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THE VOLATILITY OF STOCK MARKET RETURNS: APPLICATION OF MONTE CARLO SIMULATION

Abstract

Stock exchange is the ''mirror'' of the economy and helps industry (and commerce) to accelerate the development of the country. The prices on the stock exchanges increase or decrease over the particular period and that rate represents stock market volatility. Higher stock price volatility is often associated with higher risk and indicates future fluctuations to investors in order to evaluate them. Predicting future stock price volatility can provide important information to market participants and enable them to make adequate decisions. The aim of this paper is to evaluate the stock price volatility of the Apple Company using the Monte Carlo simulation.

Key words: *Monte Carlo Simulation, Forecast, Volatility, Stock Exchange.*

JEL classification: *C15, G17*

ВОЛАТИЛНОСТ ПРИНОСА НА БЕРЗИ: ПРИМЕНА МОНТЕ КАРЛО СИМУЛАЦИЈЕ

Апстракт

Берза је "огледало" економије сваке земље и омогућава развој привреде и трговине. Цене на берзама расту или опадају током одређеног периода а та стопа представља волатилност тржишта акција. Већа волатилност цена акција често значи већи ризик и помаже инвеститору да процени флуктуације које се могу десити у будућности. Предвиђање будуће волатилности цена акција може пружити важне информације учесницима на тржишту и омогућити им да донесу адекватне одлуке. Циљ овог рада је да се процени волатилност цене акција компаније Аппле коришћењем Монте Карло симулације.

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Introduction

The set of sellers and buyers of securities, which represent the owner's receivables, makes up the stock exchange. These include shares that are traded only privately, such as shares of private companies that are sold to investors through group capital financing platforms, as well as securities listed on a public stock exchange. Shares are categorized according to the country in which the company is headquartered. For example, part of the Swiss stock market includes Nestle and Novastist, based in Switzerland, which are traded on the SIX Swiss Stock Exchange. Some securities can be traded in other countries. Thus we get certain time series, which dictate different trading prices over a certain period of time. Stock volatility is the degree of variation of series, and is usually measured by the standard deviation of ligorithmic yields. Volatility during crisis situations, such as the oil crisis or the pandemic and the Great Depression, is very important.

The volatility of the stock exchange is very important and that is why it is necessary to perform an analysis in emergency situations. Especially since the emergency is something that is not common in the financial world, its consequences can be long-term, and we have a pandemic as a new phenomenon in the world, which will affect the world's largest stock exchange - the New York Stock Exchange (Analytical Steps, 2021).

When it comes to the topic of volatility, it is very important to distinguish between real and implied volatility. More precisely, real volatility represents the actual current volatility of a financial instrument for a given period on the basis of historical prices. It can take more than four months to process all the analyses, and that could be one example. An option's expiration date may represent actual future volatility, as it is the volatility of a financial instrument during a given period that starts at the current time and ends in the future (on a certain date). The real historical volatility is the volatility of the past with the last observation on the date in the past and has one synonymous term - realized volatility. The volatility observed from the current prices of a financial instrument is current, future and historical implied volatility. Historical volatility, which takes historical prices, is most often used for common options.

In some periods, prices can hardly move (Investopedia 2022), and there are periods where they can fall or rise very quickly, these are periods of high and low volatility. Thus, in some foreign exchange markets are seasonally heteroskedastic with periods of one day and one week (Müller et al., 1990; Petrov et al 2019). This phenomenon is called autoregressive conditional heteroskedasticity (ARCH), because it is caused by extreme movements larger than usual. ARCH statistical model is a model of innovation as a function of real size of the term error in pre-period periods, which often refers to the squares of previous innovations (Engle, 1982), and also describes variance of increasing volatility that does not always show a further increase, but can return again. Given the extreme movements, it is difficult to say whether these large movements have the same direction or not. Volatility does not depend only on the period when measured and when the effect is observed, from the chosen time resolution, because the flow of information between short-term and long-term traders is asymmetric. High-resolution variability and vice versa is based on information that is not covered by low-resolution variability (Müller et al., 1997). For example, if we observe the period from 1974 to 2014 for risk-weighted parity variability of three assets - gold, treasury bonds and NASDAQ - which acts as an intermediary for the market portfolio, there is a 4% low point after 8 times upwards in this period.

