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Volatility and tail dependence between sustainable stock indices during the COVID-19 pandemic

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Abstract

Motivation: The motivation behind the study was to analyze the risk of sustainable stock indices (SSIs) and their conventional peers during the COVID-19 health crisis. We wanted to check if SSIs were more resistant to market risk in the times of huge volatility as well as what the correlation between particular SSIs was and, similarly, between their conventional peers.

Aim: The main objective of the study was to analyze volatility spillover among sustainability stock indices (SSIs) and their conventional peers during the COVID-19 health crisis. The authors analyze conditional volatility among SSIs, which was obtained from univariate GARCH-type models, and the tail dependence coefficient, which was derived from the Copula-GARCH models. The indices from FTSE4Good family for the USA, Europe and Japan markets together with their corresponding conventional indices have been chosen.

Results: The research shows that during the COVID-19 health crisis SSIs were less volatile than their conventional peers. Moreover the relations between particular SSIs in most cases were weaker, whereas extreme observations which occurred were less concordant for conventional indices. It implies that the stability of sustainable stock indices from FTSE4good family is greater than for their conventional peers.

Keywords: socially responsible investment (SRI); sustainable investments; ESG risk
JEL: C13; G11; M14; O16

1. Introduction

Sustainable investments (SIs) are these which consider both financial return and social good. Their significant growth in financial markets around the world has led to an intensive debate. It is also evident that investing with ethical concerns in mind has clearly gone from the margins to the mainstream (Revelli, 2017). This was especially true during the COVID-19 pandemic. Assets in European sustainable funds surged by 52% in one year to hit EUR 1.1 trillion in December 2020. It was due to such various reasons as, firstly, significant inflows of assets, secondly, conventional assets were repurposed, and thirdly, rising financial markets (Morningstar, 2021).

Taking into consideration the interest of investors in sustainable investing during the COVID-19 pandemic, the aim of the study was formed, i.e. to analyze volatility spillover and tail dependence among sustainability stock indices (SSIs) and among their conventional peers during the COVID-19 health crisis. The previous research results obtained by Albuquerque et al.(2020), Broadstock et al. (2020) and Whieldon et al. (2020) confirm that companies with high ESG (Environmental Social Governance) ratings achieved higher stock returns and lower volatility during the COVID-19 pandemic. Moreover, tail dependence among SSIs was studied as well. The earlier research conducted by Le et al. (2020) showed that tail dependence between stocks in the pandemic period increased significantly. Though this thesis was confirmed by the above mentioned authors, we would like to check the performance of sustainable stocks in terms of volatility and tail dependence coefficient. Le et al. (2020) identified static tail dependence using quantile cross-spectral analysis. We, on the contrary, obtained dynamic tail dependence coefficient using DCC-copula method. It allowed us to conduct a much more precise analysis of changes in tail dependence during the analyzed period. The subject of our study were Sustainability Stock Indices (SSIs), which constitute passive portfolios with high ESG ratings. We assumed the a priori term Sustainability Stock Indices (SSIs) instead of Socially Responsible Indices (SRI), which is compatible with current financial market trends. Following Fernández (2019 as cited in BBVA, 2019), environmentalist and professor at the Instituto Superior de Medioambiente, ‚sustainability indexes are designed and built with the goal of providing information to institutional and retail investors that value the importance of the companies' environmental and social responsibility and corporate governance in their everyday management, in addition to economic results, in their decisions to purchase shares'.

Our study encompasses stock indices from FTSE family to avoid methodological mistakes due to different methods of selecting companies to particular indices.

The paper is organized into the following sections: Section 2 presents a review of the literature; Section 3 describes the methodology and the main characteristics of the presented data; Section 4 presents the research results, and Section 5 discusses the study results.

2. Literature review

In this study we would like to analyze only the risk of SIs, which was also the subject of debates in other studies (Bouslah et. al., 2011; Hemingway & Maclagan, 2004; Lee & Faff, 2009; Maraqa & Bein, 2020; Sassen et al. 2016; Verheyden et al. 2016). Generally, studies indicate a positive, negative or mixed influence of ESG factors on financial risk in the context of different industries and countries (Jo & Harjoto, 2014; Muhammad et al., 2015; Shakil, 2020), and also emphasize that firms which reveal social and environmental responsibility lessen information asymmetry and volatility of stock prices in the market (Jia et al., 2020; Lueg et al., 2019; Shakil, 2020). The impact of religious screening on the firm risk was presented by Kabir Hassan et al. (2021). The authors argue that the engagement in sustainable activities mitigates risks for both Sharia-compliant and conventional firms. There also exist a number of research which prove that companies with high performance of ESG record higher risk-adjusted returns (Ashwin Kumar et al., 2016; Sherwood & Pollard, 2018; Verheyden et al., 2016).

