3.5. Risk modelling of alternative investments

Modern financial investments can be structured into two types. The first type is traditional investments, which include publicly traded equities, fixed income securities, and cash. The second type is alternative investments, which are broadly defined as all those that are not traditional. Such an approach to definition covers a very wide class of investments, which are sometimes difficult to consider as financial. Often, they cannot be used by financial institutions in the design of their portfolios. For example, antiques, collection wines, and others fall into this category. In our study, we are based on the approach to characterize alternative investments through the "by inclusion" approach. There are also arises of multidirectional inclusion of various assets represented by various publications. At the same time, we take as a base the classes of alternative assets presented in [1]. There are four basic classes of alternative investments indicated there:

Real assets

Hedge funds

Private Equities

Structured products

They are different parts of total capitalization. The distribution of capitalization in 2017 was as follows [1]. The class of real assets has 36% of total capitalization, the class of hedge funds indicates 28% and the class of private equities indicates 35%. The class of structured products has only 1% of total capitalization. According to PwC estimates, in the baseline scenario, the market capitalization of the first three classes will be 13.6 trillion USD in 2020 [2]. It should be noted that another asset class, which has been actively developing over the past 5 years, is not included in this structuring. We are talking about cryptocurrencies, which according to [3] in March 2020 already had more than 5.2 thousand types. At the same time, the cryptocurrency market as an alternative investment is still small in comparison with the above. It is approximately

190 bln USD in march of 2020 [4]. Therefore, in this study, we did not analyze it. However, such an analysis is presented in [5].

The alternative investment market is an actively developing segment that brings new opportunities for investors. Opportunities are determined by two properties of such investments. The first is the risk-return ratio, which is different from similar ratios for different classes of traditional assets. To simplify, we can talk about higher returns associated with greater risk. The second property is the low correlation of alternative investments with traditional assets and between different classes of alternative assets. This determines the main interest of portfolio investors in alternative investments. Because, by adding a certain percentage of alternative assets to the portfolio of traditional assets, the expected return on the portfolio increases. However, the risk may not be increased due to the diversification effect. Thus, increasing the expected return while maintaining the risk level of the portfolio is of investment interest.

A special impetus for the use of alternative investments is the emergence and development of such tools as ETFs (Exchanged Traded Funds). Using this tool can greatly simplify the formation of investment portfolios, including ETFs that reflect alternative investments. Moreover, this allows us to systematize the risk analysis of various alternative assets, which, in fact, is the basis of our study.

Materials and Methods. Our study was based on several methodological starting points. In fact, the choice of these points which determined the significance of the calculations and the possibility of applying the results.

The first point is the use of ETFs as a basic investment tool. ETFs returns on alternative investments are at the core of our risk analysis and modeling. The first ETF was introduced in 1989 and now this is a very popular financial instrument. The capitalization of ETF exceeded 4 trillion USD. Exchange-traded funds are set up to mirror the performance of indexes or sub-indexes. It is very suitable for modeling alternative investments return. Because typically institutional investors do not want to buy “real” commodities or precious metals. ETFs provide the possibility to form portfolios through the financial instrument which indicates indices of many alternative investments. ETFs trade on stock exchanges, just like stocks. That's different from mutual funds, which you can only buy at the end of the day at a price that reflects the fund's value at the close of trading. ETFs are less expensive to hold in the portfolio. ETFs give a low-cost way to invest in a narrow market segment. That's typically cheaper than investing in a mutual fund with a similar focus. They also more simply and understandable which attract individual investors from middle class.

It is necessary to note that general market includes ETFs and ETNs (Exchange Traded Notes). Our research combine in one class for which we use the term "ETF".

As the second starting point of the study, we have chosen the breadth of coverage of alternative investments. This, in turn, led to a representative sample of the types of alternative investments included in the analysis. As a basis, we chose the following ETF database: ETF Database [6]. This database was established in 2009 year. From our point of view now it is the world's largest ETF-focused digital database. This database structured alternative investments for ten categories of ETF and we have included categories into our sample presented into Table1. The figures into the braces show how much ETF are involving into corresponding categories.

