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ESG INVESTING STRATEGY THROUGH COVID-19 TURMOIL: ETF-BASED COMPARATIVE ANALYSIS OF RISK-RETURN CORRESPONDENCE

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Abstract. *This paper examines the risk-return correspondence of ESG investing strategy through turmoil induced by the COVID-19 pandemic. The ESG segment demonstrates growth in the attractiveness of investments, and the investigation of their risk-return characteristics is significant. The goal of this article is to present the results of our research devoted to two ETF groups passing through a pandemic. One group of ETFs corresponds to low-level ESGs (ESG score <2.5), and another to high-level ESGs (ESG score >7.5). A comparative analysis focuses on risk estimations before, during, and after shock. It applies three approaches to measuring risk and a specially constructed pair of indicators. Additionally, trading volume parameters are analyzed. The results indicate differences in passing through shock for the abovementioned groups. Before shock, the second group was slightly less risky. During shock, the first group demonstrated strong linear dependency between the deepness of the shock and recovery rate, unlike the second. After shock, the second group showed a sharper increase in risk. Moreover, it demonstrated a higher correlation inside the group and a correlation with S&P500 returns. These results also reveal that dependency risk changes from the diversification level of the ETF portfolio. A complex analysis of trading volume activity and the Cowles-Johns ratio indicated the essential difference between groups. The final results indicate that ETFs from the ESG score >7.5 group were more strongly affected by COVID-19 shock. This can be expressed by the more severe "jitters" of returns and trading after the shock. The obtained results can be applied in the practice of forming portfolio investment strategies.*

Keywords: *risk measurement, COVID-19, shock, portfolio management, investment, stock market, ETF, ESG score.*

JEL Codes: *G11, G34, O16, R42*

1. Introduction

The COVID-19 pandemic profoundly affected a large majority of economic activity areas. Investment markets were not spared from the scourge. They experienced jitters at the end of January 2020 and crashed in mid-March. This was an exclusively deep shock that covered all segments of financial markets and almost all national stock markets. The nature of such a shock stemmed from the high uncertainty linked to the pandemic and its fallout on the economy. Thus, Altig et al. (2020) analyzed different indicators of uncertainty and presented great changes in these indicators during the COVID-19 pandemic. Moreover, analysis of the Global Economic Policy Uncertainty Index (n.d.) indicates that the Index had been rapidly increasing in April 2020, when its value increased by more than 1.8 times in comparison with January 2020. Conversely, during late 2020 and at the beginning of 2021, it was essential that uncertainty decrease. Thereby, shock gave rise to uncertainty for investment portfolio management. This recovery was coupled with decreasing uncertainty. In February 2021, the uncertainty index demonstrated values that lower than its values at the end of 2019.

Some of the main questions that arose in every investor's mind were: "Is it necessary to reconstruct an investment portfolio throughout this turmoil? What investment strategy is better for roll-out? What types of securities are more stable in returns?" Of course, all of these questions are accompanied by risk-return correspondence dynamics. These questions are as significant for individuals as they are for institutional investors. One of the segments which is in focus here is ESG investing. This segment supposes considering investments with an analysis of three criteria: E (Environmental), S (Social), and G (Corporate Governance). Research (TKB investment, 2019) revealed that 97% of investors in one way or another analyze indicators of ESG. The background for such an approach stem from two points. The first point, the correspondence between sustainability and ESG, is discussed as an example by Niemoller (2021). The second interesting point is: Does this segment demonstrate sustainability through pandemic turmoil? To substantiate this, there are some publications that serve as examples (Drenik, 2020).

The goal of this article is to present the results of our research devoted to two ETF groups passing through the pandemic pipeline. The first group corresponds to ETFs with a low ESG score. The second group corresponds to ETFs with high ESG scores. ESG scoring produced by MSCI was applied.

The logic of our research was as follows. The first step included the creation of two samples of ETFs based on the ETF Database (n.d.). The first sample that we created included 22 ETFs with ESG score >7.5, and the second included 22 ETFs with ESG score <2.5. The second step focused on the structure of the risk assessment system. We utilized three basic approaches: variability, losses in negative situation, and sensitivity. All approaches were applied to two-time intervals: before and after COVID-19 shock. Additionally, we constructed two indicators for the estimation of shock directly using trading volumes statistics. The third step involved the use of comparative risk analysis. The results indicate differences in risk changes for both groups. During shock, the first group demonstrated a strong linear dependency between deepness of shock and recovery rate, in contrast to the second. The "after shock" time interval showed a sharper increase in risk for the second group. Moreover, higher beta-coefficients with S&P500 returns were revealed in this group. A complex analysis of trading volume activity and the Cowles-Johns ratio indicated essential differences between groups. Outcomes of this research include the observation that ETFs with an ESG score >7.5 were more strongly affected by COVID-19 shock. This can be expressed by more severe "jitters" of returns and trading after shock. The obtained results can be used for understanding the specificities of ESG investing, involving transition risk among other factors.

2. Literature review

The problems of sustainable development are actively discussed by scientists. One way to address these challenges is to promote investment in ESG, which aims to encourage businesses to move to sustainable ways of manufacturing and doing business.

The literature studying the impact of COVID-19 on stock markets is growing rapidly. In particular, Díaz et al. (2021) examine the impact of COVID-19 on the creation of ESG investing strategies. The authors concluded the following: ESG explains the returns of sectoral portfolios during the pandemic; the environmental and social components of ESG are key factors in the observed patterns studied; and the impact of ESG varies across different sectors.

A study of socially responsible stock indices during COVID-19 was conducted by Capelle-Blancard et al. (2021). Their paper notes that the financial performance of SR strategies varied in the COVID-19 pandemic, but the resilience of SR strategies was comparatively higher.

Lööf et al. (2022) investigated the downside risk of stocks based on ESG ratings. The authors concluded that companies with a higher ESG rating are characterized by lower risk, and at the same time such companies have a lower probability of risk.

An analysis of ESG implementation by Latvian companies was conducted by Zumente et al. (2022). The authors noted that companies listed on stock exchanges have the highest level of ESG implementation, followed by international branches of companies. The researchers recommended that policy makers form the motivation to promote ESG principles.

The question of the true motivations of managers of large companies regarding sustainability was discussed by Adams and Abhayawansa (2022). The authors criticized the reporting approaches used in ESG investing and discussed three myths of sustainable development.

Research on the effect of ESG scores on stock returns and volatility during the COVID-19 crisis was conducted by Yoo et al. (2021). The authors concluded that during a financial crisis an increase in ESG score, especially E score, leads to higher returns and lower volatility, while an increase in GC score correlates with lower stock returns and higher volatility.

Among other problems, researchers such as Vasylieva et al. (2021), Derbentsev et al. (2020), Zyma et al. (2022), Izonin et al. (2020), and Sova and Lukianenko (2020) have explored this phenomenon. Kanuri (2020) discussed attracting ESG ETFs for different types of investors. Cardenas et al. (2020) investigated ESG finance in the post-COVID world. Omura et al. (2020) examined the performance of SRI/ESG investments against conventional investments during the COVID-19 pandemic. Ferriani & Natoli (2020) analyzed whether investors take risks related to

ESG factors into account when making portfolio decisions during COVID-19. Rubbaniy et al. (2021) found a co-movement between the health fear index of COVID-19 and returns on ESG stocks. The authors also observed that the safe-haven properties of ESG stocks are contingent upon the proxy of the COVID-19 pandemic. Folger-Laronde et al. (2020) analyzed the differences and relationships between the financial returns of ETFs and their eco-fund ratings during the COVID-19 pandemic-related financial market crash. Pavlova & de Boyrie (2021) showed that higher sustainability ratings of ESG ETFs did not protect ETFs from losses during the downturn, but they did not perform worse than the market.

