Bachelor Thesis

Comparison of Forecasting Methods for Stock Prices of Consumer Electronics Market

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I) Affidavit

I hereby affirm that this Bachelor's Thesis represents my own written work and that I have used no sources and aids other than those indicated. All passages quoted from publications or paraphrased from these sources are properly cited and attributed.

The thesis was not submitted in the same or in a substantially similar version, not even partially, to another examination board and was not published elsewhere.

Date: 14/8/2017 Signature

II) Abstract

Nowadays the consumer electronics market has been booming with nearly 15% yearly growth rate of sales (FMI (Future market insights), 2016). It is extremely competitive. In this market, Apple Corporation, Microsoft Corporation, Toshiba Corporation, HP Inc. are the most well-known stocks, which are traded competitively on the market. Many investors are monitoring these stocks and their competitors daily. Analyzing and forecasting of these stocks could give some ideas about historic, current, and future market value of those stocks to investors and to researchers for the consumer electronics markets and the market's direction. Therefore, it was considered a reasonable topic for this bachelor thesis. The thesis will focus on analyzing the stocks with the time series analysis methods. It is planned to be mostly quantitative by using eViews for time series analysis. Additionally, all the methods used will be explained in the methodology part. The methodology goes very basic and in literature review all the methods and necessary terms and jargon will be explained. Therefore, this study could be understood by any individual with no finance knowledge. For instance, a potential investor with capital but lacking financial information. Therefore, this thesis can be seen as a handbook for a starting investor, which would be another purpose of this thesis.

The study will answer if there is an increasing trend on the consumer electronics market and if this could be explained by time series data. As mentioned, main financial terms and topics to understand how to use time series analysis and assessing volatility will be explained. Stock data from Yahoo Finance will be used. The calculations will mainly be done through Microsoft Excel.

III) Acknowledgement

I would like to express my gratitude to everybody, who gave me the opportunity to complete this thesis. I want to express my thanks to my supervisor Dr. Irem Önder, who told me about this topic and encouraged me to write about it. I also want to thank to Dr. Ulrich Gunter, who taught us in Forecasting Lecture and he also taught about ARIMA method, which encouraged me also to write about this topic. Furthermore, I would like to thank to my parents Mustafa and Claudia Üzelgecici, who were supporting me financially and motivationally during my entire academic career. It would not be possible to complete this thesis without the help of my professors and my family. I am very grateful to all of them.

Contents

1) Introduction

In the 1950s stock trade was quite different to how it is done now. Exchanging was always over the counter, mostly via brokers. It was time consuming, expensive, and risky (Investopedia, n.d.). The main issue in the past was that the stock exchange was not liquid, which is the opposite of its characteristics in today's finance world. One of the most essential characteristics of the stock exchange nowadays is that stock trading is very liquid. Undoubtedly the level of liquidity depends on the traded security. Nonetheless, the main difference is that all the processes have become faster through financial and technological development. Investors can buy and sell securities with a few clicks and no necessity to go to counter, except for very special securities, including forward contracts. When it comes to liquidity, stocks are one of the most liquid means of exchange after cash. A huge part of this change was caused by the introduction of electronical stock trading by Depositary Trust Company in US (Investopedia, n.d.).

Another difference is that today market is much more complicated than it was before. More regulations, more traders, more capital (Investopedia, n.d.). As a matter of fact, the whole network is in some ways connected to each other. One stock influences another one. A big trade in Asia influences prices of some stocks in Europe. In fact, there are millions of variables which change the market situation continuously and which make it practically impossible to predict a stock price very accurately. All stock analyzing is about considering the most important variables and making the best guess out of it. As markets got more complicated, the analysis went further than just an accurate prediction. Since there are hundreds of variables effecting the stocks, analyzing the dependency of independent variables on dependent variable would be very hard to asses. Therefore, time series analysis is chosen in this research, more specifically ARIMA, which uses just its own observation series to forecast, will be used.

In addition, some researchers started to find methods of simulations, such as Monte Carlo Simulation - a method giving partially random results in a specific variation - which makes the whole stock predicting process more realistic, but is still not helpful at all times. Thus, mainly ARIMA model will be used in this thesis. Always new developments and changes will take place in the equity markets. Therefore, stock prediction methods and literature should be studied more often and developments should be followed quickly and carefully to adapt to the market.

Moving on to the specific field of the consumer electronics market. It is possible to mention that in the last 20 years, the market has been booming. As new technologies were discovered and consumer electronics become daily life routine of people, the consumer electronics market became tremendous, extremely competitive and more investment opportunities arose in this field. Moreover, the most important point is the segments the market targets, which includes nearly everybody, low, middle, and high-income classes, practically each person uses electronics. As 2016 figures show Global Consumer Electronics´ Market revenues was 1,712.9 Billion $ at the end of 2016 and it is expected to reach to 2,976.1 Billion $ by the end of 2020 (Persistence Market Research, 2016). This is one of the reasons that the study researches this enormous field, which still has a huge growth potential. According to Nasdaq, some of the most frequently traded stocks are Apple Corporation, Microsoft Corporation, Toshiba Corporation, HP Inc. (Nasdaq, 2017). Many investors are monitoring these stocks and their competitors on daily basis. Therefore, analyzing and forecasting of these stocks could give some ideas to investors and to researchers about the consumer electronics markets and the market's direction. Therefore, it was regarded as useful to research this market in combination with the time series forecasting.

1.1) Presentation of the problem

As mentioned before, stock markets are growing dramatically every day and there are lots of investors, who are new in the market and struggling in the beginning phase to figure out how the valuation, forecast works, which securities they should invest in, why they should invest, what the regulations are about their capital and how they should use their capital complying with the regulations. Especially after the launch of the online trading platforms such as plus500.com and tradestation.com. Further increasingly more individuals got involved in the stock markets and become traders professionally or involved in freelance-trading from home. However, they might not have the essential information in the beginning phase. Therefore, they need more sources to evaluate and make a reasonable investment decision.

For instance, an investor with capital, but without any trading knowledge would need a source to analyze the stocks and to trade efficiently.

Further problems that this thesis will address are forecasting issues, such as which methods to choose for forecasting, which variables to use for ARIMA, ARCH, GARCH or regression analysis, in which cases simulations should be used. Mostly there is not an accurate result, even when all these measures were applied. Shortly, there are few sources, which are focusing on these basic concepts briefly and concentrating on optimizing the process.

Besides general information about stock markets and trading, there is the issue about the consumer electronics market that it is highly volatile and hard to forecast, when it comes to market situation, value, growth and return of the stocks. Because it nearly impossible to guess when new technologies, devices will come out, which would cause a change in stock prices. For instance, quick raise in the stocks of a company, that brought the technology and quick fall in the competitors´.

Another challenge in the consumer electronics market is the issue of regulatory requirements, which are changing very frequently and are indirectly affecting the prices of the stocks (Quality Digest, 2012). Moreover, the variables to be considered for consumer electronics markets are complicated to decide on, because there are not really variables for some factors, like technological developments in the market. Yet, those csn be followed just by staying up to date in the market and reading the news about it. Furthermore, another method to follow news for the market could be mention sentiment analysis, that is not always accurate and again complicated as well as costly to conduct. Notwithstanding, for the thesis time series analysis will be used therefore there will be no need to choose such a variable.

1.2) Aims of the bachelor thesis

The thesis will firstly focus on basic concepts such as, analyzing the stocks, volatility, time series methods, that will be explained in detail in the methodology part for the starting traders. As mentioned before, it could be understood by any individual with no finance knowledge. Therefore, this thesis, which squeeze all financial information together and can be used as a handbook for beginner investors. Moreover, as the aim of stock analyzing is to forecast revenue and growth in value, to calculate the return of an investment, this study will mention also the forecasting methods, which will try to estimate the revenue and growth, that will lead to the forecast of the stock prices. Furthermore, giving the essential information about time series analysis and more importantly showing how an ARIMA forecast works and how it is applied in eViews application.

Additionally, the thesis will try to explain basic facts and concepts about consumer electronics markets and how the investors in this field should act. Likewise, the thesis will try to investigate the further problems of the consumer electronics market.

Shortly in bullet points the aims of the study are as follows:

- Mentioning the basic concepts about stock the market and consumer electronics market and trying to find solutions to the problems.
- Explaining essential forecasting methods focusing on time series methods (ARIMA, ARCH, GARCH, regressions, simulations, and other basic methods).
- Choosing the most convenient forecasting application for the stocks of consumer electronics market.
- Explaining how an ARIMA forecast is conducted on eViews and conduct forecasts for chosen consumer electronics market stocks.
- Drawing a conclusion out of the results and note the limitations of the study.

In Bullet points the research questions:

Question 1: How can a more realistic forecast analysis be done?

Question 2: What is the best method of forecast for stocks of consumer electronics market?

Question 3: How could an ARIMA model for prediction of stock value be developed and applied in eViews?

Question 4: As conclusion: How useful is a time series analysis for stock prediction?

The thesis will mention all the bullet points and try to draw a conclusion. Disregarding if the study will be able to answer all the questions, as mentioned it should serve as an important source for beginner traders and important piece of literature when it comes to stock market forecasting basics.

1.2.1) The Hypothesis of the Thesis

As the thesis aim is to focus on ARIMA time series analysis model for consumer electronics market the hypothesis will be:

H0 = ARIMA analysis for chosen stocks give less than %3 MAPE

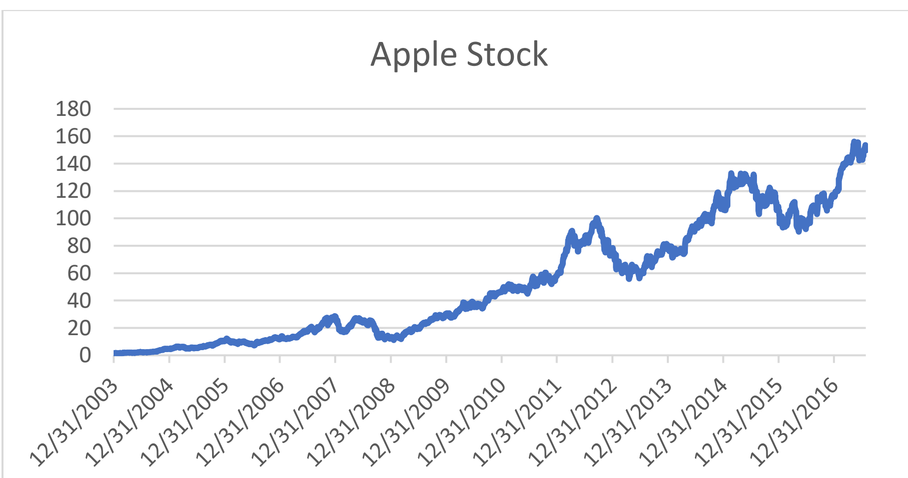
H1 = ARIMA analysis for chosen stocks does not give less than %3 MAPE

2) Business Description

This section will briefly give information about the companies that will be examined. Points under examination will be their business model, company strategy and place in the consumer electronics market to provide some background information, which should help to comment on their development according to the analysis.

2.1) Apple

Apple Inc. is a California based customer electronics corporation established in 1976, which had revenue of $7.8 Billion and total assets of $176.06 Billion in the last quarter of 2016 (Apple, 2017). Below is a graph of the Apple stock price development from 2003 until 2017.



(Yahoo Finance, 2017)

Looking at the graph, it can be concluded that this stock has over time experienced significant growth and is still growing considerably. Thus, it could be a potential opportunity for investors. Other than the financial facts, Apple has great potential because the corporation keeps making updates to improve their CSR and PR. For instance, Apple's Green Bond, which is a project that aims to make the world better place by adjusting their production with the goal of decreasing environmental impact (Apple, 2017) . It is possible to see the allocation of their budget for the developments of specific environmental issues in the graph below:

(Apple, 2017)

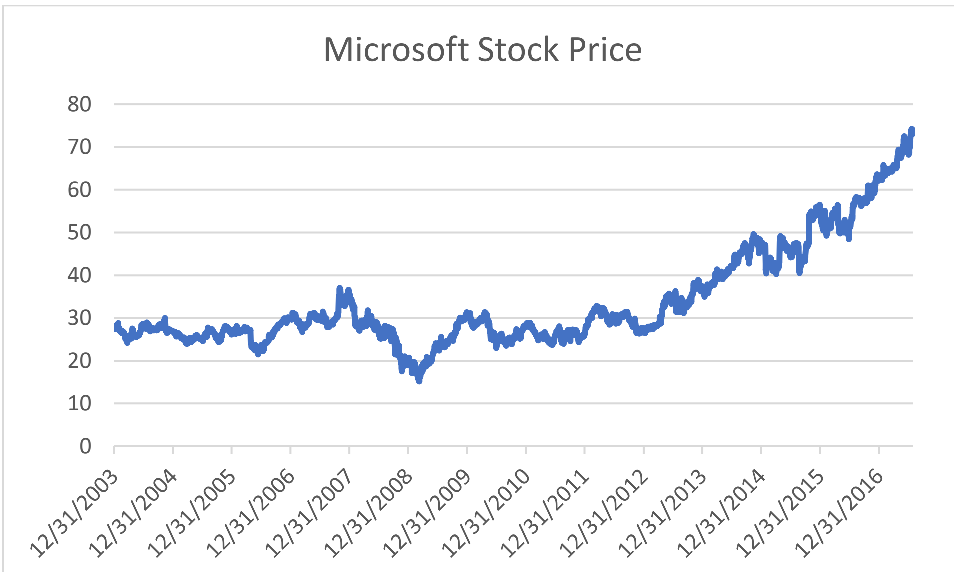
One of the solutions to these environmental issues is a project called Liam. It is a robot developed by Apple to separate the components of used Apple electronic devices that lowers the cost of production and helps to decrease CO2 emission to the atmosphere.

