

RISK AND RETURN FOR CRYPTOCURRENCIES AS ALTERNATIVE INVESTMENT: KOHONEN MAPS CLUSTERING

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The active development of cryptocurrencies in recent years allows identifying the process of forming new class of alternative investment assets. There was formed a sample of cryptocurrencies based on criteria capitalization and historical returns for estimation investment risk of this asset class. The sample included 327 cryptocurrencies, each of which has a capitalization of more than \$ 1 mln. Measurement of investment risk was carried out on the basis of five approaches. The first one is grounded on the variability indicators. The second approach includes risk assessment in the context of asymmetry. The third is based on the concept of capital formation as part of the risk measures VaR and CVaR. The fourth focuses on measuring sensitivity risk. The fifth approach supposes using the Hurst exponent to measure risk. Based on the measures of these approaches, a comprehensive risk assessment was carried out. To cluster cryptocurrencies by riskiness, indicators from each group were selected, to which the technique of Kohonen self-organizing map was applied. The result was a partition of cryptocurrencies into three clusters. The analysis of the results is proposed and the corresponding conclusions and recommendations are made.

Keywords: *cryptocurrencies, alternative investments, risk measurement, Hurst exponent, Kohonen self-organizing map.*

РИЗИК ТА ДОХІДНІСТЬ КРИПТОВАЛЮТ ЯК АЛЬТЕРНАТИВНИХ ІНВЕСТИЦІЙ: КЛАСТЕРИЗАЦІЯ НА ОСНОВІ КАРТ КОХОНЕНА

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Активний розвиток криптовалют у останні роки дозволяє ідентифікувати процес формування нового класу альтернативних інвестиційних активів. Для оцінки інвестиційного ризику цього класу активів у дослідженні була сформована вибірка криптовалют, заснована на критеріях капіталізації та історичної доходності. Вибірка включала 327 криптовалют, які мали капіталізацію більше 1 млн дол. США. Вимірювання інвестиційного ризику здійснювалося на основі п'яти підходів. Перший з них заснований на показниках варіативності. Другий підхід включав оцінки ризику в контексті асиметрії. Третій ґрунтувався на концепції формування капіталу в межах мір ризику VaR та CVaR. Четвертий був сфокусований на ризику чутливості. П'ятий підхід передбачав використання для вимірювання ризику показника Херста. На основі мір із зазначених підходів було здійснено комплексне оцінювання ризику. Для кластеризації криптовалют за ризиковістю були вибрані індикатори з кожної групи, до яких була застосована технологія самоорганізаційних карт Кохонена. Результатом стало розбиття криптовалют у три кластери. Наведено аналіз отриманих результатів та зроблені відповідні висновки і рекомендації.

Ключові слова: *криптовалюта, альтернативні інвестиції, вимірювання ризику, показник Херста, самоорганізаційні карти Кохонена.*

РИСК И ДОХОДНОСТЬ КРИПТОВАЛЮТ КАК АЛЬТЕРНАТИВНЫХ ИНВЕСТИЦИЙ: КЛАСТЕРИЗАЦИЯ НА ОСНОВЕ КАРТ КОХОНЕНА

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Активное развитие криптовалют за последние годы позволяет идентифицировать процесс формирования нового класса альтернативных инвестиционных активов. Для оценки инвестиционного риска этого класса активов в исследовании была сформирована выборка криптовалют, основанная на критериях капитализации и исторической доходности. Выборка включала 327 криптовалют, которые имели капитализацию больше 1 млн дол. США. Измерение инвестиционного риска осуществлялось на основе пяти подходов. Первый из них основан на применении показателей вариативности. Второй подход включал оценки риска в контексте асимметрии. Третий основывался на концепции формирования капитала в рамках мер риска VaR и CVaR. Четвертый был сфокусирован на риске чувствительности. Пятый подход предполагал использование для измерения риска показателя Херста. На основе мер из указанных подходов была осуществлена комплексная оценка риска. Для кластеризации криптовалют по их рисковости были выбраны индикаторы из каждой группы, к которым была применена технология самоорганизующихся карт Кохонена. Результатом стало разбиение криптовалют на три кластера. Приведен анализ полученных результатов и сделаны соответствующие выводы и рекомендации.