3. Data and methodology

3.1. Data for research

We chose ETFs (Exchange Traded Funds) for analysis to achieve the goal of our research. This is due to the fact that we focused more on portfolio investors. Using ETFs as an investment instrument is relatively easier for portfolio forming with the desired level of ESG score than creating a portfolio using the classical approach – i.e., creating a mutual fund by buying equities or bonds directly on the market and then calculating the portfolio ETF score as a weighted score value. Our choice was based on Equity ETFs, which invest in various stock assets.

The ETFs database was used to create a sample for the research (in the category "Equity"). The preference of using this database lies in the possibility to use a wide range of different parameters, including ESG scores. Such scores, calculated by the MSCI ESG Quality Score (Moen, 2016), take values from 0 to 10. This scoring represents the ESG quality of ETF constituents. A higher score reflects the fact that the ETF (from the standpoint of holding assets) corresponds more strongly to the parameters of E, S, and G. A score of 10 indicates the underlying holdings as best the ESG (either best globally or best in corresponding branch). A score of 0 corresponds to the worst in class in the sense of ESG. Of course, the "best" and "worst" should be used in the framework of MSCI ESG Fund Metrics (MSCI, 2017). We used ESG score values from 2021.

Two groups were selected from the ETFs database. The criteria of including the ETF into a group was as follows:

- Low ESG score group: ESG score <2.5. Such ETFs correspond to the very low ESG level.
- High ESG score group: ESG score >7.5. Such ETFs correspond to the very high ESG level.

In each group, we ordered ETFs by capitalization level. Samples were formed from the 22 most capitalized ETFs in each group. Hence, the first group included 22 ETFs with ESG scores <2.5, and the second sample included 22 ETFs with ESG scores >7.5. The full list of chosen ETFs is presented in Table 1 and Table 2.

It is necessary to note some remarks about the specificity of forming these groups. First, not all ETFs have ESG scores because not all ETFs reference instruments issued by companies. Secondly, it is logical that our procedure of sample creation was narrowed to only include those parts of ETFs which were scored by the abovementioned MSCI methodology.

The next basic methodological point for the creation of our database was structuring the time period into three sub-intervals. The first interval, which was selected in our research as 01

July 2019–15 January 2020, corresponds to the period "before shock". This period was interpreted as a starting point. Put simply, this period is characterized by stability before the pandemic. The second interval was defined as 16 January 2020–31 March 2020. This period directly corresponds to the shock generated by the COVID-19 pandemic occurring. At the beginning of this period, markets felt jittery and crashed in mid-March 2020 after the announcement of a pandemic by the World Health Organization. The third time interval was identified as the recovery period; it was indicated in our research as 01 April 2020–14 October 2020.

The database for research involved daily prices and trading volumes of chosen ETFs in all three periods. The source of these data is: https://www.investing.com.

3.2. Risk measurement methodology

Risk measurement is an essential element in assessing the attractiveness of an investment. The risk measurement methodology is today highly developed. It includes a wide range of different risk measures which focus on a particular aspect of risk. High-quality statistical data provide the possibility to verify the reasonableness of risk measures. The systematic point of view allows for the combination of these measures in the conceptual approaches to risk measurement (Szegö, 2004).

In methodological terms, we consider four such approaches (Kaminskyi et al., 2019):

- return variability approach;
- quantile-based approach;
- sensitivity approach;
- risk-premium based approach.

We used the first three of these approaches in our investigation. The fourth approach supposes considering risk attitudes which were not included in our set of objectives.

All approaches are based primarily on the estimation of the rate of return, which is identified in arithmetic form $R_{t,t+1} = \frac{(P_{t+1}-P_t)}{P_t}$ or logarithmic form $r_{t,t+1} = ln\frac{P_{t+1}}{P_t}$, where P_t is the price of asset at time *t*. We applied the arithmetic form for daily returns.

In the first approach, we used two indicators. The first is a range = max-min. This indicator shows the framework in which there are fluctuations in profitability. However, it depends on "crisis deviations". Therefore, we applied it to the period before the onset of pandemic shock and during the recovery process. We also applied a baseline in this approach – standard deviation – which leads to H. Markowitz's approach to risk measurement. Generalizations of this measure form a pair of semi-standard deviations (up and down). The consideration of such a pair provides the possibility to divide deviation up and down from the expected return. Investors prefer to interpret risk measures through the lower semi-variation. As part of this approach, we also considered risk assessment by such indicators as skewness and kurtosis. The former includes asymmetry estimation, and the latter is an indicator of the "heavy tail" of distribution. Expected utility theory notes that investors typically tend to increase skewness and decrease kurtosis (Scott & Horvath, 1980).

The second approach is primarily based on such risk measures as Value-at-Risk (VaR). VaR was elaborated in the mid-1970s and is now widely implemented as a regulative measure of market risk (for example, Holton, 2003). The main advantage of this measure is the transparency of its economic logic. This value involves three components: losses, probabilities, and time horizon. The disadvantage of VaR is that it offers only one point (quantile) of the curve of loss distribution. Some generalization, via the Conditional Value-at-Risk (CVaR) measure, provides more advance estimation and has coherency properties (ADEH, 1999). CVaR is the conditional average of losses beyond the quantile corresponding to VaR. From our point of view, this risk measure is more adequate when considering sharp falls in crisis conditions. We have applied risk measuring procedures for both measures.

The third approach involves risk measurement in the form of some sensitivity indicators. The *β-coefficient* is most used in investment risk measurement sensitivity indicators. Analysis of *β-coefficients* considers signs and values of *β-as.* Such coefficients involve regression coefficients on some market indicators as a market index. We analyzed its application to the leading USA index, the S&P500.

The fourth approach supposes the calculation of risk premium, which involves the risk attitude of the investor. This approach was initially based on the Arrow-Pratt coefficient of risk aversion, and was later highly developed (Levy & Levy, 1991). The application of the fourth approach for shock analysis also raises discussions. This is because risk attitude may change to a great extent through times of turmoil, and this approach supposes the involvement of additional variables that estimate such changes.

Of course, these four approaches are not exhaustive. A more complete view is presented in Szegö (2004).

A special methodological focus was placed on the estimation of risks explicitly in relation to their passing through shock. We introduced two measures for characterizing "risk-return" correspondence in shock.

The first indicator is "shock deepness" (briefly denoted as SD) which is defined as:

$$Shock\ deepness = \frac{Minimum\ price\ at\ second\ sub\text{–}interval}{Average\ price\ at\ first\ sub\text{–}interval} - 1$$

The second indicator is "recovery rate" (briefly denoted as RR) which is defined as:

$$Recovery\ rate = \frac{Average\ price\ at\ third\ sub\text{–}interval}{Average\ price\ at\ first\ sub\text{–}interval}$$

The first indicator can be interpreted as a "risk measure" and the second as a "return measure" (this is a not classical return). SD has the nature of a classical return with some specifications which are linked to the average price through the first sub-interval. This is due to its exclusion from consideration in price volatility before falling. RR is concerned with the correspondence between post-shock prices and pre-shock prices. The logic of using such a form of RR is the desire to achieve a comparison with the pre-shock period, not with the "bottom price" in the second period.

It is necessary to note that the nature of the SD and RR indicators is attached to the conditions of the length of the first and third intervals. The consideration of simple average price through the interval would be contrary to the estimation of possible dynamic increases or decreases. Therefore, the starting and ending point of the first interval were grounded by the balance between "too short" and "too long" periods.

In addition, we used the Cowles-Jones ratio indicator (Campbell et al., 1997). Jitters, in our view, methodologically indicate one of the important aspects of risk – namely, deviation from random walks.

Liquidity risk analysis presents another methodological approach which we applied. More generally, indicators of the change in the intensity of trading operations were considered.

