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A multi-dimensional connectedness and spillover between green bond and Islamic banking equity: Evidence from country level analysis

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A B S T R A C T

The paper delves into the multidimensional connections and spillover between green bonds and Islamic banking stocks from eleven countries. Throughout this study, we further explored optimal hedging mechanisms, as well as optimal portfolio weighting mechanisms, with Islamic banking equities and green bonds. Our empirical results show that there is a moderate level of interrelation between green bonds and Islamic banking indices, with low connectedness throughout the long-term and medium-term. The time-varying spillover effects become higher, albeit low, in the early periods of both SOR and COVID-19 at short-, medium-, and long-term scales, which suggests some diversification and hedging benefits from holding portfolios of the two assets. Country-based Islamic bank markets are not largely affected by disturbances that emerged in some other markets in the short-, medium-, or long-term timescales. The Chinese green bond market has a tendency to be the greatest net risk transceiver for both the green bond and Islamic bank markets over the medium and long term, whilst the global green bond index has been the leading net risk transmitter during the short term. Only the UAE and Saudi Islamic Banking indices act as net risk transmitters in the short and medium term. The empirical findings further suggest that global risk variables are dependable drivers of the extent of spillover between Islamic banking indices and green bonds. Our research shows that owning Islamic bank stocks during COVID-19 and SOR minimizes the significant risk linked to holding green bonds, which has profound implications for risk management and portfolio creation. Thus, our study offers important implications for economic agents.

1. Introduction

With each passing year of disastrous climate change effects, the global community needs to embrace even more urgent and forceful measures to deal with the issue. In order to lessen the potentially devastating effects of climate change, the global economy would need to invest approximately USD 125 trillion by 2050 to achieve carbon-neutral or zero-net objectives (Climate Champions, 2023). As a result of the importance of finance in creating a low-carbon or climate-resilient economy, the sustainable financing sector has been growing rapidly in recent years, and an innovative form of sustainable financing called 'green bonds' and 'climate bonds' has emerged (Reboredo and Ugolini, 2020; Hyun et al., 2021). These financial instruments aid in funding green initiatives by spreading the expense of mitigating climate change over several generations, making the shift to a low-carbon economy more financially feasible (Flaherty et al., 2017; Monasterolo and Raberto, 2019; Reboredo, 2018). According to the Climate Bond Initiatives (2023), cumulative green

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bond issuance surpassed USD 2 trillion in 2022. In 2022, the total green bond issuance amounted to USD 487.1 billion, with the United States, China, and France accounting for approximately 42.5% of the total issuance. A report from the Climate Bond Initiatives (2023) predicts that this figure could reach $5 trillion annually by the year 2025. The increasing popularity of green bonds as a sustainable financial product has offered attractive investment options for both individual and institutional investors, especially those interested in environmental stewardship.

While green bonds appear to be a viable financial alternative, no investment is without its ups and downs, and green bonds are no exception. Therefore, there is a certain degree of uncertainty and risk associated with investing in green bonds, which can be influenced by factors such as cross-market attractiveness, volatilities, climate policy uncertainty, and economic policy uncertainty. Theoretically, green bonds are linked to the activities and volatilities of the financial market. In this regard, the green bond market is susceptible to the 'butterfly effect,' wherein the volatility of one financial market prompts investors to rebalance their portfolios and allocate their funds elsewhere (Gao et al., 2021). Hence, green bond investors are also in need of some financial tools that could hedge or protect their green bond portfolios without sacrificing much of their environmental stewardship. Consequently, it has become essential to comprehend the transmission mechanisms that exist between green bonds and financial markets to evaluate the potential roles that other assets may play in hedging and minimizing the risks associated with green bond portfolios. In such cases, investors may be particularly interested in understanding how green bonds relate to other principle-based financial vehicles or even sectoral equities.

Green bond investment is considered a moral investment, while Islamic instrument investment is viewed as both faith-based and moral (Billah et al., 2023a). Alongside other Islamic equities, Islamic banks' stocks are regarded as the purest Islamic equity in the financial market because their operations are based on Sharia principles and overseen by the Sharia council (Khan, 2010; Meslier et al., 2020). Islamic banks also provide funding for ecologically friendly and green initiatives through green loans. Furthermore, Islamic financial banks or institutions place a strong emphasis on environmental stewardship and resource utilization, adhering to principles that discourage excessive consumption and wastage of resources (Ahmed et al., 2015; Kunhibava et al., 2018; Ali and Reardon, 2023). This promotes environmental care and responsibility in achieving environmental sustainability. The first step in this sector is to recognize the climate as a divinely bestowed resource worthy of careful stewardship. Therefore, one could argue that the financing and investment activities of Islamic banks are aligned with green activities and financing. As a result, an investor who is interested in green investments may diversify their capital allocation with Islamic banking stocks without compromising their concerns about environmental hazards. Thus, investors may be attracted to both green bonds and Islamic banking equity. Furthermore, investors may perceive green bonds and Islamic banking equity investments as moral and responsible investments. However, the returns on Islamic banking equity can differ from those of green bonds, as Islamic banking equity returns exhibit their own dynamics. Therefore, a deeper understanding of the spillovers between Islamic equities and green bonds is necessary, particularly in terms of Islamic banking stock returns.

The literature on the linkages and cross-market connections of green bonds with other financial markets and instruments continues to expand. Most studies have examined how green bonds interact with and are influenced by non-Sharia-based financial markets and asset classes, such as conventional equity markets (e.g., Reboredo, 2018; Elsayed et al., 2022), conventional bond markets (Reboredo, 2018; Billah et al., 2023c;; Elsayed et al., 2022; Jiang et al., 2022), commodities (Mensi et al., 2022a; Mensi et al., 2023), currencies (Jiang et al., 2022; Mensi et al., 2023), green energy (Ferrer et al., 2021; Tiwari et al., 2022), and green equity markets (Reboredo et al., 2022; Tiwari et al., 2023a). Empirical studies have focused on the connectedness of green bonds with sectoral bonds (Mensi et al., 2022b) and sectoral equity indices (Fernandes et al., 2023; Balli et al., 2022). Some researchers have explored the transmission and risk linkages between green bonds, the Islamic market, and Sukuk (Billah et al., 2024;; Rabbani et al., 2023; Billah et al., 2023a; Tiwari et al., 2023b). Despite ongoing discussions, little is known about the connection between Green Bonds and Islamic Banking stock returns, even though Islamic Banking indices appear to be crucial for Green Bond asset allocation and risk hedging. Moreover, there is a lack of examination into the interconnection and spillover effects between Islamic banking equities and green bonds, as well as an investigation into the risk-hedging capabilities of green bonds and Islamic banks with respect to each other.

In light of these considerations, the main objective behind this investigation is to examine the information spillovers that occur between green bonds and Islamic banking stock returns in the time-frequency domain. To accomplish this, we make use of the time-varying parameter vector autoregression (TVP-VAR) model developed by Antonakakis et al. (2020). This approach allows one to explore not just the network's dynamic features, but also its directional and magnitude connections. Additionally, considering a TVP-VAR for the time-frequency domain spillover index has advantages as it overcomes issues related to Diebold and Yılmaz (2012) and Baruník and Křehlík (2018). It does not need a certain window size to be chosen arbitrarily. Using the TVP-VAR model, we also prevent the loss of information or observations. This model is more resistant to changes in parameters and can more accurately identify outliers. What's more, investors' responses vary depending on the length of their investment horizons. As noted by Mensi et al. (2022a), market spillover effects have been influenced in large part by how often they occur, with short-term spillover effects being the primary focus of arbitrage traders, hedge funds, and speculators, medium-term spillover effects being the primary focus of mutual and hedge funds, and long-term spillover effects being the primary focus of institutional investors and policymakers. So, consideration of the asymmetry in connections between markets and the time-varying nature of risk transmission is therefore beneficial for financial risk management. Thus, this study partitions frequencies into short-, medium-, and long-term timeframes. This approach may provide useful insights to investors who operate across different investment horizons or domains.

Furthermore, using DCC-GARCH t-Copula, Antonakakis et al. (2018) investigate the hedging potential of Islamic banking stocks to green bond portfolios (2020). We perform risk management with the full sample period, full sample period, the period of the COVID-19 pandemic, and the period of the Shale Oil Revolution. This study uses these analyses to determine the optimal portfolio weights for reducing risk without sacrificing returns, determine if hedging is value, and assess hedging effectiveness. Moreover, the market dynamic move with macro-economic events uncertainty factors such as economic policy uncertainty (EPU), volatility in the stock market, uncertainty in the oil market (OVX), volatility in the gold market (GVZ), global financial stress (GFS), macroeconomic news surprises (GMNS) and the climate change (CLMT) index (Balli et al., 2019; Mensi et al., 2022a; Billah et al., 2023b). So, this study also examines the effects of uncertainty factors on connectedness of green bonds and Islamic banking stock returns. In doing so, this study addresses the following unanswered questions:

(i) Is there time-frequency dependent interconnectivity and spillover between green bonds and Islamic banking stock returns?
(ii) Could Islamic banking stocks help reduce volatility risk in green bond portfolios?
(iii) Is the connectedness between green bonds and Islamic banking stock returns affected by uncertainty factors?

Therefore, the current study offers a number of promising contributions to the growing bodies of literature on both green assets and Islamic financial assets in the following ways. First, there is no study that has examined the connectedness between Islamic banks and green bonds. To address this knowledge vacuum and provide a useful contribution, this study analyzes the frequency spillovers between Islamic banks in eleven countries and four green bonds. Second, the current study considers 11 Asian countries' Islamic equities with green bonds. Hence, this study extends the studies of Sarita and Naeem (2022) and Tiwari et al. (2023a). Third, we study heterogeneous links and total spillover, including short-term (1–5 days), medium-term (5–22 days), and long-term (22-inf days) connectedness and spillover. Our study depicts a time-varying connectedness and spillover between Islamic banks and green bonds, which further extends the understanding of the interaction between green investments and Islamic financial instruments (e.g., Sarita and Naeem, 2022; Billah et al., 2023a; Tiwari et al., 2023b). Fourth, unlike other past studies, this study observes how connectivity during periods of uncertainty, like the period of the COVID-19 pandemic and the period of the Shale Oil Revolution, decreases connectedness between Islamic banks in eleven countries and four green bonds, especially in the short and medium term. Fifth, Fernandes et al. (2023) demonstrated that sectoral equity could mitigate risk in green bond investments. However, Fernandes et al. (2023) have not investigated their linkage and risk transmission mechanism. Consequently, we address this profound gap in the literature through investigating the assets' changing interdependencies over time.

The remaining part is organized as follows: Section 2 discusses related empirical studies and presents the research gap. Section 3 deliberates on dataset description and empirical methods. In the subsequent section, empirical results are shown and discussed. In the concluding section, a summary of the results, their practical implications, and future research directions are given.

2. Literature review

Green bonds are a kind of environmentally responsible financing that is issued in order to finance environmentally responsible initiatives. Bonds that are good for the environment are also sometimes called climate bonds. In the past few years, there seems to have been an unforeseen growth in the prevalence of worries around climate change as well as other problems connected to it, which has also prompted a rise in discussions surrounding green bonds. A great number of research have focused on the connections and spillovers that exist between various asset classes and green bonds.

For example, Reboredo (2018) employed static and time varying copula functions to evaluate the interdependency structure of the green bond market in comparison with traditional bonds, equity securities, and energy markets. Their empirical evidence indicated that the three bond markets are heavily reliant on and linked to one another. They discovered that price fluctuations in conventional bonds influenced the pricing of green bonds. They revealed that there has not been a significant association between the prices of green bonds and the prices of stocks and between the prices of green bonds and energy commodities.

In a similar context, Reboredo and Ugolini (2020) have employed a SVAR approach to explore the interdependence of green bonds with other financial markets. They discover that the fixed-income markets have a major impact on green bonds. The fact that green bonds have only a tenuous link to the stock, energy, and corporate bond markets is additional evidence that they provide tremendous prospects for diversification. Using the frequency spillover method, Ferrer et al. (2021) assessed the multiscale spillovers across the GB, financial, and energy sectors, and they concluded that the three markets are significantly intertwined in the short term. Using a cross-quantile dependence and frequency analysis, Pham (2021) explored the link between the green bond and green stock markets. Their research showed that the association between green bonds and equities is rather weak while market circumstances are calm but becomes much stronger during times of market volatility. In addition to this, they discovered that in the medium to long term, regardless of market circumstances, the impacts of spillovers across green bonds and green stocks remain transient.

Elsayed et al. (2022) investigated multi-dimensional relationship of green bonds and financial markets considering time scale and time varying. They used techniques like Ensemble Empirical Mode Decomposition (EEMD) with the spillover indexing techniques. Their spillover study revealed that the connection among green bonds and financial markets changes with time., with that of the global stock market acting as the net spillover transmitter and the corporate bond and green bond markets serving as the net spillover recipients among the chosen markets. Using different quantile methods, Jiang et al. (2022) investigated the connection between green bonds and conventional financial markets. The results show that green bonds may protect investors against currency and stock market fluctuations and provide diversification for downturns in the treasury market in the medium term. Spillover across three markets, including the green bond market, the crude oil market, and the stock market, has been studied by Mensi et al. (2022a), who used both the wavelet coherency technique and the frequency spillover approach. Their findings indicates that spillover effects were much more substantial in the short run compared to the medium or long term. Subsequently, they demonstrate that green bonds, in contrast to crude oil, have been a strong diversifier itself against uncertainty of the G7 equity market. Mensi et al. (2022b) utilized three different methods, including copulas, CoVaR, and quantile regression methods, in order to investigate the influence of COVID-19 pandemic and global risk variables on the extreme spillovers in the global green bonds market and sector-specific green bonds.

They discovered tail dependency spillovers among green bonds, which are further driven by financial condition factors, macro risk measures, and COVID-19. Using a combination of daily data and TVP-VAR, Tiwari et al. (2022) explored the propagation of return structures among green bonds, carbon prices, and renewable energy stocks. The researchers discovered evidence of heterogeneous and event-dependent dynamic connectivity among green bonds, carbon pricing, and renewable energy equity, where clean energy, green bonds, and solactive global wind all work together to operate as net shock transmitters in the network, while the other markets function as net shock receivers in the network.

Fernandes et al. (2023) looked into the Multifractal Cross-Correlations of green bonds, sectoral equity indices, and sectoral bond indices, and they were particularly interested in the market efficiencies of these three types of indices. Researchers revealed green bonds as inefficient assets and the real state sector acts as hedge for green bonds. Mensi et al. (2023) recently explored the time-frequency return spillover with volatility spillovers in Green Bond markets, precious metal markets, the oil market, and the US dollar value. They also investigated the volatility index in relation to declining US stock prices during and before to the COVID-19 pandemic outbreak. The researchers discover that short-term volatility spillovers outweigh long-term volatility. Green played two roles: short-term net transmitters and long-term net receivers. They also emphasized that short-term spillover was at its peak during the early COVID-19 crisis. When investigating the potential for diversification benefits for portfolios composed of low-carbon and green bonds, Reboredo et al. (2022) found that the returns on green bonds and low-carbon stocks fluctuate in opposing directions or are entirely independent of either the Chinese, European, and American markets. Employing quantile cross-spectral coherence approach, Tiwari et al. (2023a) explored the coherence in the presence of extreme returns among green bonds and stocks. The research reveals a minimal connection between green bonds and green stocks, but a strong dependence during periods of market turbulence that occur with short to medium frequency. Their findings indicated that green debt instruments act as more of a hedge, diversifier, or safe haven against negative market environment indices across all time scales.

Some studies also looked at how green bonds interact with faith-based investments, Sukuk, and Islamic stocks. For example, Sarita and Naeem (2022) employed TVP-VAR and wavelet coherence methodology along with spanning December 2008 through May 2021, to analyze the interdependence of green, Islamic, and traditional financial markets, and identify the factors that influence their interconnectedness. Their research shows that there is linkage, with Islamic equities serving as net transmitters and sukuks with green bonds serving as net receivers of spillovers. They also demonstrated the interconnectedness of financial markets during times of stress triggered by global factors. Using the new quantile connectedness approach and daily frequency data, Billah et al. (2023b) explored the return interconnectedness between sukuk markets and green bonds markets. They revealed that sukuk and green bonds exhibit higher connectedness throughout both bullish and bearish markets. Moreover, they discovered that the left and right quantiles had less variation in time-varying connectedness. Also, they discovered that when market circumstances are bullish and bearish, the US dollar seems to have a significant effect on linkages, whereas equity market uncertainty has a positive influence. Tiwari et al. (2023b) used quantile coherency and findings show that green bond price returns have some adverse long-run spillover impact on Islamic equities. Moreover, they further revealed that under the turbulent market conditions the S&P 500 Bond index, the S&P 500 Stock Composite, green bonds, and Islamic stock tends to be weak.