Table 1

Classes of alternative investment

Real Assets		***Hedge Funds***	***Private equities***
Commodities	***Real Estate***		
Agricultural commodities ETFs (19)	Real estate ETFs (30)	Hedge Funds ETFs (23)	Private equities ETFs (8)
Commodities ETFs (9)	Global Real Estate ETFs (6)	Long short funds ETFs (26)	
Metals ETFs (9)			
Oil & Gas ETFs (15)			
Precious Metals ETFs (25)			

Totally the initial sample of alternatives includes 194 with capitalization 149,1 billion USD and the middle of March 2020.

Next, our step in this direction was withdrawing from consideration ETF with capitalization lower 10 mln USD. The basic reasons for the following. First of all, it relatively small for portfolio investment strategies of institutional investors. Also, it may be a very volatile price when some large buying will be held. After withdrawing from consideration small ETFs we have analyzed the availability of data. There was formulated condition about the available data of ETF trading for 5 years. This condition was raised from a desire to construct a representative data sample. There are 5*52=260 weekly data of return and we think that sample is representative. After applying all conditions we have received 83 ETF with total capitalization 138,6 bln USD. Total capitalization did not change essentially (93%).

Third, our crucial focus was based on the complex understanding risk of investing. Classically, risk is potential losses as a consequence of uncertainty [7]. We have structured our research in two directions. The first direction involves represented risk by one number. This approach named risk measurement and logically include mapping from the probabilistic nature of uncertainty to positive numbers. If R represents the return of investment asset, then risk measurement is:

$$\rho(R) \rightarrow [0;+\infty] \tag{1}$$

In our research we use weekly returns of ETFs from the sample.

So, risk measurement supposes to introduce some mapping ρ which each random variable R assigned a non-negative number.

There are many risk measures are using in theoretical researches and practice application. See for example [8]. We divided risk measuring in our research into 3 groups:

1. Risk measurement through volatility approach.
2. Risk measurement through Value-at-Risk (VaR) methodology.
3. Risk measurement through sensitivity indicators.

Combining results of risk measurement obtained in different approaches we formed a complex vision for risk of alternative investments. It follows to achieve the goal of our research.

The second direction of our risk modeling is the estimation of probability distribution functions (pdf) of chosen ETF`s returns. This purpose was realized by using product EasyFit 5.6. EasyFit supports over 50 continuous and discrete probability distributions. The estimation of better fitting of pdf for historical data is possible to do by means of 3 criteria. They are Kolmogorov-Smirnov, Darling-Anderson, χ-squared

The logic of it modeling is finding what class of distributions is fitting better for corresponding ETF classes. One of the important questions here is to analyze the behavior of the tail of the distribution. Long and/or heavy tails are indicators of the potential high risk of extremal deviations.

Risk measurement through volatility approach. This approach was originated from Harry Markowitz's papers devoted to portfolio theory foundations [9]. Markowitz proposed standard deviation as a portfolio risk measure and created efficient frontier at the plain “standard deviation-expected return”. So, the picture of investment options at this plain is standard for visualization risk-return correspondence. Below we illustrate the presentation of our sample of ETFs at this plain.

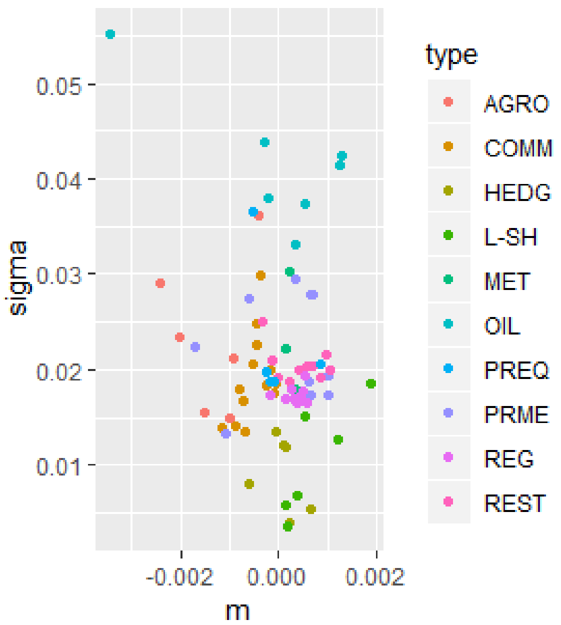

Fig. 1. A figure caption is always placed below the illustration. Short captions are centered, while long ones are justified. The macro button chooses the correct format automatically