Ключевые слова: криптовалюта, альтернативные инвестиции, оценка риска, показатель Хёрста, самоорганизующаяся карта Кохонена.

JEL Classification: C45, F31

1. Introduction

Origin of cryptocurrencies and their rapid growth illustrate the many-sided phenomenon of modern financial relations. This phenomenon is reflected in four characteristics of cryptocurrencies, which can be distinguished as fundamental [1, 2]. They are: decentralization, pseudoanonymity, transparency and low transaction costs. These characteristics provide attractability and genuine interest for cryptocurrencies. Decentralization is lack of any intermediary and regulator for account management and payments with cryptocurrencies. In contrast of classical banking payments cryptocurrencies payments can be fulfilled directly peer-to-peer. Pseudoanonymity and transparency are reflected in fact that participants of cryptocurrency's transaction (as example, buyers and sellers) typically use "public and private keys" [3]. They typically are not reflected real identifiers like surname, address etc. The lack of intermediary (such as bank in classical transaction) makes it difficult to identify the participator of transaction. However, given that cryptocurrencies use blockchain technology, it is incorrect to talk about complete anonymity. Blockchain technology is completely open in design. Every transaction has been recorded on the blockchain, which is publicly viewable. Public record of all transactions provides some possibilities to identify the parties of transactions, especially if a person's identity is linked to a public key. This means that in reality anonymity is being replaced by pseudo-anonymity.

Low transaction costs property is well illustrated by an example shown in [2, p. 10]: transaction fees in Bitcoin system on average 0,16 USD, whereas average transaction fees of international money transfer approximatively equal 7,09 % at the end of 2017.

The foregoing properties have proven to be useful. This is illustrated by extreme development of cryptocurrencies market. There were 2110 cryptocurrencies in March 2019 [4]. The capitalization of cryptocurrencies market in that time was 137,6B USD [5], but changing through the time essentially. There are different goals of possible using cryptocurrencies, which are described in [6]. If we

concentrate to cryptocurrency users, it is possible to indicate three basic directions of their using in aggregate form [3].

The first direction includes, in fact, the use of cryptocurrencies to pay for goods and services. Payments are realized without regulators and intermediators. There is no doubt that Bitcoin is atop. It is possible to pay by Bitcoin in many shops, restaurants and hotels. The net of sales outlet where possible to pay by Bitcoin is constantly raising. Other cryptocurrencies lag Bitcoin in this direction.

Second direction involve peer-to-peer payments. Peer-to-peer cash systems allow each person directly hand it to another person without any confirmations or approvals from anyone. The logic of peer-to-peer payments was established by unknown inventor of Bitcoin Satoshi Nakamoto in the paper “A Peer-to-Peer Electronic Cash System” [7].

Third direction of cryptocurrency concerns to hold them for investment purposes. It may be investment into one cryptocurrency or create portfolio from cryptocurrencies. More advanced investment strategies include combination cryptocurrencies with “classical investments” in one portfolio.

We focus our research within the framework of third direction. Taking into account modern division of investment classes on traditional and alternative [8] we consider cryptocurrencies as alternative investment assets. The important question of considering cryptocurrencies as alternative investment concerns analysis of “risk-return correspondence” inside this asset class. We have considered risk in our research from different points of view and have used different risk measures. Classification of cryptocurrencies based on risk-return correspondence with different risk measures is the goal of our research. We have applied tools of self-organizing maps (SOM) for goal attainment.

