2.10. Passing through COVID-19 financial shock by Artificial Intelligence ETFs: changes in risk-return correspondence

1. Introduction

COVID-19 pandemic gave rise to unprecedented affecting to all spheres of life, including economics. This scourge has not spared the financial sector. World Health Organization (WHO) has announced about pandemic raised from wide dissemination of coronavirus in the first half of March 2020. Immediately financial shock was started. The shock was characterized by very sharply dropping and comparably greatest depth. The bottom of drop was demonstrated typically at the period 15-25 of March 2020. Great uncertainty connected with pandemic raised fears for stock market participants. They started to sell some assets and sought the variants for safe investment.

These drops in stock prices were different in different countries and different geographical regions. Variations in shock symptoms also were appeared in different economic sectors, which indicated sufficiently in the McKinsey bulletin [1]. At the same time, one of the interesting differences of this shock was (again, in comparison with other shocks) recovery after a shock. The economic recovery aspect is discussed in detail in the paper [2]. Authors have emphasized that the global economy after the shock of COVID-19 is recovering faster than expected. Moreover, a number of publications highlight different types of recovery, which, among other things, are characterized by V–, U–, L– or W–shaped [3].

The idea of our research is to study the impact of the financial crisis on the fast-growing segment of the tech industry. More precisely focus was concentrated on two segments of this industry. The first segment includes the tech industry which specializing in artificial intelligence (AI). The second segment is so-called FAANG. This acronym invokes the five most popular and good-performing USA technology companies: Facebook, Amazon, Apple, Netflix, and Alphabet (Google). We have applied the methodology of using ETFs (Exchanged Trades Funds). AI and FAANG ETFs are funds that invest in companies involved in the construction of new products and services related to artificial intelligence or FAANG companies. The methodology focuses on risk-return correspondence analysis before and after COVID-19 induced financial shock. The comparison of the deepness of fall through shock and recovery rate also was under the focus of our research.

The paper is organized as follows. The paper starts by outline the methodology of research. One of the points describes a sample of ETFs and data which was used. Next, the basic results of the research are present. The substantive findings and brief discussion of the following researches in this direction conclude the paper.

2. Materials and Methods

Risk measurement approaches. One of the crucial elements of investors' decision rationale is risk measurement. The analysis of correspondence “risk-return” is the starting point for the creation, monitoring, and rebalancing of investing portfolios. Risk measurement is grounded on introducing some risk measure or a more wide set of risk measures. The logic of using risk measures is to represent random variables by figures. Random variable typically reflects the return of investing into some asset for some time horizon. So, the return (in our research constituents over a period [t; t + 1] will be presented through the formula:

$$R_{t,t+1} = (P_{t+1} – P_t) / P_t, \tag{1}$$

where the price in period t+1 is unknown and consequently return is a random variable.

The sphere of constructing and applying risk measures is being actively developed (one of the best fundamental monographs is [4]). From our point of view, structuring investment risk measures into 4 classes is quite grounded for complex risk consideration [5]:

- measures of variability,
- quantile measures,

- measures of sensitivity,
- risk premium.

Although, of course, this is far from exhausting all modern approaches.

Our research in the context of targeted objectives supposes to structure applying risk measurement twofold. The first direction focuses on the measurement of risk by using the abovementioned classes. It was applied for time periods before and after COVID-19 induced financial shock. The second direction was based on the construction method to coupling together estimation “falling” and “recovery” explicitly in shock deployment. The essence of the proposed method is represented in point 2.3.

At the frameworks of the consideration 4 abovementioned classes, we have opted for the first two classes in analysis risks before and aftershock. The logic of such priority is based on the non-relevant significance of risk measurement by third and fourth classes at the bounds of shock.

The first class is grounded on the conception of variability as reflecting the riskiness of investments. It includes first of all such metrics as range and inter-quantile range. The importance of consideration ranges lies in delineating risk areas. They demonstrate the general framework in which the returns are “scattered”. Next, first-class involves standard deviation as a risk measure. This risk measure dates back to the origination of portfolio theory in the 1950-s. From one side this measure is deeply involved in modern portfolio optimization procedures. On another side, its definite disadvantage is the estimation of the deviation from the mean in both directions. Investors really worried about deviations downside. Semivariations (upper and lower) correct this defect. One of the widely used in this context is the Fisher measure [6]. By the way, this measure satisfies conditions of coherency.

