TIME SERIES ANALYSIS OF MOROCCAN STOCKS:
Attijariwafa Bank, BMCE Bank, and La Banque Populaire

Capstone design

May 2018

Youssef Ourkia

Supervised by: Dr. Lahcen Laayouni
Capstone student: Youssef Ourkia

Approved by the Supervisor(s)

Supervisor: Dr. Lahcen Laayouni
Table of Contents

Abstract ........................................................................................................................................... 4
Abstract (French) ............................................................................................................................... 5
Introduction: .................................................................................................................................. 6
Definitions: ...................................................................................................................................... 7
Methodology: .................................................................................................................................. 9
Procedure undertaken in the study: ................................................................................................. 10
Attijariwafa Bank: ......................................................................................................................... 10
  Gathering the data: ......................................................................................................................... 10
  Importing the data to RStudio: ...................................................................................................... 11
  Plotting the time series: ................................................................................................................. 12
  Data smoothing: ............................................................................................................................ 14
  Data forecasting: ............................................................................................................................. 17
  Data Testing: ................................................................................................................................ 19
  Forecasting using a different ARIMA model: .................................................................................. 20
BMCE: ............................................................................................................................................. 24
  Plotting the time series: ................................................................................................................. 24
  Data smoothing: ............................................................................................................................ 26
  The seasonal part of the ARIMA model: ....................................................................................... 29
La Banque Populaire: ..................................................................................................................... 34
  Plotting the time series: ................................................................................................................. 34
  Smoothing the data: ....................................................................................................................... 36
  Building the ARIMA model: non-seasonal parameters ................................................................. 38
STEEPLE Analysis: .......................................................................................................................... 43
  Social Aspect: ............................................................................................................................... 43
  Technological Aspect: .................................................................................................................. 43
  Economic Aspect: ........................................................................................................................ 43
  Environmental Aspect: ................................................................................................................ 44
  Political and Legal Aspect: .......................................................................................................... 44
  Ethical Aspect: ............................................................................................................................... 44
Conclusion: ....................................................................................................................................... 45
References: ....................................................................................................................................... 46
Abstract

The financial sector in Morocco is still undergoing major development as stock trading doesn’t play a significant role in the Moroccan culture compared to other countries, mostly the United States of America, England, and Japan. However, Morocco is directing a significant amount of its efforts towards enriching the financial domain as we can see from the recent projects undertaken mainly the Casablanca Finance City. The CFC project aims to create a financial hub in Casablanca inspired by Wall Street in New York to encourage people to invest in stocks and become more accustomed with finance. For the time being, the financial activity in Morocco comes down to the selling and buying of stocks in the Casablanca Stock Exchange. This shows that the financial field in Morocco is still growing and has a lot of room of improvement. The financial decisions in Morocco are based on different news and available information rather than models and mathematical forecasts. In this project, we will extract the data for the three biggest banks traded in Casablanca Stock Exchange: Attijariwafa Bank, Banque Populaire, and BMCE Bank from the website. Based on the information of the year 2017, we will create a time series analysis in the R language to forecast the upcoming values of the stock prices for the different companies for the month of January 2018. This mathematical and statistical approach could not be trusted fully in making a decisive financial decision, but it can greatly help direct our focus to a specific stock. We will therefore, gather different news that might be related to the companies we are interested in and to the market itself in order to explain fluctuation in the price of stocks for the year of 2017. The month of January will be used in order to verify the accuracy of our forecasts.
Abstract (French)

Le secteur financier marocain est en pleine évolution car la bourse ne joue pas encore un rôle très significatif dans la culture du Maroc comparé aux autres pays, principalement les Etats-Unis, l'Angleterre et le Japon. Cependant, le Maroc consacre une grande partie de ses efforts à l'enrichissement et le développement du domaine financier, comme en témoignent les récents projets menés principalement le project du Casablanca Finance City. Le projet CFC vise à créer un centre financier à Casablanca inspiré par Wall Street à New York pour encourager les gens à investir et à s'habituer à la finance. Pour le moment, l'activité financière au Maroc se résume à la vente et à l'achat d’actions à la Bourse de Casablanca. Cela montre que le secteur financier au Maroc continue de croître et peut encore progresser. Les décisions financières au Maroc sont plus basées sur différentes informations plutôt que sur des modèles et des prévisions mathématiques. Dans ce projet, nous allons extraire les données des trois plus grandes banques cotées à la Bourse de Casablanca: Attijariwafa Bank, Banque Populaire et BMCE Bank. En utilisant les informations de l'année 2017, nous allons créer une analyse de séries chronologiques en langage R pour prévoir les prochaines valeurs des cours des actions des différentes sociétés pour le mois de janvier 2018. Cette approche mathématique ne peut pas être pleinement prise en compte pour prendre une décision financière décisive, mais elle peut grandement aider à orienter notre attention vers un stock spécifique. Nous allons donc rassembler différentes nouvelles qui pourraient être liées aux sociétés qui nous intéressent et au marché lui-même afin d'expliquer la fluctuation du prix des actions pour l'année 2017. Le mois de janvier sera utilisé afin de vérifier l'exactitude de nos prévisions.
**Introduction:**

In this Study we will use the R language to perform a time series analysis for three different Moroccan companies listed in the Casablanca stock exchange with the aim of finding a viable model that could be used to forecast their future values. The choice of the companies was based on their sector of activity: banking and their capitalization. The three chosen banks are: Attjariwafa Bank, BMCE Bank, and La Banque Populaire which are the most traded Banks in the stock exchange the thing that gives us enough data to conduct our study. The modeling technique that will be used in the study is called ARIMA that stands for Auto-Regressive Integrated Moving Average and which will be defined further in the paper.
Definitions:

Finance is a field of study dealing with the management of valuable assets, notably money. In this field, applied mathematics are used in order to get ahold of the way the market is behaving and get a slight idea on what will be its movement in the coming years. Two main technics are used in order to forecast future prices of different financial products. The first one is the use of stochastic differential equations, notably Thiele’s differential equation and Black-Scholes differential equation in determining future prices of different financial product in the financial market. The second method and the one that we will be using in this project, is the application of statistics in predicting future prices of different stocks. This technique is based mainly on the use of time series in the forecasting of the future prices.