In relation to the COVID-19 pandemic, published research indicated higher returns and lower risk for SIs during the period mentioned above (Albuquerque et al., 2020; Broadstock et al., 2020; Whieldon et al., 2020). Singh (2020) shows that risk averse investors sought shelter in high ESG ratings portfolios during the discussed period.

Le et al. (2020) showed that tail dependence between stocks in the pandemic period increased significantly. The survey conducted among investors by McLachlan and Gardner (2004) show that socially responsible investors are younger and better educated. They make decisions less nervously and more sustainably, and have less tendency to use speculate strategies. Similar theses are obtained by Diouf (2016) and Junkus and Berry (2010). In this context, the research results obtained by Le et al. (2020) are surprising since sustainable investors seem not to withdraw from the market immediately after the first deep drops. So, in the case of sustainable investments, tail dependence should not be so big.

3. Methods

On the basis of other research results, the following research hypotheses were formed:

H1: SSIs had lower volatility than their conventional peers during the COVID-19 health crisis.

The H1 was confirmed by Albuquerque et al. (2020), Broadstock et al. (2020) and Whieldon et al. (2020). They indicate that companies with high ESG ratings achieved lower volatility during the COVID-19 pandemic. However, the research itself analyzed the companies alone not their portfolios.

H2: The dependence (measured by Kendall's τ) between SSIs was smaller than between their conventional peers during the COVID-19 health crisis.

H3: Extremal observation occurred less concordantly for SSIs than for their conventional peers during the COVID-19 health crisis.

To verifying the above hypotheses, we adjusted dynamic copula models to four time series of daily logarithmic returns from sustainable stock indices (SSIs) and conventional stock indices (CSIs) from FTSE family: FTSE4Good USA Index, FTSE4Good Europe Index and FTSE4Good UK Index, FTSE4Good Japan Index; FTSE USA Index, FTSE Developed Europe Index, FTSE 350 Index, FTSE Japan Index. As we emphasized in section two herein, there exist papers in which similar hypotheses were verified. They base their analysis on typical parametric models or on quantile analysis. Applied herein dynamic copula models respond better to the properties of the analyzed series. Hence, this approach allows for a more appropriate description of dynamics. In section four, we describe the advantages of applied models with regards to alternative approaches. The analysis was based on daily log returns in the period from January 1, 2018 to December 31, 2020.

3.1. Data

FTSE4good indices are based on stocks which reflect high ESG factors measured by FTSE Russell's ESG Ratings. FTSE4good companies in developed markets are newly included in the index if their rating exceeds 3.3, and are removed from the index if it falls below 2.9. The indices exclude companies due to their involvement in tobacco production, nuclear weapons, conventional weapon systems or coal power industry. Conventional FTSE indices cover large and midcap stocks related to all market sectors from particular markets.

Table 1 and Table 2 presents descriptive statistics of daily logarithmic returns of FTSE4good (FTSE4G) sustainable indices and FTSE conventional indices from the considered period. The data in Table 1 show that the FTSE4good for all markets except the Japanese one are less volatile and have bigger kurtosis than their conventional peers, whereas FTSE4good indices have bigger kurtosis and stronger left-hand side skewness. According to the data presented by the FTSE Russell Research Portal (2022), it seems that there are definitely fewer companies in FTSE4good indices than in the case of their conventional peers. However, no significant differences can be observed in terms of the companies' share in particular FTSE4good indices and conventional ones. The only exception are the indices for the American market. In this case, the share of technological companies in FTSE4good is higher by 12.5% than for the FTSE USA index, whereas in the FTSE index the same consumer discretionary is higher by 6.5%. Also, the list of the biggest companies is different for the American indices since the criteria of social responsibility are not fulfilled by such companies as Amazon or Tesla. Apart from the above examples, the share of companies in other sectors do show a slight difference of not more than 2%. Hence, it may be concluded that the composition of FTSE4good indices and respective socially responsible companies is similar. Moreover, while analyzing the data presented in the FTSE Russell Research Portal (2022) it may be observed that the mean and median of companies' capitalization in FTSE4good indices is about 30–50% higher than if compared to conventional peers. It may result from the fact that satisfying the requirements of social responsibility involves significant expenses. Therefore, these are usually small companies which suffer most. For example, capitalization of the smallest company included in the FTSE4good index in the UK does not exceed GBP 80 m.