Also, this class includes such risk measures as skewness, which reflects the asymmetry of the distribution of returns, and kurtosis, which is an indicator of “heavy tails”. Expected utility theory shows that investors prefer to maximize the (positive) skew and minimize kurtosis [7].

The second class of risk measures is based on a quantile approach. One of the substantive measures of risk is Value-at-Risk (VaR). This risk measure was constructed in the middle of 1970 [8] and then was promptly implemented as in practice as in regulative techniques of risk measurement. The essence of VaR is to look for 95%-quantile of the distr[ibution function of income/losses (at the framework considered time period). The bottom line of the VaR application is to identify the capital amount for coverage possible losses below VaR.

It is possible to notice, that VaR is a universal measure that couples together 3 components:

- losses,
- time interval,
- investor's risk attitude.

The main disadvantage of this measure used is the lack of coherency for a large class of returns distributions.

The universalization of VaR is the Conditional Value-at-Risk (CVaR). This risk measure is defined as average losses beyond the quantile corresponding to VaR. CVaR is more adequate to sharp falls in crisis conditions and is coherent. The ratio of CVaR/VaR also an important indicator, which provides the correspondence between “catastrophic” losses and losses in “calm” times.

Method for the estimation risk-return correspondence in shock passing. The basic point of our method is to separate the whole time period into three sub-intervals. The first interval, which was indicated in our research as 07/01/2019 – 01/15/2020 corresponds to the period “before shock”. At this period world markets (including ETF`s market) were relatively stable and it may be considered as a starting point for following a risk assessment.

The second interval was indicated as 16/01/2020 –03/31/2020. This period includes explicitly shock induced by COVID-19. At the beginning of this period, markets got the jitters and crashed in mid-March 2020.

The third interval was identified as a recovery period. It was indicated by the proposed approach as 04/01/2020 to 10/14/2020.

One point of our methodology focuses on comparative analysis of risk-return correspondence in the first above-mentioned period and third. The logic involves estimates changes upon completion shock. This estimation was considered by applying risk measures from the variation approach and quantile approach.

We introduced two indicators that directly captured shock. The first indicator, which is the risk indicator, is defined as the "deepness". It indicates the maximum negative return from the average price in the first period. A second indicator named recovery rate was defined as the average price for third-time intervals divided by the average price in the first period.

It is necessary to note, that the nature of introduced indicators attached conditions to the length of first and third intervals. The consideration of simply average price though interval be contrary to possible increased or decreased dynamically. So, the starting point of the first interval and ending point was grounded by a balance between "too short" and "too long" periods.

Sample and Source Data. Our research was focus on crises passing by companies specializing in the tech industry. The USA stock market was chosen as the object of study. Because from our point of view this market in eminently effective reflects achievements of companies and market pricing. Let us concretize. Investigated segment largely corresponds to intangible assets. Particularities of companies with intangible assets involve the fact that under U.S. GAAP they are not presented in the balance sheet. Therefore, the balance sheets of these companies do not fully reflect the value of their intangible assets. One of the useful approaches is to estimate value by market indicators rather than a balance sheet. On this track, our research is elucidated values changing through passing shock induced by COVID-19.

We used two groups of ETFs which provide exposure in two fields. The first group is Artificial Intelligence exchange-traded funds (AI ETFs) and the second group is ETFs related to FAANG. Advantages of ETF-based approach based on reducing the specific risk of a concrete company. Because typical ETF corresponds to fund, which carries with it systematic risk than specific. So, it will be more adequate to estimate risk-return to the whole system.

It was used information resource https://etfdb.com/, from which was chosen 11 AI ETFs and 20 FAANG ETFs. Data for the analysis was used from [9] ETF SPY, which corresponds to the index S&P500 was used for comparative analysis.

