J. Int. Financ. Markets Inst. Money 95 (2024) 102027

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

The nexus of conventional, religious and ethical indexes during crisis

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ARTICLE INFO

Keywords:
Covid-19
Conventional
Ethical
Islamic
Stock index
Networks
VAR

ABSTRACT

This study examines the interconnectedness between conventional and ethical indexes. Using a Bayesian graphical vector autoregressive model, we derive the contemporaneous and temporal interdependencies among these stock index returns before and during the Covid-19 pandemic. Our model specification strategy combines vector autoregressive models with networks. The findings provide empirical evidence of increased interconnectedness during the Covid-19 period across all networks. Notably, the religious and FTSE Islamic networks exhibited greater resilience during the pandemic. This could be attributed to the rigorous screening processes for religious portfolios, which focus on lower-leveraged equity stocks, contributing to their stability. Additionally, our results show that the Covid-19 crisis affected network density and the roles of key player shock transmitter entities, as indicated by changes in hub and authority scores, with new key players emerging during the crisis.

1. Introduction

The recent Covid-19 pandemic, European sovereign debt crisis, and Global Financial Crises (GFC) have highlighted the importance of systemic risk and renewed the interest of researchers in financial and macroeconomic interconnectedness. Evidence suggests that periods of market distress can lead to prolonged worldwide fear contagion and fundamental changes in the linkages among international financial markets. These periods of heightened volatility and propagated shocks underscore the need to explore alternative investment modes and their dynamic interrelationships. Connectedness, as a fundamental aspect of systemic risk analysis, has gained significant attention across various areas of research, including risk management, portfolio allocation, and economic policies. As noted by Diebold and Yilmaz (2014), achieving optimal portfolio allocation necessitates an understanding and measurement of connectedness, to minimize portfolio risk. During market turbulence, investors seek safe havens and portfolio diversifiers to safeguard their investments. Ethical investments[2] gained popularity, especially during/after the 2008 global financial crisis, as they exhibited greater stability compared to their conventional counterparts, making them more attractive as safe-haven assets (Abdelsalam et al., 2014; Akhtar and Jahromi, 2017; Ahmed and Elsayed, 2019; Nofsinger and Varma, 2014).

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[2] In our study with ethical investments we refer to both Socially Responsible Investing (SRI) as well as to Shariah-compliant investments.

https://doi.org/10.1016/j.intfin.2024.102027
Received 7 March 2023; Accepted 2 July 2024
Available online 23 July 2024

The ethical investments examined in this research encompass both religious (Islamic) and socially responsible investing (SRI). Since these investments are developed on religious and ethical beliefs, they are subject to constraints and must align with religious/ethical principles. One significant challenge for ethical equity investors is the existence of various screening frameworks (Novethic, 2014; Ho, 2015; Derigs and Marzban, 2008; Bakar et al., 2023). All major index data providers, such as the Financial Times Stock Exchange (FTSE), Standard and Poor's (S&P), Dow Jones (DJ), and Morgan Stanley Capital International (MSCI), develop and offer data on Socially Responsible Investing (SRI) and Islamic equity indexes based on independent and distinct screening criteria for the inclusion/exclusion of equities[3]. Different ethical screening frameworks not only impact the composition of the portfolio but also provide investors with different risk and performance profiles (Ashraf and Khawaja, 2016; Bakar et al., 2023).

Religious and SRI investments share some similarities as they both exclude industries from their investment universe that are deemed unethical, such as tobacco, armaments, alcohol, etc. Both screening processes apply non-financial criteria to filter out companies that do not comply with their beliefs and value systems. However, Islamic investment portfolios differ in that they also screen out conventional (interest-based) financial sectors and apply additional financial criteria to ensure that the level of conventional debt does not exceed the tolerated Shariah threshold. This is because interest-based activities are not compliant with Shariah principles (Siddiqi, 2004). SRI, on the other hand, places its focus on issues such as environmental risk, corporate governance, and the social practices of corporations concerning their stakeholders, such as employees, customers, and society as a whole. Additionally, Islamic screening frameworks focus on the different lines of the business, checking whether they meet Shariah requirements and assessing their exposure to interest-based activities. However, Islamic screening tends to overlook the social and environmental concerns of businesses, which are integral components of SRI screening criteria. Therefore, although Islamic investment portfolios are categorized under the broad umbrella of SRI portfolios by definition, and while both types consider some industries as impermissible, the practices of the two investment groups differ significantly.

The adoption of ethical/religious screens in investment portfolios partially conflicts with modern portfolio theory, which hypothesizes that portfolios constructed with SRI/religious screens could suffer from a lack of diversification (Rudd, 1981). Furthermore, these portfolios incur additional costs due to the monitoring expenses associated with screening activities. According to these theoretical arguments, SRI/Sharia-compliant indexes are expected to underperform compared to their conventional counterparts. On the other hand, proponents of ethical investing argue that companies with high levels of ethical performance are expected to outperform their conventional counterparts in the long term due to the higher level of loyalty and trust from their stakeholders and market participants.

Our study is motivated by the growth of ethical investing and the increasing interest of investors, especially during the recent Covid-19 period[4]. This growth has attracted attention from academics and institutional investors. Additionally, our research agenda aims to investigate how ethical investments differ from their conventional counterparts, specifically during periods of turbulence like the recent Covid-19 pandemic. While there is extensive empirical literature comparing the performance of ethical investments with their conventional counterparts (see, for instance, (see for instance Abdelsalam et al., 2014, 2017; Hamilton et al., 1993; Climent and Soriano, 2011; Brooks and Oikonomou, 2018; Ho et al., 2014; Ashraf and Khawaja, 2016, among others), the network connectedness has not been thoroughly investigated, especially during the recent Covid-19 pandemic. This paper aims to address this gap by investigating the intra- and inter-layer connectivity among various indexes from different industries.

Our paper makes several contributions to the literature. First, to the best of our knowledge, this is the first study that examines how and to what extent the interconnections among stocks from different industries and providers have been impacted, modified, and ultimately reshaped due to the Covid-19 pandemic. We pay particular attention to the interconnections within the entire system, within each industry, and each provider.

Secondly, in the same study, we employ a variety of actively managed ethical stocks developed by major index data providers such as S&P, DJ, FTSE, and MSCI. These stocks cover different investment regions (World, Europe, US), thus highlighting the heterogeneity in the type and stringency of screening strategies.

Thirdly, we contribute to the body of literature that explores the interconnections and connectedness of stock market data through network-based VAR models (see Billio et al., 2012; Diebold and Yilmaz, 2014; Ahelegbey et al., 2016; Basu et al., 2016; Barigozzi and Brownlees, 2019; Barigozzi and Hallin, 2017; Ahelegbey et al., 2021; Yarovaya et al., 2021; Reboredo et al., 2020; Reboredo and Ugolini, 2020; Umar et al., 2020). Specifically, our work explores how the different financial systems around the globe react to catastrophic events such as the COVID-19 pandemic, considering differences in industries and index providers.

Empirically, our paper demonstrates that each of the networks analyzed in our study exhibited different behavior following the outbreak of the Covid-19 crisis. Specifically, network density significantly increased during the Covid-19 pandemic for all networks, illustrating how an exogenous shock can impact the interconnections and stability among agents in terms of systemic risk. Our study also provides evidence of heterogeneous behavior among the various industry and provider networks, with the religious and FTSE networks displaying greater resilience during the Covid pandemic. Furthermore, the Covid-19 crisis has not only affected network density but also the roles played by key player shock transmitter entities, as indicated by hub and authority scores. This has led to the emergence of new players during the crisis.

The paper is organized as follows. Section 2 documents the literature review. Section 3 describes the major screening criteria. In Section 4, we discuss the network VAR model with Bayesian estimation. We present a description of the data and report the results in Section 5. Section 7 concludes the paper with a final discussion.

[3] Please refer to Section 2 for more details about the various screening criteria.

[4] see *e.g.*, Aegon Asset Management 2020; J.P. Morgan 2020.

2. Literature review

Despite the classical argument in Modern Portfolio Theory, which suggests under-diversification costs for screened portfolios (Markowitz, 1952), several studies have reached contradictory conclusions. These studies challenge the traditional argument by indicating that a reduction in the stock universe introduces an additional set of constraints in the optimization problem faced by return-maximizing investors. Various studies have shown a positive relationship between corporate social responsibility (CSR) and corporate financial performance and stability (Eccles et al., 2014; Fatemi et al., 2015; Ghoul et al., 2017; Nguyen et al., 2020; Bakar et al., 2023).

In particular, firms' CSR efforts improve stakeholder cooperation, leading to economic benefits in the form of higher cash flows and/or a risk reduction (Edmans, 2011; Ferrell et al., 2016; Guiso et al., 2015; Servaes and Tamayo, 2013). The positive valuation effect of CSR is reflected in increased stakeholder engagement resulting from a company's commitment to establishing long-term relationships with its stakeholders based on mutual trust and cooperation. Lins et al. (2017) document the significant role of trust and social capital in well-functioning capital markets. Using CSR performance as a proxy for firms' trust and social capital, they show that US firms with higher CSR levels before the Global Financial Crisis show higher returns during the crisis period, suggesting that CSR activities contribute to building trust with stakeholders and investors, yielding benefits during periods of market distress. These findings also support the notion of an insurance-like function associated with CSR, protecting firms by mitigating investors' negative reactions to unexpected harmful events (Christensen, 2016; Liang and Renneboog, 2017).

The ethical finance industry has experienced extraordinary growth over the last decade due to the increasing demand for ethical investment products, the strong willingness of regulators to support the development of ethical financial markets, and the better resilience shown by ethical products during the Global Financial Crisis of 2007–2009. In this context, the development of ethical products may provide international investors with an alternative to diversify their investments and construct portfolios that are resilient during crises. The ethical finance literature has seen unprecedented growth in recent decades.

A subset of this literature deals with the comparative performance of ethical stock indexes and their conventional counterparts in terms of risk and return (Al-Zoubi and Maghyereh, 2007; Ashraf and Mohammad, 2014; Abbes, 2012; Girard and Hassan, 2008; Managi et al., 2012; Belghitar et al., 2014; Śliwiński and Łobza, 2017, among others), or investigates the relative performance of ethical stock markets during the global financial crisis period (Al-Khazali et al., 2014; Ho et al., 2014; Jawadi et al., 2014; Nofsinger and Varma, 2014; Lean and Pizzutilo, 2020, among others). These studies, which examined the performance of ethical vis-a-vis conventional equities, yielded mixed results.

In contrast to studies on the financial performance of ethical and conventional stock markets, the empirical literature examining the interconnections and risk transmission of ethical indexes is still very limited. Starting with religious empirical studies, Aloui et al. (2016) employed wavelet squared coherence and asymmetric causality tests and did not detect significant differences in the co-movement between investors' sentiment and U.S. Islamic and conventional stock returns. They showed that Islamic equities and their mainstream counterparts behave similarly, questioning the validity of the decoupling hypothesis. On the other hand, using the DCC-GARCH model, Rizvi and Arshad (2014) documented that a large set of Islamic and conventional equity market indexes exhibit weak correlations, especially during the recent global financial crisis. This implies that Islamic equities offer partial insulation for investors in times of financial turmoil. Kenourgios et al. (2016) show that during a period of turmoil, bonds and Islamic equities can provide effective diversification benefits to investors. Their study supports the decoupling hypothesis of Islamic equities from their conventional counterparts in various developed and emerging countries.

