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THE IMPACT OF ENERGY CRISIS ON VARIANCE- AND GINI-OPTIMIZED PORTFOLIO STRUCTURES – CASE OF HUNGARY

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Abstract

Crises in the 2020s have shocked global stock markets with unprecedented sud- denness. This has had a particularly strong impact on the Central European countries outside the euro area and exposed to heightened geopolitical conflicts, and within them, Hungary, which has had a particular government response to the crisis. Our research objective was to investigate the impact of the energy crisis on the Hungarian stock market as a consequence of the combination of greening policies, the post-Covid reopening and the EU sanctions policy on Russian energy imports, focusing on the portfolio optimization of the Hungarian blue chips and the stocks of the biggest complex (renewable and non-renewable) energy producer and trader company in the Hungarian market. In this context, our aim is to determine the impact of the turbulent crisis phenomena in the period 2020-2023, with a focus on energy price inflation, on the structure of a portfolio of the 5 stocks mentioned above optimized based on mean-variance and mean-Gini model. Since based on both methods, although differently, significantly increased the portfolio weight of the same energy company stocks in the energy crisis, it can be concluded that the change in the composition of the diversified portfolio reflected the impact of macroeconomic conditions on the stock market.

1. Literature review

1.1. Returns and risks of investment portfolios

When making investment decisions, the risk of the asset is a key factor in addition to the return available, as it is the return and the risk together that show us the utility of an investment [10]; [11]; [17]; [18]]; [47]. The assessment of the return on equity investments can also be supported by fundamental data that can be found in accounting reports, which may contribute to the determination of financial ratios that differ across industries [6]; [16]; [19], [40]; [28]. A rational investor prefers, ceteris paribus, the highest possible return while keeping the risk as low as possible. [30] pointed out the relationships between different investments, to what extent and in what direction they move together, and thus made a huge leap forward in portfolio optimization and selection. He was primarily concerned with the risk-reducing effect of diversification and showed that if investors buy stocks that move together less and correlate less, the more they can reduce the risk of their portfolios. This has highlighted that investors who hold a portion of their wealth in multiple types of investments and securities face significantly lower risk than if they choose only one type of investment [7]; [51]. There are several examples of the model's widespread application in the financial literature [22]; [34]; [12]; [48]; [31]; [32], and many portfolio optimization techniques are known [21]; [3]; [49]; [26]. In addition to variance-based risk measurement, the Gini model can be used to quantify the co-movement of portfolio element returns.

The expected return of a portfolio can be defined as the weighted arithmetic average of the expected returns of the assets in the portfolio, and is thus a linear function of the expected return, while the weights are the proportion of assets in the portfolio [39]. A cornerstone of the Markowitz model is the definition of efficient portfolios. The efficient portfolios curve illustrates the return-risk pairs that have the highest return for a given level of risk and the lowest risk for a given level of return. A rational investor chooses his investment from this curve, because if he chooses a point that does not fit the curve, he is choosing an investment that could be accessed at less risk.

There are two main types of risk, individual risk and market risk. Individual, or company-specific, risk refers to the performance of a particular security and is the part of the total risk that can be reduced by diversification, as changes in one company do not affect other companies [1]. Market, or systemic, risk refers to the factors that affect the performance of all companies in general, i.e. all risks that affect all or most companies. Market risk cannot therefore be reduced by diversification. It is basically composed of four types of risk: interest rate, equity, commodity and exchange rate. Interest rate risk can arise from changes in the base rate of the central bank or other monetary policy decisions and is mainly associated with variable rate securities and bank deposits. Equity risk arises from the volatility of the stock market, most commonly due to, for example, an increase in tax rates, which reduces the total return on all equities and hence the market price of equities [7].

Commodity risk expresses the risks arising from fluctuations in the price of raw materials, while exchange rate risk refers to the risks arising from fluctuations in the exchange rates of foreign currencies that affect firms involved in international trade [1]. Market or systemic risk, although not mitigated by diversification, can be mitigated in other ways. The best example is the purchase of a put option, which embodies the right (not the obligation) of the holder to sell the shares held by that person at a predetermined price within a predetermined time frame. This allows one to sell the security held at the predetermined price in the event of a significant fall in the market price of the stock [31]. Because it contains numerous of nonco-moving securities due to its high number of elements, the effect of diversification is maximized, reducing the individual risk to zero, which means that its total risk is now only equal to the systematic risk. The portion of the return of a market portfolio containing only risky assets that exceeds the risk-free return is called the market risk premium, which thus represents the additional return for assuming market risk [33].

1.2. Impact of the energy crisis on stock markets

By 2021, the lack of preparation for a sharp shift away from cheaper fossil fuels, the end of restrictions imposed under Covid-19 [4] and rising energy demand due to recovering economies have set the sector-specific market prices trend on an inflationary path reminiscent of the 1970s. This has been reinforced by the EU trade sanctions imposed following the Russian invasion, which have had a strong impact on international stock market indices in parallel with energy prices, similar to the period of disruption caused by Covid-19 [20]; [36]. Although on the consumer side, fears of the direct impact of the increase in fuel prices and overheads dominated, the main problem was that these price increases were also passed on to the cost of production and transport at company level [24], which were offset by increases in selling prices, justified or, in many cases, unjustified, in order to take advantage of the market opportunity to increase profits, leading to an overall increase in price levels.

In addition to soaring inflation, the fact that Hungary is a net importer of energy, meaning that the costs of energy in and outflows from foreign currency have to be financed using domestically generated income, has been a huge problem [38]. This also has a significant negative impact on the country's external balance, as import prices have risen and export prices have stagnated. This process is shifting income from energy-importing countries to energy-exporting countries, and as a consequence, the crisis is putting significant pressure on the Hungarian forint exchange rate, among other things. As a consequence, the income generated in the country is leaking out of the domestic economy, with the consequence that a significant drop in demand further complicates the situation of companies and hampers economic growth [9].

The impact of the crises on the domestic stock market has been strikingly negative, in line with international stock market indices, as manifested during the Covid-19 epidemic and the Russian-Ukrainian conflict [35]. In general, the crises have led to an increase in the market risk of companies and to a greater uncertainty of survival and solvency, resulting in a significant drop in the market price of shares in most cases. The negative effects of the crisis seem to have fully stabilized in the stock market in September 2023 [37].