Table 1

Source data

ETFs	**Before shock**		**Shock**		**Post-shock**	
	Price	**Daily trading volume**	**Price**	**Daily trading volume**	**Price**	**Daily trading volume**
1	2	3	4	5	6	7
SPY	303,55	63982701	222,95	167332642	314,44	88654015
QQQ	196,65	25258623	169,30	67017500	250,49	45883066
IWF	164,91	1311527	131,63	2533100	195,72	1850758
ONEQ	327,06	34827	266,23	97531	394,12	55699
IVW	45,97	1720500	36,14	5084231	52,80	2640000
SCHG	86,92	407470	69,19	867429	103,60	616386
TQQQ	35,00	33520145	17,75	91332692	51,81	78436496
IUSG	64,39	577247	49,63	989689	73,12	566263
MGK	136,27	163368	111,48	530746	166,61	445747
SPYG	39,82	1162137	31,23	3686955	45,74	2787760
SKYY	58,57	201530	46,00	422549	72,35	615874
VONG	169,54	68846	134,98	189353	201,24	130005
VOOG	165,60	84134	129,79	348553	190,29	164842
QLD	52,54	2031574	36,31	4855000	76,36	3089562
IWY	89,98	68541	73,46	182333	109,13	201598
IGM	225,89	34076	188,85	93165	280,55	65728
QYLD	23,11	317067	17,99	706169	21,00	597567
XLG	218,68	34289	171,98	67980	242,94	57614
FNGU	4,29	1278865	2,65	4570962	13,25	5791460
SQQQ	147,36	2893865	79,95	11359615	40,46	34145036
IYW	53,17	427936	45,35	926239	67,51	681340
VGT	224,41	498918	185,49	1362543	278,80	872739
BOTZ	20,49	567293	15,11	981448	24,26	889218

Table 1 (ending)

1	2	3	4	5	6	7
PNQI	136,34	18724	111,99	28934	178,93	32451
XT	39,89	110164	30,69	434813	44,86	233250
XLK	83,66	10251087	70,40	23545192	104,74	12100894
FDN	138,54	357278	107,38	557754	170,59	652217
FTEC	66,36	269177	54,79	798794	82,38	481452
IXN	191,61	71946	160,27	148842	235,83	91357
ARKQ	33,71	18933	27,51	63698	48,97	164251
KOMP	34,15	44020	24,34	312690	37,95	177390
ROBO	39,33	128705	28,96	222518	43,78	175162

The source data demonstrate big changes in prices through shock pipeline.

3. Results and Discussion

Measurement impact of shock and recovery rate. Financial shock induced by Covid-19 was realized in the middle of March. This shock has spread to nearly every stock market. It concerns traditional financial instruments as an alternative. The uncertainties relating to the impact on the world economy were suddenly raised. Economic Policy Uncertainty Index has grown in May 2020 two times in comparison to January 2020 [10]. Baker, et al. [11] structured this uncertainty for different components, one of which is stock market volatility. But at a short time recovering was starting. This process is quite different for companies from various spheres. The stocks of Boeing Co, for example, demonstrated very slow price recovering but stocks of Apple Inc. demonstrated recovery which moved to high speed increasing price [12].

We introduced two measures for characterizing "risk-return" correspondence in shock.

The first indicator is "shock deepness" which is defined as:

$$Shock\ deepness = \frac{Minimum\ price\ at\ second\ sub-interval}{Average\ price\ at\ first\ sub-interval} - 1,\ \text{briefly } (SD)$$

$$Recovery\ rate = \frac{Average\ price\ at\ third\ sub-interval}{Average\ price\ at\ first\ sub-interval},\qquad \text{briefly } (RR)$$

First can be interpreted as “risk measure” and second as “return measure” (this is not classical return).

SD has the nature of classical return with some specification which is linked to average price through first sub-interval. It was due to exclusion from consideration price volatility before fallen. RR concern with corresponding after-shock price to before shock price. The logic of using such a form of RR is to desire estimate comparison with before shock period, not with the “bottom price”.

The application of this estimation to FAANG and AI ETFs constituents is presenting in Fig. 1.