The structure of our article is following. Chapter 2 is devoted to the approaches for investment risk measurement. Strengths and weaknesses of each approach have been discussed. Additionally, we have added into consideration Hurst exponent. The logic of interpretation of Hurst exponent as risk measurement is presented at [9]. Chapter 3 presents data mining for cryptocurrencies. Chapter 4 contains basic results of our research — using the SOM for clustering cryptocurrencies by riskiness based on parameter sets of with and without Hurst exponent. Chapter 4 also covers issues of risk-return correspondence analysis, which disclose the specificity of crypto-

currencies as alternative assets. Last Chapter presents conclusions from our research.

2. Investment risk measurement

One of the basic characteristics of investment is return. The classical return of asset over a period of time $[t; t + 1]$ will be expressed through formula:

$$R_{t,t+1} = \frac{P_{t+1} - P_t}{P_t},$$

where P_t and P_{t+1} prices of such asset at times t and $t + 1$ correspondingly. Our research considers P_t as price of corresponding cryptocurrency in USD. Typically, $R_{t,t+1}$ will be a random variable, because future price P_{t+1} is unknown. Thereafter R , which reflect return through the time, is also random variable.

Other approach is based on the using logarithmic return which define by formula:

$$R_t = \ln\left(\frac{P_{t+1}}{P_t}\right).$$

In our research we use classical returns. This type of return we apply to cryptocurrencies, the values of which are presented in USD.

Risk measurement supposes to introduce some mapping ρ , to which for each random variable R (representing return of investment asset) assigned non-negative number $\rho(R) \in [0; +\infty]$. The representation of $\rho(R)$ is characterized by approach which selected for risk measurement. In reality there are very many risk measures which were introduced during consideration of risk in finance and investments. We have structured “risk measurement environment” into 5 approaches which are presented below. These approaches are not comprehensive set, but they present basic logical considerations adopted in modern investments.

First approach which we have analyzed for risk measurement is variability approach. This approach is based on the classical point of view, which originate by H. Markowitz. In some extend, this approach may be considering as “theoretical approach”, because it has been applied for modern portfolio theory. The simplest risk measure

here is a range, which equals to difference between maximum and minimum possible values on the considered time interval $[0; T]$:

$$L(R) = \max_{[0,T]} R(t) - \min_{[0,T]} R(t).$$

The range is important indicator from the point of view of getting a general understanding of future possibilities (it is assumed that future distribution will be the same as historical distribution). The shortcoming of range is that maximum and minimum prices were realized on peak and crisis time. These may be rare events and not relevant for periods of stability. This range also depends from time horizon, which we considered. Consequently, it is more efficient to use inter-quartile range as difference between 75 % and 25 % quantiles:

$$Q(R) = Q_{75\%}(R(t)) - Q_{25\%}(R(t)).$$

Of course, the best known risk measure using in this approach is standard deviation which characterizes deviation from mean value. Also, in the frameworks can be effectively used Absolute Mean Deviation (AMD).

Second approach of risk measurement concerns asymmetry. In reality, deviations from the mean up and down illustrate a different significance in terms of risk. One of such approach is based on division standard deviation into pair of semi-standard deviations: upper and lower. They have following representations:

$$\sigma^+(R) = \sqrt{\frac{1}{T} \cdot \sum_1^T (R(t) - E(R))^2}, \text{ where } R(t) > E(R),$$

$$\sigma^-(R) = \sqrt{\frac{1}{T} \cdot \sum_1^T (R(t) - E(R))^2}, \text{ where } R(t) \leq E(R).$$

This pair $(\sigma^+(R), \sigma^-(R))$ more deeply reflect deviations then standard deviation. The benefits of such measures concern with clear visibility of asymmetry when it done graphically at the plane.

One of the important asymmetry indicators is skewness. Skewness reflects the expectation of the deviation from the mean to the third power:

$$S(R) = E \left(\frac{R - E(R)}{\sigma(R)} \right)^3 = \frac{E(R - E(R))^3}{\sigma^3(R)}.$$

Negative skewness indicates a long left tail of distribution, or the possibility of larger losses than profits. Positive skewness is desirable characteristic for risk-averse investors. The motivation of that is grounding at the expected utility theory. Typically, the third derivative of utility function of risk-averse investor is positive (see e.g. [10]) and this derivative is multiplier for skewness in Taylor expansion of expected utility.