It is suspected that implied volatility and realized volatility are measures that look forward and backward and do not maintain current volatility. As a solution to this problem, the idea of collective measures of volatility is given. Some authors consider the regular sequence of changes of direction as a proxy for current volatility (Petrov et al., 2019), while others define measures as a standard deviation of ensemble yield instead of time series of yield (Sarkissian, 2016), SVI and gSVI (Damghani & Kos, 2013).

When it comes to the sophisticated composition of the model of predicting maximum variability, critics believe that their predictive power is alike to that of ordinary measures, such as simple variable volatility (Cumby et al., 1993; Jorion, 1995), especially out-of-sample, where different data are used to evaluate models and test them (Brooks & Persand, 2003). However, there are other authors (Andersen & Bollerslev, 1998) who agreed with this, but also believe that the previous ones failed to properly implement more complicated models, while some portfolio managers and practitioners ignore or dismiss predictive models. Thus, Emanuel Derman pointed out his disappointing opinion about the large number of empirical models that are not accompanied by adequate theory and believes that "theories are attempts to discover hidden principles that support the world around us, as Albert Einstein did with his theory of relativity", and say to remember that "models of metaphors - analogies that describe one thing in relation to another" (Derman, 2011). Daniel Goldstein and Nassim Taleb stated, in relation to portfolio management: "We don't know exactly what we are talking about when we talk about volatility" (Goldstein & Taleb, 2007).

Many studies predicting and modelling the volatility of financial returns have a great impact even today, as from JPMorgan Chase in 2019, where the influence of Donald Trump was determined, tweets and called the Volfefe index that combines cofefememe and volatility. It is difficult to talk about the first papers on this topic, but we can take into account Roll's research which shows that volatility is influenced by market microstructure (Roll, 1984) or Gloucester and Milgrom's work which demonstrates that at least one source of volatility can be clarified by the provisioning process liquidity. This means that when market makers conclude the possibility of unfavourable selection, they adjust their trading volumes, which increases the range of price oscillations (Glosten & Milgrom, 1985). Today, investors can worry about volatility, more than before, because they can trade it directly by using derivative securities - options and variations. This work is especially important for several reasons concerning investors, such as: the higher the price changes in the price of the investment, the harder it is not to worry; when it is dictated for a certain date by a certain cash flow during the sale of securities, thus the chances of a deficit are higher due to higher volatility; higher volatility of returns after retirement gives withdrawals a greater lasting impact on portfolio value; the size of the portfolio position is affected by the volatility of returns after retirement; the size of the portfolio position is defined by the price volatility of the trading instrument; higher volatility of return with retirement savings results in a wider distribution of possible final portfolio values; the complex annual growth rate (CAGR) portfolio is negatively affected by its volatility; for cheap property purchase and sale when it is overestimated, price volatility plays a big role; volatility affects option prices, which is a parameter of the Black-Scholes model.

The primary aim of this paper is to determine the possible movement of market prices of shares on an adequate sample from stock exchange using Monte Carlo

simulation. Thus, we can determine how the pandemic could have affected prices. It will be important for a later conclusion, if the current situation in the world with the virus worsens or if a similar one appears in the future. In the second part we provide a review of the literature on market variability and application of the Monte Carlo method, while in the third part, the research methodology applied in the paper is discussed. The fourth part presents the research methodology applied in the paper and gives the results and the discussion. Finally, the fifth part includes concluding remarks.