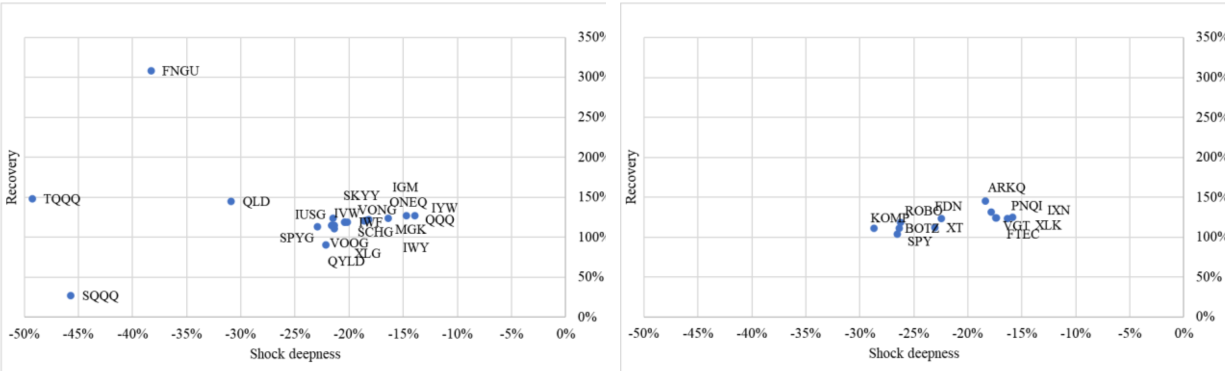

Fig. 1. Deepness of Fallen for FAANG and AI ETFs

The analysis of this diagram can detect the close to the linear dependency between *RR* and *SD*. Namely:

RR=-0,85*SD*+1,05 (*R*-squared = 0,03) – for FAANG ETFs,

RR=1,66*SD*+1,57 (*R*-squared = 0,51) – for AI ETFs.

Changing risk-return correspondence from variability approach. The estimations of basic variability risk measures were applied for the first- and third- time sub-intervals. All returns were calculated on the daily basis. The results are presented in Table 2.

Moreover, risk-return correspondence on the base of the classical H. Markowitz approach is given in Fig. 2 (before shock) and Fig. 3 (after shock).