Next approach includes losses in negative situation. This approach conceptually based on interpretation of such situations and measurement of losses under their occurrence. The most used measure among this group is Value-at-Risk (VaR) [11].

This measure presents quantile of distribution function of random variable R which correspond for some probability (or confidence) level (typically 99 %, 95 %). The main advantage of VaR is intuitively understandable value of losses, based on reliability logic. Really, if investor forms capital for covering possible losses in 99 % than this number indicate reliability level 99 %. VaR integrally combines three crucial elements: 1) confidence level; 2) possible losses; 3) time horizon during which losses may be happened. One of the basic problems with VaR arises from the fact that it is only one point of distribution function. It concerns to the possibility of presence of long thin tail of distribution which will not take into account by VaR.

Risk measure CVaR (Conditional value-at-risk) is generalization of VaR. CVaR is defined through VaR and shows average losses higher than VaR:

$$CVaR(R) = E(Losses | Losses \geq VaR).$$

The advantage of CVaR is coherency property which is very important for assessing the risk of investment portfolio. VaR cannot support the subadditivity property for probability distribution functions which are different from elliptical class. The subadditivity is mathematical formalization of diversification.

At the framework analysis of possible essential losses, an important indicator is the ratio CVaR/VaR. This ratio can be considered as risk measure which characterize heavy tail risks.

Fourth approach of risk measurement is based on sensitivity assessment. Namely, investment risk can be measured by approach based on estimation of sensitivity level of return for some index or

factor. Mathematically this can be expressed by simple linear regression:

$$R_A = \alpha_A + \beta_A R_I + \varepsilon_A,$$

where R_I is a market index return and ε_A is “own” return of asset A. It is supposed that $Cov(R_I; \varepsilon_A) = 0$.

Such approach is very important with purpose to divide risk to so called systematic and non-systematic parts. In general, systematic risk is generated by market as a whole (more correctly, by factors which affect to the whole market). Non-systematic risk is raised from own randomness of asset's return. This division can be good presented through applying variance operator to the abovementioned formula. Really, applying to this formula operator of variation we will receive following decomposition:

$$\sigma^2(R_A) = \beta_A^2 \sigma^2(R_I) + \sigma^2(\varepsilon_A).$$

The pair of indicators (systematic risk; non-systematic risk) can be presented by percentages of risk constituents:

$$\left(\frac{\beta_A^2 \sigma^2(R_I)}{\sigma^2(R_A)}; \frac{\sigma^2(\varepsilon_A)}{\sigma^2(R_A)} \right).$$

Our research supposes the analysis of the CRIX cryptocurrency index [12] for this approach.

Last from the considered approaches includes Hurst exponent (H), which is a statistical measure applied to classify time series. Risk measuring based on this exponent is presented in [9]. The core of risk measuring by means H lies in higher predictability for a higher level of H . Thus, $H = 0,5$ indicates a random series, but $H > 0,5$ indicates some trends. Conversely, the inequality $H < 0,5$ characterizes anti-persistent quality.

So, abovementioned 5 approaches were considered to assess the risk of cryptocurrencies.

3. Data which was used in researches

We used in our research data from four information resources [13-16] devoted to cryptocurrencies. These resources contain significant information for carrying out statistical research in accordance with objectives of our investigation. First of all, these resources present statistical data of cryptocurrencies prices in USD. Secondly, market capitalization indicators and trading volumes can be founded there. We apply these indicators to build the sample. Thirdly, resources show prices changing (including graphically) through different time periods.