3.4. Comparative analysis methodology

The basic methodological point of our research is to provide a comparative analysis of risk-return correspondence for two samples of ETFs. Comparison is considered by applying risk measures from the abovementioned approaches. The daily trading value is given by similar logic. This comparison was realized through three time periods: before shock, during shock, and after shock (see section 3.1. for corresponding years).

The comparative analysis of dynamic risk-return correspondence for three-time intervals is considered to represent a comparison between the reactions to COVID-19 turmoil of ETFs with high and low ESG scores. Table 1 and Table 2 contain data for the jumping-off points for comparative analysis.

Table 1. Source data (ESG score <2.5)

	Before shock		Shock		After shock	
	Average price	Daily trading volume	Minimal price	Daily trading volume	Average price	Daily trading volume
XLC	51.09	2,985,735	51.18	6,258,462	55.67	3,556,277
VOX	89.78	154,773	89.36	394,889	95.72	211,389
ASHR	28.04	3,850,389	27.98	9,890,577	31.32	4,150,657
KBA	31.01	210,641	31.33	255,169	35.83	147,049
KSA	30.74	629,451	26.93	778,645	27.14	406,759
FCOM	34.25	92,081	34.02	192,611	36.31	133,258
CNYA	28.63	60,988	29.31	83,033	33.37	74,410
IPO	30.60	34,042	30.77	25,482	41.02	103,850
SOCL	33.10	15,875	33.43	28,200	42.59	39,245
IXP	58.94	45,505	58.68	91,204	62.77	26,386
KURE	21.94	13,296	24.42	41,053	31.14	72,530
TUR	25.71	501,996	24.95	600,743	21.03	249,715
PGJ	38.16	17,375	40.95	32,856	47.95	21,694
PSCE	7.15	40,259	4.53	85,299	3.33	66,824
PBS	32.77	11,703	30.90	7,819	32.36	8,463
XWEB	82.60	2,688	77.73	2,953	103.65	7,788

CNXT	27.40	10,268	30.70	37,300	36.60	27,131
GLCN	39.94	5,550	38.12	31,806	42.29	7,948
CHIS	20.88	6,546	20.93	5,488	26.23	6,998
CHIC	22.87	2,744	23.90	7,155	25.09	2,616
ASHX	20.01	1,625	20.24	963	23.08	922
KFYP	27.35	10,734	26.14	13,701	27.74	4,196

Source: *Investing.com*

Table 2. Source data (ESG score >7.5)

	Before shock		Shock		After shock	
	Average price	Daily trading volume	Minimal price	Daily trading volume	Average price	Daily trading volume
EFA	66.26	23,374,275	62.42	45,584,231	61.22	27,039,635
XLF	28.64	46,143,333	26.98	89,618,654	23.62	66,792,847
VGK	54.97	3,138,271	52.03	6,481,923	50.57	4,687,664
EFG	82.09	184,530	80.01	406,095	83.98	485,408
XLB	58.48	5,826,884	54.06	11,175,192	57.97	6,709,051
BBEU	24.11	504,198	22.80	2,296,282	22.14	2,359,947
SOXX	221.35	487,374	234.77	965,555	271.72	871,968
ESGD	65.21	127,473	61.91	327,471	60.95	290,216
BBCA	25.13	164,132	23.51	335,796	22.84	258,952
SMH	124.78	4,297,681	133.35	5,916,154	154.82	3,641,606
IEUR	46.74	591,375	44.30	1,135,528	43.05	502,852
RDVY	32.82	201,670	31.86	571,833	31.02	285,136
IDV	31.34	730,324	29.57	1,743,387	25.04	1,036,261
EWC	28.92	2,003,941	26.92	4,065,385	26.20	2,656,038
SOXL	13.13	12,597,319	14.46	30,818,269	13.03	26,995,109
BBAX	25.42	111,444	23.25	345,623	22.16	315,934
VAW	127.47	57,620	116.63	180,820	123.71	105,028
EWU	31.99	2,414,865	29.26	4,093,408	25.82	3,484,672
IQLT	30.40	214,095	29.51	514,854	29.75	523,998
IXG	64.97	79,380	60.14	164,354	52.57	38,844
RYT	184.79	42,553	187.11	75,811	198.32	41,478
EPP	45.76	492,927	41.65	858,241	39.58	542,106

Source: *Investing.com*

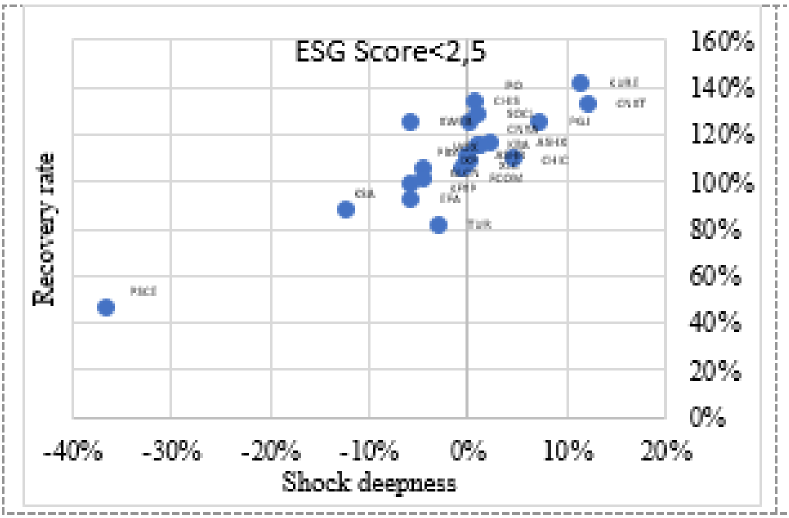
The source data demonstrate higher changes in average prices through the shock pipeline.

4. Results

4.1. Measuring the impact of shock and recovery rate

Applying the SD and RR indicators allows us to set interesting dependencies. Figure 1 provides a visualization of this in a 2-dimensional space. Comparative analysis shows the differences in the passing of shock. The first difference is expressed in the more compact nature of high ESG-scoring ETFs. The second difference is in the form of dependency between RR and SD. This tendency looks like a linear form in the case of the group with ESG scores <2.5. The below linear regressions demonstrate this – namely:

$$RR = 1.87 \cdot SD + 1.13 \; (R^2 = 0.74) \text{ for ESG score} < 2.5,$$
$$RR = 1.68 \cdot SD + 1.01 \; (R^2 = 0.58) \text{ for ESG score} > 7.5.$$



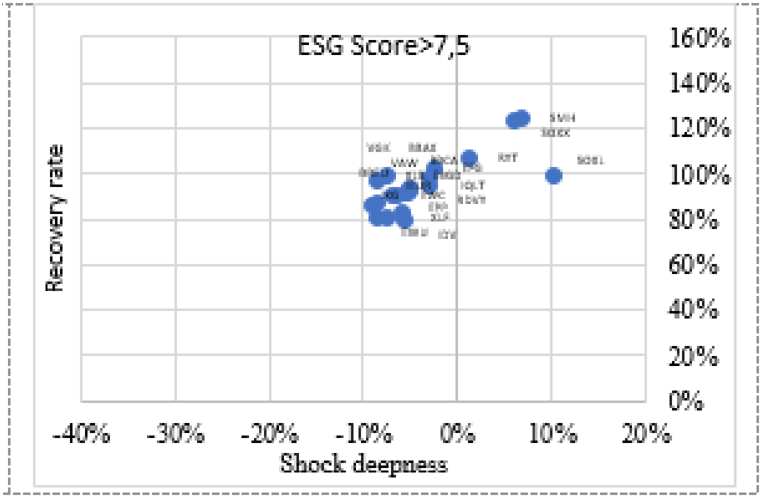


Figure 1. Correspondences between fall and recovery

Source: *Constructed by authors*

This can be economically interpreted as follows. The passing through shock of high ESG-score ETFs is more homogeneous. The low ESG-score ETFs demonstrated a more direct tendency towards a "deeper fall", corresponding to lower "recovery rate". The mean value approach indicates that the low-scoring group demonstrates better values

Mean-value approach		
	ETFs with ESG scores <2.5	ETFs with ESG scores >7.5
Average SD	−1.68%	−3.79%
Average RR	109.86%	94.89%

Moreover, the linear coefficient for the low-scoring group is higher (1.87 vs 1.68).