Table 2

Statistical analysis for risk measures

Stocks	min		max		mean		Std		skewness		kurtosis	
	Before shock	Post-shock	Before shock	Post-shock	Before shock	Post-shock	Before shock	Post-shock	Before shock	Post-shock	Before shock	Post-shock
SPY	-0,0301	-0,0576	0,0196	0,0672	0,0008	0,0023	0,0078	0,0155	-1,0450	-0,2719	3,2240	3,1314
QQQ	-0,0353	-0,0507	0,0219	0,0715	0,0012	0,0033	0,0094	0,0178	-0,8135	-0,3754	2,0138	1,9604
IWF	-0,0328	-0,0543	0,0223	0,0729	0,0010	0,0031	0,0085	0,0169	-0,8771	-0,3326	2,3670	2,6150
ONEQ	-0,0365	-0,0518	0,0235	0,0729	0,0010	0,0033	0,0092	0,0171	-0,8323	-0,3669	2,3031	2,4124
IVW	-0,0291	-0,0532	0,0200	0,0729	0,0008	0,0029	0,0079	0,0163	-0,9136	-0,2213	2,3788	2,9262
SCHG	-0,0321	-0,0544	0,0207	0,0745	0,0010	0,0032	0,0083	0,0169	-0,9007	-0,2820	2,6172	2,7804
TQQQ	-0,1050	-0,1537	0,0661	0,2093	0,0033	0,0098	0,0280	0,0528	-0,8218	-0,4079	2,0312	1,9222
IUSG	-0,0282	-0,0546	0,0197	0,0729	0,0008	0,0029	0,0079	0,0162	-0,8609	-0,2065	2,3032	3,0001
MGK	-0,0332	-0,0521	0,0233	0,0760	0,0011	0,0032	0,0089	0,0173	-0,7972	-0,2653	2,0992	2,5562
SPYG	-0,0297	-0,0528	0,0207	0,0729	0,0008	0,0029	0,0080	0,0163	-0,8801	-0,2005	2,4293	2,9144
SKYY	-0,0377	-0,0570	0,0262	0,0651	0,0008	0,0034	0,0110	0,0188	-0,6003	-0,4958	0,8144	1,4863
VONG	-0,0325	-0,0546	0,0218	0,0709	0,0010	0,0032	0,0085	0,0168	-0,9013	-0,3697	2,4555	2,5113
VOOG	-0,0301	-0,0535	0,0204	0,0722	0,0008	0,0028	0,0079	0,0163	-0,9039	-0,2194	2,5907	2,8345
QLD	-0,0724	-0,1025	0,0452	0,1421	0,0022	0,0066	0,0190	0,0356	-0,8490	-0,3898	2,2386	1,9183
IWY	-0,0324	-0,0540	0,0209	0,0721	0,0011	0,0031	0,0084	0,0172	-0,9093	-0,3659	2,4189	2,3965
IGM	-0,0395	-0,0548	0,0250	0,0820	0,0011	0,0033	0,0103	0,0184	-0,7601	-0,1586	1,6967	2,6449
QYLD	-0,0309	-0,0270	0,0227	0,0246	0,0003	0,0009	0,0071	0,0080	-0,9838	-0,3603	5,2775	1,8082
XLG	-0,0314	-0,0561	0,0177	0,0666	0,0009	0,0025	0,0079	0,0156	-0,9693	-0,3249	2,8057	2,7788
FNGU	-0,1381	-0,8920	0,0909	9,0031	0,0057	0,0734	0,0390	0,7750	-0,5764	11,273	1,1969	127,57
SQQQ	-0,0669	-0,2102	0,1055	0,1536	-0,0034	-0,0100	0,0281	0,0531	0,8136	0,4203	2,0349	1,9237
IYW	-0,0400	-0,0594	0,0253	0,0805	0,0015	0,0034	0,0106	0,0192	-0,7661	-0,3231	1,6966	2,4063
VGT	-0,0411	-0,0591	0,0248	0,0852	0,0013	0,0034	0,0105	0,0193	-0,7923	-0,1889	1,8553	2,7159
BOTZ	-0,0466	-0,0590	0,0284	0,0768	0,0005	0,0036	0,0127	0,0179	-0,4067	-0,1463	1,1696	2,7440
PNQI	-0,0441	-0,0486	0,0308	0,0677	0,0007	0,0042	0,0117	0,0181	-0,5258	-0,3016	1,3723	1,0526
XT	-0,0308	-0,0565	0,0180	0,0667	0,0009	0,0028	0,0084	0,0151	-0,8422	-0,2510	1,5705	3,2666
XLK	-0,0417	-0,0573	0,0250	0,0853	0,0014	0,0032	0,0106	0,0193	-0,8010	-0,1690	1,9955	2,6844
FDN	-0,0395	-0,0530	0,0213	0,0764	0,0001	0,0037	0,0107	0,0182	-0,7045	-0,1130	1,0492	1,9472
FTEC	-0,0408	-0,0581	0,0263	0,0864	0,0013	0,0034	0,0105	0,0193	-0,7625	-0,1733	1,7912	2,8532
IXN	-0,0381	-0,0564	0,0257	0,0826	0,0014	0,0031	0,0106	0,0188	-0,6746	-0,1671	1,4223	2,6256
ARKQ	-0,0367	-0,0704	0,0255	0,0920	0,0012	0,0050	0,0132	0,0229	-0,5809	-0,2011	0,5092	2,0809
KOMP	-0,0345	-0,0666	0,0206	0,0749	0,0009	0,0037	0,0090	0,0189	-0,9289	-0,3745	2,1374	2,4369
ROBO	-0,0368	-0,0619	0,0275	0,0841	0,0005	0,0032	0,0116	0,0176	-0,3909	0,1400	0,7668	3,9175
Average	-0,0434	-0,0918	0,0301	0,3712	0,0011	0,0054	0,0120	0,0447	-0,7262	0,1317	1,9809	6,5063
Rate of increa-sing		111,7%		1132%		401%		271,5%		-118%		228%