2. Methods

2.1. Data

In our study, we mainly focused on the four most heavily weighted stocks (blue chips) of the BUX basket and ALTEO Nyrt and other shareholder returns (annual dividends) presented in their financial statements [14], to construct the most optimal portfolio of these shares and to examine the changes in the portfolio under different fixed investor return assumptions. We chose the top BUX stocks because they account for more than 90 percent of the BUX basket, thus defining the Hungarian stock market, and ALTEO is the biggest Hungarian company with a central role in the current energy crisis, as it is an electricity producer and supplier. We have firstly analyzed the share price performance of the five companies over the last five years, up to September 2023, illustrating the period before 2020, when there were no crises, and the shocks in the short period immediately preceding the energy crisis. The share price data we have processed are available on the official websites of the Budapest Stock Exchange (www.bet.hu/oldalak/adatletoltes), while the annual accounts of the same companies are available on the Hungarian Ministry of Justice's website..

2.2. Mean-variance model

The basis of variance-based portfolio optimization is that portfolio risk is based on the expected value of the squared deviation from the expected value [5]. Variance as a statistical measure is a good proxy for variation around the mean: the larger the variance of an asset, the more the values fluctuate around the expected value, so that an increase in variance increases risk [20]. Variance can be acceptable in the finance for measure of market risk premiums [50]. We focused 5 stocks which analyzed to construct an optimal portfolio structure with the lowest possible relative standard deviation of return-risk factors. We construct an optimal portfolio structure of more than two stocks, but this is calculated by determining the co-movement of returns, so their covariance, for each pair of stocks. These values are used to form a matrix, called the covariance matrix, which is used to determine the risk of the multi-asset portfolio [41]. This forms a symmetric matrix, where the covariance values of the same pair of stocks are mirrored on the two sides of the main diagonal, while the individual variance values of the stocks are located in the main diagonal of the matrix [42]. The standard deviation squared, can be determined using the covariance matrix and the formula (1), which takes into account both individual and combined risks:

$$\sigma(r)^2 = \frac{1}{n}\sum_{i=1}^{n}[r_i - E(r)]^2 \tag{1}$$

where i is the returns of the stocks in each period, while w is the weight of the stocks in the portfolio, so the condition that $w_i, w_j \geq 0$, $1 \leq i \leq n$, and $\sum_{i=1}^{n} w_i = 1$. Accordingly, the objective function of the portfolio optimized with the mean-variance

$$RSD = \frac{\sigma_p}{\mu} \rightarrow min! \tag{2}$$

where the RSD is the relative standard deviation, and the denominator is the return of portfolio, for which it is true that

$$\mu = w_i r_i + w_j r_j \tag{3}$$

The relative standard deviation should be minimized because it represents the risk per unit return, so the lower its value, the less risk the investor has to take for a unit return [8].

2.3. Mean-Gini model

For better robustness, the portfolio optimization is performed using another method besides the most commonly used mean-variance model, which is based on minimizing the Gini index coefficient, which can still quantify the risk-return relationship. Correcting for the shortcomings of the mean-variance model (quadratic of preferences, assumption of normality of distributions), the portfolio optimization model was further developed based on the index introduced by the Italian economist Corrado Gini [44]; [46]. Examples of portfolio analysis based on the mean-Gini model can be found in several literatures [13]; [15]; [29]; [44]; [39]; [23]; [25]; [27]; [2]; [45], as well as comparisons with the mean-variance model [43].

In economics, the Gini-index, originally used to measure social income inequality, is a measure of the inequality of the relative distance between data, recorded in the interval between 0 and 1: while a value of 0 is due to the identity of the values of the data series, showing perfect equality (so portfolio returns do not differ between periods and hence there is no risk), an increasing shift towards 1 is the bigger distance between the values of the data series, and hence in this case indicates an increasing degree of inequality between portfolio returns of the periods.

According to the method, the Gini index of a portfolio is defined as the covariance between the portfolio's period returns (r) and its rank, divided by the number of periods (n) and the average return over all periods [2]. The presence of negative returns can make the average of the data series so low that the coefficient value can take a value higher than 1. The value of the Gini index as the target value for the optimization is based on [44]:

$$Gini = 2\frac{cov[r_p, rank(r_p)]}{n\mu} \rightarrow min! \qquad (4)$$

To test whether the portfolio structures are significantly different for given expected returns, we used a paired t-test. Our first hypothesis is the composition of optimal portfolio have changed effect of the crisis happened from 2020, and the second is that there is no significant difference the compositions of portfolio optimized by the mean-variance and mean-Gini model.

3. Results

3.1. Descriptive statistical analysis of portfolio element returns during the crisis period

The main return indicators of the portfolio elements in the period affected by the crisis are included in the Table 1. Overall, for the whole period from 2020 to the present, ALTEO shareholders have clearly achieved the highest holding period return of nearly 250 percent, which is due to the positive investor sentiment towards ALTEO's renewable energy investments, which are expected to generate stable revenue and earnings growth as energy use increases. Besides the four blue chips, Richter performed the best on the HPR, with a holding period return of more than 50 percent, mainly due to a significant increase in revenue from export sales. Only OTP's shareholders failed to achieve a return over the whole period, with a holding period loss of more than 4 percent.

Table 1. The main return indicators of the portfolio elements from 2020 to 2023

Name	MOL	MTELEKOM	OTP	RICHTER	ALTEO
HPR	15.33%	22,00%	-4.48%	51.84%	247.88%
Exchange rate changes	-10.07%	3.81%	-9.23%	37.92%	232.94%

Source: own calculations

If the exchange rate changes refer to the period 2020-2023 (see Figure 1), we can draw conclusions from the minimum, maximum and median values of the periods, taking into account the quartiles. The difference between the minimum and maximum values, so the spread of the exchange rates, is high for MOL and OTP, for the former for the period 2020-2021 and for the latter for both periods. This high spread reflects the high risk of the shares, while the low spread indicates a low risk level, as exemplified by Magyar Telekom shares for the period 2020-2021. In terms of median values, we can highlight the pandemic period for ALTEO and the war period for OTP. ALTEO's monthly returns were above 3.5 percent in half of the cases, while OTP's median was -1.5 percent, so in more than 50 percent of the cases, negative monthly returns were achieved with these shares, confirming the HPR-based results.

Overall, as the higher standard deviations meant that the averages gave less reliable results for these periods only, it can be said that the higher the medians and the smaller the difference between the extremes, the better the stocks performed. This suggests that OTP shares were most negatively affected by the energy crisis period, as the spread of the share price remained at an exceptionally high level in the period after 2022, in addition to the lowest median value.

