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Optimization of Cryptocurrency Investment Portfolio Based on Modern Portfolio Theory

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Abstract

Purpose of the article: The article examines the suitability of using the Modern Portfolio Theory (MPT) principle in cryptocurrency portfolio optimization.
Methodology/methods: The input data comprised the daily data of 10 most traded cryptocurrencies extracted from the web CoinMarketCap. The data for the period from 2 January 2021 to 1 September 2021 was selected as a sample. The Python programming language was used as a tool for implementation of the Modern Portfolio Theory. The Pandas open-source tool was used for data analysis and manipulation. Mathematical operations were performed using the NumPy package. Library Matplotlib was used for creating static, animated, and interactive visualizations in Python.
Scientific aim: The research objective is to determine the possibilities of diversifying the cryptocurrency investment portfolio risk based on MPT including processing of programming code.
Findings: The proposed optimal investment portfolio demonstrates that its performance is profitable not only in the optimisation period but also in the validation period. Validation of the optimal investment portfolio confirms that the risk and profitability characteristics are fully respected by the proposed model. The article benefit is also the presentation of a comprehensive methodology for the creation and validation of an optimal portfolio based on MPT principles in the context of software support.
Conclusions: The case study of investment portfolio optimisation (with the top 10 most traded cryptocurrencies) using MPT was developed, including validation of the proposed investment portfolio. Compared to traditional approaches, which include investor's or portfolio manager's decision-making, this approach provides investors with automated portfolio optimisation processing based on mathematical and statistical calculations.

Keywords: cryptocurrencies, financial market, crypto market, investment portfolio, modern portfolio theory

JEL Classification: G11, G23

1. Introduction

The paper deals with the issue of Modern Portfolio Theory (MPT) as a possible concept of risk diversification in optimising a portfolio of investments in cryptocurrencies. The topicality of the paper is substantiated due the fact that there is still the high level of volatility in the cryptocurrency. This is the the reason why the investment decision-making in cryptocurrencies extremely is complex and complicated. The research by (Ram, 2019) shows that Bitcoin represents next alternative option for the investors. The difference from traditional investment assets is mainly due to its decentralisation in relation to the political or economic system. Bitcoin is a significant investment opportunity in the modern financial market because it shares small or no correlation with other assets. Based on Sharpe's ratios Bitcoin provides a return (adjusted for risk) on most assets.

The implementation of investment strategies in the modern financial cryptocurrency market is nowadays one of the common proactive financial management activities of both legal and natural persons. These investment strategies represent an attractive option to work with free financial capital effectively.

For successful application of investment activities not only in the cryptocurrency market, it is necessary to have a quality investment strategy or method of creating an investment portfolio. This investment strategy may be composed of several investment sub-strategies, with a knowledge base defining a list of all the steps and rules that are used to implement the actual investment strategies.

The application of an active approach, with selected elements of technical analysis, plays a significant role in financial decision-making today. The overall objective of these analyses is to identify information and knowledge that supports the decision-making of financial experts in the global financial markets as quickly and efficiently as possible (Pervaiz *et al.*, 2021; Sperka, Szarowska, 2016)where the role of financial markets has even become more intensified to provide financial services to increasing economic and financial activities. Asian financial market has momentously suffered during the Asian, and global financial crisis. The mass destruction was mainly caused due to the mounting uncertainty, which spillover throughout the region, where investors lost their confidence. Considering the pivotal economic role of financial markets, and implications evolve due to sovereign credit rating announcements, this study aims to model the role of sovereign credit rating announcements by Standard and Poor's, and Moody's on financial market development of the Asian region. For 24 Asian countries/regions, we perform a regression analysis on sovereign credit rating changes based on financial market development index and its factors. The findings of Driscoll Kraay's robust estimator reveals that improvement in sovereign credit rating score enhances the financial market development in the region. Moreover, we applied several robustness checks, such as alternative estimators, alternative measures, and three sub-dimensions of financial market development. According to the findings from these robustness checks, the positive impact of sovereign credit ratings on financial market development in the region is robust. Unlike prior literature (which is confined to the event study approach. Information and knowledge is usually generated from large amounts of data (big data) using selected business intelligence and artificial intelligence tools. The subject of these analysis is usually finding the relationships using standard algorithmic methods. It is very complicated process for such big data.

The article examines the suitability of using the Modern Portfolio Theory (MPT) principle in cryptocurrency portfolio optimisation in objective to determine the possibilities of diversifying the investment portfolio risk including processing of programming code.

