Influencing Factors Analysis on European and World Regional Economies Development Caused by War in Ukraine Based on Multi-Criteria Decision-Making Theory

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Abstract

The paper examines the level of unfavorable factors influencing the indicators of the development of the economies of Europe and the world, which were caused by the war in Ukraine. Taking into account the consequences of the war in Ukraine were considered from various points of view: economic, social, political, environmental, etc. The catastrophic consequences of the war in Ukraine negatively affected and continue to affect the development of European economies. The paper found that the rate of economic growth is rapidly decreasing, especially in Eastern European countries. The studied forecasts indicate a high probability of signs of recession in the countries of Eastern Europe. Under the influence of the war in Ukraine, the article identifies the signs of a migration crisis and a rapid increase in prices for necessities. Among the adverse impact criteria, which are recommended to be taken into account by the governments of the countries in the process of making management decisions, the volatility of prices for wheat, gold and gas, as well as fluctuations in the exchange rates of the dollar and the yen to the euro, are highlighted. It is recommended to consider the amount of 400 billion US dollars given in the report of the World Bank as a tenfold underestimated value when assessing the scale of damage caused to the economy of Ukraine. It is substantiated that the computational methods (cluster analysis, correlation analysis, etc.) used in the work are sufficient for determining the level of adverse effects of the factors of the war in Ukraine on the indicators of the development of the economies of the countries of Europe and the world.

Keywords

Multi-criteria decision-making, MCDM, economic crisis, economic indicators, economic risks, cluster analysis, correlation analysis, GDP, migration, dollar, euro, the hryvnia, gold, Japanese yen, wheat

1. Introduction

Any large-scale event in the economic and political space, especially war, clearly has a significant negative impact on the development of the regional economy. The war collapsed not only the economy of Ukraine but also created challenges for the economies of other countries, especially on the territory of Europe. At the same time, Eastern European countries feel the burden of war more than other countries. Russia's war against Ukraine caused large-scale damage to the Ukrainian economy. In a new

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World Bank report, their total amount is estimated at 400 billion US dollars. Also, the Russian invasion of Ukraine slows down the pace of economic recovery after the pandemic in the transition economies of Europe and Central Asia. The pace of economic growth is rapidly falling, and according to forecasts, a recession is possible in some countries of Eastern Europe. European countries, especially Eastern European countries, suffer the most [1]. But what exactly are the factors, trends and indicators that significantly change and affect other indicators - this is the goal of our research. Of course, there are basic indicators, such as the migration of the people (refugees from Ukraine after the start of the full-scale invasion of Russia [2]), inflation for goods and services, a jump in the exchange rate, etc. The pace of economic growth is rapidly falling, and according to forecasts, a recession is possible in some countries of Eastern Europe [1-6]. The war in Ukraine has had a significant negative impact on the world economy. The world economy is increasingly weakened by the war due to significant interruptions in trade and a jump in food and fuel prices [3]. Activity in the Eurozone, the largest economic partner of transition and developing countries in the Europe and Central Asia region, suffered a significant decline in the second half of 2022, due to disrupted supply chains, increased stress in financial markets and declining levels of consumer and business confidence [7-14]. However, the most devastating consequences of the invasion are rapidly increasing energy prices due to a significant reduction in Russian energy supplies. The reduction in growth forecasts for 2023 extends to all countries in the Europe and Central Asia region, as uncertainty significantly affects forecasts. Continuation of the war or its escalation could lead to much greater economic and environmental damage [15, 16], and a greater likelihood of fragmentation of international trade and investment. The risk of financial stress also remains high, given high levels of debt and inflation.

The purpose of the work is to conduct a study of the level of unfavorable factors influencing the development indicators of the economies of Europe and the world, which were caused by the war in Ukraine, as well as to determine the priority of the selection of criteria for the adoption of managerial decisions by the governments of countries based on the theory of multi-criteria decision-making (MCDM). Tasks:

1. Classify the consequences of the war in Ukraine by groups of factors of influence: economic, social, political, environmental, etc.
2. To establish the factors that negatively influenced and continue to influence the development of the economies of European countries, with the aim of their further use in decision-making in the MCDM theory.
3. To study the signs of recession in the countries of Eastern Europe and to determine their level:

- to recommend a range of key destructive factors caused by the war in Ukraine, which should be taken into account by the governments of countries in the process of making management decisions.
- justify the need for a deeper assessment by the World Bank of the scale of damage caused to the economy of Ukraine due to Russia's aggression.
- to conduct a cluster analysis and correlational analysis of indicators of the development of the economies of European and world countries and their changes under the influence of the war.

2. Related works

Most believe that on February 24, 2023, one year will pass since the beginning of the full-scale war that Russia unleashed against Ukraine. But in fact, the war began in 2014. Since then, Ukraine has been successfully developing its economy independently and defending itself. Although since 2014, as a result of the Russian invasion, Ukrainian cities and villages in the east of the country have been destroyed, and thousands of our military and civilian compatriots have died. Of course, since 2022, Russia's special operation has acquired a larger and more brutal character with tens of thousands of our military and civilian compatriots killed, mass migration both within the country and beyond its borders. And it has become even more difficult for the country to independently support and develop its economy. Hundreds of infrastructure facilities and enterprises, thousands of medium and small businesses were destroyed, and millions of Ukrainians were forced to seek refuge either in safer regions of the country or abroad. As of September 2022, the UN recorded 7 million Ukrainians in Europe [2]. Of them, 4 million applied for temporary shelter. Currently, according to forecasts, Ukraine's economy will shrink by 35% this year, as economic activity has suffered significant damage due to the pollution of agricultural land, the destruction of production facilities, and the reduction of the workforce, as more than 14 million people have become displaced persons [3].

But this war hit not only Ukraine, its negativity is felt in all corners of the world. The global economy has not yet had time to recover from the devastating impact of Covid-19, as Russian aggression once again drags the world economy into the grip of an economic crisis. Global economic growth after accelerating in 2021 (6%) began to slow down rapidly (3.2%) [1]. This is the lowest rate in the previous 20 years, excluding the crises of 2008 and 2020. In 2023, a minimum growth rate of 0.3% is expected, as the jump in energy prices will continue to affect the future, and the volume of production will decrease by 0.2% [3]. The hybrid energy war of Russia against Europe has pushed energy prices high, and the destruction of the food industry and agricultural sector in Ukraine and the blockade of Ukrainian exports are one of the main criteria for the increase in food prices in the world.

According to the results of a recent assessment of the World Bank, the needs for recovery and reconstruction (social, productive sectors and infrastructure) require about 400 billion US dollars [4]. This figure is 1.5 times higher than the size of the pre-war economy of Ukraine.

Russia's war in Ukraine slowed down world economic development and almost doubled the growth of world prices. In 2022, global inflation reached 9% compared to 5% in 2021 [1]. And some poor countries, which are dependent on food prices and grain imports, found themselves on the brink of starvation. GDP is forecast to grow by 1.9% in 2023 against 2.7% in 2022, as the world is struggling with many economic and political problems [5]. Weaker growth could lead to a modest slowdown in inflation to 4.7% in 2023 after averaging 7.6% in 2022. The countries of Central and Eastern Europe suffered a significant shock from the full-scale war in Ukraine. Due to their economic interconnections and geographical proximity to Ukraine, the countries of Central and Eastern Europe are particularly at risk when it comes to separating the Russian economy from the West. It is expected that the negative consequences of the war in Ukraine, as well as the sanctions imposed on the Russian Federation and Belarus, against the background of the unfolding energy challenges, will drag on well into 2023 and threaten the economic indicators and growth of the region. Therefore, we should expect at least a technical recession in some countries of Central and Eastern Europe [5-6]. A sharp rise in the prices of key commodities such as energy and metals could seriously undermine the region's economy. This will particularly affect energy importers such as Georgia, Ukraine, Turkey, Slovakia, Hungary and Serbia. In addition, 90% of wheat imports to Turkey and Georgia are accounted for by Russia and Ukraine. However, prices are expected to remain volatile and continue to rise, fueling inflation and putting further pressure on public finances and the budget balance.

The theory of multi-criteria decision-making (MCDM) is very often used to solve complex socio-economic issues [17-29]. In the conditions of war, it is difficult to determine the number of criteria, and the order of preference when evaluating and choosing the best option among many alternatives of management decisions, which the leaders of the countries aim to implement to obtain the desired result - sustainable development of the economy, balanced social development of communities, etc. [29-36]. When conducting a multi-criteria decision analysis (MCDA), one should analyze those factors that in this situation have the greatest (critical) influence on the choice of the optimal value [37-41]. In everyday life, which is studied by the social sciences, there are still few successful practices of applying the MCDM theory [42-44]. There is even less experience in using this decision-making tool in wartime [45-48]. Therefore, the theory of multi-criteria decision-making (MCDM) needs to be studied and researched in the real conditions of the war in Ukraine [49-55].

The authors of the works [32-33] believe that the analysis of influence criteria should be completed with a conclusion about whether the criterion is favorable or unfavorable when choosing the MCDM theory. When analyzing influencing factors, it is advisable [32] to compare a group of homogeneous influencing factors to choose the criterion that, in combination with the already selected criteria, will provide the opportunity to obtain the maximum result with the least losses. Researchers [33] worked on the study of different ways of choosing a management decision from all other possible decision-making options and proposed a method of choosing an option with minimal compromise and maximum benefits. This greatly simplified the decision-making process for the decision-making manager. Many scientists [32, 33] believe that the criteria used in the analysis of these criteria can be both qualitative and quantitative. There are two groups of MCDM methods for determining the weight of each alternative [31, 32]. One of them is called the compensatory decision-making method. This method allows evaluating the criteria from both weak and strong sides, taking into account the advantages of the strengths of the criteria to compensate for their weaknesses. This method is sometimes called a compensatory decision-making tool. It includes the Analytical Hierarchy Process (AHP) technology, which is especially valuable when studying environments that are extremely difficult to study [32]. This tool is used to compare qualitative criteria or criteria that are difficult to describe with quantitative values [49-57]. Another method is called anticipatory decision-making [32]. This method is used when comparing pairs of criteria. Here, in each pair of criteria, it is established which criterion is more important than the other [58-69]. The anticipatory decision-making method includes [32] tools of elimination and selection. Because of this, it is called ELECTRE, indicating that it expresses reality. This method is also used to select, rank and sort alternatives to solve a problem when making managerial decisions [70-99].

3. Materials and methods

Among the methods used in the work, it is possible to single out the methods of descriptive statistics (for the distribution of temporarily displaced persons), the trend method of forecasting (for researching the dynamics of food prices), data visualization in the Cartesian and polar coordinate systems, correlation and regression analysis were also used, carried out cluster analysis. In the work, the results of the analysis of factors influencing the development of economies are visualized using histograms, correlograms and dendrograms. So, to study the negative economic impact of the war in Ukraine, we analyzed several indicators, including the following:

1. Refugee distribution from Ukraine after the beginning of the full-scale invasion of russia (Fig. 1) [7].

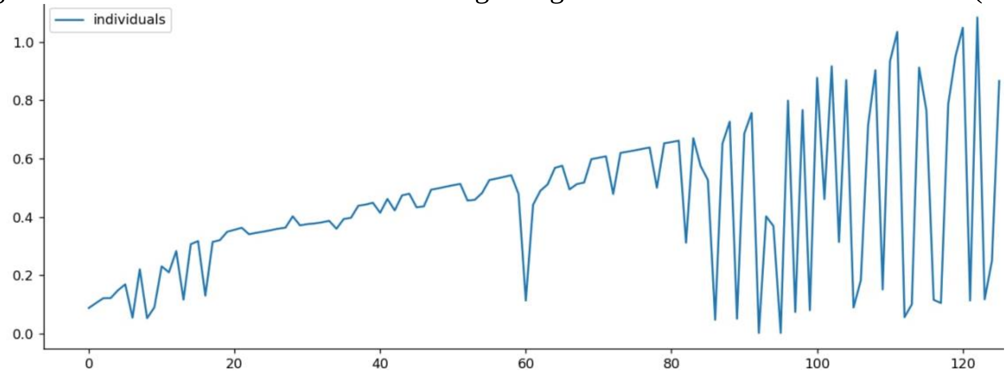


Figure 1: Descriptive statistics

2. Dynamics of growth/decrease in prices for food products in the world (in particular, for wheat) caused by the Russian-Ukrainian war in 2022 (Fig. 2) [8].

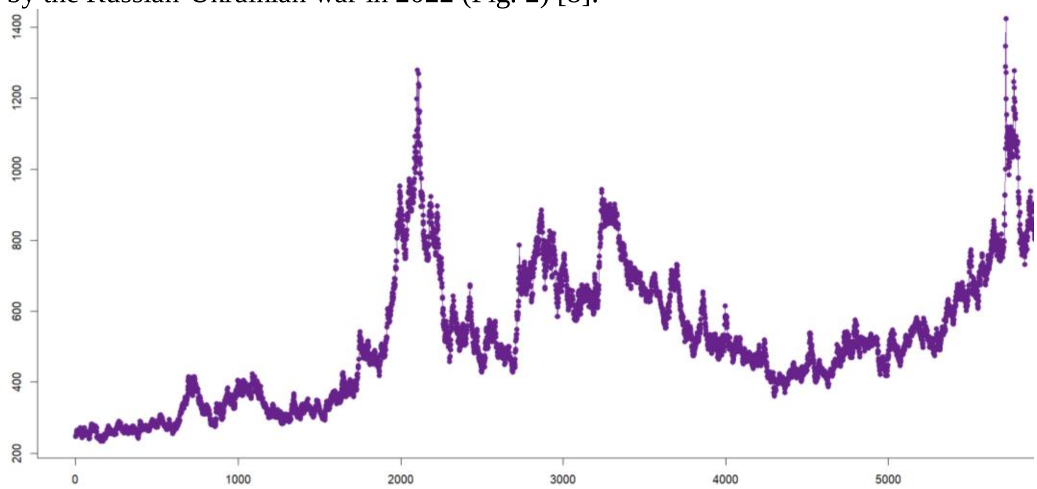


Figure 2: Plotting in the Cartesian coordinate system (dynamics of changing price of wheat, where X is the day from 2000 to 2022 and Y is the price of wheat in EUR)

3. Dynamics of the inflation rate in Europe (Fig. 3) [32].

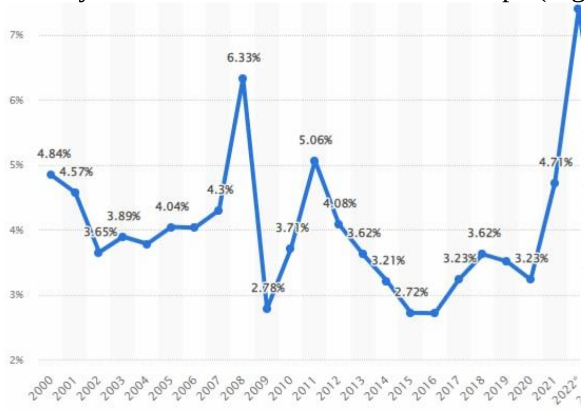


Figure 3: Graph of inflation in Europe **Figure 4**: Changes indicator in prices for eggs

4. Dynamics of the indicator of changes in egg prices in Ukraine (Fig. 4) [32]

5. Dynamics of the euro exchange rate and its changes during conversion to the following currencies: Euro to USD and Euro to Japanese yen (Fig. 5) [9].