Using the causality-in-variance test proposed by Hafner and Herwartz (2009) and generalized impulse response functions, Nazlioglu et al. (2015) found significant volatility transfers between the Dow Jones Islamic equity market and the conventional equity markets in the US, Europe, and Asia over the pre-financial crisis, as well as during the in- and post-financial crisis periods. This evidence suggests the contagion effects among these global stock markets, which remained unaffected by the international financial crises. Employing various multivariate GARCH models, Majdoub and Mansour (2014) did not provide any evidence of significant volatility spillovers from the U.S. Islamic stock market into five Islamic emerging stock markets (Turkey, Indonesia, Pakistan, Qatar, and Malaysia). Shahzad et al. (2017) examined the return and volatility spillovers across the global Islamic stock market, three main conventional national stock markets (the US, the UK, and Japan), and several influential macroeconomic and financial variables over the period from July 1996 to June 2016. Relying on a spillover index based on the generalized forecast-error variance decomposition framework of Diebold and Yilmaz (2012), the authors provided evidence of strong interactions in return and volatility among the global Islamic stock market, the conventional stock markets, and the set of major risk factors considered.

More recently, Yarovaya et al. (2021) analyzed the spillover effects between conventional and Islamic stock and bond markets during the Covid-19 period. Using a VARMA-BEKK-AGARCH model, they provided evidence of significant and positive return spillovers from the conventional to the Islamic stock markets over the study periods considered. Studies focusing on the comparative connectedness and contagion of SRI markets are limited. For instance, Reboredo and Ugolini (2020) used a structural vector autoregressive model to examine the connectedness between green bonds and financial markets. Their results documented evidence that the green bond market is a net spillover receiver, while treasury and currency markets are net spillover transmitters. In the same vein, Reboredo et al. (2020) also showed that green bonds are net receivers of risk spillover from both treasury and corporate bond prices. Umar et al. (2020) used the generalized forecast-error variance decomposition framework to investigate the connectedness between major ESG leader equity indexes over a period characterized by the Eurozone and the Covid-19 crisis. Their results provide evidence of dynamic and statistically significant risk transmission between the considered indexes over the sample period.

Building on this body of research, our study is, to the best of our knowledge, the first in the literature to shed light on the network connectedness between ethical stock markets and their conventional counterparts during the Covid-19 pandemic. We rely on the newly developed BGSVAR model and consider the heterogeneity and stringency of various screening criteria, as indicated in the introduction section.

Table 1
A comparison of the various Shariah screening adopted by the four major Shariah screening providers such as Standard & Poor (S&P), Dow Jones (DJ), Morgan Stanley Capital International (MSCI), Financial Times Stock Exchange (FTSE) is presented below. Part (A) of the table describes the business activity screening, *e.g.* all types of impermissible activities. Part (B) of the table illustrates how the various financial ratios are calculated and their tolerance levels. BVTD is the book value of total debt, BVTA is the book value of total assets, MVE is the market value of equity, IBS is interest-bearing securities and AR is accounts receivable. (Note: $MVE_{tr.36} = MVE_{trailing36-}$ and $MVE_{tr.24} = MVE_{trailing24-}$).

Financial screening			
Standard	Leverage ratio	Interest bearing liabilities ratio	Quick assets ratio
S&P	$BVTD/MVE_{tr.36}$ <33% *month-average*	$(Cash+IBS)/MVE_{tr.36}$ <33% *month-average*	$AR/MVE_{tr.36}$ <49% *month-average*
DJ	$BVTD/MVE_{tr.24}$ <33% *month-average*	$(Cash+IBS)/MVE_{tr.24}$ <33% *month-average*	$AR/MVE_{tr.24}$ <33% *month-average*
MSCI	BVTD/BVTA <33.33%	(Cash+IBS)/BVTA<33.33%	(Cash+AR)/BVTA<33.33%
FTSE	BVTD/BVTA<33.333%	(Cash+IBS)/BVTA<33.333%	(Cash+AR)/BVTA<50%

3. An overview of the main screening criteria for equities

Ethical investors are prohibited from investing in stocks of companies engaged in non-permissible activities. Funds designed to meet the needs of ethical investors are restricted to investing in only a set of companies considered ethical. However, in practice, several screening frameworks are present in the literature, and this constitutes one of the major challenges for ethical investors. Therefore, investigating possible differences in the various screening frameworks and their effects on the composition and diversification of portfolios is of extreme relevance.

Table 1 summarizes the Shariah[5] screening standards adopted by the main index providers such as S&P, DJ, MSCI, and FTSE. All the Shariah screening criteria are generally developed following a two-step procedure. Qualitative screening filters out all corporations whose primary business activity is considered impermissible. In particular, it screens all corporations with a major source of revenue (usually 95% or more)[6] derived from non-permissible activities, such as financial transactions involving interest, gambling activities, production and distribution of alcohol, the production and distribution of pork or pork-related products, and/or excessive risk-taking such as insurance and speculative investments. Qualitative screening is very similar among all four index providers, except the S&P Shariah framework, which also filters companies engaged in cloning and the trading of precious commodities, *i.e.*, gold and silver as cash on a deferred basis; all other three providers are silent on these issues[7].

To qualify as a Shariah-compliant investment, corporations that fulfill the qualitative step are subjected to a financial screening as well. In particular, the quantitative-financial screening step is employed to screen further the companies that comply with the qualitative screening; however, they generate part of their revenue from non-permissible activities such as borrowing or lending money on interest and/or having a major proportion of assets in liquid form. These financial screening ratios are not uniform among the various index providers. Three financial ratios for financial screening need to be fulfilled, namely, the leverage ratio, interest-bearing liabilities ratio, and quick assets ratio. The quantitative financial screening (Panel B) presents two major differences related to the choice of divisor for the financial ratios calculation and their tolerance level. In particular, MSCI and FTSE employ the book value of total assets as a divisor, while the S&P and DJ rely on the trailing market value of equity as a divisor to calculate the financial ratios[8]. Regarding the tolerance level for financial ratios, the FTSE provider sets a higher threshold of 50% for the liquid asset ratio, as compared to a ratio of 49% for the S&P, while all other providers set a maximum of 33% (see Derigs and Marzban, 2008, for more details).

Table 2 provides details about the ESG/ SRI indexes developed by different index suppliers, the ESG rating agency[9], the selection approach with additional financial and sector criteria, the type of weights used to develop the indexes, and their benchmarks. The ESG index supplier integrates non-financial criteria into the investment process by applying a set of investment screens designed to select (positive screens) or exclude (negative screens) assets from their indexes. Negative screens exclude stocks of companies that perform poorly in terms of ESG indicators or are involved in socially undesirable activities (*e.g.*, tobacco, gambling, alcohol, armaments). These companies are often referred to as "sin stocks" (please refer to Fabozzi et al. (2008), Grougiou et al. (2016), Hartzmark and Sussman (2019), Kim and Venkatachalam (2011), Leventis et al. (2013) for more details.). On the other hand, positive screens identify companies with good records of ESG performance in specific stakeholder-oriented issues, such as labor and community relations, and the environment. Following the classification suggested by the Global Sustainable Investment

[5] Shariah equity screening is a continuous procedure to understand whether a certain company meets the shariah/Islamic requirements to be considered lawful, hence, it provides guidelines on whether it is permissible to invest in that company.

[6] In today's business activities corporations with a lawful primary activity may obtain a proportion of their revenue from unlawful activities. Investing in these corporations is allowed by Shariah scholars, subject to the condition that the revenue from the unlawful activities of these corporations does not exceed the threshold of 5%, and investors must donate the proportion of the unlawful income to purify their investment (see for example the case of a hotel activity).

[7] Impermissible activities allowed are 5% of the total revenue. However, the investor should purify their income by distributing the impermissible income as a donation to charity. For more details refer to the material available on the websites for each standard.

[8] Please refer to Ashraf and Khawaja (2016) and Obaidullah (2005) for more details about the advantage and disadvantage of each approach.

[9] Please refer to Novethic (2014) for an overview of ESG rating agencies.

Table 2
Information on ESG indexes.

Indexes	S&P ESG	DJSI	MSCI ESG	FTSE4Good
Indexes supplier	S&P Dow Jones	S&P Dow Jones	MSCI Group	FTSE Group
ESG rating agency	RebecoSAM	RebecoSAM	MSCI	EIRIS
Selection criteria	Best-in-class approach	Best-in-class approach	Best-in-class approach	Integration of ESG factors
Financial criteria	–	–	50% of the market cap. in each sector	–
sector criteria	75% of the market cap. in each sector	top 10% of ESG scores from each sector	sector weights	exclusion of controversial sectors
index construction	float-adjusted market cap.	float-adjusted market cap.	float-adjusted market cap.	float-adjusted market cap.
Benchmarks	S&P 500 index	DJIA index	MSCI US	FTSE US index

Alliance[10], S&P, DJSI, and MSCI rely on the best-in-class strategy, with additional exclusion and financial criteria for the S&P, while FTSE4Good relies on the integration of ESG factors and exclusionary screening strategies. All the indexes are constructed using a float-adjusted market capitalization strategy and overcome the small-cap bias[11] by focusing on stocks with a large market capitalization. Therefore, our study aims to explore the intra- and inter-layer connectivity between various indexes belonging to different industries, considering particularly the divergences in the various screening frameworks and their effect on the composition and diversification of portfolios.

4. Methodology

4.1. SVAR and network VAR models

In this study, we employ Bayesian Graphical Structural VAR (BGSVAR) models to analyze the dynamic relationships among conventional, Islamic, and ethical stock market indexes. SVAR models are widely used in econometrics for capturing the linear interdependencies among multiple time series, while BGSVAR models extend this framework by incorporating a network structure and Bayesian inference to handle parameter uncertainty and sparsity in the data. This methodology builds on the foundational work in Ahelegbey et al. (2016).

Let R_t^C denote the returns of n conventional stock market indexes at time t, R_t^I denote the returns of their Islamic stock market counterparts, and R_t^E denote the returns of ethical stock market counterparts. Define the vector $Y_t = (R_t^C, R_t^I, R_t^E)$, which is an $N \times 1$ vector with $N = 3n$. The dynamic evolution of Y_t can be described by a SVAR(p) process:

$$Y_t = \sum_{s=1}^{p} B_s\, Y_{t-s} + U_t \tag{1}$$

$$U_t = B_0\, U_t + \varepsilon_t \tag{2}$$

where p is the lag order, B_s is an $N \times N$ matrix of autoregressive coefficients, B_0 is a zero diagonal matrix that captures contemporaneous effects, U_t is a vector of normally distributed residuals with covariance matrix Σ_u, and ε_t is a vector of idiosyncratic structural shocks with diagonal covariance matrix Σ_ε. Σ_u can be expressed as: $\Sigma_u = (I - B_0)^{-1}\Sigma_\varepsilon(I - B_0)^{-1'}$. The expressions in (1) and (2) can be written in a more compact form as

$$Y_t = B_+ X_t \; + \; (I - B_0)^{-1}\varepsilon_t \tag{3}$$

where $B_+ = (B_1, \dots, B_p)$ is $N \times Np$ matrix of coefficients, and $X_t = (Y'_{t-1}, \dots, Y'_{t-p})'$ is $Np \times 1$ vector of stacked lagged observation of Y_t. It can be shown that the matrix $(I - B_0)^{-1}$ records the (in)direct contemporaneous effect of ε_t on Y_t. A shock to Y_{jt} can only affect Y_{it} if there is a contemporaneous link from Y_{kt} to Y_{it}.