Time series are a multitude of data points taken in different points in time spaced by the same interval. In our case, the data points will be the closing stock prices that are taken daily during the working days of the Casablanca Stock Exchange, meaning from Monday to Friday. The plotted time series will give a visual insight on the behavior of the data prices and will enable us to run different averaging methods, with which we will get the trend of the prices. Different autoregressive models are already developed to fit different data plots using a multitude of variables. In this study we will choose the ones that will suit us best.

An autoregressive model is a model that uses previous data collected of a phenomenon – in our case stock prices of listed Moroccan companies in the Casablanca stock exchange market- to predict its future behavior. These models have a mathematic correlation between the future data and the previous recordings.
The most used model for forecasting based on time series is the ARIMA model which stands for Auto-Regressive Integrated Moving Average. The ARIMA \((p, d, q)\) model has three variables: \(p\), \(d\), and \(q\) that are to be changed in order to find the best fit of the data at hand. As its name implies, the variables \(p\), \(d\), and \(q\) are respectively the auto regressive variable, the integration variable, and the moving average variable. Different combinations of variables lead to different smoothing models, mainly the first-order auto-regressive model which only takes into consideration one preceding value to get the present value of the data. The more preceding values the model takes into account, the higher its order and the more accurate it becomes. The second smoothing model is the random walk that is used mainly for non-stationary series, when the change from one period to another is arbitrary. The last model within the ARIMA is the exponential smoothing, which exponentially weights the average of the previous recordings to forecast future values.

In the second part of the project, we will be using the ARIMA model with seasonality which adds a seasonal part to the configuration. In addition to the three first parameters which are \(p\), \(d\), and \(q\), we will have \(P\), \(D\), \(Q\), and \(m\) which is called the span of seasonality. The determination of these parameters can be done using ACF and PACF which stand for Autocorrelation and Partial Autocorrelation respectively. These two plots can be used to guide us determine what parameters should be used based on the behavior of the lags. Using this method will not be deterministic on what parameters should be chosen for the seasonal ARIMA model. It can only guide our choices of parameters. For this project, we will choose a multitude of models with different parameters and compare between them using two information criterions.

The two information criterions used are the AIC and BIC which stand for the Akaike and Bayesian information criterions. They are both used to evaluate the effectiveness of models by
assigning values to the models and the lower the value the better the model fits the data. We could have used the Akaike information criterion alone but it is better to use the Bayesian in case the data set is large because it takes into account the number of points in the data set.

**Methodology:**

The goal of this capstone project is to find the model that will have the best fit to the stock prices of different companies using time series. The steps undertaken in this study with the methodologies used is as follows:

We started by gathering the data of the different Moroccan banks chosen to be a part of the study, starting by Attijariwafa Bank then BMCE, and at last La Banque Populaire. In order to fulfill this step, we went to the Casablanca Stock Exchange website where we got the stock prices for the year 2017 on which we will base our study.

The methodology used to forecast the stock prices for January 2017 is based on a standardized set of models called ARIMA. ARIMA stands for Auto Regressive Integrated Moving average which represents a combination of two methods of modeling which are: Auto Regression and Differencing. In this study we will use the full ARIMA model which has two parts: the seasonal and the non-seasonal. This technique turned out to be very effective in different sectors and mainly in forecasting stock prices according to a study that has been done constructed around Indian stocks [4]. The study was based on the two-years data collected for fifty-six companies listed in the stock exchange market with the biggest volume in India: The National Stock Exchange. The study concluded that the ARIMA models are very effective when it comes to predicting stock prices as for all the companies used, the accuracy turned out to be at
least 85%, which is very accurate in financial predictions, knowing the number of parameters that intervene in the fluctuation of the stock prices [4].

**Procedure undertaken in the study:**

The first steps of the procedure consisting of gathering the data and importing it to RStudio are the same for Attijariwafa Bank, BMCE Bank and La Banque Populaire. The steps that follow will give different results for different companies due to the variance in primary data. For convenience, the first two steps of the procedure will only be mentioned in Attijariwafa Bank’s process but it is implied that they have already been carried out as preparation for the data of the other two companies, being BMCE Bank and La Banque Populaire, in order to start the study.

**Attijariwafa Bank:**

**Gathering the data:**

The first step of this project was to gather the desired data upon which we will base our study. The first and most fundamental data set is the historical stock prices of the listed companies chosen for the study that are namely: Attijariwafa Bank, Banque Populaire, and BMCE Bank. These companies were chosen based on their field of activity and their market capitalization which directly correlates to their number of shares outstanding. The daily stock prices of 2017 of each company have been extracted from the official website of the Casablanca Stock Exchange, in addition to the stock prices of January 2018 that will be used to test the results of our predictions.
The second valuable data are the news related to the different chosen companies that will be used afterwards to explain fluctuations in the plots of the stock prices. Other world or local news could be valuable to our research as well. The news was retrieved from the Morocco World News website which has a special rubric for economy that highlights all the major changes occurring in the economy sector in Morocco. Other websites are used as well but the main events are extracted from MWN website.

**Importing the data to RStudio:**

After gathering all the data, the next step was to import it to RStudio in order to be able to manipulate it using the R language. The numbers in Morocco follow the European system, which uses commas instead of dots to separate the decimals which made RStudio unable to understand the meaning of our data. To fix this problem, we uploaded the excel sheet to SPSS and manipulated the data so that all the numbers are consistent with the American regulations. After that, we assigned each column to the right variable type to which it belongs in order to make handling tasks with R easier. The data was organized in the following way:

![Figure 1: Stock information of Attijariwafa Bank organized in SPSS](image-url)
TIME SERIES ANALYSIS OF MOROCCAN STOCKS

Even if the initial data contained different components, we only took into consideration two of them in our study: The ‘Date’ (Séance) and ‘The closing price’ (Cloture) which we assume reflects the average price of the stock for the same day. We only imported the two pieces of information of interest to our study into RStudio to have the following figure:

![Figure 2: Stock prices of Attijariwafa Bank as imported in RStudio](image)

For the data to be fully maneuverable using the R language, we had to use the haven library. This library enables us to retrieve and manipulate data using the R language, which is the first and most crucial step in our project. The following piece of code in R gets the data and displays it in the viewer of RStudio:

```r
library(haven)
Att <- read_sav("C:\Users\Youssef\Desktop\Spring 2018\Capstone\Companies\One year data\Attijariwafa Bank\Att.i.SAV")
View(Att)
```

![Figure 3: Reading and displaying the stock information in RStudio](image)

The data at this point is available and fully manageable in the R language so the next step would be to plot the prices with respect to time and find the trend with which it varies and use our method to find the most appropriate model.