3.2. The model

To achieve the aim of the study and to verify the research hypotheses we pretested our data against various statistical hypotheses to apply the appropriate model. At first, we applied univariate GARCH-type to daily returns of each daily logarithmic return series. Secondly, we adjusted dynamic copula model, developed by Patton (2002; 2006), to the cumulative distribution function of standardized residuals. The application of conditional copula model instead of the multi-GARCH model has two reasons.

The first one is that all multivariate models require elliptic innovations, while, as already mentioned, analyzed return series have strong skewness. So, it justifies the application of skewed innovation in univariate models.

The second reason is the assumption of identical univariate distribution of all modeled series in DCC, while even from the short analysis of the descriptive statistics (Table 1), we can suspect that the empirical distributions of the modeled data vary across samples. For instance, the kurtosis varies significantly across the samples both in the case of SSI indices and the general market indices.

Furthermore, copula models give us the possibility to use measures of dependence other than the Pearson coefficient. When time series distribution is not normal, using the Pearson's correlation coefficient to identify the dependencies between random variables may lead to misleading conclusions (Lindskog, 2000). This is because the Pearson's correlation coefficient is very sensitive to outliers. Moreover, the correlation equal to zero implies independence only if the variables are normally distributed. The heavier the tails are, the larger the error of the estimator is. Since our data are strongly leptokurtic (see Table 1), we decided not to use the Pearson's correlation, but concentrate on Kendall's τ. We also determined the tail dependence coefficient (λ). The latter is especially important for our analysis. It provides us with the information on the possibility of the transmission of extreme events from one market to another. Schmidt (2002) explained that asymptotic dependencies should not be identified with linear correlation coefficient. It is common knowledge that in some cases the correlation between the considered series is strong, but there exists no dependence in tails. Note that bivariate normal distribution is asymptotically tail independent if its correlation coefficient ρ is less than 1. Therefore, we decided to use dynamic t conditional t copula. More precisely, our research is based on the DCC-t-copula model. The model was applied in two steps using maximum likelihood method. In the first step, we fit each univariate series $x_{i,t}$, and the $u_t=u_{1,t},\ldots,u_{d,t}$ is the multivariate time series, with each $u_{i,t}$ having been determined as the value of cumulative distribution function for $\tilde{\varepsilon}_{i,t}$, to one of the univariate GARCH-type models with t Student or GED innovation distribution (Nelson, 1991).

$$x_{i,t} = \mu_{i,t} + y_{i,t} y_{i,t} = \sigma_{i,t}\varepsilon_{i,t}, \varepsilon_{i,t} \sim iid(0,1), u_{i,t} = F_i\left(\tilde{\varepsilon}_{i,t}\right), \tag{1}$$

where $\tilde{\varepsilon}_{i,t}$ stands for standardized residual series and F_i is the cumulative distribution function of innovation distribution from the model fitted to $x_{i,t}$. Conditional mean $\mu_{i,t}$ was modelled as an ARMA-type model of the form:

$$x_{i,t} = a_0 + \sum\nolimits_{i=1}^{p} a_i x_{t-i} + \sum\nolimits_{j=0}^{q} b_j y_{t-j}. \tag{2}$$

We considered standard GARCH models (Bollerslev, 1986), and the IGARCH (Engle & Bollerslev, 1986) with skewed t Student with υ degrees of freedom and the skew parameter ξ. In the second step, to u_t series we fit the conditional t copula, where the rank correlation matrix R_t is driven by the DCC model of Engle & Sheppard (2001).

$$C^t_{\upsilon,R_t}\left(u_1,\ldots,u_d\right) =$$

$$= \int_{-\infty}^{t^{-1}(u_1)} \cdots \int_{-\infty}^{t^{-1}(u_d)} \frac{\Gamma\left(\frac{\upsilon+d}{2}\right)}{\Gamma\left(\frac{\upsilon}{2}\right)\sqrt{(\pi\upsilon)^d |R_t|}} \left(1 \frac{\begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix}^T R_t^{-1} \begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix}}{\upsilon}\right)^{\frac{\upsilon+d}{2}} dx_1 \cdots dx_d, \tag{3}$$

where $\Gamma(x)=\int_0^{\infty} x^{t-1}e^{-x}dx$ isthegammafunction $R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$,

where the positive-definite matrix Q_t is described by the following formula:

$$Q_t = \left(1-\sum_{m=1}^{M}\alpha_m - \sum_{n=1}^{N}\beta_n\right)\bar{Q} + \sum_{m=1}^{M}\alpha_m \tilde{u}_{t-m}\tilde{u}_{t-m}^{'} + \sum_{n=1}^{N}\beta_n Q_{t-n}, \tag{4}$$

where $\tilde{u}_t = t_{\upsilon}^{-1}(u_t)$. The log-likelihood function is given by the following formula:

$$\begin{aligned} L_{St}\left(R_t,\upsilon,\theta,\tilde{u}_t\right) = & -Tln\frac{\Gamma\left(\frac{d+\upsilon}{2}\right)}{\Gamma\left(\frac{\upsilon}{2}\right)} - pTln\frac{\Gamma\left(\frac{\upsilon+1}{2}\right)}{\Gamma\left(\frac{\upsilon}{2}\right)} - \\ & -\frac{d+\upsilon}{2}\sum_{t=1}^{T} ln\left(1+\frac{\tilde{u}_t^{'}R_t^{-1}(\theta)\tilde{u}_t}{\upsilon}\right) - \sum_{t=1}^{T} ln\left|R_t(\theta)\right| + \\ & +\frac{\upsilon+1}{2}\sum_{t=1}^{T}\sum_{i=1}^{p}\left(1+\frac{\tilde{u}_{i,t}^{2}}{\upsilon}\right), \end{aligned} \tag{5}$$

where θ is the DCC parameter vector. More details about conditional copulas can be found in Doman & Doman (2013), Patton (2002; 2006).

4. Results

The results of estimations based on the GARCH-type models are presented in Table 2. The details of Box–Pierce test for standardized residuals and squared standardized residuals show that the linear and non-linear dependencies were indeed explained by the models. After estimating the univariate models, we collected standardized residuals, and fit 4-dimmensional t-copulas with conditional covariance matrix explained by DCC(1,1) model to the $u_{i,t}$ series. Taking into account our objective, the copulas were fitted to the returns of four full market indices and four SSIs induced separately. The estimation results are presented in Tables 3–6.

The results presented in Table 3 and Table 4 show that the persistence in variance is huge for all analyzed indices, but in the case of all markets except from the Japanese one, for FTSE4good indices it is slightly lower than for conventional indices. In FTSE4good the persistence is huge. Left-hand side skewed innovation was applied in all indices apart from the Japanese ones. Properly adjusted models of dynamic copula indicate a durable influence of disturbances on the correlation in conventional indices.

Presented in Chart 1 conditional variance of European conventional indices remained stable until February 24, 2020. In the same period, American and Japanese indices were more dynamic, in particular a significant increase in their volatility in the second half of 2018 could be observed when all world markets recorded downward trends. The volatility of all analyzed indices grew rapidly after April 24, 2020 when COVID-19 cases were widely recorded in Europe, the USA and Japan. It should be emphasized that this shock on the Japanese market was relatively lower if compared to other world markets. The Japanese market accepted the information about the pandemic quite peacefully, and huge social discipline resulted in lower increase in the number of COVID-19 cases. Moreover, in case of each pair of indices analysis, the value of this shock was twice as low as in the case of sustainable indices.

However, after the first shock due to the pandemic, the conditional variance of all indices decreased rapidly after the first wave of the pandemic. At the beginning of summer 2020 these levels were only a little higher than before the pandemic. Yet another increase in the conditional variance appeared in September 2020 together with the second wave of the pandemic. This growth was also short-term and at the end of the year the variance of conventional indices again reached the level similar to the beginning of the research period. It was also clearly weaker in case of sustainable indices.

As it has been mentioned, the composition of FTSE4good indices and respective conventional peers overlap to a great extent, hence such huge similarity in variance dynamics. Most importantly, the dynamics of variance of socially responsible indices remains lower in the entire period under investigation as compared to variances corresponding to their conventional peers.

The analysis presented in Chart 2 and Chart 3 shows that the dependence between pairs of sustainable indices is lower than in case of their conventional peers in the entire analyzed period. Only the pairs of American and European indices seem to be an exception here. Dynamic estimates of Kendall's τ coefficient presented in Chart 2 show that mutual relation between FTSE4good indices is weaker than in the case of conventional indices. In the case of SSIs, Kendall's τ coefficient does not reflect such a big deviation in the examined period, whereas for conventional indices this measure shows a significant increase in concordance at the moment of the pandemic outbreak. Next, it decreases and afterwards it indicates a short-term increase again after the second wave of the pandemic. This effect is even stronger in the case of the tail dependence coefficient (Chart 3). Also here, in the case of FTSE4good indices pairs it remains at the same similar level throughout the entire researched period, however in the case of conventional indices, there is a significant growth in concordance of extremal observations occurrence after February 24, 2020. It means that the concordance of extremal observations of particular conventional indices became then even higher.