4.2. Network representation

We introduce sparsity in the coefficient matrix $B = (B_0, B_1, \dots, B_p)$ to reflect the conditional independence structure in the form of a network. This sparsity is captured using an element-wise Hadamard product $B = (\Phi \circ G)$, where Φ contains the coefficients and G indicates the presence of edges in the network:

$$B_{ij,s} = \Phi_{ij,s} G_{ij,s} \tag{4}$$

[10] The Global Sustainable Investment Alliance suggests seven distinct approaches: Negative/exclusionary screening; Positive/best-in-class screening; Norms-based screening; Integration of ESG factors; Sustainability investing; Impact/community investing; and Corporate engagement and shareholder action.

[11] This refers to the relatively high investment weight of stocks with a low market capitalization.

The elements of G are binary indicators such that $G_{ij,s} = 0$ implies Y_j does not influence Y_i at lag s, and $G_{ij,s} = 1$ implies it does. Thus, the slope coefficients and shock dependence matrices of (1) and (2) can be specified through network graphs by assigning to each $B_{ij,s}$ a corresponding latent indicator in $G_{ij,s} \in \{0,1\}$, such that for $i,j = 1,\dots,N$, and $s = 0,1,\dots,p$:

$$B_{ij,s} = \begin{cases} 0 & \text{if} \quad G_{ij,s} = 0 \quad \Longrightarrow \quad Y_{j,t-s} \nrightarrow Y_{i,t} \\ \Phi_{ij,s} \in \mathbb{R} & \text{if} \quad G_{ij,s} = 1 \quad \Longrightarrow \quad Y_{j,t-s} \rightarrow Y_{i,t} \end{cases} \tag{5}$$

where $Y_{j,t-s} \nrightarrow Y_{i,t}$ means that Y_j does not influence Y_i at lag s, including $s = 0$, which correspond to contemporaneous dependence.

Let $\bar{B}_{ij} = \sum_{l=0}^{p} B_{ij,l}$ and $\bar{G}_{ij} = \sum_{l=0}^{p} G_{ij,l}$. We define two null-diagonal matrices, A and W, where $A \in \{0,1\}^{N\times N}$ is the adjacency matrix and $W \in \mathbb{R}^{N\times N}$ is the weighted adjacency matrix:

$$A_{ij} = \begin{cases} 0, & \text{if } \bar{G}_{ij} = 0 \\ 1, & \text{otherwise} \end{cases}, \quad W_{ij} = \bar{B}_{ij} \tag{6}$$

The matrices A and W are structured to model intra-layer and inter-layer connectivity among the different types of stock market indexes:

$$A = \begin{pmatrix} A_{C\leftarrow C} & A_{C\leftarrow I} & A_{C\leftarrow E} \\ A_{I\leftarrow C} & A_{I\leftarrow I} & A_{I\leftarrow E} \\ A_{E\leftarrow C} & A_{E\leftarrow I} & A_{E\leftarrow E} \end{pmatrix}, \quad W = \begin{pmatrix} W_{C\leftarrow C} & W_{C\leftarrow I} & W_{C\leftarrow E} \\ W_{I\leftarrow C} & W_{I\leftarrow I} & W_{I\leftarrow E} \\ W_{E\leftarrow C} & W_{E\leftarrow I} & W_{E\leftarrow E} \end{pmatrix} \tag{7}$$

where the diagonal terms $(A_{C\leftarrow C}, A_{I\leftarrow I}, A_{E\leftarrow E})$ models intra-layer connectivity among conventional indexes, Islamic indexes, and ethical indexes respectively. $A_{C\leftarrow C,ij} = 1 \implies R_j^C \rightarrow R_i^C$ and $A_{C\leftarrow C,ij} = 0 \implies R_j^C \nrightarrow R_i^C$. $R_j^C \rightarrow R_i^C$ exist if there is a directed contemporaneous or lagged effect from R_j^C to R_i^C. Similar reasoning holds inter-layer connectivities such that $A_{C\leftarrow I,ik} = 1 \implies R_k^I \rightarrow R_i^C$, and $A_{C\leftarrow E,il} = 1 \implies R_l^E \rightarrow R_i^C$. W specifies the weights of the linkages in A obtained as a sum of the estimated contemporaneous and lagged coefficients. For instance, $W_{C\leftarrow C}$ and $W_{C\leftarrow I}$ are sub-matrices of W that measure the cumulative effect of R_{t-s}^C and R_{t-s}^I on R_t^C for $s = 0,\dots,p$, respectively.

4.3. Prior distributions and hyperparameters

The Bayesian approach involves specifying prior distributions for the model parameters. The coefficients $\Phi_{ij,s}$ are modeled conditionally on the indicator variables $G_{ij,s}$:

$$[\Phi_{ij,s} | G_{ij,s} = 1] \sim \mathcal{N}(0,\eta), \quad G_{ij,s} \sim \mathcal{B}er(\pi_{ij,s})$$

where η is the variance of the normal distribution, and $\pi_{ij,s}$ is the prior probability that $G_{ij,s} = 1$. Typically, $\pi_{ij,s} = 0.5$ is chosen for noninformative priors.

Following standard practice, we assume the inverse of covariance matrix of the reduced-form shocks, Σ_u^{-1}, is Wishart distributed:

$$\Sigma_u^{-1} \sim \mathcal{W}(\delta_u, \Lambda_{u,0})$$

where δ_u is the degrees of freedom, and $\Lambda_{u,0}$ is scale matrix. We assume $\delta_u = n+2$, and $\Lambda_{u,0} = \delta_u I_n$.

The covariance matrix of the structural shocks, Σ_ε, is assumed to be diagonal, indicating uncorrelated shocks. The inverse, Σ_ε^{-1}, follows a G-Wishart distribution:

$$\Sigma_\varepsilon^{-1} \sim \mathcal{W}_{G\varepsilon}(\delta_\varepsilon, \Lambda_{\varepsilon,0})$$

where δ_ε is degrees of freedom, and $\Lambda_{\varepsilon,0}$ is the scale matrix. We assume $\delta_\varepsilon = n+2$, and $\Lambda_{\varepsilon,0} = \delta_\varepsilon I_n$. Here, the G-Wishart distribution is the conjugate prior for the precision matrix over the set of all symmetric, positive definite matrices with zeros in the off-diagonal elements that correspond to missing edges in G_ε, the graph associated with ε_t.

4.4. Gibbs sampling and posterior estimation

To estimate the parameters, we use a collapsed Gibbs sampler. This iterative algorithm samples from the following conditional distributions:

(1) $P(G_p | Y, p)$
(2) $P(G_0 | Y, p, G_p)$
(3) $P(\Phi_p | Y, p, G_p, \Sigma_u)$
(4) $P(\Phi_0 | Y, p, G_p, G_0, \Phi_p, \Sigma_\varepsilon, \Sigma_u)$
(5) $P(\Sigma_\varepsilon | Y, p, G_p, G_0, \Phi_p, \Phi_0, \Sigma_u)$
(6) $P(\Sigma_u | Y, p, G_p, G_0, \Phi_p, \Phi_0, \Sigma_\varepsilon)$

In our application, we set $\eta = 100$ to ensure that the priors are weakly informative, allowing the data to play a significant role in the posterior estimation.

Convergence of the Gibbs sampler is assessed using standard diagnostics such as trace plots, the Gelman–Rubin diagnostic (see Gelman and Rubin, 1992), and effective sample size. To ensure robustness, we validate our model using out-of-sample testing and cross-validation techniques. The practical implementation of the BGSVAR model is carried out using the Matlab statistical software. Computational challenges, such as ensuring the convergence of the Gibbs sampler and managing high-dimensional data, are addressed by optimizing the code and using parallel processing where applicable.

Table 3
Description of market indexes and classification.

	Index	Conventional	Religious	Ethical
2	Dow Jones World	D.W.C	D.W.I	D.W.E
3	FTSE World	F.W.C	F.W.I	F.W.E
4	MSCI World	M.W.C	M.W.I	M.W.E
5	S&P Europe	S.E.C	S.E.I	S.E.E
6	Dow Jones Europe	D.E.C	D.E.I	D.E.E
7	FTSE Europe	F.E.C	F.E.I	F.E.E
8	MSCI Europe	M.E.C	M.E.I	M.E.E
9	S&P US	S.U.C	S.U.I	S.U.E
10	Dow Jones US	D.U.C	D.U.I	D.U.E
11	FTSE US	F.U.C	F.U.I	F.U.E
12	MSCI US	M.U.C	M.U.I	M.U.E

5. Empirical application

5.1. Data description

The data for our study are daily closing prices of 36 indexes taken from the Bloomberg database, covering January 2016 to December 2020, consisting of conventional, religious, and ethical indexes from the world, Europe, and the United States. Some of the indexes are Standard & Poor (S&P), Dow Jones (DJ), Financial Times and Stock Exchange (FTSE), and Morgan Stanley Capital International (MSCI). A description of the indexes and the classification is presented in Table 3.

We report in Fig. 1 the plot of daily closing prices on a logarithmic scale. Due to differences in the values, plotting the original prices would be difficult to visualize. We, therefore, scale the prices to a zero mean and unit variance and add the absolute minimum value of each series to avoid negative outcomes[12]. This standardizes the scale of measurement for the different series (see Ahelegbey et al., 2021). The figure shows that the markets declined simultaneously during Covid-19 with the highest daily plunge in prices occurring between February 24, 2020, and March 23, 2020.

We compute daily returns as log differences of successive daily closing prices. Table 4 reports a set of summary statistics for the index returns over the sample period. The table shows that almost all index returns have a near-zero mean and a relatively low standard deviation.

In the majority of cases, the average returns recorded in 2020 by these indexes are relatively higher than in 2016–2019. More so, the associated risk recorded in 2020 is also greater than in 2016–2019. Thus, the outbreak of Covid-19 has brought a higher risk with relatively higher returns. This, in a way, confirms stylized facts about the relationship between risk and the returns of financial assets. The risk table also shows that many ethical indexes were riskier than their conventional and religious counterparts between 2016–2019, but the 2020 period records that the conventional indexes are riskier compared to their counterparts. In essence, the religious indexes appear less risky compared to the other two in both sub-periods of our sample.