4.2. Changing risk-return correspondence: variability approach

This part of the comparative analysis includes changes in the values of indicators of the variability of returns. The first metric we looked at was range (= max-min). This indicator, of course, represents a rough estimation of return variability, but still indicates frameworks. Statistical analysis indicates that high ESG-scoring ETFs had a lower average range before shock. After shock, they had a higher average range. This indicates that shock more strongly affected increased risk for the group of ETFs with scores >7.5.

Statistical estimations of means, standard deviations, skewness, and kurtoses are presented in Table 3 and Table 4.

The basic regularities are as follows.

Before the shock period, averages values (through the sample) for risk-return correspondence indicators from the ESG score >7.5 group were better than for the ESG score <2.5 group. The mean of expected returns was higher. The means of standard deviation and kurtosis were lower in the ESG score >7.5 group, as illustrated in Figure 2. Average skewness and kurtosis were the reverse – these values were better for the ESG score <2.5 group.

After the shock period, averages values (through the sample) for risk-return correspondence indicators from the ESG score <2.5 group were better than for the ESG score >7.5 group.

In terms of the changes after experiencing shock, expected returns in the ESG score <2.5 group grew more than in the ESG score >7.5 group. Other indicators, except kurtosis, transformed less than in the ESG score >7.5 group.

Table 3. Statistical risk means for the ESG score <2.5 group

ETFs	min		max		mean		std		skewness		kurtosis	
	Before shock	After shock	Before shock	After shock	Before shock	After shock	Before shock	After shock	Before shock	After shock	Be-fore shock	After shock
XLC	-0.0355	-0.0461	0.0286	0.0660	0.0009	0.0025	0.0094	0.0162	-0.6395	-0.0394	2.1387	1.9691
VOX	-0.0320	-0.0495	0.0274	0.0680	0.0009	0.0025	0.0089	0.0160	-0.5842	-0.0595	1.8851	2.3769
ASHR	-0.0419	-0.0462	0.0346	0.1124	0.0004	0.0026	0.0115	0.0176	-0.4504	1.5892	1.2423	9.7936
KBA	-0.0448	-0.0465	0.0333	0.1059	0.0005	0.0026	0.0115	0.0166	-0.5768	1.5712	1.7070	10.0045
KSA	-0.0255	-0.0478	0.0245	0.0589	-0.0005	0.0019	0.0100	0.0141	-0.0458	0.4453	-0.5460	3.9001
FCOM	-0.0311	-0.0508	0.0267	0.0680	0.0008	0.0025	0.0088	0.0160	-0.5522	-0.1613	1.8433	2.4916
CNYA	-0.0477	-0.0453	0.0335	0.1033	0.0006	0.0027	0.0115	0.0166	-0.6388	1.4048	2.3258	8.9255
IPO	-0.0391	-0.0574	0.0412	0.0770	0.0005	0.0058	0.0127	0.0215	-0.3896	-0.1045	1.0434	0.7895
SOCL	-0.0442	-0.0450	0.0257	0.0523	0.0010	0.0041	0.0109	0.0169	-0.7561	-0.2828	1.9059	0.7192
IXP	-0.0297	-0.0439	0.0258	0.0639	0.0007	0.0022	0.0078	0.0145	-0.5828	0.0514	2.4362	2.6091
KURE	-0.0495	-0.0666	0.0333	0.0456	0.0012	0.0032	0.0136	0.0200	-0.6050	-0.3775	1.8344	0.3810
TUR	-0.0414	-0.0440	0.0411	0.0495	0.0011	0.0006	0.0152	0.0183	-0.0635	-0.1338	0.3548	0.2442
PGJ	-0.0542	-0.0564	0.0613	0.0448	0.0013	0.0029	0.0156	0.0185	0.1649	-0.2988	1.9645	0.1029
PSCE	-0.0815	-0.1339	0.0994	0.1447	-0.0017	0.0038	0.0281	0.0430	0.3966	0.3072	1.0471	1.4597
PBS	-0.0359	-0.0740	0.0263	0.0744	0.0004	0.0034	0.0100	0.0192	-0.8698	-0.3494	2.1583	2.9716
XWEB	-0.0447	-0.0604	0.0193	0.0897	-0.0001	0.0052	0.0115	0.0214	-1.0524	-0.2150	1.7052	1.8559
CNXT	-0.0442	-0.0584	0.0360	0.0874	0.0014	0.0034	0.0138	0.0190	-0.2284	0.2539	0.2013	2.7298
GLCN	-0.0478	-0.0447	0.0363	0.0754	0.0004	0.0027	0.0121	0.0151	-0.7353	0.4576	2.3145	3.3770
CHIS	-0.0333	-0.0531	0.0389	0.0512	0.0007	0.0026	0.0107	0.0158	-0.0716	-0.1057	1.2243	1.4439

CHIC	-0.0556	-0.0426	0.0577	0.0607	0.0007	0.0017	0.0153	0.0157	0.0133	0.0450	1.8385	0.9389
ASHX	-0.0496	-0.0495	0.0268	0.1018	0.0004	0.0027	0.0106	0.0161	-0.9948	1.4147	3.4185	9.7346
KFYP	-0.0692	-0.0435	0.0288	0.1203	0.0001	0.0018	0.0122	0.0165	-1.3565	2.5448	6.8359	18.2393
Average	-0.0445	-0.0548	0.0367	0.0782	0.0005	0.0029	0.0123	0.0184	-0.4827	0.3617	1.8581	3.9572
Rate of increase		123.2%		213.4%		536.0%		149.0%		-74.9%		213.0%

Source: *Estimated by authors' calculation*

The average range through ETFs returns increased from 0.0811 to 0.1330 (64.0% growth).

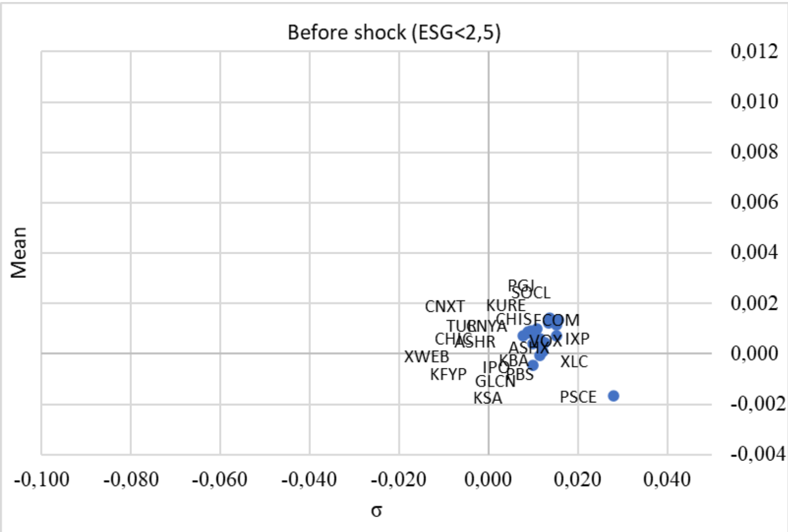
Table 4. Statistical risk means for the ESG score >7.5 group