3.2. An optimal portfolio structure during the energy crisis

In this subsection, we aim to construct an optimal portfolio with the lowest possible relative standard deviation in terms of return-risk factors, using the five stocks con- sidered above. As a first step, the return, standard deviation and individual relative standard deviation of the stocks were calculated using price changes for the monthends from September 2015 to September 2023, the end of the energy inflation period.

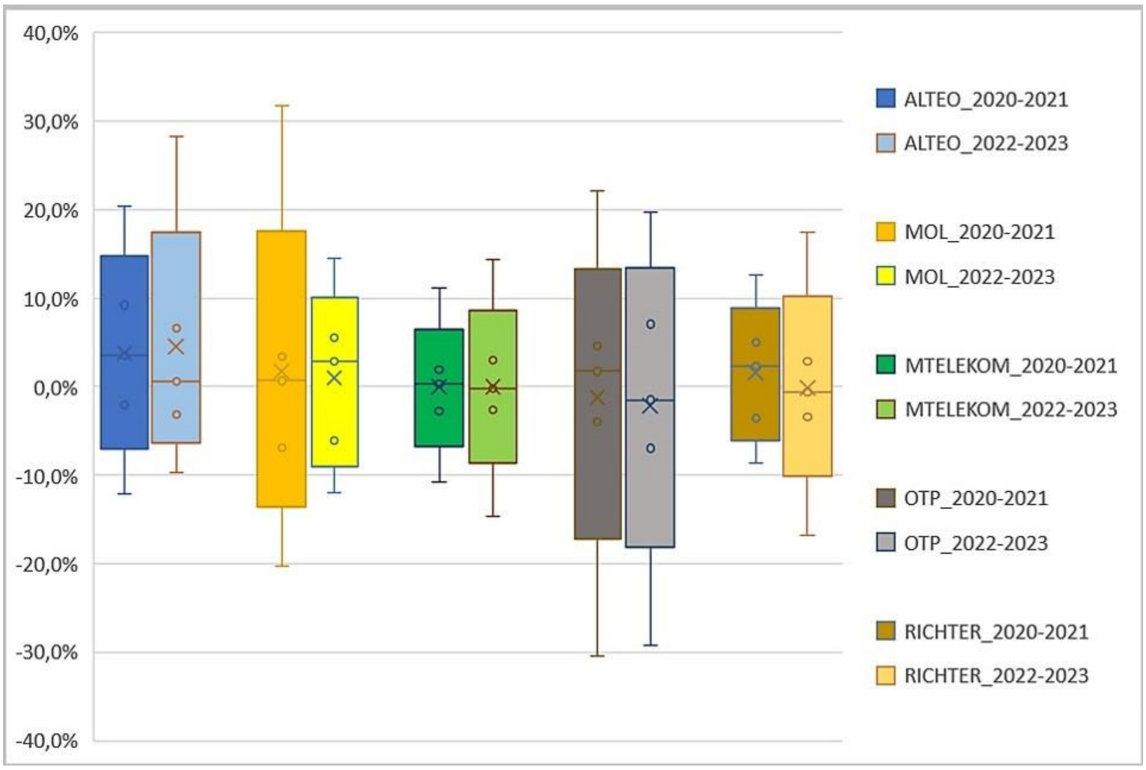

Fig. 1. Quartiles of the distribution of monthly closing stock in the period affected by the crisis, before and after the outbreak of the Ukrainian-Russian war.
Source: own edition

However, we cannot yet draw conclusions from the RSD data separately for the con- struction of our portfolio, the data will only be used in subsequent calculations. If we restrict the investment decision criterion to the relative standard deviation, ALTEO shares are the most worthwhile to buy, as they have the lowest RSD value of 2.82 (see Table 2). On the same basis, the investor would take the highest risk with Telekom shares in order to obtain a unit return. However, given the risk-mitigating effect of diversification, this does not mean that one should invest all one's assets in ALTEO shares and that it would not be worth buying Telekom shares under any circumstances, since by buying these five shares in the right proportions one can build a portfolio with the RSD even lower than ALTEO. After setting up the covariance matrix (see Table 3), it is necessary to determine the weight of the stocks by optimization to determine the total portfolio variance. With the weights determined using Solver, a portfolio with the lowest possible relative standard deviation was constructed, with a standard deviation of 5.93 percent, a return of 2.17 percent and a RSD of 2.73. This effectively confirmed my hypothesis that it is possible to construct an optimal portfolio with a relative standard deviation even lower than the relative standard deviation of ALTEO, so that it is not really worth investing all our assets in ALTEO shares alone, since these shares account for 82 percent of our optimal portfolio. The other extreme was Telekom, which had the highest RSD, so in our case we did not include any of its shares in the portfolio. This is clearly due to the extremely high risk and relatively low return of Telekom shares.

Table 2. Average and variance of returns of portfolio elements after the crises.

Name	Average mounthly return	Risk (variance)	RSD
MOL	0.68%	7.31%	10,71
MTELEKOM	0.42%	5.23%	12.31
OTP	1.24%	8.4%	6.79
RICHTER	0.88%	6.16%	6.98
ALTEO	2.37%	6.68%	2.82

Source: own calculations

Table 3. Covariance matrix and the optimal portfolio element weights after the crises.

Name	ALTEO	MOL	MTELEKOM	OTP	RICHTER
ALTEO	0.45%	0.11%	0.05%	0.09%	0.16%
MOL	0.11%	0.53%	0.15%	0.36%	0.14%
MTELEKOM	0.05%	0.15%	0.27%	0.19%	0.10%
OTP	0.09%	0.36%	0.19%	0.71%	0.18%
RICHTER	0.16%	0.14%	0.10%	0.18%	0.38%
Weight	82.00%	0.00%	0.00%	18.00%	0.00%

Source: own calculations

3.3. An optimal portfolio structure before the energy crisis

In this part of our study, the return data of the portfolio elements were taken into account from September 2015 onwards, but in this case only up to 2019, to illustrate how the optimal structure of the above stock portfolio evolved in the period before the crisis events and to what extent the latter events may have influenced optimal investor decisions. The period before the energy crisis is also closely related to the period of the Covid-19 crisis, which cannot be considered as a "normal" business period and would therefore also bias the results, which is why the time period of the analysis is set to the year before the beginning of Covid-19 (end of 2019). However, as shown in Table 4, there are significant differences in average returns, standard deviation and RSD for the four blue chips compared to the period affected by the crisis (Table 4). The reason for these significant changes is clearly the impact of the crises, which have significantly changed the Hungarian stock market. Since portfolio optimization based on RSD makes sense for long-term investments, we would not observe a significant difference in the weights in the optimal portfolio over 3 years for the reasons mentioned above (see Table 5), but this is not the case here due to macroeconomic shocks. Prior to the crisis, ALTEO and OTP shares make up a significant part of the portfolio, with 56 percent and 39 percent respectively, and MOL shares with 5 percent. However, even after 2020, MOL is already excluded from the portfolio and only ALTEO and OTP shares remain, with 82 percent and 18 percent respectively.