Other risk measures of such approach involve:

Range

Inter-quantile range

Semi-standard deviations

Skewness

Kurtosis

The range is the simplest risk measure which equals the difference between the maximum and minimum possible values of return R:

$$L(R) = \max_{[0,T]} R(t) - \min_{[0,T]} R(t) \tag{2}$$

Range as risk indicator is important for investors from the point of view of receiving a general vision about future possibilities (it is assumed that future return`s behavior will be the same as historical return`s behavior). The shortcoming of applying range is that maximum and minimum returns were on peak and crisis times. These may be rare events and not relevant for periods of stability.

Inter-quartile range to some extent change logic of range because focuses on 50% basic (or central) values. The definition of this difference between 75% and 25% quantiles:

$$Q(R)=Q_{75\%}(R(t))-Q_{25\%}(R(t)) \tag{3}$$

Risk measures as semi-standard deviations and skewness characterize risk from the point of asymmetry. The background of asymmetry is raised from the expected utility theory. Typically, the third derivative of the utility function of risk-averse investor is positive[10] and this derivative is a multiplier for skewness in Taylor's expansion of expected utility. So, expected utility will increase when positive skewness and will decrease when negative skewness. Speaking in general terms, negative skewness indicates a long left tail of the distribution, or the possibility of larger losses than profits. Positive skewness indicates a long right tail of distribution which connected with possible high returns. Analysis of asymmetry estimation based on the skewness is presented in Table 4.

Semi-standard deviations can be defined through the specific transformation of the definition of standard deviation. The logic is considered independently deviations from mean upward (designates as $\sigma^+(R)$) and downward (designates as $\sigma^-(R)$). Asymmetry can be presented graphically at the plain ($\sigma^+(R)$; $\sigma^-(R)$).

Kurtosis is an important risk measure which "tries to catch" long tail of probability distribution function.

Of course, volatility measures involved in our consideration not all possible.

We decide to consider by means comparative analysis range, standard deviation and kurtosis. Our results present in Table 2.

Table 2

Risk measures.

	Range	*STD*	*Kurtosis*
AGRO	0,1476	0,0233	0,5879
COMMODITIES	0,1058	0,0191	0,3111
PRECIOUS METALS	0,1370	0,0210	0,6569
HEDGE	0,0691	0,0091	2,1889
LONG SHORT	0,0804	0,0113	2,0206
METAL	0,1548	0,0235	1,0001
OILS	0,2487	0,0417	0,2976
REAL ESTATE	0,1278	0,0205	0,5933
PRIVATE EQUITY	0,1774	0,0229	4,3696
REAL ESTATE GLOBAL	0,1089	0,0174	0,9497

The question of classification alternatives investments according to these three measures provide us by interesting results.

We have normalizing by each measure of risk for ordering from high risk to low risk. There was applied following "natural" normalizing approach:

$$N(RM) = \frac{X_i - min(X_i)}{max(X_i) - min(X_i)} \tag{4}$$

Where RM is risk measure, X_i are risk measure values for ETF classes (see Table 3).

The values were divided for three group. First group is characterized by low risk with condition $\leq 0{,}25$. Second group correspond to average risk $0{,}25 \leq$ and $\leq 0{,}5$. Higher risk presents in third group with condition $0{,}5 \leq$.

The analysis of results leads to conclusions that risk measures range and STD provide similar ordering, but kurtosis provides different ordering. The most risk class of ETF is “Private equities” (see Table 4).

Table 3

Normalizing values of risk measures.