However, Apple's placing is quite basic in the industry. They are supporting high quality products with elegant style and user-friendly structure. Applying this strategy, they have differentiated themselves in the market from most of the competitors (Meyer, 2017). Briefly, Apple has strong financial facts and a differentiated position in the market from its other competitors.

2.2) Microsoft

Microsoft was founded by Bill Gates and Paul Allen. It has been one of the leading companies in the consumer electronics market since 1975. Microsoft Corporation had total revenue of $22.09 billion and $225.17 billion of total assets at the end of the first quarter of 2017 (Microsoft Corporation, 2017).

Stock prices from 2003 until 2016 can be seen on the graph below:

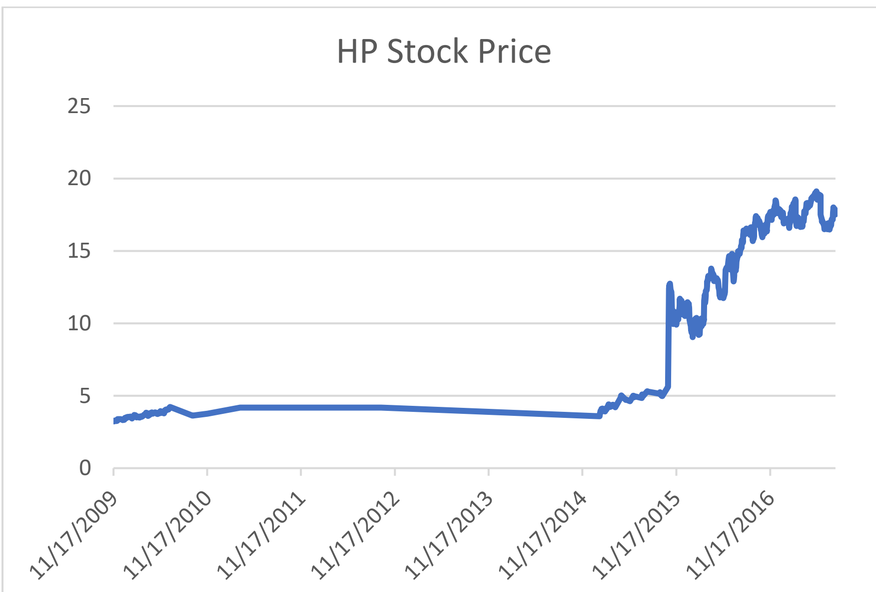


Stock price is around $ 30 from 2004 until end of 2012, then there is a general rise until today. However, Microsoft's stock value and financial performance is significantly lower than Apple's.

Microsoft's mission is "Empower every person and every organization on the planet to achieve more" (Microsoft Corporation, 2017). By this mission statement and generally by Microsoft's products, it could be understood that they target everybody. Their customer segment is everybody who uses and could be potentially using customer electronics. Nonetheless, it is more difficult to reach everyone than a chosen segment. Yet, Microsoft has had a steadily increasing stock price for the past four years. Thus, it could be that their strategy changed. The most recent strategy of Microsoft is "Build best-in-class platforms and productivity services for a mobile-first, cloud-first world". As it was mentioned previously in the company mission, Microsoft targets most of the segments, "in-class platforms and productivity services" that could include students and business people. Moreover, it mentions "for a mobile-first, cloud-first world", which shows that they keep the company´s focus on the developments to satisfy the whole customer-base in the market.

2.3) Hewlett-Packard

Hewlett-Packard Company was founded in 1939 in California. The corporation had total revenue of $12.7 billion by the end of first quarter in 2017 (Hewlett-Packard Company, 2017). It is one of the leading companies in consumer electronics. However, HP has a significantly worse financial performance compared to Apple and Microsoft. One of the indicators of financial performance of HP is shown below:

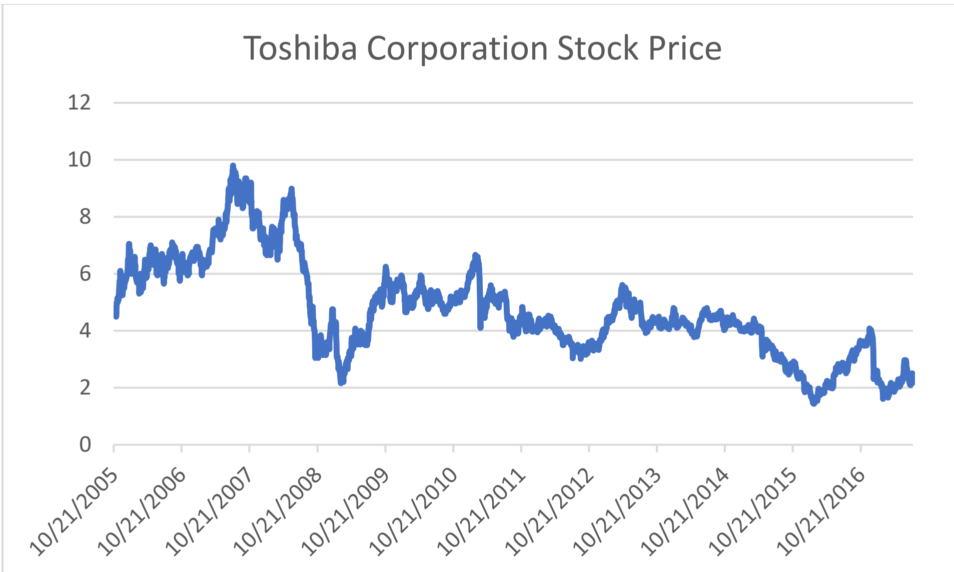


(Yahoo Finance, 2017)

HP's company mission and strategy is not really specified and emphasized. It is very broad and general. In fact, it is not differentiating HP from the rest of the market. Therefore, it will not be mentioned here - please look to this reference, if interested: (Hewlett-Packard Company, 2012). However, HP is still one of the leading companies because of its long presence in the market, brand value and also superior financial performance to the rest of the market.

2.4) Toshiba

Toshiba is a Japanese electronics company situated in Tokyo and established in 1939. Toshiba had total sales of $ 3.84 billion by the third quarter of 2016. However, an operating loss of $ 532.5 million (Toshiba, 2016). As it shown below in the graph there is a decreasing trend in the stocks of Toshiba. Further, the time series analysis will explain more about the future of the stock.



Company strategy of Toshiba is very basic and clear "Commitment to People", "Commitment to the Future" (Toshiba Corporation, 2017).

3) Literature Review

In the research, the main methodology is based on the time series models and forecasting methods. Respectively, ARIMA, ARCH, GARCH, basic forecasting methods, regression models and simulation methods will be conducted to be able to choose the best method according to the error results of these applications. Basic forecasting methods are for instance, naïve 1,2,3, single exponential smoothing, double exponential smoothing, holt winters. As regression model, multiple regression will be used. Lastly as simulation method, the Monte Carlo Simulation will be applied. All these forecasting methods will be assessed with several error measures, such as mean absolute error and mean percentage error. Hence the accuracy of the method can be tested and the most accurate model can be chosen.

3.1) Base Knowledge for Research

Methods of Analysis

The analysis of stocks and forecasting will be mainly focused on ARIMA (Autoregression Integrated Moving Average) analysis. ARIMA is the process of predicting the dependent variable, which is stock price, just with its own series. It is one of the best methods for share prices because as mentioned there are lots of variables and analyzing the independent variables such as GDP, consumption, EURO/DOLAR FX rate and the other shifting facts of the market or market related variables, make it impossible to conduct a multiple regression for instance. Moreover, the data for the chosen consumer electronics market stocks will be taken from online sources such as, Google Finance and Yahoo finance. The data collected will be analyzed through eViews and Microsoft Excel to conduct Automatic ARIMA time series analysis. Furthermore, eViews application and how to use it will be explained in more detail further in the methodology section of the research.

The data of the stocks will all be daily. The reason being that stock value prices are changing daily, actually even every second but they are mostly analyzed on a daily basis.

The companies which will be used for stock analysis are Apple Corporation, Microsoft Corporation, Toshiba Corporation, HP Inc. The reason to choose these companies is that they are the leading companies in the consumer electronics market with the largest volumes. Detailed information about the companies will be provided in the Business description section. Another fact is that they are competitors and their performance might affect each other and this could also be a point to could analyzed, if it could be observed with the analysis to be conducted.

3.1.1) Autoregressive Integrated Moving Average Models (ARIMA)

ARIMA means Autoregressive Integrated Moving Average - it is also sometimes referred to as Box-Jenkins Model. George Box and Gwilym Jenkins developed the model for time series data (North Dakota State University). Univariate ARIMA is a technique of forecasting, which refers just to its own series while doing the prediction (Morisson, n.d.). To be able to conduct ARIMA analysis time series data should include at least 40 observation points (Morisson, n.d.).

First, A time series data that will be analyzed through ARIMA should be assessed, if it is stationary or non-stationary. Time series data should be stationary to be able to conduct ARIMA, if not other processes should be applied, which will be explained in the next paragraph.

Stationarity means that properties of a time series do not depend on the time at which the series is observed (Otexts, 2017). Moreover, variance of time series data should be constant over the time. For instance, the data shown in table 1 below is not stationary. Because it shows an increase over the time, which visually shows that data is time dependent. Generally, if there is a trend affecting the change in data then the data is most likely not stationary (Morisson, n.d.).

In fact, table 2 shows the exact opposite. The data has no correlation with time and it changes randomly. Mostly seasonal data has stationary movement as the figures move as the seasons´ ups and downs get more dramatic and stationarity could easily be seen in a graph of seasonal data in most of the cases.

Table 1, (NIST Engineering Statistics, 2013)

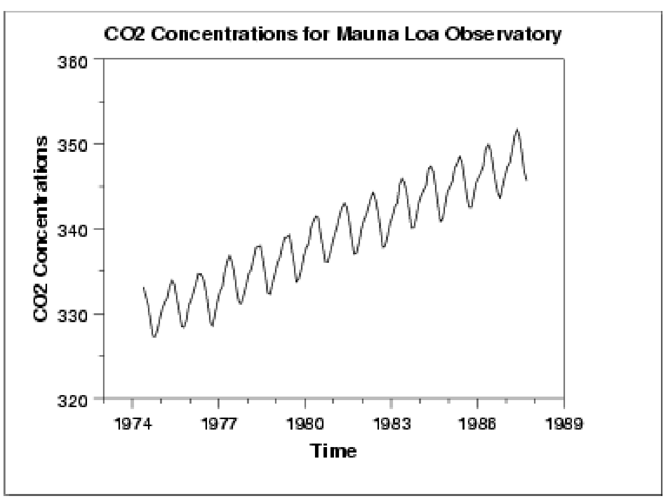
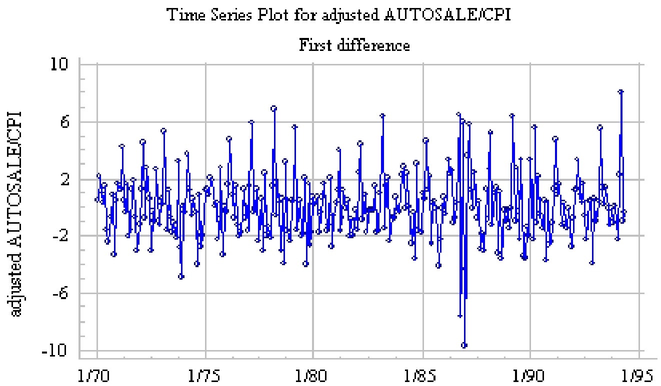


Table 2, (Duke, 2017)



As mentioned to be able to apply ARIMA model the data should be stationary. For data from a time series to be stationary, there are three important points:

- An autocovariance, which is not time-dependent
- A constant variance
- A constant mean

(University of Bristol, n.d.)

In the cases that stationarity could not be observed by graph or it is not clear, there are various tests that can be done. One of the most widely used tests is the Dickey-Fuller unit root test. According to Francis X. Diebold, the properties of the Dickey-Fuller test are significantly stronger than the properties of alternative unit root tests (Diebold, 1991). Dickey-Fuller test will be conducted in this study via eViews.

However, when a time series data is not stationary, difference method can be applied to make the existing data stationary. The difference method is basically the act of subtracting an observation from the previous one to find the difference between recent and previous observation. After subtracting is done for all observations. The difference of time series data is used instead of time series data itself. Later applying the difference method, if difference data is still not stationary, a second difference could be applied, which means that difference of the first differences should be calculated to obtain stationary data (Otexts, 2017). The first and the second difference method shown can be shown in the following equations:

$$D_t = x_t - x_{t-1}$$

$$D_t = (x_t - x_{t-1}) - (x_{t-1} - x_{t-2})$$

Another theoretical input, important for ARIMA is the concept of autocorrelations, which represents the degree of similarity between a given time series and a lagged version of itself over its time intervals (Investopedia, 2017). Lags are the number of periods removed from the observation (Morisson, n.d.). For instance, an autocorrelation at the first lag computes how the data of the series are correlated to each other over time. Autocorrelations are important to know for the time series analysis, especially for ARIMA, because it shows the dependence of data on itself and how dependence changes over time with lags to itself.