Table 4. Average and variance of returns of portfolio elements before the crises.

Name	Average mounthly return	Risk (variance)	RSD
MOL	1.06%	5.71%	5,41
MTELEKOM	0.23%	4.09%	18.09
OTP	1.93%	5.70%	2.95
RICHTER	0.67%	5.77%	8.62
ALTEO	1.82%	4.86%	2.67

Source: own calculations

Table 5. Covariance matrix and the optimal portfolio element weights before the crises.

Name	ALTEO	MOL	MTELEKOM	OTP	RICHTER
ALTEO	0.24%	0.00%	0.01%	0.04%	0.06%
MOL	0.00%	0.33%	0.10%	0.17%	0.11%
MTELEKOM	0.01%	0.10%	0.17%	0.12%	0.07%
OTP	0.04%	0.17%	0.12%	0.33%	0.10%
RICHTER	0.06%	0.11%	0.07%	0.10%	0.33%
Weight	56.00%	5.00%	0.00%	39.00%	0.00%

Source: own calculations

Prior to the crises, the portfolio's return of 1.82 percent and standard deviation of 3.82 percent were set at a RSD of 2.10, compared to the current value of 2.73, which shows a shift in the optimized value towards higher risk, in a less favorable way for investors.

3.4. Impact of the energy crisis on the composition of variance-optimized portfolios

The portfolios defined in the former way are essentially based on minimizing the risk per unit of return and a single risk-return pair is defined, although some investors may wish to achieve a higher return than this or, conversely, may be satisfied with a lower return. The method based on the RSD method can be used to determine the optimal portfolio structure of a given set of stocks with the aim of minimizing relative standard deviation, by defining a constraint on the value of the return to be achieved, which can be varied to determine the changes in the investment combinations that will provide the maximum return with the minimum risk.

Accordingly, for all potential return levels that mathematically allow for an optimal solution, the study has identified portfolios with the lowest possible risk, separately for the period up to 2019 (see Figure 2) and the period including macroeconomic shocks (see Figure 3). The Solver add-on mentioned above was used for the calculations, but in order to be able to determine all possible yield levels, it was considered appropriate to use a combination of Solver and an Excel VBA, allowing the optimization to be run with a continuously changing constraint. In our case, the average return that allowed the optimal solution was between 0.23 percent and 1.93 percent before 2020, and between 0.42 percent and 2.37 percent during the inflationary period, since the shares with the highest average return were OTP in the former case and ALTEO in the latter, and the lowest average return in both cases was Telekom. As a result, the lowest and highest returns are achieved with a 100 percent share of these particular shares and, regardless of the crisis, as the level of expected returns rise, the investor is less and less able to minimize his risk with Telekom shares.

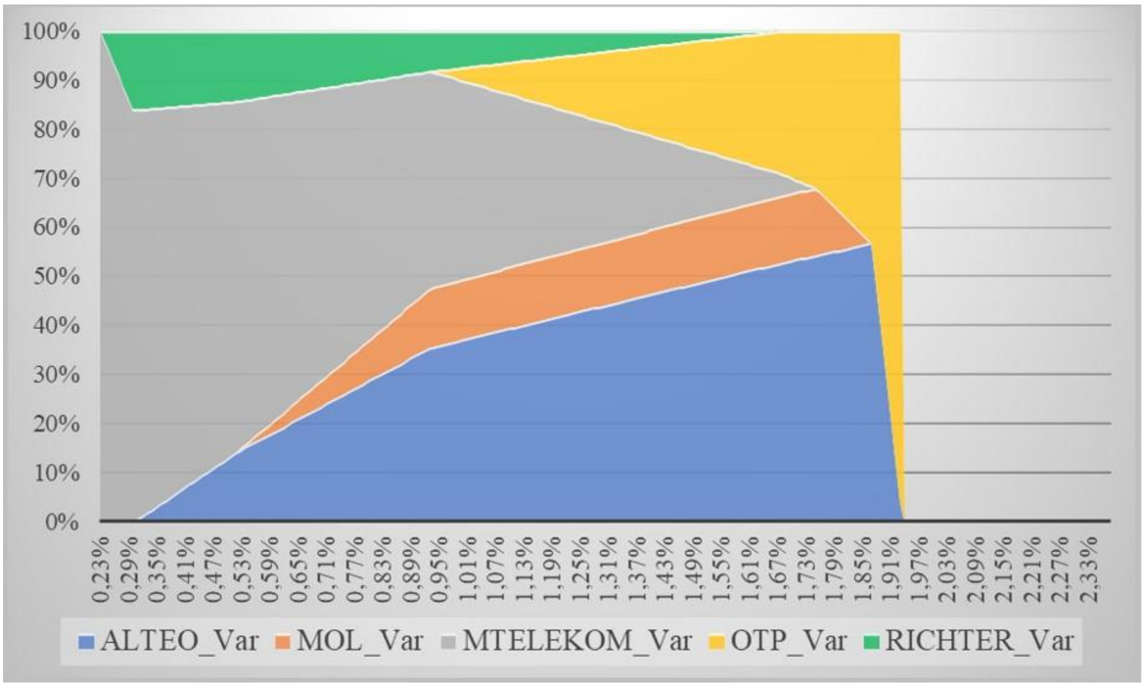

Fig. 2. Portfolio composition optimized by the mean-variance method under different expected returns in the pre-crisis period.

Source: own edition

Investors were still able to put together a minimum-risk stock package including the above stocks even with a higher expected return following the energy price increases, with the difference that before the crisis the increase in expected return - in addition to ALTEO - would have increased the weight of OTP only beyond a certain point, whereas after the crisis this was only true for the energy provider ALTEO Plc. Since the unit of change in yield levels was defined as 0.01 percent, the pre-2020 data series consisted of 171 series and the 2023 data series of 197 series.