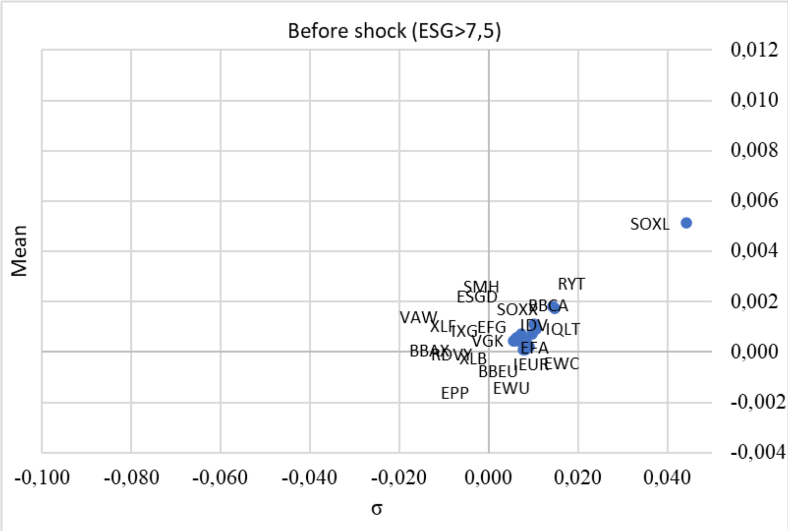
ETFs	min		max		mean		std		skew-ness	kurtosis		**kurtosis**
	Before shock	**After shock**	**Before shock**	**After shock**	**Before shock**	**After shock**	**Before shock**	**After shock**	**Before shock**	**After shock**	**Before shock**	**After shock**
EFA	-0.0274	-0.0536	0.0179	0.0530	0.0004	0.0016	0.0094	0.0146	-1.0341	-0.2549	3.0644	1.9799
XLF	-0.0371	-0.0818	0.0204	0.0718	0.0007	0.0015	0.0089	0.0227	-0.9148	-0.0871	2.0577	1.3147
VGK	-0.0284	-0.0586	0.0216	0.0494	0.0005	0.0017	0.0115	0.0160	-0.7902	-0.4023	2.4369	1.6262
EFG	-0.0282	-0.0441	0.0149	0.0487	0.0006	0.0020	0.0115	0.0129	-1.1492	-0.2257	3.0478	1.9098
XLB	-0.0317	-0.0773	0.0206	0.0744	0.0002	0.0030	0.0100	0.0195	-0.5866	-0.2973	0.8729	2.5089
BBEU	-0.0282	-0.0582	0.0203	0.0471	0.0004	0.0016	0.0088	0.0155	-0.8399	-0.3700	2.4285	1.6158
SOXX	-0.0441	-0.0635	0.0308	0.1020	0.0017	0.0037	0.0115	0.0229	-0.3428	0.1158	0.3455	2.3958
ESGD	-0.0257	-0.0548	0.0172	0.0518	0.0005	0.0016	0.0127	0.0144	-0.8794	-0.3061	2.2728	2.1138
BBCA	-0.0241	-0.0579	0.0153	0.0566	0.0005	0.0020	0.0109	0.0156	-0.9663	-0.3676	2.6873	2.6222
SMH	-0.0431	-0.0614	0.0304	0.0994	0.0018	0.0037	0.0078	0.0225	-0.3102	0.1348	0.2670	2.1080
IEUR	-0.0283	-0.0599	0.0222	0.0509	0.0005	0.0017	0.0136	0.0158	-0.8184	-0.3725	2.5320	1.8805
RDVY	-0.0362	-0.0734	0.0235	0.0884	0.0011	0.0023	0.0152	0.0204	-0.7915	0.0045	1.9653	2.8219
IDV	-0.0295	-0.0705	0.0234	0.0467	0.0007	0.0011	0.0156	0.0176	-0.7140	-0.4811	2.5668	1.8959
EWC	-0.0266	-0.0575	0.0137	0.0519	0.0004	0.0020	0.0281	0.0157	-1.0634	-0.3914	3.4778	2.1439
SOXL	-0.1302	-0.1908	0.0935	0.3051	0.0051	0.0111	0.0100	0.0688	-0.3214	0.0820	0.2442	2.2862
BBAX	-0.0354	-0.0634	0.0190	0.0664	0.0001	0.0018	0.0115	0.0168	-0.8606	-0.1458	2.4490	2.4672
VAW	-0.0324	-0.0818	0.0204	0.0751	0.0002	0.0030	0.0138	0.0200	-0.6038	-0.3162	0.8658	2.6335
EWU	-0.0286	-0.0655	0.0296	0.0459	0.0003	0.0007	0.0121	0.0174	-0.2578	-0.4868	2.7447	1.3036
IQLT	-0.0258	-0.0491	0.0153	0.0441	0.0006	0.0017	0.0107	0.0137	-0.9900	-0.3253	2.3760	1.5025
IXG	-0.0328	-0.0757	0.0198	0.0652	0.0005	0.0013	0.0153	0.0201	-0.8412	-0.1394	2.1821	1.7904

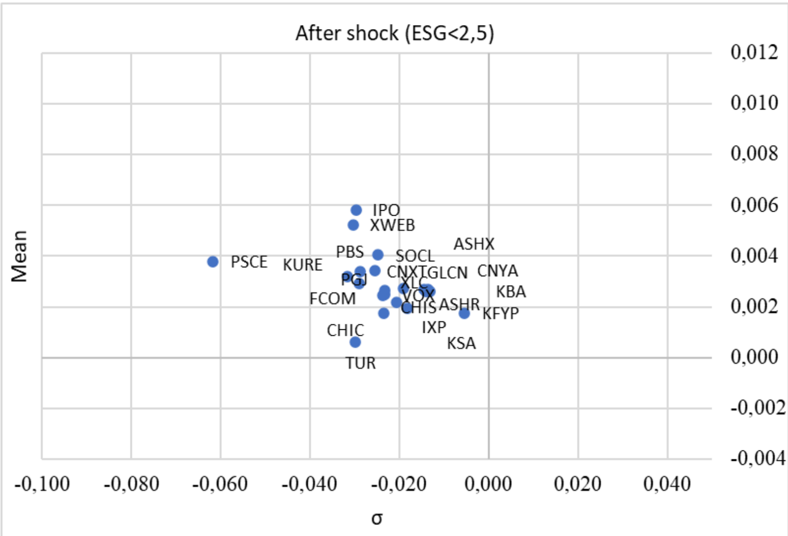
RYT	-0.0389	-0.0672	0.0265	0.0904	0.0009	0.0026	0.0106	0.0191	-0.6702	0.0521	1.5348	3.7655
EPP	-0.0388	-0.0627	0.0231	0.0671	0.0001	0.0017	0.0122	0.0168	-0.9826	-0.0387	4.1519	2.4502
Average	-0.0365	-0.0695	0.0245	0.0751	0.0008	0.0024	0.0123	0.0199	-0.7604	-0.2099	2.1169	2.1426
Rate of increase		90.6%		206.3%		198.0%		98.4%		-		1.2%

Source: *Estimated by authors' calculation*

The average range for the ESG score >7.5 group increased from 0.0610 to 0.1445 (137.1%), which is higher than for the ESG score <2.5 group. Risk-return correspondence on the basis of the classical H. Markowitz approach is given in Figure 2.