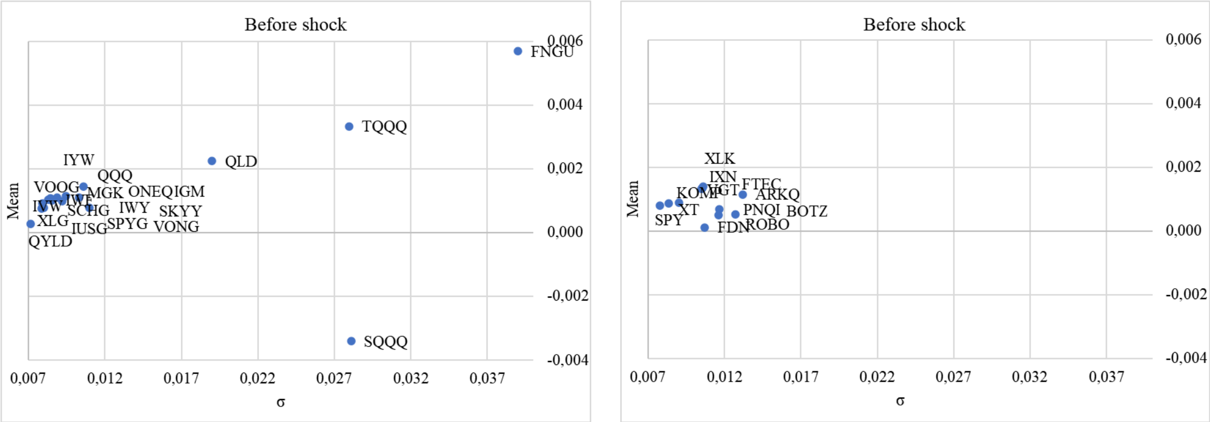

Fig. 2. Risk-return correspondence comparison before shock from variability point of view.

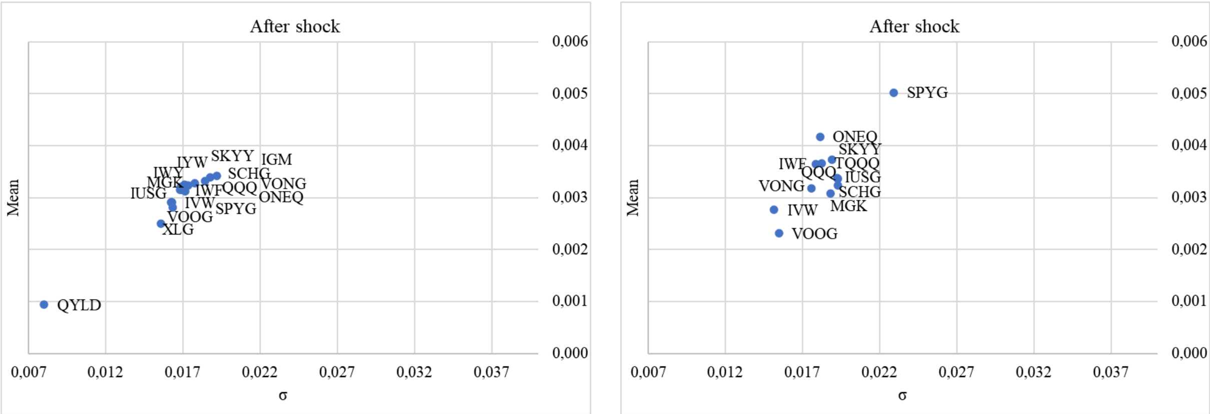

Fig. 3. Risk-return correspondence comparison after shock from variability point of view.

Analysis of received results makes it clear that all risk measures have grown. Mean and standard deviation increased by approximately 400% and 270% and kurtosis by 228%. This indicates the increased volatility of aftershock, which is natural. Also, we can see an extremely high growth of skewness. As was noted investors prefer positive skewness. The explanation of this effect that stocks of many companies leaped up aftershock.