Literature review

This topic has become especially intensified in recent years due to the COVID-19 pandemic and uncertainty that it caused. As a result, numerous researches (Boettke & Powell, 2021; Açikgöz & Günay, 2020) on this topic can be found in the modern literature. Several researchers have examined the adequacy of responses to market instability to make appropriate recommendations to policy makers (Schwert, 1990; Adam et al., 2016). In addition, there are papers that deal with the observation of macroeconomic phenomena together with variability, which is of great importance, because the COVID-19 pandemic has affected the entire economy. Some authors analysed connection between macroeconomics fundamentals and asset return volatility in approximately forty countries (Diebold & Yilmaz, 2008), one group of authors investigated relation between stock market volatility and macroeconomics activity using a new class of component models that differentiate short-run from long-run movements (Engle et al., 2013). Macroeconomics of a country can also be related to volatility by presenting a theory of excess stock market volatility, in which market movements are due to trades by very large institutional investors in relatively illiquid markets (Gabaix et al. al., 2006). This is how we can recognize and locate variability in the observed pandemic. We can only try to predict how the pandemic could have affected the stock market.

In relation to forecasting in the literature, we notice a lot of applications of Monte Carlo methods in finance, for valuation and hedging of securities, risk management, portfolio optimization and model calibration (Staum, 2009), then for valuation of derivatives (Joy et al., 1996) or for theoretical research (Creal, 2011) and calculations (Asmussen, 2018). There is also the combination of the Monte Carlo method with other methods, for example with the Malivian calculus - an attempt was made to combine these two methods (Fournie et al., 1999; Fournie et al., 2001).

The conclusion is that the Monte Carlo method can be used to determine the price of financial derivatives (Rebentrost et al., 2018) as well as for stock market valuation (Siddiqui, Patil, 2018) and for forecasting (Estember and Maraña, 2016). One of the best examples of predicting research, estimating and comparing the predictive power of the Monte Carlo simulation technique in predicting randomly selected 10 listed shares on the SET50 stock exchange of Thailand (Parungrojat & Kidsom, 2019). We also have examples of evaluating predictive performance of a selection of value-at-risk (VaR) models for Japanese stock market data, where, among others, are also considered Monte Carlo method (Lee, Saltoglu, 2002), as well as examples of yield forecasting on the Amman Stock Exchange (Alrabadi & Aljarayesh, 2015).

Such concrete examples that show the correlation between COVID-19 pandemic and shares, where COVID-19 had caused a negative shock to the global stock markets, which specifically refers to emerging markets and small firms (Harjoto et al., 2020), as well as the possibility of applying the method on the stock exchange, we can observe with the investment crisis from 2008 in relation to efficiency of the stock exchange (Anagnostidis et al., 2016). Before further investigations, we can see that COVID-19 have mostly negative effect on firms` stock returns (Nguyen et al., 2021) and investors decisions about buying and selling stocks of some companies (Ramelli & Wagner, 2020). We can further investigate this by observing only the fractal effect of COVID-19 pandemic on stock exchanges in 32 affected economies in different periods (Okorie & Lin, 2020) or by analysing the time before COVID-19 and during the stock exchange pandemics in Bursa Malaysia and Singapore Stock Exchange (Yong et al., 2021). However, some researchers are more interested in stock returns and associate COVID-19 with an increasing number of infected (Anh & Gan, 2020) or confirmed cases, due to the pandemic (Khanthavit, 2021). However, all these researches have some contact with volatility, and at the same time, they can provide a basis for further research.

This paper uses a method that has been applied to other securities, such as options (Boyle, 1977; Mehrdoust & Fallah, 2015), but there are those who question its variability (Zhang et al., 2018; Ferson, 2008), and this certainly opens up new topics for discussion.

The main objective of this paper is to investigate stock market volatility using the Monte Carlo simulation to provide insight into stock price movements, as there was a significant stock market collapse in 2020 caused by the COVID-19 pandemic and increased uncertainty, and to forecast potential returns for next period.

In 2020, there was a collapse of the market that occurred after a decade of global economic progress and constant growth, after the recovery from the 2007-2008 financial crisis. On the other hand, the quality of life has improved all over the world. At the beginning of 2020, the COVID-19 pandemic begins, which is more influential than the Spanish flu, and which decimates the economy (WBUR, 2021). The market has been exacerbated by panic disruptions in purchase and supply, leading to a global economic halt. The market was already vulnerable (Time, 2021; Capital, 2021), as indicated by the International Monetary Fund as well as other mitigating factors seen before the pandemic.