**Plotting the time series:**

In this step, we will plot the data of the stock prices with respect to time using the tools available in the R language. We will create a time series object in R studio that will contain the
data imported previously. To do so, we will need to use two famous libraries: “zoo” and “xts” that are made specifically to make handling time series in R very intuitive. These libraries are equipped with different built-in functions to create and manipulate time series objects. The function plot is then used to get a chart of stock closing prices versus their respective dates. The following piece of code was used to create a time series object and generate the plot:

```r
library(zoo)
library(xts)
Att1_ts <- xts(x = Att1, order.by = Att1$Date)
Class(Att1_ts)
plot(Att1$Date, Att1$Price, main = "Plot of Stock prices of Attijariwafa Bank in 2017", xlab = "Date", ylab = "Price", type = "n")
lines(Att1)
```

**Figure 4:** R code to create a time series object and plot the data

The following plot of stock prices in different points in time was generated in RStudio and it shows that the stock prices have a tendency to increase with time:

**Figure 5:** Data plot of stock prices of Attijariwafa Bank for the year 2017

From the plot, we can see that the data is increasing in the long term but we still cannot say that the prices will keep following this trend. At this stage of the analysis, we still can’t draw any conclusions concerning the evolution of the stock prices of the company Attijariwafa Bank.
This plot is only a mere visual representation of the data we have gathered from the Casablanca Stock Exchange.

From the graph, we can see that the stock prices started peaking with a fast pace in January 2017 and after that, it dropped until May when it started growing with a slow pace and a small amount of noise. The change that occurred in January can actually be explained by an event that occurred at the end of December 2016, where Attijariwafa Bank got awarded three different prizes in London. The year 2016 was a great year for Attijariwafa Bank, as it got awarded ‘Best Moroccan bank of the year’ in addition to other trophies by a subsidiary magazine of the Financial Times. All of these awards drew the attention of Moroccan investors towards Attijariwafa Bank, which impacted greatly its stock price.

The slow paced increase that the stock price of Attijariwafa Bank knew starting May and that lasted for the remaining of the year, excluding the perturbations that it went through during that period, is thanks to its new acquisition. In May 5th 2016, Attijariwafa Bank acquired 100% of an Egyptian Bank called ‘Barclays’, which extends its domain of practice to a new country. This event helped attract a lot of investors in the long term seen the profitability of the new acquisition. The next step of this study is the smoothing of the time series data of Attijariwafa Bank by different averaging and smoothing methods in order to run the auto.arima() function and get the non-seasonal parameters of ARIMA.

**Data smoothing:**

Data smoothing is a technique used to remove the noise from plots to better see and recognize the patterns with which the data is changing. There are different techniques that could be used to make the data at hand smoother mainly: Seasonal Adjustment and Moving Averages.
In this study we will start by averaging the data plotted weekly and monthly to see which of the two better removes noise and fits the data. The function used to compute the moving averages is the built-in function: \( \text{ma()} \) which stands for moving average. This function takes two arguments: the first one is the data to be averaged and the second one is the order of smoothing, which means the width of the period. For the weekly moving average, we took the order to be 5 instead of 7 because a week in the Casablanca Stock Exchange starts Monday and ends Friday as the market is closed for the week ends. For the ‘Monthly moving average’, the order is 20, which represents the number of working days in a month. For both averages, the data given to the function is the stock prices of Attijariwafa Bank. After plotting the original data and the two averages in one reference, we get the following plot:

\[\text{Figure 6: The moving averages compared to the original data of Attijariwafa Bank}\]

For the remaining of the project, we will be using the weekly moving average instead of the monthly moving average because of different factors. The first is that even if the monthly average cancels out a lot of noise from the graph, we might lose valuable information in the
process. The weekly average in the other hand is the closest to the original plot of data prices with a considerable smoothing and cancelation of noise, which will enable us to preserve the major information presented by the graph. All of the advantages cited above make the weekly moving average very reliable and can be used in our study.

The next step in smoothing the data is the elimination of the seasonal effect from the previous plot of stock prices. The seasonality represents any change in the evolution of the prices that occurs every definite period of time. To do so, we will first use the function \texttt{stl()} from the forecast library that will enable us to clearly see the seasonality of the data at hand. After applying the function, we will plot the resulting data and examine the seasonality of Attijariwafa Bank’s stock prices in the year 2017. The following graph represents the different seasonality and the trend of the data at hand:

![Graph](image)

**Figure 7:** The representation of the seasonality of the Attijariwafa Bank Stock prices
From the resulting graph, we can see that our data has a seasonal component that should be taken out of the equation before proceeding into the application of the ARIMA model. Taking out the seasonality from the plot will make our forecasting more accurate and closer to the real values that will be used later for testing our model. The forecast package enables us to take the seasonality out of the equation with a simple function called `seasadj()` that modifies the original plot by subtracting the seasonality.

**Data forecasting:**

The next step will be to try a model on our data to see how the prices will behave in the future. The model that we will be using at first is the ARIMA which stands for Auto Regressive Integrated Moving Average which is the most widely used to study future changes in data. It is known for its flexibility because it could be controlled by changing one or more of its parameters. The function used to find the best parameters that would generate the most accurate fit of the data is called `auto.arima()` and it belongs to the forecast library. The function runs the autocorrelation function and evaluates where the lags spikes up which gives the values of the ARIMA parameters. After using the `auto.arima()` function on the data that doesn’t have the seasonal component, we get a (3,1,3) ARIMA that give an approximated behavior for the next 20 days using the `forecast()` function. The following code in R was used in order to forecast the values:

```r
arima(Atti$Price)
fit <- auto.arima(deseasonal_Atti, seasonal = FALSE)
fcast <- forecast(fit, h=20)
plot(fcast)
```

**Figure 8:** Displaying the forecast of the prices using ARIMA model in RStudio

The following graph results from running the previous code in RStudio and represents the forecast of the data for the next twenty days given by the model ARIMA(3,1,3). The model may
not be the best fit for our data but we decided to start from it and refine the model to get the best fit. We may end up using other models throughout the study if they better fit the graphs of the stock prices.