Before shock (ESG>7,5)
Mean
σ
0,012
0,010
0,008
0,006
0,004
0,002
0,000
-0,002
-0,004
-0,100
-0,080
-0,060
-0,040
-0,020
0,000
0,020
0,040
SOXL
RYT
SMH
ESGD
VAW
VGK
EFA
IQLT
EWC
BBEU
EPP
EWU


After shock (ESG<2,5)
Mean
σ
0,012
0,010
0,008
0,006
0,004
0,002
0,000
-0,002
-0,004
-0,100
-0,080
-0,060
-0,040
-0,020
0,000
0,020
0,040
IPO
XWEB
ASHX
PSCE
KURE
PBS
SOCL
CNYA
KBA
FCOM
ASHR
KFYP
CHIC
IXP
KSA
TUR

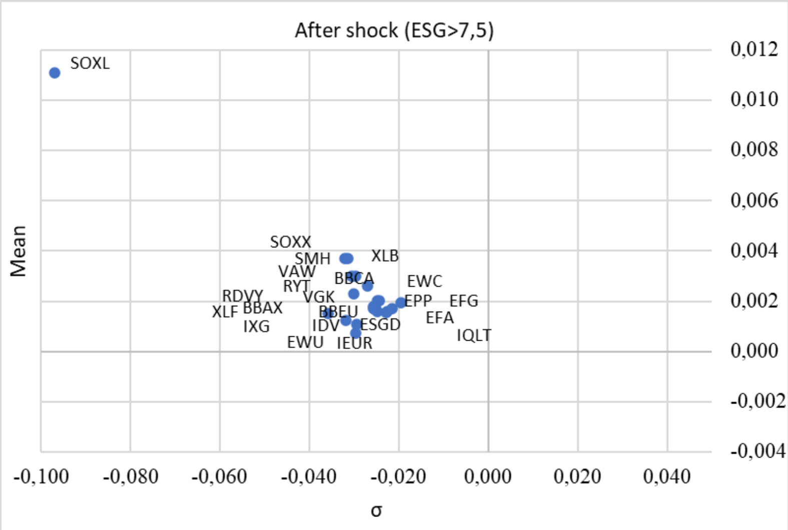


Figure 2. Risk-return correspondence comparison from variability pint of view
Source: *Estimated by authors' calculation*

These results indicate that the range and standard deviation from the before shock period were higher in the first group (ESG score <2.5). After shock, the situation became reversed. These indicators became higher in the ESG score >7.5 ETF group. In the ESG score <2.5 group, skewness changed, and kurtosis grew. Skewness remained negative and kurtosis remained the same in the ESG score >7.5 group.

4.3. Changing risk-return correspondence within the Value-at Risk approach

Consideration of the risk-return correspondence within the VaR approach presents certain differences from the previous approach. The main difference is that risk measures (VaR and CVaR) did not change essentially for the ESG score <2.5 group. In contrast, these measures grew to a considerable degree for the ESG score >7.5 group.

Another important fact is that these measures were better before the shock for the ESG score >7.5 group. However, after the shock the reverse was true. ETFs from the ESG score <2.5 group demonstrated better values of risk measures. This is similar to the results in section 4.2.

Table 5 and Table 6 present changes in the values of risk measures.

Table 5. Risk measurement by VaR and CVaR (ESG score <2.5)

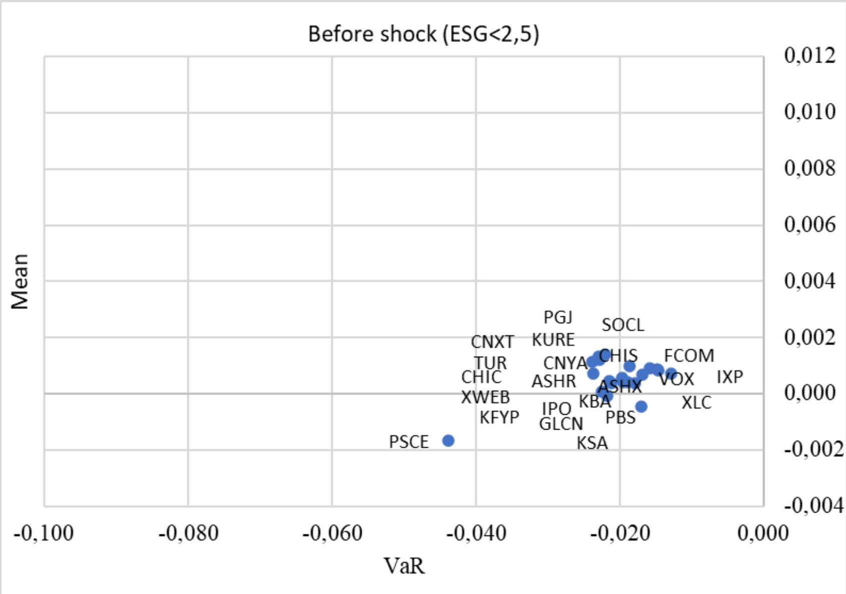
Stocks	VaR		CVaR		CVaR/VaR	
	Before shock	After shock	Before shock	After shock	Before shock	After shock
XLC	-0.0158	-0.0235	-0.0221	-0.0351	1.3965	1.4902
VOX	-0.0147	-0.0232	-0.0205	-0.0350	1.3923	1.5065
ASHR	-0.0195	-0.0141	-0.0263	-0.0305	1.3467	2.1716
KBA	-0.0197	-0.0131	-0.0261	-0.0294	1.3236	2.2474
KSA	-0.0171	-0.0182	-0.0191	-0.0301	1.1205	1.6561
FCOM	-0.0146	-0.0237	-0.0205	-0.0356	1.4025	1.5031
CNYA	-0.0196	-0.0144	-0.0265	-0.0300	1.3495	2.0940
IPO	-0.0214	-0.0296	-0.0305	-0.0413	1.4246	1.3926
SOCL	-0.0187	-0.0247	-0.0273	-0.0361	1.4577	1.4640
IXP	-0.0129	-0.0206	-0.0175	-0.0318	1.3567	1.5442
KURE	-0.0228	-0.0315	-0.0337	-0.0415	1.4807	1.3154
TUR	-0.0239	-0.0299	-0.0317	-0.0413	1.3281	1.3792
PGJ	-0.0229	-0.0288	-0.0330	-0.0386	1.4369	1.3401
PSCE	-0.0439	-0.0617	-0.0581	-0.0881	1.3239	1.4291
PBS	-0.0179	-0.0288	-0.0267	-0.0424	1.4951	1.4754
XWEB	-0.0218	-0.0303	-0.0305	-0.0457	1.4009	1.5071
CNXT	-0.0220	-0.0253	-0.0290	-0.0391	1.3165	1.5436
GLCN	-0.0212	-0.0190	-0.0309	-0.0294	1.4567	1.5494
CHIS	-0.0168	-0.0233	-0.0238	-0.0328	1.4133	1.4075
CHIC	-0.0237	-0.0235	-0.0334	-0.0315	1.4088	1.3386
ASHX	-0.0190	-0.0135	-0.0260	-0.0294	1.3684	2.1745
KFYP	-0.0226	-0.0053	-0.0290	-0.0279	1.2848	5.2383
Average	-0.0206	-0.0239	-0.0283	-0.0374	1.3766	1.7622
Rate of in-crease		16.2%		32.2%		28.0%

Source: *Estimated by authors' calculation*

Table 6. Risk measurement by VaR and CVaR (ESG score >7.5)