Since the 2007-08 financial crisis, a corporate debt bubble has emerged, increasing from 84% of world gross domestic product in 2009 to 92% in 2019, or about $ 72 trillion (The Economist, 2021). China, the United States, Japan, Britain, France, Spain, Italy and Germany, which are the eighth largest economies, have a total debt of $ 51 trillion in 2019 (for example $ 34 trillion in 2009). The biggest risks are developing markets such as China, India and Brazil, where 25-30% of bonds were issued by risky companies (McKinesey, 2021), warns in 2018 McKinsey Global Institute.

Getting back to crisis in 2020, we can say that sales increased during the first half and until mid-March same year, although the decline began on February 20, 2020. During the fall, there are multiple daily declines in the stock market on a global level. The biggest drop was on March 16, 2020, called “Black Monday II”, by 12-13% in most global markets (CNBC, 2021). We have two more significant dates of the stock market crash - March 9, 2020 known as “Black Monday I” (BBC, 2021) and March 12, 2020 with the nickname “Black Thursday” (CNBC, 2021). Banks around the world are cutting

cash flow rates and interest rates - in order to solve panic, and offer support to investors and markets (Reuters, 2021).

Methodology

Monte Carlo simulation is usually used in corporate and finance to evaluate and analyse portfolios and investments by simulating various factors of uncertainty that affect their value, and then determine the distribution of their value in the range of resulting outcomes. This is most often done on a stochastic means models basis. David B. Hertz introduced this method in finance in 1964 and published in his article in Harvard Business Review (2021). He highlighted its application in corporate finance. Boyle is considered a pioneer of application because he used it in 1977 to evaluate derivatives (Boyle, 2013, p. 323-338). Compared to other growth techniques, as the sources of uncertainty - sources of the problem increase (Palisade, 2021), the Monte Carlo method has an advantage.

This method includes any statistical sampling technique used to approximate solutions to quantitative problems. The Monte Carlo method actually solves the problem by simulating the basic process and then determining the average result. Monte Carlo simulation is a technique for simulating the probability of an outcome based on probability distribution, which achieves more accurate coverage of uncertainty. The essence of this simulation is in the random generation of data based on probability distribution, with the aim of simulating the sampling process from the actual population (Bakar & Rosbi, 2019).

The Monte Carlo method is used in finance to calculate the representative value of instruments in relation to all possible values of the underlying investment, as well as to simulate various sources (factors) of uncertainty affecting the value of the instrument, portfolio or investment which are the subject of analysis. In essence, this is the application of a neutral risk assessment in terms of financial theory. In addition, this method can be used for personal finance planning. An example is the calculation of plan 401 (k), which determines the possibility of retirement based on target income. By increasing the amount of money allocated for savings, we can determine the need to take on more risk.

The use of Monte Carlo simulations is not always appropriate, despite the fact that they provide flexibility and can deal with complex sources of uncertainty. However, these simulation methods are certainly more desirable than others only if there are several variable states. Due to a specific nature of American style derivatives, it is important to emphasize that these techniques are limited in valuation of that type of derivatives. Namely, it will be presented one of the techniques on the example of the New York Stock Exchange.

The vicious pandemic that has swept the world as well as the fall of the stock market in 2020 is making Monte Carlo simulations more significant than before. Data taken from Yahoo Finance for each of the trading days for five years as well as simulations were done using the R programming language, all in order to assess stock price volatility.