Having discussed, research on environmentally friendly bonds and their interactions with other markets and asset classes is continuing to expand, albeit it is still limited to a few aspects. First, in light of the recent growth in environmentally friendly (green) bonds as an instrument for mitigating the detrimental results of climate change and the ever-increasing interest of investors in Islamic equities as a means of diversifying investment portfolios, it is of the utmost importance to do research on the potential spillovers of Islamic equities with green bonds. This investigation avenue has constantly produced mixed evidence, and the majority of its attention has been directed toward the market in the United States. Second, the Islamic equity market seems to be mostly active in the Asian region, which has not been explored in previous empirical research. Third, Fernandes et al. (2023) demonstrated that sectoral equity could mitigate risk in green bond investments. On this premise, we envisaged that the Islamic banking sector functions as a hedge for green bonds. The facts are that green bond investment is seen as a moral investment, while Islamic stock investing is regarded as a faith-based and moral investment. In addition to other Islamic equities, Islamic banks' stock is regarded as the purest Islamic equity in the financial market since its operations are founded on Sharia principles and supervised by the Sharia council (Khan, 2010; Meslier et al., 2020). Islamic Banks also fund ecologically friendly and green initiatives. Hence, the investor who completely interested green investment may diversify their capital allocation with Islamic banking stock without sacrificing their concerns of environmental hazard. Therefore, investor might be attracted to green bond and Islamic bank equity. Hence, the further understanding on spillovers between Islamic equities and green bonds is needed. However, Fernandes et al. (2023) have not investigated their linkage and risk transmission mechanism. Therefore, we fill a significant missing piece of literature through investigating the time-varying interconnectedness of these assets. Additionally, with the construction of the Islamic banking indices of eleven countries such as Bahrain, Bangladesh, Indonesia, Jordan, Kuwait, Malaysia, Oman, Pakistan, Qatar, Saudi Arabia, United Arab Emirates, we contribute to the existing body of research.

3. Empirical method and data

3.1. Dataset and descriptive analysis

We chose Islamic banks in Jordan, four Asian countries (Bangladesh, Indonesia, Malaysia, and Pakistan), and six Gulf Cooperation Council (GCC) states (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and UAE) and have considered their daily closing share price in index construction. To represent the global green bond markets, we utilize the “Bloomberg Barclays MSCI Green Bond Index” (GB GL) (Reboredo, 2018; Reboredo and Ugolini, 2020). After making its debut in November 2014, the GB GL index quickly established itself as the industry standard for green bond indices. This index is composed entirely of investment-grade bonds, each of which has a coupon rate that is fixed. Likewise, the “FTSE Green Bond Index” (Onshore CNY) (GB CH), the “MSCI Bloomberg Barclays Euro Green Bond Index” (GB EU), and the “MSCI Bloomberg Barclays US Green Bond Index” (GB US) are used to monitor how well green bonds are doing in the Chinese, American, and European markets, respectively. These bonds have a coupon rate that is fixed and have an investment grade rating. They were issued by businesses or governments. Either the euro or the dollar have served as the issue's base currency.

Our data set covers the time span beginning in January 2014 and ending in October 2022 and contains a total of 2566 observations. This includes data for all eleven nations of Islamic banks as well as the four green markets. The beginning of the sample period is determined by the accessibility and availability of the data pertaining to the green bond market. This time span encompasses multiple periods of widespread uncertainties and catastrophes, notably the Shale Oil Revelation of 2014–2016 and the COVID-19 pandemic beginning in 2020.

We develop Islamic bank stock price indices that take into account the Islamic banking sectors of those eleven nations so that we can evaluate the potential of risk spillovers that could occur simultaneously between the four markets for green bonds and the eleven markets for Islamic bank stocks. In creating this index, we followed the recommendations of a research by Mensi et al. (2019) that the banking stock index for each nation should be built using a weighted average of the stock prices of Islamic banks in that country. Henceforth, Islamic banking sector index is constructed as follows Islamic banking sector index$=\sum_{i=1}^{n}\left(\frac{\mathrm{CB_i}}{\mathrm{CB_T}}\right)\times$ Price. Where $\mathrm{CB_i}$ represent market capitalization of bank *i* in respected countries stock market and $\mathrm{CB_T}=\sum_{i=1}^{n}\mathrm{CB_i}$, “Price” represents the daily observed *ith* Islamic bank stock price and *n* is the number of banks.

This research focuses on international markets, each of which has a distinct opening and closing time due to the many time zones associated. Furthermore, the days off that are deemed weekends and holidays differ from market to market. For instance, when compared to the trading weeks in the west and other parts of Asia, the markets in the Gulf Cooperation Council (GCC) countries and Bangladesh are closed on Fridays and Saturdays and reopen on Sundays. These differences could create issue in the empirical estimations. To address these issues, we adopt rolling window technique techniques proposed by Forbes and Rigobon (2002). Given that markets need more than a day to react to new information flows, it is evident that if any delays in shock propagation are constantly monitored by the sequence of two rolling return approaches, and the resulting data is intriguing (Arslanalp et al., 2016). Henceforth, we computed the mean rolling returns over a period of two days using a rolling window technique, which we used in empirical estimations of TVP-VAR connectedness and DCC based on optimal hedging and portfolio strategy. As shown in Table 1, a total of 54 Islamic Banks operating in eleven countries such as Bahrain, Bangladesh, Indonesia, Jordan, Kuwait, Malaysia, Oman, Pakistan, Qatar, Saudi Arabia, United Arab Emirates. The Islamic banking sectors of these countries contributes >70% to global Islamic banking assets (See Caporale et al., 2020; Puri-Mirza, 2022). All 54 Islamic banks have made contributions to the development of Islamic bank

Table 1
List of Islamic banks.

Country	Islamic banks	Country	Islamic banks
	BAHRAIN ISLAMIC BANK		ISLAMI BANK BANGLADESH
	AL SALAM BANK		FIRST SECURITY ISLAMI BANK
Bahrain	KHALEEJI COMMERCIAL BANK	Bangladesh	SHAHJALAL ISLAMI BANK
	AL SALAM BANK B S C		ICB ISLAMIC BANK
	ITHMAAR BANK		UNION BANK
	AL BARAKA GROUP		EXPORT IMPORT BANK OF BD
			AL ARAFA BANK
	AHLI UNITED BANK		
	KUWAIT FINANCE HOUSE		BANK ISLAM
Kuwait	KUWAIT INTERNATIONAL BANK	Malaysia	CIMB GROUP HOLDINGS(OTC)
	BOUBYAN BANK		ALLIANCE BANK MALAYSIA
	WARBA BANK		HONG LEONG BANK
			AFFIN BANK
	AL IZZ ISLAMIC BANK		
Oman	BANK NIZWA		PT BANK MAYBANK INDOCORP
	NATIONAL BANK OF OMAN		CIMB ISLAMIC BANK
		Indonesia	BUKOPIN SYARIAH
	QATAR INTERNATIONAL ISLAMIC BANK		BANK PANIN DUBAI SYARIAH
Qatar	QATAR ISLAMIC BANK		BANK BTPN SYARIAH
	MASRAF AL RAYAN		BANK SYARIAH INDONESIA
	LESHA BANK		BANK ALADIN SYARIAH
	AL RAJHI BANK		MEEZAN BANK
Saudi Arabia	AL BILAD BANK	Pakistan	BANKISLAMI PAKISTAN
	BANK ALJAZIRA		ASKARI BANK
	BANK ALBILAD		FAYSAL BANK
	ABU DHABI ISLAMIC BANK		JORDAN ISLAMIC BANK
United Arab Emirates	AJMAN BANK	Jordan	ARAB BANK
	SHARJAH ISLAMIC BANK		BANK OF JORDAN
	DUBAI ISLAMIC BANK		JORDAN COMMERCIAL BANK
	EMIRATES ISLAMIC BANK		

Source: Authors own calculations.

indices. Additionally, the sample data is collected from the Bloomberg database. In terms of the bank selection, we have mostly selected independent banks. However, it is possible that a large Islamic bank from one country may hold a significant proportion of stakes in Islamic banks in other countries, which are neither associated nor subsidiaries. Although significant stakes are held by Islamic banks from other countries, our empirical methodology itself accounts for the connectedness and interdependence. Therefore, it should not pose an issue in the empirical estimation. Mensi et al. (2019) have employed a similar approach to construct the Islamic bank indices of each GCC market, incorporating connectedness techniques.

We proxied uncertainty factors such as economic policy uncertainty (EPU), volatility in the stock market, uncertainty in the oil market (OVX), the volatility in the gold market (GVZ), global financial stress (GFS), macroeconomic news surprises (GMNS) and the climate change (CLMT) index to capture their effects on the dynamic connectedness of Islamic bank stocks and green bond indices. A detail description of these uncertainty factors is provided in the Table A.1.

Table 2 provides a summary on the descriptive statistics of daily returns for Islamic bank stocks of nine countries and green bond indices. Green bond market daily average returns can range from 0.014 to 0.067, with Chinese green bonds yielding low returns and US green bonds yielding high returns. The mean daily return for Islamic bank stocks ranges from 0.003 for Jordan to 0.064 for Pakistan. Metrics such as the standard deviation, minimum, and maximum demonstrate that, excluding the indices containing the Islamic bank stocks of Indonesia and Bahrain, the majority of the indexes are exposed to a broad spectrum of volatility. The values of skewness and kurtosis indicate heavy-fatter-tailed distributions for all return series. The findings of the Jarque-Bera (JB) test do not support the null hypothesis of symmetric distribution, and the results of the Augmented Dickey-Fuller (ADF) test do not support the null hypothesis that none of the series are stationary.

Fig. 1 illustrates a plot of the daily returns for each of the markets that are the focus of this investigation. A graphical illustration depicts some variations in daily log returns, including peaks and troughs at various times over the study period, including the start of period and toward the COVID-19 crisis episode in 2020. We note that the fluctuations of the returns of Islamic bank stocks are more important than those of green bond returns. These results justify the choice of the time-varying methods in modelling the connection between these two assets, described in the following section.

3.2. TVP-VAR frequency connectedness

The TVP-VAR-based frequency connectedness model was developed and proposed by Chatziantoniou et al. (2021). This framework merges together the works of Baruník and Křehlík (2018) and Antonakakis et al. (2020), although the latter had already unified Diebold and Yılmaz (2012, 2014) connectedness approach and Koop et al. (1996) TVP-VAR framework. To determine the return connectivity of between Islamic banks and green bonds, a modern connectedness approach based on Generalized Forecast Error Variance Decomposition (GFEVD) is proposed in this work. Moreover, this approach has been processed from a Time-varying Parameter Generalized Vector Autoregressive (TVP-VAR) aspect (Antonakakis et al., 2020). The following equation presents the TVP-VAR (1) under the Bayesian Information Criterion (BIC):

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t; \varepsilon_t \mid F_{t-1} \sim N(0, S_t) \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + \nu_t; \nu_t \mid F_{t-1} \sim N(0, \Xi_t) \tag{2}$$

Table 2
Descriptive statistics and unit-root test for eleven countries Islamic banks and green bonds.

	ABR	Mean	Max	Min	SD	Skew	Kurt	JB	ADF
Green bonds									
FTSE Chinese (Onshore CNY) Green Bond Index	GB CH	0.014	0.006	−0.010	0.001	−1.228	35.991	−18.639***	−38.461***
Bloomberg Barclays MSCI Euro Green Bond Index	GB EU	0.062	0.020	−0.032	0.005	−1.263	10.859	−18.730***	−19.23***
Bloomberg Barclays MSCI Green bond index	GB GL	0.032	0.035	−0.059	0.009	−1.162	11.242	−19.734***	−20.34***
Bloomberg Barclays MSCI US Green Bond Index	GB US	0.067	0.022	−0.039	0.005	−1.791	17.369	−21.695***	−22.67***
Islamic banks for eleven countries									
BAHRAIN	–	0.009	0.095	−0.105	0.023	−0.203	8.888	−15.36***	−15.841***
BANGLADESH	–	0.017	0.090	−0.101	0.015	0.968	10.400	−22.28***	−19.785***
INDONESIA	–	0.078	0.928	−0.854	0.037	1.968	319.459	−8.49***	−18.592***
JORDAN	–	0.003	0.051	−0.070	0.008	0.227	10.686	−23.23***	−17.873***
KUWAIT	–	0.034	0.067	−0.105	0.012	−0.984	14.887	−10.51***	−18.675***
MALAYSIA	–	0.007	0.082	−0.074	0.008	0.506	17.746	−13.90***	−17.78***
OMAN	–	0.008	0.105	−0.114	0.014	0.365	11.473	−15.94***	−16.439***
PAKISTAN	–	0.064	0.071	−0.099	0.017	−0.004	5.887	−17.85***	−15.657***
QATAR	–	0.034	0.094	−0.102	0.013	0.029	11.452	−12.32***	−15.569***
SAUDI ARABIA	–	0.045	0.091	−0.089	0.014	−0.271	10.006	−19.72***	−16.856***
UNITED ARAB EMIRATES	UAE	0.047	0.098	−0.080	0.013	1.301	24.021	−17.76***	−15.847***

Note: This table gives the definitive stats for the green bonds and eleven Islamic bank indices under research study. ABR, Max, Min, SD, Skew, Kurt, JB, and ADF represents Abbreviation, Maximum, Minimum, Standard Deviation, Skewness, Kurtosis, Jarque-Bera, and Augmented Dicky-Fuller test, respectively. *** Indicates significance at 1%.

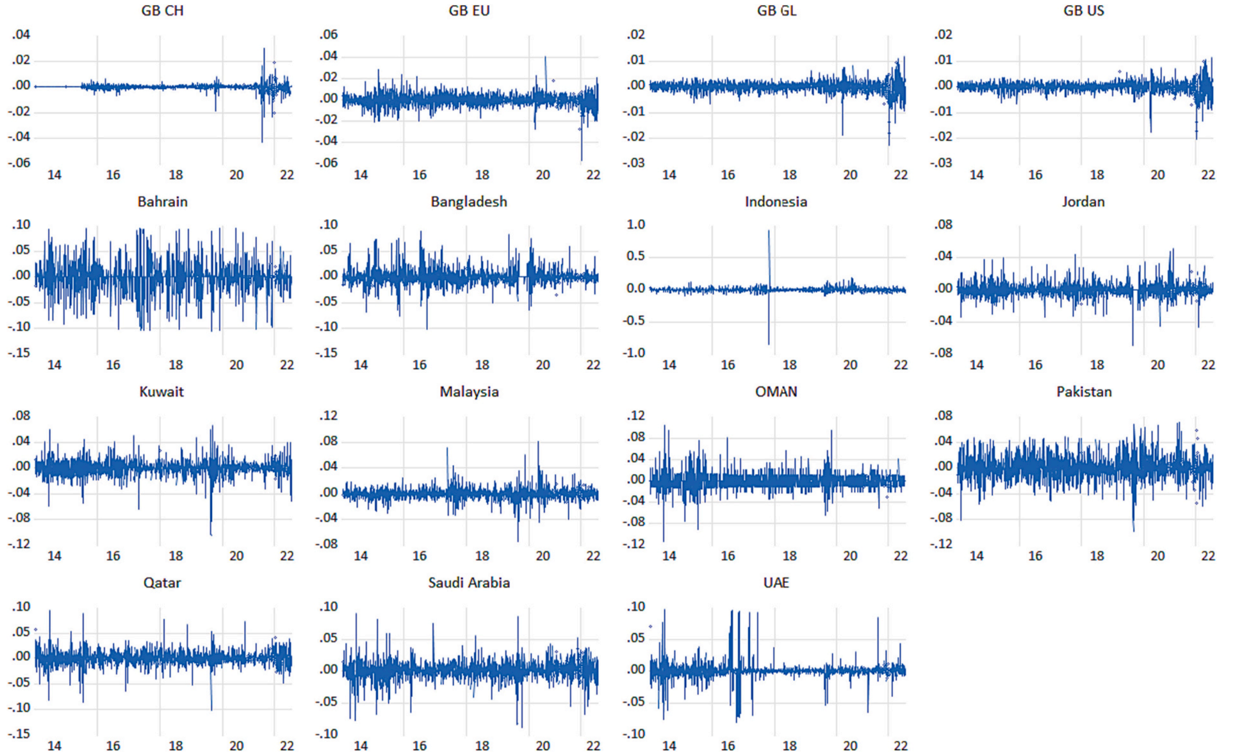

Fig. 1. Dynamic returns of Islamic bank indices and green bonds. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

In this equation, Y_t and Y_{t-1} are $N \times 1$ dimensional endogenous variable vectors, while ε_t denotes the $N \times 1$ dimensional disturbance term containing an $N \times N$ dimensional time-varying variance-covariance matrix. Additionally, the S_t; β_t denotes the $N \times N$ dimensional VAR coefficient matrix; and ν_t refers to the $N^2 \times 1$ disturbance vector that has an $N^2 \times N^2$ dimensional time-varying variance-covariance matrix, Finally, the vectorization of $vec(\beta_t)$ is represented as Ξ_t.

To determine the GFEVD, the TVP-VAR must be transformed into Vector Moving Average (VMA), which can be written as follows:

$$Y_t = \sum_{j=0}^{\infty} A_{jt}\varepsilon_{t-j} \tag{3}$$

here, A_{jt} represents the $N \times N$ dimensional matrix under the traditional Wold Representation Theorem.

