

# An empirical investigation of market risk, dependence structure, and portfolio management between green bonds and international financial markets

Rimsha Ejaz<sup>c</sup>, Sumaira Ashraf<sup>a,b,\*</sup>, Arshad Hassan<sup>c</sup>, Ankit Gupta<sup>d</sup>

<sup>a</sup> ISAL, Higher Institute of Administration and Languages, Funchal, Portugal

<sup>b</sup> CEFAGE- University of Évora, Portugal

<sup>c</sup> Faculty of Management and Social Sciences, Capital University of Science and Technology, Islamabad, Pakistan

<sup>d</sup> Interactive Technologies Institute/Larsys/Madeira Interactive Technologies Institute, Portugal

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## ABSTRACT

The study aims to explore the market risk, dependence structure, and portfolio diversification benefits of green bonds with Islamic and conventional (equity, bonds, and energy) markets. We first examine the market risk dynamics and dependence structure between green bonds and the international financial markets by using value-at-risk (VaR), copula models, and the Copula-VaR approach over the period from July 2014 to August 2020. Findings reveal the existence of the symmetric upper (lower) tail dependence between green bonds and international financial markets, except for the conventional bonds market with zero dependence. Our empirical results suggest that international financial markets possess different risk profiles, and the investors should not treat them as homogenous assets to combine with green bonds. Moreover, we also explore the portfolio diversification benefits, using hedge ratios, optimal portfolio weights, and hedging effectiveness for all pairs of green bonds-international financial markets. The results suggest that Islamic bonds and the oil markets are best to hedge green bonds, followed by conventional bonds, conventional equity, and the Islamic equity market. These results provide implications for effective risk management and fund allocation to policymakers and socially responsible investors. The study's findings are critical for current and future investors for efficient capital allocation in the environmental and ethically responsible assets.

## 1. Introduction

Global warming and climate change put pressure on policymakers to encourage a green economy. Adapting a climate-friendly economy demands the utilization of financial resources for green projects and fossil fuel divestment (OECD, 2017) to increase new green finance investment opportunities for individual and institutional investors. Green bonds (or climate bonds) are a fast-growing fixed-income asset class that fosters financial resources for eco-friendly projects, such as efficient energy consumption, bioenergy, energy renewal, and low carbon economy (Campiglio, 2016). Besides being a relatively new financial segment,

originated in developed countries, Green bonds (GBs) offer multiple benefits to society. First, they help eco-friendly and energy-saver companies by easing their financial hurdles. Second, they satisfy the demand for diversified investment opportunities by the investors. Third, they contribute to worldwide sustainable development by helping developing countries evolve into sustainable economies (Gao et al., 2021).

Since European Investment Bank issued its first GB in 2007, there has been a rapid growth in the GB market. The global GB market ramped up from USD37bn and USD43bn in 2014 and 2015, respectively, to USD81bn in 2016, USD155.5bn in 2017, and USD170.6bn in 2018. In 2019, the GB market made a new global record and reached

\* Corresponding author. Rua do Comboio, n.º 5, 9050-053, Funchal, Madeira, Portugal.

E-mail addresses: [rimsha.ejsz@gmail.com](mailto:rimsha.ejsz@gmail.com) (R. Ejaz), [sumaira.ashraf@isal.pt](mailto:sumaira.ashraf@isal.pt) (S. Ashraf), [arshad@cust.edu.pk](mailto:arshad@cust.edu.pk) (A. Hassan), [gupta.ankit894@gmail.com](mailto:gupta.ankit894@gmail.com) (A. Gupta).

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USD257.7bn, 51% up from 2018 (Climate Bonds Initiative, 2020). GBs are issued mainly by the private sector organizations, public sector organizations (state-owned, local, and national government-owned organizations), and supranational organizations (for example, European Investment Bank, World Bank, etc.) (Reboredo, 2018). Mostly, GBs are issued in United States dollar and Euro currencies (approximately 80%), with an average tenure of 5–10 years.

GBs are becoming a well-established financial instrument with growing popularity among the sustainability-oriented financial community. Because their proceeds are reserved for eco-friendly projects, they are popular amongst environmentally conscious stakeholders and investors, becoming conscious of climate change and the risk associated with this change for the governments and the companies (Ferrer et al., 2021; Reboredo, 2018). In the light of investors' interest in the ecological risk and a global initiative to move towards a climate-resilient economy in the 2015 Paris Climate Agreement – the GB market is expected to flourish by attracting the interests of a diverse range of investors, including pension funds, mutual funds, insurance companies, SMEs, and individual investors. In general, GBs have the ability to reorder the cost of alleviating climate change across generations (Flaherty et al., 2017), and that is why they are considered to be the most suitable instrument to finance the progression towards a low carbon economy (Monasterolo and Raberto, 2018; OECD, 2017).