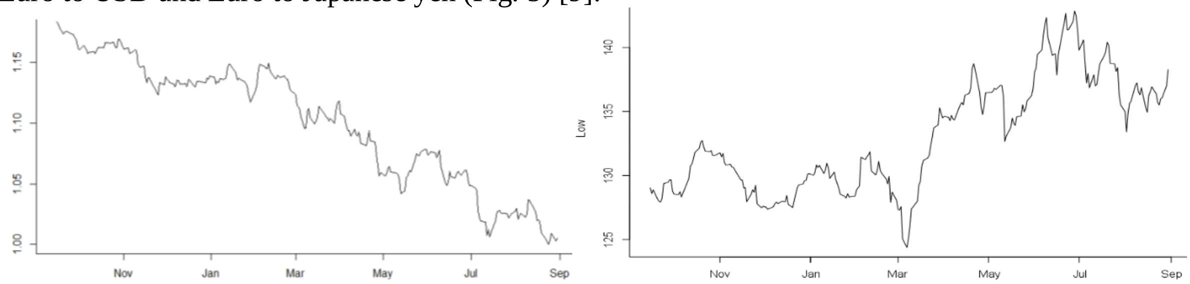
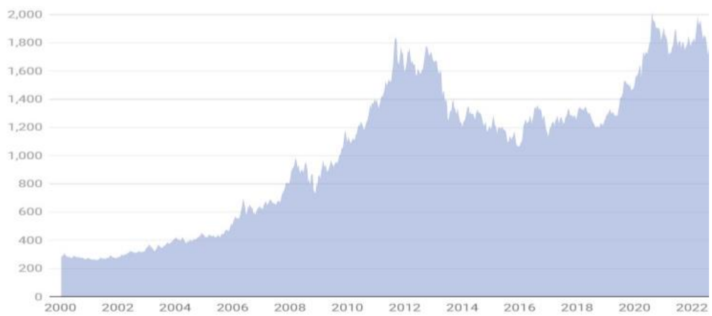


Figure 5: Dynamics of the indicator in the Cartesian coordinate system (Euro to USD and to Japanese yen), where X is the date and Y is a high price

6. Correlation of the price of gold during the period from January 1, 2000, to September 1, 2022. (Fig. 6) [10]

7. Correlation of the price of the hryvnia against the dollar (Fig. 7-10) [11-12]



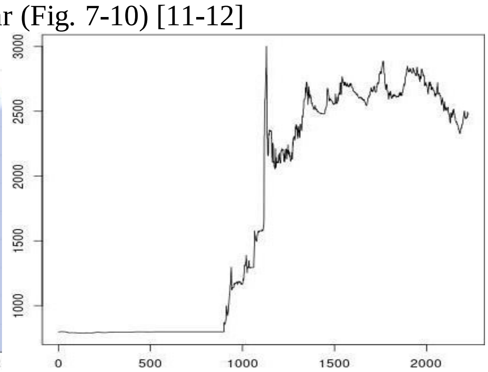


Figure 6: Gold price correlation chart **Figure 7**: Price correlation against dollar (x – day, y – price)

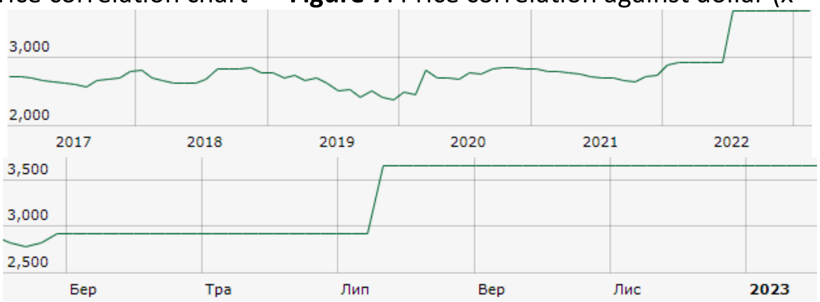


Figure 8: Graphs of price dynamics dollars for hryvnias (from 2017 to 2023 and the last year)

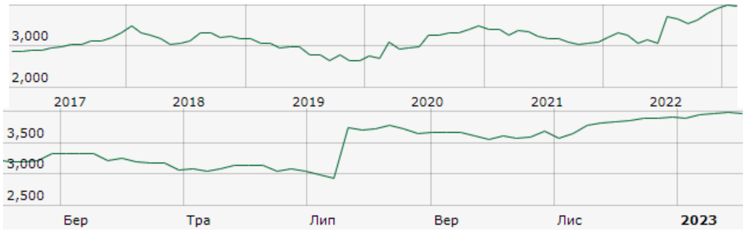


Figure 9: Graphs of price dynamics euros for hryvnias (from 2017 to 2023 and the last year)

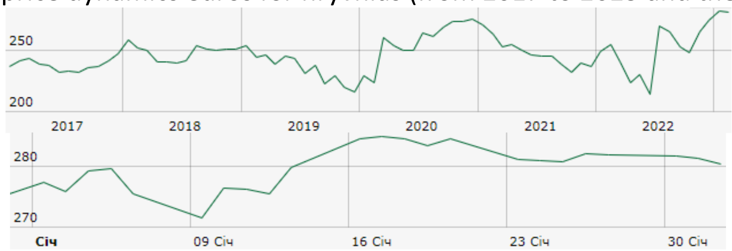


Figure 10: Graphs of price dynamics Japanese yen for hryvnias (from 2017 to 2023 and the last year)

8. Dynamics of changes in the real GDP of Ukraine in % compared to the corresponding quarter of the previous year (Fig. 11a) [11-12]. If you analyze it in terms of GDP (Fig. 11b) [13], then our economy looked like this: after the 2008 crisis, GDP decreased significantly, and as soon as everything stabilized, the next crisis occurred, which is very difficult for a young country to survive, after which the index again is falling In general, these events were not special and, like any crisis, occurred in four stages.

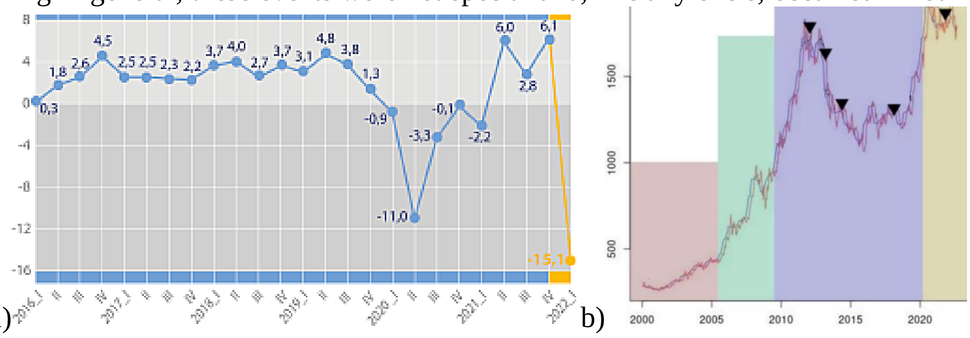


Figure 11: Dynamics of changes in the real GDP of Ukraine in % compared to the corresponding quarter of the previous year and b) chart of stages of the crisis that affected Ukraine [32]

9. Value of GDP of countries in the polar coordinate system for 2022 (Fig. 14) [14]

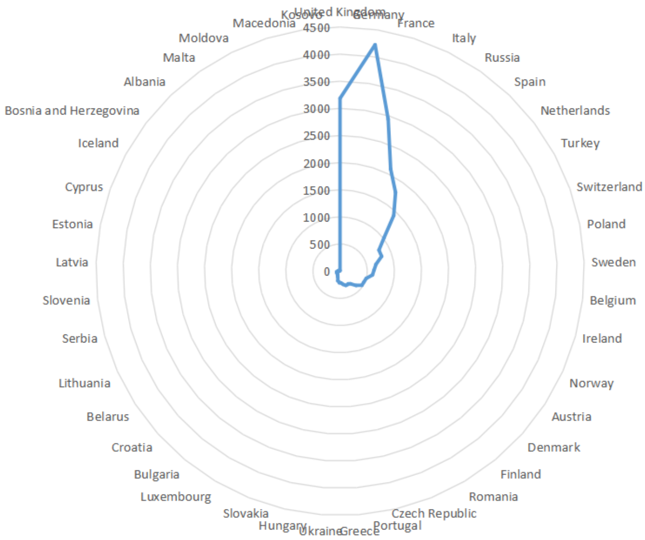


Figure 12: Graphic presentation of data on the GDP of countries in the polar coordinate system [14]

What conclusion can be reached after analyzing all these data? The economic situation in the world directly affects the economy of Ukraine. The war significantly changed not only the economic indicators of Ukraine but Europe in the first place and the whole world in general. The economy is best characterized by the GDP indicator, which changed significantly specifically for Ukraine in 2022 and negatively affected all of Europe, especially Eastern. The devaluation of the Ukrainian hryvnia was caused by crises that occur in 4 stages: crisis-depression-revival and boom, we can see all these stages on the graphs and they all affected our pre-war economy. The economy of our country is not stable and stable, but it can withstand quite destructive crises, but while it is at this level, our currency will depreciate against the dollar, which explains the reason for the correlation of the price per 100 dollar in hryvnias.

4. Experiments, results and discussion

4.1. Analysis of statistical data on the distribution of refugees from Ukraine after the beginning of the full-scale invasion of Russia

Fewest people left in the second part of June. To our surprise, the largest number of people left in September, because it seemed that at the beginning, many more people left the country.

Results of descriptive statistics:

1) Sample size – 126;
2) Arithmetic average – 4391815.412698412;
3) Mode – 16685;
4) Median – 4398175.0;
5) Scope – 10831846;
6) Standard deviation – 2523521.006447698;
7) Coefficient of variation – 57.45963273299777;
8) Dispersion – 6368158269982.803;
9) Excess – -0.284366254699147;
10) Asymmetry – 0.34268464108388286;
11) Minimum – 16654;
12) Maximum – 10848500;
13) Amount – 553368741;
14) Standard error – 224813.11939176763.

Since the capacity of the checkpoints is limited, in the beginning, due to the great panic and the large influx of refugees, fewer people could cross the border. There were long delays and you could stand in line for several days at the border. Therefore, in fact, in the first days of a full-scale invasion, most people waited at the borders but did not cross them. There were days when the borders were closed altogether, to speed up the delivery of humanitarian aid and weapons. On the graph, this can be seen from the points that are at the very bottom; the upper points grow steadily, but from time to time a "trough" is formed. These are the days when the borders were closed. Later, when everything stabilized, the flow of people slept and the panic subsided, more and more people crossed the border in one day. This is confirmed by the schedule, which is growing (not including the days when the borders were closed). The histogram displays the frequency of the number of people from the sample falling into a certain interval, that is, we can see which interval the most people fall into. In our case, it can be seen that most people fell into the third interval. So, from the beginning of the full-scale invasion, most often in one day from 3111466 to 4658872 people crossed the border.

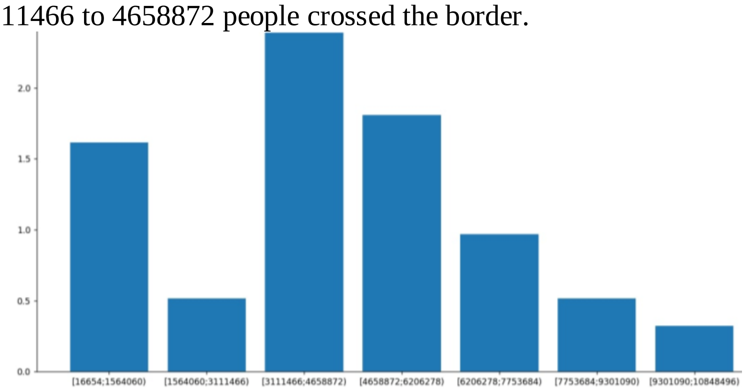


Figure 13: Histogram

Having constructed a correlation field, we see that the number of people who left increases sharply at first (up to approximately the 22nd day of the war), then a little more smoothly (up to the 195th day of the war).

It can also be seen on the correlation field that at first the points are clustered, and the further they are, the more scattered they are. In our opinion, this is because, in the first few months of the full-scale invasion, the borders were closed less frequently to allow those who were standing at the border to leave, and not to create an even larger crowd. Later, when the number of people decreased, it became possible to close them for the transportation of humanitarian goods, weapons, and inspections.

On the days when some negative events took place and the following few days, the number of people who left increased sharply. For example, on March 26 (the 30th day of the war), Russian troops launched a rocket attack on an oil depot in the Veliki Kryvytsi area (Lviv region), a total of 3 explosions were recorded, and 5 people were injured. After that, you can see on the correlation field a jump in the number of people who left. That is, there is a certain dependence between events and the mood of the population because even if you take only one region of Ukraine, there are fluctuations on the graph.

If we look at the 6 points below on the correlation field, we see that this is the month of June. Then there was almost no shelling and, accordingly, the number of people who left was very small.

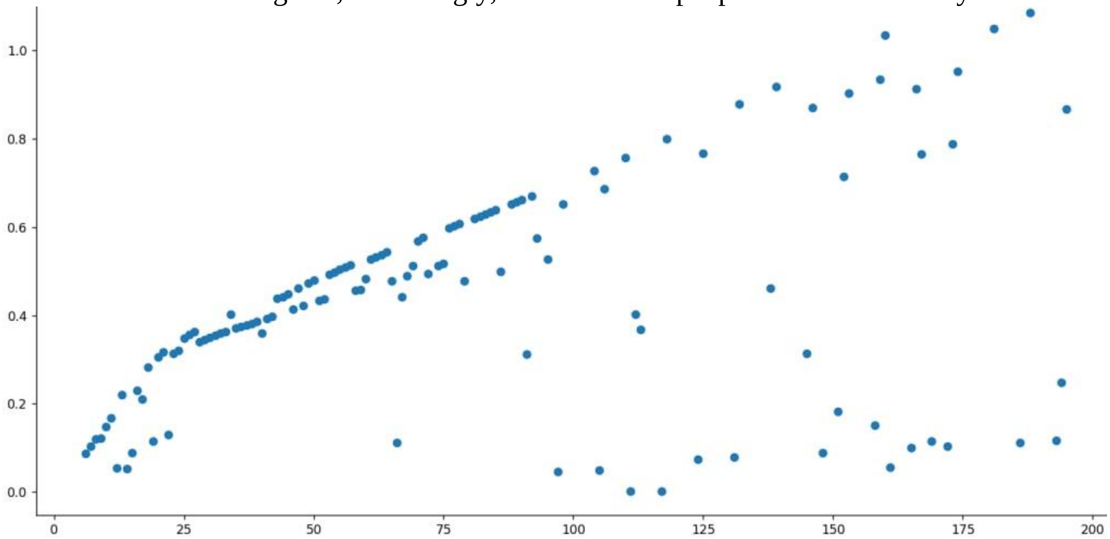


Figure 14: Correlation field of the number of refugees (y) before the day of the war (x)

The correlation coefficient ranges from -1 to 1. In our case, it is close to 1, so our dependence is close to a straight line. The correlation coefficient is 0.675287478.