Changing risk-return correspondence within the Value-at-Risk approach. Consideration of the risk-return correspondence within the VaR approach shows certain differences from the previous approach. The main difference is that risk measures do not indicate so much increase as in the variability approach. The increase has averages 71%. Table 3 presents changes in the values of risk measures.

Table 3

Risk measurement by VaR and CVaR

Stocks	VaR		CVaR		CVaR/VaR	
	Before shock	Post-shock	Before shock	Post-shock	Before shock	Post-shock
SPY	-0,0136	-0,0232	-0,0204	-0,0352	1,501	1,516827
QQQ	-0,0160	-0,0270	-0,0225	-0,0409	1,40672	1,51589
IWF	-0,0146	-0,0252	-0,0210	-0,0391	1,438303	1,550238
ONEQ	-0,0157	-0,0257	-0,0218	-0,0401	1,39033	1,563501
IVW	-0,0137	-0,0238	-0,0204	-0,0372	1,485361	1,565048
SCHG	-0,0141	-0,0248	-0,0202	-0,0388	1,433634	1,561602
TQQQ	-0,0475	-0,0806	-0,0673	-0,1228	1,416766	1,5239
IUSG	-0,0136	-0,0236	-0,0200	-0,0368	1,473574	1,556
MGK	-0,0150	-0,0256	-0,0212	-0,0396	1,416467	1,547868
SPYG	-0,0138	-0,0237	-0,0203	-0,0370	1,472223	1,560395
SKYY	-0,0189	-0,0294	-0,0259	-0,0443	1,374774	1,510171
VONG	-0,0145	-0,0253	-0,0208	-0,0390	1,433203	1,5417
VOOG	-0,0137	-0,0240	-0,0202	-0,0373	1,474425	1,553267
QLD	-0,0323	-0,0542	-0,0456	-0,0824	1,411638	1,520077
IWY	-0,0144	-0,0259	-0,0207	-0,0397	1,440005	1,532484
IGM	-0,0175	-0,0267	-0,0243	-0,0418	1,388757	1,564091
QYLD	-0,0125	-0,0127	-0,0191	-0,0188	1,532667	1,486458
XLG	-0,0136	-0,0236	-0,0198	-0,0361	1,449106	1,531617
FNGU	-0,0634	-5,1085	-0,0915	-0,2588	1,442485	0,050665
SQQQ	-0,0415	-0,0886	-0,0532	-0,1144	1,282445	1,2912
IYW	-0,0177	-0,0288	-0,0250	-0,0445	1,407306	1,545109
VGT	-0,0177	-0,0281	-0,0250	-0,0438	1,409377	1,557234
BOTZ	-0,0214	-0,0254	-0,0294	-0,0387	1,37426	1,526799
PNQI	-0,0198	-0,0267	-0,0283	-0,0386	1,430877	1,445777
XT	-0,0144	-0,0221	-0,0205	-0,0348	1,422942	1,572294
XLK	-0,0178	-0,0282	-0,0249	-0,0440	1,397301	1,556551
FDN	-0,0192	-0,0261	-0,0253	-0,0397	1,318228	1,524534
FTEC	-0,0176	-0,0281	-0,0250	-0,0443	1,415212	1,578224
IXN	-0,0176	-0,0276	-0,0245	-0,0424	1,394971	1,535173
ARKQ	-0,0224	-0,0329	-0,0323	-0,0518	1,442896	1,575184
KOMP	-0,0157	-0,0283	-0,0231	-0,0423	1,472011	1,49615
ROBO	-0,0196	-0,0235	-0,0275	-0,0375	1,401068	1,592977
Average	-0,0202	-0,1943	-0,0286	-0,0531	1,4209	1,4849
Rate of increasing		71,2%		73,0%		1,1%