To examine the variation in the risks of the indexes, Table 5 summarizes the F-test of equality between the standard deviations of two samples. The table shows that the risks of the Conventional indexes are not significantly different from their Ethical counterparts, except for the Dow Jones World index between 2016–2019. The risks of the Conventional S&P Europe and Dow Jones Europe are significantly different from their Islamic counterparts over the two sub-periods. However, the Conventional MSCI Europe is significantly different from its Ethical counterpart only in the period preceding the Covid-19 crisis. Lastly, the risks of the Ethical Dow Jones Europe are significantly different from its Islamic counterpart over the two sub-periods. The risks of MSCI Europe of Ethical and Islamic are significantly different between 2016–2019.

5.2. Results

We apply the BGSVAR estimation methodology to study the dynamics of interconnectedness among the return performance of the 36 indexes via a yearly (approximately 249 trading days) rolling window. Our choice of window size is motivated by the need to have enough data points to capture the annual (12-month) dynamic dependence among the indexes. We set the increments between successive rolling windows to one month. The first window covers January 2016 - December 2016, followed by February 2016 – January 2017, and the last from January 2020 to December 2020. In total, we have 49 rolling windows. We examine the equity interconnectedness of the major index providers covering global, European, and US conventional, religious, and ethical indexes by considering them jointly as well as within each industry and each provider separately. We compare the pre-Covid-19 and Covid-19 networks by adopting measures of the number of links, the network density, the average degree, the clustering coefficient, and the average path length.

We describe, through numerical summaries, the time-varying nature of interconnections by monitoring the number of links, density, average degree, clustering coefficient, and average path length. For a generic zero-diagonal adjacency matrix A with n-nodes, we compute the above measures of connectedness as follows:

[12] The “normalization” of the data is to help visualize the co-movements in the daily closing prices. The main result does not use such “normalized” data but log-returns of the daily close prices.

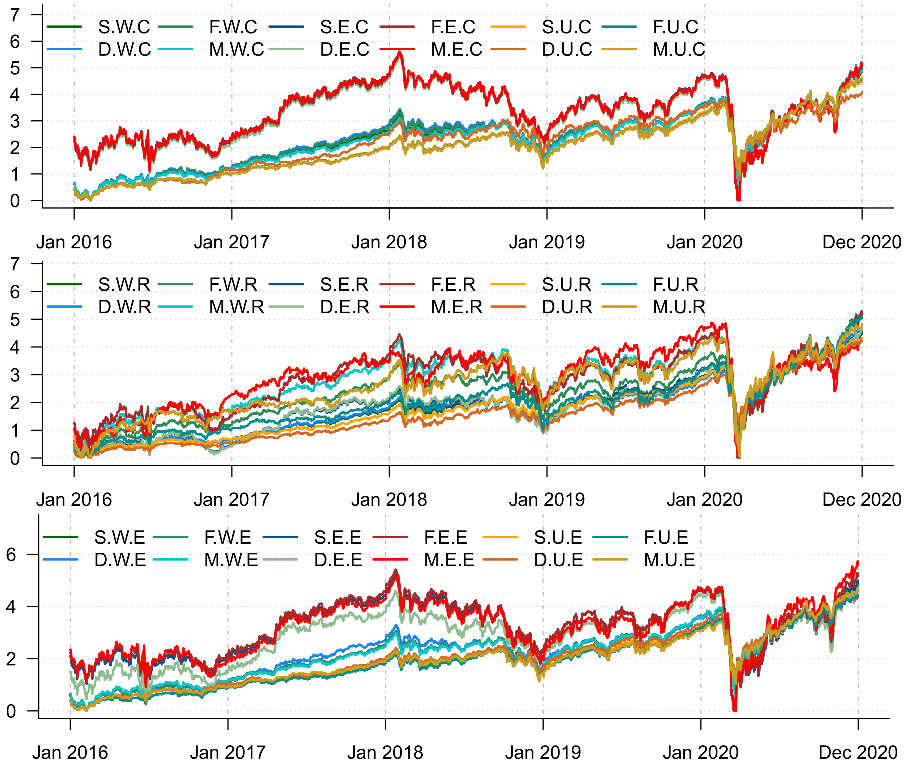


Fig. 1. Time series of daily market prices by classification on a log scale (January 2016 – December 2020).

Table 4
Statistics of daily indexes in average returns and risk.

Index	Conventional		Religious		Ethical	
	2016–2019	2020	2016–2019	2020	2016–2019	2020
			Average Returns			
S&P World	0.038	0.049	0.047	0.081	0.040	0.049
Dow Jones World	0.037	0.053	0.045	0.095	0.039	0.048
FTSE World	0.037	0.053	0.034	0.063	0.037	0.048
MSCI World	0.037	0.053	0.030	0.025	0.037	0.050
S&P Europe	0.019	0.012	0.036	0.055	0.021	0.009
Dow Jones Europe	0.020	0.016	0.034	0.059	0.025	0.005
FTSE Europe	0.020	0.013	0.028	0.027	0.019	0.014
MSCI Europe	0.019	0.012	0.030	−0.010	0.019	0.027
S&P US	0.048	0.060	0.051	0.080	0.049	0.065
Dow Jones US	0.051	0.028	0.052	0.098	0.051	0.055
FTSE US	0.048	0.069	0.040	0.084	0.053	0.070
MSCI US	0.047	0.070	0.031	0.022	0.050	0.082
			Risk			
S&P World	0.689	1.815	0.722	1.822	0.687	1.816
Dow Jones World	0.666	1.742	0.702	1.741	0.746	1.711
FTSE World	0.670	1.745	0.668	1.652	0.703	1.826
MSCI World	0.688	1.851	0.680	1.701	0.680	1.842
S&P Europe	0.919	1.890	0.859	1.637	0.940	1.897
Dow Jones Europe	0.927	1.892	0.861	1.635	0.911	1.773
FTSE Europe	0.925	1.899	0.894	1.821	0.907	1.831
MSCI Europe	0.928	1.898	0.819	1.733	0.914	1.837
S&P US	0.815	2.182	0.859	2.203	0.816	2.193
Dow Jones US	0.825	2.335	0.867	2.188	0.834	2.249
FTSE US	0.818	2.184	0.846	2.202	0.846	2.237
MSCI US	0.817	2.186	0.793	2.127	0.832	2.136

Table 5
Test of differences in standard deviations of Conventional, Islamic, and Ethical indexes before and during Covid-19. Bold values indicate p-values less than 5% significant level.

	Conventional vs Ethical		Conventional vs Islamic		Ethical vs Islamic	
	2016–2019	2020	2016–2019	2020	2016–2019	2020
S&P World	0.914	0.988	0.143	0.947	0.116	0.960
Dow Jones World	**0.000**	0.774	0.096	0.991	0.057	0.783
FTSE World	0.126	0.475	0.942	0.390	0.109	0.116
MSCI World	0.699	0.938	0.725	0.182	0.972	0.209
S&P Europe	0.481	0.956	**0.032**	**0.024**	**0.004**	**0.021**
Dow Jones Europe	0.597	0.307	**0.020**	**0.022**	0.073	0.201
FTSE Europe	0.538	0.564	0.294	0.506	0.664	0.929
MSCI Europe	0.631	0.606	**0.000**	0.151	**0.000**	0.358
S&P US	0.960	0.936	0.096	0.877	0.107	0.941
Dow Jones US	0.723	0.553	0.120	0.304	0.230	0.664
FTSE US	0.278	0.707	0.283	0.899	0.991	0.803
MSCI US	0.566	0.718	0.347	0.667	0.130	0.946

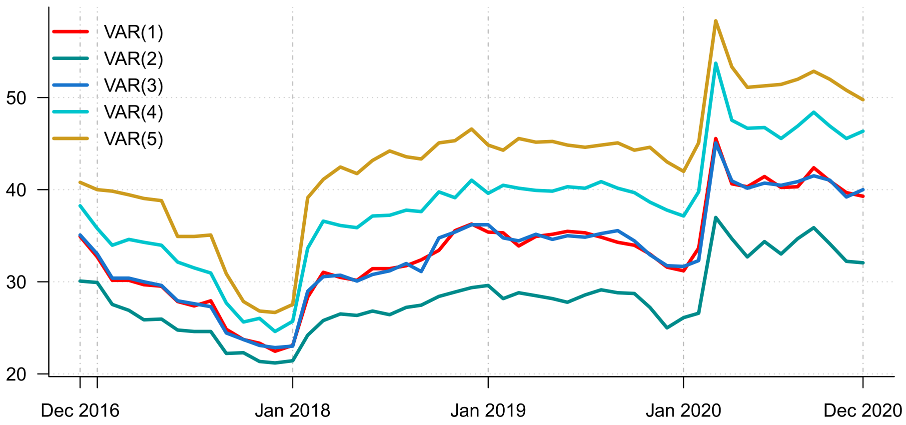


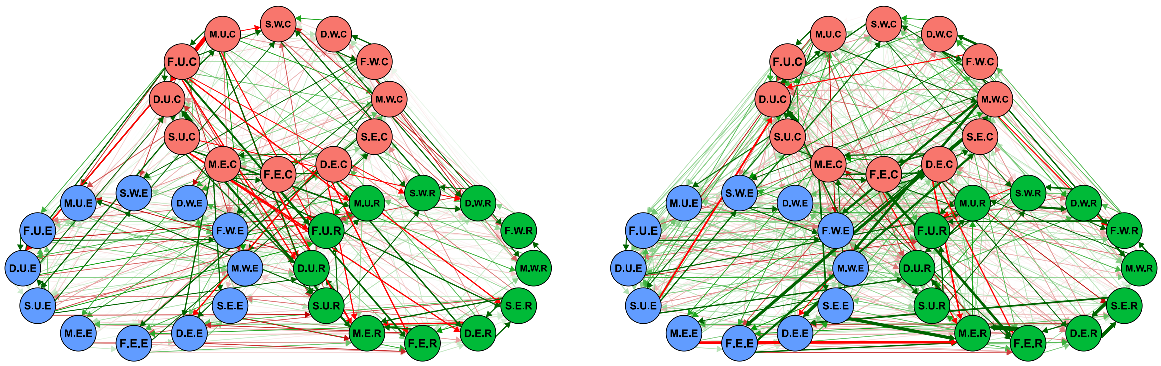
Fig. 2. Network density from VAR order $p = 1, 2, 3, 4, 5$.

- Number of Links: an unnormalized measure that reflects the total number of connections in a network. It is calculated as: $\sum_{i,j=1,i\neq j}^{n} A_{ij}$
- Density: describes the portion of the potential connections in a network that are actual connections. The density is simply the number of links normalized for all the possible combinations among n variables. It is calculated as: $\frac{1}{n^2-n}\sum_{i,j=1,i\neq j}^{n} A_{ij}$
- Average Degree: is simply the average number of edges per node in the graph. Calculated as: $\frac{1}{n}\sum_{i,j=1,i\neq j}^{n} A_{ij}$
- Clustering coefficient: the degree to which network nodes tend to cluster together and the relevance for the financial contagion process. It is calculated as: $\frac{3\times(\text{number of triangles})}{(\text{number of open triads})}$ where open triads are connected sub-graph consisting of three nodes and two edges.
- Average Path Length: the average number of steps along the shortest paths for all possible pairs of network nodes. The average path length is calculated as: $\frac{1}{n(n-1)}\sum_{i\neq j} SP_{ij}$, where SP_{ij} is the shortest path between the nodes i and j.

