RESEARCH PAPER

IN RESEARCH METHODS IN FINANCE

on the topic: Technical Analysis of the Capital Market Data

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Contents

Abstract

This research paper focuses on the use of technical analysis to analyse capital market data on the example of Lockheed Martin Corporation stock exchange data. The purpose of the paper is to explore the main methods of technical analysis of time series data and apply them in practice. The work contains the most applicable methods of technical analysis in finance in general and capital market data analysis in particular. These methods were applied to analyse the stock exchange data of Lockheed Martin Corporation, one of the largest companies in the US military-industrial complex, which is actively involved in the development and production of weapons, vehicles, and equipment used to provide the Armed Forces of NATO and to support the Armed Forces of Ukraine in the Russian-Ukrainian war, and compares its performance with other companies of the S&P 500 stock market index. Based on the results of the research, conclusions are drawn about the expediency of using technical analysis to analyse capital market data and its practical applicability.

1 Introduction and Desktop Research

The relevance of the topic stems from the fact that the development of digital technologies has brought significant changes to many industries. Technological innovations of the information age allow us to record information, collect it, process it, analyse it and transform it without significant effort and cost. The ability to use information appropriately is a very useful skill today, as it helps to make effective management decisions, which leads to better value creation.

The purpose of the research was to investigate the possibilities of technical analysis of capital market data, evaluate its main methods and apply them to a practical example to compare the development of two stock indices, namely the shares of Lockheed Martin Corporation and the well-known S&P 500 stock index.

In order to achieve this goal, the following tasks were performed:

- The history of Lockheed Martin was researched
- The possibility of importing and initially analysing the company's stock exchange data using the R programming language was researched
- The possibility of conducting an exploratory analysis of stock exchange data using R for visual conclusions was investigated
- The possibility of analysing daily returns in R to understand the profitability of these assets is investigated
- The possibility of analysing correlation in R to understand the relationship between two indices is investigated
- The possibility of forecasting data using various models in R to predict the development of share prices
- Conclusions on the practical application of technical analysis for capital market data analysis are drawn

The object of the study is Lockheed Martin Corporation, its history and data on the development of its stock, as well as data on the stock of the S&P 500 stock index.

The theoretical and practical information base for the study is the work of leading researchers from the United States of America, Germany, Australia, South Africa and other countries in the fields of finance, capital markets, technical analysis, business analytics, statistics, stochastics and data analytics.

The main methods used in the study were quick initial analysis using built-in R functions, exploratory data analysis using the ggplot package, return analysis using the normal distribution and Student t-distribution, correlation analysis using the simple correlation function and GARCH modelling, forecasting using the functions of the Prophet package and ARIMA modelling.

2 Empirical Analysis on the Example of Lockheed Martin Corporation

2.1 Company History

Lockheed Martin Corporation is a global aerospace and defense company formed by the merger of Lockheed Corporation with Martin Marietta in 1995. It has played a significant role in the 20th and 21st centuries, including both World Wars, the Cold War, and the War on Terror. Its innovative and groundbreaking technologies have helped to shape the modern world and pave the way for new discoveries and developments in the field of aerospace and defense.

Lockheed Martin Corporation shifted its focus to military production in World War II, producing successful aircraft such as the P-38 Lightning and Hudson bomber. The Postwar Era of 1945-1953 saw significant change and growth, with the introduction of jet-powered aircraft such as the P-80 Shooting Star. In 1951, the company merged with the Glenn L. Martin Company, renaming it Martin Marietta Corporation. The Cold War era of 1953-1991 was marked by significant growth and development. Lockheed Martin Corporation expanded its reach in the military and defense industries and developed advanced military technologies.

These included the F-104 Starfighter and F-16 Fighting Falcon, missile defense systems, satellite technology, and radar systems. One of the most significant achievements was the development of the U-2 spy plane and the SR-71 Blackbird, which were used for reconnaissance and intelligence gathering. The 1990s saw significant change and growth for Lockheed Martin Corporation, with the merger between Martin Marietta and Lockheed Corporation, the development of new technologies, and the expansion into commercial and civilian markets.

Lockheed Martin Corporation developed the F-22 Raptor, the world's first operational stealth fighter, and expanded its reach into commercial and civilian markets. In the 21st century, the company has expanded its global reach, developed cutting-edge technologies, and played a significant role in the War on Terror and conflicts in Iraq and Afghanistan. The company has invested heavily in research and development, with a focus on emerging technologies such as unmanned aerial vehicles (UAVs) and cybersecurity. Lockheed Martin Corporation has been a highly successful company in the aerospace and defense industry, with a strong track record of revenue and earnings growth.

Lockheed Martin Corporation has a long and storied history in the aerospace and defense industry, with a strong legacy of innovation and technological excellence. It has consistently delivered strong revenue and earnings growth, with total net sales of $67.0 billion in 2021 and earnings per share of $22.76 in 2021. However, it faces challenges and uncertainties, such as potential for government budget cuts and changes in defense priorities. Its future prospects will depend on its ability to continue innovating and developing new technologies and adapt to changes in the market and regulatory environment.

2.2 Company's Performance Compared to the Companies of the S&P 500 Stock Market Index

2.2.1 Importing and Initial Analysis

Technical analysis of a company's stock price begins with importing the company's stock exchange data. In R, this can be done using the *Quantmod* package, namely the *getSymbols*() function. To import, we need a list of specific arguments, namely:

- The stock ticker symbol, i.e. the name of the company's shares as they are listed on the stock exchange. It can be found in open sources. For Lockheed Martin Corporation, the index is called LMT, which will be our first argument in the function.
- The source from which the data on the company's share price will be taken. There are several large online databases that contain stock exchange data, such as Yahoo! Finance, Quandl, and others, but only Yahoo! Finance remains as a free alternative, so we will use it. To select it, we set the *src* argument to "*yahoo*".
- The time period to be analysed. This can be either a short or a long period, depending on the need for analysis. We take the data from the company's listing on the New York Stock Exchange, namely January 1, 1985, and until the beginning of writing, namely March 15, 2023, assigning the $from$ and *to* arguments the values "$1985-01-01$" and "$2023-03-15$" according to the international date and time standard ISO 8601.
- Additional arguments to simplify further analysis. In our case, this is the *missing* argument with the value "*remove*" to remove data that has no values (for example, weekends or holidays when exchanges are closed). We also used the *auto.assign* argument with a value of FALSE in order not to automatically create a set of values, but to give it a custom name *lmt_ohlc_xts* and operate it as a $data.frame$ table.

After importing the data, we can perform a preliminary quick analysis. To do this, we can use the *str*(), *head*(), and *tail*() functions. The *str*() function will give us information about our object, in our case it is the object type, time period, number of rows and columns, column names, indexes, and attributes. The *head*() and *tail*() functions give us the ability to look at the first and last rows of our data, respectively, without showing the entire table, which can be very large.

The process of importing Lockheed Martin's stock index data and its initial analysis are presented in Appendix A.

After doing these steps, we can see that our data is an xts object, i.e. each observation is assigned a date as an index in the UTC time zone. We have 9627 rows and 6 columns named LMT.Open, LMT.High, LMT.Low, LMT.Close, LMT.Volume, LMT.Adjusted. These columns indicate the stock price at the opening of trades, the daily high, the daily low, the closing price, the number of shares traded, and the adjusted closing price after dividend payments. You can clearly see that the trading price increased almost 40-fold in 2023 compared to 1985, rising from $13 to $480, and the adjusted price increased 100-fold, rising from $4.60 to $480.

In our work, we are most interested in the LMT.Adjusted column, because the stock price after the closing of trades and dividend payment provides the most informative view. To isolate this column, we create a new object *lmt_adj* using the *Ad*() function of the *Quantmod* package, specifying our xts object *lmt_ohlc_xts* as an argument.

To make sure that the *missing* argument of the *getSymbols*() function has done its job, we check our *lmt_adj* object for missing values (NA) using the two functions *is.na*() and *sum*(). The first function checks for all values, and if any of them are not available, it sets a 1 instead of the 0 that would be set if the value exists. The second function sums the amount of 1 and displays the sum on the screen.

Thus, we can see that our data does not contain any inaccessible values, and therefore this problem does not require further processing.

Since we are going to analyse the development of Lockheed Martin's stock price in comparison with the development of the S&P 500 index, of which it is a part, we have to take all the same steps with the S&P 500 data. The process of importing S&P 500 index data and its initial analysis are presented in Appendix B.