The following expression presents the unscaled GFEVD ($\theta^g_{ij,t}(H)$):

$$\theta^g_{ij,t}(H) = \frac{S^{-1}_{ii,t}\sum_{t=1}^{H-1}\left(e_i^{'}A_tS_te_j\right)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1}\left(e_iA_tS_tA_t^{'}e_i\right)} \tag{4}$$

In order to ensure that unity is achieved in each row (indicating that the chosen variables account for 100% of the variable *i's* predicted error variance), the scaled GFEVD ($\widetilde{\theta}^g_{ij,t}(H)$) can be calculated as:

$$\widetilde{\theta}^g_{ij,t}(H) = \frac{\theta^g_{ij,t}(H)}{\sum_{j=1}^{N}\theta^g_{ij,t}(H)} \tag{5}$$

In this equation, $\sum_{j=1}^{k}\theta^g_{ij,t}(H) = 1, \sum_{i,j=1}^{k}\widetilde{\theta}^g_{ij,t}(H) = k$, whilst e_i is a vector that only has one i^{th} element and zero otherwise. Meanwhile, $\widetilde{\theta}^g_{ij,t}(H)$ serves to measure the bidirectional connectedness from index j to index i at horizon H.

The GFEVD can be employed to calculate a variety of connectedness measures in Diebold and Yılmaz (2014) model, including the total directional connectedness of index i to all indexes ($C_{\blacksquare\leftarrow i,t}(H)$) in Eq. (6), the net total directional connectedness ($C_{i,t}(H)$) in Eq. (8), the total directional connectedness of all indexes to index $i(C_{i\leftarrow\blacksquare,t}(H))$ in Eq. (7), and the net bidirectional connectedness ($C_{ij,t}$) in Eq.

(9).

$$C_{\blacksquare\leftarrow i,t}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \widetilde{\theta}^{g}_{ji,t}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}^{g}_{ji,t}(H)} \times 100 \tag{6}$$

$$C_{i\leftarrow\blacksquare,t}(H) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \widetilde{\theta}^{g}_{ij,t}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}^{g}_{ij,t}(H)} \times 100 \tag{7}$$

$$C_{i,t}(H) = C_{\blacksquare\leftarrow i,t}(H) - C_{i\leftarrow\blacksquare,t}(H) \tag{8}$$

$$C_{ij,t} = C_{i\leftarrow j,t}(H) - C_{j\leftarrow i,t}(H) \tag{9}$$

here $C_{ij,t} > 0$ ($C_{ij,t} < 0$), and index i dominates (is dominated by) index j. This thus suggests that index j is influenced by index i to a greater extent than it influences it.

Another useful indicator that illustrates the degree of network interconnection and hence the market risk is the total connectedness index (TCI). The average number of spillovers that one index transmits (receives) from all other indexes, as determined by the TCI, which can be defined as the average total directional connectedness to (and from) others. Research by Chatziantoniou and Gabauer (2021) and Gabauer (2021) suggests that the own variance shares are always greater than or equal to cross variance in construction and that the TCI always falls within [0, $\frac{K-1}{K}$]. The adjusted TCI that can be used to acquire a TCI within [0,1] is as follows:

$$C^{g}_{t}(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{K} \widetilde{\theta}^{g}_{ij,t}(H)}{\sum_{i,j=1}^{K} \widetilde{\theta}^{g}_{ij,t}(H)} = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{K} \widetilde{\theta}^{g}_{ij,t}(H)}{K} \tag{10}$$

$$C^{g}_{t}(H) = \left(\frac{K}{K-1}\right) \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{K} \widetilde{\theta}^{g}_{ij,t}(H)}{K} \tag{11}$$

$$C^{g}_{t}(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{K} \widetilde{\theta}^{g}_{ij,t}(H)}{K-1} \quad 0 \leq C^{g}_{t}(H) \leq 1. \tag{12}$$

Thus far, this work has focused on examining connectivity in the temporal domain. In a similar vein, we keep up with the connectivity evaluation in the frequency domain. It is possible to work out the frequency response function using Stiassny (1996) approach of spectral decomposition: $\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h}\Psi_h$, where $i = \sqrt{-1}$. Thus, at a specified frequency ω, the spectral density of x_t can be defined as the Fourier Transform for $TVP - VMA(\infty)$ filtered series. This is represented in the expression below:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h}) e^{-i\omega h} = \Psi\left(e^{-i\omega h}\right)\sum\nolimits_t \Psi'\left(e^{+i\omega h}\right) \tag{13}$$

Importantly, the spectral density and GFEVD are combined to form the frequency GFEVD. We must stabilise the frequency GFEVD and this can be achieved by following these steps:

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))^{-1}_{jj} \left|\sum_{h=0}^{\infty} (\Psi(\tau)(e^{-i\omega h})\Sigma(\tau))_{ij}\right|^2}{\sum_{h=0}^{\infty} (\Psi(e^{-i\omega h})\Sigma(\tau)\Psi(\tau)(e^{i\omega h}))_{ii}} \tag{14}$$

$$\widetilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{k=1}^{N} \theta_{ij}(\omega)} \tag{15}$$

here, $\theta_{ij}(\omega)$ refers to the percentage of the variable *ith* spectrum at frequency ω attributable to the variable *jth* shock. This is thus considered to be a within-frequency indicator.

In order to assess both short-term and long-term connectedness (rather than connectedness at one single frequency), all of the frequencies that exist in a specific details range must be accumulated: $d = (a, b)$:

$$a, b \in (-\pi, \pi), a < b :$$

$$\breve{\theta}_{ij}(d) = \int_a^b \breve{\theta}_{ij}(\omega) d\omega \tag{16}$$

This enables us to identify the connectedness processes revealed by Diebold and Yılmaz (2012, 2014). which can be evaluated in the same way, although this instance they correspond to frequency connectedness stages that provide information about spillovers within certain frequency ranges d:

$$TO_i(d) = \sum_{i=1, i \neq j}^{N} \breve{\theta}_{ji}(d) \tag{17}$$

$$FROM_i(d) = \sum\nolimits_{i=1, i \neq j}^{N} \breve{\theta}_{ij}(d) \tag{18}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{19}$$

$$TCI(d) = N^{-1} \sum\nolimits_{i=1}^{N} TO_i(d) = N^{-1} \sum\nolimits_{i=1}^{N} FROM_i(d) \tag{20}$$

In the present work, three frequency bands are employed that represent short-term and long-term dynamics varying between 1 and 5 days $d_1 = (\pi/5, \pi)$, from 6 to 22 days, $d_2 = (22, \pi/5]$, and from 23 to infinite days, $d_3 = (0, \pi/22]$. Therefore, this means that $TO_i(d)$, $FROM_i(d)$, $NET_i(d)$, and $TCI(d)$ represent total directional connectedness TO others in the short term, as well as short-term total directional connectedness FROM others, the short-term total connectedness index and short-term NET total directional connectedness. Furthermore, $TO_i(d)$, $FROM_i(d)$, $NET_i(d)$, and $TCI(d)$ represent total directional connectedness TO others in the medium-term, as well as medium-term total directional connectedness FROM others, medium-term total connectedness index and medium-term NET total directional connectedness. Lastly, $TO_i(d)$, $FROM_i(d)$, $NET_i(d)$, and $TCI(d)$ represent the total directional connectedness TO others in the long term, as well as the long-term total connectedness index. Long-term total directional connectedness FROM others and long-term NET total directional connectedness.

Finally, the correlation between the frequency-domain measures and time-domain measures proposed by Baruník and Křehlík (2018), Diebold and Yılmaz (2012, 2014) are as follows:

$$TO_i(H) = \sum\nolimits_d TO_i(d) \tag{21}$$

$$FROM_i(H) = \sum\nolimits_d FROM_i(d) \tag{22}$$

$$NET_i(H) = \sum\nolimits_d NET_i(d) \tag{23}$$

$$TCI(H) = \sum_d TCI(d) \tag{24}$$

3.3. DCC-t-Copula

For the purpose of approximating the mixed DCC-GGARCH t-Copula model, we relied on Antonakakis et al. (2018, 2020). The proposed equation may also be used to compute variance-covariance and correlations in a time-varying setting.

$$X_t = V_t^{1/2} z_t \; z_t t_\eta^{\sim}, \tag{25}$$

In this case, the dynamic variance-covariance matrix is denoted byV_t, the N-dimensional student's t distribution is denoted by t_η, and the standardized residuals are denoted by z_t.

Constructing conditional distributions is attainable through the application of the DCC-GARCH t-Copula, as demonstrated below, according to Patton (2006) study.

$$C(u_1, \dots, u_N | R_t, \eta) = t_\eta \left(F_{x_1}^{-1}(u_1 | \blacksquare_1), \dots, F_{X_N}^{-1}(u_N | \blacksquare_N) \right) \tag{26}$$

$$= \int_{-\infty}^{F_1^{-1}(u_1)} \cdots \int_{-\infty}^{F_1^{-1} u_N} \frac{\Gamma\left(\frac{\eta+N}{2}\right)}{\Gamma\left(\frac{\eta}{2}\right)(\eta\pi)^{N/2}|R_t|^{1/2}} \left(1 + \frac{1}{\eta} z_t, R_t^{-1} Z_t\right)^{(\eta+N)/2} dz_1, \dots, dz_N,$$

In this context, the conditional distribution is denoted by the notation$F_{X_N}^{-1}$ ($\blacksquare_1$). The parameters of the GARCH model that have been calculated are denoted by the notation $\blacksquare_1$.

In contrast to the initial DCC-GARCH model, this one could potentially feature a large number of marginal distributions. A subsequent stage is to estimate the dynamical variance, covariances, and correlations, R_t, using the underlying Dynamic Conditional Correlation-GARCH Method of Engle (2002). To create the time-varying variance-covariances, the following steps should be followed:

$$H_t = D_t R_t R, \tag{27}$$

where $D_t = diag\,(h_{11t}, \ldots, h_{NNt})$, which adhere to a GARCH process with a single variable. An accurate estimate is performed on each constrained family GARCH model before we go on to the next step in our effort to identify the most suitable univariate GARCH model (Hentschel, 1995).[1] It is possible to formulate the family GARCH model by:

$$h_{iit}^{\lambda i} = \omega_i + \alpha_i h_{iit-1}^{\lambda i}\,(|z_{it-1} - \zeta_i| - \gamma_i(z_{it-1} - \zeta_i)\,)^{\delta_i} + \beta h_{iit-1}^{\lambda i}. \tag{28}$$

The DCC, denoted by R_t, which are calculated using conditional variance-covariances, Q_t, of the standardized residuals are computed after the time-varying variance-covariances. From this point forward, the entire procedure will follow to Engle's GARCH (1,1) model Engle (2002):

$$Q_t = (1 - a - b)\underline{Q} + a z_{t-1} \acute{z}_{t-1} + bQ_{t-1} \tag{29}$$

$$R_t = diag(Q_t)^{-1}\; diag(Q_t)^{-1/2} Qt, \tag{30}$$

where b is the persistency parameter, a is the shock parameter. $\underline{Q}$ is the matrix of unconditional residual variance and covariance. For a process to be considered stationary, it must satisfy the conditions: $a > 0, b > 0$ *and* $a + b < 1$.

This study used Kendall's t measure (Kruskal, 1958) since R_t [Eq. (18)] is extremely constrictive and cannot capture tail distribution as below:

$$\tau\,(\varepsilon_i, \varepsilon_j) = \frac{2}{\pi}\left[1 - \sum_{\varepsilon \in \mathbb{R}} P(X_i = x)^2\right] arcsin\left(R_{ijt}\right). \tag{31}$$

3.3.1. Optimal hedge ratios

Here, we compute hedge ratios using Kroner and Sultan (1993) and optimal portfolio weights for risk reduction using Kroner and Ng (1998), both of which allow us to establish appropriate hedging price. It is possible to offset the risk of holding a long position of 100 USD in variable i with a short position of β_{ijt}USD in variable j, with the hedging value being set by the hedge ratio. This can be determined by using:

$$\beta_{ijt} = \frac{h_{ijt}}{h_{jjt}}, \tag{32}$$

where h_{ijt} is a representation of the conditional covariance that exists between the variables i and j. This makes it reasonable to assume that the rise in conditional covariances will lead to an increase in the costs that are associated with hedging long positions. In addition, greater conditional variances will lead to reduced costs associated with hedging long positions.

3.3.2. Optimal portfolio weights

The following formula, developed by Kroner and Ng (1998), can be utilized to determine the optimal weighting of a portfolio based on the conditional covariances derived from DCC-t-Copula:

$$w_{xn,t} = \frac{h_{nn,t} - h_{xn,t}}{h_{xx,t} - 2h_{xn,t} + h_{nn,t}}, \text{with } w_{xn,t} = \left\{ 0\ if\ w_{xn,t} < 0\ w_{xn,t}\ if\ 0 \le w_{xn,t} \le \#1\ 1; if\ w_{xn,t} > 1 \right. \tag{33}$$

where $w_{xn,t}$ would be the percentage of asset x that was owned during the time t. The calculation for the value of asset n follows the following structure: 1–$w_{xn,t}$.

The following is a formula for calculating hedge effectiveness:

$$\text{Hedge Effectiveness} = \frac{\sigma^2 unhedged - \sigma^2 hedged}{\sigma^2 unhedged} \tag{34}$$

where σ^2_{hedged} refers to the portfolio variation, a hedging method that may also be used to portfolios consisting of two assets. Additionally, $\sigma^2_{\text{unhedged}}$ refers to the variance associated with individual assets. Furthermore, according to Antonakakis et al. (2020), they determined the importance of hedging effectiveness for this study. The method proposed by Fligner and Killeen (1976) was used to

[1] The GARCH selection criterion first presented by Antonakakis et al. (2018) was adopted by Antonakakis et al. (2020), who expanded on their methodology by taking into account more models.

account for the non-normality of data about the effectiveness of hedges.

3.4. Determinants of return spillovers

Using total, short-term, and long-term return spillovers to quantify the degree of irregularity, a second-level analysis was conducted to identify the reasons for spillovers. We use asset market returns, a modified version of the traditional gravity model for international trade. Our predictions suggest that spillover may be negligible in larger markets. Other gravitational effects are also considered, including global influences.

It was theoretically assumed that many variables could impact the shocks on Islamic banks in eleven countries and green bonds with regard to total, short-, and long-term return spillovers, and these factors include ((1) EPU, (2) VIX, (3) OVX, (4) GVZ, (5) GFS, (6) EMV, (7) GMNS, and (8) CLMT[2]. Recent studies have referred to a well-known regression model for Islamic banks and environmentally friendly bonds, such as Balli et al. (2019) and Balli et al. (2021). The Fundamental Gravity Model served as the foundation for the regression method employed in this example, but it was altered to incorporate variables connected to global indices, including the following gravity factors:

$$TCI\ (\tau) = \alpha_0 + \alpha_1 X_{it} + \varepsilon_{it} \tag{35}$$

There are three ways in which the dependent variable $TSI\ (\tau)$ can be produced, namely total, short, and long-term return spillovers between Islamic banks and green bonds i and financial markets j. DataStream was used to source the data. The term X_{it} involves several different determinants of return and volatility connectedness, such as: $EPU_{i,j}$, $VIX_{i,j}$, $OVX_{i,j,}GVZ_{i,j}$, $GFS_{i,j}$, $EMV_{i,j}$, $GMNS_{i,j}$, $CLMT_{i,j}$. It is important to note that heteroskedasticity was found to be present in the evaluations, combined with the autocorrelation corrected standard errors (HAC). To account for both the random and fixed effects, we have employed fixed effect model estimations and Hausmann tests in our computations (RESET). This also helps us to assess the normality of the error terms and model misspecification [3].

4. Empirical results

4.1. TVP-VAR based static connectedness analysis on frequency domains

To begin, we will analyze the connection between Islamic bank stocks and green bonds all across the short, medium, and long-term time scales, as shown in Tables 3–5, respectively. The results of this analysis make it possible to draw attention to both the direction and the magnitude of the information spillovers that take place between the two assets.

The findings for the short-term horizon are shown in Table 3, which focuses on the scale ranging from one to five days and indicate that, in the case of Islamic bank stocks, >53% of shocks are related to own-share spillover. Specifically, the own portion ranges from 53.97% for Kuwait to 71.62% for Bahrain. These results corroborate past empirical research on the heterogeneity in the degree to which Islamic markets are financially integrated across countries. (e.g., Naifar et al., 2016; Balli et al., 2022). Additionally, the following are the proportions attributed to own-share spillovers for the other green bond indices: 3.08% for GB.US, 49.90% for GB.EU, 43.93%; for GB.GL, and 62.09% for GB.CH. The findings of Billah et al. (2023a) about the disparities in the magnitude of green bond spillovers are supported by this conclusion. These findings also suggest that US green bond market is more integrated than the other green bond markets, which corroborates the findings of previous studies such as Long et al. (2022) and Umar et al. (2023). This result is a reflection of the U.S. green bond market as one of the world's most mature and liquid financial markets, as it is home for a significant number of large institutional investors and a diverse range of issuers. When it comes to green bonds, the global green bond index has the most significant influence on the U.S. green bond index GB.US with 42.61%, followed by the mutual impacts of 6.43% and 5.05% between the respective indices GB.GL and GB.EU. For the other indices, the impact does not exceed 2.55%. Similarly, the same result on the weak spillover levels is found for Islamic bank stocks. The highest ones originate from Kuwait to Saudi Arabia (2.97%) and from Saudi Arabia to Kuwait (2.91%). As a result, these two nations function as two-way transference and reception of shocks, exactly like GB.EU and GB.GL, but with more ties to these two eco-friendly markets. Considering the spillover between the two assets, our findings also suggest that shocks originating in other markets have a minor influence on equities and green bonds, with spillover bands ranging from 0.26% to 2.06%. This inference appears to be in line with past research that has confirmed the risk-mitigating capabilities of green bonds and Islamic stocks against unexpected shocks (e.g., Ferrer et al., 2021; Yousaf et al., 2022; Karim and Naeem, 2022). By examining the total spillover of individual markets “FROM” and “TO” other markets in the system, the results show that GB.GL has the largest impact on the other indices by 59.52%, and it is influenced by 14.12%; as a result of this, it acts as a net transmitter of shocks within the connectivity system. For Islamic bank stocks, we discover that Saudi Arabia has the most effect on the market, with 16.52% transmitted versus 17.14% received, making it a net recipient of disturbances from the network. Among all markets under examination, green bonds have a greater propensity to act as a larger transmitter of shocks compared to Islamic banks. More particularly, with the exception of UAE (GB.US), all the other Islamic bank (green bond) indices tend to be net receivers (transmitters) of shocks in

[2] The investigation that led to the selection of the 10 factors above was conducted weekly (for example, Lundgren et al., 2018; Kocaarslan and Soytas, 2019; Batten et al., 2021; Hoque et al., 2023; Tabash et al., 2022; Bouri et al., 2021; Saeed et al., 2020, 2021). In addition, the collection of these explanatory variables is defined in detail in Appendix A.1.