Results and discussion

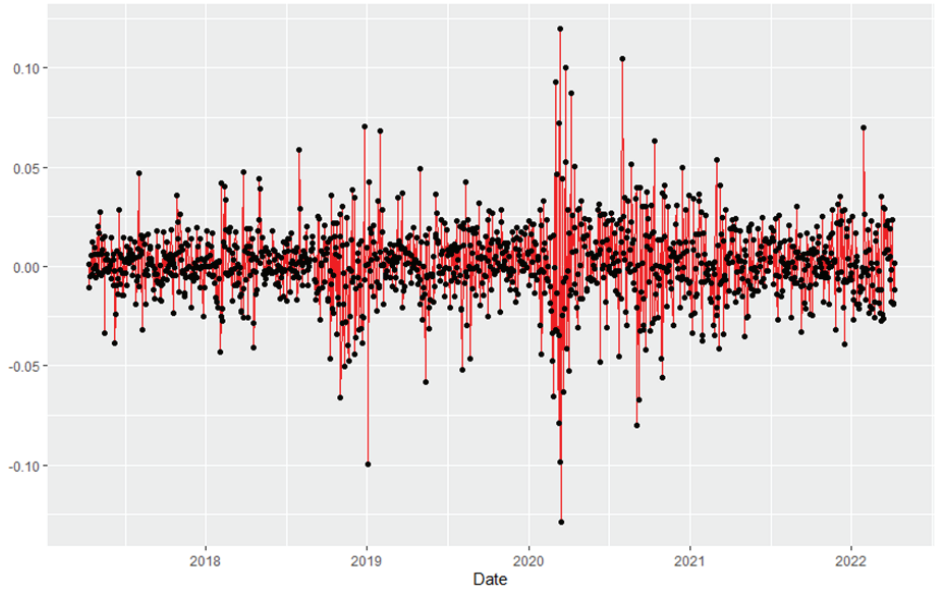
Based on data on stock price movements, Apple's average daily returns over six years were calculated using the formula:

$$Rt=(Pt-P\_(t-1))/P\_(t-1)$$

where: Rt represents the return rate at the period t, Pt stock price at the period t, and P_(t-1) stock price at the period t-1.

The movement of daily returns during the observed period recorded significant volatility, where it can be noticed that the highest volatility of returns was recorded during 2021, especially in the first half of 2020, which coincides with the period of the outbreak of the COVID-19 pandemic (Figure 1).

Figure 1. Daily return rates of AAPL stocks



Source: Authors' calculations

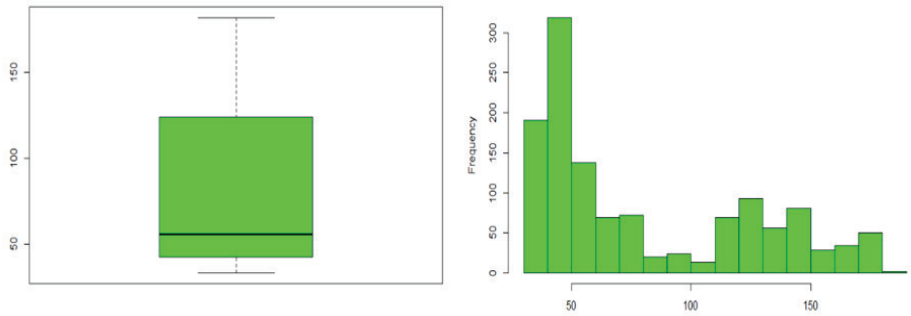
When it comes to adjusted closing prices, it can be noticed that after a short downward trend during the second half of 2018 and during the first half of 2020, there was an increase in prices that continued during 2021 and 2022, with increase in prices having moderate volatile movements (Figure 2).

Figure 2. Trend of adjusted closing price

Source: Authors' calculations

However, during most of the observed period, adjusted closing prices were less than the average values of the series, which can be seen on the basis of box plot and histogram (Figure 3).