It is necessary to note, that resources differ in saturation of information. The resource [13] was chosen as the base data source. The resource Investing.com contains information about different prices of more than 2000 cryptocurrencies. This resource is very useful because it contains information in one standard for traditional and alternative investment assets. The site [14] presents information about wide set of cryptocurrencies and resource [16] combines information about 119 cryptocurrencies with largest capitalization. Using these resources provided possibility to form an accurate database for our analysis. The issue of data accuracy is actual because sometimes data includes gaps. Additionally, many cryptocurrencies were launched relatively recently, and they were excluded from the sample.

We introduced following criteria for sampling taking into account the focus of our research on the characteristics of cryptocurrencies as an investment asset:

1. Capitalization level. The cryptocurrencies selected for the study should have a capitalization of more than 1M USD. Sense of this criterion is based on the desire to withdraw from consideration the cryptocurrencies with low capitalization. Such low capitalize cryptocurrencies are very difficult to consider as investment asset. Moreover, essential investments can significantly change the prices of such cryptocurrencies. Besides that, many cryptocurrencies have not capitalization at all because their prices equal 0.

2. Availability of trading data from approved for our research time interval. We used 2-years' time interval from 01.07.2017 to 30.06.2019. Cryptocurrencies which started trading after 01.07.2017 were withdraw from considering in our research.

3. Exclusion of cryptocurrencies with highly abnormal data. Prices of some cryptocurrencies rose extremely from 0 and indicated abnormal returns. Taking into account that such abnormality indicates possible instability of assets in the future, we also withdraw their.

As a result of using such criteria for the selected information resources, our sample amounted to 327 cryptocurrencies. For this sample, we calculated the values of daily classic R for the mentioned period.

In addition to the considered cryptocurrencies we used values of index CRIX (CRyptocurrency IndeX), which we have applied to the sensitivity analysis. Index CRIX was elaborated by specialists from Bortkiewicz Chair of Statistics at Humboldt University (Germany) together with SKBI at Singapore Management University and CoinGecko (description of index is here [12]).

Correlation analysis was applied to formed database of returns. Such analysis indicates high level of interdependency within each group of risk measures. As a consequence, we selected one risk indicator from each group. They are:

1. Inter-quantile range;
2. Skewness;
3. Value-at-Risk;
4. Beta coefficient for returns of index CRIX;
5. Hurst exponent.

These 5 risk indicators formed vector for application tools of SOM. The calculations in our research were performed in the programming language R.

4. Constructing the SOM and clustering

We have considered two alternatives for clustering through designing SOM. First alternative supposes to use all 5 selected indicators (model # 1). The second one excludes the Hurst exponent (model # 2). Given the same parameters of the clustering models, comparing the results with this approach may allow us to evaluate the relationship between risk and the expected profitability of cryptocurrencies.

Taking into account the difference in the ranges of the input variables, it was decided to normalize the data: for each characteristic in the input data the average value is calculated and divided by the

standard deviation. With this approach, the characteristics are normalized as follows:

$$X^* = \frac{X - \bar{X}}{\sigma_X},$$

where X^* is the normalized value of characteristic; X is the value of the characteristic; \bar{X} — the average value; σ_X — the standard deviation of X .

The entire sample was divided into 80 % for training sample and 20 % for verification. But given the small sample size, in some cases it makes sense to use K-fold cross-validation. In turn, to construct a SOM it is necessary to determine the optimal dimension of the neural network. In the midst of the alternatives under consideration, we have chosen a 40 by 30 map, which is 1200 neurons. This dimension allows us to visually adequately assess the quality of neural network construction and identify some patterns of data.

The optimal number of neural network training iterations was determined experimentally: after the 1500th neural network training run, the average error of the self-organization map for training and verification samples reaches its minimum. The recognition rates for these samples are approximately 99 % and 80 %, respectively.

Before starting training it is necessary to initialize the weighting coefficients of neurons. We chose an approach in which the initial weights of the map neurons would be initialized by the values of the subset of the hyperplane through which the two main eigenvectors of the covariance matrix of the input values of the training sample pass. This approach helped to accelerate the learning process of the network and obtain better clustering results.