[3] The correlation matrix between the independent variables can be seen in Appendix A.2. As the degree of correlation between the variables is somewhere between −0.26 and 0.45, there is no cause for concern regarding the potential of multicollinearity.

Table 3
Spillover index between Islamic banks and green bonds (short-term, 1–5 days).

	GB US	GB EU	GB GL	GB CH	Malaysia	Indonesia	Bangladesh	Pakistan	Bahrain	Kuwait	OMAN	Qatar	Saudi Arabia	UAE	Jordan	**FROM**
GB US	3.08	4.59	42.61	2.52	0.48	0.37	0.37	0.33	0.37	0.42	0.32	0.44	0.43	0.31	0.34	53.91
GB EU	1.64	49.95	6.43	1.81	0.56	0.42	0.35	0.66	0.45	0.41	0.32	0.33	0.5	0.43	0.42	14.73
GB GL	2.32	5.05	43.93	2.53	0.48	0.38	0.38	0.34	0.38	0.42	0.32	0.43	0.43	0.3	0.35	14.12
GB CH	0.27	0.65	0.92	62.09	0.53	0.8	0.4	0.59	0.54	0.41	0.51	0.27	0.43	0.49	0.33	7.12
Malaysia	0.52	0.58	0.93	2.06	58.85	1.07	0.52	0.8	0.64	0.78	0.71	1.34	1.04	1.17	0.65	12.8
Indonesia	0.34	0.6	0.64	1.27	1.36	64.06	0.46	0.69	0.54	0.59	0.54	0.88	0.94	0.68	0.93	10.45
Bangladesh	0.26	0.44	0.68	1.61	0.54	0.39	61.27	0.6	0.66	1.1	0.54	0.52	0.89	0.54	0.52	9.28
Pakistan	0.3	0.79	0.85	1.84	0.74	0.95	0.8	63.77	0.62	0.68	0.54	0.73	0.83	0.55	0.66	10.89
Bahrain	0.41	0.69	1.19	1.47	0.6	0.63	1.01	0.83	71.62	1.26	1.18	1.09	0.95	0.88	0.81	12.98
Kuwait	0.33	0.56	0.98	1.76	0.6	0.67	0.82	0.54	0.83	53.97	0.79	2.02	2.91	2.45	0.55	15.81
OMAN	0.66	0.75	1.18	1.55	0.72	0.6	0.58	0.69	1.17	1.13	68.09	1.61	1.77	1.7	0.68	14.77
Qatar	0.59	0.5	0.85	1.14	1.22	0.99	0.69	0.62	0.9	2.4	1.47	57.73	2.26	2.9	0.97	17.5
Saudi Arabia	0.38	0.58	0.75	1.79	0.84	1.27	0.8	0.68	0.66	2.97	1.22	2.04	54.91	2.67	0.47	17.14
UAE	0.3	0.37	0.6	0.98	0.88	0.54	0.28	0.36	0.67	2.16	1.23	2.42	2.52	54.62	0.71	14.01
Jordan	0.64	0.6	0.91	1.42	0.94	0.86	0.41	0.59	0.73	0.65	0.72	0.87	0.63	1.26	62.14	11.23
TO	8.94	16.75	59.52	23.74	10.5	9.94	7.87	8.33	9.16	15.37	10.39	14.98	16.52	16.33	8.39	**TCI**
NET	−44.98	2.03	45.4	16.62	−2.3	−0.51	−1.41	−2.56	−3.82	−0.45	−4.38	−2.52	−0.62	2.32	−2.83	**16.91**

Notes: System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.

Table 4
Spillover index between Islamic banks and green bonds (medium-term, 5–22 days).

	GB US	GB EU	GB GL	GB CH	Malaysia	Indonesia	Bangladesh	Pakistan	Bahrain	Kuwait	OMAN	Qatar	Saudi Arabia	UAE	Jordan	**FROM**
GB US	3.16	2.17	12.3	2.8	0.18	0.11	0.1	0.11	0.08	0.14	0.06	0.13	0.26	0.09	0.09	18.63
GB EU	1.95	9.6	3.31	1.44	0.19	0.07	0.06	0.11	0.09	0.1	0.06	0.08	0.28	0.07	0.11	7.92
GB GL	2.63	2.18	12.18	2.82	0.17	0.11	0.1	0.11	0.08	0.13	0.06	0.13	0.26	0.08	0.09	8.97
GB CH	0.09	0.12	0.16	13.8	0.1	0.05	0.11	0.14	0.08	0.09	0.07	0.06	0.1	0.22	0.09	1.47
Malaysia	0.18	0.15	0.27	2.06	9.86	0.24	0.11	0.21	0.16	0.3	0.12	0.39	0.52	0.44	0.26	5.42
Indonesia	0.21	0.22	0.28	0.78	0.38	10.59	0.1	0.23	0.09	0.16	0.12	0.19	0.49	0.22	0.23	3.7
Bangladesh	0.11	0.14	0.24	1.77	0.25	0.09	14.04	0.18	0.18	0.42	0.1	0.1	0.4	0.27	0.13	4.36
Pakistan	0.22	0.2	0.36	1.34	0.18	0.27	0.24	11.71	0.12	0.16	0.1	0.14	0.3	0.32	0.26	4.21
Bahrain	0.11	0.12	0.17	0.46	0.09	0.08	0.1	0.11	8.09	0.1	0.11	0.14	0.17	0.1	0.06	1.93
Kuwait	0.26	0.15	0.3	1.23	0.15	0.12	0.18	0.11	0.2	11.81	0.16	0.67	1.07	0.55	0.15	5.31
OMAN	0.16	0.13	0.22	0.72	0.16	0.09	0.09	0.11	0.15	0.19	7.15	0.25	0.4	0.27	0.11	3.06
Qatar	0.23	0.12	0.27	0.8	0.33	0.16	0.17	0.14	0.19	0.7	0.34	10.86	1.03	0.76	0.16	5.4
Saudi Arabia	0.11	0.18	0.22	1.15	0.25	0.13	0.2	0.14	0.13	0.76	0.29	0.44	11.93	0.63	0.17	4.79
UAE	0.13	0.15	0.25	1	0.38	0.13	0.08	0.12	0.12	0.66	0.32	0.48	0.72	15.07	0.25	4.79
Jordan	0.17	0.14	0.2	1.07	0.24	0.16	0.09	0.14	0.15	0.18	0.12	0.26	0.28	0.51	12.57	3.71
TO	6.57	6.17	18.54	19.45	3.07	1.82	1.75	1.96	1.8	4.09	2.04	3.46	6.28	4.53	2.15	**TCI**
NET	−12.06	−1.75	9.57	17.98	−2.36	−1.89	−2.61	−2.25	−0.13	−1.21	−1.01	−1.94	1.48	−0.26	−1.56	**5.98**

Notes: System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.

Table 5
Spillover index between Islamic banks and green bonds (long-term, >22 days).

	GB US	GB EU	GB GL	GB CH	Malaysia	Indonesia	Bangladesh	Pakistan	Bahrain	Kuwait	OMAN	Qatar	Saudi Arabia	UAE	Jordan	**FROM**
GB US	3.1	1.69	6.71	9.12	0.06	0.06	0.04	0.05	0.03	0.08	0.04	0.07	0.08	0.04	0.04	18.11
GB EU	2.19	4.46	2.86	7.83	0.06	0.04	0.03	0.04	0.03	0.06	0.03	0.04	0.09	0.03	0.04	13.35
GB GL	2.79	1.69	6.65	9.1	0.06	0.06	0.04	0.05	0.03	0.08	0.03	0.06	0.08	0.04	0.04	14.14
GB CH	0.08	0.07	0.1	14.86	0.04	0.02	0.04	0.05	0.03	0.04	0.03	0.02	0.04	0.09	0.03	0.67
Malaysia	0.14	0.1	0.18	8.11	3.53	0.09	0.04	0.08	0.06	0.11	0.05	0.14	0.17	0.18	0.1	9.53
Indonesia	0.21	0.15	0.25	5.94	0.13	3.84	0.04	0.09	0.03	0.06	0.05	0.07	0.16	0.09	0.09	7.35
Bangladesh	0.09	0.06	0.15	4.86	0.08	0.03	5.14	0.06	0.06	0.15	0.03	0.03	0.13	0.11	0.04	5.91
Pakistan	0.23	0.13	0.29	3.75	0.05	0.11	0.09	4.26	0.04	0.06	0.04	0.05	0.08	0.15	0.1	5.16
Bahrain	0.11	0.08	0.13	1.87	0.03	0.03	0.04	0.04	2.83	0.03	0.04	0.05	0.05	0.03	0.02	2.55
Kuwait	0.31	0.16	0.31	6.67	0.05	0.05	0.07	0.04	0.07	4.4	0.06	0.26	0.4	0.2	0.05	8.7
OMAN	0.14	0.08	0.16	3.45	0.05	0.03	0.03	0.04	0.05	0.07	2.49	0.09	0.11	0.1	0.03	4.44
Qatar	0.15	0.06	0.17	2.82	0.11	0.05	0.06	0.05	0.07	0.26	0.13	3.9	0.36	0.28	0.05	4.61
Saudi Arabia	0.09	0.08	0.13	5.51	0.08	0.04	0.07	0.05	0.04	0.28	0.1	0.16	4.31	0.23	0.06	6.92
UAE	0.1	0.08	0.15	4.14	0.13	0.05	0.03	0.04	0.05	0.25	0.12	0.17	0.24	5.89	0.09	5.63
Jordan	0.11	0.06	0.12	4.71	0.08	0.06	0.03	0.05	0.05	0.07	0.04	0.09	0.08	0.22	4.59	5.76
TO	6.75	4.5	11.72	77.88	0.98	0.71	0.64	0.71	0.65	1.59	0.78	1.3	2.05	1.79	0.79	**TCI**
NET	−11.37	−8.85	−2.42	77.21	−8.55	−6.64	−5.28	−4.45	−1.9	−7.11	−3.65	−3.31	−4.87	−3.84	−4.98	**8.06**

Notes: System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.

the system. Furthermore, a TCI value of 16.91% indicates a modest degree of short terms spillover among green bonds and Islamic banks.

The findings of the medium-term spillover are shown in Table 4 and they indicate that one's own spillovers are considerably less than what's been illustrated in the short-term scale. The range is of 3.16%–13.80% for green bonds and of 7.15% - 15.07% for Islamic bank indices with UAE having the greatest value for Islamic banks and GB.CH having the highest value for green bonds, respectively. This observed reduction in own-share spillovers of used markets is in line with the efficient market (Fama, 1970) and the mean reversion (Fama and French, 1988) theories. Specifically, at shorter horizons, markets are more reactive to immediate events and shocks causing higher volatility and spillover within the market. However, at longer horizons, these short-term shocks tend to be absorbed as the market adjusts, leading to reduced own-share spillovers.

In terms of the spillover across the indices that were employed, the findings showed that the greatest influence came from GB.GL to GB.EU (3.31%), followed by GB.CH on GB.GL (2.82%), and then on GB.US (2.80%). For Islamic bank stock indices, the highest impacts are recorded from Saudi Arabia to Kuwait (1.07%) and from Saudi Arabia to Qatar (1.03%). Hence, the impact of shocks across Islamic bank and green bond indexes is much less intense in comparison to which was observed for the short-term scale (in Table 3). Among all series under examination, GB.GL, GB.CH as well as Saudi Arabian Islamic bank stock index Arabia function as a net transmitter of shocks, with the greatest levels of spillover to other markets. GB.US with a net spillover value of −12.06% are the prime recipient. The average TCI is of 5.98% indicating a low level of spillover intensity in the overall spillover system.

Table 5 depicts the results of the connectedness for the information on >22 days, which represents the long-term scale. Reported results show that, similar to the medium-scale results reported in Table 4, the own-share *spillover* is moderate for all used indices and the highest ones happen in the case of GB.CH with 14.86%, for green bonds and in the case of UAE with 5.89% for Islamic bank stocks. In terms of green bonds, GB.CH has the most influence on all three green bond indexes, with a value of 9.12% on GB.US, 9.10% on GB.GL, and 7.83% on GB.EU. Interestingly, we also note that, among the two assets, GB.CH is the index with the highest impact also on Islamic bank stock indices, with a range of 2.82% - 8.11%, making it the index with the highest contribution to shocks in the system (with a value of 77.88%). For used Islamic banks, the range of spillover "TO" other markets are from 2.05% for Saudi Arabia to 1.79% for UAE, indicating a moderate contribution to risk spillover for these indices. Green bond indices have a larger proportion of shocks transmitted and absorbed than Islamic bank stock indexes. However, in this case, it seems that only GB.CH is a net transmitter of shocks within the network, as shown by its net spillover value of 77.21%. TCI has a value of roughly 8.06% within the entire connectivity system, which indicates that there are negligible levels of spillover between green bonds and Islamic banking sector equities. Long-term TCI averages suggest less interconnectedness, but short-term TCI reveal moderate interconnectedness between the green bond and Islamic banking sector equity markets. These differences provide credence to the hypothesis that spillover effects across green bond and Islamic banking sector equity markets are both time-specific and time-variant. This dynamic connectedness will be investigated in Section 4.2.

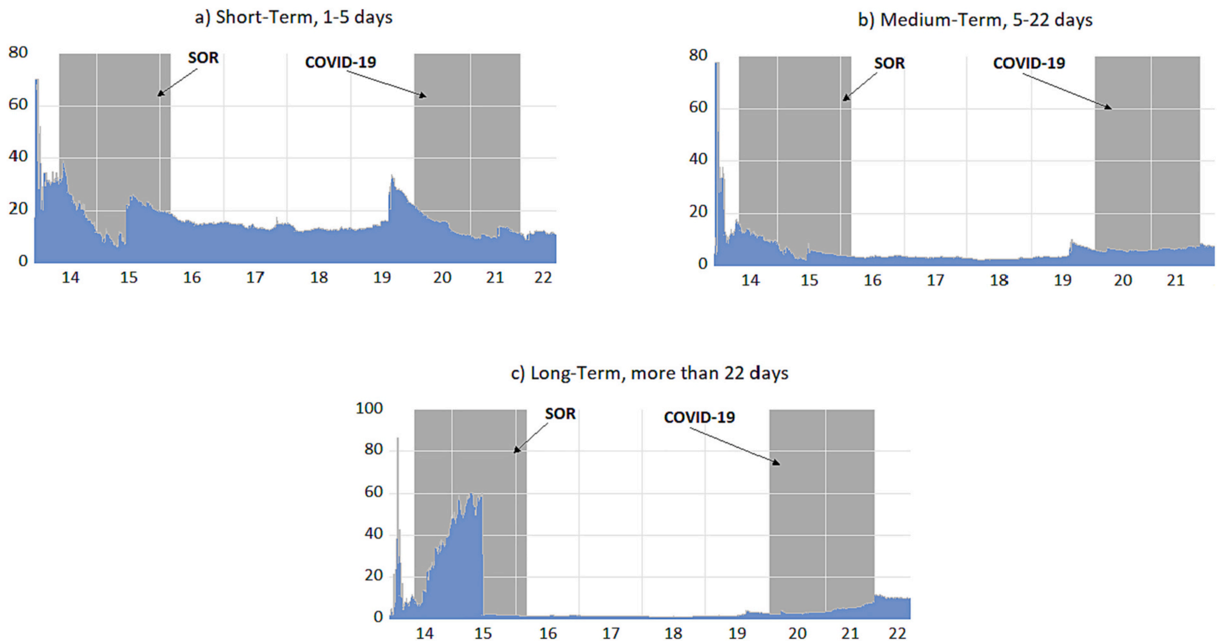

Fig. 2. Total time-varying return connectedness between Islamic banks and green bonds.
Notes: System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2. TVP-VAR based time-varying spillover analysis

In this section, we investigate the time-varying spillover between green bonds and Islamic bank stocks, which is illustrated in Fig. 2, at the short-term (graph a), medium-term (graph b), and long-term (graph c) timeframes. In order to evaluate the time-varying spillover, we use a dynamic connectedness index that is derived from a first order TVP-VAR model. This model also includes a first order lag length and a 28-level GFEVD. This analysis would provide more comprehensive feedback on this relationship, especially when considering that the study sample includes a number of events that could influence the level of connectedness between green bonds and Islamic bank stocks, such as the Shale Oil Revolution (SOR) in 2015 and the COVID-19 pandemic between 2020 and 2021.