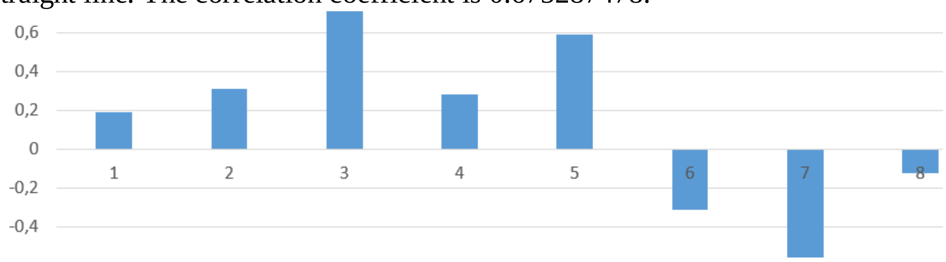
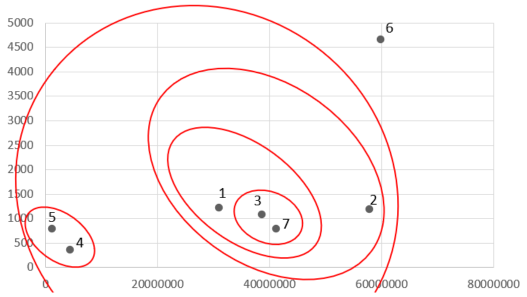


Figure 15: Correlogram

The procedure that constitutes the essence of hierarchical classification consists of the fact that the first cluster is formed in the proximity matrix of two objects, the values of which are listed following the selected strategy. The second object with a larger number of columns and tape is thrown out, and instead of the first object (with a smaller number of columns and tape) a cluster formed from these objects with the listed values is inserted. As a result, the dimension of the matrix is reduced by one. When the proximity matrix has a dimension of 2×2, the clustering procedure is stopped. Based on the information obtained at each step about the association of clusters and the minimum distance values found, a dendrogram is constructed and its interpretation is provided.

With the help of cluster analysis, objects were divided not by one parameter, but by a whole set of characteristics, namely by the number of people who left for each country and the distance to it. Moreover, the influence of each of the parameters is rather strengthened or weakened by entering the corresponding coefficients into the mathematical formulas.



1	3+7	d13	0,08
2	4+5	d14	0,11
3	1+13	d15	0,13
4	15+2	d16	0,3
5	16+14	d17	0,49
6	17+6	d18	0,81

Figure 16: The association of clusters with the minimum distance values and the cluster merging procedure (column 1 - number, 2 - union, 3 - node, 4 - metrics)

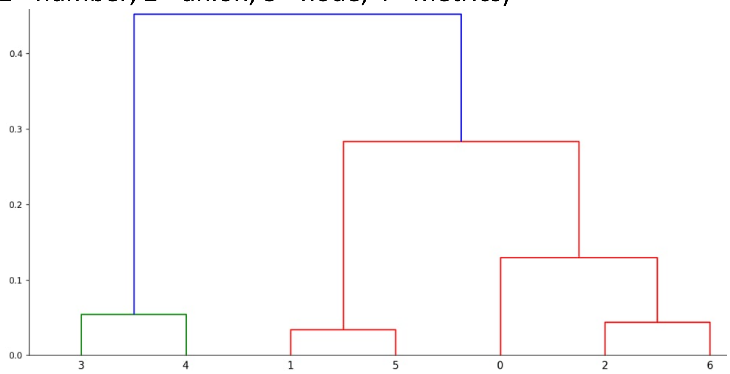


Figure 17: Dendrogram

Since cluster analysis, unlike most mathematical and statistical methods, does not impose any restrictions on the type of objects under consideration, we were able to examine a set of raw data of an almost arbitrary nature. Also, with its help, we considered a rather large amount of information and shortened, compressed a larger mass of information, and made it compact and clear. Thanks to the features of clustering, we were able to determine with the help of our algorithm the number of clusters into which the data should be divided, as well as to highlight the characteristics of these clusters.

After analyzing the node-metric union, we can see that two graphical and one manual solution coincide. The main result of hierarchical clustering is a dendrogram, which shows the hierarchical dependence between clusters. After constructing it, you can conclude the distance between clusters, the higher the column, the greater the distance between clusters (clustering is performed in the form of nested groups). As a result of clustering and dendrogram construction, we concluded that the closer the clusters are to each other, the closer they are geographically to Ukraine. Accordingly, these clusters bear a greater socio-economic burden in terms of receiving refugees from Ukraine.

4.2. Analysis of the dynamics of the increase/decrease in the prices of food products in the world (in particular, for wheat), caused by the Russian-Ukrainian war

The main questions of the work are: "To what extent do important political events (wars, crises) have a strong influence on the world market?" and "How exactly do prices for certain materials change?". First of all, we can put forward the following hypothesis: any major event in a country that affects the total output of products for export causes an increase in the price of the product that this country supplies. Revolutions and wars, economic crises and a change in the political vector - all this has a direct impact on the general picture of the global economic trade space.

Consider a specific example: the war in Ukraine and the trade crisis in Europe. Ukraine ranks first in the export of sunflower oil abroad and is one of the key exporters of wheat and grain crops in general. She consumes only a quarter of the grain crops she grows. The rest is exported. Europe is directly dependent on these imported products. Russia's blockade of Ukrainian Black Sea ports led to a global food crisis and provoked global food inflation (as of August – 6% (inflation index)). So, these are our guesses. The next step will be proof and direct analysis of the question. These graphs illustrate the correspondence between wheat price jumps and similar changes in inflation rates around the world. So, it can be concluded that there is a relationship between the inflation rate and the cost of a certain type of product that is produced for export. This is confirmed not only by the year 2022 and the Russian-Ukrainian war. Almost all of the most famous crises or economic events can be traced on an inflation graph. Fig. 18 demonstrates the year 2008 (an extraordinary jump in inflation), which corresponds to the crisis in America (loan crisis), which caused the economic crisis of the whole of Europe and beyond. A similar jump can be observed in Fig. 18 corresponds to the period of the European debt crisis. We can observe the relevant economic consequences of this event on 2 unknown graphs. This supports our thesis that the restriction of wheat available for purchase could indeed have caused the crisis in Europe. Data for graphical representation: the ratio of wheat and gas prices.

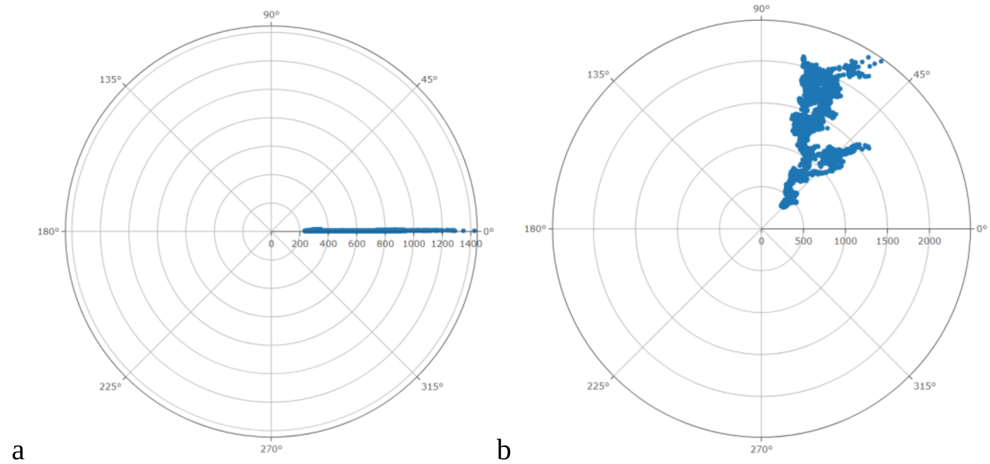


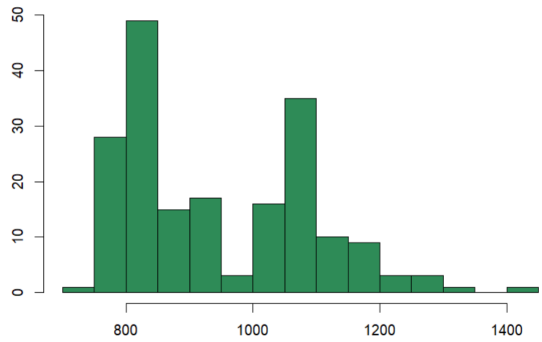
Figure 18: Graph in the polar coordinate system: a) wheat and gas and b) wheat and gold

Above, 2 variants of dependence of two quantities were given. It can be seen that the relationship "wheat - gas" is represented by an almost straight line, while "wheat - gold" has a non-linear representation. There is a logical and simple explanation for this. Since the prices of commodities, such as wheat and gas, directly depend on crises (to be more precise, the stronger the crisis, the higher the price of the resource), the relationship between them is almost linear. If we consider the wheat-gold situation, it should be noted that during the crisis, gold prices do not rise, but on the contrary, valuable materials become one of the most stable assets of the economy. So, since wheat and gold have different distributions of value concerning time, they will not have relationships (straight, linear) on the graph given above.

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
NATURAL.GAS	1	5907	4.555699	2.240085	3.9340	4.255149	1.780603	1.482	15.378	13.896	1.4473459	2.49376897	0.02914614
GOLD	2	5907	1044.003149	520.192926	1193.2000	1040.605564	675.324300	255.100	2051.500	1796.400	-0.1012721	-1.26397251	6.76832114
WTI.CRUDE	3	5907	62.504237	26.157952	59.6400	61.409268	30.497082	-37.630	145.290	182.920	0.3391104	-0.70090926	0.34034569
BRENT.CRUDE	4	5907	65.754715	29.496130	62.7000	64.540366	31.757292	17.680	146.080	128.400	0.3338681	-0.90846192	0.38377931
SOYBEANS	5	5907	966.852632	337.744121	950.2500	955.828961	446.633250	418.000	1771.000	1353.000	0.2305591	-0.87689204	4.39444783
CORN	6	5907	397.109700	162.837680	366.7500	380.360059	177.170700	174.750	831.250	656.500	0.7752071	-0.32564288	2.11870953
COPPER	7	5907	2.583949	1.123574	2.7955	2.601794	1.053387	0.606	4.929	4.323	-0.3175714	-0.95026266	0.01461902
SILVER	8	5907	15.903462	8.472887	16.0980	15.212048	7.877054	4.028	48.584	44.556	0.5761790	0.08145168	0.11024222
LOW.SULPHUR.GAS.OIL	9	5907	580.567293	263.483798	562.5000	567.367939	276.504900	148.500	1522.500	1374.000	0.4279314	-0.53626075	3.42823378
LIVE.CATTLE	10	5907	104.788903	24.537629	102.6000	103.682039	27.798750	59.400	171.000	111.600	0.3359882	-0.68248314	0.31926338
SOYBEAN.OIL	11	5907	35.472727	14.596086	32.3900	34.216004	12.646578	14.380	90.600	76.220	0.8379076	0.25599656	0.18991222
ALUMINIUM	12	5907	1966.838309	454.321861	1869.7500	1926.888680	438.849600	1246.000	3875.500	2629.500	0.7670435	0.07850286	5.91126120
SOYBEAN.MEAL	13	5907	297.810581	95.708114	306.3000	294.463994	111.788040	146.300	548.100	401.800	0.1172575	-0.85528102	1.24527501
ZINC	14	5907	2066.870874	849.570116	2061.2500	2030.469987	942.562950	724.000	4594.000	3870.000	0.2908830	-0.48398971	11.05390536
ULS.DIESEL	15	5907	189.626618	84.245271	185.3400	185.711390	91.936026	49.990	513.540	463.550	0.4244138	-0.45157659	1.09612996
NICKEL	16	5907	15936.137515	7715.452435	14529.0000	14961.851288	6161.685600	4350.000	53750.000	49400.000	1.5513710	3.57820423	100.38710101
WHEAT	17	5907	523.132978	190.768912	499.5000	507.834779	203.857500	233.500	1425.250	1191.750	0.7463849	0.39263087	2.48212768
SUGAR	18	5907	14.235207	5.776242	13.3800	13.767279	5.960052	4.650	35.310	30.660	0.7166249	0.29050519	0.07515569
GASOLINE	19	4425	211.299225	64.063530	204.1100	209.067955	71.461320	41.180	427.620	386.440	0.3401542	-0.46170482	0.96306196
COFFEE	20	5907	127.301634	50.816721	120.2000	122.716617	33.877410	41.500	304.900	263.400	0.8206133	0.55232191	0.66118525
LEAN.HOGS	21	5907	71.916370	16.874918	68.5500	70.459187	15.715560	30.050	133.875	103.825	0.8223594	0.69551776	0.21956251
HRW.WHEAT	22	5907	545.507872	201.535224	491.0000	525.630051	195.703200	270.750	1367.750	1097.000	0.8780399	0.28114546	2.62221004

Figure 19: Descriptive data statistics

The following conclusions can be drawn from the above table (Fig. 20): the most expensive metals are nickel, zinc, aluminium and gold. The largest is the range of such products as wheat (233-1435) and nickel (4350-54750), as well as aluminium and oil. Gas and nickel have the steepest increases in the distribution curve (kurtosis).



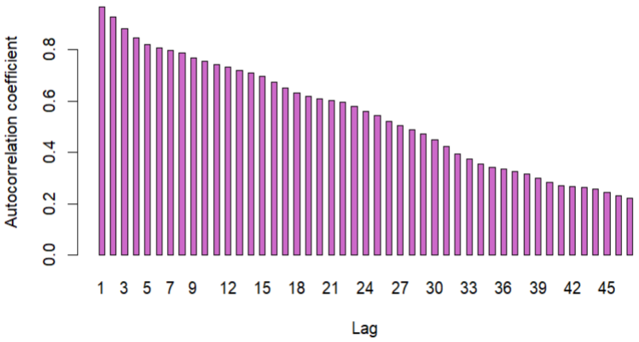


Figure 20: a) The result of constructing a histogram of the price of wheat during the war (x is grouping intervals and y is the frequency of values; b) The correlogram of the autocorrelation function

As you can see, according to the histogram, wheat prices rose sharply after a certain period after the start of the war (not immediately). The price increased about 5 times, then decreased by two-thirds and then increased again. Such "jumps" can be caused by different situations on the front line. The price rose after the territories responsible for a large part of the supply was seized, the blockade of the Black Sea ports in the spring. All this caused a sharp rise in the price of wheat in Europe. After the establishment of the grain corridor, the situation improved, but it remains unstable.

Looking at the time series graph, we can conclude that the data has a downward trend. Therefore, it is possible to assume the non-stationarity of the original time series.