2. Literature review

For the review of the relevant literature on the addressed issues, the renowned scientific database Web of Science was used, since it is generally accepted as a database with high scientific value. The scientific articles were searched based on fields such as title, topic, abstract, and using keywords such as "*cryptocurrency*", "*modern portfolio theory"*, "*Bitcoin*" and "*financial market*". These articles are analysed below.

The article by (Wang, 2024) focuses on the analysis of the needs for increased protection of cryptocurrency investors in the USA. The study analyses the effects of sociodemographic factors, digital adoption, investment behaviour and financial attitudes on cryptocurrency owners. The dependencies are examined using the logistic regression model and hierarchical cluster analysis. The input data are obtained from the Financial Lives Survey 2020. The survey shows that cryptocurrency investors usually have insufficient portfolio diversification. They prefer high-risk investments. Their investment decisions are significantly influenced by demographic factors, risk attitude, technical sophistication, emotions and intuition. In conclusion, the study points to the need for education in the field of financial investment in cryptocurrencies.

The research by (Jayawardhana, Colombage, 2024)co-movement, and causality relationships amongst the equity, debt, and cryptocurrency markets to determine the risk diversification possibilities of an investment portfolio. We employ daily data extracted from the Bloomberg data terminal from 2 August 2017 to 2 June 2022 to investigate the short- and long-run relationships between these markets. Indices from the U.S.A., Europe, China, Australia, and Japan are selected as the proxies for the analysis. The autoregressive distributed lag (ARDL analyses co-integration, co-movement and causal relationships between equity, debt and cryptocurrency markets with the aim of diversifying the risk of an investment portfolio. The study works with data from 2 August 2017 to 2 June 2022 with daily granularity. The analysis is based on the application of the autoregressive distributed lag model and unit root testing. The result shows that there is a possibility of portfolio diversification with cryptocurrencies and financial markets based on the MPT principle (Modern Portfolio Theory).

The article by (Arneric, Mateljan, 2019) deals with the issue of capital outflow from capital markets to the cryptocurrency market. A partial objective is to identify whether cryptocurrencies can serve as a safe asset during periods of high volatility. Empirical research is conducted on two key representatives of capital and cryptocurrency markets (the S&P 500 stock index and bitcoin). Engle's dynamic conditional correlation model was used for the analysis. The research shows that the correlation between the markets is time-varying. The biggest negative values occur at the end of 2015, in mid-2016 and at the beginning of 2017. This coincides with periods of high volatility of the S&P 500 index. These conclusions confirm the hypothesis that the cryptocurrency market can serve as a safe asset during periods of high volatility.

The research by (Liu, 2019) is focused on examines the investability and role of diversification in cryptocurrency market. It evaluates the out-of-sample performance of commonly used asset allocation models across cryptocurrencies. The research is based on the he empirical data of ten major cryptocurrencies. The research results show that portfolio diversification across different cryptocurrencies can significantly improve the investment results. There is also robust evidence that the maximum utility model dominates the out-of-sample utility.

The authors (Hu *et al.*, 2021) emphasise the need for the development of a cryptocurrency index and associated hedging and trading vehicles, all designed to be consistent with modern portfolio theory. In the case study, they create smart-beta-like crypto asset indexes and suggest tracking them with a tradable ETF, and they show how to value options based on such indexes. The authors provide a unified framework for applying financial theory to this new investment class, which consists primarily of risky assets (despite the commonly used label of currencies). The main research result is that risk analysis, portfolio optimisation, and derivative pricing should all be done within the same model.

The research by (Grujic, Soja, 2022) investigates the empirical verification of the efficacy of investment diversification using the main stock exchange indices in the Eurozone countries (the data used in the analysis cover the period from 2019 and 2020). The goal of the research is to examine whether it is justified and to what extent to include Bitcoin in the portfolio of an institutional investor. The results of the research show that Bitcoin is a good source of diversification in a portfolio that contains traditional financial instruments, both for an investor who is not prone to risk, and for those investors who have a greater appetite for risk.