Furthermore, to be able to understand ARIMA, the parts of it should be understood. So, ARIMA has two parts which are Autoregressive Models and Moving Average models. They will be explained respectively.

3.1.1.1) Autoregressive Models (AR)

Basically, any observation X(t) can be explained by some function of its previous observation X(t-1) adding the error variable, that is E(t) (Morisson, n.d.). Thus, this means it is possible to forecast the X(t) value with having X(t-1) and all the other necessary constants and figures, that are derived from time series. How to obtain these figures by using eViews application will be explained in a different section of the methodology. The following equation is to put the AR time series analysis in a formula (The equation is taken from the online source of Jeff Morisson):

“X(t) = A(1) * X(t-1) + E(t)

Where,

X(t) = time series under investigation

A(1) = the autoregressive parameter of order 1

X(t-1) = the time series lagged 1 period

E(t) = the error term of the model”

(Morisson, n.d.)

As mentioned constants and their figures such as A(1) and E(t) would be obtained from eViews. Furthermore, the process will be explained in one of the following sections. Coming back to the equation above, it shows an AR process with one lag which means it is just analyzing the time series based on the previous series of observation. Therefore it is an AR(1) process. An AR(2) process with second lag would be as shown below:

"X(t) = A(1) * X(t-1) + A(2) * X(t-2) + E(t)" (Morisson, n.d.)

With the equation above a forecast with two lags can be conducted, which means the X(t) value is depending on previous two observations, X(t-1), X(t-2). Next section will explain the Moving averages part which is second part of ARIMA models.

3.1.1.2) Moving Average (MA)

Second part of ARIMA process is moving average models. The difference between the autoregressive model and the moving average model is that the moving average model puts more focus on error constant of the previous observations or also called previous lags. For instance, in Moving Averages model instead of X(t-1), X(t-2), X(t-3), it evaluates the error constants such as, E(t-1), E(t-2), E(t-3). An example of a moving average equation is shown below:

"X(t) = - B (1) * E(t-1) + E(t)"

(Morisson, n.d.)

As the equation above shows B(1) is an MA of order 1 and it is multiplied with the error term of lag one. Therefore, according to moving averages model X(t), which is the forecasted future value, is always dependent on the error term. With the same logic, an equation with two lags would be:

X(t) = - B (2) * E(t-2) - B(1) * E(t-1) + E(t)

(The Pennsylvnia State University, 2017)

3.1.1.3) ARIMA

Since both models are known, the thesis now moves on to the mixed model, which is ARIMA (Box – Jenkins). ARIMA basically mixes both equations together to conduct a more accurate forecast. In practice, it works in the following way, a model can include two AR terms in ARIMA, which would be shown as ARIMA of order (2,0,0) or a model could include two MA terms, which would be shown in ARIMA as ARIMA of order (0,0,2) (The Pennsylvnia State University, 2017). Another example of an ARIMA model could be an ARIMA model order of (1,1,1) which would describe AR term of 1 order, first difference of the time series data that is analyzed and MA term of first order (The Pennsylvnia State University, 2017). Moreover, the equations are created according to orders of ARIMA and the difference. An example of ARIMA of the order and difference (1,1,2) would be as following:

$$(1-B)Y_t = \mu + \frac{(1-\theta_1 B - \theta_2 B^2)}{(1-\phi_1 B)} a_t$$

(Statistical Analysis Software (SAS), n.d.)

Besides, the formula and the notation above there are different ways of formulating it and writing it down. For instance, in most of the literature it denotes the ARIMA lags as ARMA (p , q). Using this notation p and q are the lags and difference level is not notated. Possible reason is that the difference is chosen before conducting ARIMA. For instance in eViews the notation is as follows; ARMA (1 , 1) (1 , 1).

The main issue in ARIMA model is to choose the lags and decide which combination would be the best for the time series data that we have. However, there is not always a standard answer for this issue and there is also not a right model. After all, it always depends on the difference level, the lags of ARIMA and there are a lot of combinations possible. Therefore, as mentioned there is no right model, but the best fit from the alternative possibilities of models (Pollock, 1992).

Briefly the requirements and needs for the ARIMA model are firstly stationarity, then application of difference if there is no stationarity, secondly constant variance over the time, lastly identification of the lags of autoregressive model and moving average models. For the adequacy of stationarity and the number of lags the tests in eViews will be applied, according to result of these tests the lags will be chosen.

3.1.2) ARCH & GARCH Models

These models are referred to as Autoregressive Conditional Heteroscedasticity and Generalized Autoregressive Conditional Heteroscedasticity. It is named conditional because of the fact that the next period's volatility is conditional on information from the current period (Reider, 2009). To be able to understand the ARCH AND GARCH models, firstly homoskedasticity and heteroskedasticity concepts should be explained. In the homoscedasticity concept, the expected value of all the error terms squared are equal to each other at any observation in given time series (Engle, n.d). On the other hand, according to heteroskedasticity variance of the error terms differ and are not equal to each other (Engle). Therefore, heteroskedasticity expresses non-constant volatility. If there is heteroskedasticity the ARCH model is applied mostly. If there is homoskedasticity assumption of the error variance mostly the GARCH model is used.

The main aim of these models are to estimate the volatility. The steps of the ARCH and GARCH model are to firstly to look for the variance of the error term. Then, estimate the best-fitting autoregressive model for the time series, second step is to compute autocorrelations of the error term and last step is the testing for the significance (investopedia).

On the homepage of the University of Bologna, authors go into greater detail on the ARCH and GARCH models. (Foscolo, n.d).

3.2) Other Forecasting Methods

3.2.1) Regression Models

Regression models are used to predict a dependent variable by using one or multiple independent variables and usually a constant. Regression models with one independent variable are called linear or simple regression model. On the other side, regression models with two or more independent variables are called multiple regression model. Please see the formula definitions bellow:

Y: dependent variable

X: independent variables

a : constant

b,c,….,n : multipliers for independent variables

$Y = a + b*X$ (single/linear regression)

$Y = a + b*X_1 + c*X_2 + d*X_3 + \cdots\cdots$ (multiple regression)

Dependent variable is mostly known, such as in this research the stock value. However, it remains to be answered how those independent variables are chosen. To ensure the correctness of the equation, the independent variables should depend on the dependent variable on a significance level. Therefore, the significance levels of dependence of the independent variables on the dependent variable should be examined. The first step of this process is the logical level, to choose all possible affecting variables of our stock by common sense. For instance; interest rates levels, GDP in country of origin of the stock and stock prices of competitors. The study will conduct this process using IBM SPSS software.

For the study, mainly the multiple regression will be used.

Variables:

There are two main types of variables: Discrete and continuous variables.

Discrete variables represent the categorical mainly nominal and ordinal values, for instance, gender, religion, and star rating for hotels. Whereas, continuous variables are quantitative figures, like numbers (Laerd Statics, 2013).

As stock prices depend on many variables simple regression will not be used in this research. The variables with major relevancy will be chosen and tested on IBM SPSS software for

IBM SPSS Use for Multiple regression

This section briefly explains how to use IBM SPSS in terms of helping to researchers and readers, who are interested in it.

First of all, it is necessary to put the data in SPSS. Therefore, the data should be in a excel file, including dependent and independent variables in the columns with the name of the data in the first row. If there are some categorical variables they should be converted into number, enabling SPSS to read them. As an example, if there is gender as a categorical variable instead of man, it could be denoted as a 0 and for woman as a1 in excel. Later click on the SPSS tool bar “Data”, then “Open Data”, to choose the path for your data. After plugging all the data, SPSS detects usually automatically the type of your variables, such as nominal or scale. If it is detected wrongly, there is a possibility to change it. After this step, click on the SPSS tool bar “Analyze”, then “Regression”, then “Linear”. Another window will appear, which shows all your variables on the left-side, and dependent, independent variable boxes on the right side. Drag and drop your dependent and independent variables from left side to right in the boxes. Later click on “Statistics” button in the window then choose boxes Estimates, Model fit, Descriptives, Part and partial correlations, then click Continue, then click Okay. The multiple regression will be conducted and SPSS will display all relevant results. The most important part of the results is the significance level of the constant and the variables, which is showing if a significant multiple regression model could be built with chosen variables.

3.2.2) Brownian Motion (Wiener Process)

Brownian Motion was first founded in 1827 by Robert Brown, who was a botanist (California Institute of Technology, 2013). He studied microscopic life, which led him to analyze the random movement of the particles. After spending time trying to find a pattern for the movement of particles, he developed the Brownian motion model, which would describe the movement by a drift factor, representing the random movement. Since it was first developed, the Brownian motion is used in various fields. Brownian Motion, which is a stochastic process was first used for financial research by Luis Bachelier. (Holton, n.d.) The aim was to predict the random movements of stock and derivative prices. However, the model was not as successful as it was thought to be. Norbert Wiener further developed the model in 1923 (Holton, n.d.). Therefore, it is also often called Wiener Process. As this model is not giving a specific forecast result but a range of results, this method will not be applied on chosen stocks. However, it might give some understanding about upper and lower limits of stocks. Another simulation method, similar to Brownian Motion, is the Monte Carlo simulation.

3.3) Other Terms in Finance

3.3.1) Volatility

Volatility measure is used in finance, in terms of evaluating the risk. The volatility is basically the measure of variation of the stock, which is denoted by the standard deviation, the square root of variance. Variance shows the average squared distances from the mean of a dataset. Most commonly, the symbol of the standard deviation is a sigma. Formulas are shown below:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

Where;

σ = Standard deviation

N = number of data

X_i = the absolute data

μ = mean of the data

(Mathisfun.com, 2014)

As mentioned, in financial markets volatility represents how stocks vary, which could give an idea of the upper and lower bounds of stock prices.

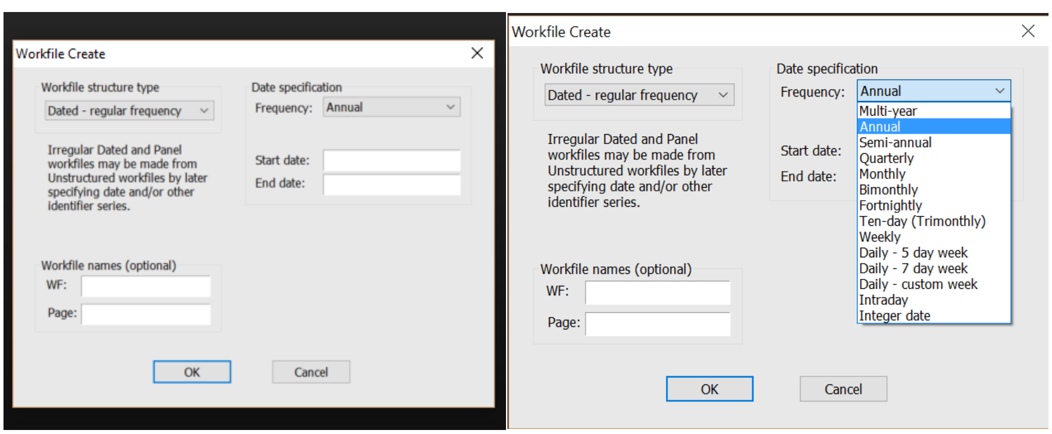
4) Methodology

This section explains the forecasting method. Information in the next paragraphs could help for any forecasting with time series. The forecast object does not have to be consumer electronics market stock or any stock or not even financial data. This method could be applied in various fields, such as tourism, physics and many others. As mentioned for any time series data providing significant results, the forecasting method can prove to be useful.

For the analysis, 9.5 Lite Student version of eViews is used, which is free of charge and could be used by anybody. However, it has some limitations to its usage. If there will be an analysis with large amount of observations, unlimited version is suggested to use.

First, the stock data was downloaded from the yahoo finance application for the chosen stocks: Apple Corporation, Microsoft Corporation, Toshiba Corporation, HP Inc. The data was downloaded for the maximum data range available. However, data used for eViews should not include more than 1500 observation points because of the limited student version of eViews that was used for this study. If there was more than 1500 observations, the most recent 1500 was chosen out of the data sets.