The financial system plays a significant role in transitioning to a climate-resilient economy. An important pillar of today's financial system is financial globalization, an individual country's linkages to international capital markets through cross-border financial flows. The benefits and risks associated with financial globalization have become an interesting topic of interest for academicians and policymakers. On one side, it brings the benefits of new low-cost investment, efficient portfolio diversification, and improved financial infrastructure. While on the other hand, it also increases cross-market comovement, which eventually increases the extent of a financial crisis (Huang, 2020).

One of the major effects of the global spread of the 2008 financial crisis was an increase in contagion and correlation between financial assets, which decreased the actual benefits associated with portfolio diversification (el Alaoui et al., 2015). Generally, investors look for alternative financial assets to effectively diversify their portfolios and decrease the risks associated with the financial market's (FM) volatility. Recently, GBs caught the eyes of various investors, regulators, policymakers, and academicians as one of the fastest-growing financial assets for portfolio risk minimization. The risk-return profile of GBs is expected to be different from other IFMs, as the proceeds from these bonds are earmarked for green projects but are backed by the issuer's whole balance sheet (Reboredo, 2018). Consequently, the performance of GBs is expected to be different from other IFMs and requires an empirical investigation. Understanding the risk profile of GBs with other IFMs is essential for investors. It helps them make optimal portfolio allocation decisions according to their risk appetite and gain benefits. Moreover, it will help transition to a climate-resilient economy to increase the investment in green projects and encourage environmentally-friendly portfolios.

The primary objective of this study is to focus on exploring the market dynamics of the rapidly growing asset class, GBs, which needs more investigation (Zhang, 2018). The study contributes to the literature on GBs in three ways. First, it estimates the market risk of investing in GBs and other IFMs, including conventional and Islamic equity markets, bonds, and energy markets. While previous studies focused on the market risk of individual series, they failed to fully reflect the portfolio risk for the pairs of GB and each IFM. The study compared the findings of VaR and CopulaVaR to provide a more comprehensive analysis of paired series risk and measure the extreme risk contributions of GBs to each IFM. The empirical results suggest that each IFM possesses a different risk profile, and the investors should not treat them homogeneously to combine them with GBs.

Second, and perhaps the most important contribution in the GBs

literature, is the analysis of the dependence structure of the GB market with different types of IFMs using copula modelling. The previous studies separately focused on the contagion and correlation with conventional bonds, energy commodities, and other IFMs. Moreover, no study to date on the dependence structure between GBs and other financial assets has explored the diversification benefits of GBs with Islamic asset classes (equity and bonds). Both types of markets possess some similar characteristics; securitization of assets, extra financial screening, and investment criteria (Atta, 2000; Reboredo, 2018), which are considered effective diversifiers during periods of economic turmoil (Naeem et al., 2021; Tuna, 2019). Hence, this study attempts to fill this gap in the literature by exploring their dependence structure and giving practical implications for investors to understand their price oscillations and portfolio diversification benefits. The results reveal the existence of symmetric maximum upper (lower) tail dependence between GBs and the IFMs, suggesting that the investors should carefully use these combinations, especially during extreme market conditions.

Third, this study provides deeper insights into portfolio diversification by hedging the market risk of alternative financial tools. While previous studies focused only on some primary markets, this study explored the portfolio diversification benefit of GBs and several other investment portfolio diversifiers, namely, World Islamic Equity, Global Sukuk Market, World Equity, Global World Bond Market, and the Energy Market. Our results reveal that GBs have different hedge effectiveness levels for each IFM. Moreover, investors should consider optimal portfolio weights to hedge against the market volatility of GBs.

The remainder of the paper is organized as follows. Section two gives a brief overview of the literature. Section three describes the data and the methodologies employed. Section four covers the potential application of results, followed by a conclusion and discussion of results in section five.