The research by (Saksonova, Kuzmina-Merlino, 2019) focuses on investment cryptocurrency strategies building, considering their risks and costs. The authors test the hypothesis that the Modern Portfolio Theory can be used to design an investment cryptocurrency portfolio with suitable characteristics of profitability and risk. They used the historical values of cryptocurrency rates from 1.6.2017 to 1.1.2018 as the inputs dat. They main research results are follows: (1) The cryptocurrency investment portfolio should be designed with investment targets in mind with the logical relationship between characteristics of profitability and risk. (2) The cryptocurrencies in the investment portfolio should be not correlated. (3) To minimise investment risk, the portfolio should be sufficiently diversified and liquid.

The research by (Mazanec, 2021) focused on diversification of cryptocurrencies portfolio, which is highly important because cryptocurrencies compared to traditional assets are very risky. The primary goal of the research is to compile an optimal cryptocurrencies portfolio with application of the Modern Portfolio Theory. This portfolio consists of 16 cryptocurrencies from 1.10.2017 to 13.1.2020. The results of the research show that the optimal portfolio identified according by the Markowitz approach is Bitcoin, Binance Coin and Cardano. Based on correlation analysis, it has been established that the cryptocurrencies are slightly correlated. The exception is only Tether, since it is an atypical cryptocurrency compared to other cryptocurrencies.

The research by (Isah, Raheem, 2019) focused on the analysis of the predictive power of cryptocurrencies on the United States stock returns. They assume that the unconventional monetary policy, specifically quantitative easing, is a fundamental factor that supports the development of cryptocurrencies. They spread two variables single factor predictive model based on Bitcoin on the multi-variables predictive model based on cryptocurrencies. The research results ware robust to different methods of measuring performance forecasting and different periods of sub-patterns. Their main findings are as follows: (1) by directly QE measuring, the preferred model looks like to be the single predictive model; (2) by indirectly QE measuring (through some transmission channels) the multifactor predictive model attempts to overcome the single-factor model; (3) given the historical average, the multifactor predictive model is a more accurate model for predicting stock returns.

The research by (Kristoufek, 2019)we are able to construct a theoretical exchange rate base of the cryptocurrency with respect to the US dollar. Through the concept of statistical equilibrium verified by the cointegration relationship, we show several interesting points. First, the Bitcoin price dynamics is very well captured by the underlying transaction data which leads to a strong fundamental basis of the cryptocurrency. Second, several historical bubbles hit the confidence intervals around the fundamental price but then start their correction back to the equilibrium. Third, the fundamental price implied by the transaction data is not ever-increasing but reflects the ups and downs of Bitcoin utility in transactions. And fourth, our theory-implied fundamental price suggests that the current (December 2018 examined the dynamics of the price of bitcoin as the most significant cryptocurrency. He constructed the theoretical basis of the cryptocurrency exchange rate with respect to the US dollar, using the unprecedented availability of bitcoin statistics data in his research. He identified follows knowledge based on the concept of statistical equilibrium: (1) The dynamic of Bitcoin prices is very well captured by the underlying transaction data. This fact leads to a strong fundamental basis of cryptocurrency. (2) Some historical bubbles included the confidence intervals around the fundamental price. Later they began to return back to equilibrium. (3) The fundamental price given by the transaction data is not constantly increasing. It correlates to the ups and downs of the utility of Bitcoins in transactions. (4) The theory based on implied fundamental price indicated that the price of bitcoin in December 2018 was very close to fundamental price. It was estimated at approximately $ 3,500.

The research by (Pengfei *et al.,* 2019) focused on the hypothesis verify if cryptocurrency is a hedge or a safe haven for international indices. As the input data they used 973 forms of cryptocurrencies and 30 international indices. They main research results are follows: (1) The cryptocurrency is a safe haven in general, but not a hedge for most international indices. (2) The safe haven is more significance in sub-groups with higher market capitalisation and higher liquidity. (3) The safe haven is more significance in developed financial markets.

The authors (Kristoufek, Vosvrda, 2019) focused on efficiency testing of the analysed coins and tokens and on comparison of the levels of efficiency on the cryptocurrencies market. They used the Efficiency index which include the long-range dependence, fractal dimension and entropy components. As the input data they used the set of historical cryptocurrencies such is Bitcoin, Litecoin, Monero, DASH, Stellar, and the set of historical tokens with market capitalisation above $ 0.5 billion. They identified the following main results: (1) The historical currencies were unanimously inefficient over the analysed period. (2) The efficiency as well as ranking are dependent on the denomination (Bitcoin or US dollar). (3) The most of tokens and coins were efficient during the time period of July 2017 – June 2018. (4) The least efficient coins are Ethereum and Litecoin. The most efficient cryptocurrency is DASH.