To more accurately determine the stationarity of the series, the correlogram of the autocorrelation function is analyzed. In the case of a stationary time series, a rapid decline with increasing t will be depicted already after the first few values. The constructed correlogram demonstrates that the studied series is not stationary, but contains a trend component. For cluster analysis: the set G, which includes m objects, each of which is characterized n by features.

	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
NATURAL.GAS	7.047602	1.3930399	6.937	7.06698	1.767259	4.402	9.68	5.278	-0.04559063	-1.0532291	0.10079683
SOYBEANS	1577.909686	120.2975178	1615.000	1584.09150	131.210100	1358.000	1769.00	411.000	-0.37375568	-1.3466098	8.70442290
CORN	713.769634	62.7406468	726.250	716.50327	70.794150	564.250	818.25	254.000	-0.28785988	-0.8806465	4.53975387
SOYBEAN.OIL	73.168429	7.0013165	72.220	72.97935	6.656874	58.600	90.60	32.000	0.29289684	-0.3334171	0.50659748
NICKEL	26531.577330	6260.6771682	24502.000	25489.03928	4160.175600	19330.000	48211.00	28881.000	1.78085332	3.3654208	453.00670108
WHEAT	946.696335	146.4998049	902.500	935.07516	165.680550	731.500	1425.25	693.750	0.59036614	-0.5654018	10.60035385
SUGAR	18.745707	0.7038955	18.660	18.72170	0.815430	17.400	20.41	3.010	0.29289884	-0.7013940	0.05093209
GASOLINE	316.465497	51.7110590	316.890	314.35327	65.471616	230.770	427.62	196.850	0.25255120	-0.9838402	3.74168091
HRW.WHEAT	1014.022251	127.4041687	976.000	1005.51471	147.889350	812.500	1367.75	555.250	0.51732510	-0.7162702	9.21864211
COTTON	115.497173	22.9032204	117.120	115.82078	30.704646	72.000	158.02	86.020	-0.02266502	-1.2800230	1.65721887

Figure 21: Table " operator - indicator " - objects indicators values according to descriptive statistics

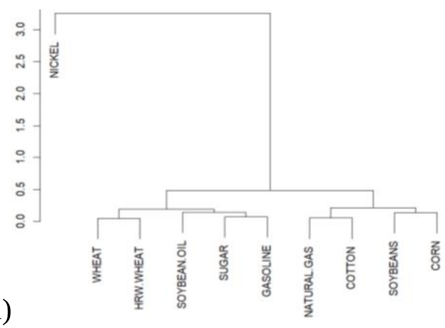
Step	Unification	Node	Metric
1	WHEAT & HRW.WHEAT	d11	0.0477108270445092
2	NATURAL.GAS & COTTON	d12	0.0508576144244462
3	SUGAR & GASOLINE	d13	0.0704643148166097
4	SOYBEANS & CORN	d14	0.131874179597205
5	SOYBEAN.OIL & SUGAR & GASOLINE	d15	0.141917655153745
6	SOYBEAN.OIL & SUGAR & GASOLINE & WHEAT & HRW.WHEAT	d16	0.191395661265014
7	NATURAL.GAS & COTTON & SOYBEANS & CORN	d17	0.216441960448093
8	NATURAL.GAS & COTTON & SOYBEANS & CORN & SOYBEAN.OIL & SUGAR & GASOLINE & WHEAT & HRW.WHEAT	d18	0.480705521393012
9	NATURAL.GAS & COTTON & SOYBEANS & CORN & SOYBEAN.OIL & SUGAR & GASOLINE & WHEAT & HRW.WHEAT&NICKEL	d19	3.25570084565205

Figure 22: The result of the software construction of the table "union - node - metric

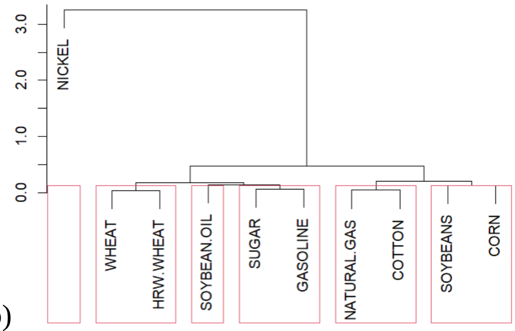
Interpretation of the result of cluster analysis

- At level 0.1, 6 clusters are formed: 1 cluster – object NICKEL; 2nd cluster – objects WHEAT, HRW.WHEAT; 3rd cluster – object SOYBEAN.OIL; 4th cluster – objects SUGAR, GASOLINE; 5th cluster – NATURAL.GAS, COTTON objects; 6th cluster - objects SOYBEANS, CORN.

- At level 0.2, 4 clusters are formed: 1 cluster – NICKEL object; 2nd cluster – objects WHEAT, HRW.WHEAT, SOYBEAN.OIL, SUGAR, GASOLINE; 3rd cluster – NATURAL.GAS, COTTON objects; 4 cluster - objects SOYBEANS, CORN.
- At level 0.3, 3 clusters are formed: 1 cluster – object NICKEL; 2nd cluster – objects WHEAT, HRW.WHEAT, SOYBEAN.OIL, SUGAR, GASOLINE; Cluster 3 – objects NATURAL.GAS, COTTON, SOYBEANS, CORN.

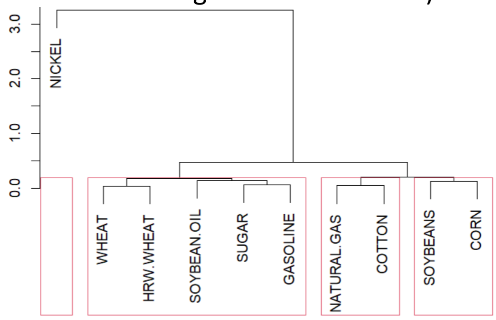


a)

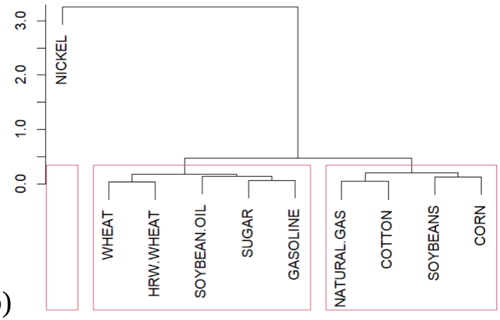


b)

Figure 23: Cluster dendrogram for Prices of a) formed clusters and b) display of clusters at level 0.1



a)



b)

Figure 24: Dendrogram of presentation of clusters at the level of a) 0.2 and b) 0.3

a)

b)

Interpretation of cluster analysis:

	cluster division on level '0.1'	cluster division on level '0.2'	cluster division on level '0.3'
NATURAL.GAS	1	1	1
SOYBEANS	2	2	1
CORN	2	2	1
SOYBEAN.OIL	3	3	2
NICKEL	4	4	3
WHEAT	5	3	2
SUGAR	6	3	2
GASOLINE	6	3	2
HRW.WHEAT	5	3	2
COTTON	1	1	1

Figure 25: a) Dendrogram of clusters at three levels simultaneously (0.1, 0.2, 0.3) and b) the result of the software implementation of the interpretation of the cluster analysis result

As a result of the cluster analysis, we obtained a division of the types of products of the world economy according to their average value. Conclusions: the most expensive product is nickel; the cheapest product is wheat; the price for sugar, petrol, gas and cotton is at the same level.

4.3. Analysis of changes in the euro currency, namely currency conversion: Euro to USD and Euro to Japanese yen

The Dataset about European Currency includes changes in the euro currency, namely the conversion of currencies: Euro to USD and Euro to Japanese yen. Why such a topic? The dollar and the euro are the two largest reserve currencies in the world, which compete with each other. The Europeans cannot raise the interest rate and restore the confidence of investors, because this will slow down the economy and it will lose its main incentive - cheap loans. The relevance of the topic: Russia's attack on Ukraine only increased the inflationary trend in the world, creating a shortage of energy and food, which pushed prices even higher.

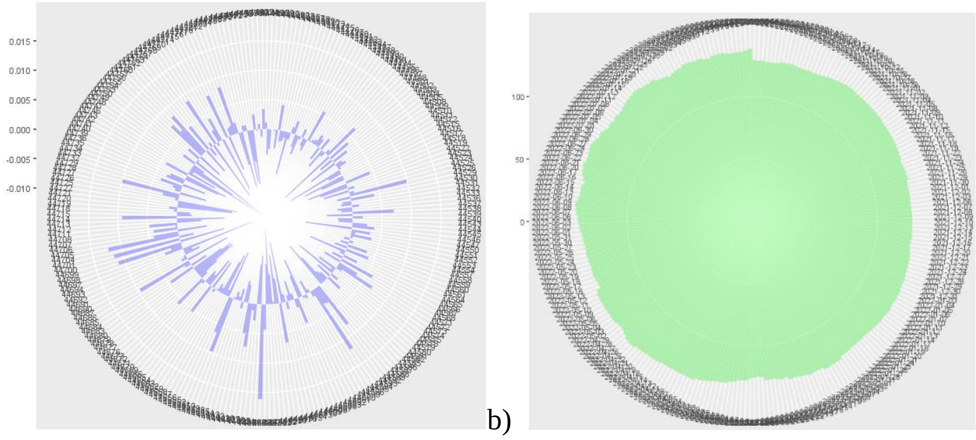


Figure 26: Graphic representation of the dynamics of a) Euro to USD and b) Euro to Japanese yen

Results of descriptive statistics for Euro to USD:

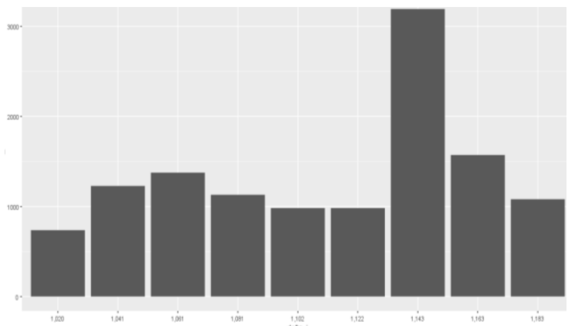
1) Sample size – 250;
2) Arithmetic average – 1.10138;
3) Mode – 1.137;
4) Median – 1.1131;
5) Scope – 0.1833;
6) Standard deviation – 0.05031769;
7) Coefficient of variation – 4.56860389;
8) Dispersion – 0.00253187;
9) Excess – -1.093598375;
10) Asymmetry – -0.37715017;
11) Minimum – 1;
12) Maximum – 1.1833;
13) Amount – 275.345;
14) Standard error – 0.00318237;
15) Interval – 0.1833;
16) Reliability level (95%) – 0.006267795.

Results of descriptive statistics for Euro to Japanese yen:

1) Sample size – 250;
2) Arithmetic average – 132.92628;
3) Mode – 128.54;
4) Median – 131.75;
5) Scope – 18.47;
6) Standard deviation – 4.337306014;
7) Coefficient of variation – 3.262940943;
8) Dispersion – 18.81222346;
9) Excess – -0.926684877;
10) Asymmetry – 0.397360339;
11) Minimum – 124.38;
12) Maximum – 142.85;
13) Amount – 33231.57;
14) Standard error – 0.274315318;
15) Interval – 18.47;
16) Reliability level (95%) – 0.540274133.

So, the graph in the Cartesian system reflects the relationship between two values (the highest price of the session and the date). The graph shows the dynamics of the rise or fall of the euro against the US dollar over a certain period, namely over the last year. Since May, the US dollar has strengthened against other currencies at a record pace. If a stronger dollar has two-fold implications for the United States economy, it is almost certainly bad news for the rest of the world. The Europeans cannot raise the interest rate and restore the confidence of investors, because this will slow down the economy and it will lose its main incentive - cheap loans. The European financial system does not have the margin of safety for such manoeuvres and cannot afford a sharp increase in rates due to the energy crisis. Another reason for switching from the euro to the dollar is uncertainty in the EU economy. The US is a self-sufficient economy with a strong labour market and a determined central bank. The country can provide itself with food, energy and stable debt payments, even if it is hit by a recession. The European Union cannot boast of this. The bloc's economic prospects are unclear due to the gas crisis and the war in Ukraine. In August, for the first time in 20 years, the euro became cheaper than the dollar. Now the rate fluctuates at the level of 1 to 1. Looking at the graph of the relationship between two values (the highest price of the session and the date) in the polar system, you can draw similar conclusions as for the Cartesian system. In June, the euro fell sharply in value, and in mid-July it equalled the dollar. The euro fell 0.7 per cent to $0.9884, its lowest level since December 2002.

The graph also shows the dynamics of growth or decline of the euro against the Japanese yen over a certain period, namely over the last year. The expected widening of the gap between key rates between Japan and the US further reduced the value of the currency. It fell 0.5% to a low of 138.10 per dollar in morning trading, a level not seen since September 1998. The yen hit multiple lows in recent weeks as traders abandoned it in pursuit of higher interest rates in the United States, where the Federal Reserve is expected to act more aggressively this year to combat soaring inflation. The Bank of Japan followed a soft monetary policy and warned only against "excessive fluctuations" in the price of the yen. Inflation in Japan reached 2.5% in June, above the bank's range. In particular, the Japanese government did not rely on the "invisible hand of the market", but actively developed and directed all economic processes at the macro level. He not only determined what the Japanese economy should do, but also contributed to the accumulation of production resources - financial, labor, and material - in the relevant areas. However, at the same time, the enterprises retained a private form of ownership, and the government did not interfere in their operational activities, which left enough space for the operation of market mechanisms. Looking at the graph of the relationship between the two values of the polar system, you can draw similar conclusions as for the Cartesian system. Japan, like Ukraine, due to the shortage of natural resources cannot independently provide itself with everything it needs. This situation forces Japan to have a large export sector. Because only at the expense of selling products and services for export, the country can buy abroad what it lacks. For Japanese exports to be strong and competitive, in this country considerable attention is paid to structural policy, that is, to the formation of such a structure of the economy under which the use of available resources (labor, natural, material) would give the country the greatest effect. In other words, the Japanese government strictly monitors that enterprises (at least at the level of large business) produce, not what anyone wants, but what can find a constant and solvent demand in the foreign market. The next step is to create a bar chart that displays the frequency data. A histogram helps to illustrate the relationship of individual elements to each other and their change over time. Quantitative ratios of the highest price indicator of the session are presented in the form of rectangles that reflect the distribution of numerical data at certain time intervals. Intervals are plotted on the abscissa axis, and frequencies are plotted on the ordinate axis. It can be concluded that the interval from 1.122 to 1.143 had the most values.

a) 