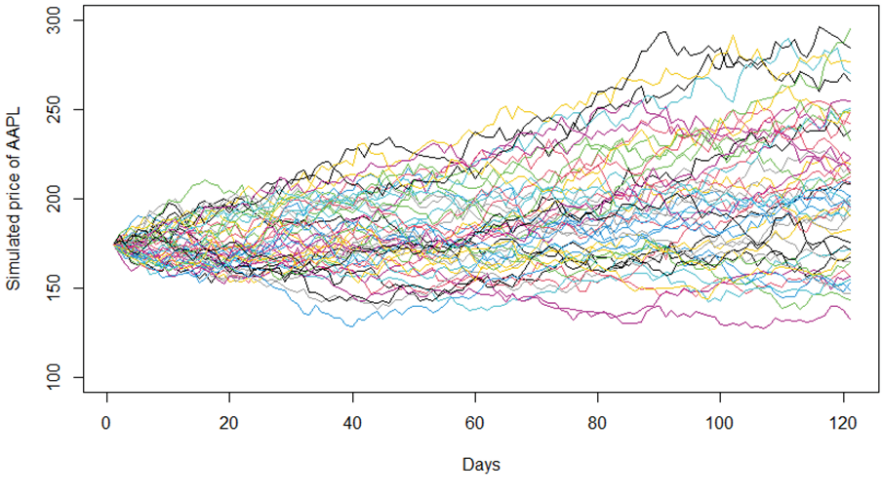
Figure 3. Box plot and histogram of the adjusted closing price



Source: Authors' calculations

The price simulation was performed for a period of 120 days, during which 1000 simulations were created (Figure 4).

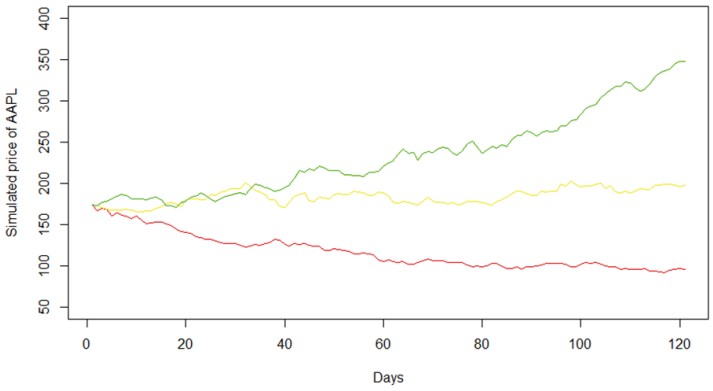
Figure 4. Simulated values of Apple adjusted closing prices



Source: Authors' calculations

Figure 5 shows the projected highest adjusted closing prices, the lowest adjusted closing prices and the mean value of projected adjusted closing prices.

Figure 5. Highest and lowest adjusted closing prices



Source: Authors' calculations

The prediction of future return was made on the basis of probability distribution, and it was determined that the probability of making more than 10% of return is 55.64436 %, while the probability of losing more than 10% is 12.68731 % during the next 120 days. Furthermore, the probability of making more than 50% of return is 6.293706 %

while the probability of losing more than 30% is 0.5994006 % and the probability of losing more than 50% is 0 %. These probabilities indicate a good investment potential of Apple's shares in the next 120 days, since the probability of creating return is higher than probability of losing.

Conclusion

Modern business is characterized by a distinct dynamism resulting from rapidly changing business conditions. Stock price movements are characterized by pronounced volatility, which leads to investors' exposure to potential losses. In order to avoid the negative consequences of stock price volatility, the information obtained by applying the Monte Carlo simulation can be extremely important. Monte Carlo method represents a methodological tool used for studying analytical intractable problems and for forecasting, and its usefulness has been more pronounced lately.

With the aim of pointing out to the possibilities and advantages of applying Monte Carlo simulations when analysing the volatility of the stock market, the paper analysed the data of the Apple Company which is listed on New York Stock Exchange. The purpose of the analysis was to examine the volatility of stock market returns. For the purpose of this research, the data were obtained for the six-year period, from 2017 up to 2022. The analysed period includes the period of the COVID-19 pandemic outbreak which affected the world and world economy leading to one of the biggest markets fall since The Great Depression in 20th century.

The results of the research indicate the expected trends of the stock prices returns in the next 120 days, which allows investors to make informed decisions. Further research in this area can be directed towards analysing the particular stock portfolio and identifying the optimal structure of the portfolio.

With the development of unexpected crisis situations, like the newest situation in Ukraine, methods that enable predictions are gaining in importance for investors and researches.

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