5. Conclusion

The majority of research concentrates on sustainable investments profitability, however, even if their authors discussed the risk factor, it rather referred to investments in single shares. In the case of portfolios, higher risk for thematic portfolios is indicated, which is due to almost no possibility of conducting proper diversification of these portfolios. The studies on SI performance in the period of higher volatility are in their initial phase because the phenomenon of socially responsible investment is relatively new. Although the first research on SIs was conducted in the 90s of 20th c., they referred only to selected markets, and Sis have become increasingly popular over the past decade. The period of high volatility during the COVID-19 pandemic allowed to conduct research to such a broad extent.

The main outcome obtained through univariate GARCH models is that SSIs had less volatility risk during the COVID-19 crisis compared to their conventional peers. To be specific, volatility of SSIs was not that strongly influenced by the first and second wave of the pandemic as it happened in case of conventional indices. This implies that investors can reduce their risk exposure by investing in companies with high ESG rating, especially in times when strong negative impacts influence the market. The analysis of tail dependence coefficients obtained by dynamic copula showed that SSIs are more resistant to be influenced strong impulses. In case of conventional indices tail dependence coefficients were particularly huge after the pandemic outbreak. In case of SSIs, we could observe only their short-term growth.

Using the above-mentioned research methods allowed to confirm H1 and H3. They also confirm them the research conducted by other authors (Albuquerque et al., 2020; Broadstock et al., 2020; Whieldon et al., 2020). Additionally, the dependence, measured by Kendall's τ, was lower SSIs than their conventional peers. Only in one case, i.e. among the USA and EU indices, the dependence was similar. Hence, H2 was partially confirmed.

The research results indicate a greater stability of sustainable stock indices from FTSE4good family. However, the study herein does not provide the reasons for this phenomenon, whereas the survey conducted by McLachlan and Gardner (2004) among investors show that socially responsible investors are younger and better educated and have less tendency to use speculative strategies. US SIF (2022) indicate that sustainable investing 'generates long-term competitive financial returns and positive societal impact', which also indicates non-speculative character of these investments.

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Appendix

Table 1.
Descriptive statistics of daily logarithmic returns of FTSE4G indices

Statistic	FTSE4G USA	FTSE4G Europe	FTSE4G UK	FTSE4G Japan
mean	0.0565	0.0090	−0.0039	0.05159
volatility	1.0526	1.0042	0.9992	1.4989
min	−8.6993	−12.1032	−11.3228	−12.9654
max	7.6213	6.8853	7.3628	9.59817
skewness	−0.9987	−2.7606	−2.2514	−0.9239
kurtosis	12.9037	32.7634	26.7602	16.0231
no of constituents	491	409	214	204

Source: Own preparation.

Table 2.
Descriptive statistics of daily logarithmic returns of FTSE indices

Statistic	FTSE USA	FTSE Developed Europe	FTSE 350	FTSE Japan
mean	0.0453	0.0020	−0.0180	0.0462
volatility	1.4577	1.1856	1.1339	1.4559
min	−12.8739	−12.3188	−11.1002	−12.8739
max	8.9886	8.1815	8.1067	8.9886
skewness	−1.0886	−1.7670	−1.9449	−1.0921
kurtosis	16.7798	21.0354	22.2828	16.8279
no of constituents	614	590	350	509

Source: Own preparation.

Table 3.
Results of the estimations of univariate GARCH models — FTSE4Good USA, FTSE4Good Europe, FTSE4Good UK, FTSE4Good Japan

	FTSE4G USA	FTSE4G Europe	FTSE4G UK	FTSE4G Japan
model	AR(1)–GARCH(1,1) with skst(0,1,υ)	AR(1)–GARCH(1,1) with skst(0,1,υ)	AR(1)–GARCH(1,1) with skst(0,1,υ)	AR(1)–GARCH(1,1) with GED(0,1,υ)
a_1	−0.0821	0.1330	0.1492	–
	(0.0168)	(0.0002)	(0.0000)	
w	0.0389	0.02288	0.03277	0.06531
	(–)	(–)	(–)	(–)
α_1	0.1761	0.1555	0.1422	0.1323
	(0.0000)	(0.0007)	(0.0000)	(0.0086)
β_1	0.8207	0.8437	0.8388	0.8267
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$ln(x)$	−0.2812	−0.2916	−0.3112	–
	(0.0000)	(0.0000)	(0.0000)	
υ	5.0836	4.1464	4.1545	0.9276
	(–)	(–)	(–)	(–)

Note:

Parameters with p-values in parentheses.

