	75.81503	75.41800	75.01559	74.81513	74.81836	74.92258	75.02468	75.07378
Alinma	35.17812	34.02765	33.51545	34.56935	34.32056	33.83747	34.41846	34.22462	33.90930	34.39329
SNB	37.05676	38.41181	38.59754	37.36627	38.18286	39.09096	37.92990	37.99252	39.31031	38.62959
Sabic	130.7324	134.1155	135.1169	132.9086	130.0283	129.2975	131.0967	133.3681	133.9053	132.4512

Figure 23. Forecast for the Final Day of the Next Ten Months

Conclusion

In summation, based on our analysis, the Sabic market emerges as the most potentially lucrative investment opportunity in the forthcoming ten-month span. This is closely followed by AlRajhi, then SNB, with Alinma trailing the pack. It is imperative to note, however, that the stock market data under scrutiny is characteristically volatile and marked by multiple inflection points, adding a layer of complexity to the forecasting process. A significant observation from the analysis was the absence of seasonality.

Our employment of ARIMA models yielded promising results, particularly in capturing the underlying trend and the autoregressive and moving average components of the series. Nonetheless, these models exhibited limitations in adequately accounting for the pronounced volatility and inflection points in the data.

To bridge this analytical gap, we introduced GARCH models, which demonstrated superior competence in capturing the inherent volatility and inflection points. Still, volatility within the data remains a persistent challenge, necessitating more robust and nuanced analysis techniques.

This report, while offering valuable insights, merely scratches the surface of the extensive analysis that can be conducted. A more detailed exploration can potentially unearth deeper patterns and trends to enhance the predictive capacity of our models.

Lastly, it must be emphasized that the paucity of historical data inherently hampers our ability to forecast over a more extended timeframe, thereby impeding long-term investment decisions. The expansion of the data timeframe in future studies might significantly improve the precision of our predictions and offer a more comprehensive view of the investment landscape.

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