The raw data was put directly in eViews, however it gave some error, such as not conducting the forecast or giving meaningless results. Therefore, the data needed some adjustment to prepare it for the analysis, before importing it to the eViews. This adjustment will be shown in the next paragraph before inserting the data to eViews. Firstly, a work file should be created. If there will be a new work file that will be created in eViews, the dates must be chosen in advance in the eViews interface as shown below:



Firstly, it is to be selected, if the time series data is having regular or not regular frequency. In the case of this study, the stock prices will have regular frequency, which will be mostly daily. Afterwards, the frequency itself must be chosen. In the case of this study, the frequency is daily. However, the stock prices are quoted only for week days, which makes the option " Daily – 5 day week " more logical to choose. After the selections were done, data should be imported to the eViews by going through the following steps:

The raw data, taken from Yahoo Finance is shown below:

A1 Date

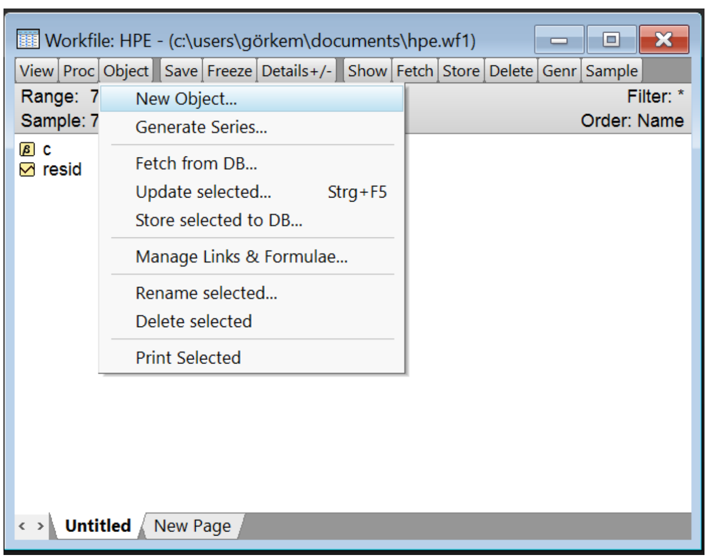
	A	B	C	D	E	F	G
1	Date	Open	High	Low	Close	Adj Close	Volume
2	03/01/2007	0.51	0.51	0.51	0.51	0.498895	0
3	04/01/2007	64.34	64.34	64.34	64.34	62.93897	0
4	05/01/2007	null	null	null	null	null	null
5	08/01/2007	0.55	0.55	0.55	0.55	0.538023	0
6	09/01/2007	null	null	null	null	null	null
7	10/01/2007	null	null	null	null	null	null
8	11/01/2007	2.65	2.65	2.65	2.65	2.592295	0
9	12/01/2007	10.58	10.58	10.58	10.58	10.34962	0
10	16/01/2007	1.94	1.94	1.94	1.94	1.897756	0
11	17/01/2007	2.59	2.59	2.59	2.59	2.533602	0
12	18/01/2007	17	17	17	17	16.62982	0
13	19/01/2007	1.33	1.33	1.33	1.33	1.301039	0
14	22/01/2007	48.01	48.01	48.01	48.01	46.96456	0
15	23/01/2007	0.79	0.79	0.79	0.79	0.772797	0
16	24/01/2007	null	null	null	null	null	null
17	25/01/2007	null	null	null	null	null	null

As old data are not always available there are some "null" result displayed. This might happen in any kind of data, that some data points are not available, written wrongly or give some sort of error. Therefore, data should always be checked before actually conducting any analysis. In this case, these nulls will not be recognized from the eViews and if these dates are just removed, the time series dataset will be unstructured with the missing observation points from some of 5 days of weeks, having null value, which might in the end lead to a violated result. Therefore, just the stock price of the day before will be used for the analysis. Thus, it will result as if there was no movement in the stock from one day to another, instead of having a huge change to 0, which would be in some cases more than 600 % change, totally violating the results. Therefore, as mentioned all the nulls are replaced with the value of the day before and these nulls should definitely not be replaced with 0 in any case.

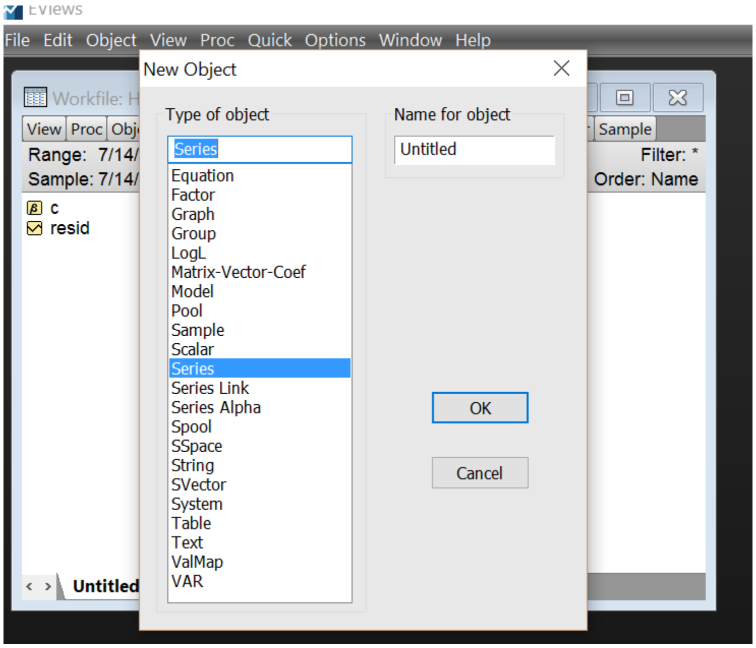
Another problem, which occurs is that the weeks are sometimes shorter than 5 working days, if there is holiday. Maybe even a full set of weekly data is not existing because of Christmas or any other holiday depending on the countries. Sometimes a week is skipped, because all the working days were holiday in that week. Furthermore, it is nearly impossible to spot just the holidays for the last 5 years data for various stocks and distinct the holidays and the weekends from each other. Therefore, to solve this problem and stay simple the same method will be applied for all holidays including weekends. The price of the day before will be taken into account for the days off and after applying all the adjustments on the data, the process of creating a work file should be redone and while creating the work file " Daily – 7 day week " should be chosen.

Another important point is to enter the starting and ending date of the time series data, while creating a work file. The date should be entered in American notation, first month then day and then year, such as: "07/23/2014". Another important point is to not enter the date until the time series data at hand, but rather the date of the time series until when it will be forecasted. In other terms, the date of the time series that will be analyzed should be entered, otherwise eViews will not conduct the forecast.

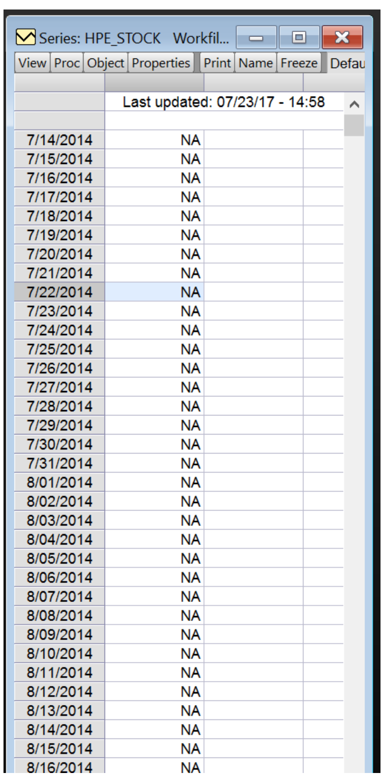
Next step is to create an object and enter the data into the object, just created. For this process, the following steps should be followed:



Click "Object" on the work file and then "New Object", then the window below will appear.



Choose “Series”, because it is a time series data. Give a name to the object, such as “hpe_stock”, then press “OK” button. The object will appear in the work file window. Double click on “hpe_stock” object and the following window will appear, which shows the time series data:

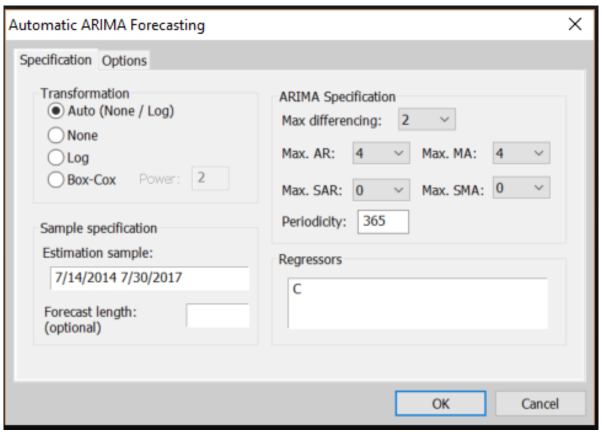


Before the data will be imported, it is important to double check if the historical data is sorted correctly and chronologically. It should be sorted starting from the oldest data to the newest data. Because after all adjustments to the data are done, the data might be mistakenly sorted wrongly, which would ruin all the time series analysis process and the forecasts. Therefore, it should always be double checked for this point. It helps to go back to the excel sheet, where the adjusted stock data is safed and double check it before starting the analysis.

Afterwards, copy the data from excel and paste it into eViews window, which is shown on the left side. EViews will require to switch to the editing mode – this should be accepted and then the data will be imported to the object. The data will be displayed in eViews.

After importing the data, there could be some quick analysis done through eViews such as descriptive statistics, i.e. generating a line graph from the data. To do this click View, then Graph and then OK. If another type of graph is desired, it should be selected in the previous window. Going for a line graph could give some visual idea about the data. It can show if it is time dependent or stationary, how significant the variance seems and if outliers happen often or not.

Next step is to conduct ARIMA forecasting. To do this click “Proc” tab shown above, that is on the same window with the object, then click on “Automatic ARIMA Forecasting…”.



The window, which is shown on the left side will appear. Thanks to automatic ARIMA forecasting, identification process could be skipped. Because it is done automatically by eViews. The EViews software chooses the most convenient lags of AR and MA for the time series that is entered. Moreover, the maximum number of AR and MA lags, that are wished, can be entered. Furthermore, if there is any seasonality in the data this seasonality level should be chosen on the “SRA” and “SMA” options. For instance, for a time series, that is analyzing the number of tourists, which are coming to a hotel in a ski resort, there would be most likely two levels of seasonality. Because of two seasons on mountains, there would be a wave of visitors during the winter for skiing and another wave during the summer due to visitors, who come to mountains for hiking. In this study, there might be some seasonality with low chance because of new products, that are launched in the consumer electronics market at specific times. However, it is more likely that there will not be any seasonality on prices of the stocks from the chosen market.

Further, periodicity should be chosen for 365 days, which indicates the period of one year. If the observations were monthly periodicity would be 12. Other important selections to be made are “Estimation sample” and “Forecast length”. Estimation sample is the set of observations, that are imported previously to the eViews. The range of estimation sample should be entered correctly in this field. If there is specific data that is not wished to include in the analysis, adjust the data accordingly. Forecast length is the number of observations, that is wished to be forecasted by the researcher. Fill in all the necessary and wished fields, then click on the "Options" tab. In this tab, there are many technical options. First option is the selection of comparison methods, which includes Akaike Information Criteria, Schwarz Information Criteria, Hannan-Quinn and Mean Square Error. All of these, methods explain the quality of the data´s fit. From these comparison methods, most essential ones will be explained briefly:

As mentioned, **Akaike Information Criterion (AIC)** is a method of comparison for the alternative models that exist. In the case of this study it would compare the alternatives of ARIMA lags, in order to choose the best fitting model. Its formula is shown below:

$$AIC = 2K - 2\ \log(\mathscr{L}(\hat{\theta}|y))$$

In the equation,

K = is the number of estimable parameters (degree of freedom)

$\mathscr{L}(\hat{\theta}|y)$ = is the log-likelihood at its maximum point of the model estimation.

(Snipes & Taylor, 2014)

The model with the smallest AIC is assumed to be the best fit (Beal, Ridge, & Corporation, 2007). In fact, eViews use it to compare it and choose the best combination. Hence, it is just chosen as a comparison method and there is no need to compare manually. It could be monitored just to have an idea regarding the general fit of the time series data to the model chosen by eViews. Thus, it can be checked, if it the value is smaller than two. Then, the fit is fairly good.

Other essential method is the **Mean Squared Error(MSE).** MSE is basically the square of the differences between the actual value and the forecasted value. This could be used to calculate errors of various models and choose the model with least error. It is one of the most essential, basic and often used error methods. The notation could be shown as below;

$$\text{MSE}\,[T(\mathbf{Y});U] = \text{E}\left[(T(\mathbf{Y}) - U)^2\right]$$

(Statitical Analysis Software (SAS), n.d.)

Continuing with the automatic ARIMA forecasting process, after choosing the fit model, there are other options such as changing the significance level. However, it is sufficient to leave it as standard 5% significance level, if there is no special need. Other options are some visual and statistic output such as, forecast comparison graph, ARMA criteria table, graph and equation output table. All of those options will be selected for this study while automatic ARIMA forecasting is done in order to get more material to evaluate the quality of the forecasted results. After making the selections click OK to execute the forecast. Later all the results will appear.

5) Forecast and Results

As mentioned before, Apple, Microsoft, HP and Toshiba stocks data was downloaded from yahoo Finance and was analyzed through eViews. More specifically, the stock tickers are:

AAPL for Apple Inc.

HPQ for HP Inc.