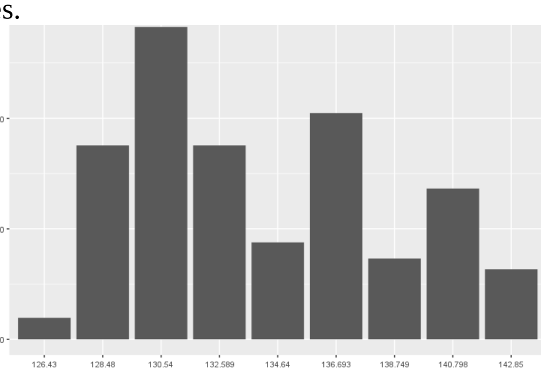
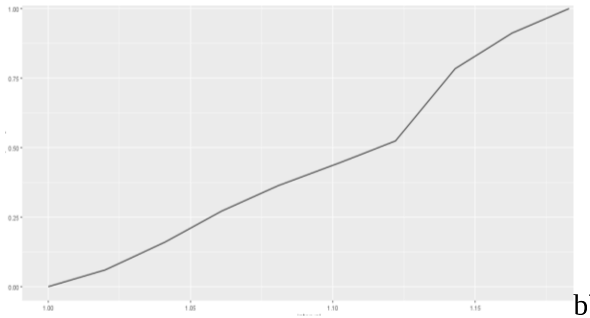
b) 

Figure 27: Histogram of a) Euro to USD and b) Euro to Japanese yen

Comparing the constructed graphs of the cumulate based on the data from the histogram and the cumulate based on the integral indicator, you can see that they are quite similar, which in turn is an indicator of the correctness of the histogram construction. The difference between these two cumulates is that the cumulate constructed according to the histogram data has k approximation nodes and is a broken curve, and the cumulate constructed according to the integral percentage has $n-1$ approximation nodes and is smoother.

a) 

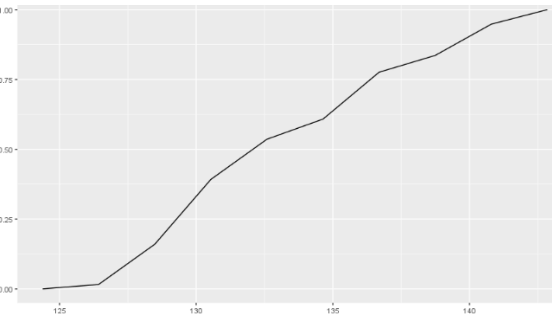
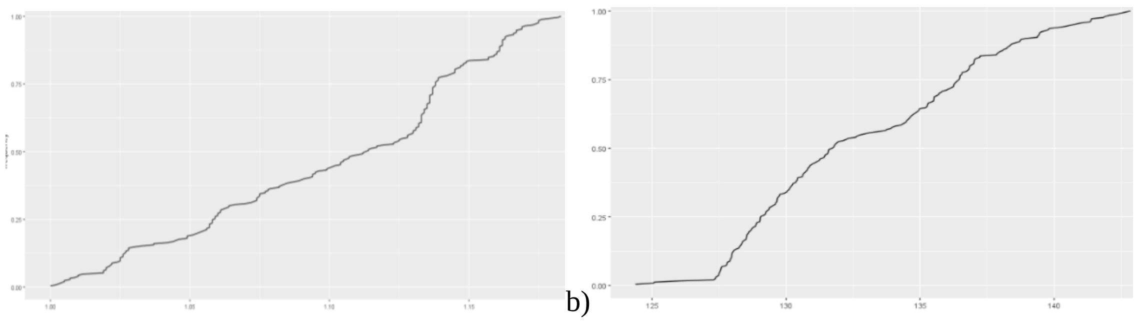
b) 

Figure 28: Cumulative are built according to the histogram data of a) Euro to USD and b) Euro to Japanese yen



a) b)

Figure 29: Cumulative are built according to the integral interest of a) Euro to USD and b) Euro to Japanese yen

In the correlation analysis, we used another sample of 250 items. The following statistics were selected: high price (the highest price of the session), low price (lowest price of the session) for Euro to USD and the open price of the session (the initial price of the session), end price of the session (final price of the session) for Euro to Japan yen.

a)

	High price X	Low price Y
1	1.0054	0.9981
2	1.0029	0.9913
3	1.0091	0.9947
4	1.0035	0.9948
5	1.0000	0.9909
6	1.0019	0.9900
7	1.0048	0.9926
8	1.0096	1.0031
9	1.0194	1.0079
10	1.0203	1.0145
11	1.0195	1.0122
12	1.0270	1.0155
13	1.0329	1.0237
14	1.0366	1.0275
15	1.0369	1.0201
16	1.0248	1.0188
17	1.0223	1.0158
18	1.0253	1.0141
19	1.0254	1.0154
20	1.0210	1.0122
21	1.0295	1.0163
22	1.0276	1.0205
23	1.0255	1.0145
24	1.0236	1.0114

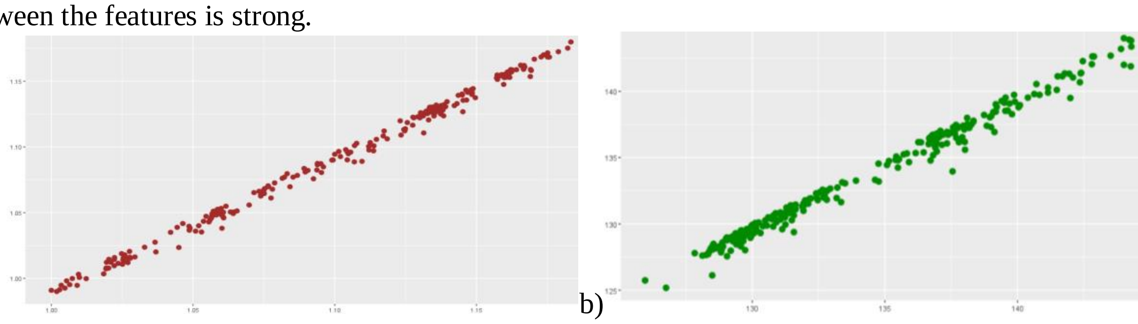
	High price X	Low price Y
227	1.1624	1.1571
228	1.1621	1.1588
229	1.1625	1.1583
230	1.1598	1.1527
231	1.1571	1.1524
232	1.1588	1.1549
233	1.1586	1.1540
234	1.1573	1.1547
235	1.1605	1.1529
236	1.1623	1.1580
237	1.1641	1.1587
238	1.1608	1.1563
239	1.1611	1.1562
240	1.1691	1.1589
241	1.1704	1.1667
242	1.1728	1.1684
243	1.1748	1.1700
244	1.1751	1.1683
245	1.1757	1.1683
246	1.1751	1.1715
247	1.1737	1.1700
248	1.1789	1.1724
249	1.1822	1.1751
250	1.1833	1.1798

b)

139.01	138.82
138.62	137.30
136.98	136.18
136.13	136.67
136.62	136.37
136.33	136.71
136.66	137.37
137.40	137.12
137.08	137.46
137.44	136.54
136.49	135.46
135.45	137.01
136.92	137.22
137.22	136.88
136.82	138.04
137.98	137.69
137.63	137.40
137.41	136.16
136.15	136.07
136.03	135.39
135.38	135.08
135.05	136.15
136.09	136.93

Figure 30: A sample of 250 items for data correlation

In Fig. 31 you can see the result of constructing the correlation field. Points are located from the bottom to the right. This means that the relationship between the values is direct. The points of the correlation field are also located very close to each other, so it can be concluded that the connection between the features is strong.



a) b)

Figure 31: Correlation field a) Euro to USD and b) Euro to Japanese yen

A sample correlation coefficient is used to quantify the closeness of the relationship. The sample correlation coefficient r does not exceed unity in absolute value. It ranges from -1 to 1. In our case, the correlation coefficient (Euro to USD) is equal to 0.99781499. And the correlation coefficient (Euro to Japanese yen) is equal to 0.98216595. If the correlation coefficient is 0.66-0.99, then we can conclude that the relationship is strong. Let's calculate the correlation ratio. First, let's calculate the number of intervals according to the Sturges formula: k=1+logn=8.85174904 ≈9.

a)

[1; 1,0253)	[1,0253;1,056)	[1,056;1,074)	[1,074;1,099)	[1,099;1,1247)	[1,1247;1,1343)	[1,1343;1,1384)	[1,1384;1,1596)	[1,1596;1,833]	
27	27	27	27	27	27	27	27	34	250
0,9769	1,0388	1,0616	1,0840	1,1098	1,1308	1,1361	1,1472	1,201426471	
26,38	28,0468	28,6621	29,2685	29,9635	30,5304	30,674	30,9742	40,8485	
1449686,524	1448912,79	1448627,731	1448346,822	1448024,904	1447762,348	1447695,844	1447556,821	1821995,513	

b)

[125,15;128,45)	[128,45;129,27)	[129,27;130,27)	[130,27;131,31)	[131,31;133,18)	[133,18;136,09)	[136,09;136,98)	[136,98;139,01)	[139,01;143,96]	
27	27	27	27	27	27	27	27	34	250
122,9948	128,9093	129,7267	130,8048	132,0456	134,9111	136,5533	137,8756	145,2144118	
3 320,86	3 480,5500	3502,62	3531,73	3565,23	3642,6	3686,94	3722,64	4937,29	
495180,149	452872,5018	447173,9339	439712,7876	431204,1288	411870,6412	400990,681	392336,5978	435727,8801	

Figure 32: Table of intervals, partial math. expectations and number of sample elements for a) Euro to USD and b) Euro to Japan yen, where lines 1 – interval, 2 – number of sample elements, 3 – mathematical expectation, 4 – the product of the previous two lines

For Euro to USD: the mathematical expectation of partial groupings is 232.6924702; group variance is 11331538.32; variance obtained from the ungrouped response is 11332392.96; correlation relation is 0.999962291. For Euro to Japan yen: the mathematical expectation of partial groupings is 258.4200913; group variance is 30238.13405; variance obtained from the ungrouped response is 30202.96483; correlation relation is 1.000582045.

a)

1	2	3	4	5	6	7	8	9
0,989572353	0,994062707	0,989113652	0,995258164	0,99164666	0,98878991	0,992784121	0,978271458	0,993649542

b)

1	2	3	4	5	6	7	8	9
0,94331136	0,991412003	0,994896524	0,994504126	0,994004146	0,986146719	0,995032359	0,995919117	0,997138276

Figure 33: Autocorrelation calculations a) Euro to USD and b) Euro to Japanese yen

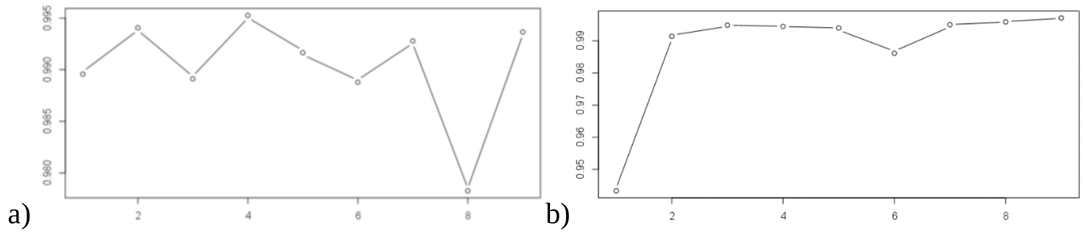


Figure 34: Autocorrelation graph for a) Euro to USD and b) Euro to Japanese yen

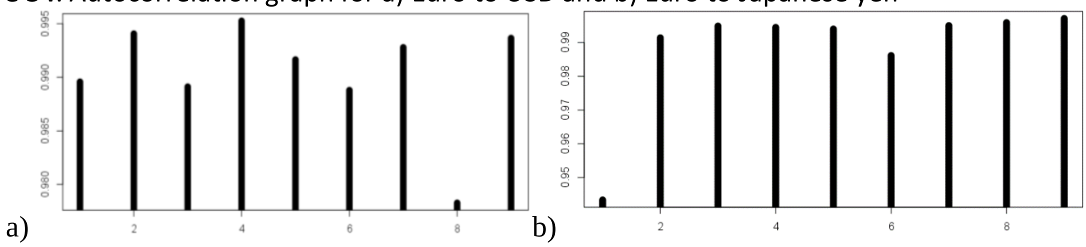


Figure 35: Histogram of the autocorrelation function for a) Euro to USD and b) Euro to Japanese yen

Splitting one of the sequences into three equal parts. The correlation matrix is a square table in which the correlation coefficient between the corresponding parameters is located at the intersection of the corresponding row and column.

a)

[1;1,0074)	[1,0074;1,0195)	[1,0195; 1,0253)
9	9	9

b)

[125,15; 127,82)	[127,82; 128,1)	[128,1;128,29)
9	9	9

Figure 36: Dividing the sequence into three equal intervals with the corresponding number of sample elements for a) Euro to USD and b) Euro to Japanese yen

a)

1		
0,918515987	1	
0,967336392	0,874430796	1

b)

1		
0,931321843	1	
0,93832086	0,933651152	1

Figure 37: Correlation matrix for a) Euro to USD and b) Euro to Japanese yen

After analyzing the graphic presentation of the relationship between the two studied sequences, it can be concluded that they have a strong linear relationship. The placement of points on the graph indicates the presence and direction of communication.

So, the correlation analysis (Euro to USD) allowed us to find out the interdependencies between various random variables and to understand that the presented signs (high price (the highest price of the session) and low price (the lowest price of the session)) have a strong dependence. A change in one or more of these values leads to a systematic change in another. As the highest price of the session increases, the lowest price of the session increases, so there is a positive relationship, in other words, there is a positive relationship between the highest price of the session and the lowest price of the session. So, in our case, the correlation is positive and positive. This can be seen from the calculated correlation coefficient, the value of which is almost 1. Thus, if the correlation coefficient is 0.66-0.99, then we can conclude that the relationship is strong.