Stocks	VaR		CVaR		CVaR/VaR	
	Before shock	After shock	Before shock	After shock	Before shock	After shock
EFA	-0.0119	-0.0229	-0.0171	-0.0322	1.4361	1.4081
XLF	-0.0172	-0.0356	-0.0257	-0.0483	1.4934	1.3544
VGK	-0.0126	-0.0257	-0.0180	-0.0364	1.4325	1.4190
EFG	-0.0121	-0.0195	-0.0172	-0.0284	1.4184	1.4535
XLB	-0.0157	-0.0296	-0.0214	-0.0421	1.3640	1.4246
BBEU	-0.0125	-0.0248	-0.0180	-0.0350	1.4361	1.4112
SOXX	-0.0237	-0.0320	-0.0324	-0.0505	1.3657	1.5800
ESGD	-0.0116	-0.0226	-0.0165	-0.0318	1.4190	1.4044
BBCA	-0.0100	-0.0243	-0.0151	-0.0364	1.5091	1.4957
SMH	-0.0229	-0.0313	-0.0310	-0.0482	1.3544	1.5408
IEUR	-0.0123	-0.0252	-0.0176	-0.0355	1.4366	1.4093
RDVY	-0.0172	-0.0300	-0.0257	-0.0440	1.4903	1.4672
IDV	-0.0124	-0.0294	-0.0183	-0.0411	1.4778	1.3977
EWC	-0.0104	-0.0248	-0.0154	-0.0366	1.4856	1.4752
SOXL	-0.0712	-0.0969	-0.0963	-0.1520	1.3525	1.5687
BBAX	-0.0148	-0.0257	-0.0201	-0.0385	1.3627	1.4990
VAW	-0.0158	-0.0305	-0.0215	-0.0427	1.3574	1.4001
EWU	-0.0132	-0.0296	-0.0194	-0.0406	1.4694	1.3688
IQLT	-0.0112	-0.0215	-0.0156	-0.0304	1.3920	1.4173
IXG	-0.0148	-0.0317	-0.0220	-0.0431	1.4859	1.3590
RYT	-0.0181	-0.0270	-0.0260	-0.0437	1.4364	1.6199
EPP	-0.0141	-0.0252	-0.0188	-0.0375	1.3313	1.4893
Average	-0.0171	-0.0303	-0.0241	-0.0443	1.4230	1.4529
Rate of increase		177.2%		184.3%		102.1%

Source: *Estimated by authors' calculation*


Before shock (ESG<2,5)
Mean
VaR
0,012
0,010
0,008
0,006
0,004
0,002
0,000
-0,002
-0,004
-0,100
-0,080
-0,060
-0,040
-0,020
0,000
PGJ
SOCL
CNXT
KURE
TUR
CNYA
CHIS
FCOM
CHIC
ASHR
VOX
IXP
XWEB
ASHX
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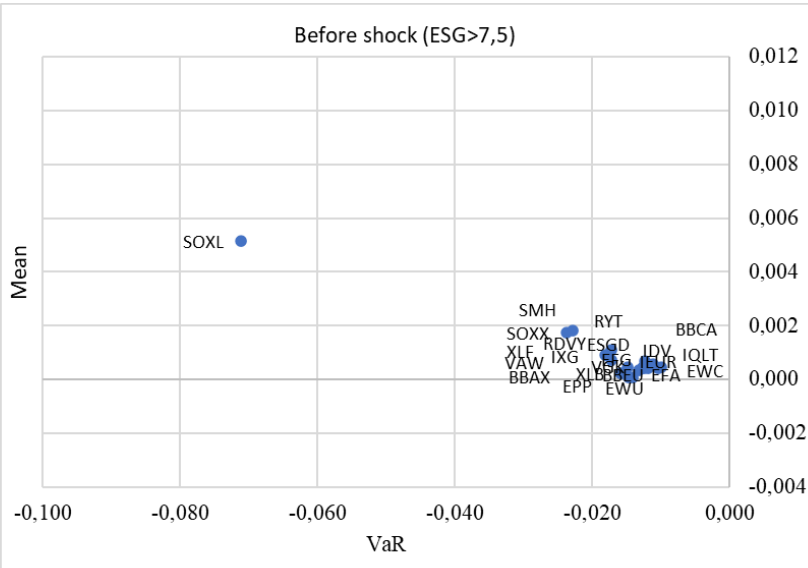
GLCN
PBS
PSCE
KSA


Before shock (ESG>7,5)
Mean
VaR
0,012
0,010
0,008
0,006
0,004
0,002
0,000
-0,002
-0,004
-0,100
-0,080
-0,060
-0,040
-0,020
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EWU

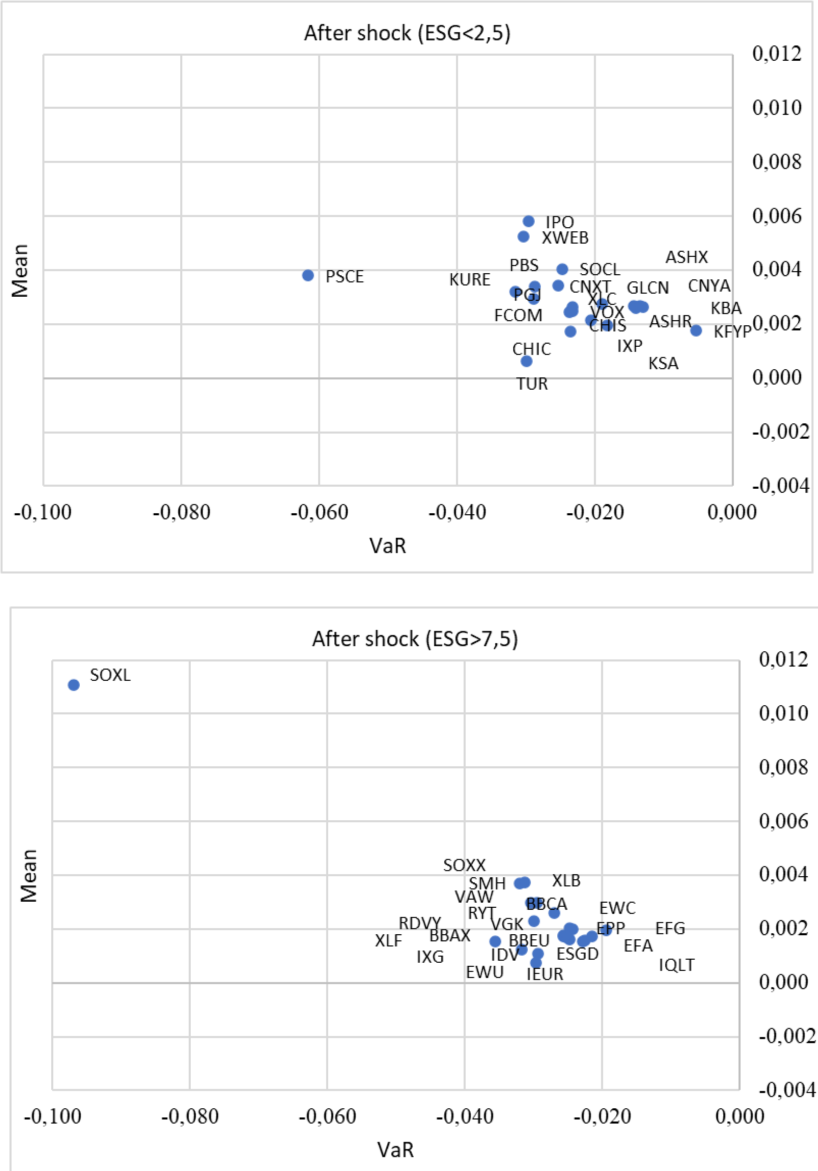


Figure 3. Value-at-Risk estimation

Source: *Estimated by authors' calculation*

4.4. Diversification effect

We have indicated some special effects during our research. Namely, the analysis presented in sections 4.2 and 4.3 involved the consideration of the diversification effect. Changes for low diversification ETFs were sharper. The ETFs considered in this research differ by number of components, ranging from 25 to 1,361. We divided each group into 3 diversification levels (Table 7.). These results disclose the diversification effect. The amount of risk at the level of low diversification is higher than in other segments. Moreover, this effect is more pronounced for the second group (ESG score >7.5).