We also analyze and compare the estimated networks using the centrality measures over the three non-overlapping study sub-periods. Node centrality in networks addresses the question of how important a node/variable is in the network. Commonly discussed centrality measures include in-degree (number of in-bounds links), out-degree (number of outbound links), authority, and hub scores. The authority score of node-i is a weighted sum of the power/hub score of the vertices with directed links to node-i. The hub score of node-j is the weighted sum of the power/authority score of vertices with a directed link from node-j. The authority and hub scores can be obtained via the eigendecomposition of (AA') and $(A'A)$. The absolute value of the eigenvectors associated with the largest eigenvalue is usually used as the authority and hub centrality score. A hub node usually has a large out-degree and authority has a large in-degree. From a financial viewpoint, nodes with high authority scores/in-degree are highly influenced by others, while high hub scores/out-degree nodes are the influencers.

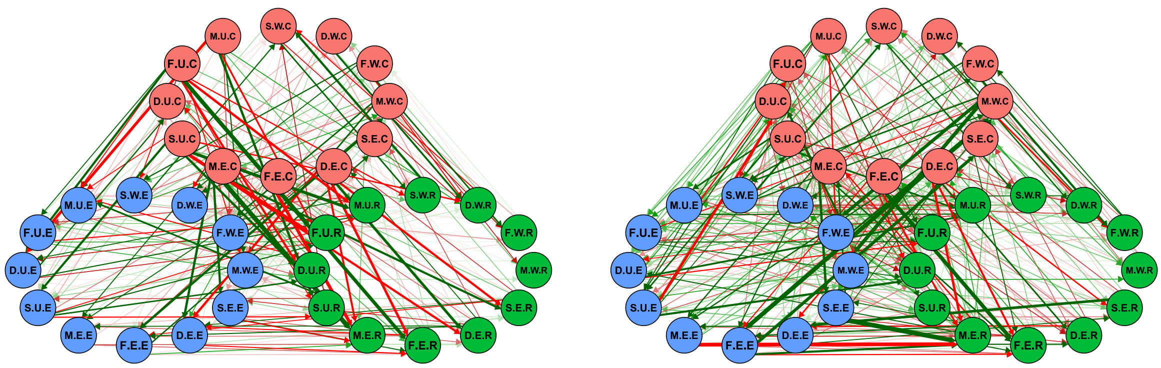
In Fig. 2 we present the network densities associated with the VAR order $1, 2, 3, 4, 5$. The figure shows that VAR(1) and VAR(5) are lower and upper bound approximations to model the interconnectedness among the stock returns. The VAR(3) presents a relatively robust model. Following this result, we conduct our analysis by choosing VAR(3) as our approximating model.

To investigate the impact of the Covid-19 pandemic on the system composed of conventional, religious, and ethical indexes, we split our data into pre and during Covid-19 periods. Fig. 3 presents the results of the interconnectedness among the indexes



(a) Pre-Covid (b) Covid

Fig. 3. Network of All Indexes.



(a) Pre-Covid (b) Covid

Fig. 4. Network of Inter-Market Linkages.

Table 6
The network statistics for sub-period interconnectedness before and during the Covid-19 period.

Period	Links	Density	Average degree	Clustering coefficient	Average path length
All Indexes					
Pre-Covid-19	611	48.492	16.972	0.798	1.541
Covid-19	717	56.905	19.917	0.802	1.431
Inter-Market Linkages					
Pre-Covid-19	409	32.460	11.361	0.428	1.907
Covid-19	467	37.063	12.972	0.414	1.726

during the two sub-periods. Figs. 4 and 5 present a decomposition of the full network of all indexes into within (intra) and between (inter) markets[13]. A look at the network of all the indexes shows an increase in the interconnectedness among the entities during the Covid-19 pandemic. Table 6 summarizes the metrics market linkages in terms of direct connectivity measures (links, density, average degree), local indirect connectivity (clustering coefficient), and global indirect connectivity (average path length). We observe noticeable changes in the Covid-19 metrics for both cases. In particular, the number of links, the density, and average degree metrics increase, and the average path length decreases during the Covid-19 period in both cases. A look at the centrality of the network in terms of hub and authority scores Table 7 shows that the S.U.C/F.U.C was central to risk transmission during the pre-Covid period while the S.E.E/S.E.E dominated during the Covid-19 period in the case of both all/inter-market index linkages. Table 7 also shows that in both cases the U.S indexes dominated the top 5 risk transmitter/receiver indexes during the pre-Covid period while during the Covid-19 period, this role was played by the European indexes. These results provide evidence of the increasing integration and the deep interconnections between the financial markets.

[13] In our study with inter-market linkages we assess the transmission of shocks from one market to another market, for example from conventional to Islamic indexes and vice versa.

Table 7
Hub and Authority Centrality before and during Covid-19 period.

	Pre-Covid-19		Covid-19	
Rank	Hub (Score)	Auth (Score)	Hub (Score)	Auth (Score)
All Indexes				
1	S.U.C (0.698)	D.U.C (0.871)	S.E.E (0.411)	M.E.I (0.521)
2	M.U.C (0.649)	F.U.I (0.268)	F.E.I (0.319)	D.U.C (0.321)
3	F.U.C (0.237)	D.U.I (0.203)	D.E.C (0.307)	D.E.E (0.279)
4	S.U.I (0.102)	M.U.I (0.185)	F.E.C (0.289)	F.E.I (0.256)
5	D.U.E (0.080)	D.U.E (0.147)	S.U.C (0.271)	F.E.E (0.197)
Inter-Market Linkages				
1	F.U.C (0.644)	F.U.I (0.616)	S.E.E (0.497)	M.E.I (0.726)
2	S.U.C (0.569)	M.U.I (0.420)	D.E.C (0.434)	F.E.I (0.453)
3	M.U.C (0.436)	D.U.I (0.413)	F.E.C (0.427)	F.E.E (0.229)
4	S.U.E (0.181)	D.U.E (0.301)	M.E.E (0.388)	D.E.I (0.224)
5	F.U.E (0.106)	M.U.E (0.219)	F.E.E (0.285)	M.E.E (0.144)

Table 8
The network statistics for sub-period interconnectedness before and during Covid-19 period.

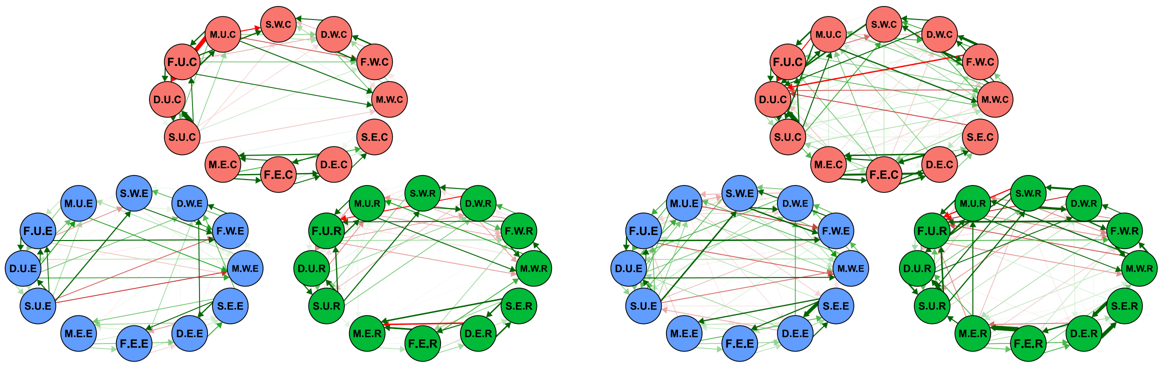
Period	Links	Density	Average degree	Clustering coefficient	Average path length
Among Conventional Indexes					
Pre-Covid-19	55	41.667	4.583	0.964	1.221
Covid-19	91	68.939	7.583	0.910	1.311
Among Religious Indexes					
Pre-Covid-19	76	57.575	6.333	0.769	1.507
Covid-19	78	59.090	6.500	0.718	1.409
Among Ethical Indexes					
Pre-Covid-19	71	53.788	5.917	0.765	1.561
Covid-19	81	61.364	6.750	0.857	1.455

To further investigate the Covid-19 pandemic effects on our system, we divide the analysis into several sub-analysis, namely: within each industry and each provider. In particular, we first investigate the structure of the conventional, religious, and ethical networks separately during both of the periods, *e.g.* focusing only on the intra-industry layer linkages. Starting with the conventional industry, Fig. 5 and Table 8 present the results. In particular, Table 8 discloses the pattern of the network along the two periods: similar to the previous results the network among the conventional indexes reacted more during the Covid-19 period, with all metrics increasing during the Covid-19 period, except the clustering coefficient which decreases. As we would have expected, there is a huge number of links that remain rather stable, confirming the deep interconnection of the conventional industry. For instance, the M.W.C indexes react negatively to the S.U.C during the pre-Covid period and change to positive during the Covid-19 period. Here, the centrality ranking of the indexes in Table 9 shows that despite some slight changes in the top 5 companies, S.U.C and D.U.C remain the most central indexes in terms of shock transmission and receiving risk, respectively, over both sub-periods.

In investigating the religious industry, Fig. 5 shows the resulting network structure over both sub-periods. We, however, notice that although the connections remain almost unchanged during the pre-Covid and Covid periods, the sign and magnitude of the interactions seem to change over the two sub-periods. More specifically, M.U.I and M.E.I seem to exhibit a bi-directional relationship throughout all periods. While the pre-Covid reported a negative impact of M.U.I on M.E.I, the Covid-19 period recorded a more significant positive reverse impact of M.E.I on M.U.I, indicating a possible contagion effect during the pandemic. A look at the centrality of the network in Table 9 confirms the different behavior of the religious indexes: while the M.E.I index is the key player in both periods according to the authority score, the religious hub indexes during the pandemic change and increase in coefficient magnitude, with the D.E.I central to risk transmission during the pre-Covid periods, and the F.E.I dominate in the Covid period.

Fig. 5 and Table 8 show the network structure and its summary statistics for the Ethical industry over the two periods. What immediately emerges is the presence of much more connected networks during the Covid-19 period. Table 9 confirms the change in the network structure: in particular the key player in the pandemic emerge, namely the S.E.E, M.E.E, F.E.E, and D.E.E for the hub score and D.E.E, M.E.E and F.E.E for the authority scores.

A comparison of the networks and summary statistics for the three industries can immediately lead us to several relevant facts: the conventional/religious industry presents the higher/smaller number of links during the Covid-19 period. We can also observe that the conventional/religious industry presents a higher/smaller clustering coefficient, while the average path length is higher/smaller in the case of the ethical/conventional industry during the Covid-19 period. Therefore the conventional/religious system appears to be less/more resilient to the Covid-19 crisis. This suggests that the pandemic has deeply affected the conventional industry, as it is plausibly to be expected.



(a) Pre-Covid (b) Covid

Fig. 5. Network of Intra-Market Linkages.