![Graph of Stock Price Forecast](image)

**Figure 9:** The forecast of the Stock prices for the January 2018 for Attijariwafa Bank using auto.arima

The blue portion of the graph represents the values generated by the `forecast()` function using the ARIMA(3,1,3) model. In our study, other models should be used in order to find the most appropriate fit to the data at hand. The most accurate model will be determined by comparing the values predicted by the model and the real stock values of the year 2017. The same analysis should be conducted on the other stocks and news will be taken into account when coming up with a theory about the fluctuation of the stock prices.
Data Testing:

The next step that comes after forecasting the data is to test its accuracy by comparing it with the daily prices of the stock for the month of January 2018. To do so, we will have to import the data of January 2018 to RStudio and suppress the seasonality using the function `seasadj()`.

The resulted deseasonalized function will be then plotted in the same graph as the forecast that resulted from applying the `auto.arima()` function in order to see how close our predictions are to the real values. The following figure shows the gap between the forecasted values and the real deseasonalized values:

![Comparison between the real deseasonalized values and the forecasted values](image)

**Figure 10:** Comparison between the real deseasonalized values and the forecasted values

We can see from the graph that the difference between the two is very significant. This forecasting ARIMA model doesn’t give us a real insight on how the stock prices of Attijariwafa
Bank will behave in January 2018. We conclude that we need a different ARIMA model in order to be able to predict more accurately the future fluctuations of our data.

**Forecasting using a different ARIMA model:**

In order to achieve our goal and get the maximum accuracy, we will use a more complex ARIMA model by adding the seasonality component which adds three parameters to the equation. Concerning the non-seasonal part of the ARIMA model, we will use the parameters that resulted from running the `auto.arima()` function on the time series after removing the seasonality. The parameters used will then be 3, 1, and 3 respectively. When it comes to the seasonal part, we will compare different models using different parameters and get the closest to the real values by using two evaluation criterions: AKAIKE and BAYESIAN information criterions. These two parameters show how accurate our model is and the smaller they are, the better the model suits our data.

**Seasonal part of the model:**

To get the best results, we will compare different ARIMA models with 3, 1, and 3 as non-seasonal parameters and different seasonal parameters. Based on the two criterions discussed before, we will choose the closest model to our data and compare its forecasting of January 2018 to the real values of the same month. The next table shows the AIC and BIC of different ARIMA models that can be fitted to Attijariwafa Bank’s stock price:
When we compare the AICs of the different models chosen, we get that the one with the lowest value is (3,1,3)(1,0,0) but the one with the lowest BIC value is (3,1,3)(2,2,0). To choose between the two previous models with the best AIC and BIC, we will compare their Variance. For the (3,1,3)(2,2,0), the variance is equal to 47.14 and it is equal to 28.82 for the (3,1,3)(3,1,0) model. The difference is very significant so the one we will be choosing is the (3,1,3)(3,1,0) model.

*Testing the model:*

After plugging different parameters and selecting one combination based on the two information criterions, we found that the ARIMA(3,1,3)(3,1,0) is the best fit for our data and gives the closest forecast to the real values. The first three parameters that represent the non-seasonal part of our model were retrieved from running the `auto.arima()` function on the deseasonalized stock prices of Attijariwafa Bank. The parameters of the seasonal part of the model, however, were chosen after the trial of different model with different parameters. The following plot represents the results of the forecasting using the new model in comparison with the real data retrieved from the Casablanca Stock Exchange website of January 2018:
From the above graph, we can see that our predictions follow the path of the real stock price values. To further confirm that our predictions are very close to the real values, we will calculate the mean of the error between the model used to forecast the values and the real values. We will take the error to be the difference between the real stock values and the values given by the chosen model to compute its mean and see how close our predicted data is to the real numbers. By using the function $mean()$ on the resulting error, we can get mean of the error which depending on how small it is, can affirm how close the model resulting data is to the real values for the year 2017. The function returns the value 0.06253916 which means that our generated values using the model are close to the real data at an average error of $+\text{-} 0.06253916$. 

Figure 12: The comparison of the forecasted stock prices with the real values
**Predicted Values:**

In order to further demonstrate the accuracy of the chosen model, we will extract the numerical values given by the model for the month of January of the year 2018 to compare them with the real values recorded that same month. The following table shows the comparison between the two values and the percent accuracy for each day:

<table>
<thead>
<tr>
<th>Date</th>
<th>Actual Values</th>
<th>Predicted values</th>
<th>Percent accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>2/01/2018</td>
<td>481</td>
<td>482.0887</td>
<td>99.77%</td>
</tr>
<tr>
<td>3/01/2018</td>
<td>490</td>
<td>482.8619</td>
<td>98.54%</td>
</tr>
<tr>
<td>4/01/2018</td>
<td>490</td>
<td>480.3277</td>
<td>98.03%</td>
</tr>
<tr>
<td>5/01/2018</td>
<td>497.85</td>
<td>484.5535</td>
<td>97.33%</td>
</tr>
<tr>
<td>8/01/2018</td>
<td>492</td>
<td>485.9737</td>
<td>98.78%</td>
</tr>
<tr>
<td>9/01/2018</td>
<td>496.05</td>
<td>486.1239</td>
<td>98.00%</td>
</tr>
<tr>
<td>10/01/2018</td>
<td>500</td>
<td>490.557</td>
<td>98.11%</td>
</tr>
<tr>
<td>12/01/2018</td>
<td>500</td>
<td>487.8013</td>
<td>97.54%</td>
</tr>
<tr>
<td>15/01/2018</td>
<td>508</td>
<td>490.1353</td>
<td>96.48%</td>
</tr>
<tr>
<td>16/01/2018</td>
<td>500</td>
<td>489.9918</td>
<td>98.00%</td>
</tr>
<tr>
<td>17/01/2018</td>
<td>500</td>
<td>486.2508</td>
<td>97.25%</td>
</tr>
<tr>
<td>18/01/2018</td>
<td>500</td>
<td>484.6241</td>
<td>96.92%</td>
</tr>
<tr>
<td>19/01/2018</td>
<td>500</td>
<td>486.3941</td>
<td>97.28%</td>
</tr>
<tr>
<td>22/01/2018</td>
<td>505</td>
<td>487.2518</td>
<td>96.49%</td>
</tr>
<tr>
<td>23/01/2018</td>
<td>500</td>
<td>484.2151</td>
<td>96.84%</td>
</tr>
<tr>
<td>24/01/2018</td>
<td>501</td>
<td>486.7986</td>
<td>97.17%</td>
</tr>
<tr>
<td>25/01/2018</td>
<td>509.3</td>
<td>489.574</td>
<td>96.13%</td>
</tr>
<tr>
<td>26/01/2018</td>
<td>507.9</td>
<td>492.2242</td>
<td>96.91%</td>
</tr>
<tr>
<td>29/01/2018</td>
<td>503.6</td>
<td>493.3753</td>
<td>97.97%</td>
</tr>
<tr>
<td>30/01/2018</td>
<td>507.7</td>
<td>494.6857</td>
<td>97.44%</td>
</tr>
<tr>
<td>31/01/2018</td>
<td>500</td>
<td>492.5919</td>
<td>98.52%</td>
</tr>
</tbody>
</table>