Source: Own preparation.

Table 4.
Results of the estimations of univariate GARCH models — FTSE USA, FTSE Developed Europe, FTSE350, FTSE Japan

	FTSE USA	FTSE Developed Europe	FTSE 350	FTSE Japan
model	AR(1)–GARCH(1,1) with skst(0,1,υ)	AR(1)–GARCH(1,1) with skst(0,1,υ)	AR(1)–GARCH(1,1) with skst(0,1,υ)	AR(1)–GARCH(1,1) with GED(0,1,υ)
a_1	−0.0775	−0.0617	–	−0.1098
	(0.0223)	(0.0888)		
w	0.0315	0.0347	0.0282	0.0513
	(–)	(–)	(–)	
α_1	0.1779	0.1771	0.1463	0.0968
	(0.0000)	(0.0000)	(0.053)	
β_1	0.8221	0.8229	0.8536	0.8572
	(–)	(–)	(–)	
$ln(x)$	−0.2857	−0.2010	−0.1287	–
	(0.0000)	(0.0000)	(0.0000)	
υ	5.0042	3.9941	4.5863	1.1984
	(–)	(–)	(–)	(–)

Note:

Parameters with p-values in parentheses.

Source: Own preparation.

Table 5.
Estimation results of 4-dimensional DCC-t-copulas with conditional matrix Rt explained by DCC(1,1) model — SSIs

Parameter	Estimate	Std. error	t-stats	p-value
υ	15.033	4.484	3.3523	0.0008
α_1	0.0488	0.017	2.8462	0.0044

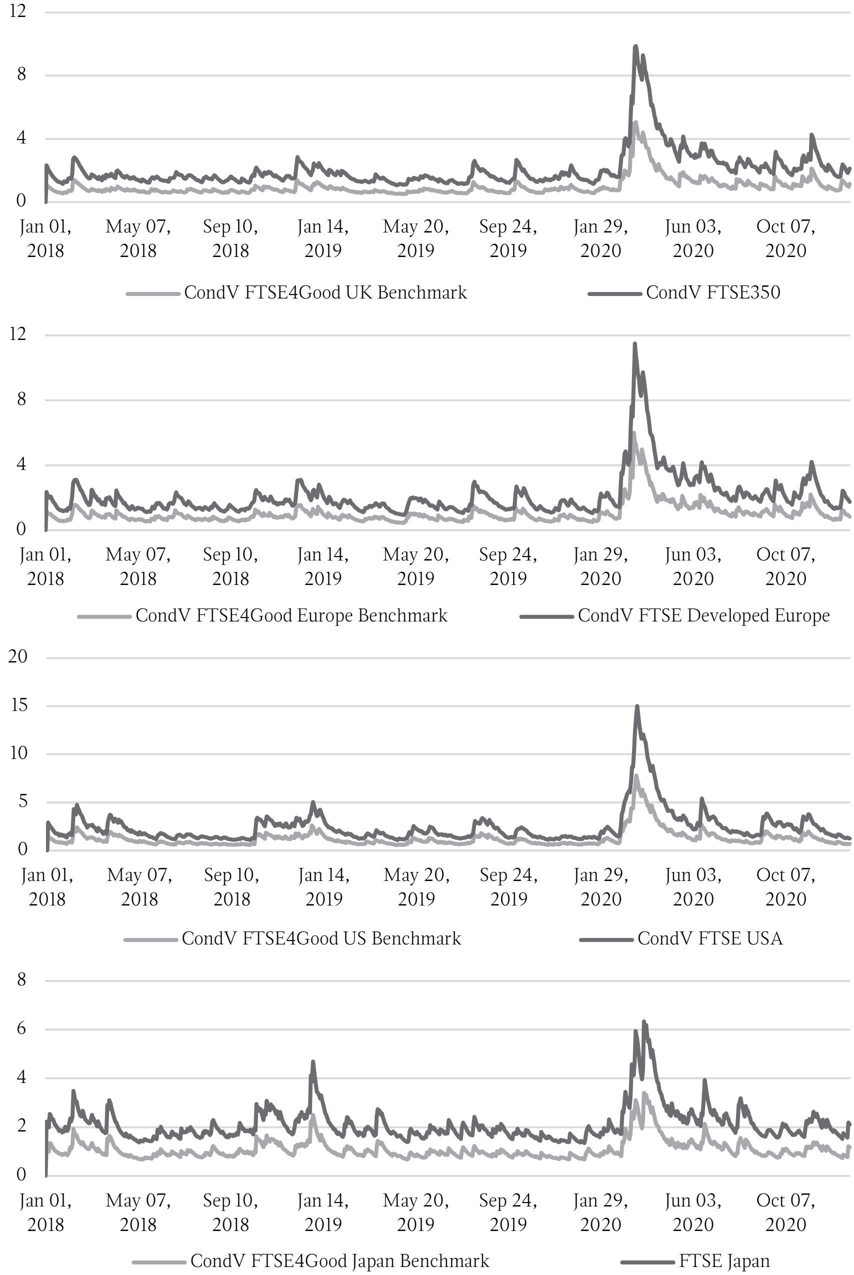
Source: Own preparation.