Spillovers on the short-term scale (graph a) reached 70 at the early sample period. It, then, decreased to <40 during the rest of the sample. The following highest spillover index values are recorded at the early periods of both SOR and COVID-19. Indicatively, in the short-term, the total spillover reached 39 in 2014. Immediately after a period of relative tranquility that spanned between 2015 and 2019, it spiked to a high of 36 during the COVID-19 pandemic that occurred in early 2020. This is consistent with expectations, since the dynamic interconnection across financial markets is anticipated to strengthen after the COVID-19-led turbulence that heightened market volatility (e.g., Aslam et al., 2020; Adekoya and Oliyide, 2021; Guo et al., 2021). Interestingly, the spillover index showed a decline to <20 during the rest of the pandemic period. It would suggest some risk-hedging characteristics of these assets at this time, reinforcing the emphasis of the important risk-reducing capabilities of green bonds during the COVID-19 episode (Naeem et al., 2021; Arfaoui et al., 2022; Billah et al., 2023b).

Looking at the medium- (graph b) and the long-term (graph c) scales, fluctuations of the total connectedness index indicate moderate to low volatility over most of the sample period. In particular, the spillover under the medium-scale peaked at 80 in the early sample period and subsequently showed a somewhat stable trend of volatility throughout the rest of the sample. Although we note some peaks that coincide with the periods of SOR and COVID-19, these are still moderate and do not exceed 20. For the long-term scale, our results join those derived from Table 5 on the very low interdependency across used indices and show that this conclusion is consistent over time. The only exception is noted for the SOR period during which the connectedness index reached up to 60. This finding might very well imply that energy-related shocks may have an effect on the dynamic interconnectedness of green bonds and Islamic bank stocks. Specifically, as SOR resulted in a supply response to increased demand accompanied by a growth in the global industry, these demand and supply shocks have rapidly impacted the dependency among markets, especially for economies that heavily rely on energy. Additionally, Green bond markets have grown dramatically since 2014, and their increasing integration into global financial markets is a major reason for this outcome. These markets are essential to the achievement of sustainable development objectives (see Elsayed et al., 2022).

In overall, we conclude that there were significant, although moderate, shifts in the spillover between Islamic bank equities and

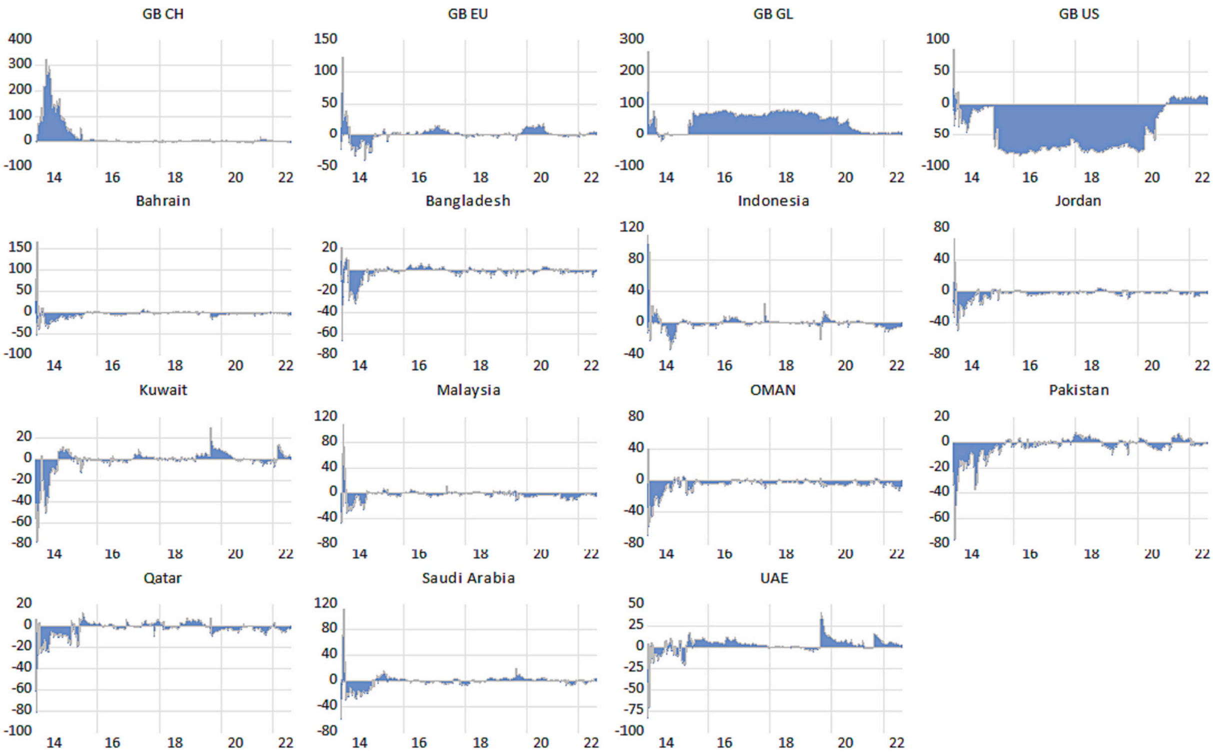

Fig. 3. Net total return spillovers (short – term, 1–5 days).
Notes: See Fig. 2.

green bonds during the entire time frame of our analysis. Importantly, while we find that these interconnections vary over time, our results also indicate that used Islamic bank stocks and green bonds present some important diversification potential, especially for medium- and long-term investors.

We also analyze the time-varying contribution that each index makes to the connectivity system by looking at its net directional spillover and how, over the period of the investigation, it shifts from being a net transmitter to a net receiver of shocks, and vice versa. Figs. 3 to 5 illustrate the interconnectivity of the time-varying net spillovers that occur over the short, medium, and long periods, respectively.

When looking at the short term in Fig. 3, mostly indices exhibit just time varying net spillover across the system. For green bonds, the GB.CH, GB.EU, and GB.GL all have a propensity to be net transmitters of shocks across the entire period of analysis. Additionally, GB.US tends to become net transmitter during 2021 and 2022. Comparing these results to those of Table 3 that indicate that, among all investigated indices, the highest spillover is recorded from GB.GL to GB.US, we can say that GB.GL and GB.US were mostly integrated during this period in which GB.US appeared to received shocks from GB.GL. Also, we note a net and significant contribution to shocks from GB.CH recorded highest level during year 2014 and 2015. This episode coincides with China issuing its first green bond in 2015 that, then, becomes the second most important issuer of green bonds after the United States (Chen and Zhao, 2021). This entrance of China, an emerging country, to the global green bond market that was dominated by developed economies such as America and Europe, motivated by its willingness to participate to achieving SDGs has caused a rapid growth of this new market that has become significantly integrated with the other financial markets such as green markets and emerging stock markets.

The net spillover indices of Islamic bank stocks also exhibit time-varying net positions within the system. However, they mostly functioned as net shock receivers. During the period of 2014–2015, more substantial spillover roles as receivers of shocks can be observed for the most indices, with Kuwait, Pakistan, Qatar, and the UAE being the largest shock receivers. These results may imply that the prolonged consequences of the Euro Debt Crisis, which started in 2013, have had a significant effect on Islamic banks in these countries, which depend mostly on oil income. This crisis was precipitated by a collapse in the prices of most commodities, particularly energy commodities, which was caused by a combination of reduced worldwide demand, increasing supply in nations such as the United States, and increased investments in renewable energy.

Figs. 4 and 5 show the medium- and long-term fluctuations in estimated net spillover, respectively. Typically, results for the medium-term scale are, qualitatively, similar to those of the short-term scale. Having said that, we observe that the information in the long-term scale shows more significant peaks of the spillover indices in 2015, reaching >80, for all used green bonds and Islamic bank stocks. During this period, all markets tend to be net receivers of shocks except for GB.CH. A comparison with the results in Table 5 indicates that all used indices have, exclusively, received the most important portion of shocks from GB.CH in 2015. A possible explanation for this could be due to China's green bond market being dominant in the global green bond market with new issuance. The

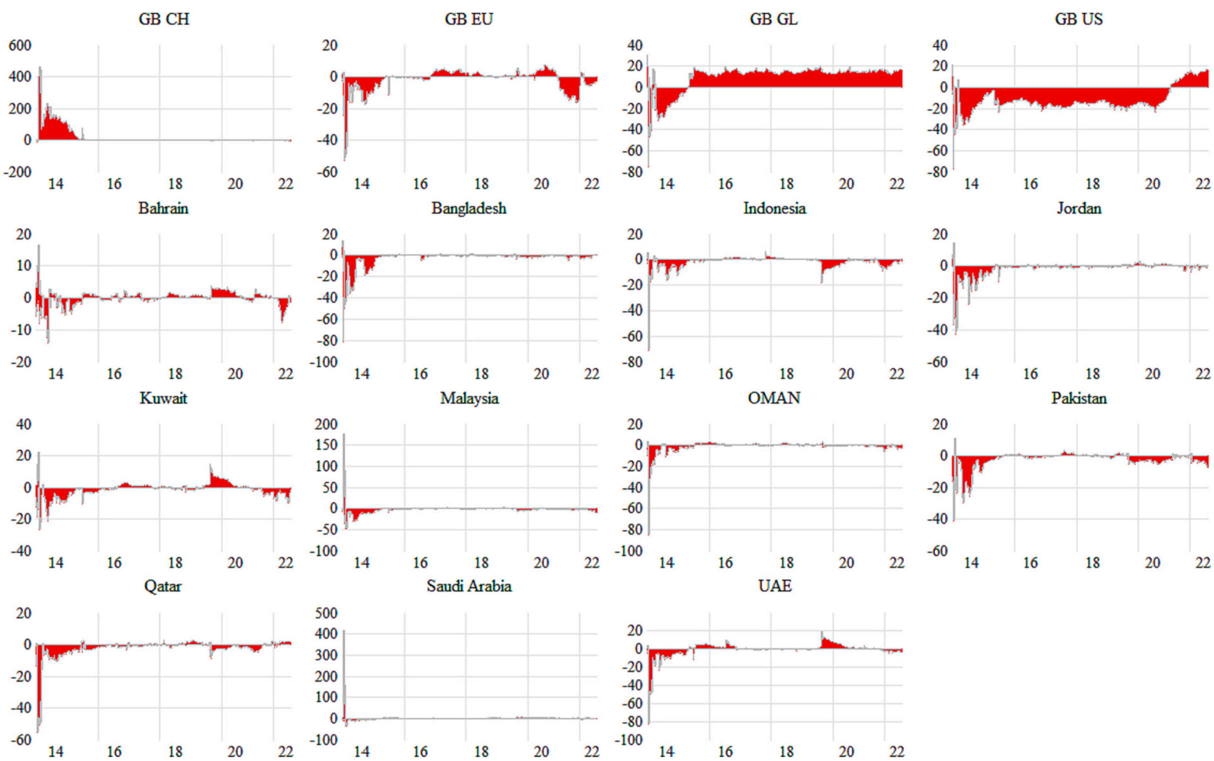

Fig. 4. Net total positive return spillovers (medium – term, 5–22 days).
Notes: See Fig. 2.

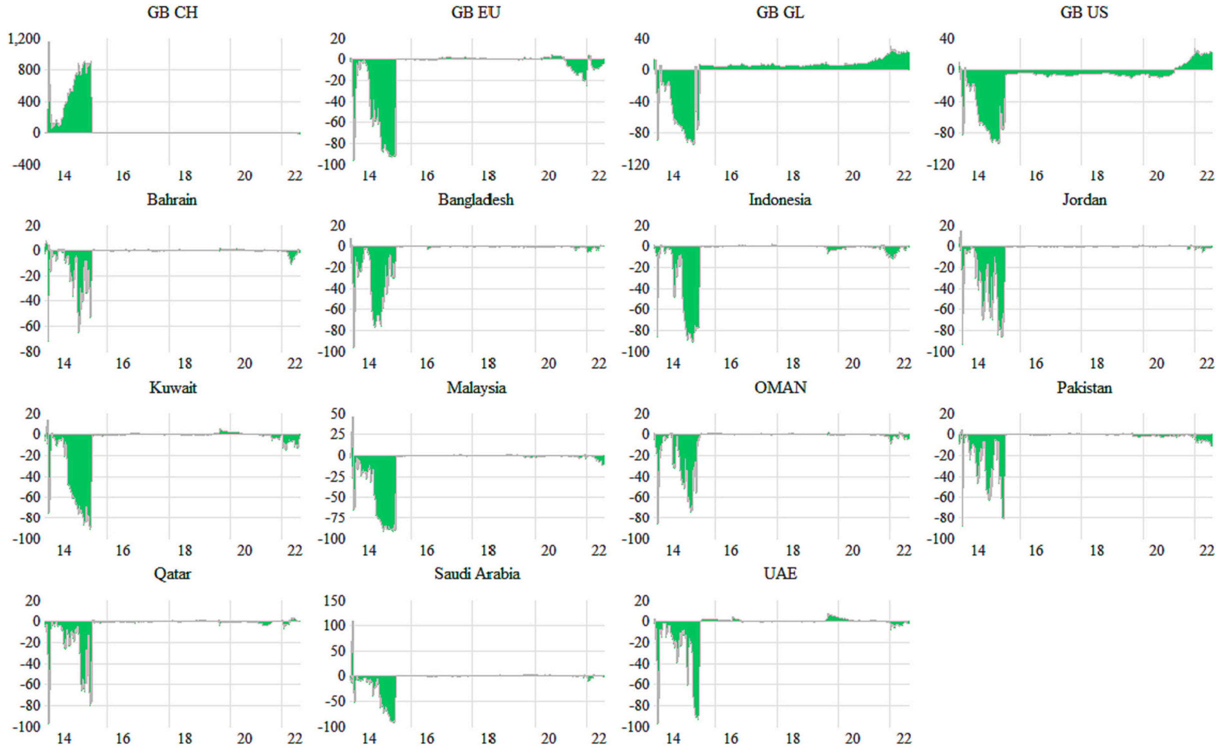

Fig. 5. Net total negative return spillovers (long – term, >22 days).
Notes: See Fig. 2.

fast market expansion may be ascribed to the increasing integration of the Chinese green bond market with other financial markets, particularly those focused on environmentally sustainable investments. Hence, GB.CH has a notable influence in propagating shocks across different markets, especially over long run periods. Moreover, they have since exhibited a low sensitivity to external shocks afterwards. This result is important as it helps to calibrate those of Table 5.

4.3. Results of the pairwise spillover in sub-samples

In the previous section, we examine the time-varying transitions of individual indices from a net contributor to a net recipient of shocks in the system. As our analysis has shown some significant net spillover positions in particular points of time that, typically, coincide for most of used indices with the early period of the sample, we attempt, in this section, to better elucidate the direction of these spillovers as well as their strength in the period that corresponds to the SOR between 2014 and 2015. We, also, focus on the episode of the second major event in our sample period which is the COVID-19 period to provide better feedback on the connections between used green bonds and Islamic bank stock indices in period of crisis. Figs. 6 and 7 depict the network of directional spillover among used markets at the short-term (graph a), medium-term (graph b) and long-term (graph c) scales for the periods of SOR and COVID-19, respectively. It can be deduced from the fact that the arrow is pointing from one market (x) to another market (y) that market y is one that is affected by shocks that originate in market x. The extent of the spillover that occurs on average between the pair is represented by the width of the arrow, with the colors red and black indicating the strongest and weakest directions for the spillover, respectively. The size of the nodes provides a measure of the extent to which each variable contributes to the connectivity of the system. The color green is used to represent net contributors, and the color pink represents net recipients of shocks.