After doing all these steps again, we can see that our data is also an xts object. We have once more 9627 rows and 6 columns named LMT.Open, LMT.High, LMT.Low, LMT.Close, LMT.Volume, LMT.Adjusted. We can clearly see that the trading price increased almost 25-fold in 2023 compared to 1985, rising from $165 to $3900, and the adjusted price also increased 25-fold, rising from $165 to $3900.

2.2.2 Exploratory Analysis

For the next step of our technical analysis, we can use exploratory data analysis, i.e. analysis aimed at graphically displaying data and making visual conclusions. First of all, it will be best to visualise the development of our two indices using a plot. To do this, we can use the ggplot() function of the ggplot2 package. On the graphs, we will highlight the time periods of major crises, the behaviour of the stock price during which may be interesting. These critical periods include:

- The global financial crisis of 2007-2009
- The first waves of the COVID-19 pandemic in 2020
- The first year of the full-scale invasion of Ukraine by the russian federation 2022-2023

The results of creating graphs of the development of the stock price of Lockheed Martin Corporation and the S&P 500 stock index, which includes these shares, are shown in Figures C1 and C2 of the Appendix C.

After analysing these graphs (Figure C1 & Figure C2), we can draw certain conclusions:

1. The development curves of both indices are generally similar and show a gradual increase in prices with an increasing rate over time. Also, both charts have moments of high volatility. However, a closer look at the specific moments reveals strong differences.
2. The Lockheed Martin Corporation weathered the Global Financial Crisis of 2007-2009 better than the S&P 500, even though S&P 500 recovered from it faster. The stock market index began a gradual decline from the very beginning of the crisis, which then became faster and sharper until the collapse at the peak of the crisis in 2008. After that, however, the trends became a little better, with a slight stagnation, a slight drop and a gradual increase starting in 2009. Lockheed Martin stock, on the other hand, showed neither a gradual nor a sharp decline at the beginning of the crisis, stagnating until the very peak of the crisis, when the price fell sharply but not too much.

However, this decline was followed by stagnation, which lasted almost until 2013. The reason for this is most likely that Lockheed Martin is closely linked to the US military-industrial complex, namely government orders and contracts. This, along with the fact that the company is high-tech and innovative, helped its shares not to fall during the global financial crisis, as the company is almost strategically important for US defence.

3. The first massive wave of the global COVID-19 pandemic was met by both indices in almost the same way, with a rapid, sharp drop in prices. There may be several reasons for this. The pandemic shook up financial markets, investments became more risky, and people began to withdraw money to save it or to redirect it into less risky types of investments (dollars, gold). However, just after the fall, the value of the S&P 500 index began to grow rapidly at a high rate. This is due to the fact that the index included large pharmaceutical companies (Pfizer, Moderna, Johnson & Johnson) that were developing a vaccine against COVID-19, which greatly raised the value of their shares and dragged the index along. Lockheed Martin Corporation, in turn, is engaged in the aircraft and military equipment industries, which were unattractive to investors during the pandemic, and its share price, after recovering from a slight drop, began to stagnate with periodic ups and downs throughout the pandemic.

4. The situation is quite different since the beginning of the full-scale invasion of Ukraine by the russian federation. The S&P 500 index is a universal index, as it includes companies operating in a wide variety of industries. Before the war started, the index was growing quite rapidly, but with the start of the full-scale invasion, it quickly collapsed, losing value rapidly for six months, and then began to stagnate with short-term increases and decreases, which continues to this day. However, one of the few industries that did not suffer, but rather gained a second wind during the war was the defence industry. Even before the war started, Lockheed Martin's shares had skyrocketed. There are two reasons for this. Firstly, many people start investing in defence companies when there is a military threat, because during a war, defence companies have large orders and their value increases dramatically. Secondly, Lockheed Martin had very large orders for its defence products, including Javelin anti-tank guided missile systems, which were supplied by the United States to Ukraine in hundreds of units before the war began. After the outbreak of the war, the company's share price also sank significantly, supporting the general market trends, but seeing that Ukraine had withstood the conflict and that it would be a protracted conflict, investments flowed into US defence companies, both public and private, which resulted in a very rapid rise in the stock price to its historical high. This was primarily driven by large defence orders for Ukraine, such as the production of Javelin ATGMs, Himars and M270 MLRSs, and defence orders for NATO's revised military doctrine, such as F-16 and F-35 aircraft. Secondly, we should not underestimate the advertising that the Ukrainian Armed Forces do by successfully using the company's products. For example, the Ukrainian Armed Forces set a record for the effectiveness of using Javelin ATGMs, and also advertised Himars MLRS very well, after which the demand for these products increased significantly.

A good way to visualise OHLC data is with a candlestick chart. It is designed to show all four aspects of the OHLC concept, namely the price at the opening of the trade, the daily high, the daily low, and the price at the closing of the trade. The highest point of the candlestick is the daily high, and the lowest point is the daily low. The body of a candlestick can be coloured green (white) if the price at the close of trading was higher than at the opening, and red (black) if it was the opposite. The height of the candlestick's rectangle, in turn, directly depends on the price difference at the opening and closing of the trading session, as they are both either the highest or the lowest boundary of the rectangle, depending on which value is greater. In R, such graphs can be displayed using the *ggplot*() function of the *ggplot2* package, but with the mandatory installation of the *tidyquant* package, as it has a number of important financial functions, including the *geom_candlestick* graph type for the *ggplot*() function.

Looking at the graphs in Figures C1 and C2 of Appendix C, we can see the critical moments when the stocks behaved in a very strange way:

- For Lockheed Martin stock, it is very strange to see the upward spike in share price somewhere between October and November 2022. Before that, the share price had been falling since the beginning of the war in Ukraine, and then suddenly it jumped up very sharply, almost reaching a historic high, and then staying almost at the same level.
- For the S&P 500, a short period in the summer of 2022 is surprising, when, after almost six months of falling, stock price started to rise and showed good growth rates, which, however, did not last long, as in the autumn the stocks again lost their value rapidly until they began to rise again.

Let us therefore illustrate this information with the graphs in Figures D1 and D2 of Appendix D, and try to explain it by looking at the short-term data more closely.

Having analysed these charts, we can draw the following conclusions:

1. Figure D1 shows that until mid-October, Lockheed Martin stock was stagnant, with variable success in the form of small increases and decreases. However, everything changed dramatically on 18 October. In one day, the company's shares rose from $403.15 at the opening of trading to $430.84 at the close. The daily high was $435.51, which is 8.4% higher than the daily low of $401.54. This trend continued for several weeks until the share price almost reached its all-time high. On 8 November, the share price at the close of trading was $494.12, up 24.36% from $397.31 at the close of trading on 17 October. The reason for this is most likely due to the fact that on 18 October, Lockheed Martin Corporation published its quarterly report for Q3 2022, which contained the following aspects:

   - Net sales of $16.6 billion and net earnings of $1.8 billion, or $6.71 per share
   - Cash from operations of $3.1 billion and free cash flow of $2.7 billion
   - Returned $2.1 billion of cash to shareholders through share repurchases and dividends
   - Increased share repurchase authority by $14.0 billion
   - Increased quarterly dividend rate 7% to $3.00 per share
   - Increased backlog to $140 billion

   Obviously, such steps made the company's shares more valuable and investing in the company more profitable, which led to a rapid increase in demand for the corporation's shares, which also led to an increase in their price.

2. Figure D2 shows the graph of changes in the value of the S&P 500 stock index during the summer of 2022. We can see that until mid-June, the stock price was falling, reaching $3,666.77 per share on 16 June. However, immediately after that, the stock began to move sharply upwards. Particularly noteworthy during this period were June 24 with a mark of $3936.69, July 27-29 with an increase to $4130.29, and August 12-16 when the indicator reached a periodic high of $4305.20, which is 17.41% higher than on June 16. However, after reaching this peak, a galloping fall began again. Particularly noteworthy during the fall were August 19-22, when the price dropped to $4137.99, August 26 with a figure of $4057.66, and September 21-27, when the price reached $3647.29, which

is even lower than on June 16. However, it is very difficult to say what caused this ups and downs, because the S&P 500 is an index that contains 500 major stocks from completely different industries, which can simultaneously pull the share price up and down.

To better understand the overall development of such a volatile phenomenon as a stock price, stochastic analysis uses the concept of a moving average. A moving average is a calculated value of the mean of a subset. In the analysis of time series in general and stock market processes in particular, the moving average graph helps to better understand the development trend, because it smoothes the line of our graph, eliminating sharp jumps and making it smoother and more understandable. The greater the number of values for which the average is taken, the smoother the line is and the more it can deviate from the actual value of the price at a given point. Theoretically, if the number of observations used to calculate the moving average tends to infinity, the line on a chart plotted in this way will approach a straight line.