TOSBF for Toshiba Corporation

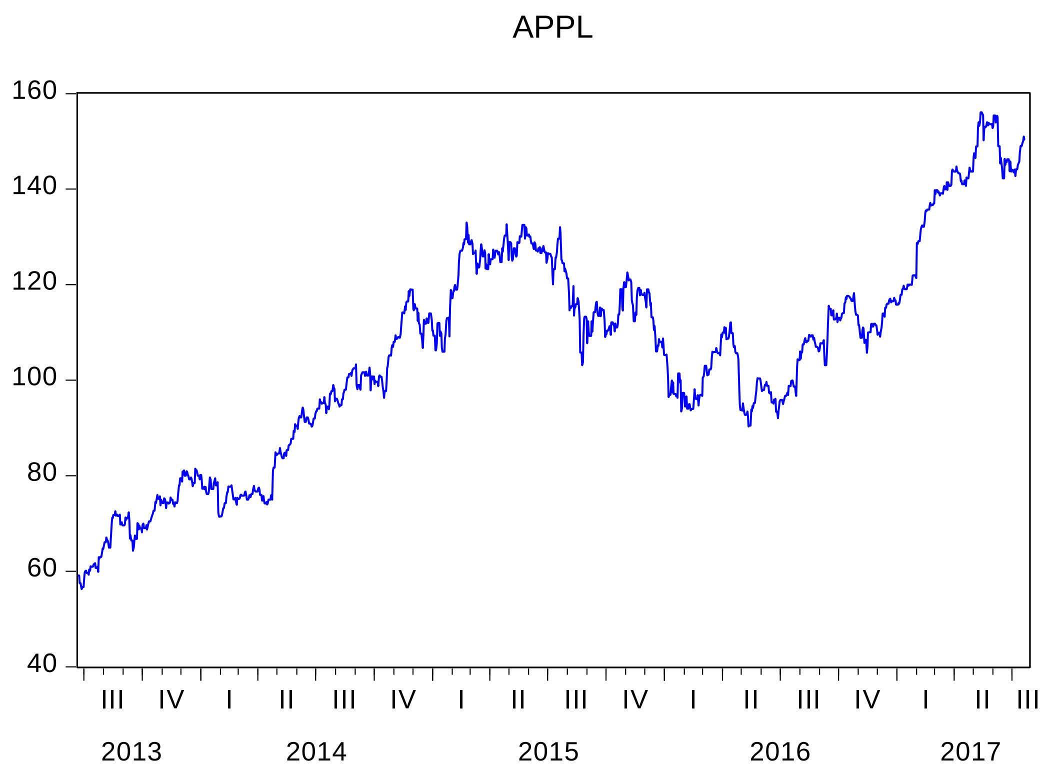
MSFT for Microsoft Corporation

With the tickers above specific stocks could be found easily. Later daily stock data for each stock is downloaded from 21. June 2013 to 21. July 2017 (All the data is in the appendices). Those dates are chosen due to the observation restriction of eViews for the limited version. In fact, with more data included, it should lead to a more accurate analysis. After having downloaded the data, it will be adjusted as mentioned in the eViews section. Moreover, for each stock 7 points will be forecasted, which is a week of data. Since it is the broadly used comparison method for ARIMA akaike information criterion will be used as model comparison method. As mentioned before, eViews will choose the most fitting method and will automatically apply it into the equation of ARIMA of automatically chosen lags. Therefore, the forecast results will also come from the eViews automatically and will be displayed in a new object in eViews. After conducting the forecast ARMA result tables, error terms and significance levels will be evaluated. Furthermore, the forecasted results of eViews will be compared to the actual stock prices.

This section will mostly show the outputs of eViews with all methods applied to the chosen consumer electronics market stocks. The graphs and tables will be analyzed and commented on.

5.1) Apple

First of all, stationarity should be assessed. The graph, displaying apple stock prices below will be examined for that.



Visually it is hard to asses in this case, if the stock is clearly stationary or not, because it shows some fluctuations over time during the whole period. Moreover, there has mostly been a rise until the end of second quarter of 2015 and followed by a decline until the end of 2015. Further it has been fluctuating up and down during 2016 and in 2017 the stock is increasing almost steadily. Therefore, it is suggested to look to the eViews for a Dickey-Fuller test, as demonstrated below via eViews output.

Null Hypothesis: APPL has a unit root
Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=23)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.158069	0.6944
Test critical values:	1% level	-3.434528	
	5% level	-2.863273	
	10% level	-2.567741	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(APPL)
Method: Least Squares
Date: 07/25/17 Time: 22:29
Sample (adjusted): 6/22/2013 7/21/2017
Included observations: 1491 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
APPL(-1)	-0.001671	0.001443	-1.158069	0.2470
C	0.237739	0.155937	1.524580	0.1276

R-squared	0.000900	Mean dependent var	0.061166
Adjusted R-squared	0.000229	S.D. dependent var	1.262516
S.E. of regression	1.262371	Akaike info criterion	3.305201
Sum squared resid	2372.842	Schwarz criterion	3.312320
Log likelihood	-2462.028	Hannan-Quinn criter.	3.307854
F-statistic	1.341124	Durbin-Watson stat	1.991219
Prob(F-statistic)	0.247022		

Dickey Fuller tests if the time series is stationary or not. Thus, for the test there should be a null and alternative hypothesis set. As it states on the table above "Null Hypothesis: APPL has a unit root", that means null hypothesis states the data concerning Apple stock is not stationary.

H0 = Apple stock has non-stationary time series behavior.

H1 = Apple stock has stationary time series behavior.

For testing t-statistics values need to be compared. Augmented dickey fuller t-statistic value is 1.158069 and 1% level value is 3.434528 - expressed in absolute values. Augmented Dickey fuller value is smaller than 1% and 5% values. Thus, Dickey fuller values show for non-stationarity. Next step is to look to significance level of t-test. T-test shows a significance level of 0.6944, which means it is highly not significant. Because it is dramatically higher than

0.05 significance level. Therefore, H0 significantly can not be accepted, which concludes that the data is significantly not non-stationary and is more likely to be stationary. As it is possible to see below in the summary of the Apple stock time series analysis from the eViews, difference level of 0 is chosen, similarly, to the analysis done above. Moreover, the summary includes more details regarding the Dickey Fuller test.

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(APPL)
Date: 07/24/17 Time: 21:25
Sample: 6/21/2013 7/21/2017
Included observations: 1491
Forecast length: 7

Number of estimated ARMA models: 25
Number of non-converged estimations: 0
Selected ARMA model: (3,3)(0,0)
AIC value: -5.98836626148

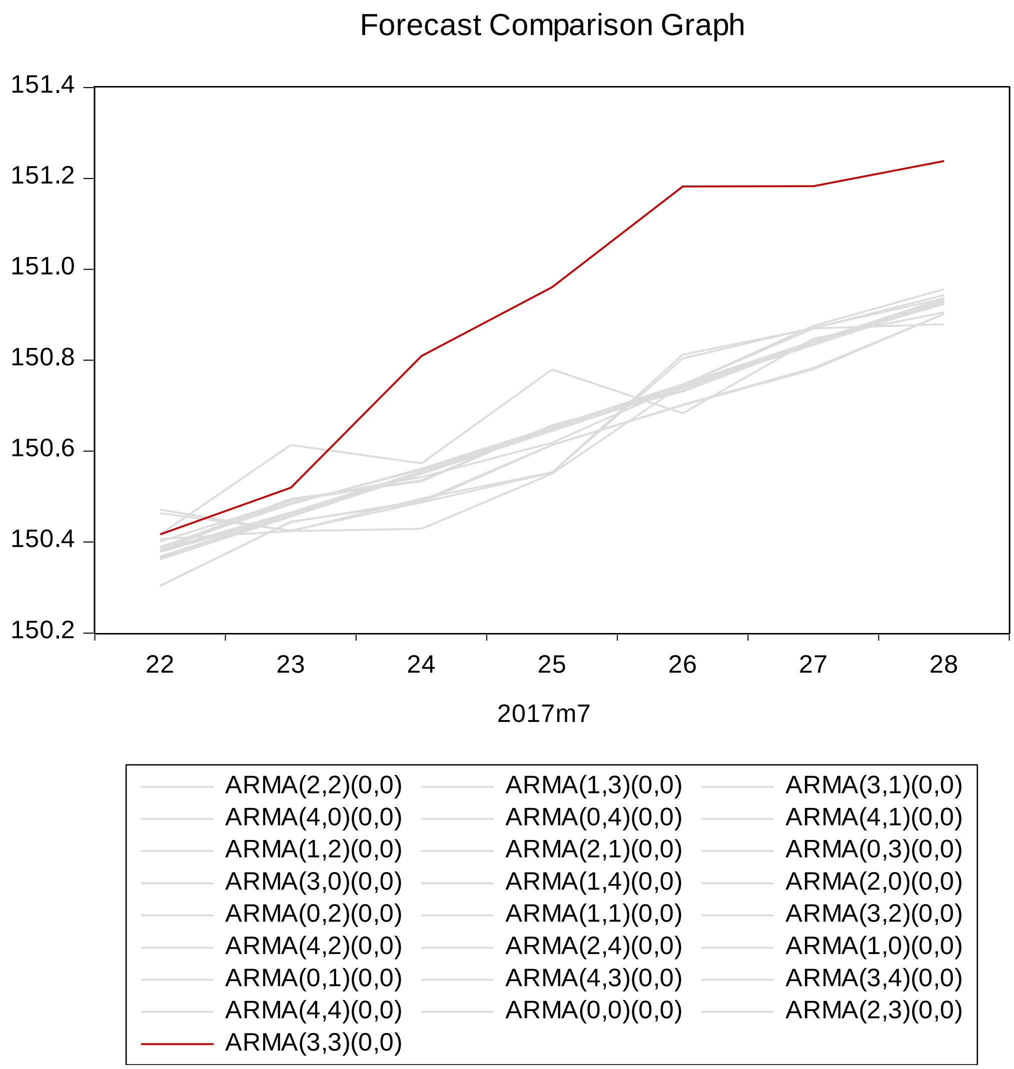
As the table above displays, eViews has chosen an ARIMA method of the 3 lags. This means there is 3. lag of AR and 3. lag of MA. According to the results, it gives an AIC (Akaike information criteria) value of -5.9883662. This value is the best result out of the generated combinations. As the eView output shows below:

Model Selection Criteria Table
Dependent Variable: DLOG(APPL)
Date: 07/25/17 Time: 18:35
Sample: 6/21/2013 7/21/2017
Included observations: 1491

Model	LogL	AIC*	BIC	HQ
(3,3)(0,0)	4472.327048	-5.988366	-5.959890	-5.977755
(2,3)(0,0)	4469.856905	-5.986394	-5.961478	-5.977109
(0,0)(0,0)	4463.703635	-5.984847	-5.977728	-5.982194
(4,4)(0,0)	4471.412316	-5.984456	-5.948862	-5.971192
(3,4)(0,0)	4470.099837	-5.984037	-5.952002	-5.972099
(4,3)(0,0)	4470.099191	-5.984036	-5.952001	-5.972099
(0,1)(0,0)	4463.803520	-5.983640	-5.972961	-5.979661
(1,0)(0,0)	4463.802771	-5.983639	-5.972960	-5.979660
(2,4)(0,0)	4468.622583	-5.983397	-5.954921	-5.972786
(4,2)(0,0)	4468.602936	-5.983371	-5.954895	-5.972759
(3,2)(0,0)	4467.364016	-5.983050	-5.958134	-5.973765
(1,1)(0,0)	4463.824619	-5.982327	-5.968089	-5.977021
(0,2)(0,0)	4463.814360	-5.982313	-5.968075	-5.977007
(2,0)(0,0)	4463.812478	-5.982310	-5.968073	-5.977005
(1,4)(0,0)	4466.120009	-5.981382	-5.956465	-5.972097
(3,0)(0,0)	4464.056406	-5.981296	-5.963499	-5.974664
(0,3)(0,0)	4464.036877	-5.981270	-5.963473	-5.974638

(2,1)(0,0)	4463.830299	-5.980993	-5.963196	-5.974361
(1,2)(0,0)	4463.829691	-5.980992	-5.963195	-5.974360
(4,1)(0,0)	4465.785247	-5.980933	-5.956016	-5.971648
(0,4)(0,0)	4464.371446	-5.980378	-5.959021	-5.972419
(4,0)(0,0)	4464.286460	-5.980264	-5.958907	-5.972305
(3,1)(0,0)	4464.095007	-5.980007	-5.958650	-5.972048
(1,3)(0,0)	4464.091401	-5.980002	-5.958645	-5.972043
(2,2)(0,0)	4463.831569	-5.979653	-5.958296	-5.971695

Moreover, eViews compare results of different lags ARIMA in case users want to have an overview about the other lags. The red line shows the results of the chosen lags.



As the model is chosen eViews automatically forms a formula with the constant and variables of the time series analysis, which was conducted by eViews from the data that is shown below:

It is possible to see that the significance level of the variables are fairly high with all 0.0000 values. Only the constant is having 0.0532 level of significance, which is not so bad and rather close to 0.05. Therefore, it is acceptable.