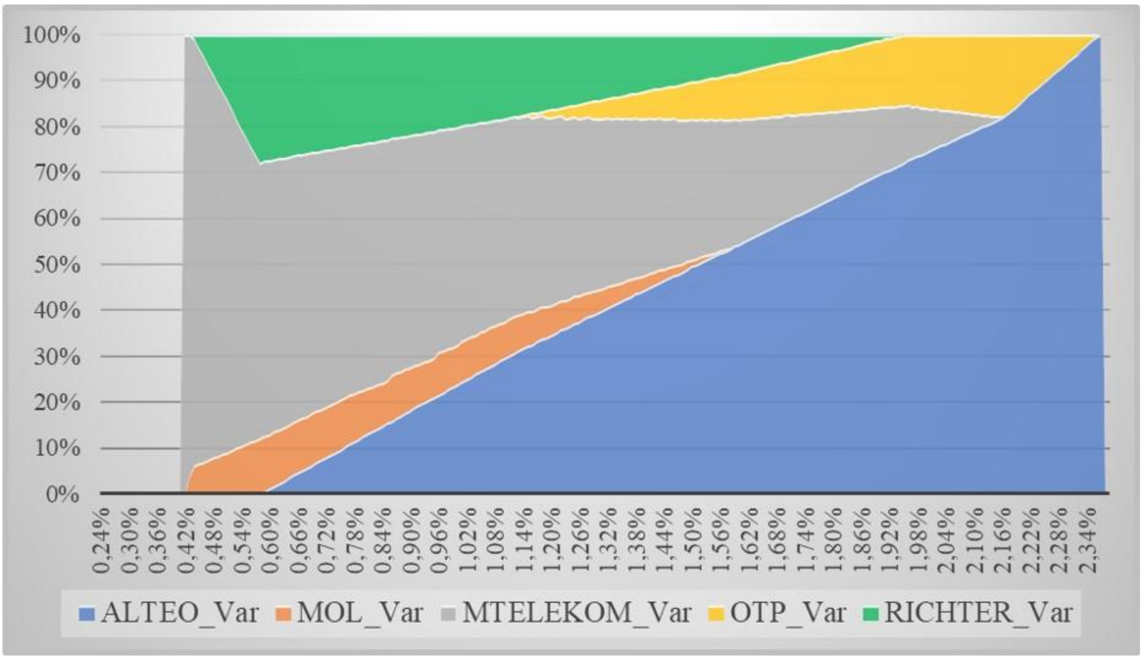

Fig. 3. Portfolio composition optimized by the mean-variance method under different expected returns taking into account the crisis.
Source: own edition

3.5. Impact of the energy crisis on the composition of Gini-optimized portfolios

In order to make our calculations more robust and to make a comprehensive and consistent investment decision, the optimization of the same stock portfolio was also determined using the mean-Gini method based on Gini index minimization, in addition to the methodology based on relative standard deviation minimization, both for the pre-crisis period (to 2019) and the post-crisis period (from 2020).

In the optimal portfolio structure obtained by minimizing the Gini index, the same stock elements are included for both time periods, with MOL and OTP having 1-2 percent higher weighting and ALTEO having the same proportion of lower weighting compared to the mean-variance model results for the period before 2020. However, taking into account the energy crisis, in the optimal portfolio structure, the Gini model already favored ALTEO's shares and weighted its share 5 percent higher, while MOL's shares would not have been included in the portfolio in 2023 by the Gini model, despite its higher share in the past. Overall, based on the results obtained, there were no material differences between the two optimization methods, confirming and at the same time confirming the reliability of the results obtained by the mean-variance method.

The investment combinations optimized by the Gini model show a nearly identical picture under different expected returns, both before 2020 (see Figure 4) and after 2020 (see Figure 5). The interval of optimal returns calculated using this method is also shifted to the same extent in the positive direction and, on this basis, the increase in expected returns has reduced the weight of Telekom's shares, while the weight of OTP (before the crisis) and ALTEO (after the crisis) shares has increased significantly. The only difference in the differences in the investment mix is the role of MOL, which, according to the Gini model, can be considered as a component of a narrower return range (from 1.4 percent before the crisis) and a broader one after the crisis.

Overall, although the composition of Gini index and variance-optimized portfolios at different return levels before and after the crisis differs significantly, there is no significant difference between the two methods for the same periods, as confirmed by the results of the correlated sample t-test ($p > 0.05$) of the portfolio ratios for the same periods.

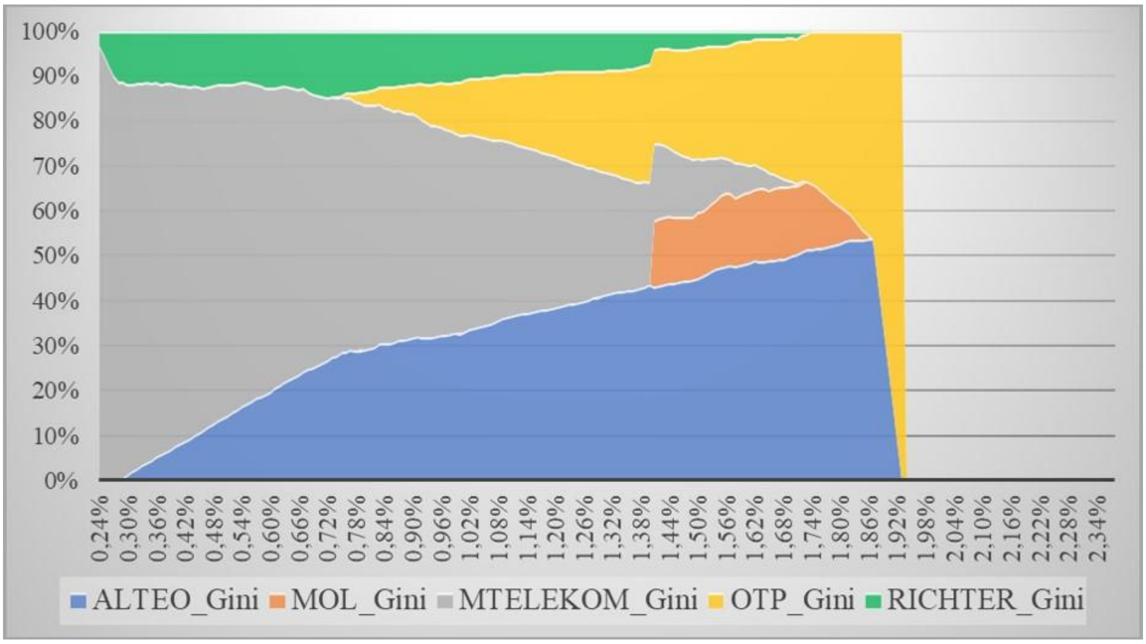

Fig. 4. Portfolio composition optimized by the mean-Gini method under different expected returns in the pre-crisis period.