Correlation analysis (Euro to Japan yen) allowed us to find out the interdependencies between various random variables and understand that the presented signs (open price (opening price of the session) and low price (ending price of the session)) have a strong dependence. A change in one or more of these values leads to a systematic change in another. As the initial price of the session increases, the final price of the session increases, so there is a positive relationship, in other words, there is a positive relationship between the initial price of the session and the final price of the session. So, in our case, the correlation is positive and positive. This can be seen from the calculated correlation coefficient, the value of which is almost 1. Thus, if the correlation coefficient is 0.66-0.99, then we can conclude that the relationship is strong. The correlation coefficient varies from 0 to 1 and is always in absolute value no less than the Pearson coefficient for the same variables, which is correct in our case. A value of 0 for the correlation coefficient indicates no connection, and a value of 1 indicates a functional connection. After analyzing our correlation coefficient, we can conclude that we have a functional relationship between two signs (high price (the highest price of the session) and low price (the lowest price of the session)). The greater the value of this coefficient, the closer the connection. It also follows from the difference between the correlation coefficient and the corresponding Pearson correlation coefficient. The greater the difference, the more non-linear the relationship. In our case, the difference is insignificant, which indicates the linearity of the relationship. (Pearson coefficient = 0.9978 and correlation ratio = 0.9999). As a result of the primary processing of data using descriptive statistics within the parameters defined for this, a table was built, which is called the "object-property" table. So, for cluster analysis, a set G is submitted, which includes m objects, each of which is characterized by n features. The data are presented below in Fig. 38(a-b). As shown in Fig. 38(c-d) indicators in size and dimension are very heterogeneous, which means the impossibility of a reasonable interpretation of the obtained result of the cluster analysis. Therefore, there is a need to standardize this table. The formation of the closely located "original table" and "copy table" from them. Standardization is a transition to some uniform description for all features and the introduction of a new conventional unit of measurement that allows formal comparison of objects or their features.

a)

698599	1,008636364	1,013673
832440	1,012671429	1,019381
798333	1,051759091	1,057332
734288	1,052636364	1,057345
721466	1,077280952	1,083005
770414	1,096547826	1,102535
749882	1,12963	1,13409
636188	1,128533333	1,132362
785677	1,127056522	1,130561
832841	1,137368182	1,141791
617278	1,15727619	1,16001

b)

234 992	136,0659091	136,7768
231 894	138,3561905	139,431
233248	140,6672727	141,4832
210115	135,41	136,2227
200004	135,8190476	136,4505
181385	129,8621739	130,5313
183353	130,0415	130,664
160852	129,5961905	130,0681
179053	128,3652174	128,7065
197698	129,6913636	130,2764
149170	130,7704762	131,1429

c)

0,3772	0	0
0,9981	0,0271466	0,039007
0,8399	0,2901156	0,298347
0,5428	0,2960176	0,29844
0,4833	0,4618183	0,473784
0,7104	0,5914395	0,607243
0,6151	0,8140055	0,822878
0,0877	0,8066275	0,811069
0,7812	0,796692	0,798761
1	0,8660654	0,875502
0	1	1
617278	1,0086364	1,013673
832841	1,1572762	1,16001

d)

1	0,6259679	0,631644
0,9639	0,8121385	0,839377
0,9797	1	1
0,7101	0,5726509	0,588276
0,5923	0,6059012	0,606102
0,3754	0,1216834	0,142822
0,3983	0,1362604	0,153207
0,1361	0,1000624	0,106567
0,3482	0	0
0,5654	0,1077988	0,122868
0	0,1955168	0,190686
149170	128,36522	128,7065
234992	140,66727	141,4832

Figure 38: The "object-property" table by month (from August to October) for a) Euro to USD and b) Euro to Japanese yen and Normalized table "object-property" for c) Euro to USD and d) Euro to Japanese yen, where column 1 - volume, 2 - the lowest price, 3 - the beginning of the session (red line 1 - minimum value, 2 - maximum)

A proximity table was constructed using hierarchical cluster analysis. (Fig. 39). For convenience, the names of the months have been replaced by serial numbers. Thus, with the help of the nearest neighbour strategy, we obtained the union of all objects into 1 cluster (Fig. 40).

a)

1	0	0,622705339	0,622284	0,451777	0,670075	0,910788	1,181664	1,18	1,1982969	1,379997	1,463666
2	0,62271	0	0,401801	0,589	0,801872	0,850947	1,174853	1,4257	1,1029447	1,184699	1,692994
3	0,62228	0,401801336	0	0,297164	0,432912	0,450541	0,77467	1,0466	0,7144798	0,830936	1,304496
4	0,45178	0,58900045	0,297164	0	0,248542	0,459043	0,740662	0,8548	0,7468785	0,931117	1,13244
5	0,67008	0,801871534	0,432912	0,248542	0	0,293555	0,513107	0,6238	0,5536049	0,769247	0,894511
6	0,91079	0,850947405	0,450541	0,459043	0,293555	0	0,324202	0,6896	0,2895176	0,480885	0,908762
7	1,18166	1,174853365	0,77467	0,740662	0,513107	0,324202	0	0,5276	0,1686864	0,391906	0,666614
8	1,17996	1,425665892	1,046642	0,854759	0,623826	0,689621	0,527609	0	0,6936586	0,916478	0,284224
9	1,1983	1,102944718	0,71448	0,746879	0,553605	0,289518	0,168686	0,6937	0	0,242022	0,83193
10	1,38	1,184698998	0,830936	0,931117	0,769247	0,480885	0,391906	0,9165	0,2420217	0	1,016582
11	1,46367	1,692994401	1,304496	1,13244	0,894511	0,908762	0,666614	0,2842	0,83193	1,016582	0

b)

1		0,28127485	0,525356	0,297904	0,408969	0,939897	0,911457	1,1395	1,1025692	0,846279	1,17462
2	0,28127		0,24767	0,42989	0,484791	1,143802	1,116934	1,315	1,3203096	1,080854	1,315344
3	0,52536	0,247670441		0,651766	0,678612	1,367983	1,342051	1,5231	1,5487964	1,317942	1,503978
4	0,2979	0,42988983	0,651766		0,123703	0,716843	0,690622	0,8859	0,8972157	0,673518	0,896992
5	0,40897	0,48479133	0,678612	0,123703		0,704387	0,680676	0,8447	0,8911081	0,694509	0,831764
6	0,9399	1,143801622	1,367983	0,716843	0,704387		0,029087	0,2429	0,1895879	0,19162	0,38555
7	0,91146	1,116934285	1,342051	0,690622	0,680676	0,029087		0,2687	0,2110691	0,172243	0,404427
8	1,13955	1,315021797	1,523055	0,885929	0,844705	0,242948	0,268746		0,2575735	0,429704	0,186325
9	1,10257	1,320309608	1,548796	0,897216	0,891108	0,189588	0,211069	0,2576		0,271874	0,442525
10	0,84628	1,080854384	1,317942	0,673518	0,694509	0,19162	0,172243	0,4297	0,2718737		0,576215
11	1,17462	1,315343844	1,503978	0,896992	0,831764	0,38555	0,404427	0,1863	0,4425248	0,576215	

Figure 39: Proximity table for a) Euro to USD and b) Euro to Japanese yen

a)

1	7+9	d12	0,168686
2	4+5	d13	0,248542
3	8+11	d14	0,284224
4	6+16	d15	0,290
5	10+22	d16	0,2945
6	2+3	d17	0,401801
7	1+9	d18	0,451777
8	10+5	d19	0,589
9	32+19	d20	0,689621
10	15+51	d21	0,910788

b)

1	6+7	d12	0,029087
2	4+5	d13	0,123703
3	10+13	d14	0,172243
4	8+11	d15	0,186
5	23+9	d16	0,189588
6	2+3	d17	0,24767
7	1+9	d18	0,297904
8	32+19	d19	0,3454
9	10+5	d20	0,42989
10	15+51	d21	0,846279

Figure 40: Join-node-metric table for a) Euro to USD and b) Euro to Japanese yen (column 1 - number, 2 - union, 3 - node, 4 metric)

We can conclude that the result of hierarchical cluster analysis is the construction of a dendrogram. It, in turn, describes the proximity of individual points and clusters to each other and graphically represents the sequence of merging clusters. In other words, with the help of a dendrogram, you can depict a nested grouping of objects that changes at different levels of the hierarchy.

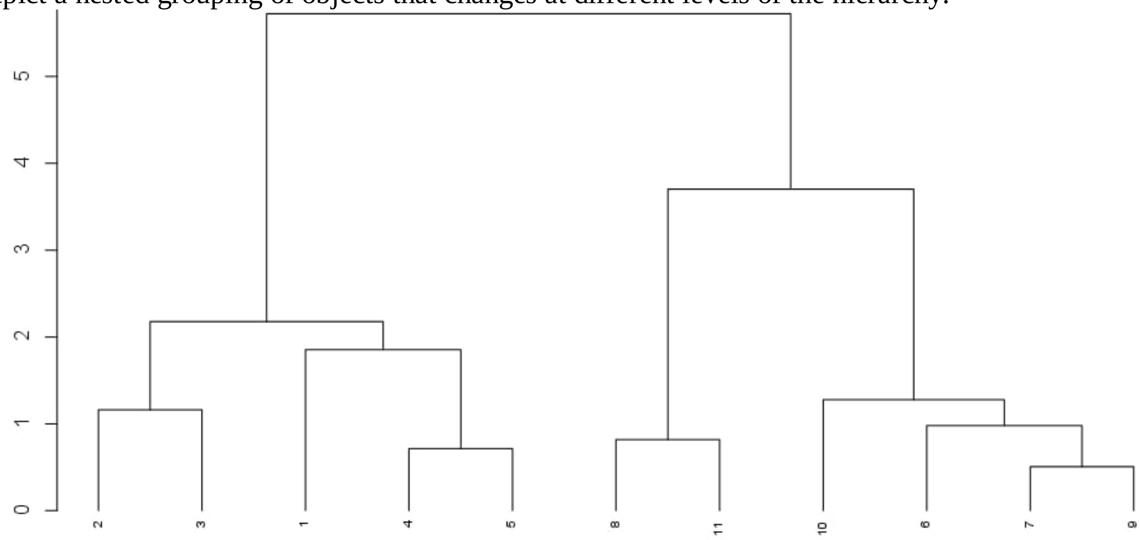


Figure 41: The result of constructing a dendrogram (Euro to USD)

Drawing horizontal lines in the plane of the dendrogram (Euro to USD) at a given height, in this case, allows you to highlight individual clusters. Namely:

- At level 1, we have four clusters: 1st cluster – objects 7,9; 2nd cluster – objects 4,5; 3rd cluster – objects 8,11; 4 cluster - objects 6,7,9.
- At level 1.5, we have three clusters that include the following objects: 1st cluster - objects 10, 6, 7, 9; cluster 2 – objects 1, 4, 5; Cluster 3 - objects 2, 3.
- At level 2 we have two clusters: 1st cluster - objects 1-5; 2nd cluster - objects 8, 11, 10, 6, 7, 9.
- At level 5.5 we have one cluster: 1 cluster - objects 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11.

Drawing horizontal lines in the plane of the dendrogram (Euro to Japan yen) at a given height, in this case, allows you to highlight individual clusters. Namely:

- At level 1, we have four clusters: 1st cluster – objects 6,7; 2nd cluster – objects 4,5; 3rd cluster – objects 10, 6, 7; 4 cluster - objects 8,11.
- At level 1.5, we have three clusters that include the following objects: 1st cluster - objects 10, 6, 7, 9; cluster 2 – objects 1, 4, 5; Cluster 3 - objects 2, 3.
- At level 2 we have two clusters: 1st cluster - objects v; 2nd cluster - objects 8, 11, 10, 6, 7, 9.
- At level 7 we have one cluster: 1 cluster - objects 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11.

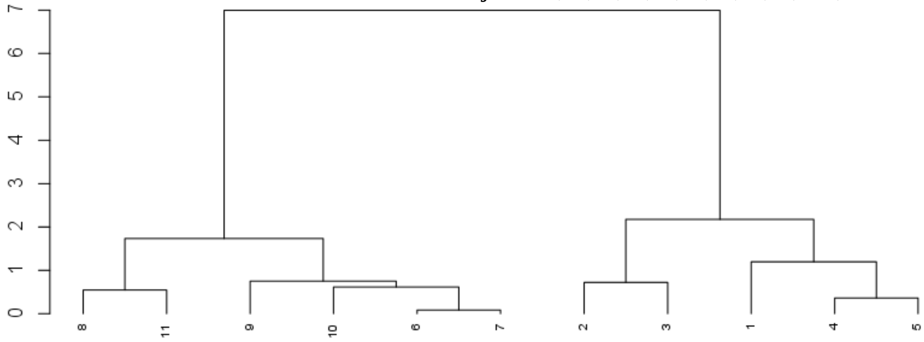


Figure 42: The result of constructing a dendrogram (Euro to Japan yen)

So, with the help of cluster analysis, we were able to reduce the dimensionality of the data by grouping similar objects into clusters using the nearest-neighbour strategy. Namely, we will form clusters grouped by months, which at the initial stage were recorded by days. Also, as a result of constructing the dendrogram, we were able to reveal the hierarchical structure of the input data, that is, we received data in a more visual structure, which in turn allows us to graphically see which objects are the most distant from each other, and which are the closest to each other.

4.4. Gold price correlation

According to the data on the correlation of the price of gold during the period from January 1, 2000, to September 1, 2022. to investigate exactly how changes in the value of gold occurred, to explain why the value of gold is a very important criterion, as it shows how world events affect the economy in the world (Fig. 43).

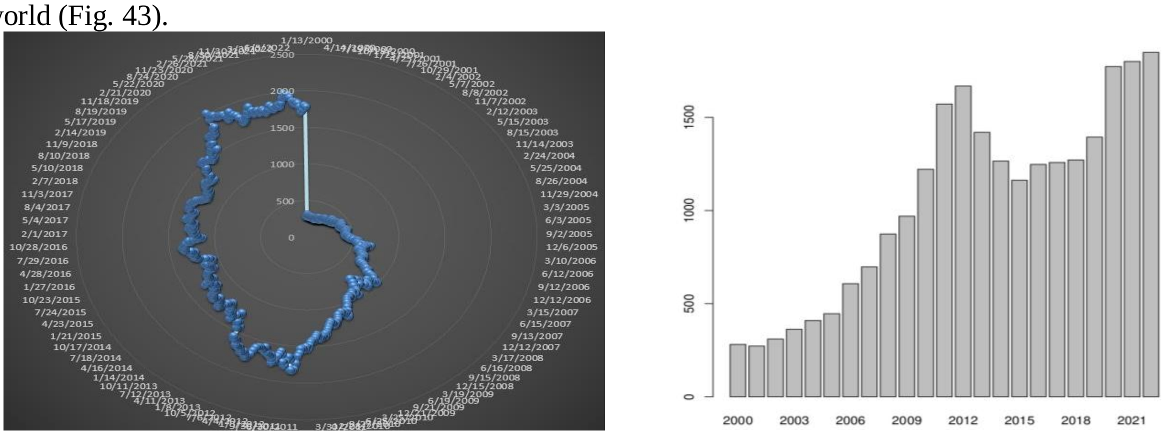


Figure 43: Pie chart and histogram for gold price correlation

Thanks to this visualization, the correlations of gold prices in certain periods are quite clearly visible.