Range normalizing		*STD normalizing*		*Kurtosis normalizing*	
ETF classes	N(C1)	ETF classes	N(C2)	ETF classes	N(C3)
OILS	1,000	OILS	1,000	PRIVATE EQUITY	1,000
PRIVATE EQUITY	0,603	METAL	0,443	HEDGE	0,464
METAL	0,477	AGRO	0,437	LONG SHORT	0,423
AGRO	0,437	PRIVATE EQUITY	0,422	METAL	0,173
PRECIOUS METALS	0,378	PRECIOUS METALS	0,366	REAL ESTATE GLOBAL	0,160
REAL ESTATE	0,327	REAL ESTATE	0,350	PRECIOUS METALS	0,088
REAL ESTATE GLOBAL	0,222	COMMODITIES	0,307	REAL ESTATE	0,073
COMMODITIES	0,204	REAL ESTATE GLOBAL	0,254	AGRO	0,071
LONG SHORT	0,063	LONG SHORT	0,067	COMMODITIES	0,003
HEDGE	0,000	HEDGE	0,000	OILS	0,000

There are interesting results: domination negative skewness. Only classes corresponding with metals demonstrates positive asymmetry and AGRO has not clearly marked domination.

Risk measurement based on the methodology of VaR is regulatory adopted for banks and insurance companies. From an economic point of view, VaR is used to estimate the minimum capital requirements which can be used for compensation losses raising from market risk. It presented in Basel III and Solvency II. Teoretical and practical points of view for VaR is presented in [12].

This risk measure presents quantile corresponded to some level of safety (example 95%, 99% or 99,5%). If for example, VaR orients for 95% than 5% biggest losses will throw off. VaR will cover maximum losses at the framework of 95% possibilities. As an example, in Solvency II capital requirements are determined on the level 99,5% over one year. This means that capital of insurance company should cover potential market losses (arising from changes in market values of the asset including into investment portfolio) with confidence level 99,5% for one year [13].

Table 4

Analysis risk in the asymmetry context

Type	*Percentage of negative skewness*	*Percentage of positive skewness*	*Average values of negative skewness*	*Average values of positive skewness*	*Characteristic*
AGRO	50%	50%	-0,0776	0,2140	No clearly marked domination
COMMODITIES	100%	0%	-0,2082		Strongly negative e
PRECIOUS METALS	31%	69%	-0,2545	0,1117	Domination positive
HEDGE	100%		-0,2545	0,1117	Strongly negative
LONG SHORT	100%		-0,6564		Strongly negative
METAL		100%	-0,4223		Strongly positive
OILS	86%	14%	-0,1798	0,1396	Domination negative
REAL ESTATE	100%		-0,6564		Strongly negative
PRIVATE EQUITY	100%		-1,0336		Strongly negative
REAL ESTATE GLOBAL	100%			0,4722	Strongly negative

VaR is a very efficient measure for market risk measurement. It includes three parameters in one number: 1) confidence level 2) time horizon 3) losses. Together with the advantages, this measure has shortcomings. The first shortcoming raises from the fact that VaR really only one point of probability distribution function (pdf). The behavior of pdf left-side and right-side from VaR is out of consideration. Second, the gap of VaR is absent from coherency property.

Coherency property of Value-at-Risk occurs only for the elliptical class of distributions.

The generalization of VaR is Conditional Value-at-Risk (CVaR) (or another name is ES – Expected Shortfall). This is conditional mathematical expectation:

$$CVaR(R) = E(R| \leq VaR) \tag{5}$$

The advantages of CVaR include the coherency of this risk measure and more correct consideration of possible losses. More correctness means that it oriented for average losses through the tail, not one point as VaR.

The application both risk measures to the sample of ETF`s return we have obtain presentation of risk pictured at Fig. 2.