Source: own edition

4. Discussion

Overall, the crisis did not have a significant impact on the types and number of stocks included in the optimal portfolio, but only changed the composition of the stocks included. The share of ALTEO shares increased from 56 percent to 82 percent after the energy crisis, while the share of OTP shares decreased from 39 percent to 18 percent and MOL shares were excluded from the optimal portfolio. The increase in ALTEO's weighting is clearly due to the appreciation of the energy sector and the company's performance, the decline of OTP is due to its recent loss-making returns and the exclusion of MOL is due to the volatility of fuel prices and its second-lowest holding period return next to OTP.

The indicators presented in this study have provided a good insight into the impact of the energy crisis and the partly related Covid-19 crisis on the Hungarian stock market. As confirmed by the results, the Central European stock markets, which are more exposed to external risks, and among them the Hungarian one, have been more sensitive to the crisis due to their higher vulnerability, and thus have had a significant impact on the decisions of optimal portfolio investors. The optimal portfolio was considered to be higher risk in the crisis period compared to the pre-crisis period, in line with the findings of [37], [20]; [36]. Crises tend to increase the risk of investing in equities and the demand for less risky, value-sensitive assets, so that as investors are willing to pay less for a share, its price falls significantly. These falls in share prices occurred for all five companies in the days following the outbreak of Covid-19 and the Russian-Ukrainian war. Later, however, the share prices of most stocks corrected to their pre-crisis levels, so the conclusion from the results is that in a crisis situation, despite the many uncertainties and negative prospects, it is not advisable to immediately sell your existing shares, because if there are no persistent and insoluble problems in the operations of the company issuing the shares, you can make a profit on the same shares in the longer term.

If we consider the price movements for the five stocks, it can be said that, despite the falls following the crises, by 1 September 2023 all stocks had almost reached the price level of 1 January 2020. In Table 1, the sum of these price changes and the returns for the full holding period after 2020 multiplied by the weights in the optimal portfolio we have defined for the pre-crisis situation is used to determine the price return and total return that could have been achieved with this portfolio between 1 January 2020 and 1 September 2023. In a structure optimized to minimize relative standard deviation, the portfolio price would have risen by a total of 126.34 percent and the total return over the holding period would have been 137.83 percent, which includes the dividend yield in addition to the price gain. If we consider the optimization procedure based on the Gini index, we obtain similar results, with a 119.08 percent exchange rate gain and a total return of 130.72 percent. This means that if an investor had invested his total savings in a portfolio with this structure on 1 January 2020, he would have had almost 2.5 times the value of his savings by 1 September 2023, and would have been able to achieve further returns by using the dividends received.

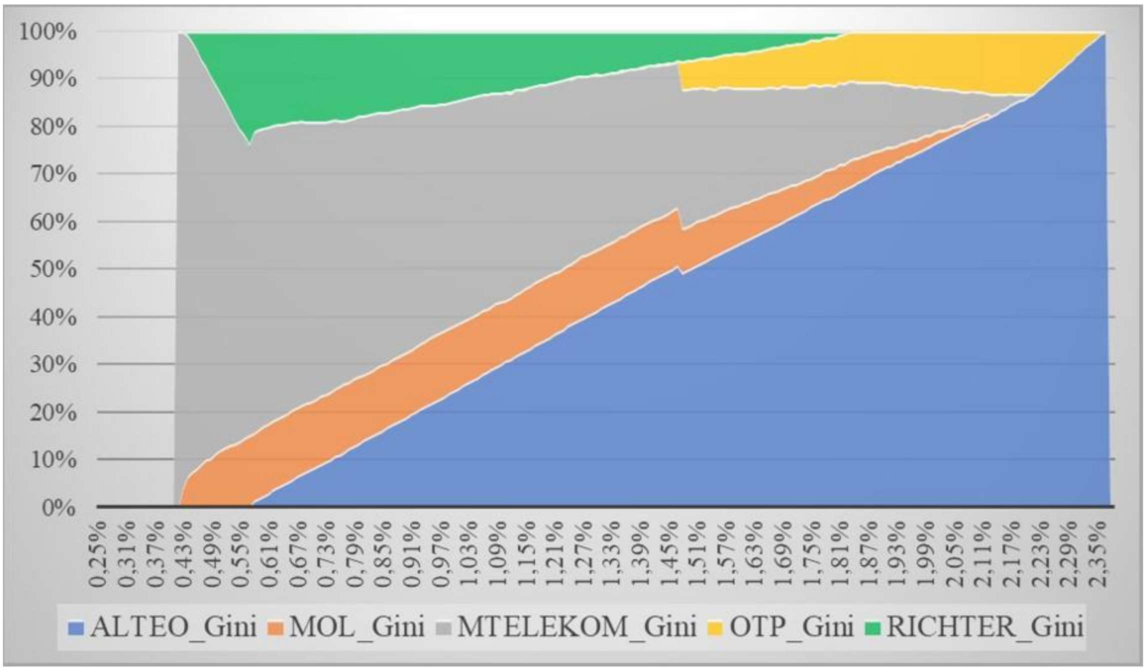

Fig. 5. Portfolio composition optimized by the mean-Gini method under different expected returns taking into account the crisis.

Source: own edition

Since the stock market is very sensitive to all the developments in the economy and a myriad of events can affect the share price, the indicators in Table 1 do not allow us to draw clear conclusions about which stocks perform best overall. However, we can say that the share price of MOL and OTP was most negatively affected by the 2020 crises, as reflected in the decrease in the share of both stocks in the structure optimized by both methods. OTP's shares have been the lowest performing, with a loss of around 4.5 percent for holding the stock since before 2020. The main reason for this is the weakening of the forint exchange rate, with which the performance of a country's banking sector is highly correlated.