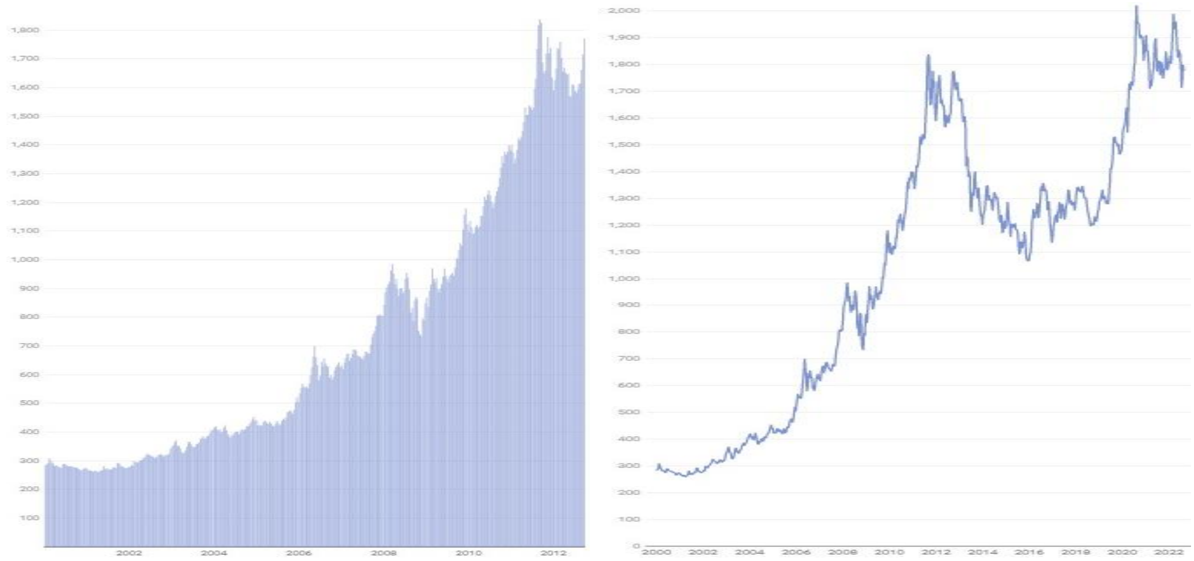


Figure 44: Histograms for gold price correlation

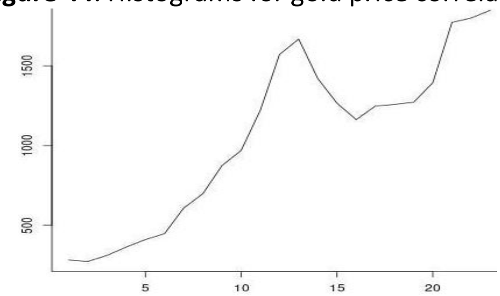


Figure 45: Cumulative and descriptive statistics

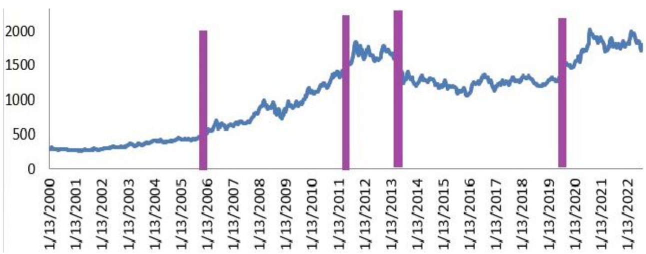


Figure 46: Gold price correlation chart

Results of descriptive statistics for correlations of gold prices:

1) Sample size – 712;
2) Arithmetic average – 1039.51938202247;
3) Median – 1190.95625;
4) Standard deviation – 518.597396331107;
5) Dispersion – 268943.259481404;
6) Excess – 1.75036169809394;
7) Amount – 740137.8;
8) Asymmetry – -0.0847406208547518;
9) Minimum – 259.175;
10) Maximum – 2020.5125;
11) Standard error – 19.4352591190456.

The main events that took place in the world in the period from 01.01.2000 were analyzed. to September 1, 2022, when there were significant changes in the schedule. In this way, the following analysis was obtained (Fig. 46). We see that every significant increase in the price of gold on the histogram is the result of certain market mechanisms. For example, in 2006 we can see an increase in the price of gold by more than 250 dollars per ounce of gold (31.1 g) compared to the beginning of 2005. This is caused by such a market mechanism as the devaluation of the national currency.

Currency devaluation is an official decrease in the gold content of a monetary unit or a decrease in the rate of the national currency to gold, silver, or a certain foreign currency. In modern conditions, the term is used for situations of a significant decrease in the rate of the national currency relative to "hard" currencies (usually relative to the US dollar).

After the Great Depression in the USA, President Roosevelt's government introduced the Federal Reserve System (FED), which enabled central planning and stabilization of state economies.

From 2006 to 2008, inflationary phenomena manifested themselves with relatively greater force. This wave of increasing inflationary processes is related not so much to the current state of the economy but to the manifestation of symptoms of the global economic crisis in general.

In 2008, the US Federal Reserve began mass issuance of the national currency, causing the dollar to devalue. Nevertheless, until 2008, there was a tendency towards a revaluation of the dollar against foreign currencies (for example, the hryvnia). Revaluation takes place by exchanging foreign currency for national currency with the help of currency speculation. Revaluation is an increase in the value of the national currency relative to foreign or international currencies.

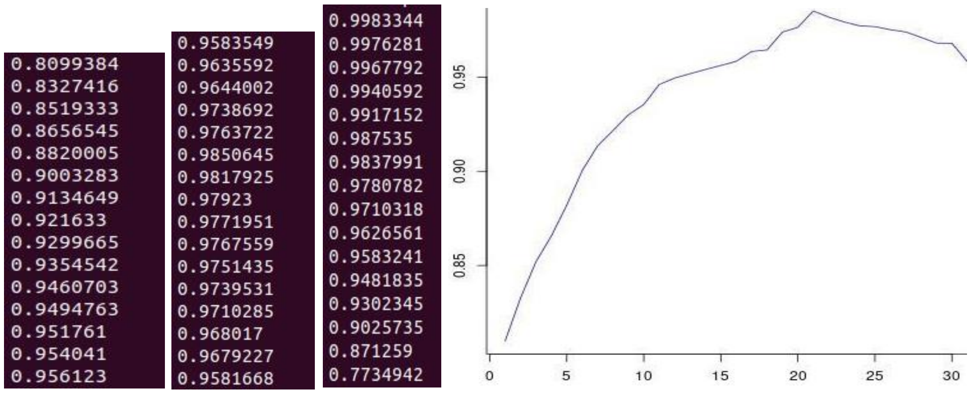


Figure 47: Execution of autocorrelation of our data and cumulative autocorrelation of our data

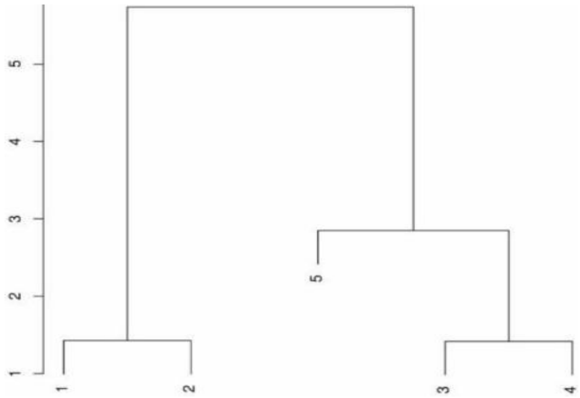


Figure 48: Visualization of cluster analysis using a dendrogram

At level 1.6, 2 clusters are formed: cluster–association 2008-2009 (d8); cluster - association 2010-2011 (d9). At level 2.8, 1 cluster is formed: the cluster is the union of 2012 and d9 (2008-2009 (d8)).

4.5. Correlation of the hryvnia price against the dollar

Fig. 49-50 shows the correlation of the hryvnia price against the dollar.

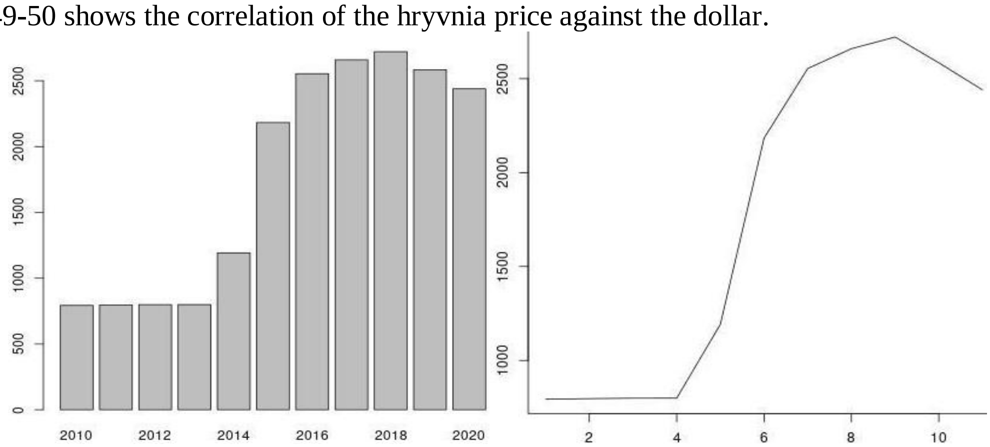


Figure 49: Histogram and cumulate in the language using the tools of the plot.r library

Results of descriptive statistics for correlation of the hryvnia price against the dollar:

1) Sample size – 2227;
2) Arithmetic average – 1719.68729506062;
3) Median – 1615.7817;
4) Standard deviation – 856.315950045983;
5) Dispersion – 733277.006303154;
6) Excess – 1.13853180346934;
7) Amount – 3829743.6061;
8) Asymmetry – 0.00222181320354175;
9) Minimum – 788.61;
10) Maximum – 3001.0175;
11) Standard error – 18.1457082906201.

```
   vars    n    mean     sd  median trimmed     mad    min     max   range skew
X1    1 2227 1719.69 856.32 1615.78 1704.06 1214.31 788.61 3001.02 2212.41    0
   kurtosis    se
X1    -1.86 18.15
```

Figure 50: Descriptive statistics using the library Psych.r

4.6. GDP of European countries for 2022

Consider 42 European countries and territories, in particular:

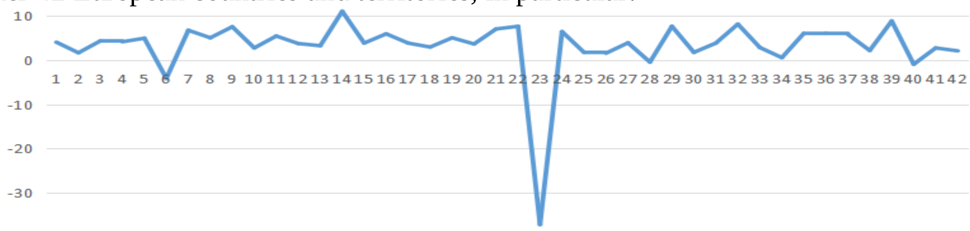


Figure 51: Cumulative, where Euro Area -1, Germany -2, United Kingdom -3, France – 4, Italy -5, Russia -6, Spain -7, Netherlands -8, Turkey -9, Switzerland -10, Poland - 11, Sweden -12, Belgium -13, Ireland -14, Norway -15, Austria -16, Denmark -17, Finland -18, Romania -19, Czech Republic -20, Portugal -21, Greece -22, Ukraine -23, Hungary -24, Slovakia -25, Luxembourg -26, Bulgaria -27, Croatia -28, Belarus -29, Lithuania -30, Serbia -31, Slovenia -32, Latvia -33, Estonia -34, Cyprus -35, Iceland -36, Bosnia and Herzegovina -37, Albania -38, Malta -39, Moldova -40, Macedonia -41, Kosovo -42

```
> plot(data$Inflation.Rate, data$GDP, type = "p")
> summary(data)
   Country               GDP            GDP.Year.over.Year GDP.Quarter.over.Quarterr Interest.Rate        Inflation.Rate    Jobless.Rate
 Length:42          Min.   :    9.00   Min.   :-37.200    Length:42                 Length:42           Min.   : 3.300   Min.   : 1.900
 Class :character   1st Qu.:   62.25   1st Qu.:  2.373    Class :character          Class :character    1st Qu.: 9.075   1st Qu.: 4.000
 Mode  :character   Median :  233.00   Median :  3.930    Mode  :character          Mode  :character    Median :11.635   Median : 5.750
                    Mean   :  930.67   Mean   :  3.246                                                  Mean   :14.950   Mean   : 7.104
                    3rd Qu.:  662.25   3rd Qu.:  6.075                                                  3rd Qu.:17.350   3rd Qu.: 8.400
                    Max.   :14493.00   Max.   : 11.100                                                  Max.   :83.450   Max.   :30.170
  Gov..Budget          Debt.GDP       Current.Account        Population
 Min.   :-8.900   Min.   : 18.10   Min.   :-11.6000   Min.   :  0.370
 1st Qu.:-6.150   1st Qu.: 41.52   1st Qu.: -2.8500   1st Qu.:  2.808
 Median :-3.900   Median : 54.90   Median : -0.7500   Median :  7.770
 Mean   :-3.569   Mean   : 64.83   Mean   :  0.1929   Mean   : 27.893
 3rd Qu.:-1.175   3rd Qu.: 79.38   3rd Qu.:  2.9500   3rd Qu.: 18.770
 Max.   : 9.100   Max.   :193.30   Max.   : 15.0000   Max.   :342.560
> 
```

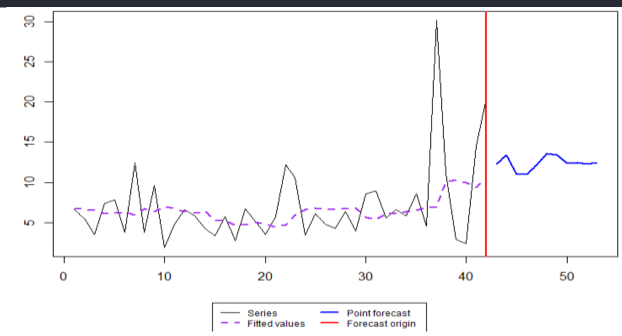
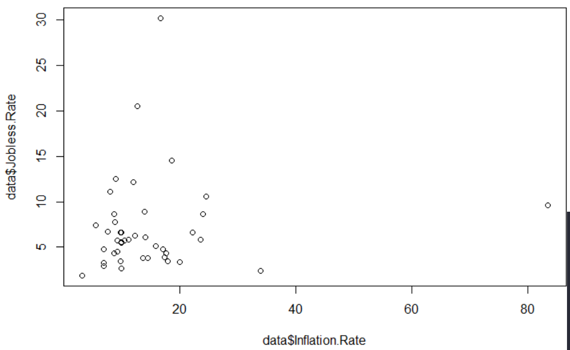


Figure 52: Smoothing schedule with forecasting

Let's construct a correlation of the inflation rating to the unemployment rating




```
> cor(data$Inflation.Rate, data$Jobless.Rate, method = 'kendall')
[1] 0.06690145
> cor(data$Inflation.Rate, data$Jobless.Rate, method = 'pearson')
[1] 0.1046556
> cor(data$Inflation.Rate, data$Jobless.Rate, method = 'spearman')
[1] 0.1123322
```

Figure 53: Correlation field and Correlation coefficients

A sample correlation coefficient is used to quantify the closeness of the relationship. The sample correlation coefficient r does not exceed unity in absolute value. For independent random variables, the correlation coefficient is zero, but it can be zero for some dependent variables, which are called uncorrelated. To determine the correlation coefficient, we will use three different methods: the Kendel, Pearson, and Spearman methods. When the paired statistical dependence deviates from the linear one, the correlation coefficient loses its meaning as a characteristic of the degree of closeness of the relationship. In this case, such a measure of communication as a correlation relation is used (Fig. 55a). Let's divide the sequence into three equal parts to build a correlation matrix for them (Fig. 55b).

```
df['Jobless Rate'] = df['Jobless Rate'].fillna(0)
df['Inflation Rate'] = df['Inflation Rate'].fillna(0)
X = np.array(df['Jobless Rate'])
Y = np.array(df['Inflation Rate'])
job = np.var(X)
inf = np.var(Y)
summ = job + inf
res = inf / summ
```

```
N = int(len(df['Inflation Rate']) / 3)
arr = [[random.randrange(0,10) for y in range(3)] for x in range(N)]
for i in range(int(len(df['Inflation Rate']))):
    if i < int(len(df['Inflation Rate']) / 3):
        arr[i][0] = (df['Jobless Rate'][i])
    elif len(df['Inflation Rate']) / 3 < i < 2 * len(df['Inflation Rate']) / 3:
        k = int(i - len(df['Inflation Rate']) / 3)
        arr[k][1] = (df['Jobless Rate'][i])
    else:
        k = int(i - 2 * len(df['Inflation Rate']) / 3)
        arr[k][2] = (df['Jobless Rate'][i])
print(arr)
```