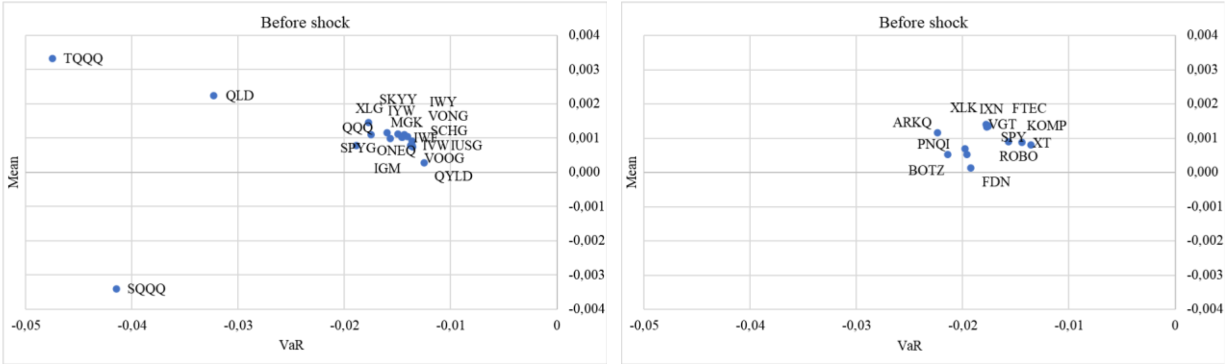

Fig. 4. Stocks Value-at-Risk before shock

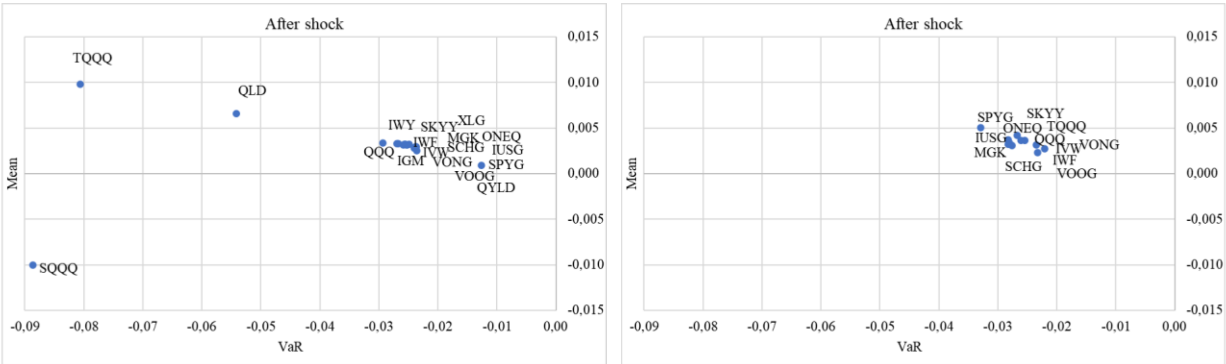

Fig. 5. Stocks Value-at-Risk after shock

The difference in displaying risk between the two approaches is as follows. After the shock, a relatively quick recovery began. The upward bursts of profitability were more than downward. At the same time, VaR and CVaR evaluate the quantiles of the left end of the distribution.

Conclusions

Induced by the pandemic of COVID-19 financial shock demonstrated a strong impact on financial markets. A high level of turmoil and uncertainty was generated. Meanwhile, we have observed a relatively quick recovery. So, the analysis of specificities of shock deployment is a multifaced actual scientific problem. One block of specificities indicates differences of passing shock by different financial instruments. The objectives of our research were devoted to analyzing particularities of shock passing by Artificial Intelligence and FAANG ETFs. These ETFs involves stocks of American high-tech companies which develop and implement artificial intelligence device. This segment is characterized by wide parts of intangible assets. After that, it is possible to apply the methodology of analysis risk-return correspondence to companies with intangible assets.

The analysis included two approaches for estimation risk-return correspondences. The first approach was based on variability assessment. The second approach was based on VaR.

The results of our investigation show relatively quick recovery as AI ETFs as FAANG ETFs. There some differences in risk-returns correspondence at the period aftershock. AI ETFs demonstrate increasing risks as returns. But FAANG ETFs show increasing risk and moderate decrease of returns.

Summing up, that analysis of risks induced by COVID-19 and their assessment pointed out several effects which have the research potential. We think that comparative analysis of recovery should provide specific characteristics for the difference.

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