5. Conclusion

ALTEO's shares generated the highest return over the period, mainly due to the company's investments in renewable energy, which helped the company to achieve a huge increase in earnings. This has confirmed our hypothesis that, comparing the situation before and after the energy crisis, the shares of the company with the greatest interest in the energy sector have been the most profitable under different return expectations. In this context, it can be suggested that the positive impact of potential crises on certain industries should be taken into account when formulating investment strategies. It is also worth highlighting the shares of Magyar Telekom, which is currently showing the most stable growth in terms of share price, mainly due to a reformed dividend policy and a new pricing policy for services, and which could ultimately be used as a management policy tool to offset the negative impact of a broader crisis on share prices.

The results of the correlated sample t-test at the end of our study also supported the hypothesis that there is no statistically significant difference ($p > 0.05$) between variance and Gini-index optimized portfolio structures under each return expectation, thus investors are advised to use both methods together when designing more reliable investment strategies. Overall, it can be said that the uncertainties arising from the effects of the crises no longer threaten the stock market for the most part, and that a stabilizing trend in share prices can therefore be observed. In our view, lower government bond yields due to the stabilizing economic conditions should lead to a rebound in stock trading, so that potential investors with savings can now achieve very favourable returns by investing in equities, even with a diversification strategy that is suited to their risk tolerance.

References

[1]: Acharya VV, Pedersen LH, Philippon T, Richardson M (2017). Measuring systematic risk. *The Review of Financial Studies*, 30(1): 2–47. DOI: 10.1093/rfs/hhw088

[2]: Agouram J, Lakhnati G (2016). Mean-Gini and mean-extended gini portfolio selec- tion: An empirical analysis. *Risk Governance and Control: Financial Markets and Institutions*, 6(3-1): 59-66. https://doi.org/10.22495/rcgv6i3c1art7

[3]: Anagnostopoulos KP, Mamanis G (2010). A portfolio optimization model with three objectives and discrete variables. *Computers and Operations Research*, 37(7): 1285-1297. https://doi.org/10.1016/j.cor.2009.09.009

[4]: Bakos P (2020). *A COVID-19 hatása a tőkepiacokra*, https://www.bet.hu/Rolunk/Sajtoszoba/szakmai-cikkek-es-tanulmanyok/a-covid-19-hatasa-a-tokepiacokra. Accessed 12 October 2023

[5]: Best MJ (2010) *Portfolio optimization*. CRC Press.

[6]: Böcskei E., Orbán I., Bács Z., & Fenyves V. (2017): Az IFRS beszámolóban rejlő sajátosságok controlling szemléletű vizsgálata – döntéstámogató vezetői számvitel előtérbe kerülése a pénzügyi számvitel szabályozásán keresztül. *Controller Info,* 5 : 4 pp. 2-8.

[7]: Brealey RA, Myers SC (2005). *Modern corporate finance*. Budapest, Panem.

[8]: Brown CE (1998). Coefficient of variation. *Applied multivariate statistics in geohydrology and related sciences*. Berlin, Heidelberg, https://doi.org/10.1007/978-3-642-80328-4 13

[9]: Brückner G (2023). Háború, energiaválság, különadók: a BUX-index tavaly 13,6 százalékkal gyengült, https://telex.hu/gazdasag/2023/01/01/tozsde-reszveny-valsag-haborukulonadok-bux-index-minusz13-6-szazalek. Accessed 21 October 2023

[10]: Bugár Gy, Uzsoki M (2006) Befektetések kockázatának mérése. *Statisztikai Szemle*. 84(9): 876-898.

[11]: Bugár G, Uzsoki M (2011). Portfolio optimization strategies: Performance evalua- tion with respect to different objectives. *Journal of Transnational Management*, 16(3): 135-148. https://doi.org/10.1080/15475778.2011.596773

[12]: Chaweewanchon, A., Chaysiri, R. (2022). Markowitz Mean-Variance Portfolio Opti- mization with Predictive Stock Selection Using Machine Learning. *International Journal of Financial Studies*, 10(3): 64. https://doi.org/10.3390/ijfs10030064

[13]: Cheung CS, Kwan CC, Miu PC (2007). Mean-Gini portfolio analysis: A pedagogic illustration. *Spreadsheets in Education*, 2(2): 194-207.

[14] Dékán T-né Orbán I. (2013): Reporting companies' performance – in respect of the International Financial Reporting Standards (IFRS). *APSTRACT - APPLIED STUDIES IN AGRIBUSINESS AND COMMERCE* 7 : 4-5 pp. 107-112. , 6 p. (2013)

[15]: Douglas MC, Runger GC (1994). *Applied Statistics and Probability for Engineers*. New York, Chichester, John Wiley and Sons.

[16]: Erdey, L. (2005). Hagyományos módszerek és új kihívások az ágazaton belüli kereskedelem mérésében. *Statisztikai Szemle*, 83(3), pp. 258–283.

[17]: Fazekas B. & Becsky-Nagy P. (2018). Az állam a kockázati tőkés szerepében. *Közgazdasági szemle*, 65: 12 pp. 1257-1280., 24 p.

[18]: Fazekas B. & Becsky-Nagy P. (2021). A new theoretical model of government backed venture capital funding. *Acta oeconomica*, 71: 3 pp. 487-506., 20 p

[19]: Fenyves V., Tarnóczi T., & Orbán I. (2024). Application of text mining in the analysis of notes to financial statements: A Hungarian case. *Journal of International Studies*, 17 : 1

[20]: Goldthau AC, Youngs, R (2023). The EU energy crisis and a new geopolitics of climate transition. *Journal of Common Market Studies*, 61: 115- https://doi.org/10.1111/jcms.13539

[21]: Gunjan A, Bhattacharyya S (2023). A brief review of portfolio optimization techniques. *Artificial Intelligence Review*, 56(5): 3847-3886. https://doi.org/10.1007/s10462-022-10273-7

[22]: Hali NA, Yuliati A (2020). Markowitz model investment portfolio optimization: a review theory. *International Journal of Research in Community Services*, 1(3): 14-18. https://doi.org/10.46336/ijrcs.v1i3.104

[23]: Hoe LW, Jaaman SH, Siew LW (2020). Portfolio optimization of technology companies in Malaysia with Mean-Gini Model. *Menemui Matematik* (Discovering Mathematics), 42(1): 45-50.