Dependent Variable: DLOG(APPL)
Method: ARMA Maximum Likelihood (BFGS)
Date: 07/25/17 Time: 18:35
Sample: 6/22/2013 7/21/2017
Included observations: 1491
Convergence achieved after 236 iterations
Coefficient covariance computed using outer product of gradients

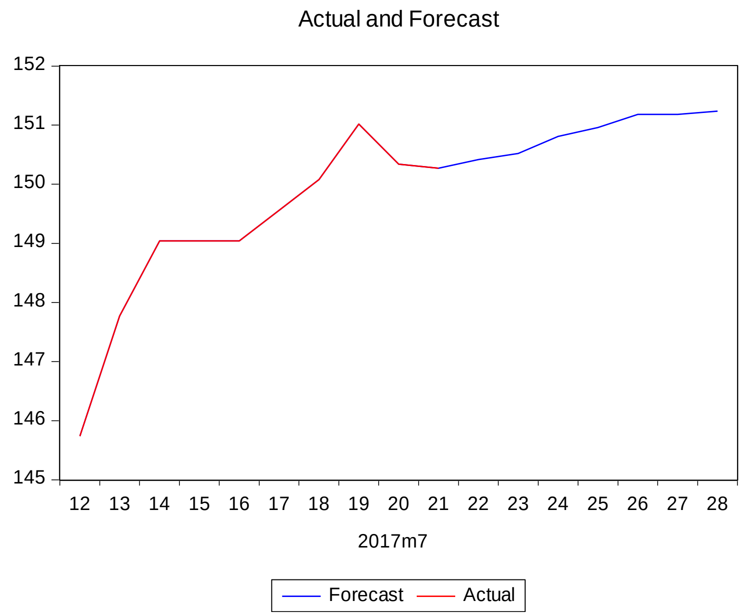
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000629	0.000325	1.934545	0.0532
AR(1)	0.535633	0.020484	26.14890	0.0000
AR(2)	0.533549	0.031759	16.79991	0.0000
AR(3)	-0.987270	0.021479	-45.96480	0.0000
MA(1)	-0.529533	0.019207	-27.57005	0.0000
MA(2)	-0.526889	0.029383	-17.93149	0.0000
MA(3)	0.994955	0.019957	49.85370	0.0000
SIGMASQ	0.000145	2.60E-06	55.80873	0.0000

R-squared	0.013057	Mean dependent var	0.000626
Adjusted R-squared	0.008399	S.D. dependent var	0.012126
S.E. of regression	0.012075	Akaike info criterion	-5.988368
Sum squared resid	0.216244	Schwarz criterion	-5.959892
Log likelihood	4472.328	Hannan-Quinn criter.	-5.977756
F-statistic	2.802891	Durbin-Watson stat	2.007611
Prob(F-statistic)	0.006694		

Inverted AR Roots	.77+.64i	.77-.64i	-1.00
Inverted MA Roots	.76+.64i	.76-.64i	-1.00

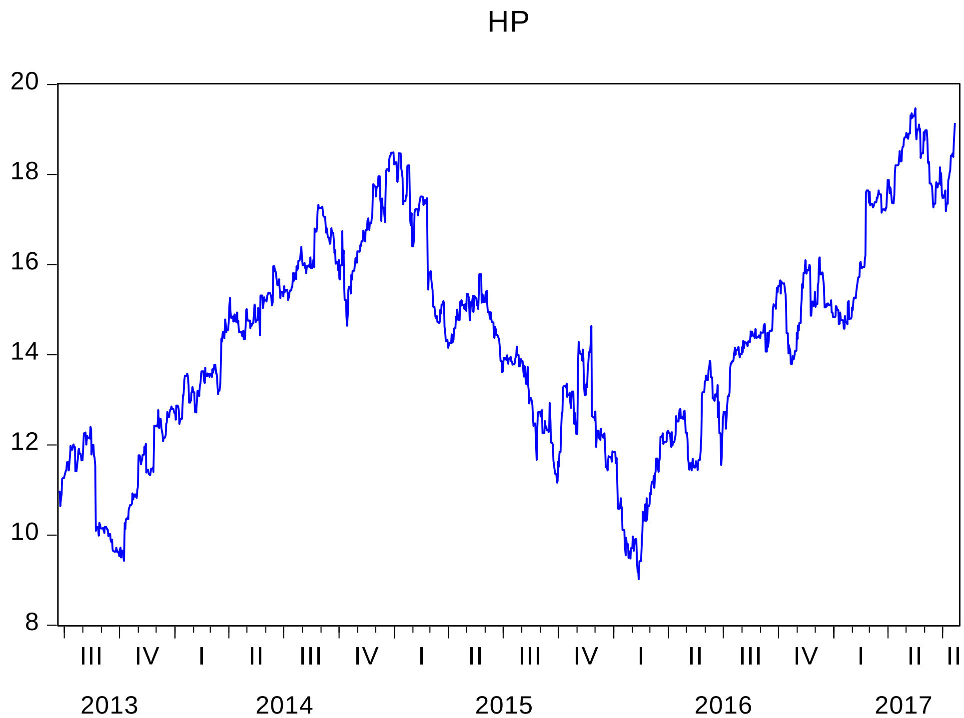
After the equation is set up and conducted by eViews it yields the results as shown:

Apple	
7/22/2017	150.4173
7/23/2017	150.5199
7/24/2017	150.8094
7/25/2017	150.961
7/26/2017	151.1823
7/27/2017	151.1827
7/28/2017	151.2383



Graph above gives a visual idea of the forecasted stock, displaying data from 12. July 2017 to 21. July 2017 and the other seven forecasted points. There is a continuous slight rise of the forecasted results.

5.2) HP



Again, stationarity should be assessed. The graph of HP stock seems more volatile and stationary than the Apple counterpart. However, for being sure about the stationarity the Dickey Fuller test was conducted again.

Null Hypothesis: HP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=23)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.423141	0.5722
Test critical values:	1% level	-3.434528	
	5% level	-2.863273	
	10% level	-2.567741	

*MacKinnon (1996) one-sided p-values.

The results of Dickey Fuller test show again non-significance for being non-stationary, which means it is more likely to be stationary and it is also indicated by the shape of the graph. Therefore, stationarity can be assumed.

The details of the eViews forecast is shown again below this time for the HP stock prices:

Automatic ARIMA Forecasting
Selected dependent variable: D(HP)
Date: 07/25/17 Time: 18:47
Sample: 6/21/2013 7/21/2017
Included observations: 1491
Forecast length: 7

Number of estimated ARMA models: 25
Number of non-converged estimations: 0
Selected ARMA model: (3,2)(0,0)
AIC value: -0.251625186822

For this time series data third lag of AR and second lag of MA is chosen with the lowest AIC value. Method comparison test results can be seen below again:

Model Selection Criteria Table
Dependent Variable: D(HP)
Date: 07/25/17 Time: 18:47
Sample: 6/21/2013 7/21/2017
Included observations: 1491

Model	LogL	AIC*	BIC	HQ
(3,2)(0,0)	194.586577	-0.251625	-0.226709	-0.242340
(2,3)(0,0)	194.534840	-0.251556	-0.226639	-0.242271
(0,0)(0,0)	186.854554	-0.247961	-0.240842	-0.245308
(4,4)(0,0)	194.812048	-0.247903	-0.212309	-0.234639
(1,0)(0,0)	187.555122	-0.247559	-0.236880	-0.243580
(0,1)(0,0)	187.531458	-0.247527	-0.236849	-0.243548
(2,2)(0,0)	190.378678	-0.247322	-0.225965	-0.239364
(0,2)(0,0)	187.788082	-0.246530	-0.232292	-0.241224
(2,0)(0,0)	187.768836	-0.246504	-0.232266	-0.241198
(1,1)(0,0)	187.669542	-0.246371	-0.232133	-0.241065
(2,4)(0,0)	191.226783	-0.245777	-0.217301	-0.235166
(4,2)(0,0)	191.220388	-0.245768	-0.217293	-0.235157
(0,3)(0,0)	187.789448	-0.245190	-0.227393	-0.238558
(1,2)(0,0)	187.788417	-0.245189	-0.227392	-0.238557
(3,0)(0,0)	187.783560	-0.245183	-0.227385	-0.238550
(2,1)(0,0)	187.772090	-0.245167	-0.227370	-0.238535
(3,3)(0,0)	190.714636	-0.245090	-0.216614	-0.234479
(4,3)(0,0)	191.689626	-0.245057	-0.213021	-0.233119
(0,4)(0,0)	188.476349	-0.244770	-0.223413	-0.236812
(4,0)(0,0)	188.452815	-0.244739	-0.223382	-0.236780
(3,1)(0,0)	187.944604	-0.244057	-0.222700	-0.236099
(1,3)(0,0)	187.922850	-0.244028	-0.222671	-0.236069
(1,4)(0,0)	188.484945	-0.243441	-0.218524	-0.234155
(4,1)(0,0)	188.455919	-0.243402	-0.218485	-0.234117
(3,4)(0,0)	188.401687	-0.240646	-0.208611	-0.228708

Moreover, the variables and the constant are to be seen below for the equation:

Variables are mostly significant except MA second lag with the 0.2297 significance level, which is extremely insignificant. However, eViews chose this result, with the reason being unknown. Presumably due to the AIC selection, another comparison method could be chosen. All the comparison methods show a significant result as displayed in the table below. For instance, as it is shown in the table of Black Information Crieteria (BIC) above, the smallest number is 0.208611, which would be the method chosen according to BIC. However, it shows lags AR 3 and MA 4, which would be extremely insignificant. Additionally, it already includes MA 2, which is very insignificant. After all, according to Hannan-Quinn method ARMA(3,4) should be chosen.

Dependent Variable: D(HP)
Method: ARMA Maximum Likelihood (BFGS)
Date: 07/25/17 Time: 18:47
Sample: 6/22/2013 7/21/2017
Included observations: 1491
Failure to improve objective (non-zero gradients) after 117 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005516	0.005492	1.004384	0.3154
AR(1)	0.564610	0.022481	25.11504	0.0000
AR(2)	-0.972028	0.014578	-66.67553	0.0000
AR(3)	-0.041211	0.022397	-1.840080	0.0660
MA(1)	-0.599051	0.250620	-2.390278	0.0170
MA(2)	1.000000	0.832229	1.201592	0.2297
SIGMASQ	0.044957	0.018516	2.427940	0.0153

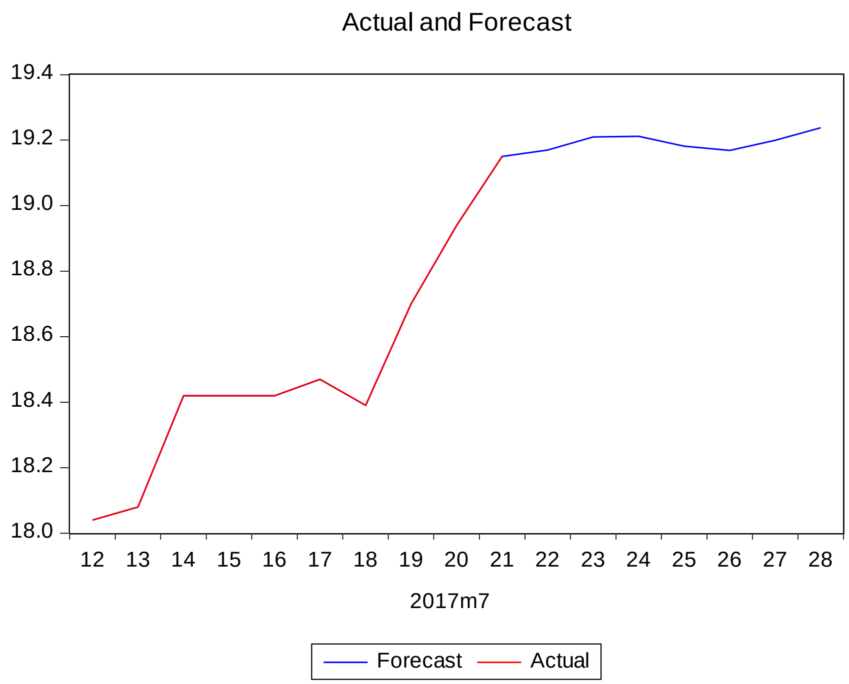
R-squared	0.013443	Mean dependent var	0.005488
Adjusted R-squared	0.009454	S.D. dependent var	0.213541
S.E. of regression	0.212530	Akaike info criterion	-0.251625
Sum squared resid	67.03051	Schwarz criterion	-0.226709
Log likelihood	194.5866	Hannan-Quinn criter.	-0.242340
F-statistic	3.370192	Durbin-Watson stat	1.997595
Prob(F-statistic)	0.002645		

Inverted AR Roots	.30+.95i	.30-.95i	-.04
Inverted MA Roots	.30-.95i	.30+.95i	

Below a table with the forecasted results of HP from 22.July to 28. July can be found:

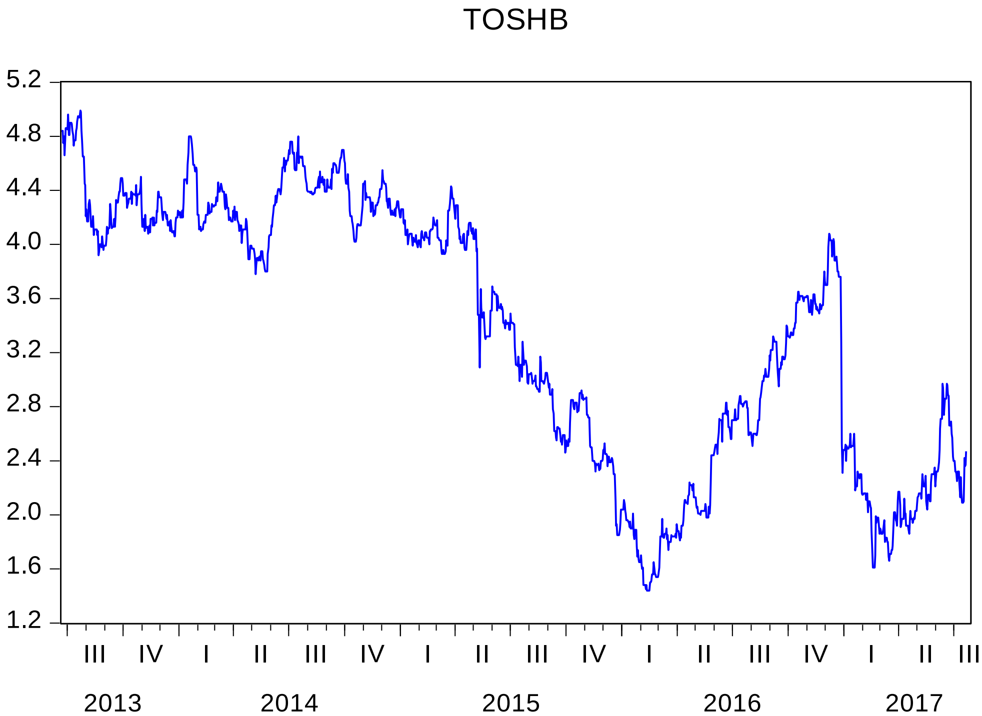
Hp	
7/22/2017	19.17036
7/23/2017	19.21013
7/24/2017	19.21213
7/25/2017	19.18175

7/26/2017	19.16901
7/27/2017	19.19925
7/28/2017	19.23795



5.3) Toshiba

The previously used process is also applied for Toshiba share.