**Figure 13:** Comparison between the real and forecasted values of Attijariwafa Bank

We can see from the table that the lowest accuracy percentage is equal to 96.13%, which is a good indicator of the performance of the model at hand. After calculating the average of the percentages, which turned out to be 97.59%, we had a better idea on the precision of the forecasting. This value shows that the model chosen is highly accurate. This finding is unexpected because it models a Moroccan company in the Casablanca stock exchange where the trades are not usually based on mathematical models and algorithms which make the stock prices hardly predictable.
Concerning the two other banks used in our study being La Banque Populaire and BMCE, we will directly use the seasonal ARIMA model in order to have the best fits possible to the data and therefore get the most accurate forecasting. The ARIMA models’ parameters will differ between the three data samples at hand but the processes of determining the best fit of the data will be similar to Attijariwafa Bank.

**BMCE:**

For the forecasting of the future stock prices of BMCE, the process is similar to Attijariwafa bank. The first step would be to get the parameters of the ARIMA model which will be composed of two parts: the non-seasonal parameters and the seasonal parameters and the second step will consist of testing the results of the forecast with the real values of January 2018 in order to assess the accuracy of our prediction.

**Plotting the time series:**

The first step after gathering the data and importing to RStudio following the same steps of Attijariwafa Bank is plotting the time series generated from this data. This step is crucial because it gives a first insight on how the data behaved during the year 2017. To perform this action, we will used a prebuilt function in the R language called `plot()` with the function `lines()`:

```r
plot(BMCE$Date,BMCE$Price,main="Plot of Stock prices of BMCE in 2017",xlab="Date",ylab="Price", type = "n")
lines(BMCE)
```
We call the function `plot()` by giving it the name of the graph using the parameter `main` and the x and y axis names using respectively `xlab` and `ylab`. The type = “n” is used in order to avoid plotting each point of the time series so only the `plot()` function would give us a blank graph. The function `lines` is then added in order to plot the BMCE times series by linking the points in time without plotting the dots. The result of the combination of these two functions is given in the following graph where we can see the evolution of the stock prices of BMCE throughout the year 2017:

![Plot of Stock prices of BMCE in 2017](image)

**Figure 14:** Data plot of stock prices of BMCE for the year 2017

We can see from the graph that the stock prices of BMCE didn’t vary much throughout the year 2017 except the drop that happened between January and March and the clear peak in July 2017. These two occurrences can be explained by going back to the major events that BMCE went through in the year 2017. The news concerning the company in question was
retrieved from the business section in the Website Morocco World News after making a careful search of the history of BMCE Bank. The massive drop in January can be linked to the fact that BMCE was ordered to pay a huge amount of taxes for the years ranging from 2012 to 2015, that constituted half of its revenues according to MWN. This news constituted a massive hit to the companies’ revenues and created a tremendous fear for investors that started withdrawing their money from its stocks.

The peak that the stock prices knew in July 2017 is due to the speculations that investors and financial analysts had about the new project of BMCE that was announced a little later during the same month. The speculations were about the tower that was to be constructed in Rabat by BMCE. The project required a huge investment in order to create the biggest tower in Africa that will be mainly the bank’s headquarter. The tower was announced in July 20 after the official signing of the contract and the project launch.

The previous explanations were intended to know the irregularities in the graph of the stock prices knowing that the Casablanca Stock Exchange is not as active as other stock exchanges throughout the world. The next steps will deal with the statistical approach to forecast the future stock prices of BMCE starting by the choice of a moving average to base our study on and ending by the testing and comparison of the results. The best fitting ARIMA model will be chosen and its results will be compared to the real values of the stock prices of the month January 2018 extracted previously from the Casablanca Stock Exchange website.

**Data smoothing:**

The next step will be smoothing the data in order to get the non-seasonal parameters of the ARIMA model. The goal from this step is to check if there is any seasonality in the data and remove it in order to have a smooth data to which we can apply the `auto.arima()` function in
order to get the non-seasonal part of the ARIMA model. To get a deseasonalized set of data, we will have first to make the data smoother by applying the moving average method.

Concerning the moving average, we will test two different periods: weekly moving average and monthly moving average. For the weekly moving average, we will apply the function `ma()` with a period of 5 which is the number of working days in a week in the Casablanca Stock exchange. The monthly moving average will have a period of 20 representing the number of working days in a month. The following graph will contain the original set of data in comparison with the weekly and the monthly moving averages:

![Plot of weekly and monthly moving averages versus original data](image)

**Figure 15:** The moving averages compared to the original data of BMCE
TIME SERIES ANALYSIS OF MOROCCAN STOCKS

We can see that the monthly moving average smoothens the original data by removing the variations, but it loses a considerable amount of information during the process. The weekly moving average, however, makes the data smoother without losing its significance. For this matter, we will be using the weekly moving average over the monthly as the basis to check for the seasonality and remove if it is present.

The function that will be used in the `auto.arima()` function is the deseasonalized weekly moving averages of the stock prices. To remove the seasonality from our data, we will have to run first the function `stl()` that takes the time series and divides it into three main component which are the seasonality, the trend, and the noise. The result of this function can be plotted so that the seasonality is clearly visible.