We begin with the results for the SOR period. Based on the information shown in Graph (a) of Fig. 6, we may deduce that, in the short-term, the interconnections between Islamic banks and green bonds are either very weak or nonexistent. The only exception is the connection between GB.GL and GB.US. The results, in particular, suggest that the global green bond market is responsible for a sizeable portion of the shocks that manifest themselves in the short-term in the green bond market in the United States during the SOR period. This result may be logically explained by the substantial degree of financial integration that exists across these markets, given that the United States is the leading issuer in terms of total green bond issuance globally. Both graph (b) and (c) of Fig. 6 illustrate the connection system across both medium and long-term time horizons, respectively. We find that the significantly largest degree of pairwise connections are from GB.GL to GB.US and from GB.CH to GB.US, GB.GL, GB.EU and Bangladesh Islamic bank stock index in the medium-term. GBCH, like the medium-term frequency, is the primary source of systemic risk in the longterm owing to its propensity to transmit shocks to the same indices. Additionally, in the short to long-term horizons, we find no significant transmission of shocks between Islamic bank stocks of used markets. This finding does not seem to corroborate the findings of previous studies on the

a) Short – Term return spillovers between Islamic banks and green bonds (1-5 days)

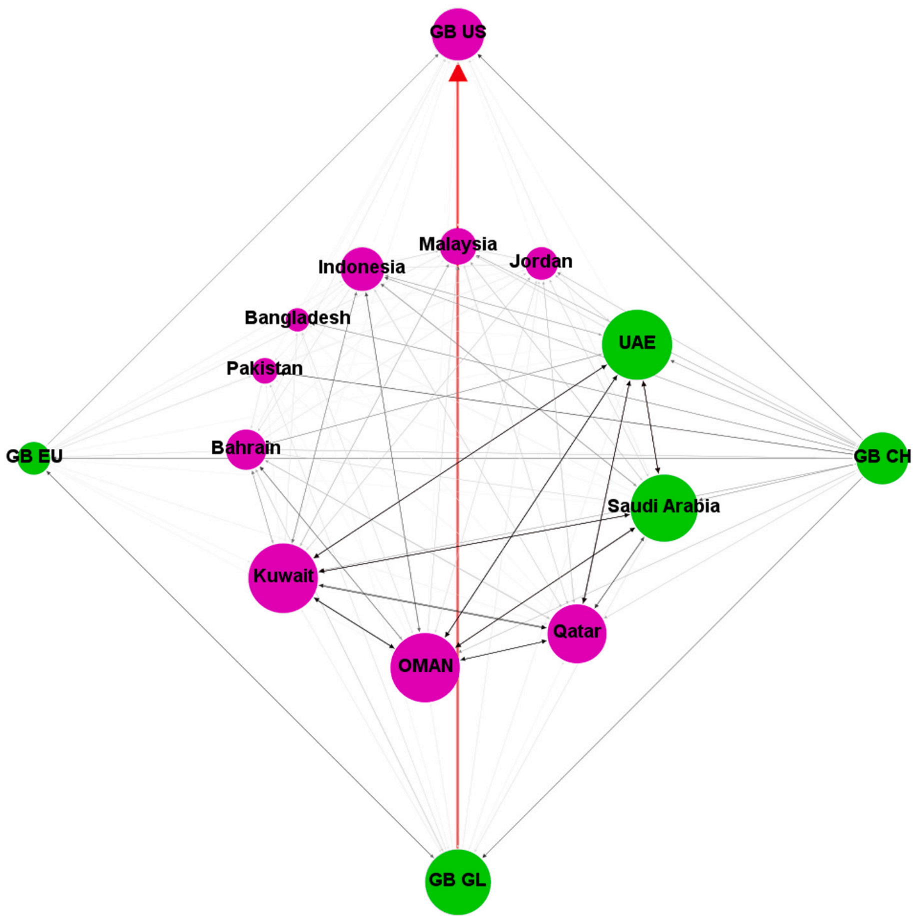

Fig. 6. Return connectedness networks during Shale Oil Revelation (SOR) between Islamic banks and green bonds. System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.
Notes: This network graph illustrates the degree of total connectedness in a system that consists of Islamic banks and green bond returns over the full sample period. The size of the node shows the magnitude of contribution of each variable to system connectedness, while the color indicates the origin of connectedness. Node size signifies the extent of spillovers effect and color specifies whether a market is a net transmitter (green) or recipient (pink) of spillovers. The forced directed layout algorithm set node location where the sum of the vectors set the node route. Arrow width signifies the strength of the pairwise spillovers and color specifies strongest (red) to weakest (black) directions of spillovers. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

substantial links between volatilities of in Islamic countries stock markets (e.g., Akhtar et al., 2017; Sclip et al., 2016).

In summary, Fig. 6 confirms the results of the established linkages as well as net spillover positions derived from Tables 3–5 for the full-sample period and complements those derived from Figs. 3–5. The figure demonstrates an essential component of consistency in the link between global and US. green bond markets in the short and medium terms, and between the four used green bond markets in the medium and long-terms during the SOR period. Hence, investors are able to comprehend these linkages, and they will be able to diversify their risk among a larger variety of ethical investments.

Next, we will have a look at the findings for the COVID-19 time period in Fig. 7. The results shown in graph (a) indicates that the pairwise links between GB.US and GB.GL as well as GB.GL and GB.EU are the strongest ones. Moreover, a much less but still significant connection has been established between GB.US and GB.EU. In addition to these relationships, the graph also shows how various green bond and Islamic bank stock indexes might provide exciting diversification opportunities for short-term investors during the COVID-19 timeframe. Graphs (b) and (c) indicate the same results which suggests a stability feature in the connections between the aforementioned indices in the short, medium and long-terms during the period of the pandemic as well as diversification benefits of holding portfolios including the other used indices in both the medium and long terms.

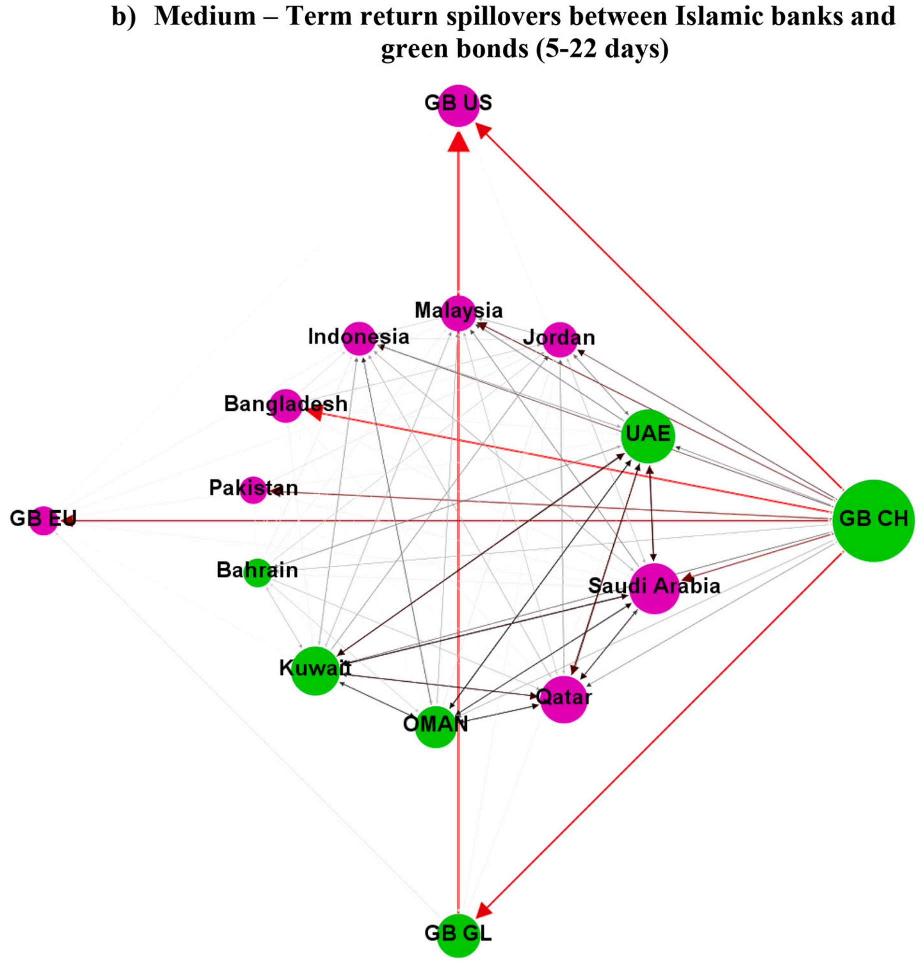

Fig. 6. (*continued*).

4.4. Determinants of connectedness

Tables 6–8 report the results for the determinants of connectedness between green bonds and Islamic bank stocks in the different time-scales. The used risk variables are the economic policy uncertainty (EPU) index, two measures of the volatility in the stock market namely VIX and EMV, a proxy of uncertainty in the oil market (OVX), the volatility in the gold market (GVZ), global financial stress (GFS), macroeconomic news surprises (GMNS) and the climate change (CLMT) index. The regression analysis is carried out for each of the individual risk variables, and then an estimate is carried out using all uncertainty factors in the final column.

Results in Table 6 show that all variables, except GMNS, are statistically significant at the 1% level (Models 1–8). This result indicates that the strength of the spillover information in the short-term among used assets could be predicted using global risk factors. Specifically, the relation is statistically positive (negative) for VIX, EMV and CLMT (EPU, OVX, GVZ and GFS). For VIX (Model 2), for example, results indicate that an increase in the stock market volatility index is associated to an increase in the degree of total connectedness among used markets. The same reasoning holds for the other factors. Results of Model 9, that uses all risk factors together, show some differences in the sign of the relation for EPU and GVZ. For the other factors, the sign of the coefficients holds. The R^2 coefficient that measures how well the model predicts the outcome is of 47.69%, suggesting a good explanatory power of the used model in predicting total connectedness.

Findings in Table 7 are for the determinants of connectedness in the medium-term between used markets. Results of the individual models (1–8) show a significantly negative (positive) relation between EPU, VIX, OVX, GVZ, GMNS and CLMT (GFS and EMV) and the magnitude of the connectedness between markets at the 10% level or higher. When used together (Model 9), risk factors show no difference in sign and significance as compared to the results of the individual testing. The R^2 coefficient of model 9 is of 61%, which indicates a strong linear relationship between the used risk factors and the spillover effects.

Results in Table 8 are for the long-term scale. They are qualitatively the same as the short-term results reported in Table 6 with respect to both the sign and the significance of the models' coefficients. Overall, our empirical results suggest the effectiveness of global risk factors in explaining the degree of connectedness between used green bonds and Islamic bank stocks.

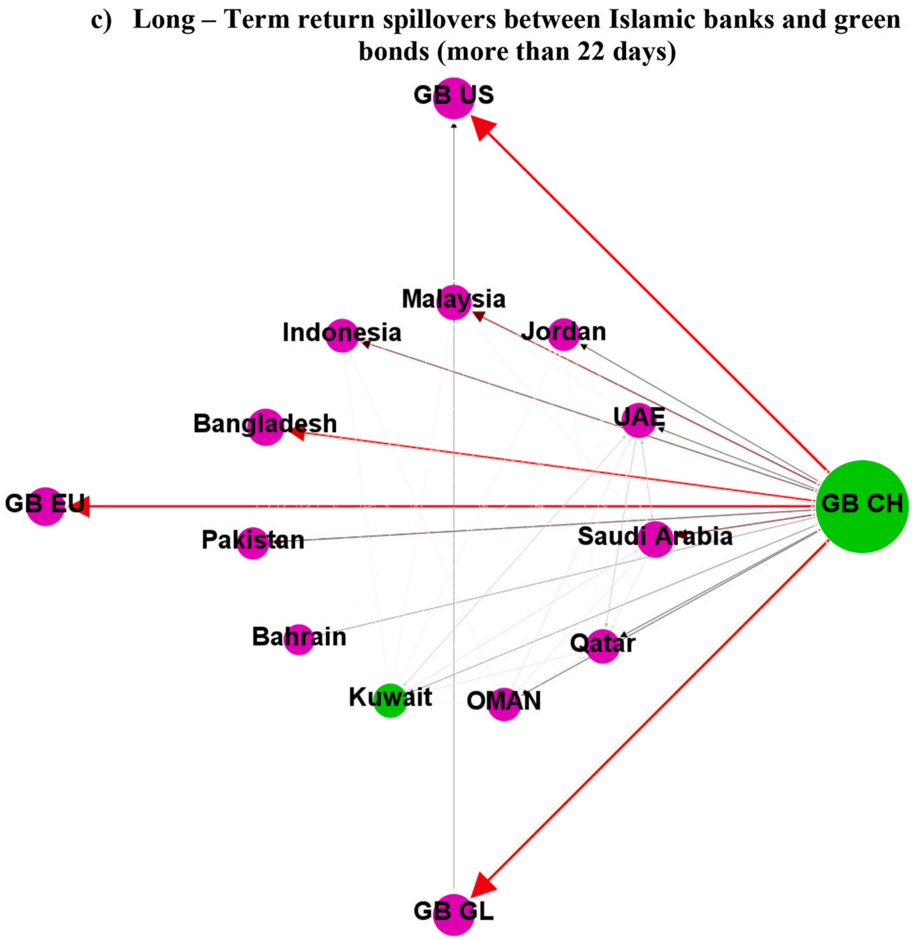

Fig. 6. (*continued*).

4.5. Portfolio analysis

In this section, we dig deeper into the portfolio diversification and risk management for the used green bonds and Islamic bank stock markets. We focus on examining the optimal hedge ratios (Table 9), the optimal portfolio weights (Table 10) as well as the hedging effectiveness (Table 11) of two-assets portfolios consisting of green bonds and Islamic bank stocks. The results are given for the full sample period, the period of the COVID-19 pandemic, and the period of the Shale Oil Revolution.

Table 9 displays the optimal hedging ratios (HR) for portfolios that include both long positions in green bonds and short positions in Islamic bank stocks. Using the information provided, hedging a long position of one dollar in the green bond index with a short position of the value of HR in the country-based Islamic bank stock index might help reduce the risk of a Green bonds-Islamic bank stocks portfolio. For example, the findings presented in Table 9 suggest that an investor in a portfolio consisting of GBGL and Malaysian Islamic bank stocks can reduce their exposure to risk by hedging a long position worth US$ 100 in GBGL with a short position worth US $ 35 in the Malaysian Islamic bank stock index over the course of the entire sample period. The standpoint is applicable to the other pairings as well.

Table 10 is a summary of optimal portfolio weights, often known as OPW. The proportion of green bonds that should constitute the optimal addition to an Islamic bank stock index with a value of one dollar is shown by the figures in the table. For example, a portfolio that is composed of GB.US and Indonesian Islamic bank stocks has to have a weighting of 23%. This suggests that an investor may reduce the amount of risk she was exposed to by owning 77% of the stocks issued by Indonesian Islamic banks inside a portfolio that included included GB.US. The results of the overall OPW in green bonds-Islamic bank stocks portfolios show that, with the exception of Oman and Jordan (Bangladesh and Pakistan), investors should have a higher allocation to Islamic bank stocks (Green bonds) than to green bonds (Islamic bank stocks) in their two-asset portfolios if they want to reduce risk while maintaining the same expected return. The exceptions are Oman and Jordan (Bangladesh and Pakistan) with respect to GB.GL, GB.US or GB.EU (GB.CH). These optimal weights results for the COVID-19 and SOR periods show that an investor can reduce the risks associated with green bonds by owning equities in Islamic banks. In accordance with the findings, making an investment in the stocks of Islamic banks seems to bring some considerable advantages in terms of diversification.

a) Short – Term return spillovers between Islamic banks and green bonds (1-5 days)

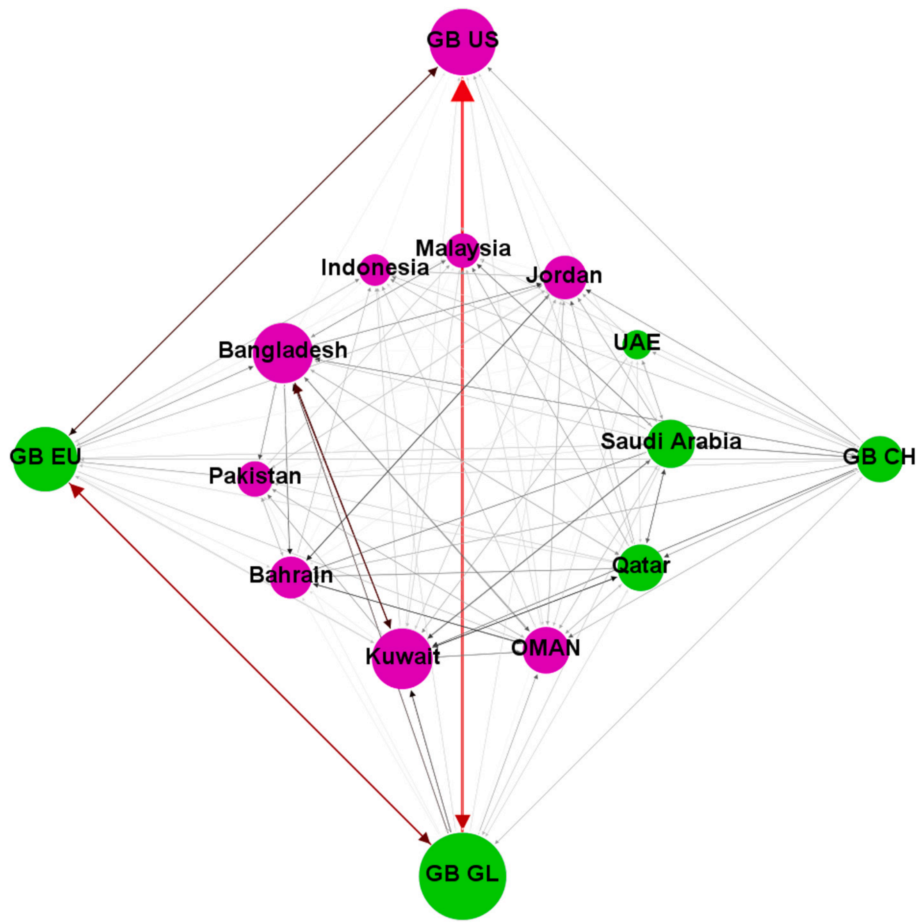

Fig. 7. Return connectedness networks during COVID-19 between Islamic banks and green bonds. System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.
Notes: See Fig. 6. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

When we take a look at the hedge effectiveness ratios (HE) in Table 11, we discover that the consistent HE for GB.US, GB.EU, and GB.CH in all Islamic bank stock markets at over 823% on average in comparison to the GB.CH-Qatar portfolio. This result, which demonstrates the effectiveness of Islamic bank stocks in lowering the risk associated with holding green bonds, was also confirmed for the COVID-19 and SOR time periods.