In R, a simple moving average can be calculated using the *rollaply*() function, which allows applying other functions, in this case the *mean*() function, to a specified number of observations. Let's calculate the simple moving average for our two stocks based on 100 and 500 observations. Let's graph the calculations using the *ggplot*() function and the *geom_line* graph type. The results are shown in Figures E1 and E2 in Appendix E.

Looking at these figures, we can draw certain conclusions:

1. First of all, we can see that the lines on the chart make it easier to see the general trend of our indices. In moments of high volatility, when the black line, which represents the adjusted price at the close of trading, jumps sharply up or down, the red line, which represents the moving average based on 100 previous values, also follows this trend, but on a much smaller scale, rising and falling more smoothly. The blue line, which represents a moving average based on the previous 500 values, reacts even less to sharp spikes, changing its behaviour only slightly or ignoring short-term deviations entirely. Nevertheless, such moving averages make it much easier to understand where a stock's value is headed in the medium-term (MA 100) and long-term (MA 500).
2. Looking at the chart of the development of the value of Lockheed Martin's shares in moments of high volatility, namely since 2017, several points can be distinguished:
    - In 2017-2019, the company's share price fluctuated greatly, showing sharp upward and downward movements. However, from a medium-term perspective, using a moving average based on 100 previous observations, it is clearly visible that the share price during this period had a clear downward trend, which occurred in two stages until a new growth began around the spring of 2019. Nevertheless, looking at the long-term trend built using a moving average based on 500 values, it is clear that this period of volatility had almost no effect on the overall upward trend of the corporation's shares.
    - In 2020-2021, there was also a very volatile period in which it was impossible to tell whether the stock was going up or down. However, using the MA100, we can see that it was a stagnation with a large amplitude, when it rose very strongly, then fell sharply, and at the end it still showed a downward trend, which continued until the beginning of 2022, when the stock went up sharply. The MA 500 only confirms this, as the overall upward trend first slowed, then stopped, and even slightly declined before starting a new upward trend in 2022.
3. The graph of the development of the share price of the S&P 500 stock index shows a smoother development. The medium-term trend plotted using the MA 100 has been on a fairly smooth

upward trend since 2009, when the global financial crisis ended and the recovery and growth in financial markets began. Only the stagnation of 2015-2016 and two small downturns in late 2018 and early 2020 stand out a little. The MA 500 only confirms this, showing a trend of almost permanent growth for 13 years, which is only now approaching stagnation. This relative smoothness is explained again by the fact that this index contains shares of 500 completely different companies from different industries, which helps the index grow in line with the growth of the global economy, without drastic changes in the long term.

2.2.3 Returns Analysis

Returns are an important tool for analysing capital market data. There are two types of returns: discrete and continuous. Discrete returns are the usual percentage change in the value of a share compared to the previous value (day, week, month) and can be represented by a formula:

$$R_d = \frac{S_1 - S_0}{S_0} \tag{1}$$

where R_d is the return, and S_0 and S_1 are the value of the shares in the previous and current periods, respectively.

The problem with discrete returns is that they are very inconvenient to analyse. The minimum value for such a return is -1. This value is achieved when the company's share price has reached 0, which means that the shares have lost 100% of their value. However, the problem lies in the maximum value, because it is virtually unlimited and can take on values of 2 or more, making the use of stochastic distributions to compare them with such data completely useless.

Continuous returns, on the other hand, use the natural logarithm and are calculated using the formula:

$$R_c = \ln \frac{S_1}{S_0} = \ln(S_1) - \ln(S_0) \tag{2}$$

By using the natural logarithm, it becomes possible to reduce the critical values, since as the gap between the two indicators increases, the value of the returns grows according to a logarithmic function, making it more realistic to compare such data with stochastic distribution models.

In R, periodic returns can be calculated using a chain of $diff()$ and $log()$ functions, as well as by specifying the lag parameter, i.e., the period. Since we are calculating daily returns, this parameter should be set to 1.

Having calculated our returns, it would be good to display them for visual analysis. As in the previous cases, this can be done using the *ggplot*() function of the *ggplot*2 package. In the graph, we will highlight the time periods of major recent crises, as we did when visualising the development of the company's share price over the course of its history.

Figure F1 in Appendix F shows the daily continuous returns of Lockheed Martin stock. What immediately strikes the eye is the very large critical value of -0.28 at the end of 1987. If you look at the data more closely, you will see that this happened on 19 October, when the share price plummeted by 24.94% from \$14.91 to \$10.97 in one day. This was most likely caused by the 1987 crisis, which was triggered by investors' capital outflows from the markets after a severe decline in the capitalisation of several large companies in the US. The US stock index Dow Jones Industrial, for example, fell by 22.6% at that time.

The period of the late 90s was also very volatile. The global financial crisis also had a strong impact on returns, especially in 2008, when they ranged from 0.10 to -0.10. The first waves of COVID-19 also had a significant impact on returns, with returns ranging from 0.10 to -0.13. These figures are quite serious deviations, but they are two or even three times lower than the return on 19 October 1987, which is an absolute record. However, the impact of the war in Ukraine is not as great, but this is most likely due to the generally high value of the company's shares at the time. Imagining a drop from $14 to $10 is much more realistic than imagining a drop from $400 to $300 in one day.

Daily returns are almost never normally distributed. This, as already mentioned, is due to the fact that they take values from -1 to infinity, even if they are logarithmic, i.e. they are asymmetric. Normally distributed observations in this case could only take symmetric values with respect to the mean μ and depending on the volatility parameter σ, i.e., for example, a range from -1 to 1. Nevertheless, the comparison of returns with the normal distribution is often used because of its simplicity, since no additional arguments are required besides the parameters μ and σ and the number of observations.

In Figure F2 of Appendix F, we can superficially depict the deviation of the distribution of our daily returns from the normal distribution. In R, this can be done using the *qqplot*() function to plot the distribution of returns and *qqline*() with the *distribution* = *qnorm* argument to plot the normal distribution from the same data. Looking at this graph, we can see that although the graphs are almost on the same line closer to the middle, closer to the edge, the graph of returns begins to deviate more and more from the normal distribution. The normal distribution has symmetrical maximum values around 0.05 and -0.05, while the maximum value of the returns is approximately 0.17 and the minimum is -0.28, which is a completely unacceptable value for a normal distribution under such conditions.

To get a more detailed look at the distribution of our returns compared to the normal distribution, we can plot a histogram of our returns. In R, this can be done with the *hist*() function. To plot a normal distribution line, we need to calculate the parameters μ and σ based on our returns data. To do this, we can use the simple *mean*() function to calculate μ and the standard deviation function *sd*() to determine σ, then build a distribution function with the *dnorm*() function and overlay it on our histogram with the *curve*() function. Additionally, we will also mark our mean value, i.e. μ, with a dotted line. In the graph shown in Figure G1 of Appendix G, we can see the histogram and the normal distribution curve.

Analysing this histogram, we can see many differences:

1. Firstly, our returns are very heavily weighted towards the mean, showing 1.5 times the number of observations adjacent to μ compared to the normal distribution, which has the same μ and σ as our data.

2. In the intervals from -0.05 to -0.03 and from 0.3 to 0.5, the number of observations of our returns lags behind the number of observations in the normal distribution by about 30% in each part of the histogram.

3. Our graph is skewed to the left relative to the mean, which means it is asymmetrical. To confirm this information, we can make some calculations. The skewness is a measure of the asymmetry of a distribution. It can take both negative values, indicating a skewness to the left, and positive values, which indicate a skewness to the right. The greater is the value of the skewness by absolute value, the greater is the skewness in one direction or another. If the skewness is zero, it means that there is no skewness, and thus the distribution is symmetrical, as in the case of a normal distribution. In

R, the skewness can be calculated using the $skewness()$ function applied to our set of returns. We get a value of -0.47, which is negative and confirms that our distribution is skewed to the left.