[24]: Hutter C, Weber E (2022). *Russia-Ukraine war: Short-run production and labour market effects of the energy crisis*, 10. https://doi.org/10.48720/IAB.DP.2210

[25]: Jamal A, Ghizlane L (2015). A Comparative Study of Mean-Variance and Mean Gini Portfolio Selection Using VaR and CVaR. *Journal of Financial Risk Management*, 4: 72-81. https://doi.org/10.4236/jfrm.2015.42007
[26]: Ji R (2016). *Models and Algorithms for Portfolio Optimization Under Uncertainty*. The George Washington University
[27]: Ji R, Lejeune MA, & Prasad SY (2018). Interactive portfolio optimization using Mean- Gini criteria. *Financial Decision Aid Using Multiple Criteria: Recent Models and Applications*, 49-91.
[28]: Lakatos, V., Erdey, L., Szűcs, N., Rózsa, A., & Nagy, A. (2019). Establishment of the Customer Perspective of the Balanced Scorecard System at Sports Enterprises through the Example of a Hungarian Football Club. *Apstract - Applied Studies In Agribusiness And Commerce*, 13(1–2), pp. 5–16. http://doi.org/10.19041/APSTRACT/2019/1-2/1
[29]: Mansini R, Ogryczak W, Speranza MG (2015). Linear models for portfolio optimization. *Linear and Mixed Integer Programming for Portfolio Optimization*, 19-45.
[30]: Markowitz HM (1952). Portfolio Selection. *The Journal of Finance*. 7(1): 77-91.
[31]: Mba JC, Ababio KA, Agyei SK (2022). Markowitz mean-variance portfolio selection and optimization under a behavioral spectacle: *New empirical evidence*. *International Journal of Financial Studies*, 10(2): 28. https://doi.org/10.3390/ijfs10020028
[32]: Mukhopadhyay, D. (2023). Does Green Investing Generate Return Over Conventional Funds? A Comparative Portfolio Analysis with Indian Stock Market. In *Economic, Environmental and Health Consequences of Conservation Capital: A Global Perspective* (pp. 85-96). Singapore: Springer Nature Singapore. DOI: 10.1007/978-981-99-4137-7_7
[33]: Myles EM (2013). A simplified perspective of the Markowitz portfolio theory. *Global journal of businnes research*, 7(1): 59-70.
[34]: Naccarato A, Pierini A, Ferraro G (2021). Markowitz portfolio optimization through pairs trading cointegrated strategy in long-term investment. *Annals of Operations Research*, 299 (1-2): 81-99. https://doi.org/10.1007/s10479-019-03225-y
[35] Orbán, I., Tamimi, O. (2023): The Impact of IFRS 9 on Financial Reporting during Covid-19 from the Point of View of Experts in Europe. Australasian Accounting, Business and Finance Journal 17 : 4 pp. 21-36. , 16 p. (2023)
[36]: Ozili PK, Ozen E (2023) Global energy crisis: impact on the global economy. *The Impact of Climate Change and Sustainability Standards on the Insurance Market*, 439-454. https://doi.org/10.1002/9781394167944.ch29
[37]: Pálos M (2023). Az Oroszországban maradt nagy európai cégek 100 milliárd eurót buktak, https://g7.hu/vallalat/20230808/az-oroszorszagban-maradt-nagy-europai-cegek- 100-milliard-eurot-buktak/. Accessed 12 October 2023
[38]: Popp, J., Harangi-Rákos, M., Pető, K., & Nagy A. (2013). Bioenergy: Risks to food-, energy- and environmental security. *Applied Studies in Agribusiness and Commerce*, 7(4-5), pp. 121-130. https://doi.org/10.19041/APSTRACT/2013/4-5/17
[39]: Pupos T (2013). Pénzügyi ismeretek, *Debreceni Egyetem*, 56-58.
[40]: Rákos, M., Szenderak, J., Erdey, L., Komives, P. M., & Fenyves, V. (2022). Analysis of the economic situation of energy companies in Central and Eastern Europe. *International Journal of Energy Economics and Policy*, 12(4), pp. 553-562.
[41]: Ringuest JL, Graves SB, Case RH (2004) Mean–Gini analysis in RandD portfolio selection. *European Journal of Operational Research*, 154(1): 157-169. https://doi.org/10.1016/S0377-2217(02)00708-7
[42]: Yang B, Berger J (1994) Estimation of a covariance matrix using the reference prior. *The Annals of Statistics*, 22(3): 1195-1211.
[43]: Schechtman E, Yitzhaki S, Artsev Y (2006) The similarity between mean-variance and mean-Gini: Testing for equality of Gini correlations. *Advances in Investment Analysis and Portfolio Management*, 3: 97-122. DOI: 10.2139/ssrn.938178
[44]: Shalit H, Yitzhaki S (1984) Mean-Gini, Portfolio Theory, and the Pricing of Risky Assets. *The Journal of Finance*, 39 (5): 1449-1468. https://doi.org/10.1111/j.1540-6261.1984.tb04917.x
[45]: Shalit H, Yitzhaki S (2005) The mean-Gini efficient portfolio frontier. *Journal of Financial Research*, 28(1): 59-75. https://doi.org/10.1111/j.1475-6803.2005.00114.x
[46]: Siew LW, Jaaman SH, Hoe LW (2019) Mathematical modelling of risk in portfolio optimization with Mean-Gini approach. In *Journal of Physics: Conference Series*, 1212(1): 12-31. https://doi.org/10.1088/1742-6596/1212/1/012031
[47] Tamimi, O.; Orbán, I. (2022): Financial engineering and its impact on audit efficiency in the opinion of experts. *JOURNAL OF INTERNATIONAL STUDIES* 15 : 2 pp. 50-62. , 13 p.
[48]: Trichilli Y, Abbes MB, Masmoudi A (2020) Islamic and conventional portfolios optimization under investor sentiment states: Bayesian vs Markowitz portfolio analysis. *Research in International Business and Finance*, 51: 101071. https://doi.org/10.1016/j.ribaf.2019.1010711
[49]: Tola V, Lillo F, Gallegati M, Mantegna RN (2008) Cluster analysis for portfolio optimization. *Journal of Economic Dynamics and Control*, 32(1): 235-258.
[50]: Ubukata M, Watanabe T (2014) Market variance risk premiums in Japan for asset predictability. *Empirical Economics*, 47, 169-198. https://doi.org/10.1007/s00181-013-0741-2
[51]: Zanjirdar M. (2020) Overview of portfolio optimization models. *Advances in mathematical finance and applications*, 5(4): 419-435. https://doi.org/10.22034/amfa.2020.1897346.1407