The final parameter of network learning is the neighborhood function, which defines the topological zone of influence of the winning neuron. In our case, the Gaussian function was chosen since it takes into account all the neurons in the network, but with varying degrees of impact. With this approach, the learning process takes a little longer, but the quality of the clustering results may be better than with other neighborhood functions.

As a result of modeling we obtained SOMs for two considered models. First model includes the entire list of input indicators. The Fig. 1 illustrates the SOM and Sammon's projection for the model # 1.

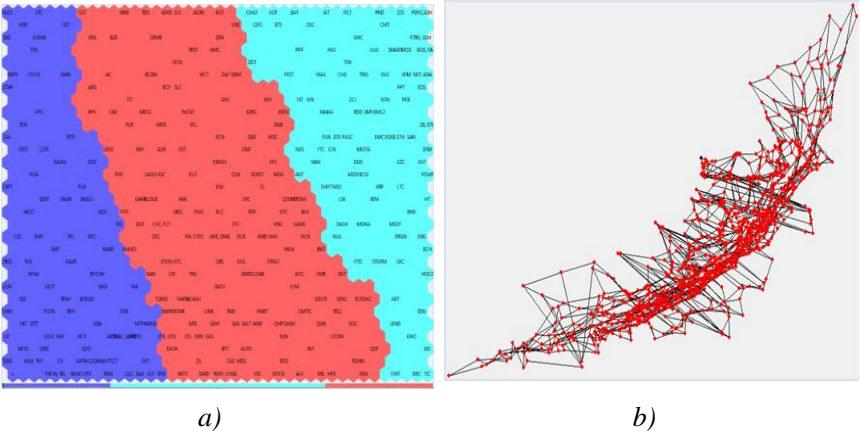


Fig. 1. Visualization of cryptocurrency clustering by model # 1:

- a) self-organizing map;
- b) Sammon's projection.

Second model was constructed without Hurst exponent. The SOM and Sammon's projection are presented at the Fig. 2.

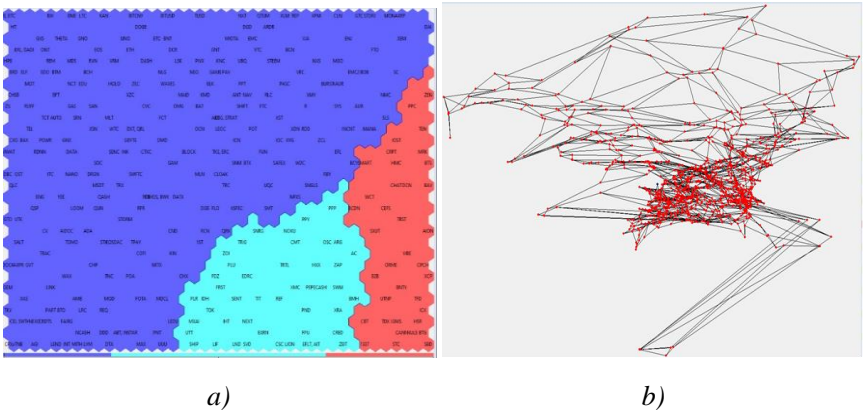


Fig. 2. Visualization of cryptocurrency clustering by model # 2:

- a) self-organizing map;
- b) Sammon's projection.

As can be seen from the simulation results, the model based on all indicators (Fig. 1) shows a certain polarity of cryptocurrencies, while the alternative model (Fig. 2) does not have such properties. This is confirmed by the projection of Sammon. At the same time, model # 1 demonstrates a higher contrast of the distribution of cryptocurrencies capitalization across clusters (see Table 1, where CAP is the capitalization of the corresponding cluster).

Table 1

MEAN AND STANDARD DEVIATION OF INPUTS BY CLUSTERS

Clusters	Model 1			Model 2		
	1	2	3	1	2	3
Mean CAP	19 468 341	2 284 887 859	63 099 457	906 751 538	7 871 438	102 514 982
RMSE CAP	31 182 828	15 366 292 314	261 012 706	9 588 895 624	11 612 761	383 205 452

For the purpose of comparing the measures of risk and profitability of cryptocurrencies of various clusters, we consider Tables 2 (for model # 1) and 3 (for model # 2).