4. The distribution of our returns, although very rare and very few, can take on very critical values, such as -0.28 or 0.17, which in turn is absolutely impossible in a normal distribution under the same conditions. The parameter that can be used to estimate such so-called "fat tails" is called kurtosis. In a normal distribution, the excess kurtosis has a zero value, and the distribution itself is then called mesocurtic, i.e., one that has almost no extreme deviations, but also does not have an excessive concentration of values in the centre. In R, the kurtosis can be calculated using the $kurt()$ function applied to the set of our returns. This yields a value of 16.9, which equals 13.9, when subtracting 3 for estimating an excess kurtosis, and which is a very high value and indicates the leptocurtic nature of our distribution, i.e. the presence of "heavy tails" in our data, as we have already observed in Figure F2 of Appendix F.

A more appropriate distribution that takes into account the "fat tails" feature of our function is the Student t-distribution. In addition to the already mentioned parameters μ and σ, it also has a parameter ν, which can take values from 1 to infinity, and which indicates the number of degrees of freedom. The larger this parameter is, the more the t-distribution approaches the normal distribution. In R, we can apply the t-distribution to our returns using the $fit.st()$ function. As a result, we get an object that contains three parameters, namely ν, μ, and σ, which we can extract from it to build a distribution for these parameters, which we do in the form of a function using $dt()$ and our three parameters.

With all the necessary calculations in order, we can now depict them in a graph. The results are presented in Figure G2 of Appendix G. In this figure, we have the distribution of our returns depicted by a histogram, as well as their density curve compared to the normal distribution and the Student t-distribution. It is quite clear that the t-distribution fits our data much better, as its curve is almost exactly the same as the density curve of our returns.

2.2.4 Correlation analysis

To study the relation and dependence of two objects, the concept of correlation is used. Correlation is a statistical measure of the dependence of two quantities, in our case it will be the dependence between two time series, namely the series of closing adjusted share prices of Lockheed Martin Corporation and the S&P 500 stock index. The most popular correlation coefficient is the Pearson correlation coefficient, which is used to calculate the correlation of two numerical vectors. The maximum value of this coefficient is 1, which means a full 100% positive dependence between the two vectors. The minimum value is -1, which in turn is the opposite of 1 and means a perfect inverse relationship between the two vectors. A correlation value that tends to 0 indicates that the series are almost independent or very weakly dependent on each other.

The easiest way to calculate Pearson's correlation is to use the standard $cor()$ function in R. You can also do it manually by dividing the covariance of the two series calculated with the $cov()$ function by the product of the standard deviations of both series calculated with the $sd()$ function.

Applying one of these methods to our lmt_adj and $sp500\_adj$ objects, we get a value of 0.9433559, which is a fairly high positive value. This means that our two time series have a strong positive linear relationship on average over the entire observation period. However, this measure only tells us general information, it is static, and our data is dynamic, so it would be nice to find a dynamic correlation measure.

One such indicator is the conditional correlation calculated using the Generalised Autoregressive Heteroscedasticity (GARCH) model. The GARCH model is a time series model that allows modelling the conditional volatility (conditional standard deviation) of a time series. This model assumes that the conditional volatility of a time series is dependent on both the previous values of the indicator itself and the previous values of the conditional volatility indicator.

To calculate the correlation between two time series, we can use one of the types of multivariate GARCH models, also called MGARCH, namely the dynamic conditional correlation model or DCC. The building of such a model consists of two steps:

1. First, a univariate GARCH model is specified and estimated for both time series. These models provide estimates of the conditional volatility and standardised residuals for each time series.
2. Then the correlation model can then be estimated for the standardised residuals calculated in the first step, thereby obtaining estimates of the conditional correlation matrix between the time series.

To build such a model in R, we can use the *rmgarch* package specially created for this purpose. First, we need to create a spec object, i.e. characterise the specification of our model. For the DCC model, we do this using the *dccspec*() function of the *rmgarch* package.

However, before analysing multiple models, we run the simulation on each time series separately. This is done with the *ugarchspec*() function and first of all, the model orders for the *mean.model* and *variance.model* arguments must be selected. In financial time series analytics, ARMA(1,1) is most often used as the mean model and GARCH (1,1) as the covariance model, which we assign to the above arguments by creating a list with the list() function.

For this model, we apply the *replicate*() function with a value of 2 to use the model for both time series, and then apply the *multispec*() function to combine the two specifications of the univariate GARCH models into one multispecification. And this whole chain should be assigned as a value for the *uspec* argument of the *dccspec*() function.

After that, we can fit our data to the created specification using the $dccfit()$ function by specifying the *spec* argument and also assigning the data argument a data.frame with the values of our two time series. After that, we can calculate the correlation using the fitted data using the *rcor*() function and specifying the column numbers of our table.

As a result, we get a large vector with 38504 elements of the conditional correlation between the two time series. If desired, this information can be visualised and analysed visually, but we will do it in a simpler way. Using the simple mean and standard deviation function, we can calculate the average of the conditional correlation and its standard deviation. In our case, we get the values of 0.4023246 and 0.1358579, respectively. From these indicators, we can understand that our two stocks have a positive linear relationship, but in some time periods, it decreases significantly, because indices sometimes react differently to different events, reaching critical values.

2.3 Price Forecasting

Statistical forecasting is often used to predict a wide variety of time series data, from macroeconomic indicators such as GDP, purchasing power, mortality and birth rates, to microeconomic indicators such as sales, labour productivity or a company's net profit forecast.

The ability to predict stock price movements, whether they will rise or fall, would always be a desirable tool. However, this is a very difficult task. Because share prices are almost entirely unpredictable, their forecasts are not always practical, meaning that the data may be very different from reality or even meaningless.

In time series analysis, it is important to distinguish between three main components: trend, seasonality, and noise.

- A trend is a general direction of change in a time series over a long period of time. A trend can be upward, downward, or stable.
- Seasonality is a recurring fluctuation in a time series that occurs due to seasonal factors. For example, ice cream sales may increase in summer and decrease in winter.
- Noise is random fluctuations in a time series that cannot be explained by a trend or seasonality. Noise can be caused by a variety of factors, such as measurement errors or unexpected events.

One of the most popular methods of time series forecasting, apart from the simplest methods such as linear regression, is forecasting using the autoregressive integrated moving average, or ARIMA (p,d,q) model. This model takes into account three important parameters of the time series, namely seasonality, trend, and noise, and assigns them corresponding values of p, d, q, which can take integer values from 0 and more. p is responsible for the autoregressive (AR) part of the model. It represents the number of lags that are used as predictive indicators. In other words, it is the order of the autoregressive model. d is responsible for the integrated (I) part of the model. It represents the number of times the data had previous values that were calculated (the so-called differentiation). This differentiation is done to make a non-stationary time series stationary. q is responsible for the moving average (MA) part of the model. It represents the number of lagged forecast errors that should be included in the ARIMA model.

For short-term stock price forecasting, ARIMA(0,1,0) is most often used. This is a model without autoregressive and moving average components, but with one order of differentiation, i.e. it was differentiated once to achieve stationarity. This type of model is also called a random walk model, which assumes that the future values of the time series are the sum of the previous value and a random error. This model can be applied to our data by using the $ARIMA()$ function with the arguments p, d, q as $0, 1, 0$. After that, we can use the model to interpolate the values for the next year and forecast them using the $interpolate()$ and $forecast()$ functions.

The results of the forecast are shown in Figure H1 of Appendix H. We have a trend line, as well as a range of acceptable values with 80 and 95 percent confidence levels. After analysing them, all we can see is that the stock is trending upwards, which we can already see with the naked eye and which we saw when we built the moving average. This trend doesn't tell us anything else, because the limits are very large and don't carry much information, because they are calculated based on the total volatility over time, which is not static in stock prices, but rather chaotic. In addition, this framework also does not show how much a share will move up or down and when, but only shows the area of its acceptable values, which is quite clear to the naked eye with such a framing. Thus, it can be concluded that this tool is not very suitable for forecasting, as it does not provide any precise information.

A more sophisticated and advanced forecasting tool is Prophet. This is a forecasting package in R and Python developed by Meta. The forecasting process using this procedure is the creation of an additive model in which nonlinear trends are fitted to daily, weekly, and annual seasonality, and also takes into account holidays and weekends. In other words, it is an additive regression model that has four main components:

- The model is based on a piecewise linear trend or logistic growth curve
- Annual seasonal component modelled using Fourier series, i.e. annual periodic seasonality represented as a sum of sine and cosine waves
- Weekly seasonal component using dummy variables to include or exclude a particular day of the week in the model
- Holiday component that uses an indicator variable for each holiday

Prophet automatically detects changes in trends by selecting change points from the data. There is almost nothing the developer needs to do to build the model, it is fully automated. All we need to do is to convert our data from xts format to $data.frame$ table, because to build the model we need to have dates as a separate column called ds. Then we simply use $prophet()$ to build the model and then $predict()$ to make the forecast.