## 2. Literature review

### 2.1. Empirical studies in the green bonds market

The growth in the GB market gains the attention of investors who wish to invest in alternate environment-friendly financial instruments and makes it an interesting topic of research for academicians. As the first school of literature on GBs, the researchers focus on measuring the GBs premium with respect to their conventional counterparts. Several studies showed that the GBs have a negative yield (Gianfrate and Peri, 2019; Hachenberg and Schiereck, 2018; Immel et al., 2021), suggesting that the environmental-conscious investors are willing to sacrifice their return to help transition toward a green sustainable economy. On the contrary, the researchers, including MacAskill et al. (2021), Larcker and Watts (2020), Bachelet et al. (2019), and Karpf and Mandel (2018), found that the GBs have higher premiums and liquidity than their 'brown' bond neighbours.

From another angle, few researchers have investigated the volatility spillover and comovement pattern of GBs with other FMs and asset classes. Pham (2016) is the first researcher to analyze the correlation pattern between green and conventional bond markets. The empirical evidence showed that the labelled GB market has a more robust volatility clustering than the unlabeled traditional bond market. Broadstock and Cheng (2019) suggested that the relationship between both markets is affected by numerous macroeconomic conditions, including news-based sentiment for GBs, crude oil prices, and economic activity.

In a similar vein, a prominent study by Reboredo (2018) used bivariate copula models to examine the comovement, diversification, and price spillover between GBs and FMs. The findings suggested that the prices of GBs weakly co-move with the conventional stocks and energy markets, providing ample portfolio diversification benefits to investors in these markets. Nevertheless, the diversification benefit is negligible for treasury and corporate bond market investors. Reboredo and Ugolini (2020) extended the work of Reboredo (2018) to capture

multivariate dependence patterns and network links between GBs and other FMs. In support of [Reboredo \(2018\)](#), the work proved that the GB market is weakly linked to stock and energy markets. However, the connection is strong with the fixed income and currency markets, suggesting that the GB market gets significant price spillovers from these markets and slight spillovers towards them.

[Daszynska-Zygadlo et al. \(2018\)](#) used a multivariate GARCH model to explore the volatility patterns among four international GB indexes and the traditional bond index. The study results are in line with the findings of [Reboredo \(2018\)](#); GBs appear to be highly correlated with traditional bonds, particularly because of the small market size and the volatility transmission from their traditional counterparts. Similarly, [Huynh \(2022\)](#) found a strong comovement between green and Triple-A rated prime government bonds. [Kanamura \(2020\)](#) examined the greenness by comparing the performance of GBs with energy stocks and found that GBs are negatively correlated with WTI and Brent oil prices. Besides, they possess greenness and outperform conventional bonds. Furthermore, [Jin et al. \(2020\)](#) found that only the GB index is the most effective and reasonable hedge for carbon market risk out of the four major market indices.

More recently, [Nguyen et al. \(2021\)](#) examined the comovement between GBs and other asset classes and found a strong comovement between stocks, clean energy, and commodities. However, there is a low or negative correlation of GBs with stocks and commodities, revealing the diversification benefits of GBs. [Gao et al. \(2021\)](#) examined the asymmetric connectedness between the green and conventional bond markets. The findings revealed a two-way risk spillover between the green and conventional bond markets; on the other hand, there is no significant risk spillover between the GB market, monetary market, and foreign exchange market. [Liu et al. \(2021\)](#) examined the relationship between GBs and clean energy stocks and found a significant positive dependence and risk spillover in both directions. Further, [Naeem et al. \(2021\)](#) examined the spillover between the GBs and other classes of commodity assets, including precious metals (gold and silver), agricultural commodities (wheat and corn), and energy markets (crude oil and natural gas). The study's findings revealed a stronger spillover between GBs and the commodities of the same asset class, gold, and silver, regardless of the periods. While in the long run, the GBs observe a strong connection with crude oil.

## 2.2. Islamic market

In the last decade, the demand for Sharia-compliant portfolio diversification tools increased due to the apparent fungibility of Islamic investments during the global 2008 financial crisis. Moreover, the Sharia-compliant stocks are considered more profitable than their conventional counterparts due to the company's extra-financial screening criterion ([Atta, 2000](#); [Hussein and Omran, 2005](#)). Most of the previous literature focuses on performance comparison, comovement, and portfolio diversification benefits of Islamic and conventional FMs ([Al-Zoubi and Maghyreh, 2007](#); [Ashraf and Mohammad, 2014](#); [Hussein, 2004](#)). [Hussein \(2004\)](#) showed that the performance of Islamic and conventional FMs was similar; however, highly volatile Islamic indices give comparatively high returns in bullish markets compared to bearish markets. On the other hand, [Al-Zoubi and Maghyreh \(2007\)](#) found that Islamic indices are less riskier than the benchmarked World Index. In the same vein, [Ashraf and Mohammad \(2014\)](#) showed that the Islamic indices have superior performance as compared to the conventional stock indices. Later, a number of researchers, including [Al-Khazali et al. \(2014\)](#), [Jawadi et al. \(2014\)](#), and [Akhtar and Jahromi \(2017\)](#), correspondingly found that the Islamic FMs show superior performance during the condition of global financial turmoil. These results could be attributed to the unique features of Islamic stocks, such as profit-loss sharing, lower financial leverage, and the conservative nature of Sharia-compliant assets.