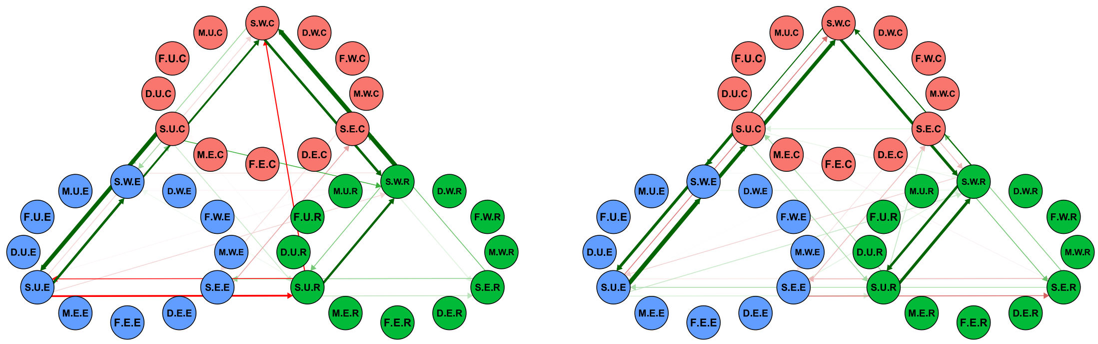
Table 9
Hub and Authority Centrality before and during Covid-19 period.

	Pre-Covid-19		Covid-19	
Rank	Hub (Score)	Auth (Score)	Hub (Score)	Auth (Score)
Among Conventional Indexes				
1	S.U.C (0.719)	D.U.C (0.991)	S.U.C (0.815)	D.U.C (0.899)
2	M.U.C (0.687)	F.U.C (0.102)	F.W.C (0.289)	F.U.C (0.206)
3	F.U.C (0.104)	S.W.C (0.059)	S.W.C (0.253)	S.W.C (0.197)
4	D.W.C (0.007)	M.W.C (0.047)	M.U.C (0.237)	D.W.C (0.189)
5	F.W.C (0.003)	F.W.C (0.025)	D.W.C (0.204)	M.U.C (0.185)
Among Religious Indexes				
1	D.E.I (0.608)	M.E.I (0.892)	F.E.I (0.817)	M.E.I (0.814)
2	S.E.I (0.563)	S.E.I (0.314)	F.W.I (0.259)	F.U.I (0.280)
3	F.E.I (0.558)	D.E.I (0.273)	D.E.I (0.253)	S.E.I (0.211)
4	F.W.I (0.026)	F.E.I (0.158)	S.U.I (0.231)	D.E.I (0.208)
5	M.U.I (0.026)	M.W.I (0.068)	S.W.I (0.221)	D.U.I (0.208)
Among Ethical Indexes				
1	S.U.E (0.778)	D.U.E (0.630)	S.E.E (0.989)	D.E.E (0.921)
2	F.U.E (0.534)	S.W.E (0.509)	M.E.E (0.096)	M.E.E (0.272)
3	D.U.E (0.197)	F.W.E (0.399)	F.E.E (0.057)	F.E.E (0.255)
4	M.U.E (0.149)	M.W.E (0.262)	M.U.E (0.053)	F.W.E (0.065)
5	S.W.E (0.124)	F.U.E (0.256)	D.E.E (0.041)	F.U.E (0.065)

Moving now to the analysis within each provide, we can also point to several relevant facts. Fig. 6 shows the resulting network structure of the S&P provider over the two periods. What immediately emerges is the presence of a much more connected network especially during the Covid-19 period. For instance, the S.E.E/S.U.E index positively/negatively affects the S.E.I/S.U.I index during the pre-Covid period, however, during the Covid-19 period we observed a change in the signs of the relationship with the S.E.I/S.U.I index negatively/positively affecting the S.E.I/S.U.I index. From Table 10, we also notice a slight variation in the metrics of the Covid-19 period, with all metrics increasing except the average path length, which decreases. The centrality ranking of the S&P indexes network, Table 11, shows that despite some slight changes in the top 5 indexes, the S.W.C index remains the most central risk receiver over both periods according to the authority score, while the S.U.E indexes dominate in the Covid-19 period according to the hub score.

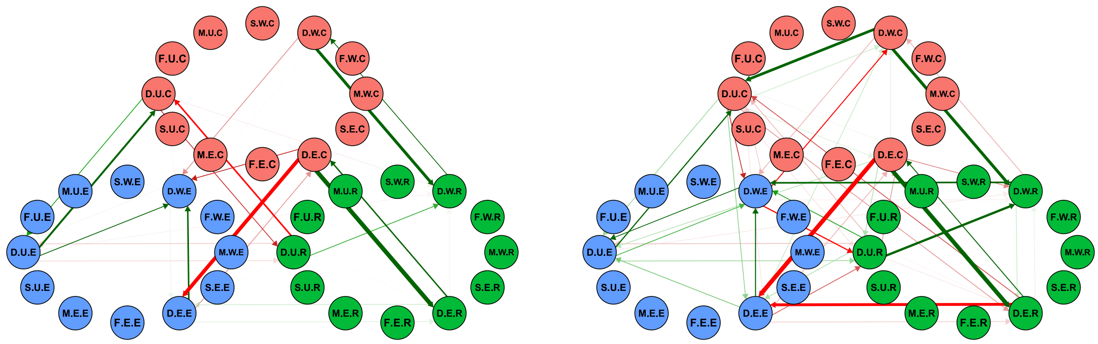
The DJ provider network and summary statistics are presented in Fig. 7 and Table 10. Similar to the S&P network, the links in Fig. 7 are mixed, for example, the D.E.I index positively affects the D.E.E index during the pre-Covid period; however, during the Covid-19 period, the effect of the D.E.I index on the D.E.E increases significantly in magnitude and is negative. A look at the centrality of the network in terms of hub and authority scores in Table 11 indicates that of the 5 indexes, D.E.C indexes were central to risk transmission during both periods according to the hub score, while D.E.I/D.E.E are the key risk receivers in the pre/Covid periods according to the authority score.

Figs. 8 and 9 and Table 10 present the results of the network structures and the summary statistics for the FTSE and the MSCI providers over both periods. We can easily observe a slight change in the number of links, density, average degree, and average path length during the Covid-19 period. In particular, while all the metrics increased during the Covid-19 period the average path length decreased for both of the providers. The centrality ranking of the indexes presented in Table 11 shows that in the case of the



(a) Pre-Covid (b) Covid

Fig. 6. Among S&P Indexes.



(a) Pre-Covid (b) Covid

Fig. 7. Among Dow-Jones Indexes.

FTSE network, the F.E.C/F.E.I is the main transmitter/receiver of risk according to the hub/authority scores, while the M.E.I/M.W.E is the key player according to the hub/authority scores in the case of the MSCI network.

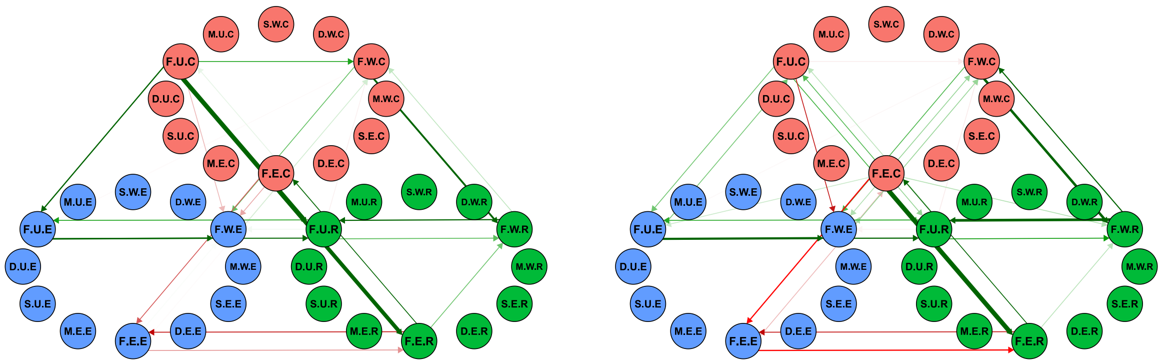
In conclusion, we can say that for all the providers it is the conventional system that played the key role of risk transmitter to the religious and ethical systems during the pre-Covid period; however, during the Covid-19 period the structure of the network became more interconnected and we observe more interactions between all the systems even though the conventional system seems to maintain its leading role. A comparison of the four provider networks and matrices shows that the DJ/FTSE networks present the higher/smaller number of links during the Covid-19 period, while the FTSE/S&P providers present the higher/smaller average path length during the Covid-19 period. Therefore, the religious/FTSE system appears to be the more resilient network during the Covid-19 pandemic.

6. Sensitivity analysis

We conduct several robustness checks to validate the sensitivity of our empirical results using different rolling window sizes. So far, our analyses have been conducted using a window length of 12 months, however, we consider a window length of 6 and 18 months and re-estimate the models of Section 4. For the sake of brevity, we focus on the network statistics conducted for the pre-Covid-19 and during the Covid-19 crisis. The results of the robustness of the check are presented in the appendix (see Table A.12 to Table A.18) and generally confirm the results of the main analysis. In particular, the results of Tables A.12 and A.13 show the market linkages in terms of direct connectivity measures (links, density, average degree) are not different from that of the 12-month rolling windows reported in the main analysis, respectively. More precisely, the level of interconnectedness among the returns of the indexes was higher during the COVID-19 period than in the preceding sub-period. In terms of Hub and Authority scores Table A.15-Table A.18 show the results of the centrality measures which do not show any significant differences from the results of the main analysis except some small differences in the ranking of the main players in terms of Hub and Authority scores.

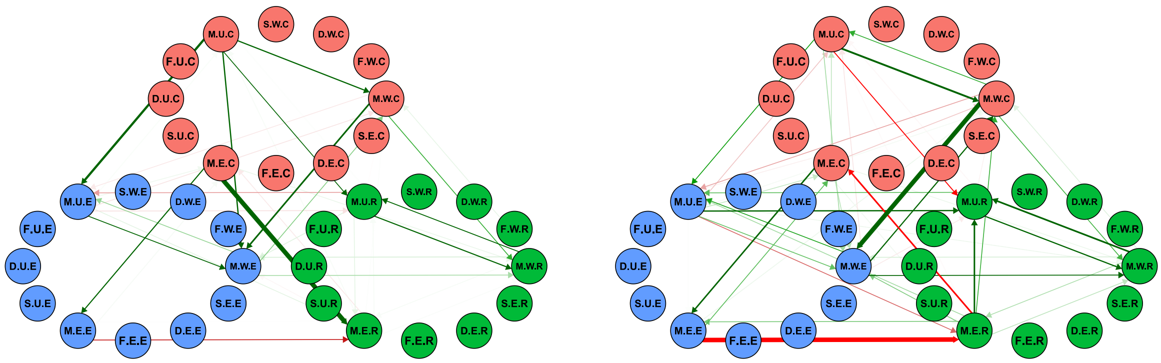
7. Conclusions and implications

The Covid-19 pandemic has significantly impacted economic and financial activities worldwide. Researchers have focused on investigating, measuring, and assessing its consequences at various levels. In our study, we examined the effects of the COVID-19 pandemic on financial markets, considering different industries and stock index providers. We employed advanced network



(a) Pre-Covid (b) Covid

Fig. 8. Among FTSE Indexes.