3. Methodology

3.1 Methods and tools

The Modern Portfolio Theory (MPT) method was applied to identify the optimal cryptocurrency investment portfolio.

The MPT is a financial mathematic model, created by Harry Markowitz (Kurach, 2017; Markowitz, 1952) for assembling an asset portfolio that optimizes the risk-return trade-off.

In the research by Turcas *et al.*, there are some reminders concerning the shortages in the application of statistics methods on the financial market, focusing on the MPT (Turcas *et al.,* 2017).

William Sharpe's parameter, called the Sharpe ratio (Chitnis, 2010; Chou *et al.*, 2017; Dashti *et al.*, 2007)NIFTY 50 has been considered as the market index. Stocks listed on the National Stock Exchange constitute the population. Two samples each comprising of 26 stocks (most of them being large caps is one of the most important risk and return measures used on the finance market. It describes how much excessive return you are receiving for extraordinary volatility that you withstand holding in a riskier asset.

The Sharpe ratio (SR) is calculated using the following formula:

$$SR = \frac{r_p - r_f}{\sigma_p} . \quad (1)$$

Where:

r_p is the expected portfolio return,
r_f is the risk-free rate of return (the investor's risk tolerance),
σ_p is the standard deviation of the portfolio returns.

The aim of the MPT is to create a portfolio whose overall risk is lower than the risk of individual assets in the portfolio. This can be achieved due to the fact that there is a presumption of normal distribution of risks of individual assets and thus the risks of individual assets cancel each other out. MPT represents the concept of diversification of investment risk measured on selected investment assets. The investment risk is represented by the variance or standard deviation in this model. The key principles of the MPT are as follows:

- Diversification: The MPT emphasises the importance of diversifying investments across different asset classes to minimize risk.
- Mean-Variance optimization: This involves selecting a portfolio that offers the highest expected return for a given level of risk or the lowest risk for a given level of expected return. This is achieved by calculating the expected returns and the standard deviation of returns for each asset.
- Covariance analysis: The MPT considers the covariation between different assets. By investing in assets with low correlations, the overall portfolio risk can be reduced.
- Efficient Frontier: This is a graphical representation of optimal portfolios that offer the best possible expected return for a given level of risk. Portfolios on the efficient frontier are considered optimal.
- The investors can lower their exposure to risk of individual asset by holding of the diversified portfolio of assets. The diversification can provide expected return with reduced risk for the same portfolio. MPT treats asset returns as random variables. It models the optimal portfolio as a weighted combination of individual asset returns.

The optimal investment portfolio represents the best possible combination of expected return and risk for the investor (Sharpe ratio). The objective is to maximise return for a given level of risk or minimise risk for a given level of expected return. The optimal portfolio is located at the so-called efficient frontier, which is a curve representing the best possible portfolios for different levels of risk.

The Python programming language ('Welcome to Python.Org', 2024) was used as a tool for implementation of the Modern Portfolio Theory. The Pandas open source tool which is built on top of the Python programming language ('Pandas – Python Data Analysis Library', 2024) was used for data analysis and manipulation. Mathematical operations were performed using the NumPy package. It is the fundamental package for scientific computing with Python ('NumPy', 2024). Library Matplotlib was used for creating static, animated, and interactive visualizations in Python ("Matplotlib: Python Plotting – Matplotlib 3.4.2 Documentation", 2024).

The process of cryptocurrency investments portfolio optimising based on the MPT principle is divided in two sub-processes – portfolio optimisation and portfolio validation.

The optimisation process it the process which the portfolio is adjusted to achieve the best possible balance between risk and return. During this period, various asset allocations are tested to find the optimal mix that maximises returns for a given level of risk. The validation process involves testing the suggested model to ensure how much accurately represents the reality. It includes back testing the model with historical data to verify its predictive power and reliability.

3.2 Data collection

From a total of more than 4,500 ("Statista", 2021) cryptocurrencies available as of 1 January 2021, a selection of the top 10 most traded cryptocurrencies was made. The selection criterion was the average daily traded volume as of 31 December 2020. This data represented the input data for portfolio optimisation. The validation of the proposed portfolio was carried out on data for the period from 2 January 2021 to 1 September 2021.