Null Hypothesis: TOSHB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=23)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.589465	0.4877
Test critical values:	1% level	-3.434528	
	5% level	-2.863273	
	10% level	-2.567741	

*MacKinnon (1996) one-sided p-values.

Dickey Fuller shows again a non-significance for being non-stationary. Therefore, it is accepted that it is more likely to be stationary. Moreover, as data is more likely to be stationary no difference is taken.

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(TOSHB)
Date: 07/25/17 Time: 18:52
Sample: 6/21/2013 7/21/2017
Included observations: 1491
Forecast length: 7

Number of estimated ARMA models: 25
Number of non-converged estimations: 0
Selected ARMA model: (4,4)(0,0)
AIC value: -4.6889281147

Model Selection Criteria Table
Dependent Variable: DLOG(TOSHB)
Date: 07/25/17 Time: 18:52
Sample: 6/21/2013 7/21/2017
Included observations: 1491

Model	LogL	AIC*	BIC	HQ
(4,4)(0,0)	3505.595910	-4.688928	-4.653333	-4.675664
(0,1)(0,0)	3497.976051	-4.688097	-4.677418	-4.684117
(1,0)(0,0)	3497.925679	-4.688029	-4.677351	-4.684050
(3,0)(0,0)	3499.845814	-4.687922	-4.670124	-4.681290
(0,3)(0,0)	3499.744808	-4.687786	-4.669989	-4.681154
(1,1)(0,0)	3498.451175	-4.687393	-4.673155	-4.682087
(3,2)(0,0)	3501.136905	-4.686971	-4.662055	-4.677686
(0,2)(0,0)	3498.094269	-4.686914	-4.672676	-4.681608
(2,3)(0,0)	3501.062840	-4.686872	-4.661955	-4.677587
(2,0)(0,0)	3498.001519	-4.686789	-4.672551	-4.681484
(2,4)(0,0)	3501.952423	-4.686724	-4.658248	-4.676112
(4,0)(0,0)	3499.942841	-4.686711	-4.665354	-4.678752
(3,1)(0,0)	3499.882134	-4.686629	-4.665272	-4.678671
(0,0)(0,0)	3495.759260	-4.686464	-4.679345	-4.683812
(0,4)(0,0)	3499.746335	-4.686447	-4.665090	-4.678488
(1,3)(0,0)	3499.745326	-4.686446	-4.665089	-4.678487
(2,1)(0,0)	3498.452570	-4.686053	-4.668256	-4.679421
(1,2)(0,0)	3498.452306	-4.686053	-4.668255	-4.679421
(4,1)(0,0)	3500.286270	-4.685830	-4.660914	-4.676545
(4,2)(0,0)	3501.146092	-4.685642	-4.657166	-4.675030
(3,3)(0,0)	3501.143770	-4.685639	-4.657163	-4.675027
(3,4)(0,0)	3501.951470	-4.685381	-4.653345	-4.673443
(1,4)(0,0)	3499.744925	-4.685104	-4.660187	-4.675819
(2,2)(0,0)	3498.689299	-4.685029	-4.663672	-4.677071
(4,3)(0,0)	3501.215135	-4.684393	-4.652358	-4.672455

As it shown above ARMA(4,4) is chosen.

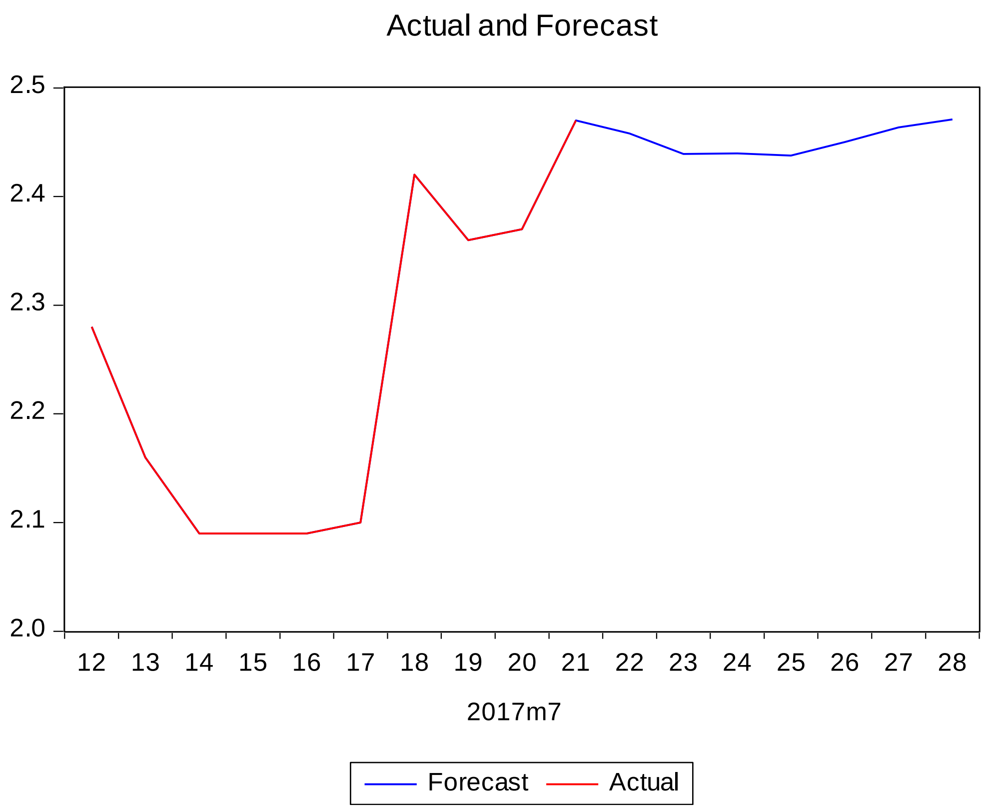
Dependent Variable: DLOG(TOSHB)
Method: ARMA Maximum Likelihood (BFGS)
Date: 07/25/17 Time: 18:52
Sample: 6/22/2013 7/21/2017
Included observations: 1491
Convergence achieved after 133 iterations
Coefficient covariance computed using outer product of gradients

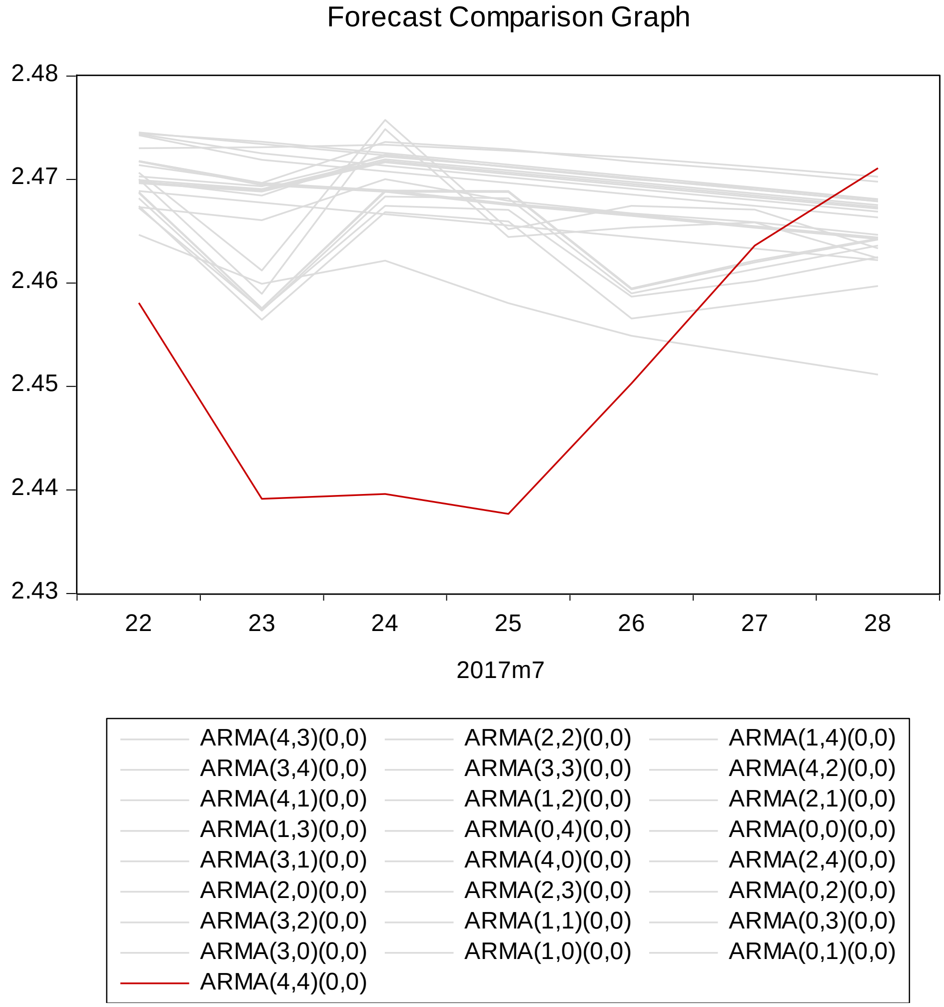
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000454	0.000654	-0.694457	0.4875
AR(1)	0.072103	0.124454	0.579357	0.5624
AR(2)	0.621855	0.129584	4.798845	0.0000

AR(3)	-0.237657	0.094679	-2.510143	0.0122
AR(4)	-0.801117	0.100893	-7.940281	0.0000
MA(1)	-0.019496	0.120256	-0.162123	0.8712
MA(2)	-0.655070	0.118667	-5.520215	0.0000
MA(3)	0.229644	0.086382	2.658471	0.0079
MA(4)	0.830804	0.099463	8.352885	0.0000
SIGMASQ	0.000531	8.34E-06	63.68451	0.0000

R-squared	0.013877	Mean dependent var	-0.000451
Adjusted R-squared	0.007884	S.D. dependent var	0.023210
S.E. of regression	0.023118	Akaike info criterion	-4.688928
Sum squared resid	0.791523	Schwarz criterion	-4.653333
Log likelihood	3505.596	Hannan-Quinn criter.	-4.675664
F-statistic	2.315682	Durbin-Watson stat	1.997654
Prob(F-statistic)	0.013834		

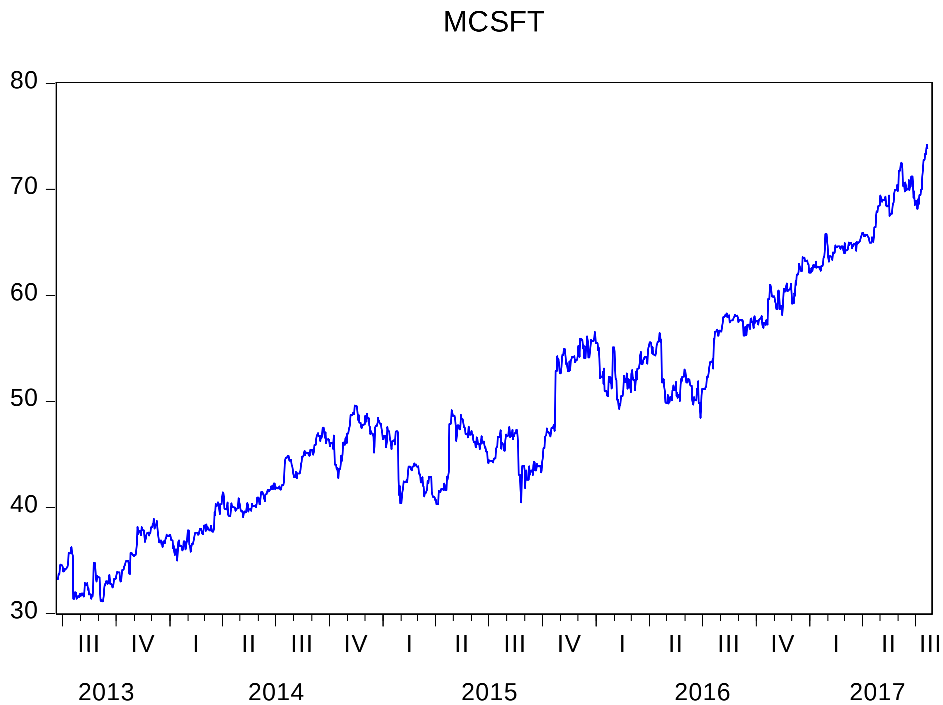
Inverted AR Roots	.80-.60i	.80+.60i	-.76-.47i	-.76+.47i
Inverted MA Roots	.79-.60i	.79+.60i	-.78-.47i	-.78+.47i





5.4) Microsoft

For Microsoft´s share prices, the graph makes it seem as if the data is rather more non-stationary and time dependent. However, as usual the Dickey Fuller test will be conducted to have a quantifiable fact at hand.



Null Hypothesis: MCSFT has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=23)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.227636	0.9325
Test critical values:	1% level	-3.434528	
	5% level	-2.863273	
	10% level	-2.567741	

*MacKinnon (1996) one-sided p-values.

Despite how the graph looks like, the Dickey fuller test shows highly non-significance for this set of time series data. Thus, no difference is taken while the automatic ARIMA is done.