The following figure shows the seasonality, trend and noise of the BMCE stock:

![Figure 16: The representation of the seasonality of the BMCE Stock prices](image)

TIME SERIES ANALYSIS OF MOROCCAN STOCKS

The seasonality component is clearly represented in the above graph. To remove this element from our data we will need to call the function `seasadj()` that only keeps the other two components. After deseasonalizing the BMCE stock prices, we will call the `auto.arima()` function with a “seasonal = FALSE” parameter in order to know that the data doesn’t contain seasonality. The parameters returned by the function: 2, 1, and 3 will be given to the ARIMA model as the non-seasonal components.

**The seasonal part of the ARIMA model:**

For the seasonal components, we tried different parameters in our ARIMA model in order to get the best fit possible for the data at hand. The First Step is to try the different models with different seasonal part and choose the best fit based on the AKAIKE information criteria and the Bayesian information criteria. The second step is to plot the model with the real values of the month of January 2018 in order to check the accuracy of the model. The last step will be to compare the resulted values for the forecast with the real values retrieved for the testing month and get the percent accuracy for each date.

**Models comparison:**

The first step is to compare different models with different seasonal parameters in order to find the one with the best AIC and BIC. In addition to those two criterions, we calculated the variance for the cases where we will have similar or close AIC and BIC values. The following table shows different models with different seasonal parameters with their AIC, BIC and Variance:
In the case of BMCE, the choice is straightforward because we can see that the model with \((2,1,3)(0,2,2)\) has the lowest AIC and BIC which makes it the best choice. To know how accurate our prediction is, we will plot the forecasts with the real values of January 2018.

**Testing the Model:**

In this step, we will test the chosen model by plotting its forecast with the real values of the month January of the year 2018 retrieved from the Casablanca stock exchange. This step gives a visual insight on how the predicted values compare to the real values. The next graph will contain both plots in order to be able to get a hold of the accuracy of our predictions:
From the above graph we can see that the predicted values are fairly close to the real value extracted from the Casablanca stock exchange. In order to affirm the closeness of the forecasted data to the real values, we will calculate the error between the model and the weekly moving averages of the data. We calculated the error for each point in time and executed the `mean()` function in order to get the average of the errors which was -0.09674665. The value returned is in the order of $10^{-2}$ which shows how accurate our predictions are.

**Predicted values:**

The last step can give a visual insight on how close the predicted data is to the real values but it only shows that our predictions follow the trend of evolution of the market. In this step we will extract the values predicted and the real values retrieved from the market and calculate the percentage of accuracy of our forecasting for the values of each day of the month of January.
2018. The following table shows those values in addition to the calculation of the percentage of accuracy:

<table>
<thead>
<tr>
<th>Date</th>
<th>Actual values</th>
<th>Predicted values</th>
<th>Percent accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>2/01/2018</td>
<td>213.9</td>
<td>213.2697</td>
<td>99.71%</td>
</tr>
<tr>
<td>3/01/2018</td>
<td>207.5</td>
<td>212.4594</td>
<td>97.67%</td>
</tr>
<tr>
<td>4/01/2018</td>
<td>206.5</td>
<td>210.505</td>
<td>98.10%</td>
</tr>
<tr>
<td>5/01/2018</td>
<td>207.5</td>
<td>209.2027</td>
<td>99.19%</td>
</tr>
<tr>
<td>8/01/2018</td>
<td>208</td>
<td>210.3827</td>
<td>98.87%</td>
</tr>
<tr>
<td>9/01/2018</td>
<td>207</td>
<td>211.3476</td>
<td>97.94%</td>
</tr>
<tr>
<td>10/01/2018</td>
<td>207</td>
<td>214.1892</td>
<td>96.64%</td>
</tr>
<tr>
<td>12/01/2018</td>
<td>212</td>
<td>213.4879</td>
<td>99.30%</td>
</tr>
<tr>
<td>15/01/2018</td>
<td>211.9</td>
<td>213.3418</td>
<td>99.32%</td>
</tr>
<tr>
<td>16/01/2018</td>
<td>210</td>
<td>211.7913</td>
<td>99.15%</td>
</tr>
<tr>
<td>17/01/2018</td>
<td>211.9</td>
<td>212.4287</td>
<td>99.75%</td>
</tr>
<tr>
<td>18/01/2018</td>
<td>210</td>
<td>209.7412</td>
<td>99.88%</td>
</tr>
<tr>
<td>19/01/2018</td>
<td>216.8</td>
<td>209.7732</td>
<td>96.76%</td>
</tr>
<tr>
<td>22/01/2018</td>
<td>215</td>
<td>209.0472</td>
<td>97.23%</td>
</tr>
<tr>
<td>23/01/2018</td>
<td>210.65</td>
<td>212.8036</td>
<td>98.99%</td>
</tr>
<tr>
<td>24/01/2018</td>
<td>210.65</td>
<td>212.6178</td>
<td>99.07%</td>
</tr>
<tr>
<td>25/01/2018</td>
<td>214.95</td>
<td>214.2909</td>
<td>99.69%</td>
</tr>
<tr>
<td>26/01/2018</td>
<td>210.65</td>
<td>214.1603</td>
<td>98.36%</td>
</tr>
<tr>
<td>29/01/2018</td>
<td>215</td>
<td>215.2777</td>
<td>99.87%</td>
</tr>
<tr>
<td>30/01/2018</td>
<td>216.75</td>
<td>215.5351</td>
<td>99.44%</td>
</tr>
<tr>
<td>31/01/2018</td>
<td>225</td>
<td>214.8604</td>
<td>95.49%</td>
</tr>
</tbody>
</table>

**Figure 19:** Comparison between the real and forecasted values of BMCE

All the accuracy percentages calculated from the predicted and the actual numbers are very high and most of them are more than 99% which indicates the accuracy of the forecasting done using the model chosen based on the AIC and BIC criterions. The average of the percentages is 98.59%, which is very high and shows that this model could be trusted in predicting the stock values.