The input data was downloaded by using the Yahoo! Finance (Aroussi, 2021) package for Python directly from CoinMarketCap ("Cryptocurrency Prices, Charts And Market Capitalizations", 2021). Here, real historical price data with daily granularity can be obtained for each cryptocurrency. The data is available in UTC time zone and is recorded 7 days a week for 24 hours. The cryptocurrency market is continuous compared to the stock and commodity market. For each cryptocurrency, data that contains the "Open", "High", "Low", "Close", "Adj Close" and "Volume" values for each day (see Table 1) can be downloaded. A "package" programmed in Python was used to import the input data, which is connected to a database of historical prices.

3.3 Preparation of input data for optimisation process

For each cryptocurrency, only the Close value (Closing Price as of 31 December 2020)

Table 1. BTC/USD input data sample.

Data	Open	High	Low	Close	Adj Close	Volume
2021-08-27	46,894.554688	49,112.785156	46,394.281250	49,058.667969	49,058.667969	34,511,076,995
2021-08-28	49,072.585938	49,283.503906	48,499.238281	48,902.402344	48,902.402344	28,568,103,401
2021-08-29	48,911.250000	49,644.113281	47,925.855469	48,829.832031	48,829.832031	25,889,650,240
2021-08-30	48,834.851562	48,925.605469	46,950.273438	47,054.984375	47,054.984375	31,847,007,016
2021-08-31	47,024.339844	48,189.550781	46,750.093750	47,166.687500	47,166.687500	34,730,363,427

Source: Cryptocurrency Prices, Charts And Market Capitalizations, 2021.

Table 2. Input data: Top 10 most traded cryptocurrencies.

Cryptocurrency	Trading Volume [USD]	Closing Price [USD]
BTC-USD	46,754,964,848	29,001.72070
ETH-USD	139,26,846,861	737.80340
LTC-USD	6,274,573,135	124.69032
XRP-USD	5,363,979,601	0.21984
BCH-USD	3,783,477,587	343.05264
EOS-USD	2,183,017,128	2.59797
LINK-USD	1,206,737,630	11.27053
ADA-USD	1,132,268,397	0.18139
XMR-USD	1,095,354,071	156.57231
TRX-USD	921,675,059	0.02677

Source: Cryptocurrency Prices, Charts And Market Capitalizations, 2021.

and the Volume value (Trading Volume as of 31 December 2020) are extracted from the historical data.

The Volume value was used to select the top 10 cryptocurrencies. This data represented the input data for portfolio optimisation. These values have not been transformed in any way.

The Close values for the period from 1 January 2019 to 31 December 2020 are first converted into a relative expression of the daily percentage changes of the analysed cryptocurrencies (see Table 2). These adjusted values of Closing Price represent the input values to the optimization process according to the MPT method.

Other available values of historical cryptocurrency prices ("Open", "High", "Low", "Adj Close") are not used in this model.

4. Results

The case study is conducted as an experiment on a model investment portfolio the size of the top 10 most traded cryptocurrencies. The approach based on the Sharpe ratio in this case study is applied for the purposes of constructing the optimal investment cryptocurrencies portfolio.

The process of optimising a portfolio of cryptocurrency investments using MPT is divided into two main sub-processes, which are portfolio optimisation (sub--chapter 3.1) and portfolio validation (sub--chapter 3.2).

4.1 Portfolio optimisation

The portfolio optimisation sub-process is divided into 7 steps. Their description, including the source code of the MPT-based optimisation programme, is provided below:

(1) Loading libraries for the portfolio optimisation.

The initial phase of the optimisation process is to load all the necessary libraries (see Figure 1).

(2) Initial input data download of available cryptocurrencies.

The next phase of the optimisation process is to download the input data from the available cryptocurrencies as of 1 January 2021 (see sub-chapter 2.2). The model works with a time series from 1 January 2019 to 31 December 2020 with more than 4,500 cryptocurrencies (see Figure 2).