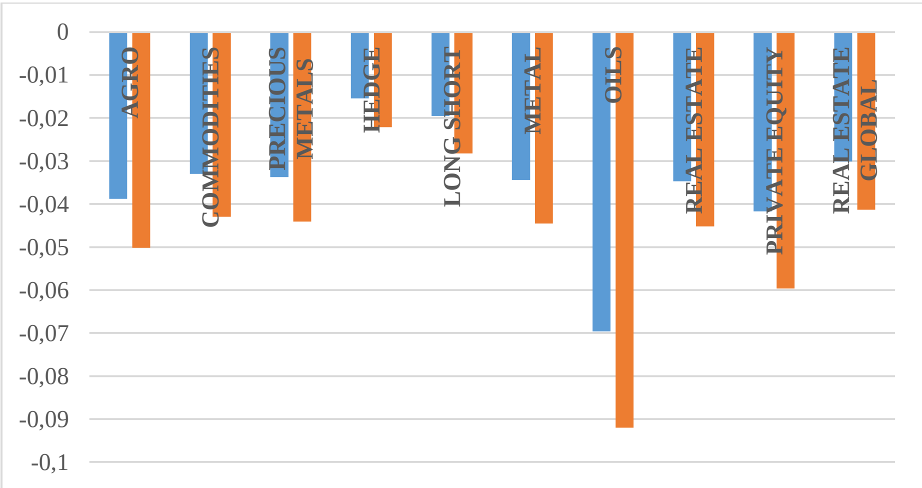

Fig. 2. VaR and CVaR

So, it is interesting that at the frameworks of this risk measurement there are two classes market out: Oil and Private equity.

Risk measurement based on the sensitivity indicators supposes estimation changes of returns as a consequence of changes of some factor (or factors). The strength of this approach is grounded on the possibility to divide risk into two parts. One part corresponds to systematic risk and the other part represents non-systematic risks. Systematic risk reflects the impact of factor (or factors) to return the asset. Sensitivity analysis involves procedures for assessment of such impacts. The classical approach consists of using a linear regression model for return:

$$R_A = \alpha_A + \beta_{A1} \cdot F_1 + \cdots + \beta_{Ak} \cdot F_k + \epsilon_A. \quad (6)$$

Where $F_1, \ldots, F_k$ represent chosen factors as sources of systematic risks. It may be different macroeconomic factors or index values. The division of risk for systematic and nonsystematic can be realizing if the procedure of factors orthogonalization will be done. The main logic of this is to delete the correlation between factors. One of the typical approaches is PCA (Principle Component Analysis). When factors will be orthogonal (non-correlated) is it possible to use the following two component vector for estimation systematic and non-systematic risks:

$$\left(\frac{\sum_1^k {\beta_{Ai}}^2 {\sigma_i}^2}{\sum_1^k {\beta_{Ai}}^2 {\sigma_i}^2 + \sigma^2(\epsilon_A)}; \frac{\sigma^2(\epsilon_A)}{\sum_1^k {\beta_{Ai}}^2 {\sigma_i}^2 + \sigma^2(\epsilon_A)}\right). \quad (7)$$

The first part of this vector will be interpreted as systematic risk, the second part is non-systematic.

In our research, we have investigated sensitivity analysis for two systematic risk factors. First is SPDR SP500 (ETF for SP500 index), Second is iShares Core U.S. Aggregate Bond ETF (AGG) (ETF for aggregated bond index). We used a one-factor models. The background for such approach is sensitivity analysis to factors raised from two basic classes of traditional investments: equities and bonds. Results are below.

Table 5

Risk measurement for systematic risk raised from index S&P500

SPY	b_1	b_0	R^2	*P-value*
AGRO	0,1080	0,0021	0,0160	0,1634
COMMODITIES	0,3539	0,0021	0,1389	0,0000
PRECIOUS METALS	-0,0508	0,0020	0,0138	0,2249
HEDGE	1,1273	0,0016	0,3150	0,0357
LONG SHORT	1,3828	0,0013	0,6355	0,0000
METAL	0,2266	0,0019	0,0847	0,0000
OILS	0,1335	0,0019	0,0950	0,0065
REAL ESTATE	0,4003	0,0017	0,2409	0,0134
PRIVATE EQUITY	-0,0382	0,0001	0,0309	0,0069
REAL ESTATE GLOBAL	0,6284	0,0017	0,3795	0,0000