For the BMCE stock, we have another model that gives very good results after comparing the predicted values and the actual data visually and using the exact numbers. This case shows that some models can be a good fit even if they don’t have the best AIC and BIC among the selected model. That is why the data retrieved from each model was compared to the real data. In
the case of Attijariwafa Bank, no other model gave better or similar results to the one chosen using the two criterions. The other model that gives very decent results has the following parameters (2,1,3)(2,2,0). This model captured my interest when visually comparing the results of the forecast with the real values because they seem very similar. The following graph can show the strong similarity between the two plots:

![Forecasts from ARIMA(2,1,3)(2,2,0)[20]](image)

**Figure 20:** The comparison of the forecasted stock prices with the real values for BMCE using a different model.

After seeing this eye-catching resemblance, I further investigated this model by comparing the values it predicted with the real values of January 2018 and calculating the percentage of accuracy for each day. The following table shows the results obtained:
From the table we can see that the values predicted are very close to the real recordings of the stock prices of BMCE. The lowest percentage of accuracy is 95.08% and the average of all the percentages is 98.61% which is also very high and very close to the previous model. In addition to this, the mean of the error between the stock prices of the year 2017 and the values of the model is very small with a value of -0.06449976. This shows that the criterions can give an insight on which model is better to model the data but other models should also be considered in the study and we should look for other indicators and further investigate any interesting model.

**La Banque Populaire:**

**Plotting the time series:**

In order to start this analysis and be able to forecast the price accurately we should first plot the time series at hand and explain the sudden fluctuations of the data at hand. The following graph will represent the raw data of the stock prices of La Banque Populaire plotted in a graph:
Figure 22: Data plot of stock prices of La Banque Populaire for the year 2017

From the graph we can see that there is a significant rise in the stock prices of La Banque Populaire starting the month of January until February where it relapses. This rapid fluctuation could be explained by the speculations of the market about an award that a subsidiary of La Banque Populaire could get in the near future. The stocks of La Banque Populaire have known a significant rush where their price has risen until the news became public where it relapsed quickly. A subsidiary of La Banque Populaire has been awarded two awards from S&P Global for their high level of security and managerial quality in the third of February of the year 2017. This shows that there is a movement in the Casablanca stock exchange and people are getting interested in buying and selling stocks, but the number of investors is small, which can be seen in the fast and vertically linear drop or rise that stock prices know. This vertical and sudden drop
can be explained by the fact that one or very small number of investors withdraw or deposit large amounts of money in one transaction.

**Smoothing the data:**

The next phase in analyzing the data of La Banque Populaire is to remove the seasonality component from our data in order to run the `auto.arima()` and get the non-seasonal parameters of the ARIMA model. We will start first by making the data a little smoother by applying the moving average technique with different orders as we have done for the two previous companies. The graph that we will plot will have a representation of the real values in green, the weekly moving average in blue and the monthly moving average in red. The next graph displays the three plots:

![Plot of weekly and monthly moving averages versus original data](image)

**Figure 23:** The moving averages compared to the original data of La Banque Populaire
As we saw for the two previous companies: Attijariwafa Bank and BMCE Bank, the monthly moving average smoothen the data but loses very important information which can be valuable to our study. So we will take the weekly moving averages as they make the data smoother and at the same time keep the maximum information about the original data set.

After choosing the order with which we will compute our moving average and keep the most of the information that we could about the data, we should check for the seasonality in the stock prices time series and remove it if present. We will plot the result of the function \texttt{stl()} which separates the different components of our time series and the results will be shown in the following figure:

![Figure 24: The representation of the seasonality of La Banque Populaire Stock prices](image-url)
From the graph above, we can see that our data set has a clear and non-negligible seasonal component that should be removed in order to apply the non-seasonal `auto.arima()` function to get the non-seasonal part of the ARIMA model.

To remove the seasonality, we will apply the function `seasadj()` on the result of the function `stl()` which we named `decomp` in our program:

```r
decomp = stl(Popu_ma, s.window="periodic")
plot(decomp)
deseasonal_Popu <- seasadj(decomp)
```

After removing the seasonality, we will run the `auto.arima()` function without the seasonality component by adding “seasonal = FALSE” to our function. The returned numbers being 2, 1, and 2 are then used as the non-seasonal parameters of the ARIMA model.

**Building the ARIMA model: non-seasonal parameters**

When it comes to the seasonal parameters of the ARIMA model, they will be chosen after a trial of different sequences of numbers and finding the best fit for our data based on different criterions. The AIC and BIC will be the main factors in determining the model that best fits the data at hand as it was done for the two previous companies.

**Models comparison:**

The first step towards finding the best seasonal parameters for the ARIMA model is to use different combination of numbers and choose the one with the lowest AIC and BIC. The following table contains different models from which we will choose one based on the criterions cited above:
From the table above, we can see that the one with the model with the lowest AIC and BIC have the following parameters $(2,1,2)(2,1,2)$. Even though this model is clearly the best pick when it comes to the evaluation of the two criterions, we run simulations to see the forecasts of the other models. This step enables us to see if one of the other models is interesting enough to be investigated but fortunately for this company, the other models were far from the real values and the difference is clearly visible.

**Testing the model:**

The chosen model will be tested in this phase by plotting the forecasted values in the same graph with the values of the BMCE stock for the month of January 2018 retrieved from the Casablanca stock Exchange website. The following graph shows the forecasts made by this model in comparison to the real values of the stock prices:
In contrary to the two other companies, the predicted values do not seem very close to the real values from the graph. In order to see how close the values generated by the ARIMA model and the real stock prices we will calculate the error between the two values. The error will be calculated at any point in time by taking the difference between the two values: the model and the real.

By visualizing this computed error at any point in time using the function `as.numeric()` we get an array of number shown in the next figure:
Figure 27: The values of the error between the ARIMA model generated values and the real values

This array already shows that the values are in the order of $10^{-2}$, which is showing the closeness of the values generated by the ARIMA model that has those specific parameters to the real values retrieved from the Casablanca stock Exchange website. In order to get a better representation of the accuracy of the model, we will calculate the average of those values using the function `mean()`. The returned value by this function is 0.01280953 which affirms that our prediction is accurate.