(a) Pre-Covid (b) Covid

Fig. 9. Among MSCI Indexes.

Table 10
The network statistics for sub-period interconnectedness before and during COVID-19 period.

Period	Links	Density	Average degree	Clustering coefficient	Average path length
Among S&P Indexes					
Pre-Covid-19	33	45.833	3.667	0.900	1.685
Covid-19	40	55.556	4.444	0.761	1.259
Among Dow-Jones Indexes					
Pre-Covid-19	33	45.833	3.667	0.64	1.681
Covid-19	49	68.056	5.444	0.75	1.319
Among FTSE Indexes					
Pre-Covid-19	30	41.667	3.333	0.662	1.574
Covid-19	34	47.222	3.778	0.785	1.389
Among MSCI Indexes					
Pre-Covid-19	38	52.778	4.222	0.757	1.542
Covid-19	48	66.667	5.333	0.847	1.333

approaches to leverage the temporal-dynamic aspect of the phenomenon through a novel specification of a Bayesian graphical structural vector autoregressive (BGSVAR) framework. collected daily closing prices of 36 indexes from the Bloomberg database, spanning from January 2016 to December 2020. This study covered both conventional and ethical indexes from around the world, including Europe and the United States. The sample period encompassed the recent Covid-19 pandemic. We analyzed networks, nodes, and edges for both the pre-Covid-19 and during the Covid-19 crisis periods.

Our investigation yielded several interesting findings. The onset of the Covid-19 crisis affected all industries and index providers by increasing interconnections and, consequently, system risk. However, different industries and indexes demonstrated varying reactions to the pandemic. Notably, the religious indexes and those belonging to the FTSE provider appeared to be more resilient to the Covid-19 pandemic, while the conventional industry exhibited the strongest interconnections. Additionally, when examining

Table 11
Hub and Authority Centrality before and during COVID-19 period.

	Pre-Covid-19		Covid-19	
Rank	Hub (Score)	Auth (Score)	Hub (Score)	Auth (Score)
Among S&P Indexes				
1	S.W.I (0.664)	S.W.C (0.787)	S.U.E (0.564)	S.W.C (0.608)
2	S.U.I (0.457)	S.U.E (0.431)	S.W.E (0.490)	S.W.E (0.525)
3	S.U.C (0.435)	S.W.I (0.387)	S.U.C (0.427)	S.U.E (0.372)
4	S.W.E (0.300)	S.W.E (0.152)	S.W.C (0.343)	S.W.I (0.361)
5	S.W.C (0.206)	S.U.I (0.151)	S.W.I (0.296)	S.U.I (0.210)
Among Dow-Jones Indexes				
1	D.E.C (1.000)	D.E.I (0.760)	D.E.C (0.717)	D.E.E (0.651)
2	D.E.E (0.027)	D.E.E (0.644)	D.E.I (0.401)	D.E.I (0.455)
3	D.E.I (0.011)	D.W.E (0.083)	D.W.C (0.328)	D.W.I (0.377)
4	D.U.E (0.009)	D.E.C (0.003)	D.U.I (0.316)	D.U.C (0.302)
5	D.W.C (0.004)	D.U.C (0.003)	D.U.C (0.203)	D.W.E (0.258)
Among FTSE Indexes				
1	F.U.C (0.979)	F.U.I (0.980)	F.E.C (0.954)	F.E.I (0.928)
2	F.W.I (0.152)	F.U.E (0.177)	F.E.E (0.237)	F.E.E (0.247)
3	F.U.E (0.133)	F.W.C (0.076)	F.W.I (0.119)	F.U.I (0.166)
4	F.U.I (0.014)	F.W.E (0.055)	F.U.E (0.105)	F.U.C (0.125)
5	F.E.C (0.005)	F.E.I (0.004)	F.W.C (0.060)	F.W.E (0.120)
Among MSCI Indexes				
1	M.E.C (0.996)	M.E.I (0.986)	M.W.C (0.797)	M.W.E (0.803)
2	M.E.E (0.090)	M.E.E (0.166)	M.E.E (0.479)	M.E.I (0.485)
3	M.U.I (0.012)	M.W.I (0.010)	M.E.I (0.212)	M.U.I (0.195)
4	M.U.E (0.010)	M.W.E (0.002)	M.U.E (0.199)	M.W.I (0.143)
5	M.W.I (0.003)	M.U.I (0.001)	M.U.C (0.154)	M.E.C (0.135)

the most important hubs and authority indexes, we observed a common pattern. In most cases, U.S. indexes played a key role as the primary risk transmitter/receiver indexes during the pre-Covid crisis, followed by European and global indexes. During the Covid-19 crisis, this ranking shifted slightly, with European indexes becoming the leading risk transmitter/receiver indexes, followed by U.S. indexes, while world indexes maintained their position.

This research carries multiple and significant implications, as explained below:

First, due to the fundamental differences between SRI/ESG investing and religious investing strategies and resilience, it is recommended that investors consider including both types in their portfolio diversification strategies or risk control efforts.

Second, similar to the ongoing debate in the ESG literature and profession regarding the harmonization of its criteria (KPIs), there should be a similar debate in the Islamic finance literature regarding the harmonization of the religious screening criteria. Additionally, it is highly recommended that Islamic indexes start incorporating the ESG with its basic screening criteria to strengthen its alignment with the broader Shariah principles and enhance the ethical threshold of Shariah-compliant equity (Bakar et al., 2023).

CRediT authorship contribution statement

Omneya Abdelsalam: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Daniel Felix Ahelegbey:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yassine Essanaani:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation.

Data availability

Data will be made available on request.

Acknowledgment

The authors acknowledge the financial support of the El Shaarani Centre for Ethical Finance, Accountability & Governance at Durham University. This research has also received funding from the European Union's Horizon 2020 research and innovation program "PERISCOPE: Pan European Response to the ImpactS of Covid-19 and future Pandemics and Epidemics", under the Grant Agreement No. 101016233, H2020-SC1-PHE-CORONAVIRUS-2020-2-RTD.

Table A.12
Network statistics before and during the Covid-19 period using 6 and 18 months rolling windows.

Period	Links	Density	Average degree	Clustering coefficient	Average path length
6-month Rolling Window					
All Indexes					
Pre-Covid-19	700	55.556	19.444	0.785	1.448
Covid-19	833	66.111	23.139	0.890	1.339
Inter-Market Linkages					
Pre-Covid-19	471	37.381	13.083	0.418	1.726
Covid-19	558	44.286	15.500	0.457	1.617
18-month Rolling Window					
All Indexes					
Pre-Covid-19	588	46.667	16.333	0.745	1.608
Covid-19	672	53.333	18.667	0.766	1.467
Inter-Market Linkages					
Pre-Covid-19	390	30.952	10.833	0.414	1.943
Covid-19	436	34.603	12.111	0.400	1.780

Table A.13
Statistics among indexes before and during Covid-19 using 6 and 18 months rolling windows.

Period	Links	Density	Average degree	Clustering coefficient	Average path length
6-month Rolling Window					
Among Conventional Indexes					
Pre-Covid-19	69	52.273	5.750	0.794	1.727
Covid-19	97	73.485	8.083	0.971	1.265
Among Religious Indexes					
Pre-Covid-19	78	59.091	6.50	0.768	1.424
Covid-19	81	61.364	6.75	0.792	1.386
Among Ethical Indexes					
Pre-Covid-19	82	62.121	6.833	0.765	1.394
Covid-19	97	73.485	8.083	0.938	1.371
18-month Rolling Window					
Among Conventional Indexes					
Pre-Covid-19	55	41.667	4.583	0.843	2.076
Covid-19	81	61.364	6.750	0.846	1.386
Among Religious Indexes					
Pre-Covid-19	78	59.091	6.500	0.728	1.447
Covid-19	84	63.636	7.000	0.772	1.364
Among Ethical Indexes					
Pre-Covid-19	65	49.242	5.417	0.729	1.705
Covid-19	71	53.788	5.917	0.812	1.568

Appendix A. Details of sensitivity analysis

We conduct several robustness checks to validate the sensitivity of our empirical results using different rolling window sizes, *i.e.*, 6 months, and 18 months. For the sake of brevity, we focus on the network statistics conducted during the pre-Covid-19 and during the Covid-19 crisis (see Tables A.14, A.16, A.17 and A.19).

The results of Tables A.12 and A.13 show the market linkages in terms of direct connectivity measures (links, density, average degree) are not different from that of the 12-month rolling windows reported in Tables 6 and 8, respectively. More precisely, the level of interconnectedness among the returns of the indexes was higher during the Covid-19 period than the preceding sub-period.

Table A.14
Statistics among indexes before and during Covid-19 using 6 and 18 months rolling windows.

Period	Links	Density	Average degree	Clustering coefficient	Average path length
6-month Rolling Window					
Among S&P Indexes					
Pre-Covid-19	38	52.778	4.222	0.818	1.370
Covid-19	46	63.889	5.111	0.900	1.148
Among Dow-Jones Indexes					
Pre-Covid-19	36	50	4.000	0.692	1.694
Covid-19	54	75	6.000	0.889	1.250
Among FTSE Indexes					
Pre-Covid-19	37	51.389	4.111	0.706	1.653
Covid-19	37	51.389	4.111	0.756	1.315
Among MSCI Indexes					
Pre-Covid-19	43	59.722	4.778	0.782	1.458
Covid-19	53	73.611	5.889	0.971	1.375
18-month Rolling Window					
Among S&P Indexes					
Pre-Covid-19	33	45.833	3.667	0.802	1.833
Covid-19	37	51.389	4.111	0.758	1.667
Among Dow-Jones Indexes					
Pre-Covid-19	29	40.278	3.222	0.581	1.903
Covid-19	47	65.278	5.222	0.755	1.347
Among FTSE Indexes					
Pre-Covid-19	28	38.889	3.111	0.577	2.069
Covid-19	30	41.667	3.333	0.609	1.519
Among MSCI Indexes					
Pre-Covid-19	37	51.389	4.111	0.638	1.556
Covid-19	40	55.556	4.444	0.845	1.556

Table A.15
Centrality before and during Covid-19 period using 6 and 18-month rolling windows.

	Pre-Covid-19		Covid-19	
Rank	Hub (Score)	Auth (Score)	Hub (Score)	Auth (Score)
6-month Rolling Window				
All Indexes				
1	S.U.C (0.740)	D.U.C (0.844)	M.E.C (0.622)	D.U.C (0.403)
2	M.U.C (0.586)	F.U.I (0.294)	F.E.C (0.592)	M.U.E (0.247)
3	F.U.C (0.209)	D.U.I (0.232)	S.E.E (0.200)	F.U.I (0.236)
4	S.U.I (0.152)	M.U.I (0.202)	M.U.C (0.188)	S.U.C (0.207)
5	D.U.E (0.103)	D.U.E (0.159)	S.U.C (0.182)	M.U.I (0.206)
18-month Rolling Window				
All Indexes				
1	M.U.C (0.677)	D.U.C (0.857)	F.E.C (0.471)	D.U.C (0.634)
2	S.U.C (0.647)	F.U.I (0.297)	S.U.C (0.412)	M.U.I (0.275)
3	F.U.C (0.295)	D.U.I (0.202)	M.E.C (0.314)	M.W.E (0.232)
4	S.U.I (0.110)	M.U.I (0.164)	S.U.E (0.287)	D.U.I (0.214)
5	S.U.E (0.074)	D.U.E (0.162)	F.U.C (0.252)	M.E.I (0.195)

Table A.16
Centrality before and during Covid-19 period using 6 and 18-month rolling windows.