(3) Data download for selection of top 10 cryptocurrencies (input data for portfolio optimisation).

```
import yfinance as yf            #data source
import pandas as pd              #data analysis
import numpy as np               #scientific computing
import matplotlib.pyplot as plt  #visualization
```

Figure 1. Loading libraries. Source: own research.

```
start_date_optimization = '2019-01-01'
end_date_optimization = '2021-01-01'

#historical data downloading
for tick in all_tickers['Symbol']:
    volatility[tick[1]] = yf.download(tick[1], start=end_date_optimization, end=end_date_optimization,
                                      group_by="ticker" ,interval = "1d")['Volume']
```

Figure 2. Initial input data downloading. Source: own research.

```
#top 10 selection base on volume
top10_tickers = volatility.iloc[0].sort_values(ascending=False)[0:10].index

#historical data downloading for optimization
for tick in top10_tickers:
    data_optimization[tick] = yf.download(tick, start=start_date_optimization, end=end_date_optimization,
                                          group_by="ticker" ,interval = "1d")['Close']
```

Figure 3. Data downloading for selection of top 10 cryptocurrencies. Source: own research.

```
#visualization of optimization data
plt.figure(figsize = (17,5))
plt.plot(data_optimization.pct_change().cumsum(), ls=st, color='black');
plt.xlabel('date')
plt.ylabel('returns [%]')
plt.title('Relative performance of cryptocurrencies')
plt.legend(top10_tickers)
plt.plot();
```

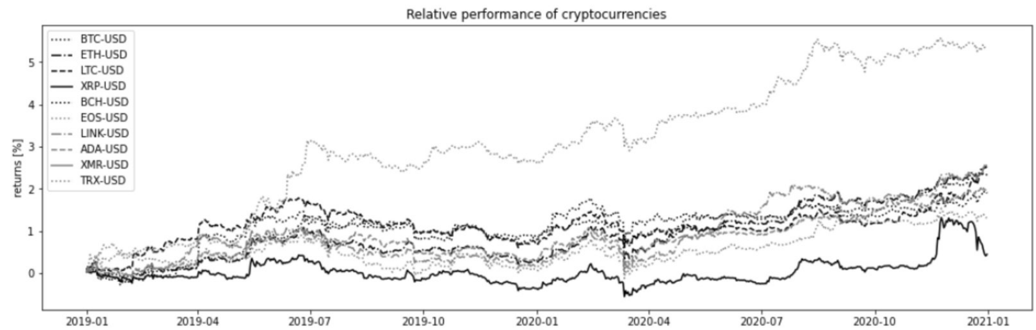

Figure 4. Visualization of top 10 selected cryptocurrencies. Source: own research.

```
#number of portfolio simulations
num_ports = 20000

all_weights = np.zeros((num_ports, len(top10_tickers)))

log_ret = data_optimization.pct_change()
ret_arr = np.zeros(num_ports)
vol_arr = np.zeros(num_ports)
sharpe_arr = np.zeros(num_ports)

#portfolio simulation
for x in range(num_ports):
    weights = np.array(np.random.random(len(top10_tickers)))
    weights = weights/np.sum(weights)
    all_weights[x,:] = weights
    ret_arr[x] = np.sum( (log_ret.mean() * weights * days_forward))
    vol_arr[x] = np.sqrt(np.dot(weights.T, np.dot(log_ret.cov()*days_forward, weights)))
    sharpe_arr[x] = ret_arr[x]/vol_arr[x]

#selection of portfolio with best Sharpe ratio value
max_sr_ret = ret_arr[sharpe_arr.argmax()]
max_sr_vol = vol_arr[sharpe_arr.argmax()]
```

Figure 5. Simulation of investment portfolios. Source: own research.

From more than 4,500 available cryptocurrencies, the top 10 cryptocurrencies were selected based on Trading Volume (see sub-chapter 2.3). The model works with a time series of top 10 cryptocurrencies from 1 January 2019 to 31 December 2020, which represent the input data for the optimization process (see Figure 3).

(4) Visualisation of top 10 selected data.

A graphical representation of the evolution of the yields of the top 10 cryptocurrencies (input data for the optimisation) over the period under review is presented in Figure 4.

(5) Simulation of investment portfolios and calculation of the optimal investment portfolio.

The simulation process of portfolio optimisation is based on a random variable that represents the return of a portfolio (optimisation criterion being the maximisation of the Sharpe ratio) and on a random variable that represents the return of the *i*-th cryptocurrency (relative average values of day changes of the Closing Price) in the portfolio. 20,000 random simulations with randomly calculated weights of portfolios are used in the optimisation model (see Figure 5).

(6) Visualisation of investment portfolio simulations and the optimal portfolio.