5. Conclusion

Climate-change concerns and the emergence of green bonds have encouraged environmentally conscious investment practices. Similarly, Islamic banking practices encourage environmental care and responsibility in the pursuit of environmental sustainability, which aligns their financing and investment activities with green activities and financing, and Islamic banking indices appear to be extremely important for Green Bond asset allocation and risk hedging. Therefore, investors might be attracted to green bonds and Islamic bank equity. In this research, we explore the spillover effects along with the portfolio possibilities for four of the most important regional green bonds as well as Islamic bank stocks from 11 different Islamic nations using a TVP-VAR-based frequency spillover framework and explore the hedging effectiveness with different hedging strategies and portfolio strategies.

The findings of our investigation are fascinating, and they may be summed up in the following ways. First, there is a moderate level of interrelation between green bonds and Islamic banking indices, with low connectedness in the medium and long term, where green bond markets are more integrated than Islamic banks. Additionally, Country-based Islamic bank markets are not largely affected by shocks originating from other markets in the short, medium, and long-term horizons. In the medium and long term, the Chinese green bond market tends to be the largest net risk transmitter for both green bond and Islamic bank markets, whereas the global green bond

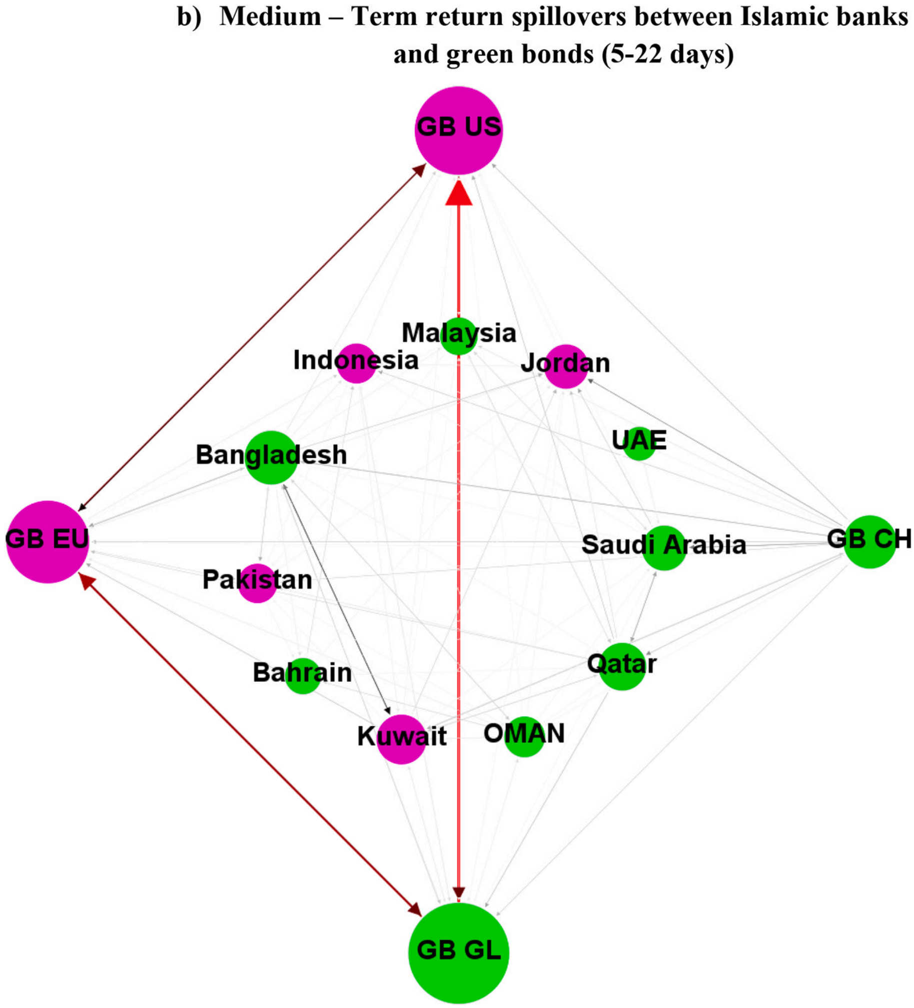

Fig. 7. (*continued*).

index is the largest net risk transmitter in the short term. Besides, UAE and Saudi Islamic Banking indices act as net risk transmitters in the short and medium term. Second, the time-varying connectedness and spillover effects become higher albeit moderate in the early-periods of both SOR and COVID-19 at the three-time scales, where China green bond market paly a shock drivers' role the system. Third, the sub-sample analysis indicates low or inexistent connections between used green bonds and Islamic bank markets during the period of COVID-19. Fourth, we find that global risk factors are reliable determinants of the magnitude of spillover between used markets. In last, the findings confirmed that diversifying a portfolio that already includes green bonds by adding Islamic bank equities can help offset some of the risks associated with holding green bonds.

Our study has important implications for investors, Islamic banks and market regulators. Our findings provide helpful insights for investors in terms of portfolio structure and risk management and suggest that including green bonds and Islamic bank stocks in a portfolio can provide significant diversification and risk reduction benefits. Investors in these markets are advised to be cautious about the direction and the magnitude of shocks to maximize diversification benefits. Rational investors should monitor movements of global risk factors to effectively determine when and how they should take short or long positions. Our results should also be of interest and use to market regulators in the formulation of forecasts amid severe occurrences, given the structure of the fundamental complexities between green bonds and the Islamic banking system. Islamic financial institutions are also encouraged to set-up green financing frameworks to manage their financial risks. Particularly, our results show that green fixed-income investing could help fill the supply gap for Islamic investors with a particular environmental purpose, and vice versa. Overall, as the development of green Islamic financial markets is encouraged by the finance community, the findings of this paper suggest that the issuance and/or the use of green assets has the potential to encourage green and sustainable investments by Islamic investors and to further bridge the gap between Islamic and conventional finance worlds.

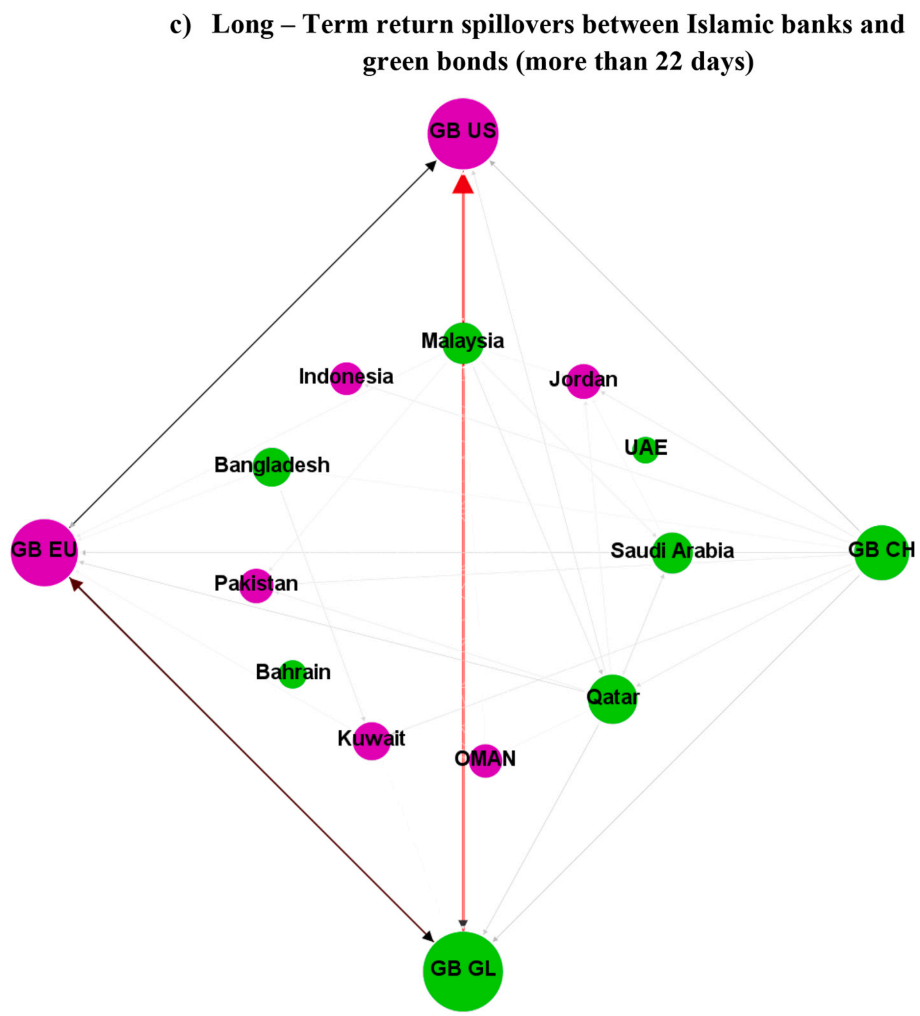

Fig. 7. (*continued*).

Table 6
Determinants of dynamic short – term (1–5 days) total return spillovers for Islamic banks and green bonds.

Coefficient	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
EPU	−0.045*** (0.005)								0.078*** (0.006)
VIX		0.354*** (0.066)							0.287*** (0.077)
OVX			−0.132*** (0.033)						−0.086*** (0.038)
GVZ				−0.488*** (0.069)					0.746*** (0.088)
GFS					−5.659*** (0.355)				−3.388*** (0.404)
EMV						0.525*** (0.044)			0.375*** (0.034)
GMNS							0.088 (0.085)		0.077 (0.088)
CLMT								0.045*** (0.008)	0.014*** (0.003)
R^2(%)	19.54	21.20	29.00	30.3	28.07	29.80	28.00	27.29	47.69
N	2165	2165	2165	2165	2165	2165	2165	2165	2165

Note: Standard errors are printed in parenthesis. *, ** and *** show that the relevant coefficient is significant at the 10%, 5% and 1% level respectively.

Table 7
Determinants of dynamic medium – term (5–22 days) total return spillovers for Islamic banks and green bonds.

Coefficient	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
EPU	−0.057***								−0.088***
	(0.004)								(0.007)
VIX		−0.555***							−0.435***
		(0.034)							(0.044)
OVX			−0.100***						−0.099***
			(0.010)						(0.012)
GVZ				−2.010***					−1.786***
				(0.046)					(0.077)
GFS					3.399***				1.922***
					(0.367)				(0.367)
EMV						0.079***			0.088***
						(0.019)			(0.054)
GMNS							−0.144*		−0.100**
							(0.076)		(0.076)
CLMT								−0.009***	−0.009***
								(0.010)	(0.003)
R^2(%)	20.07	28.68	32.00	31.23	29.07	30.80	26.23	30.50	61.00
N	2165	2165	2165	2165	2165	2165	2165	2165	2165

Note: Standard errors are printed in parenthesis. *, ** and *** show that the relevant coefficient is significant at the 10%, 5% and 1% level respectively.

Table 8
Determinants of dynamic long – term (>22 days) total return spillovers for Islamic banks and green bonds.

Coefficient	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
EPU	−0.044***								0.077***
	(0.005)								(0.006)
VIX		0.481***							0.201***
		(0.055)							(0.055)
OVX			−0.334***						−0.086***
			(0.034)						(0.021)
GVZ				−0.697***					0.564***
				(0.066)					(0.095)
GFS					−5.231***				−3.283***
					(0.566)				(0.403)
EMV						0.512***			0.265***
						(0.044)			(0.021)
GMNS							0.100		0.088
							(0.088)		(0.049)
CLMT								0.034***	0.013***
								(0.005)	(0.005)
R^2(%)	23.34	30.20	29.00	30.3	28.07	29.80	28.00	27.29	49.69
N	2165	2165	2165	2165	2165	2165	2165	2165	2165

Note: Standard errors are printed in parenthesis. *, ** and *** show that the relevant coefficient is significant at the 10%, 5% and 1% level respectively.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A.1
Variables to determine the spillovers.

Variable	Description
EPU	There are three forms that called Economic Policy Uncertainty index (EPU). Those forms are the economy (E), policy (P) and uncertainty (U). This index shows the newspaper information of their own country. According to Billah et al., this index can have the negative connections with green markets, therefore we are expecting negative sign.

(continued on next page)

Table 9
Optimal hedge ratios.

Pairs (GB GL/Islamic banks)	Full sample				COVID-19				SOR			
	MN	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*
GB GL/Malaysia	0.35	1.46	−1.34	3.06	0.04	0.31	−0.38	0.61	−0.04	0.24	−0.45	0.27
GB GL/Indonesia	0.44	1.14	−0.6	2.62	0.01	0.02	−0.04	0.04	−0.14	0.26	−0.61	0.31
GB GL/Bangladesh	0.01	0.06	−0.05	0.1	0.01	0.03	−0.01	0.05	0	0.02	−0.04	0.04
GB GL/Pakistan	0	0.01	0	0.01	0	0.01	−0.01	0.01	0	0.01	−0.03	0.02
GB GL/Bahrain	−0.04	0.56	−1.01	0.73	0.02	0.11	−0.17	0.21	−0.02	0.09	−0.2	0.13
GB GL/Kuwait	0.13	0.62	−0.5	0.82	0.03	0.1	−0.09	0.25	0	0.23	−0.19	0.49
GB GL/OMAN	1.54	2.91	−1.34	7.13	−0.52	1.53	−4.07	1.35	−0.08	0.3	−0.6	0.35
GB GL/Qatar	0.1	0.32	−0.21	0.63	0.07	0.17	−0.13	0.44	0.04	0.1	−0.09	0.21
GB GL/Saudi Arabia	0.32	1.2	−0.13	1.62	0.04	0.2	−0.09	0.23	−0.01	0.26	−0.46	0.38
GB GL/UAE	−0.04	0.21	−0.27	0.16	0.09	0.21	−0.02	0.36	−0.03	0.11	−0.23	0.11
GB GL/Jordan	1.16	5.88	−4.4	11.33	1.15	3.82	−1.32	9.09	−0.21	1.09	−2.21	1.07

Pairs (GB US/Islamic banks)	Full sample				COVID-19				SOR			
	MN	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*
GB US/Malaysia	0.34	1.43	−1.32	2.98	0.03	0.3	−0.35	0.51	−0.04	0.22	−0.42	0.22
GB US/Indonesia	0.43	1.12	−0.59	2.59	0.01	0.02	−0.04	0.04	−0.13	0.25	−0.58	0.32
GB US/Bangladesh	0.01	0.06	−0.05	0.09	0.01	0.02	−0.01	0.05	0	0.03	−0.04	0.04
GB US/Pakistan	0	0.01	0	0.01	0	0.01	−0.01	0.01	0	0.01	−0.03	0.02
GB US/Bahrain	−0.04	0.55	−0.99	0.71	0.01	0.11	−0.19	0.16	−0.02	0.09	−0.21	0.12
GB US/Kuwait	0.13	0.61	−0.48	0.81	0.03	0.1	−0.09	0.24	0	0.21	−0.19	0.44
GB US/OMAN	1.49	2.82	−1.31	6.87	−0.45	1.28	−3.13	1.11	−0.08	0.3	−0.62	0.39
GB US/Qatar	0.1	0.32	−0.21	0.62	0.06	0.16	−0.11	0.41	0.04	0.1	−0.09	0.21
GB US/Saudi Arabia	0.31	1.18	−0.12	1.59	0.02	0.21	−0.17	0.22	−0.01	0.26	−0.41	0.36
GB US/UAE	−0.04	0.2	−0.26	0.16	0.08	0.18	−0.04	0.36	−0.03	0.11	−0.24	0.1
GB US/Jordan	1.1	5.68	−4.33	10.88	0.94	3.02	−0.99	6.59	−0.2	1.09	−2.32	1.01

Pairs (GB EU/Islamic banks)	Full sample				COVID-19				SOR			
	MN	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*
GB EU/Malaysia	0.24	1.39	−2.17	2.34	0.22	0.81	−0.59	1.52	0.27	0.67	−0.73	1.06
GB EU/Indonesia	0.01	1.51	−2.51	1.53	0.03	0.04	−0.02	0.09	0.92	1.63	−1.04	4.05
GB EU/Bangladesh	0	0.06	−0.08	0.09	0.03	0.09	−0.03	0.15	−0.01	0.19	−0.37	0.25
GB EU/Pakistan	0	0.02	−0.01	0.02	0	0.02	−0.01	0.03	0.02	0.1	−0.13	0.23
GB EU/Bahrain	0.06	0.37	−0.49	0.56	0.06	0.3	−0.4	0.42	0.25	0.65	−0.69	1.77
GB EU/Kuwait	0.09	0.81	−0.92	0.88	0.02	0.21	−0.25	0.25	0.34	0.42	−0.16	0.9
GB EU/OMAN	0.36	3.2	−5.03	5.95	−1.77	4.31	−10.73	4.38	0.48	2.65	−4.31	5.45
GB EU/Qatar	0.04	0.16	−0.15	0.33	0.15	0.45	−0.38	1.06	−0.07	0.8	−1.72	1.14
GB EU/Saudi Arabia	0.1	0.87	−1.04	1.01	0.18	0.3	−0.06	0.54	−0.05	1.39	−2.64	1.65
GB EU/UAE	−0.03	0.35	−0.39	0.3	0.22	0.69	−0.2	1.11	0.25	1.06	−1.15	2.33
GB EU/Jordan	0.78	5.56	−5.68	10.15	2.98	10.79	−3.71	26.3	2.74	8.3	−7.37	19.38

Pairs (GB CH/Islamic banks)	Full sample				COVID-19				SOR			
	MN	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*
GB CH/Malaysia	10.32	71.31	−37.53	74.49	0.41	6.95	−7.69	10.77	−0.08	0.1	−0.27	0.03
GB CH/Indonesia	25.92	72.37	−2.78	189.6	0.36	1.02	−0.04	2.47	−0.01	0.04	−0.09	0.05
GB CH/Bangladesh	0.89	3.03	−0.33	4.48	−0.04	0.16	−0.33	0.12	0.5	1.73	−1.79	4.1
GB CH/Pakistan	0.14	0.26	−0.03	0.74	−0.01	0.03	−0.06	0.02	−0.3	0.86	−2.07	1.12
GB CH/Bahrain	−6.04	14.07	−33.51	4.16	−1.41	3.29	−9.45	0.51	−0.02	0.06	−0.13	0.08
GB CH/Kuwait	6.23	45.05	−0.84	65.31	−1.25	3.7	−9.8	1.98	−0.1	0.11	−0.31	0
GB CH/OMAN	18.74	55.73	−27.62	97.5	−6.89	29.25	−62.25	31.69	0	0.04	−0.07	0.09
GB CH/Qatar	1.85	3.66	−1.74	8.71	−0.36	1.08	−2.62	0.76	−0.04	0.09	−0.22	0.1
GB CH/Saudi Arabia	13.06	46.73	−1.21	95.62	−0.27	0.93	−2.19	0.53	−0.07	0.08	−0.21	0.01
GB CH/UAE	0.61	2.12	−1.02	2.23	−0.05	1.1	−1.96	1.76	0	0.12	−0.13	0.28
GB CH/Jordan	22.47	237.22	−129.82	305.07	2.16	15.11	−11.94	30.85	0	0.01	−0.02	0.02

Notes: This table illustrate the hedge ratios, among Green bonds and Islamic Banks within Full Sample, COVID-19 and SOR.