	Pre-Covid-19		Covid-19	
Rank	Hub (Score)	Auth (Score)	Hub (Score)	Auth (Score)
	6-month Rolling Window			
Inter-Market Linkages				
1	M.E.C (0.714)	M.E.I (0.734)	M.E.C (0.663)	M.U.E (0.327)
2	D.E.C (0.504)	F.E.I (0.322)	F.E.C (0.653)	F.U.I (0.308)
3	F.E.C (0.454)	D.E.E (0.312)	M.U.C (0.175)	M.U.I (0.263)
4	S.E.E (0.118)	D.E.I (0.309)	S.E.E (0.136)	D.W.I (0.259)
5	S.E.C (0.066)	S.E.I (0.298)	S.U.C (0.129)	S.U.I (0.252)
	18-month Rolling Window			
Inter-Market Linkages				
1	F.U.C (0.667)	F.U.I (0.647)	F.E.C (0.663)	M.E.I (0.513)
2	S.U.C (0.517)	M.U.I (0.39)	D.E.C (0.503)	F.E.I (0.495)
3	M.U.C (0.482)	D.U.I (0.347)	S.E.E (0.222)	D.E.I (0.227)
4	S.U.E (0.159)	D.U.E (0.32)	M.E.C (0.221)	D.U.I (0.227)
5	M.W.C (0.088)	M.W.E (0.267)	S.E.C (0.175)	F.E.E (0.207)

Table A.17
Centrality before and during Covid-19 period using 6 and 18 months rolling windows.

	Pre-Covid-19		Covid-19	
Rank	Hub (Score)	Auth (Score)	Hub (Score)	Auth (Score)
	6-month Rolling Window			
Among Conventional Indexes				
1	S.U.C (0.788)	D.U.C (0.989)	M.E.C (0.647)	D.U.C (0.648)
2	M.U.C (0.612)	F.U.C (0.125)	F.E.C (0.579)	S.U.C (0.316)
3	F.U.C (0.062)	M.W.C (0.054)	S.U.C (0.288)	S.W.C (0.312)
4	M.W.C (0.004)	S.U.C (0.038)	F.U.C (0.247)	M.W.C (0.294)
5	S.W.C (0.002)	M.U.C (0.029)	M.U.C (0.233)	D.W.C (0.283)
Among Religious Indexes				
1	D.E.I (0.625)	M.E.I (0.868)	D.E.I (0.67)	M.E.I (0.626)
2	S.E.I (0.593)	S.E.I (0.347)	F.E.I (0.602)	S.E.I (0.548)
3	F.E.I (0.505)	D.E.I (0.306)	M.E.I (0.244)	F.E.I (0.365)
4	M.U.I (0.033)	F.E.I (0.174)	S.U.I (0.205)	M.W.I (0.179)
5	F.W.I (0.021)	M.W.I (0.044)	S.E.I (0.172)	D.E.I (0.176)
Among Ethical Indexes				
1	S.U.E (0.733)	D.U.E (0.771)	S.E.E (0.825)	D.E.E (0.534)
2	F.U.E (0.578)	F.U.E (0.311)	F.U.E (0.295)	S.W.E (0.352)
3	D.U.E (0.246)	M.U.E (0.282)	S.U.E (0.279)	D.U.E (0.341)
4	M.U.E (0.191)	S.W.E (0.277)	S.W.E (0.204)	S.U.E (0.322)
5	S.E.E (0.127)	F.W.E (0.263)	F.W.E (0.15)	M.W.E (0.303)
	18-month Rolling Window			
Among Conventional Indexes				
1	M.U.C (0.719)	D.U.C (0.988)	S.U.C (0.775)	D.U.C (0.9)
2	S.U.C (0.671)	S.W.C (0.105)	F.E.C (0.304)	F.U.C (0.21)
3	F.U.C (0.18)	F.U.C (0.097)	F.W.C (0.288)	M.U.C (0.181)
4	D.W.C (0.013)	M.W.C (0.049)	M.E.C (0.261)	D.W.C (0.168)
5	F.W.C (0.004)	M.U.C (0.029)	M.U.C (0.236)	S.W.C (0.134)
Among Religious Indexes				
1	D.E.I (0.638)	M.E.I (0.922)	F.E.I (0.784)	M.E.I (0.853)
2	S.E.I (0.597)	S.E.I (0.269)	D.E.I (0.469)	S.E.I (0.31)
3	F.E.I (0.482)	D.E.I (0.239)	S.E.I (0.263)	D.E.I (0.223)
4	M.U.I (0.05)	F.E.I (0.132)	F.W.I (0.174)	M.W.I (0.182)
5	F.W.I (0.02)	M.W.I (0.045)	M.E.I (0.123)	F.E.I (0.159)

(continued on next page)

Table A.17 (*continued*).

Among Ethical Indexes				
1	S.U.E (0.803)	S.W.E (0.59)	F.U.E (0.611)	F.W.E (0.583)
2	F.U.E (0.51)	D.U.E (0.556)	S.U.E (0.513)	S.W.E (0.395)
3	D.U.E (0.197)	F.W.E (0.413)	S.W.E (0.353)	D.W.E (0.367)
4	M.U.E (0.14)	M.W.E (0.28)	D.U.E (0.269)	D.U.E (0.35)
5	F.W.E (0.126)	F.U.E (0.231)	F.W.E (0.257)	M.W.E (0.345)

Table A.18
Centrality before and during Covid-19 period using 6 rolling windows.

	Pre-Covid-19		Covid-19	
Rank	Hub (Score)	Auth (Score)	Hub (Score)	Auth (Score)
	6-month Rolling Window			
Among S&P Indexes				
1	S.U.C (0.848)	S.U.E (0.844)	S.E.E (0.667)	S.W.C (0.545)
2	S.U.I (0.493)	S.W.I (0.462)	S.U.E (0.442)	S.W.E (0.46)
3	S.W.I (0.128)	S.W.C (0.243)	S.U.C (0.376)	S.U.E (0.452)
4	S.W.C (0.097)	S.U.I (0.09)	S.W.E (0.352)	S.W.I (0.315)
5	S.U.E (0.089)	S.W.E (0.084)	S.U.I (0.203)	S.U.I (0.312)
Among Dow-Jones Indexes				
1	D.E.C (1)	D.E.I (0.763)	D.E.C (0.711)	D.U.C (0.485)
2	D.E.I (0.02)	D.E.E (0.647)	D.U.I (0.388)	D.U.I (0.415)
3	D.E.E (0.011)	D.W.E (0.013)	D.E.E (0.34)	D.E.I (0.354)
4	D.W.E (0.006)	D.E.C (0.004)	D.E.I (0.285)	D.W.C (0.339)
5	D.U.E (0.006)	D.U.C (0.002)	D.U.C (0.263)	D.W.I (0.324)
Among FTSE Indexes				
1	F.E.C (0.947)	F.E.I (0.942)	F.E.C (0.969)	F.U.I (0.537)
2	F.U.C (0.308)	F.U.I (0.311)	F.U.E (0.191)	F.U.C (0.458)
3	F.U.E (0.078)	F.W.E (0.106)	F.W.I (0.107)	F.W.E (0.36)
4	F.E.E (0.042)	F.U.E (0.054)	F.W.C (0.073)	F.U.E (0.321)
5	F.W.I (0.031)	F.E.E (0.031)	F.U.I (0.062)	F.E.I (0.305)
Among MSCI Indexes				
1	M.E.C (0.999)	M.E.I (0.988)	M.E.C (0.94)	M.W.C (0.434)
2	M.E.E (0.05)	M.E.E (0.153)	M.U.C (0.188)	M.U.I (0.421)
3	M.U.I (0.016)	M.W.I (0.01)	M.E.I (0.166)	M.W.E (0.42)
4	M.U.C (0.001)	M.E.C (0.001)	M.W.C (0.139)	M.U.E (0.402)
5	M.E.I (0.001)	M.U.E (0.001)	M.W.E (0.113)	M.W.I (0.373)

Table A.19
Centrality before and during Covid-19 period using 18 months rolling windows.

	Pre-Covid-19		Covid-19	
Rank	Hub (Score)	Auth (Score)	Hub (Score)	Auth (Score)
	18-month Rolling Window			
Among S&P Indexes				
1	S.W.I (0.706)	S.W.C (0.869)	S.U.E (0.625)	S.W.I (0.658)
2	S.W.E (0.41)	S.W.I (0.27)	S.W.C (0.445)	S.W.E (0.573)
3	S.U.E (0.34)	S.U.E (0.26)	S.U.C (0.428)	S.W.C (0.335)
4	S.U.I (0.32)	S.W.E (0.252)	S.U.I (0.368)	S.U.E (0.257)
5	S.U.C (0.3)	S.U.I (0.201)	S.W.E (0.2)	S.U.C (0.176)
Among Dow-Jones Indexes				
1	D.E.C (0.999)	D.E.I (0.765)	D.E.C (0.87)	D.E.I (0.588)
2	D.E.E (0.038)	D.E.E (0.635)	D.U.I (0.251)	D.E.E (0.487)
3	D.W.C (0.019)	D.W.E (0.106)	D.U.E (0.228)	D.U.C (0.445)
4	D.U.I (0.011)	D.W.I (0.017)	D.E.I (0.223)	D.W.I (0.268)
5	D.U.E (0.011)	D.U.C (0.007)	D.W.C (0.172)	D.U.I (0.251)

(*continued on next page*)

Table A.19 (*continued*).

Among FTSE Indexes				
1	F.U.C (0.977)	F.U.I (0.996)	F.E.C (0.979)	F.E.I (0.891)
2	F.W.I (0.188)	F.U.E (0.071)	F.W.C (0.111)	F.E.E (0.265)
3	F.U.E (0.102)	F.W.E (0.046)	F.U.E (0.105)	F.U.C (0.224)
4	F.W.C (0.004)	F.W.C (0.014)	F.E.E (0.103)	F.W.E (0.195)
5	F.U.I (0.004)	F.W.I (0.002)	F.U.C (0.052)	F.W.I (0.19)
Among MSCI Indexes				
1	M.E.C (0.997)	M.E.I (0.983)	M.W.C (0.639)	M.W.E (0.686)
2	M.U.I (0.049)	M.E.E (0.185)	M.E.I (0.463)	M.W.I (0.474)
3	M.E.E (0.048)	M.W.I (0.008)	M.U.C (0.402)	M.U.I (0.37)
4	M.U.E (0.027)	M.W.E (0.006)	M.W.I (0.273)	M.W.C (0.33)
5	M.W.C (0.004)	M.U.E (0.003)	M.W.E (0.232)	M.U.E (0.16)

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