A growing literature also explores the portfolio diversification

benefits, comovement, and cointegration of Shariah-compliant stocks, along with traditional FMs, commodity markets, energy markets, and cryptocurrencies. For instance, [Saiti et al. \(2014\)](#) proved that Shariah-compliant stock indices offer better diversification than conventional stocks. Likewise, the study conducted by [Mensi et al. \(2015\)](#) found that both Islamic stocks and gold are effective portfolio diversification tools during a financial crisis. Furthermore, [Ajmi et al. \(2014\)](#) found a significant positive relationship between Islamic and conventional stock markets. [el Alaoui et al. \(2015\)](#) documented the pure contagion between Sukuk bonds and the conventional stock market by about 3 h. [Mensi et al. \(2017\)](#) analyzed the time-varying risk spillover between the large stock exchanges (USA, Japan, Europe, and Asia) and the precious metals (gold, silver, palladium, and platinum). The research results revealed the presence of the volatility spread between precious metals and Islamic stock markets.

The above strands of literature have explored the relationship between GBs and other traditional assets, including equity, conventional bonds, energy, and commodity markets. Moreover, the studies also focus on the comovement of Islamic stock markets with other financial assets. However, the relationship between GBs and Islamic financial instruments has been largely unexplored. Our research primarily focuses on unveiling the portfolio diversification opportunities for the eco-friendly investors of the GBs and the investors prone to invest in stocks designed specially according to the tenets of Shariah-based Islamic laws. In sum, the literature reports mixed results concerning the relationship, dependence structure, and diversification benefits of GBs with different asset classes, hence necessitating further exploration. The critical contribution of this research is to explore the portfolio diversification benefits of the GBs, along with other IFMs, including conventional and Islamic equity and bond markets and the energy market.

## 3. Data and methodology

### 3.1. Data

Our data set consists of the global GB index and several other IFMs to explore their market risk, dependence structure, and portfolio risk diversification. To account for the performance of GBs, we use S&P Green Bond Index, a multicurrency benchmark that broadly covers the GBs issued by the multilateral, government, and global corporate agencies ([Pham, 2021](#)). The IFMs are classified into three main categories: equity (traditional and Islamic), bonds (conventional and Islamic), and energy (oil). Specifically, we use the S&P Global 1200 Index (*CE*) and Dow Jones Islamic Market World Index (*IE*) as indicators of the global conventional and Islamic world equity market, respectively. The performance of the world conventional and Islamic bond markets are approximated using the FTSE World Government Bond Index (*CB*) and Dow Jones Sukuk Total Return Index (*S*), respectively. Moreover, we use the S&P Global Oil Index (*O*) to capture the oil market dynamics. Data of all indices are US dollar-denominated and extracted from the S&P Dow Jones Indices and Thomson Reuters data source. The data period of all indices is from July 2014 to August 2020, except for the FTSE World Government Bond Index, which is from December 2017 to October 2019, due to the unavailability of paid financial databases. We matched the data of the S&P Green Bond Index with FTSE World Government Bond Index to make them comparable. The choice of the starting period corresponds to the launching date of the S&P Green Bond Index.

### 3.2. Econometric models

This section consists of four main steps. First, we use VaR to estimate the risk of individual markets. Second, we estimate copula models to examine the dependence of GBs and IFM pairs and estimate the tail dependence of each pair by using several copula families. Third, we calculate CopulaVaR to measure the extreme risk contribution of the GBs to other IFMs. In the final step, we evaluate the effectiveness of

hedging GB with each IFM using hedging effectiveness and optimal portfolio weights.