Table 6.
Estimation results of 4-dimensional DCC-t-copulas with conditional matrix Rt explained by DCC(1,1) model — CSIs

Parameter	Estimate	Std. error	t-stats	p-value
υ	10.0918	2.2000	4.5879	0.0000
α_1	0.0354	0.0027	12.8700	0.0000
β_1	0.8618	0.1950	4.4256	0.0000

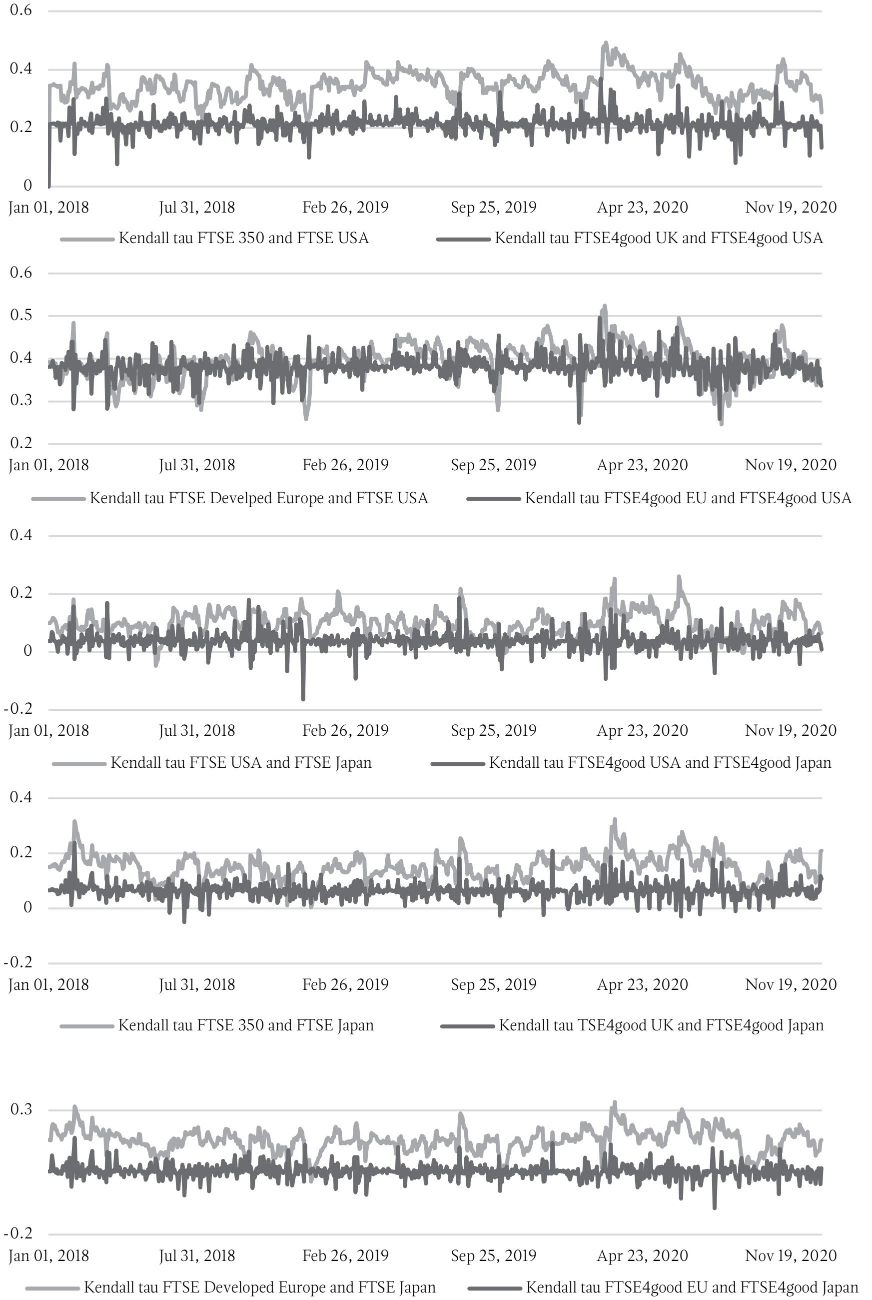
Source: the authors' own calculations