The result of the forecast is shown in Figure H2 of Appendix H. It can be seen that the model takes into account most of the minor long-term deviations before 2015, but in periods of very high volatility since 2018, the trend line almost completely ignores it, not taking into account fluctuations caused by the coronavirus crisis and the war in Ukraine. This trend most closely resembles the MA 300-500 chart, and in turn is more informative for analysis than the ARIMA model, although it is still not a panacea for predicting the growth and decline of the stock, but only for a general understanding of the trend.

Thus, we can conclude that it is possible to predict the development of a company's share price to a very limited extent. Share price development is difficult to predict due to the dynamic and non-linear nature of the stock market. The share price depends on many macro and micro factors, such as politics, global economic conditions, unexpected events, the company's financial performance, etc. This makes accurate share price forecasting an extremely difficult task.

3 Summary and Conclusion

Based on the results of the research, the following conclusions can be drawn:

1. Technical analysis can be used to conduct a quick initial analysis of imported data to better understand its structure, early and late values, and the most obvious trends. Using such a cursory analysis, it was determined that the closing price of Lockheed Martin shares increased more than 100 times from $4.60 to $480 between 1985 and 2023. The same can be said for the S&P 500 stock index, whose price increased almost 25 times from $165 to $3900.

2. A lot of information can be analysed using expository data analysis. The *ggplot*() package, which can be used in R, is perfect for this. Having plotted the price development of both indices, we can say that in general, both indices have common upward trends over time and have high volatility at certain moments. However, at these specific moments, the share price of these indices behaves differently. Lockheed Martin is better able to weather most crises than other companies because it is quite strongly integrated into the US military-industrial complex and can weather hard times with the help of government orders. However, after the crisis is over and the market starts to recover, most companies begin to grow rapidly, while Lockheed Martin Corporation stagnates due to its lesser focus on the free market. For a more general view of the development of the share price, the moving average tool can be used. It removes the strong volatility from the chart and helps to better understand the global trend.

3. In addition to analysing price developments, technical analysis can also be used to analyse information on returns from stock market speculation. This is best done with contineous returns, which take on less critical values as they grow on a logarithmic curve rather than a straight line, unlike discrete returns. Comparison of the returns hystogram with a normal distribution shows that the probability of the returns being normally distributed is almost zero, because the returns are heavily weighted towards the mean and also have fat tails. In such cases, it is better to use the Student t-distribution, which fits the density of our data very well.

4. Technical analysis can also be used to analyse the correlation between two indices. Unconditional correlation analysis can be performed using standard built-in functions. We obtained a value of 0.94, which indicates that the stocks of our two indices have a close positive correlation over time. However, the calculation of the conditional correlation using GARCH modelling showed that the average dynamic correlation is 0.40, which indicates a positive linear relationship, but with strong deviations in certain time periods, as the indices react differently to different events, which greatly affects the overall value.

5. Technical analysis can also be used for forecasting, but to a very limited extent. Forecasting using ARIMA modelling and the Prophet package can only provide certain trends in the overall development of indices and approximate frameworks, but this information is very imprecise, as stocks are often very, very chaotic.

In general, technical analysis is an excellent tool for analysing most data, especially if it is retrospective. However, it also has its limitations, such as forecasting in our case. Therefore, the use of technical analysis to analyse capital market data should be treated with appropriate understanding.

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Appendices

Appendix A

Importing Lockheed Martin's Daily Stock Data and its Initial Analysis

```
library(zoo)
library(xts)
library(quantmod)
lmt_ohlc_xts <- getSymbols("LMT",
                           src = "yahoo",
                           from = "1985-01-01",
                           to = "2023-03-15",
                           missing = "remove",
                           auto.assign = FALSE)
str(lmt_ohlc_xts)
```

```
## An 'xts' object on 1985-01-02/2023-03-14 containing:
##   Data: num [1:9627, 1:6] 13.4 13.4 13.3 13.2 12.8 ...
##  - attr(*, "dimnames")=List of 2
##   ..$ : NULL
##   ..$ : chr [1:6] "LMT.Open" "LMT.High" "LMT.Low" "LMT.Close" ...
##   Indexed by objects of class: [Date] TZ: UTC
##   xts Attributes:
##  NULL
```

```
head(lmt_ohlc_xts, 3)
```

```
##            LMT.Open LMT.High  LMT.Low LMT.Close LMT.Volume LMT.Adjusted
## 1985-01-02 13.38190 13.45859 13.30521  13.42025     415324     4.745631
## 1985-01-03 13.42025 13.45859 13.26687  13.34356    1257056     4.718515
## 1985-01-04 13.26687 13.30521 13.11350  13.15184     187124     4.650720
```

```
tail(lmt_ohlc_xts, 3)
```

```
##            LMT.Open LMT.High LMT.Low LMT.Close LMT.Volume LMT.Adjusted
## 2023-03-10   475.71   482.30  474.42    475.50    1335000       475.50
## 2023-03-13   471.87   478.90  470.80    477.33    1701000       477.33
## 2023-03-14   480.29   481.27  474.87    478.87    1761400       478.87
```

```
lmt_adj <- Ad(lmt_ohlc_xts)
sum(is.na(lmt_adj))
```

```
## [1] 0
```

Appendix B

Importing S&P 500 Index Daily Data and its Initial Analysis

```
sp500_ohlc_xts <- getSymbols("^GSPC",
                             src = "yahoo",
                             from = "1985-01-01",
                             to = "2023-03-15",
                             missing = "remove",
                             auto.assign = FALSE)
str(sp500_ohlc_xts)
```

```
## An 'xts' object on 1985-01-02/2023-03-14 containing:
##   Data: num [1:9627, 1:6] 167 165 165 164 164 ...
##  - attr(*, "dimnames")=List of 2
##   ..$ : NULL
##   ..$ : chr [1:6] "GSPC.Open" "GSPC.High" "GSPC.Low" "GSPC.Close" ...
##   Indexed by objects of class: [Date] TZ: UTC
##   xts Attributes:
##  NULL
```

```
head(sp500_ohlc_xts, 3)
```

```
##            GSPC.Open GSPC.High GSPC.Low GSPC.Close GSPC.Volume GSPC.Adjusted
## 1985-01-02    167.20    167.20   165.19     165.37    67820000        165.37
## 1985-01-03    165.37    166.11   164.38     164.57    88880000        164.57
## 1985-01-04    164.55    164.55   163.36     163.68    77480000        163.68
```

```
tail(sp500_ohlc_xts, 3)
```

```
##            GSPC.Open GSPC.High GSPC.Low GSPC.Close GSPC.Volume GSPC.Adjusted
## 2023-03-10   3912.77   3934.05  3846.32    3861.59  5518190000       3861.59
## 2023-03-13   3835.12   3905.05  3808.86    3855.76  6558020000       3855.76
## 2023-03-14   3894.01   3937.29  3873.63    3919.29  5665870000       3919.29
```

```
sp500_adj <- Ad(sp500_ohlc_xts)
sum(is.na(sp500_adj))
```

```
## [1] 0
```

Appendix C

Development of the Stock Price of Lockheed Martin Corporation and S&P 500 Market Index Price in 1985-2023