Graphical visualisation of investment portfolio simulations is shown in Figure 6. Each

```
plt.figure(figsize=(17,6))
plt.scatter(vol_arr, ret_arr, c=sharpe_arr, cmap='viridis')
plt.colorbar(label='Sharpe Ratio')
plt.xlabel('Volatility')
plt.ylabel('Return')
plt.scatter(max_sr_vol, max_sr_ret,c='red', s=50) # red dot
plt.show()
```

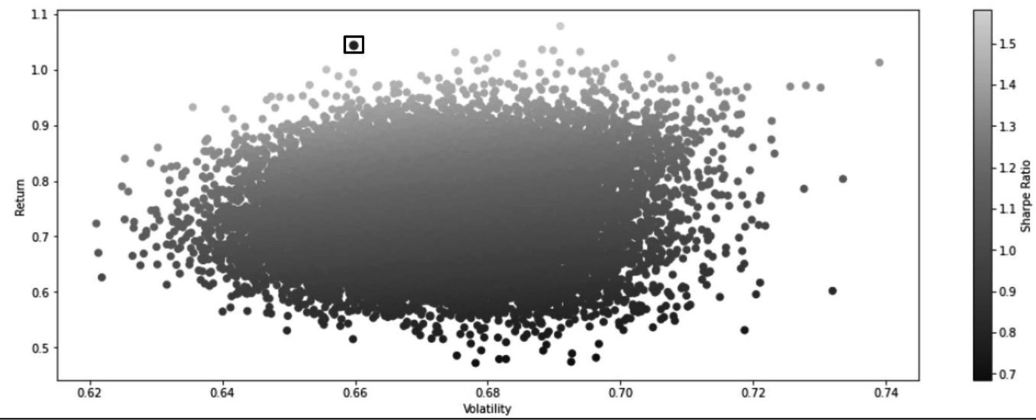

Figure 6. Simulation of investment portfolios. Source: own research.

```
optimal_portfolio = pd.DataFrame()
optimal_portfolio['Ticker'] = top10_tickers
optimal_portfolio['Weight'] = all_weights[sharpe_arr.argmax()]
optimal_portfolio = optimal_portfolio.set_index('Ticker')
optimal_portfolio
```

Ticker	Weight
BTC-USD	0.248363
ETH-USD	0.050672
LTC-USD	0.131816
XRP-USD	0.018035
BCH-USD	0.043841
EOS-USD	0.015789
LINK-USD	0.264575
ADA-USD	0.055788
XMR-USD	0.169527
TRX-USD	0.001595

Figure 7. Distribution of optimal portfolio weights. Source: own research.

point in the graph is composed of standard deviation (Volatility) and averages of Closing Price changes (Return). The optimal portfolio (portfolio with the maximum Sharpe ratio) is highlighted in black circle in the square. It was identified based on the maximum value of the Share Ratio.

(7) Distribution of optimal portfolio weights
The normalised weights of the optimal portfolio are presented in Figure 7. All weights are real numbers between 0 and 1, and they all sum up to 1.

4.2 Portfolio validation

The portfolio validation sub-process is divided into 2 steps. Their description, including the source code of the MPT-based optimisation programme, is provided below:

(1) Data download for portfolio validation.
Download of the top 10 cryptocurrencies data to verify the optimal portfolio. The model works with a time series from 2 January 2021 to 1 September 2021 (see Figure 8).

(2) Visualization of validation portfolio performance.

```
start_date_validation = '2021-01-02'
end_date_validation = '2021-09-01'

#historical data downloading - validation data
for tick in top10_tickers:
    data_validation[tick] = yf.download(tick, start=start_date_validation, end=end_date_validation,
                                        group_by="ticker" ,interval = "1d")['Close']
```

Figure 8. Data download for portfolio validation. Source: own research.

```
#visualization of validation
plt.figure(figsize = (17,6))
plt.plot(data_validation_pct_weights['portfolio'].cumsum());
plt.xlabel('date')
plt.ylabel('returns [%]')
plt.title('Portfolio validation')
plt.plot();
```