Table 2

RISK AND PROFITABILITY MEASURES FOR MODEL # 1 CLUSTERS

Indicators	Cluster 1		Cluster 2		Cluster 3	
	Average*	Standard deviation*	Average*	Standard deviation*	Average*	Standard deviation*
Interquantile range	0,235	1,207	-0,079	1,104	-0,080	0,770
Skew	0,197	1,342	-0,101	0,658	-0,040	0,947
VaR	-0,152	0,945	-0,033	1,382	0,104	0,702
Beta CRIX	0,050	1,241	-0,104	0,908	0,036	0,906
Hurst exponent	-1,262	0,519	1,196	0,484	-0,043	0,343
Expected Return	-0,052	0,305	0,213	1,797	-0,104	0,290

*normalized values

Table 3

RISK AND PROFITABILITY MEASURES FOR MODEL # 2 CLUSTERS

Indicators	Cluster 1		Cluster 2		Cluster 3	
	<i>Average*</i>	<i>Standard deviation*</i>	<i>Average*</i>	<i>Standard deviation*</i>	<i>Average*</i>	<i>Standard deviation*</i>
Interquantile range	-0,359	0,478	1,890	1,075	0,080	0,876
Skew	-0,365	0,350	0,042	0,669	2,369	1,009
VaR	0,324	0,345	-1,613	1,660	-0,184	0,948
Beta CRIX	0,181	1,069	-0,535	0,308	-0,545	0,568
Expected Return	-0,102	0,960	0,211	0,522	0,384	1,337

**normalized values*

An analysis of the results enables to make findings about better visualization at the model # 1, where Hurst exponent was involving into consideration. It follows from the completion of the clusters and Sammon`s projections. We think that such results indicate the role of Hurst exponent for the estimation risk of cryptocurrencies.

One of the directions of our research was focused to the verification of classical “risk-return” relationship (when higher risk is compensated by higher return). The results have shown that such classical relationship is absent between clusters of SOM. There is some divergency of correspondence between risk and return.

5. Conclusions and outlook for future research

Cryptocurrencies is one of the dynamically growing segments of modern financial system. Currently, there are about 2000 types of cryptocurrencies. They perform different financial functions, one of which is investing. From this point of view, cryptocurrencies can be considered as an investment asset. Investment means that cryptocurrency can provide growth in price and it is possible to sell it more valuably.

The aim of our research was clustering cryptocurrencies by risk level on the base of Kohonen self-organizing map techniques. It’s

supposed that clustering will represent investment structuring within the frameworks of the risk-return ratio. A set of risk measures has been formed that represent different approaches to measuring risk. The results of risk assessment by these measures allowed forming the vectors of cryptocurrency estimations, which became the basic for applying the Kohonen SOM methodology.

As a result of study, two models based on SOM were built, one of which includes Hurst exponent, and the other without it. We have found that including into consideration Hurst exponent significantly affects to the SOM structure — the map in this case looks like more substantive.

The hypothesis of the existence of classical dependency between risk and return was rejected by our research. We can explain this result with two arguments. First argument is that the change in the price of cryptocurrency depends on supply-demand factors. But the supply and demand for cryptocurrencies are not realized on an investment basis. Participants of cryptocurrencies market make demands for buying or selling dominantly out of investment logic.

Second argument is that cryptocurrencies are not tangible assets for most part. They are typical examples of intangible assets [17]. It is possible to assume, that classical approaches to risk measurement are not quite adequate for such assets as cryptocurrencies.

The perspectives of risk-return concordance investigations for these assets underpin the development of specific procedures of risk measurement. Moreover, it may be logical to divide the set of cryptocurrencies into two types, one of which should include cryptocurrencies with investment properties, and another should include all the others.

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