Chart 1.
Conditional variance of FTSE compared to FTSE4good indices



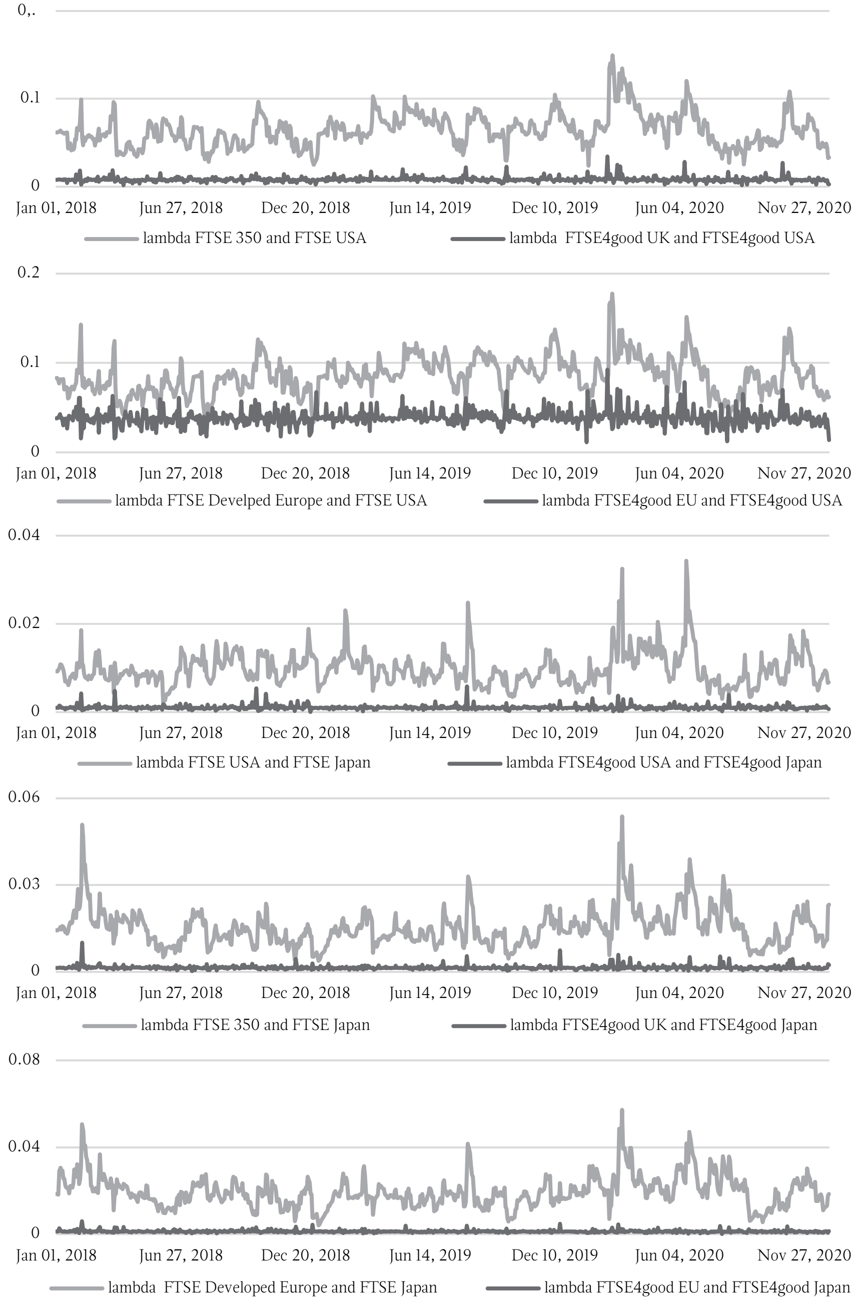
Source: Own preparation.

Chart 2.
Kendall's τ of FTSE compared to FTSE4good indices



Source: Own preparation.

Chart 3.
Tail dependence coefficient of FTSE compared to FTSE4good indices



Source: Own preparation.