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(MCSFT)
Date: 07/25/17 Time: 18:55
Sample: 6/21/2013 7/21/2017
Included observations: 1491
Forecast length: 7

Number of estimated ARMA models: 25
Number of non-converged estimations: 0
Selected ARMA model: (1,2)(0,0)
AIC value: -5.98876713215

This time ARMA(1,2) is chosen due to the results of AIC:

Model Selection Criteria Table
Dependent Variable: DLOG(MCSFT)
Date: 07/25/17 Time: 18:55
Sample: 6/21/2013 7/21/2017
Included observations: 1491

Model	LogL	AIC*	BIC	HQ
(1,2)(0,0)	4469.625897	-5.988767	-5.970970	-5.982135
(2,1)(0,0)	4469.621686	-5.988761	-5.970964	-5.982129
(2,2)(0,0)	4469.651145	-5.987460	-5.966103	-5.979501
(1,3)(0,0)	4469.646855	-5.987454	-5.966097	-5.979495
(3,1)(0,0)	4469.644053	-5.987450	-5.966093	-5.979491
(3,3)(0,0)	4471.367096	-5.987079	-5.958603	-5.976467
(3,4)(0,0)	4472.062004	-5.986669	-5.954634	-5.974731
(4,3)(0,0)	4472.058184	-5.986664	-5.954629	-5.974726
(2,3)(0,0)	4469.724879	-5.986217	-5.961301	-5.976932
(3,2)(0,0)	4469.719090	-5.986209	-5.961293	-5.976924
(4,1)(0,0)	4469.716317	-5.986206	-5.961289	-5.976921
(1,4)(0,0)	4469.701285	-5.986185	-5.961269	-5.976900
(4,4)(0,0)	4472.132926	-5.985423	-5.949828	-5.972159
(4,2)(0,0)	4470.092979	-5.985370	-5.956894	-5.974758
(2,4)(0,0)	4469.757484	-5.984919	-5.956444	-5.974308
(0,0)(0,0)	4463.315305	-5.984326	-5.977207	-5.981673
(0,1)(0,0)	4463.434901	-5.983145	-5.972467	-5.979166
(1,0)(0,0)	4463.431214	-5.983140	-5.972462	-5.979161
(2,0)(0,0)	4463.610244	-5.982039	-5.967801	-5.976733
(0,2)(0,0)	4463.608750	-5.982037	-5.967799	-5.976731
(1,1)(0,0)	4463.503739	-5.981896	-5.967658	-5.976591
(0,3)(0,0)	4463.612438	-5.980701	-5.962903	-5.974069
(3,0)(0,0)	4463.610247	-5.980698	-5.962900	-5.974066
(0,4)(0,0)	4463.618828	-5.979368	-5.958011	-5.971409
(4,0)(0,0)	4463.612467	-5.979359	-5.958002	-5.971401

Dependent Variable: DLOG(MCSFT)
Method: ARMA Maximum Likelihood (BFGS)
Date: 07/25/17 Time: 18:55
Sample: 6/22/2013 7/21/2017
Included observations: 1491
Failure to improve objective (non-zero gradients) after 65 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000477	4.73E-05	10.07233	0.0000
AR(1)	0.979615	0.006664	147.0115	0.0000
MA(1)	-0.976850	9.357368	-0.104394	0.9169
MA(2)	-0.023150	0.496380	-0.046637	0.9628
SIGMASQ	0.000146	0.000184	0.789345	0.4300

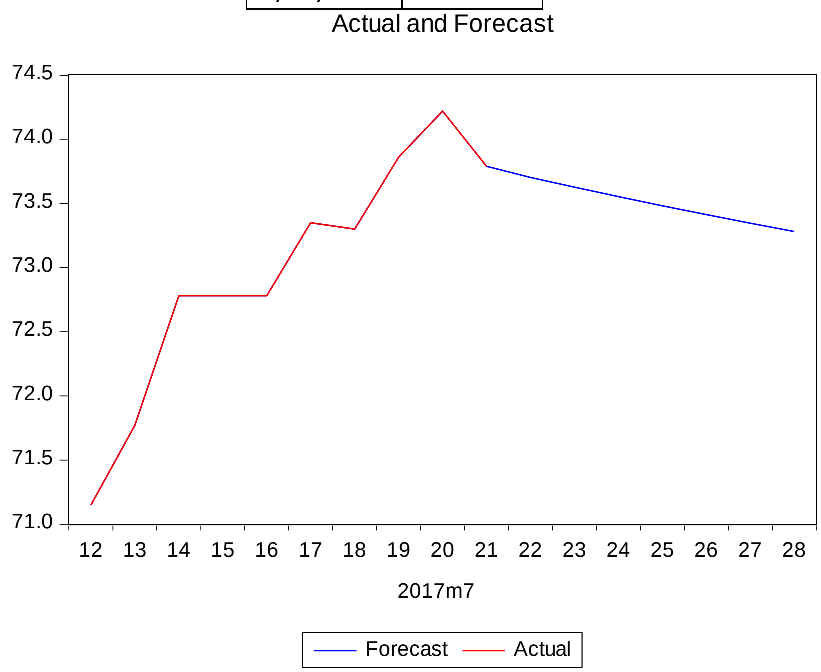
R-squared	0.010285	Mean dependent var	0.000534
Adjusted R-squared	0.007621	S.D. dependent var	0.012130
S.E. of regression	0.012083	Akaike info criterion	-5.988767

Sum squared resid	0.216964	Schwarz criterion	-5.970970
Log likelihood	4469.626	Hannan-Quinn criter.	-5.982135
F-statistic	3.860669	Durbin-Watson stat	2.000124
Prob(F-statistic)	0.003986		

Inverted AR Roots	.98	
Inverted MA Roots	1.00	-.02

The significance levels of the MAs for Microsoft´s stock prices are quite poor. Therefore, the accuracy of the forecast for Microsoft´s stock is questionable:

Microsoft	
7/22/2017	73.70331
7/23/2017	73.6273
7/24/2017	73.55363
7/25/2017	73.48224
7/26/2017	73.4131
7/27/2017	73.34613
7/28/2017	73.28131



5.5) Brief Forecast Results

Below you see the MAPE ratios for the ARIMA forecast, which was conducted in eViews. It is compared with applied Naïve 1 and 2 forecasting methods MAPE results. This is done to have a comparison of ARIMA method with other basic methods.

Naïve 1 method is basically applying the figures of the period before for next period, Naïve 2 works in the same way takes the figures of 2 periods before. MAPE is the average of the results of MAE, which is mean absolute error. Mean Absolute Error is another basic error method. It is basically calculated as follows:

$|Xt - Xf| / Xt$

Where, Xt is actualy value, Xf is forecasted value.

Larger forecasted data is more meaningful to compare MAPE results since MAPE is average of mean absolute errors. Thus, the forecast from 1 January 2017 to 28 July 2017 was conducted to MAPE results of ARIMA forecasts.

APPLE	**Forecasting Models Apple**	MAPE	Rank
	ARIMA (4,4,0)	0.1253	3
	Naive 1	0.0046	1
	Naive 2	0.0070	2

HP	**Forecasting Models HP**	MAPE	Rank
	ARIMA (3,2,0)	0.1204	3
	Naive 1	0.0063	1
	Naive 2	0.0101	2

Microsoft	**Forecasting Models Microsoft**	MAPE	Rank
	ARIMA (3,4,0)	0.0454	3
	Naive 1	0.0043	1
	Naive 2	0.0065	2

Toshiba	**Forecasting Models Toshiba**	MAPE	Rank
	ARIMA (2,1,1)	0.1541	3
	Naive 1	0.0218	1
	Naive 2	0.0348	2

Furthermore, the results of eViews for the forecast of the stocks from 22. July 2017 to 27. July 2017 is shown. Moreover, the actual share price for the listed stocks are shown and compared with and mean absolute error. Forecast results for 1 January 2017 to 28 July 2017 are not shown here because of the size of data.

The brief forecasting results are shown below:

Toshiba			
Date	**Forecast**	**Actual**	**MAE**
7/22/2017	2.458067	2.47	0.483%
7/23/2017	2.439148	2.47	1.249%
7/24/2017	2.439607	2.51	2.805%
7/25/2017	2.437686	2.44	0.095%
7/26/2017	2.45031	2.50	1.988%
7/27/2017	2.463618	2.41	2.225%
7/28/2017	2.47109	2.18	13.353%

Microsoft			
Date	**Forecast**	**Actual**	**MAE**
7/22/2017	73.70331	73.790001	0.117%
7/23/2017	73.6273	73.790001	0.220%
7/24/2017	73.55363	73.599998	0.063%
7/25/2017	73.48224	74.190002	0.954%
7/26/2017	73.4131	74.050003	0.860%
7/27/2017	73.34613	73.160004	0.254%
7/28/2017	73.28131	73.040001	0.330%

HP			
Date	**Forecast**	**Actual**	**MAE**
7/22/2017	19.17036	18.01	6.443%
7/23/2017	19.21013	18.01	6.664%

7/24/2017	19.21213	17.84	7.691%
7/25/2017	19.18175	17.879999	7.280%
7/26/2017	19.16901	17.610001	8.853%
7/27/2017	19.19925	17.549999	9.397%
7/28/2017	19.23795	17.51	9.868%

	Apple		
Date	**Forecast**	**Actual**	**MAE**
7/22/2017	150.4173	150.270004	0.098%
7/23/2017	150.5199	150.270004	0.166%
7/24/2017	150.8094	152.089996	0.842%
7/25/2017	150.961	152.740005	1.165%
7/26/2017	151.1823	153.460007	1.484%
7/27/2017	151.1827	150.559998	0.414%
7/28/2017	151.2383	149.5	1.163%

As it is shown, Apple and Microsoft stock are having the smallest percentage of errors and provide more accurate forecasts. To the contrary, HP stock forecast is having a considerably high 8% mean of error. Microsoft has 0.23%, Apple has 0.24%, Toshiba has 1.23%.

6)Conclusion

Before drawing a conclusion, a quick look at the hypothesis could be helpful:

H0 = ARIMA analysis for chosen stocks give less than %3 MAPE

H1 = ARIMA analysis for chosen stocks does not give less than %3 MAPE

Considering the time series analysis done, ARIMA method is significantly good to evaluate the stocks of consumer electronics market for short-term forecasting. Three out of four stocks gave significantly less MAPE error than 3%, which were forecasted for one week with the following MAPE ratios: for Microsoft 0.23%, for Apple 0.24% and for Toshiba 1.23%. HP stock, which gave a mean error of 8% and was not giving an extreme high error. In most of the cases, time series analysis for the consumer electronics market works well. Therefore, H0 hypothesis should be accepted for the short-term forecasts according to this thesis.

On the other hand, all the long-term forecasts were not giving significant MAPE ratio. The reasoning behind this could be that stock prices are highly volatile and the prices change drastically in long term. Therefore, the MAPE ratios for the forecasts from 1 January 2017 to 28 July 2017 were not significant. Accordingly, H0 could not be accepted for long term forecasting.

Moreover, the companies should also be assessed individually. However, this interpretation will be done just examining general information, but not the forecasts. Because the forecasts are done just for one week, which would make it meaningful to make a general evaluation of the company.

Toshiba has a continuous drop and a loss of 500 million last year. Apple, Microsoft and HP seem to perform well and their stocks have been increasing during said timeframe. It could be a possibility that some of the stocks will experience a huge increase, while the competitor experiencing a decrease in the stock, like Microsoft and Apple – the big rivals in the consumer electronics market. However, most of these stocks have been having a dramatic increase in stock price over the past 5 years, which would be an indicator that the market is growing continuously. Yet there is the fact that Toshiba has been performing poorly over the past 10 years. Thus, customers of Toshiba could have switched to other brands. However, there is a huge increase in the other stocks, which could not just be due to the of reallocation of Toshiba customers to other brands. Bearing that in mind, it can be concluded that the consumer electronics market is continuously growing and it still has future growth potential. Moreover, this field should be further researched and more time series analysis with more companies – including more data - should be conducted. In this research, only one week was forecasted. This was due to the constraints of eViews and the fact that it is more realistic to only forecast one week. However, this research is still useful for the investors, who want to buy and sell stocks on a short-term horizon, like a few days or a one week period.

7)Limitations & Recommendations

Another limitation of the study was that the limited version of eViews was used, which allowed only 1500 observation points to be analyzed. This number of observations might not be sufficient for many analysts. After all, more observation points and data analyzed in the time series, yields more accurate results. In the best case, all data should be used.

As the graph on page 14 shows, HP stock seemed quite non-stationary. However, eViews did not choose to take the difference of the data. Therefore, Automatic ARIMA forecasting in eViews might not choose the best combination each time. Also for trials eViews was choosing some insignificant lags of AR and MA.

For evaluating the general consumer electronics market, more stocks should be analyzed. There are a lot more companies, such as Intel, LG, Panasonic and Sony. However, all of those could not be included due to the scope of the bachelor thesis.

Moreover, to be able to draw a conclusion for the individual companies, concerning the direction their stock will move on the long term, more data points should be forecasted. As mentioned, just the period of one week was forecasted just. However, two or three months should be forecasted to be able to evaluate the long-term performance of the company. In this case, it would be useful to have data of at least the past 15 years. Furthermore, after the long-term assessment of the companies more accurate predictions of where market is going to could be made.

Furthermore, methods such as ARCH, GARCH could also be used for time series forecasting. Although these methods are similar to ARIMA. They would certainly give various accuracy results which could be more accurate and got chosen for some specific case. However, because of the scope of this research ARCH and GARCH forecasting were not conducted.

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