Figure 54: a) Code to the task of correlation relation search – 0.8541093457326192 and b) dividing the sequence into three equal parts

The result of splitting the sequence:

```
[[6.6, 4, 3.9], [5.5, 5.7, 8.6], [3.5, 2.7, 8.9], [7.4, 6.7, 5.6], [7.8, 5.1, 6.6],
    [3.8, 3.5, 5.8], [12.48, 5.7, 8.6], [3.8, 12.2, 4.5], [9.6, 10.6, 30.17], [1.9,
    3.4, 11.1], [4.8, 6.1, 2.9], [6.6, 4.8, 2.4], [5.8, 4.3, 14.5], [4.3, 6.3, 20.5]
```

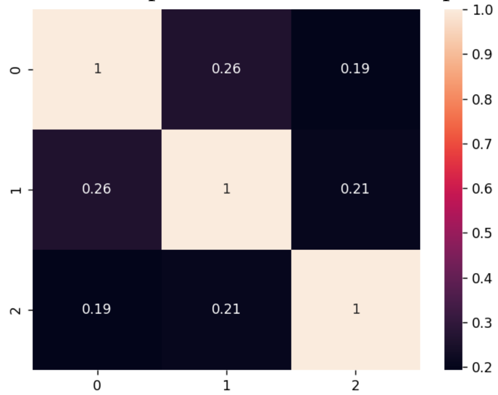
In the case of a large number of observations, when correlation coefficients must be calculated sequentially for several samples, for convenience, the obtained coefficients are summarized in tables, which are called correlation matrices.

```
data = pd.DataFrame(arr)
correl_matrix = data.corr()
print(correl_matrix)
```

```
          0         1         2
0  1.000000  0.261852  0.193440
1  0.261852  1.000000  0.209019
2  0.193440  0.209019  1.000000
```

Figure 55: Derivation of the correlation matrix

A heatmap was created to better represent the correlation.



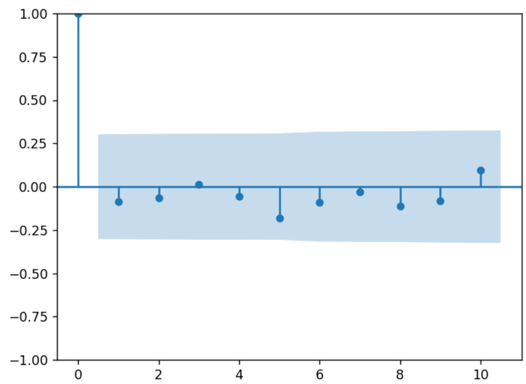


Figure 56: Heatmap and Autocorrelation Graph

The phenomenon of autocorrelation takes place in those cases when the correlation analysis is carried out on data for certain periods, the phenomenon of autocorrelation may appear, that is, the connection between data for previous and subsequent periods. In the presence of a trend and cyclical fluctuations, the values of each subsequent level of the series depend on the previous values. The correlation dependence between successive levels of a time series is called autocorrelation of the levels of the series. Cluster analysis for the GDP of Ukraine is one of the methods of multivariate statistical analysis, that is, data analysis when each observation is represented not by a single indicator, but by a set of values of different indicators (Country, GDP, GDP Year-over-Year, GDP Quarter-over-Quarter, Interest Rate, Inflation Rate, Jobless Rate, Gov. Budget, Debt/GDP, Current Account, Population). It includes some algorithms, with the help of which the formation of the clusters themselves and the distribution of objects by clusters is carried out. Cluster analysis, first of all, solves the problem of adding structure to the data, that is, their group homogeneity, and also ensures the selection of compact, distant groups of objects, that is, it looks for a "natural" division of the population into areas of accumulation of objects. Cluster analysis allows us to consider fairly significant volumes of data, sharply shorten and compress them, and make them compact and visual. To begin with, it is necessary to normalize the statistical data table built at the beginning of the work to obtain "object-property" table.

599,87805	1167,832968	68	233	14484	2341,577107	390,3421891	28,70864595	5,060396903	9	4223	39088	243,7020445
3,1483333	7,053353865	3,9	3,93	1,96	6,994027787	222,1501679	28,47422129	-4,896531893	-37,2	11,1	136,33	0,727910632
0,1319048	3,474733121	0,9	0,75	-3,1	3,40636926	2582,44601	28,07507106	-4,872300791	-19,2	3,9	6,34	0,354521382
3,887619	5,618767314	1,25	1,25	-1,75	5,480739113	140,9793255	6,55638671	2,529001501	0	25	164,53	0,570413557
14,711905	12,72078829	10	11,635	-2,7	12,46537037	84,72981966	22,76367185	4,289148564	3,3	83,45	627,9	1,297346236
6,9464286	4,78193491	6,6	5,75	-13,9	5,151837854	74,16527502	9,734989858	2,749748	1,9	30,17	298,35	0,536182821
-3,447619	3,563175868	-2,6	-3,9	-4,2	3,501880198	-101,5738732	2,626629411	1,150974438	-8,9	9,1	-149,9	0,364461781
62,553333	37,96181552	36,7	54,9	72,26	37,71827046	60,29777863	2,211769709	1,336074214	18,1	193,3	2722,84	3,925567772
0,1333333	5,495201335	2,5	-0,75	11,1	5,772406729	4329,305047	0,47345193	0,613500161	-11,6	15	8,1	0,600769164

Figure 57: Table "object-property" for GDP of Ukraine, where line 1 - GDP of Ukraine, 2 - GDP per year, 3 - GDP per quarter, 4 - interest rate, 5 - inflation, 6 - unemployment, 7 - budget, 8 - debt, 9 – account (column 1– Arithmetic average, 2 – Standard error, 3 – Mode, 4 – Median, 5 – Standard deviation, 6 – Dispersion, 7 – Coefficient of variation, 8 – Excess, 9 – Asymmetry, 10 – Minimum, 11 – Maximum, 12 – Amount, 13 – Reliability level).

Next, we build a proximity matrix.

59379,62616	41988,57491	42067,09283	41988,30437	41992,61516	41988,87827	41988,1297	42076,61546	42210,3483
41988,57491	375,2918275	2596,289693	343,6930121	692,9277702	407,8224364	321,6458795	2746,268222	4337,502029
42067,09283	2596,289693	3652,478115	2591,910704	2660,831657	2601,191141	2589,079428	3760,567159	5041,210179
41988,30437	343,6930121	2591,910704	308,8783213	676,3355864	378,9459994	284,1425744	2742,128749	4334,882327
41992,61516	692,9277702	2660,831657	676,3355864	905,2368936	711,0724847	665,4028935	2807,36426	4376,440196
41988,87827	407,8224364	2601,191141	378,9459994	711,0724847	437,943288	359,0699872	2750,902458	4340,437655
41988,1297	321,6458795	2589,079428	284,1425744	665,4028935	359,0699872	257,0373278	2739,452731	4333,190045
42076,61546	2746,268222	3760,567159	2742,128749	2807,36426	2750,902458	2739,452731	3865,63505	5120,065336
42210,3483	4337,502029	5041,210179	4334,882327	4376,440196	4340,437655	4333,190045	5120,065336	6122,663126

Figure 58: Proximity table for GDP of Ukraine, where line/column 1 - GDP of Ukraine, 2 - GDP per year, 3 - GDP per quarter, 4 - interest rate, 5 - inflation, 6 - unemployment, 7 - budget, 8 - debt, 9 – account

The cluster analysis procedure is based on recalculating the values of the proximity matrix and, as a result, at each such calculation step, objects, an object with a group, or two groups are combined. After each such union, the dimension of the matrix decreases by one, and the number of clusters or the number of objects in a particular cluster increases by one. The nearest neighbour strategy was chosen for the study of this dataset. The distance between two groups is defined as the distance between the two nearest elements from these groups. This strategy is monotonous and strongly compresses the feature space.

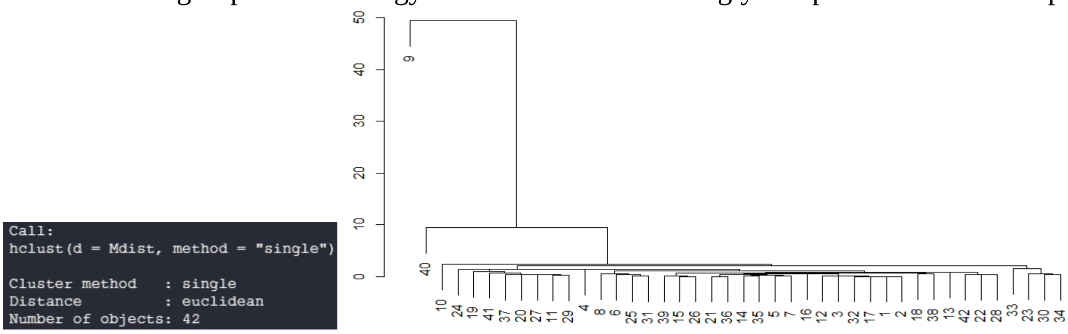


Figure 59: Cluster dendrogram for GDP of Ukraine

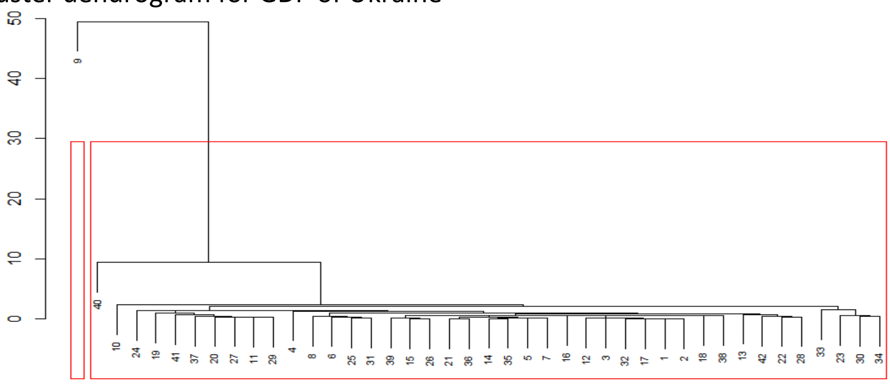


Figure 60: Dendrogram for two clusters for GDP of Ukraine

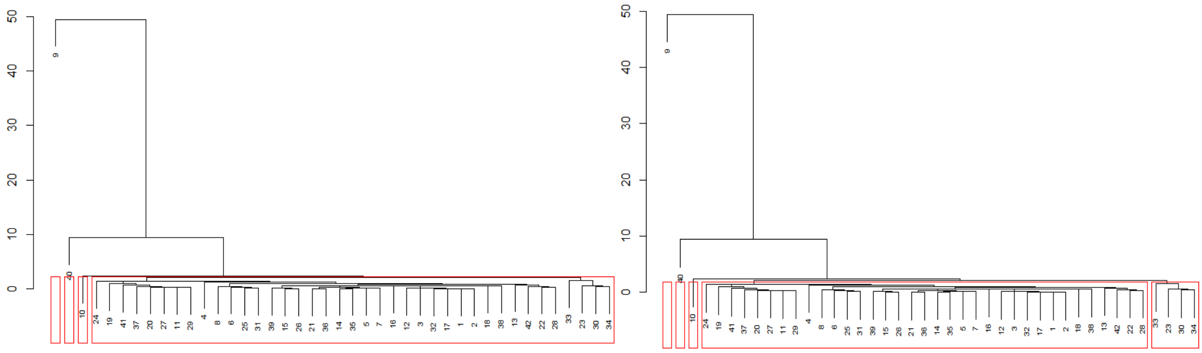


Figure 61: Dendrogram for four and five clusters for the GDP of Ukraine

During the study, a dataset with 250 elements was analyzed, which contains data on the change of the European currency against the dollar during the last year. The dataset contains the following data: date, session end price, session start price, session high price, session low price, session volume and price change percentage. Summing up the results of the analysis, we can say that the main hypothesis about the influence of political events on the economic situation in the world has been confirmed. With graphical representations of wheat prices and world inflation lines, as well as historical background on world crises, patterns such as war, political change, revolutions => inflation => and rising prices could be seen. To make the situation in Ukraine more specific, the war caused inflation, but it did not have such an impact on the world economy as the blockade of seaports, one of the main ways of supplying grain and other goods for export. This was the cause of inflation in Europe, rising prices for both wheat and other imported goods and the first steps of the food crisis. The situation stabilized after the "grain corridor" was established. Downward trends can be traced on the smoothing graphs, i.e. predictions that over time the situation will return to the pre-war norm or remain at a stable level (provided there are no new factors). Also, as a conclusion of the analysis, it can be stated that the price growth trends for gold and gas (or wheat) are different and, if in peacetime mainly money, gas or goods are in circulation, then during a crisis it is gold and precious metals (by value which political events have a much smaller, if not the opposite, impact). Market volatility and investor concerns may lead to a deterioration in the financial conditions of world countries. Currency depreciation and rising borrowing costs have opened up vulnerabilities and increased the risk of related consequences. In 2023, for the global economy, KPMG predicts GDP growth of 1.9% and inflation at the level of 4.7%.

5. Conclusions

The paper examines the level of unfavorable factors influencing the indicators of the development of the economies of Europe and the world, which were caused by the war in Ukraine. Taking into account the consequences of the war in Ukraine were considered from various points of view: economic, social, political, environmental, etc. The catastrophic consequences of the war in Ukraine negatively affected and continue to affect the development of European economies. The paper found that the rate of economic growth is rapidly decreasing, especially in Eastern European countries. The studied forecasts indicate a high probability of signs of recession in the countries of Eastern Europe. Under the influence of the war in Ukraine, the article identifies the signs of a migration crisis and a rapid increase in prices for necessities. Among the adverse impact criteria, which are recommended to be taken into account by the governments of the countries in the process of making management decisions, the volatility of prices for wheat, gold and gas, as well as fluctuations in the exchange rates of the dollar and the yen to the euro, are highlighted. It is recommended to consider the amount of 400 billion US dollars given in the report of the World Bank as a tenfold underestimated value when assessing the scale of damage caused to the economy of Ukraine. It is substantiated that the computational methods (cluster analysis, correlation analysis, etc.) used in the work are sufficient for determining the level of adverse effects of the factors of the war in Ukraine on the indicators of the development of the economies of the countries of Europe and the world

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