Table 10
Optimal portfolio weights.

Pairs (GB GL/Islamic banks)	Full sample				COVID-19				SOR			
	MN	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*
GB GL/Malaysia	0.32	0.41	0	1	0.13	0.24	0	0.67	0.92	0.13	0.63	0.37
GB GL/Indonesia	0.24	0.4	0	1	0.01	0.01	0	0.04	0.82	0.19	0.43	0.57
GB GL/Bangladesh	0.01	0.04	0	0.07	0	0.01	0	0.02	0.99	0.02	0.94	0.06
GB GL/Pakistan	0	0.01	0	0.01	0	0	0	0.01	1	0.01	0.97	0.03
GB GL/Bahrain	0.2	0.29	0	0.85	0.03	0.06	0	0.19	0.95	0.07	0.81	0.19
GB GL/Kuwait	0.09	0.25	0	0.88	0.02	0.07	0	0.1	0.9	0.21	0.33	0.67
GB GL/OMAN	0.53	0.46	0	1	0.4	0.37	0	1	0.84	0.18	0.45	0.55
GB GL/Qatar	0.07	0.21	0	0.6	0.05	0.12	0	0.37	0.98	0.04	0.89	0.11
GB GL/Saudi Arabia	0.18	0.37	0	1	0.03	0.12	0	0.18	0.89	0.18	0.56	0.44
GB GL/UAE	0.05	0.12	0	0.22	0.04	0.15	0	0.38	0.95	0.08	0.78	0.22
GB GL/Jordan	0.67	0.36	0	1	0.33	0.43	0	1	0.62	0.34	0	1

Pairs (GB US/Islamic banks)	Full sample				COVID-19				SOR			
	MN	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*
GB US/Malaysia	0.32	0.4	0	1	0.12	0.23	0	0.63	0.92	0.12	0.66	0.34
GB US/Indonesia	0.23	0.39	0	1	0.01	0.01	0	0.04	0.83	0.17	0.48	0.52
GB US/Bangladesh	0.01	0.04	0	0.07	0	0.01	0	0.02	0.99	0.02	0.94	0.06
GB US/Pakistan	0	0.01	0	0.01	0	0	0	0.01	0.99	0.01	0.97	0.03
GB US/Bahrain	0.2	0.28	0	0.84	0.04	0.07	0	0.2	0.95	0.07	0.8	0.2
GB US/Kuwait	0.09	0.25	0	0.82	0.03	0.07	0	0.11	0.91	0.19	0.38	0.62
GB US/OMAN	0.53	0.46	0	1	0.39	0.35	0	1	0.84	0.18	0.48	0.52
GB US/Qatar	0.07	0.2	0	0.58	0.05	0.11	0	0.35	0.98	0.04	0.89	0.11
GB US/Saudi Arabia	0.18	0.37	0	1	0.04	0.13	0	0.21	0.9	0.18	0.54	0.46
GB US/UAE	0.05	0.12	0	0.21	0.03	0.14	0	0.25	0.95	0.08	0.76	0.24
GB US/Jordan	0.67	0.36	0	1	0.32	0.43	0	1	0.63	0.34	0	1

Pairs (GB EU/Islamic banks)	Full sample				COVID-19				SOR			
	MN	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*
GB EU/Malaysia	0.28	0.4	0	1	0.2	0.33	0	1	0.73	0.35	0	0.85
GB EU/Indonesia	0.27	0.38	0	1	0	0.01	0	0.02	0.43	0.4	0	1
GB EU/Bangladesh	0.02	0.03	0	0.09	0.01	0.03	0	0.06	0.91	0.22	0.27	0.23
GB EU/Pakistan	0	0.01	0	0.01	0	0.01	0	0.01	0.98	0.05	0.86	1
GB EU/Bahrain	0.11	0.2	0	0.54	0.08	0.15	0	0.33	0.7	0.39	0	1
GB EU/Kuwait	0.13	0.28	0	0.91	0.07	0.16	0	0.43	0.87	0.27	0.12	0.73
GB EU/OMAN	0.51	0.4	0	1	0.59	0.36	0	1	0.39	0.39	0	0.14
GB EU/Qatar	0.04	0.08	0	0.14	0.17	0.32	0	1	0.73	0.37	0	1
GB EU/Saudi Arabia	0.19	0.31	0	1	0.06	0.21	0	0.6	0.61	0.38	0	0.88
GB EU/UAE	0.1	0.21	0	0.62	0.13	0.29	0	1	0.72	0.41	0	1
GB EU/Jordan	0.68	0.35	0	1	0.41	0.42	0	1	0.2	0.29	0	1

Pairs (GB CH/Islamic banks)	Full sample				COVID-19				SOR			
	MN	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*	*MN*	*STD·D*	*5%*	*95%*
GB CH/Malaysia	0.66	0.42	0	1	0.47	0.42	0	1	0.91	0.12	0.7	0.3
GB CH/Indonesia	0.64	0.45	0	1	0.25	0.42	0	1	0.98	0.03	0.9	0.1
GB CH/Bangladesh	0.27	0.39	0	1	0.06	0.1	0	0.25	0.55	0.44	0	1
GB CH/Pakistan	0.02	0.09	0	0.05	0.01	0.02	0	0.06	0.53	0.36	0	1
GB CH/Bahrain	0.6	0.42	0	1	0.31	0.39	0	0.95	0.95	0.06	0.81	0.19
GB CH/Kuwait	0.41	0.46	0	1	0.32	0.41	0	1	0.89	0.12	0.66	0.34
GB CH/OMAN	0.87	0.28	0.06	1	0.83	0.28	0	1	0.99	0.03	0.91	0.09
GB CH/Qatar	0.5	0.46	0	1	0.31	0.33	0	0.83	0.92	0.1	0.7	0.3
GB CH/Saudi Arabia	0.62	0.44	0	1	0.2	0.29	0	0.7	0.91	0.1	0.75	0.25
GB CH/UAE	0.47	0.42	0	1	0.28	0.36	0	1	0.91	0.12	0.68	0.32
GB CH/Jordan	0.83	0.3	0	1	0.65	0.39	0	1	1	0.01	0.98	0.02

Notes: This table illustrate the optimal portfolio weights, among Green bonds and Islamic Banks within Full Sample, COVID-19 and SOR.

Table 11
Hedging effectiveness.

Pairs (GB GL/Islamic banks)	Full sample				COVID-19				SOR			
	Optimal portfolio weights		*Optimal hedge ratios*		*Optimal portfolio weights*		*Optimal hedge ratios*		*Optimal portfolio weights*		*Optimal hedge ratios*	
	HE	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*
GB GL/Malaysia	0.02	0	17.63	0	0.10	0	0.26	0	0.08	0	1.05	0
GB GL/Indonesia	−0.01	0	1.17	0	0.00	0	3.45	0	0.03	0	0.10	0
GB GL/Bangladesh	−0.01	0	5.69	0	0.03	0	0.23	0	0.54	0	0.77	0
GB GL/Pakistan	−0.01	0	2.95	0	0.07	0	1.14	0	0.14	0	0.31	0
GB GL/Bahrain	0.00	0.54	11.51	0	0.01	0	11.74	0	0.06	0	0.23	0
GB GL/Kuwait	−0.01	0	3.55	0	0.04	0	0.78	0	0.04	0	0.53	0
GB GL/OMAN	0.02	0	3.40	0	0.04	0	0.02	0	0.02	0	0.16	0
GB GL/Qatar	−0.01	0	8.24	0	0.42	0	0.48	0	0.06	0	0.66	0
GB GL/Saudi Arabia	−0.01	0	2.74	0	0.00	0.34	0.18	0	0.03	0	0.09	0
GB GL/UAE	−0.01	0	0.52	0	1.24	0	0.14	0	0.18	0	0.65	0
GB GL/Jordan	0.12	0	11.91	0	0.15	0	0.20	0	0.09	0	1.83	0

Pairs (GB US/Islamic banks)	Full sample				COVID-19				SOR			
	Optimal portfolio weights		*Optimal hedge ratios*		*Optimal portfolio weights*		*Optimal hedge ratios*		*Optimal portfolio weights*		*Optimal hedge ratios*	
	HE	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*
GB US/Malaysia	0.25	0	17.26	0	0.12	0	1.44	0	0.07	0	0.90	0
GB US/Indonesia	0.04	0	0.78	0	0.01	0	0.26	0	0.03	0	0.09	0
GB US/Bangladesh	0.47	0	4.83	0	0.04	0	13.65	0	0.64	0	0.87	0
GB US/Pakistan	0.10	0	2.18	0	0.09	0	0.91	0	0.15	0	0.31	0
GB US/Bahrain	0.12	0	10.90	0	0.02	0	0.02	0	0.06	0	0.24	0
GB US/Kuwait	0.02	0	2.47	0	0.05	0	0.46	0	0.04	0	0.44	0
GB US/OMAN	0.00	0	3.21	0	0.04	0	0.23	0	0.02	0	0.17	0
GB US/Qatar	0.72	0	7.31	0	0.46	0	0.16	0	0.07	0	0.71	0
GB US/Saudi Arabia	0.01	0	1.87	0	0.00	0.11	0.25	0	0.03	0	0.09	0
GB US/UAE	0.83	0	0.52	0	1.27	0	1.94	0	0.20	0	0.70	0
GB US/Jordan	0.02	0	10.01	0	0.19	0	1.44	0	0.10	0	1.87	0

Pairs (GB EU/Islamic banks)	Full sample				COVID-19				SOR			
	Optimal portfolio weights		*Optimal hedge ratios*		*Optimal portfolio weights*		*Optimal hedge ratios*		*Optimal portfolio weights*		*Optimal hedge ratios*	
	HE	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*
GB EU/Malaysia	0.19	0	1.84	0	0.03	0	0.93	0	0.01	0	0.39	0
GB EU/Indonesia	0.05	0	0.12	0	0.00	0	1.37	0	0.01	0	0.66	0
GB EU/Bangladesh	0.40	0	1.34	0	0.07	0	5.70	0	1.79	0	0.90	0
GB EU/Pakistan	0.10	0	0.41	0	0.08	0	8.57	0	0.15	0	1.23	0
GB EU/Bahrain	0.04	0	1.20	0	0.01	0	1.51	0	0.06	0	1.51	0
GB EU/Kuwait	0.02	0	0.86	0	0.03	0	2.80	0	0.00	0	1.04	0
GB EU/OMAN	0.01	0	0.90	0	0.01	0	5.15	0	0.00	0	1.53	0
GB EU/Qatar	0.11	0	0.62	0	0.41	0	4.33	0	0.17	0	3.01	0
GB EU/Saudi Arabia	0.01	0	0.21	0	0.00	0.56	5.03	0	0.01	0	0.41	0
GB EU/UAE	2.36	0	1.05	0	0.68	0	4.54	0	0.15	0	4.55	0
GB EU/Jordan	0.04	0	1.44	0	0.03	0	16.70	0	0.00	0	0.84	0

Pairs (GB CH/Islamic banks)	Full sample				COVID-19				SOR			
	Optimal portfolio weights		*Optimal hedge ratios*		*Optimal portfolio weights*		*Optimal hedge ratios*		*Optimal portfolio weights*		*Optimal hedge ratios*	
	HE	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*
GB CH/Malaysia	−0.01	0	42.87	0	0.03	0	1.07	0	0.01	0	5.81	0
GB CH/Indonesia	0.83	0	0.35	0	0.02	0	0.09	0	−0.01	0	0.38	0
GB CH/Bangladesh	0.04	0	15.63	0	0.01	0	0.05	0	0.11	0	0.57	0
GB CH/Pakistan	0.00	0	3.29	0	0.00	0	0.01	0	0.27	0	0.70	0
GB CH/Bahrain	−0.01	0	38.64	0	0.02	0	0.32	0	0.00	0	0.38	0
GB CH/Kuwait	0.45	0	1.41	0	0.02	0	0.68	0	−0.01	0.66	0.12	0

(*continued on next page*)

Table 11 (*continued*)

Pairs (GB CH/Islamic banks)	Full sample				COVID-19				SOR			
	Optimal portfolio weights		*Optimal hedge ratios*		*Optimal portfolio weights*		*Optimal hedge ratios*		*Optimal portfolio weights*		*Optimal hedge ratios*	
	HE	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*
GB CH/OMAN	0.11	0	7.98	0	0.02	0	2.22	0	−0.01	0	0.80	0
GB CH/Qatar	8.23	0	21.01	0	0.00	0	0.15	0	0.01	0	0.31	0
GB CH/Saudi Arabia	0.01	0	1.53	0	0.02	0	0.00	0	−0.01	0	1.46	0
GB CH/UAE	0.51	0	4.55	0	0.00	0	0.26	0	0.02	0	0.05	0
GB CH/Jordan	0.00	0	16.25	0	0.05	0	0.23	0	0.00	0	7.87	0

Notes: This table illustrate the hedging effectiveness, among Green bonds and Islamic Banks within Full Sample, COVID-19 and SOR.

Table A.1 (*continued*)

Variable	Description
VIX	The VIX index shows volatility of the market within the next 30 days. This is also called real-time market index. According to Billah e al., the VIX may have negative impact to green bonds as VIX increases which decreases the Total Spillover Index. Therefore, we are expecting the VIX may have the negative sign.
OVX	OVX is the expected 30-day crude oil volatility estimate since the US Oil Fund (USO) set the price. Whenever, the US Oil Fund (USO) set the price, from that day to 30 days the volatility of the crude oil has been estimated, which is called OVX. According to Billah et al., and Seed et al., OVX may have a negative impact on green bonds when OVX increases. Therefore, also we are expecting negative impact from OVX.
GVZ	GVZ is an estimation regarding the anticipated 30-day volatility of returns on the SPDR Gold Shares ETF (GLD).
GFS	Anticipated through Bank of America Merrill Lynch, the Global Financial Stress Index is a method regarding cross-market risk, demand protection, and financial investment flows in the worldwide financial process.
EMV	Baker et al. (2019) developed an index which is called Equity Market Volatility (EMV) tracker, and it is being based on the eleven major U.S. newspapers. Moreover, this index closely moves with the VIX and with realized volatility on the S&P 500.
GMNS	We have another interesting variable that we have taken, which is called global macroeconomic news surprises and has been developed by Scotti (2016). As we know the aggregate demand and supply conditions may have higher uncertainty through macroeconomic news surprises. Therefore, considered that sukuk and commodity prices, are strongly sensitive to demand and supply conditions, a rise in the uncertainty encompassing the macroeconomy may cause a higher volatility in sukuk and commodity prices.
CLMT	The MSCI Global Climate Change Index (CLMT) measures the opportunities and risks of transitioning to a low-carbon economy. Through this index, those investors invest in global equity markets, will help to understand the climate risk.

Table A.2
Correlation coefficients of explanatory variables.

Explanatory variables	EPU	VIX	OVX	GVZ	GFS	EMV	GMNS	CLMT
EPU	1.00							
VIX	0.17	1.00						
OVX	0.13	0.48	1.00					
GVZ	0.11	0.45	0.27	1.00				
GFS	−0.18	0.05	0.31	0.13	1.00			
EMV	0.23	−0.06	0.27	−0.26	−0.13	1.00		
GMNS	0.10	0.13	−0.07	0.11	−0.32	0.14	1.00	
CLMT	0.03	0.57	0.22	0.25	0.40	−0.05	−0.14	1.00

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