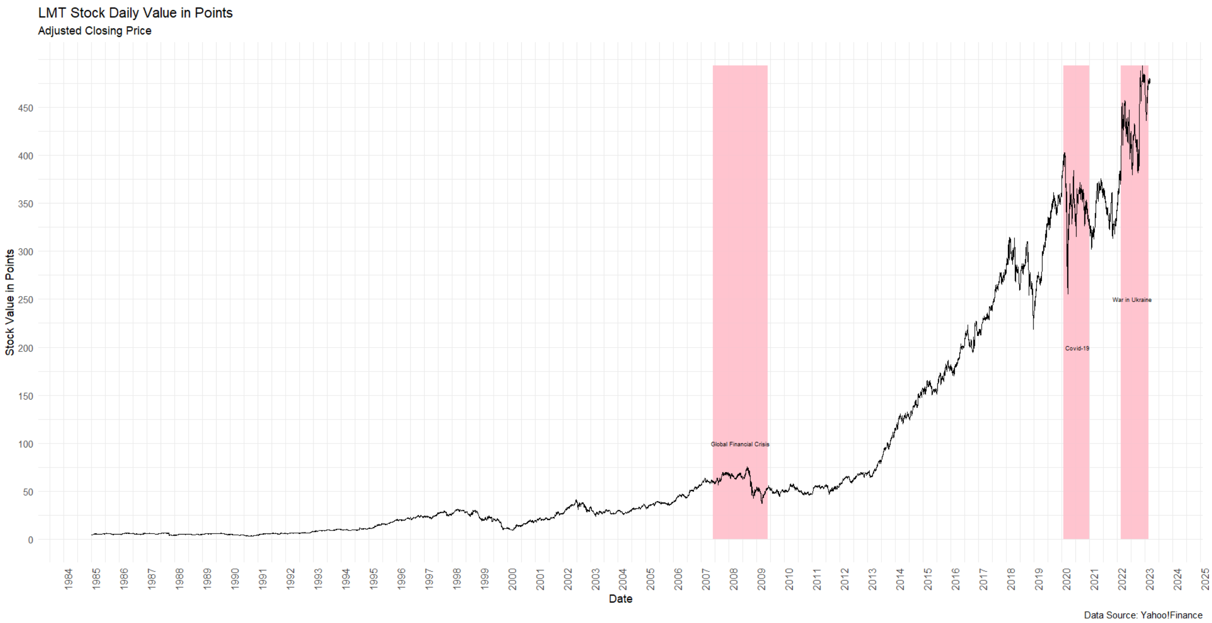

Figure C.1: Development of the stock price of Lockheed Martin Corporation in 1985-2023, source: created by the author based on Yahoo!Finance data

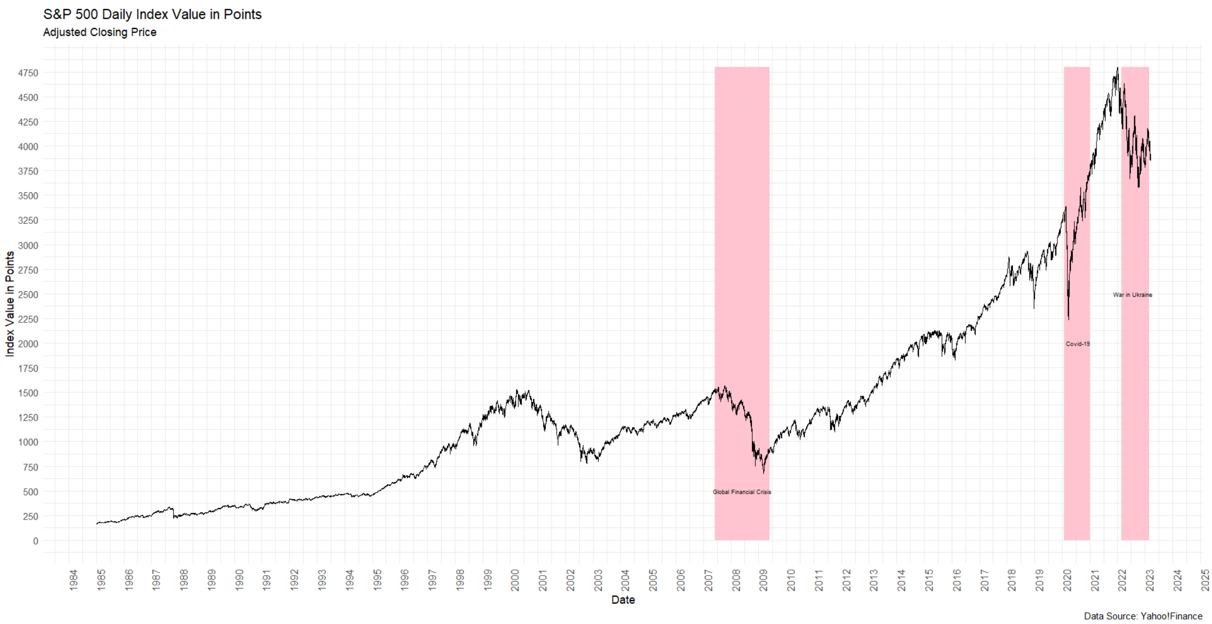

Figure C.2: Development of the S&P 500 market index price in 1985-2023, source: created by the author based on Yahoo!Finance data

Appendix D

Development of the Stock Price of Lockheed Martin Corporation and S&P 500 Market Index Price During Unexpected Jumps in 2022

Figure D.1: Development of the stock price of Lockheed Martin Corporation during October-November 2022, source: created by the author based on Yahoo!Finance data

Figure D.2: Development of the S&P 500 market index price during June-September 2022, source: created by the author based on Yahoo!Finance data

Appendix E

Development of the Stock Price of Lockheed Martin Corporation and S&P 500 Market Index Price Using Simple Moving Averages

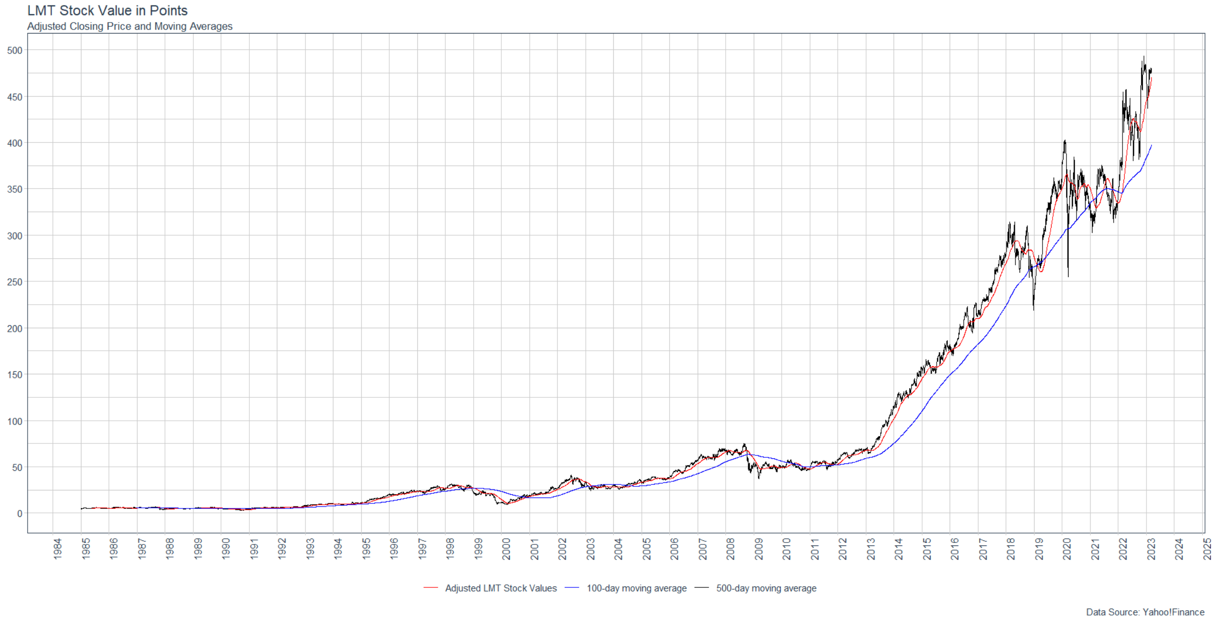

Figure E.1: Development of the stock price of Lockheed Martin Corporation using moving averages, source: created by the author based on Yahoo!Finance data