Table 6

Risk measurement for systematic risk raised from index AGG

AGG	b_1	b_0	R^2	*P-value*
AGRO	-0,0308	0,0000	0,0190	0,1338
COMMODITIES	-0,0208	0,0001	0,0084	0,2287
PRECIOUS METALS	0,1066	0,0000	0,2039	0,0017
HEDGE	0,0133	0,0001	0,0227	0,2030
LONG SHORT	0,0185	0,0001	0,0560	0,1019
METAL	-0,0104	0,0001	0,0246	0,0365
OILS	-0,0118	0,0001	0,0108	0,1284
REAL ESTATE	0,0580	0,0000	0,0780	0,0337
PRIVATE EQUITY	-0,0382	0,0001	0,0309	0,0069
REAL ESTATE GLOBAL	0,0644	0,0001	0,0621	0,0117

The basic result that affecting of considered systematic factors is different for ETFs classes. Thus, S&P500 return affects on return ETF from classes HEDGE FUNDS, LONG SHORT and REAL ESTATE GLOBAL. Other classes have not essential sensitivity to changes in S&P500 returns.

There is no evidence about strong sensitivities of ETFs to bond index AGG. At the same time half classes indicate negative beta-coefficients.

One of the approaches to risk modeling is the *probability distribution function modeling.* The simulation is based on historical data. This approach is more general because the risk is reflected not by a single point (as present in risk measure) but by a whole probability distribution curve. With such a curve, it possible to calculate all of the specified measures of volatility risk and VaR and CVaR. Identifying the distributions that best approximate the return of the ETF classes allows to apply comparative analysis in the context of distribution types.

For this simulation, we used the program EasyFit 5.6. The program provides for the selection of the optimal distribution by three criteria Kolmogorov-Smirnov, Anderson-Darling and Chi-square. Selection is made from more than 55 types of distributions.

Five distributions were allocated to each ETF in the simulation process, with the highest level of significance. Each of these five distributions met the adequacy condition with a 99% confidence level. They were then assigned a relative score: five points for the most acceptable distribution, four points for the second-best option, and so on. The valuation for each distribution, within one asset group, was added and sorted in descending order. In addition, the allocation was most often characterized by the best level of value for most single-class exchange-traded investment funds. The comparative table is Table 7.

To evaluate the risk and to identify commonalities in certain groups of alternative investment assets, it is worth analyzing the left tail of the distribution. Because it reflects negative performance indicators. Long-tail reflects the likelihood of extreme financial results.

Analyzing the results, it can be noted that for certain categories of alternative assets, one can distinguish the type of distribution that best characterizes the profitability of a particular group ETF. Thus, the four-parameter distribution of Burr (8) and the inverse of the four-parameter distribution of Dagum (2), characterized by long left-sided tails, best characterize the returns on hedge funds, short-long strategies, precious metals, and real estate investments in local and global real estate. These allocations are widely used in researching the risks associated with stock market operations [10]. Based on the nature of the tailings of the simulated distributions, it can be concluded that these alternative asset classes are characterized by a potentially higher risk of critical losses.

$$f_{Burr}(x) = \frac{\alpha k(\frac{x-\gamma}{\beta})^{\alpha-1}}{\beta(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha})^{k+1}} \tag{8}$$

$$f_{Dagum}(x) = \frac{\alpha k(\frac{x-\gamma}{\beta})^{\alpha k-1}}{\beta(1+\left(\frac{x-\gamma}{\beta}\right)^{\alpha})^{k+1}} \tag{9}$$

The Johnson distribution (10) best characterizes the distribution of ETF returns in the categories Private equity, Oil, Commodities and AGRO. Based on the analysis included in each of the categories of exchange-traded funds, it can be observed that Johnson's distribution is characterized, as stated above, by a smaller left-hand slant, and therefore these alternative asset categories have, in this aspect, a lower level of risk of critical losses than those characterized by Dagum or Burr distributions.