Predicted values:

This step consists of comparing the everyday recorded values of the stock and the predicted values using the model we chose. After visualizing the closeness of the prediction by plotting the forecasting with the real values, we will compare the numbers given by the model with the real figures and compute the percentage of accuracy for each day.
The following table shows the two figures with the percentage of accuracy:

<table>
<thead>
<tr>
<th>Date</th>
<th>Actual Values</th>
<th>Predicted values</th>
<th>Percent accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>2/01/2018</td>
<td>293</td>
<td>295.719</td>
<td>99.08%</td>
</tr>
<tr>
<td>3/01/2018</td>
<td>289.9</td>
<td>295.554</td>
<td>98.09%</td>
</tr>
<tr>
<td>4/01/2018</td>
<td>285.3</td>
<td>294.718</td>
<td>96.80%</td>
</tr>
<tr>
<td>5/01/2018</td>
<td>283</td>
<td>295.8713</td>
<td>95.65%</td>
</tr>
<tr>
<td>8/01/2018</td>
<td>285.4</td>
<td>296.4455</td>
<td>96.27%</td>
</tr>
<tr>
<td>9/01/2018</td>
<td>287</td>
<td>295.1611</td>
<td>97.24%</td>
</tr>
<tr>
<td>10/01/2018</td>
<td>286.65</td>
<td>295.9829</td>
<td>96.85%</td>
</tr>
<tr>
<td>12/01/2018</td>
<td>292.95</td>
<td>293.7964</td>
<td>99.71%</td>
</tr>
<tr>
<td>15/01/2018</td>
<td>302</td>
<td>293.5284</td>
<td>97.19%</td>
</tr>
<tr>
<td>16/01/2018</td>
<td>303</td>
<td>291.7972</td>
<td>96.30%</td>
</tr>
<tr>
<td>17/01/2018</td>
<td>297.35</td>
<td>290.2371</td>
<td>97.61%</td>
</tr>
<tr>
<td>18/01/2018</td>
<td>297.3</td>
<td>289.7822</td>
<td>97.47%</td>
</tr>
<tr>
<td>19/01/2018</td>
<td>297.7</td>
<td>291.1544</td>
<td>97.80%</td>
</tr>
<tr>
<td>22/01/2018</td>
<td>297.95</td>
<td>293.5917</td>
<td>98.54%</td>
</tr>
<tr>
<td>23/01/2018</td>
<td>297</td>
<td>292.4871</td>
<td>98.48%</td>
</tr>
<tr>
<td>24/01/2018</td>
<td>297.6</td>
<td>291.5109</td>
<td>97.95%</td>
</tr>
<tr>
<td>25/01/2018</td>
<td>297.6</td>
<td>292.5524</td>
<td>98.30%</td>
</tr>
<tr>
<td>26/01/2018</td>
<td>297</td>
<td>291.9885</td>
<td>98.31%</td>
</tr>
<tr>
<td>29/01/2018</td>
<td>296.5</td>
<td>292.4545</td>
<td>98.64%</td>
</tr>
<tr>
<td>30/01/2018</td>
<td>294</td>
<td>293.3681</td>
<td>99.79%</td>
</tr>
<tr>
<td>31/01/2018</td>
<td>294</td>
<td>294.8018</td>
<td>99.73%</td>
</tr>
</tbody>
</table>

**Figure 28:** Comparison between the real and forecasted values of La Banque Populaire

This table shows the closeness of the predicted data to the real stock prices using numbers and percentages. The percentage of accuracy for our predictions using the model with the parameters (2,1,2)(2,1,2) for La Banque Populaire is very high because it never goes below 95.65%. The average of the accuracy percentages is 97.9% which shows the extent to which our predictions are accurate.
STEEPLE Analysis:

Social Aspect:

One of the aims of this study is to encourage people to invest in stocks by showing them how they can be studied and informed decisions could be made. By encouraging Moroccans to invest in companies listed in the stock exchange, we will boost entrepreneurs to establish new businesses that will help in the development of Morocco. Investing in stocks can represent a combination of personal gain and social responsibility because we can help developing our country by joining small individual investments with the efforts of managers of big corporations.

Technological Aspect:

The technological aspect in this capstone project resides in the use of computer science to find mathematical models that could be fitted to the data at hand and forecast future stock prices. Computer science is a huge added value to the domain of finance as new data could be added in real time and predictions calculated and refined. The program could be connected directly to the source website of data and the model could be refined in real time.

Economic Aspect:

By encouraging people to invest in stocks, the Moroccan economy will flourish. This study can help people see that buying and selling stocks is far from gambling. Moroccans should know that finance can help them not only grow their riches but it can also help in the development in their country.
Environmental Aspect:

This study has no environmental implications as it only deals with the financial sector in Morocco. We could have used stock prices of environmental businesses in our study in order to work in the intersection of the two fields.

Political and Legal Aspect:

Concerning the stock exchange in Morocco, the rules governing it are made to suit Moroccan people’s needs and encourage them to invest. The rules are made to limit the risk of losing money but the drawback is that one can’t get a huge profit out of it. When it comes to insider trading, the law is still not enforced and we can see it from the fluctuation that market knows before publicly announcing major events.

Ethical Aspect:

This project was conducted following the ethical rules as we used only data that is publicly available. All the resources used did not require permission and the RStudio offers a free version that suited our needs.
Conclusion:

In this capstone project, we studied different companies listed in Casablanca stock exchange in order to find mathematical models that could be used to predict future stock price values. The companies chosen were the three highest traded bank stocks in the market in order to have enough data to conduct our research. The method used to model the stock prices is called ARIMA which is short for Auto Regressive Integrated Moving Average. A different model with different parameters was chosen for each data set and it was tested using the data of the first month of the year 2018. All the predictions were fairly precise and the percent accuracy is very high. But even though the numbers are very convincing, predictions could not be made only based on the model. News and events should be taken into consideration as well as the model. In Morocco, Financial decisions of withdrawal or deposit of money are not made based on mathematical and statistical methods but rather based on news. Due to the lack of supervision, insider trading is still a wide spread practice in Morocco and can be seen in the graphs where the plots peak before the publication of a major announcement and suddenly fall afterwards. The financial sector in Morocco needs more attention and regulations should be enforced in order to make the Casablanca stock exchange more appealing to small investors.
References:

[1] Time Series Analysis of Stock Prices Using the Box-Jenkins ... (n.d.). Retrieved March 1, 2018, from:
https://digitalcommons.georgiasouthern.edu/cgi/viewcontent.cgi?article=1668&context=etd

https://www.statmethods.net/r-tutorial/index.html


https://www.datacamp.com/community/blog/r-xts-cheat-sheet


TIME SERIES ANALYSIS OF MOROCCAN STOCKS