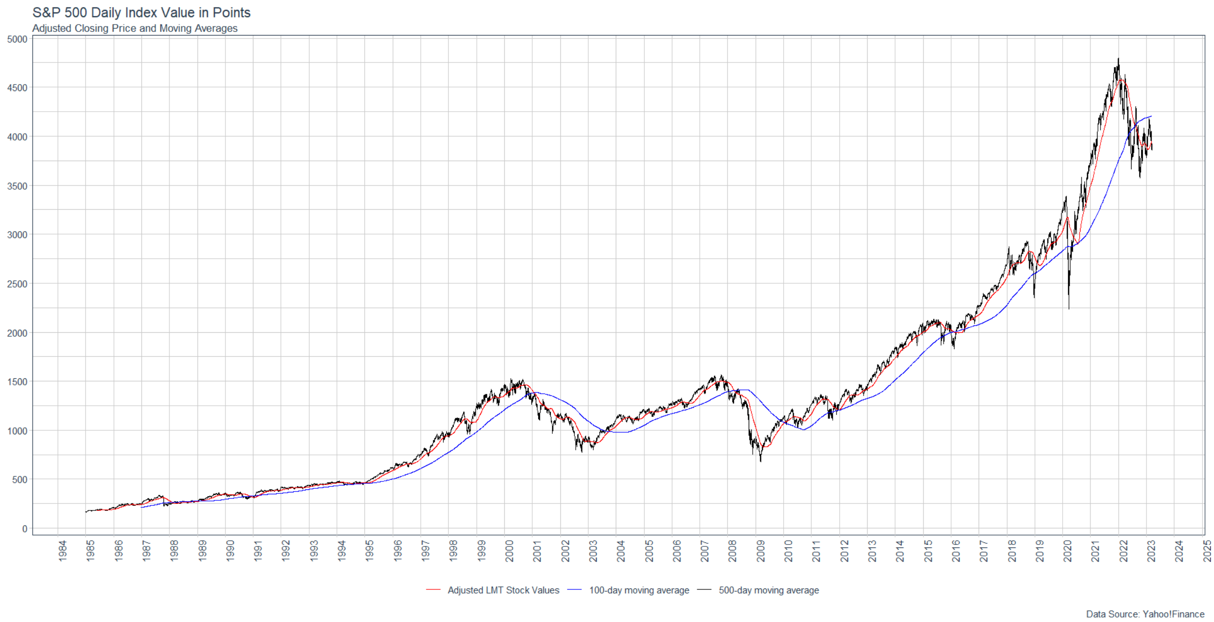

Figure E.2: Development of the S&P 500 market index price using moving averages, source: created by the author based on Yahoo!Finance data

Appendix F

Daily Returns of Lockheed Martin Corporation in 1985-2023

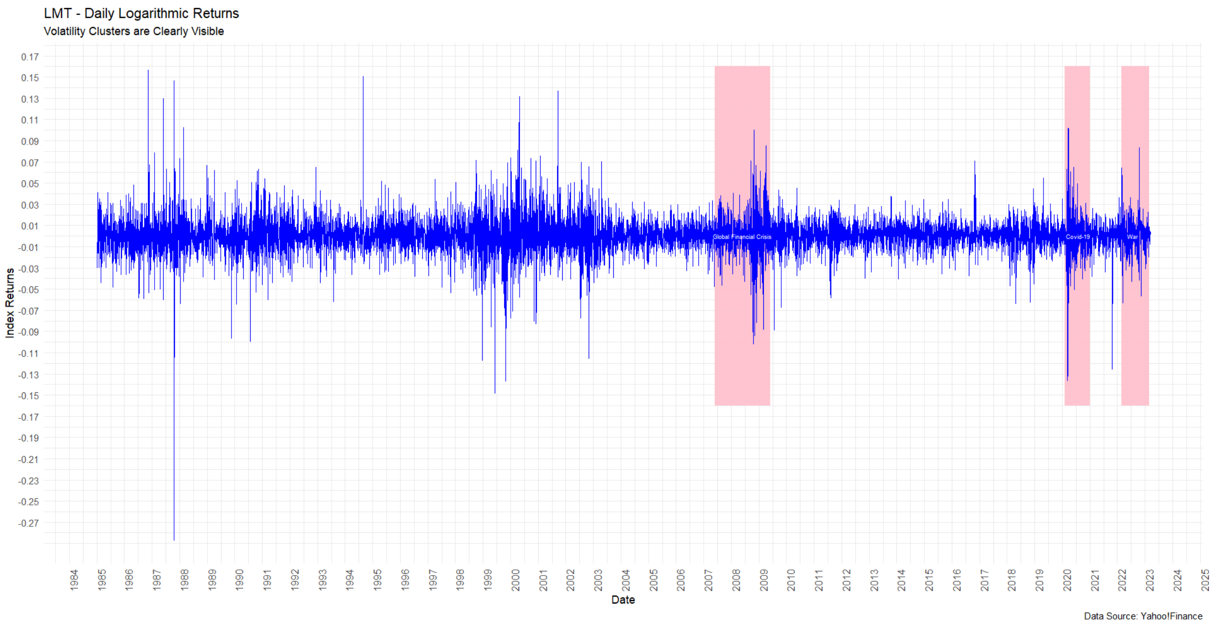

Figure F.1: Dewelopment of Daily Returns of Lockheed Martin Corporation in 1985-2023, source: created by the author based on Yahoo!Finance data

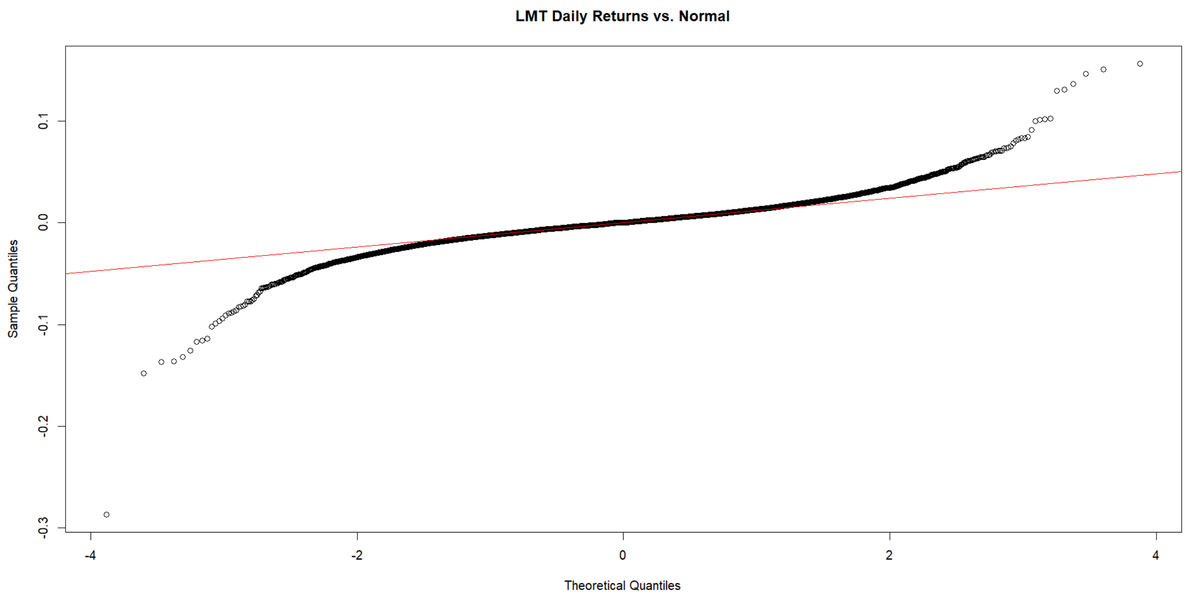

Figure F.2: Deviation of daily returns from the normal distribution, source: created by the author based on Yahoo!Finance data

Appendix G

Daily Returns of Lockheed Martin Corporation vs Different Distribution Types

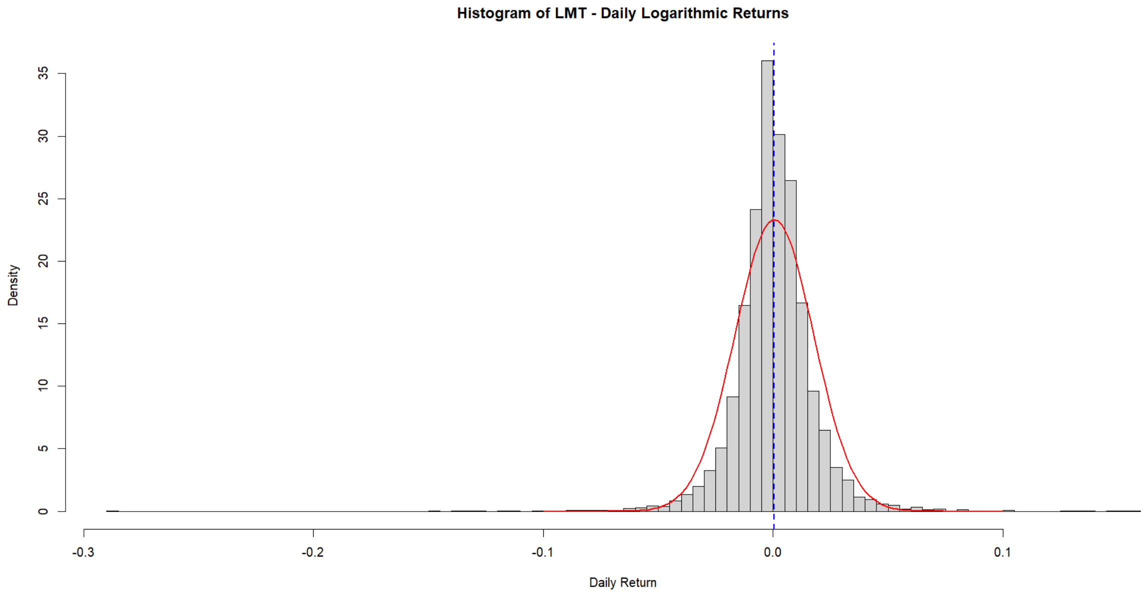

Figure G.1: Lockheed Martin stock vs normal distribution, source: created by the author based on Yahoo!Finance data