Table 7

Probability Distribution Functions Modelling

Classes of ETF	**Number of ETFs**	**The most often pdf best type**	**A typical distribution**		
			Number	**Type of PDF based on complex estimations**	**Scores**
AGRO	6	Three-parameter Log-Logistic / Johnson	2	Johnson	17
				Four-parameter Burr	14
				Three-parameter Log-Logistic	12
COMMODITIES	13	Four-parameter Burr	4	Johnson	39
				Four-parameter Burr	34
				Beta	20
PRECIOUS METALS	13	Four-parameter Burr / Four-parameter Dagum	4	Four-parameter Burr	40
				Four-parameter Dagum	33
				Three-parameter Log-Logistic	29
HEDGE	6	Johnson	2	Four-parameter Dagum	21
				Four-parameter Burr	17
				Three-parameter Log-Logistic	16
LONG SHORT	7	Four-parameter Burr	3	Four-parameter Burr	27
				Johnson	19
				Three-parameter Log-Logistic	19
METAL	3	Four-parameter Dagum	2	Three-parameter Log-Logistic	12
				Four-parameter Dagum	10
				Four-parameter Burr	7
OILS	7	Three-parameter Log-Logistic	3	Johnson	24
				Four-parameter Burr	23
				Three-parameter Log-Logistic	21
REAL ESTATE	14	Four-parameter Bar / Four-parameter Dagum	5	Four-parameter Burr	57
				Johnson	45
				Four-parameter Dagum	39
PRIVATE EQUITY	5	Four-parameter Dagum	3	Johnson	19
				Four-parameter Bar	18
				Four-parameter Dagum	15
REAL ESTATE GLOBAL	9	Four-parameter Bar	6	Four-parameter Bar	42
				Johnson	31
				Four-parameter Dagum	22

$$f(x) = \frac{\delta}{\lambda\sqrt{2\pi}\sqrt{z^2+1}} \exp(-\frac{1}{2}(\gamma + \delta \ln(z + \sqrt{z^2 + 1}))^2) \tag{10}$$

The three-parameter Log-logistic Distribution (11) characterizes the yield in the category of metals, which is generally characterized by a significant skew to the right, indicating a low level of risk in this category of investment assets.

$$f(x) = \frac{\alpha}{\beta}\left(\frac{x-\gamma}{\beta}\right)^{\alpha-1}\left(1 + \left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{-2} \tag{11}$$

Conclusion. Alternative investments have been presented by exchanged traded funds (ETF) and such approach may be effective for the analysis. At the frameworks of our research alternative investments were structured into 10 classes ETFs. Each class includes sample of ETF corresponds to some type of alternative investments. The risk measurement was applied to ETFs from this classes. The applying was considered from complex point of view which supposed involving different conceptual approaches.

The application of risk measurement approach based on volatility conception leaded to following results. First of all was identified most risky classes. They are classes of Private equities and Oils. It is interesting thing that risk estimation by standard deviation and kurtosis is essentially non-homogeneous. Second, the asymmetric analysis grounded on skewness indicates that vast majority of classes are characterizes by strong negative skew.

The application of approach based on Value-at-Risk methodology volatility conception indicated wo classes with high VaR and CVaR. They are also Private equities and Oils. Combine together results from two approaches we can conclude that these classes are most risky from alternative investments.

The consideration of risk measurement through sensitivity approach indicates relatively low sensitivity except ETFs classes of hedge funds and long short. Changes of returns of ETF from these two classes shows reaction to changes of return ETF fund SPDR. This ETF correspond to index S&P500. Sensitivity to ETF which adequate bond index AGG is not essential.

Fitting of probability distribution functions for returns of ETFs it is possible to conclude, that most suitable types of pdf are: Johnson, Burr, Dagum and

Log-logistic. First one is pdf with rapidly decreasing tail. Three other types have relatively heavy tail (in comparison with normal distribution).

ETF classes are differing by risk level and risk characteristics. Investment choice should estimate risk from different approaches for better understanding risks and forming portfolio from ETF.

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