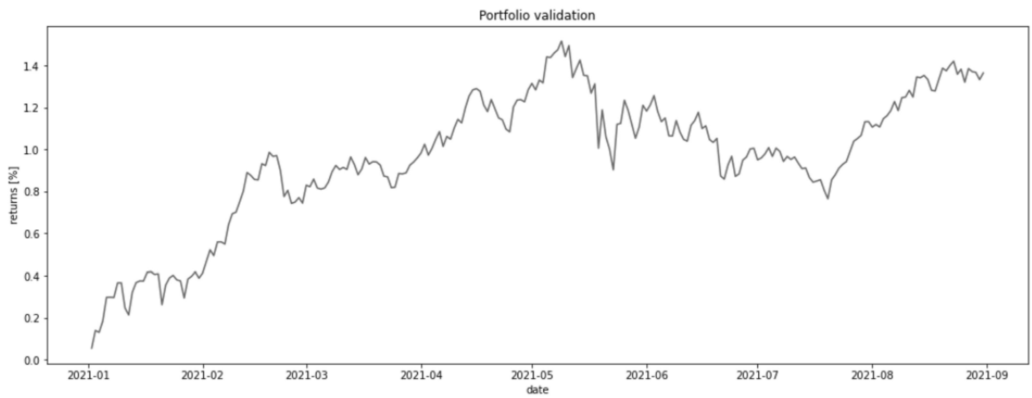

Figure 9. Visualization of validation portfolio performance. Source: own research.

Graphical visualisation of validation portfolio performance is presented in Figure 9. Each point in the graph is composed of standard deviation (Volatility) and averages of Closing Price changes.

5. Discussions

From the literature review (see the Chapter 1) conducted, it is evident that there are already publications dealing with the application of the MPT for optimising investment portfolios in the cryptocurrency market. However, these publications have only addressed the process of investment portfolio construction. The process of validation of the optimal portfolio has not been usually presented. Only on the basis of the results of the validation process can it be objectively stated whether or not the MPT is suitable for the purpose of optimising a cryptocurrency investment portfolio, or under what conditions.

The validation of the proposed optimal investment portfolio confirms that the risk and return / profitability characteristics are fully respected by the proposed model. Its performance is profitable not only in the optimisation period but also in the validation period. Despite frequent short-term declines in the value of the investment portfolio, there is always a tendency for the portfolio value to return to its original value and then to increase to a higher value. The use of diversification complies with the rules for managing investment portfolios based on the MPT. It can by stated, the MPT is possible to apply as a suitable method to the risk diversification in the decision-making process on cryptocurrency investments.

The article's benefit also consists in the presentation of a comprehensive methodology for the creation and validation of an optimal portfolio based on the MPT principles in the context of software support. The methodology is described in the form of gradual steps that logically follow one another, including the presentation of the source code both for the optimal portfolio creation stage and for the portfolio validation stage.

Compared to traditional approaches, the proposed model provides investors the automated portfolio optimisation processing based on mathematical and statistical calculations, including the possibility of simulation and experimenting with the model.

These findings, together with the presentation of a comprehensive methodology for the creation and validation of an optimal portfolio based on MPT in the context of software support, including the presentation of the source code, are the main contributions of the paper.

Transaction costs and inefficiency of trade order execution may be a limitation of the analysed model. For this reason, a limit has been set for the top 10 most traded cryptocurrencies, even though it would be more accurate to expand the investment portfolio to, for example, 100–200 cryptocurrencies under optimal market conditions. This issue could be subject of further research.

The results of the case study are based on input data and therefore cannot be generalised more broadly. However, the proposed approach can be generalised, including the presented programming code of the optimisation of cryptocurrency investment portfolio in context of the MPT. The proposed model is a simplification of reality and therefore does not capture all aspects (elements, relationships) of the real system. This fact is already due to the selection of input data, which is a sample, which is certainly a limitation of the model. However, the validation process proves that the proposed model is sufficiently reliable and acceptably accurate. Under the above assumptions, it is therefore practically applicable. In addition, the analyses performed within the modelling process assume a more detailed analysis of the problem being solved and are thus useful for understanding the functioning of the real system and its interpretation.

6. Conclusion

The paper dealt with the issue of the Modern Portfolio Theory (MPT) as a possible concept of risk diversification in optimizing a portfolio of investments in cryptocurrencies.

In order to fulfil research objective a case study of investment portfolio optimisation (with the top 10 most traded cryptocurrencies) using the MPT was developed, including validation of the proposed investment portfolio. The validation of the model confirms that the identified optimal portfolio fully respects the risk and profitability characteristics.

Compared to traditional approaches, which include investor's or portfolio manager's decision-making, this approach provides investors with automated portfolio optimisation processing based on mathematical and statistical calculations. The possibility of experimenting, *etc.* in the form of simulations, is an integral part of the proposed model. The proposed model helps in identifying the most efficient cryptocurrencies portfolios, thereby guiding investors towards better investment strategies.

This approach significantly influences how the investors could approach cryptocurrencies portfolio management.

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