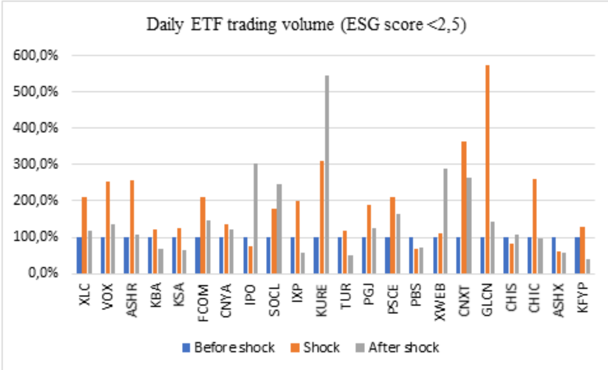
Table 7. Diversification effect

ESG score <2.5	STD estimations				ESG score <2.5	VaR estimations		
Number equities in ETF	Before shock	After shock	Ratio of increasing		Number equities in ETF	Before shock	After shock	Ratio of increasing
>100	0.011	0.017	1.508		>100	-0.019	-0.019	1.020
51-100	0.012	0.018	1.505		51-100	-0.020	-0.022	1.128
<51	0.015	0.022	1.454		<51	-0.024	-0.032	1.335
ESG score >7.5	STD estimations				ESG score >7.5	VaR estimations		
Number equities in ETF	Before shock	After shock	Ratio of increasing		Number equities in ETF	Before shock	After shock	Ratio of increasing
>100	0.007	0.016	2.192		>100	-0.013	-0.025	1.952
51-100	0.008	0.018	2.209		51-100	-0.014	-0.029	1.990
<51	0.021	0.033	1.625		<51	-0.033	-0.047	1.422

Source*: Estimated by authors' calculation*

4.5. Changes in liquidity and correlation: complimentary estimations

Liquidity was considered by using such indicators as average daily trading volume for ETFs. Our consideration of changes in risk-return supports the assumption regarding changes in daily trading activity through different periods. A comparison of this is presented in Figure 4. Average trading volume increased in the during shock and after shock periods in comparison with the before shock period.



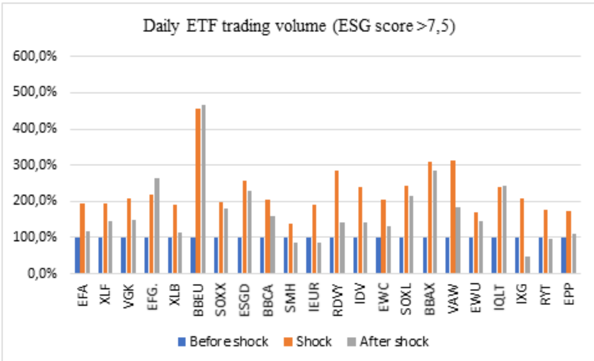


Figure 4. Daily trading volume for ETF

Source: *created by authors*

The ratio of trading volume increases for the second group is higher than for the first group – approximately 22% for shock and 27% after shock (in comparison to before shock).

Table 8. The ratio of increasing average daily volume in comparison with its level before shock

ESG score <2.5		
Number equities in ETF	Before shock	After shock
>100	2.647	1.185
51–100	1.288	1.323
<51	1.744	1.249

ESG score >7.5		
Number equities in ETF	Before shock	After shock
>100	2.509	1.933
51–100	2.055	1.364
<51	1.931	1.483

More detailed analysis involves sensitivity analysis. We analyzed correlations and the beta-coefficient between the returns of ETFs and the returns of the S&P500. This analysis demonstrates the differences between groups and is presented in Table 9. It should be noted that sensitivities and correlations are higher for the ESG score >7.5 group.

Table 9. Sensitivity analysis

	CORRELATION WITH S&P		BETA WITH S&P	
	ESG score >7.5	ESG score <2.5	ESG score >7.5	ESG score <2.5
Whole period	0.91	0.74	1.09	0.76
Before shock	0.85	0.65	1.11	1.00
During shock	0.95	0.84	1.08	0.74
After shock	0.87	0.62	1.10	0.72

This effect is supported by the estimation of the CJ coefficient. The aftershock in the group of ETFs with ESG score >7.5 demonstrates a lower value of this indicator: 0.83 against 1.01 for the ESG score <2.5 group. Before the shock, the average values of the CJ coefficient are approximately equal in both groups.

Liquidity (trading volume indicator) can be considered an additional parameter that complements risk measuring. The basic logic of using a liquidity framework can be explained by no less than three factors. The first factor focuses on the possible problem of low liquidity. As liquidity shows a very low level, it may impact price and, correspondingly, return. Each large trade will affect the returns of assets. Therefore, it may not be correct in this situation to apply measures of ETF market risk (because “market risk” is distorted). The second factor reflects the interdependency between risk-return correspondence and liquidity changing. When risk grows and returns to growth (or the reverse), investors will reconstruct their portfolios, which tend to have higher liquidity. The third factor is connected to portfolio reconstruction during the shock period. We find that the third factor is dominant in the situation under consideration. Investors who focus on ETFs with a high level of ESG score started to more intensively reconstruct their portfolios throughout the pandemic.

The explanation of our results corresponds to the rapid change of investors’ preferences. Investors who were stable before the shock period, preferring higher quality of E, S, and G scores, started to switch over to performance measures during shock times. This led to the intensive reconstruction of their portfolios and increases in the risk of return dynamic for high ESG-scoring ETFs. Investors who preferred low-scoring ETFs focused on those most likely to perform initially. Therefore, they also reconstructed their portfolios, but not so intensively.

Discussion

It is necessary to note that the nature of the indicators introduced attach conditions to the length of the first and third intervals. The consideration of simple average price through the time interval under study may be contrary to perceiving possible increased or decreased price dynamics of concrete ETFs. Therefore, the starting point and ending point of these intervals should be grounded on some balance between periods being too short or too long.

This research was conducted on a sample of ETFs which were ESG scored. The background to this is a special methodology of ESG scoring proposed by MSCI ESG Fund Metrics. The preference of using this scoring is raised from the methodology of estimate ESG score directly for ETF. At the same time, another approach can be performed, involving the application of S&P Global ESG Scores (S&P Global, 2021). The crucial differences in these ESG scores arise from the estimation of companies directly. To some extent, this is a focus on "raw materials". The question of which approach is better for the estimation of passing turmoil remains open.

Conclusion

COVID-19 induced shock effects for the whole of economics, and its consequences will be felt for a long time. This "black swan" had a significant impact on investor sentiments. Rapidly increasing uncertainty in March 2020 led to the reformatting of investment portfolios. Contemporary researchers analyze various aspects of the shock felt by the financial markets. The aim of our study was a comparative analysis of the passing through of shock of ETFs with high- and low-level ESG scores. The basic grounding statement of such a goal was an ever-growing interest in companies that focus on the components of E, S, and G.

In our opinion, these results indicate several interesting points. The first point is that ETFs with high ESG scores were affected more by shock. Considering a pair of imposed indicators, SD and RR, allowed us to reveal some patterns. The first of these was a strong linear dependency between RR and SD for the ESG score <2.5 group. Secondly, comparative analysis of risk levels identifies the following risk changing pattern: before shock, the second group (ESG score > 7.5) was slightly less risky; after shock, the second group showed a sharper increase in risk. Moreover, it demonstrated a higher correlation inside the group and a correlation with S&P500 returns. These results also reveal that dependency risk changes with the diversification level of the ETF portfolio. The complex analysis of trading volume activity and Cowles-John's ratio indicated essential differences between groups. The results suggest that ETFs from the ESG score >7.5 group were more strongly affected by COVID-19 shock. This can be expressed by more severe "jitters" of returns and trading after shock.

By combining the results of the evaluation according to different approaches, indicators of the daily average trading volumes, and CJ indicators, we have formed the following explanation.

The implementation of ESG criteria is a wide-ranging process. It includes many risks, one of which is the "transition risk" to ESG. However, investors are not yet certain in maturity of ESG transformations. As a result of the shock, they do not have a single vision. They actively reconstructed their portfolios at shock, and the growth of trading volumes, which was expressed in the volatility of returns, is one such indicator of this. At the same time, ETFs with low ESG scores were more understandable for investors. Thus, it can be concluded that to a large extent these results show the evidence of "transition risk" during shock.

We observe that the dynamic of risk-return correspondence for investments with high implementation of the ESG principle should continue. This is important for better understanding their role in investment portfolio management.

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