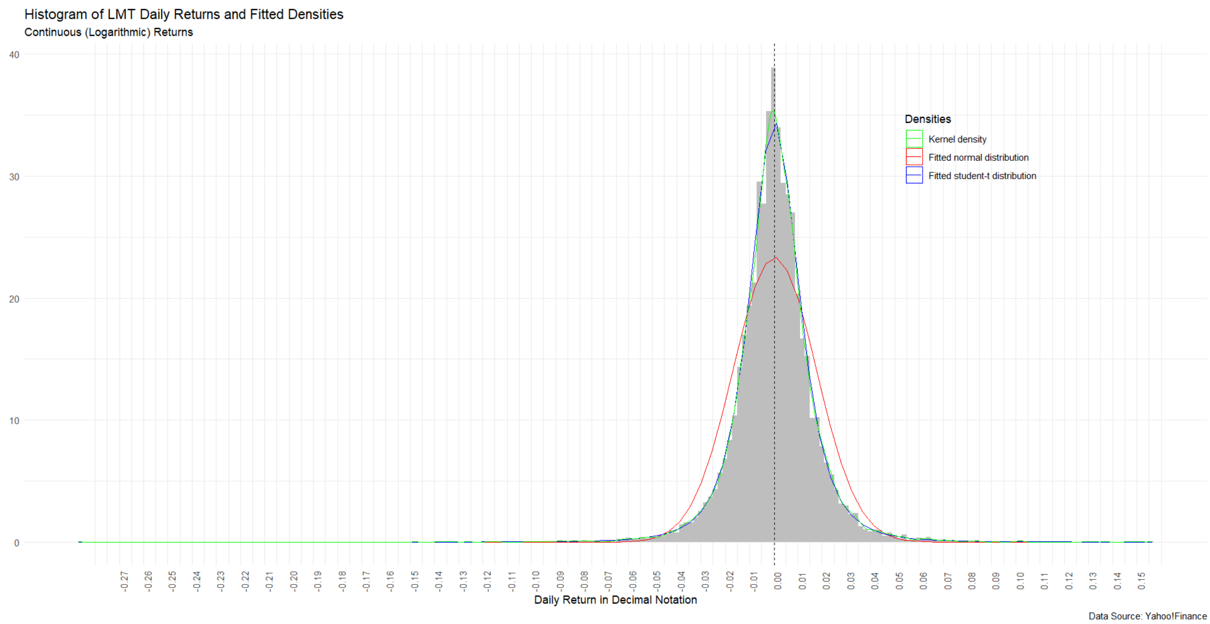

Figure G.2: Lockheed Martin stock vs normal distribution and student-t distribution, source: created by the author based on Yahoo!Finance data

Appendix H

Forecast of Lockheed Martin Corporation Stock Price Dewelopment

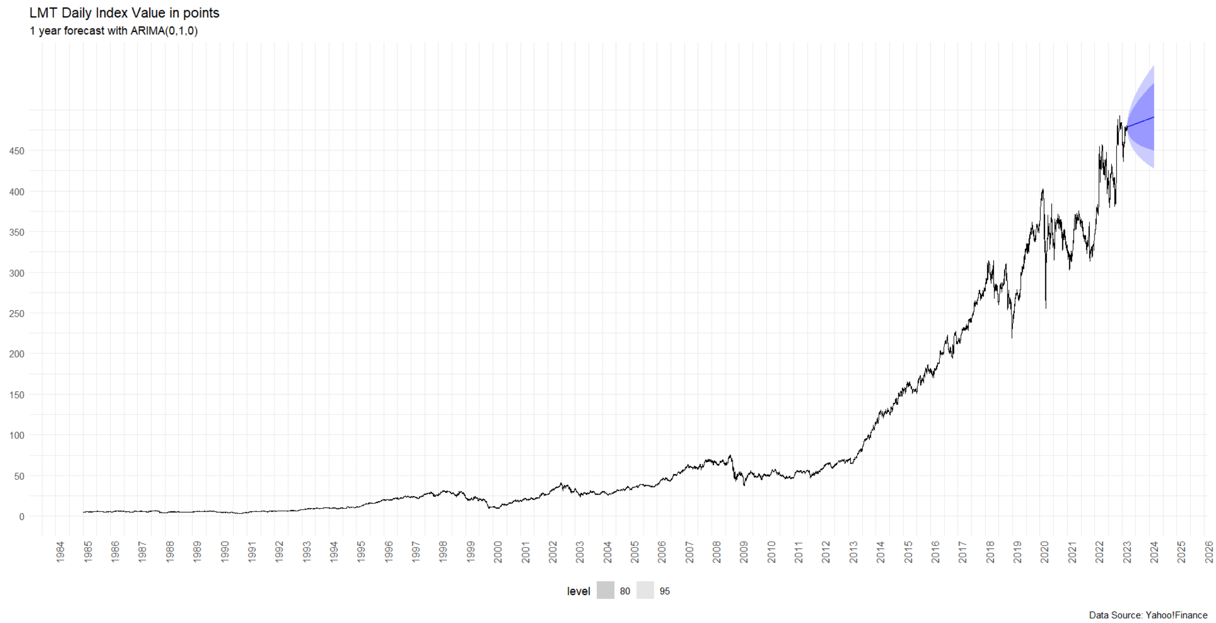

Figure H.1: Lockheed Martin stock forecast for 2023 using ARIMA (0,1,0) model

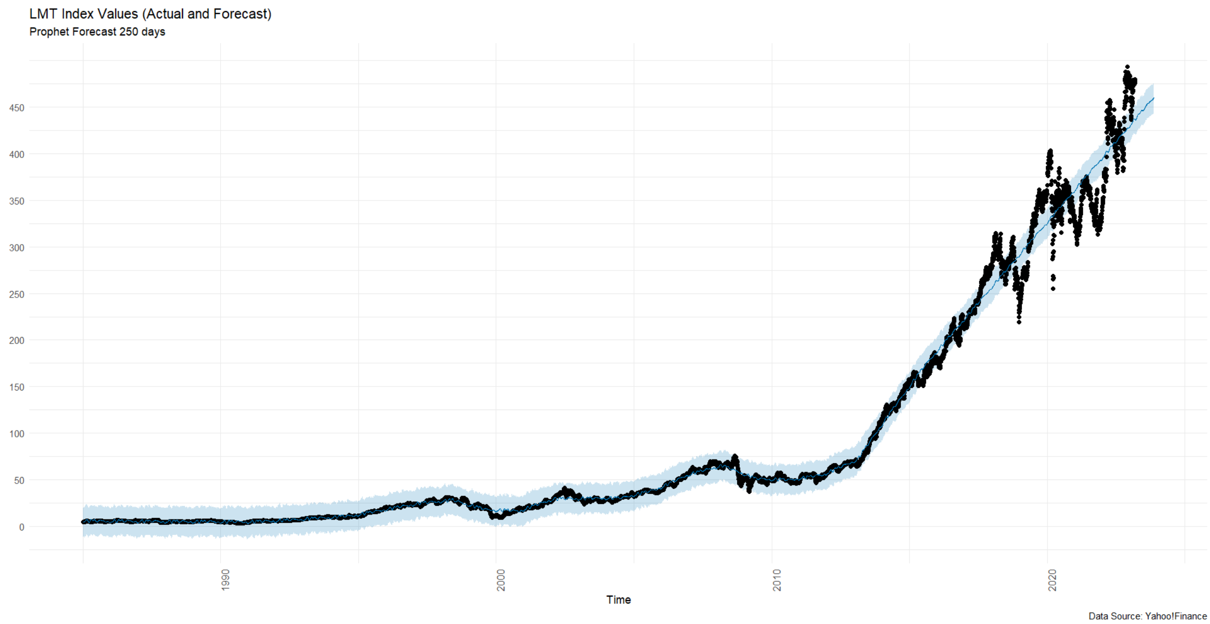

Figure H.2: Lockheed Martin stock forecast for 2023 using Prophet model