### 3.2.1. Value at risk (VaR)

The effective measurement and control of market risk is the major concern of investors, financial institutions, and practitioners. We employed VaR to estimate market risk. VaR is a numerical value that gives an insight into the estimated maximum loss over a specific period at a given confidence interval  $(1 - \alpha)$ , where  $\alpha$  is a significance level. Given returns of financial returns area represented by  $M = \{m_1, m_2, m_3, \dots, m_n\}$ , where  $m_i$  are identically distributed random variables with  $\alpha = (0,1]$ , VaR can be mathematically defined as:

$$Var_\alpha(M) = -quant(\alpha) \quad (1)$$

where  $quant$  depicts the quantile and  $\mathbb{P}(M \leq i)$  is a cumulative density function (CDF) of  $M$ . Assuming that  $M$  follows a normal distribution given by  $N(\mu, \sigma^2)$  then, VaR can be mathematically defined as:

$$quant(\alpha) = \mu + \varepsilon \quad (2)$$

where,  $\varepsilon$  is the error term, defined as  $\sigma Z_\alpha$ .  $Z_\alpha$  denotes the  $\alpha$  - quantile of the Gaussian distribution, and  $\sigma$  is the standard deviation. It is worth mentioning that  $\sigma$  and  $\mu$  needs to be estimated from the historical data. Putting the value of  $\varepsilon$  in (2) gives:

$$quant(\alpha) = \mu + \sigma Z_\alpha \quad (3)$$

Given historical data defined by  $\varphi$ ,  $\mu$  can be computed, whereas  $\sigma$  can be estimated by calculating variance ( $\sigma^2$ ) as follows:

$$\sigma^2 = E(Z_\alpha^2 | \varphi) \quad (4)$$

where  $Z_\alpha$  follows conditional distribution given by  $G(z) = P(Z_\alpha < z | \varphi)$ . Therefore, VaR model for a set of returns defined by  $M$  can be estimated as:

$$Var_\alpha(M) = CDF^{-1}(\alpha) = \mu + \sigma G^{-1}(\alpha) \quad (5)$$

The CDF and  $G$  in the above equation were estimated through the semi-parametric nonlinear Monte-Carlo method, which estimates distribution and parameters using historical data. Other methods for VaR model calculations are based on historical data (assuming history repetition) and variance-covariance (assuming data is normally distributed), which are impractical for real-world situations.

### 3.2.2. Copula approach

Nelsen (2006) defines copulas as "functions that 'join' or 'couple' multivariate distribution functions to their one-dimensional marginal distribution functions". Copula models are most appropriate for analyzing the nonlinear dependence structure between FMs (Reboredo, 2018; Sklar, 1959). Hence, copulas provide a realistic description of the FMs' dependence, including symmetric and asymmetric, linear and nonlinear, and extreme or tail dependence (Abakah et al., 2021).

Suppose  $X_1, X_2, \dots, X_n$  represents the set of  $n$  random variables (financial markets) with a joint probability function, given by:

$$F_{x_1, x_2, \dots, x_n}(x_1, x_2, \dots, x_n) = P(X_1 \leq x_1, X_2 \leq x_2, \dots, X_n \leq x_n) \quad (6)$$

The marginal distribution function of  $X_1, X_2, \dots, X_n$  are.

$$F_{x_1}(x_1) = P(X_1 \leq x_1)$$

$$F_{x_2}(x_2) = P(X_2 \leq x_2) \quad (7)$$

$$F_{x_n}(x_n) = P(X_n \leq x_n)$$

According to Sklar (1959) theorem, if  $F_{x_1}, F_{x_2}, \dots, F_{x_n}$  are continuous functions, then there exists a unique copula such that

$$F_{x_1, x_2, \dots, x_n}(x_1, x_2, \dots, x_n) = c(F_{x_1}(x_1), F_{x_2}(x_2), \dots, F_{x_n}(x_n)) \quad (8)$$

For bivariate variables such as the returns of the green bonds  $r_{gb}$  and change in international financial markets  $r_{ifm}$ , the above equation can be rewritten as:

$$C(a, b) = P(Z_{gb} \leq z_{gb}, Z_{ifm} \leq z_{ifm}), \text{ for } (a, b) \in [0, 1]^2 \quad (9)$$

$Z_{gb}$  and  $Z_{ifm}$  are the marginal distribution functions of the return residual sets of  $z_{gb}$  and  $z_{ifm}$ , respectively,  $a$  and  $b$  are the uniform distribution of GBs and IFMs, and  $C(a, b)$  is the copula function. We consider several copula models with different tail dependence structures: Gaussian, t-student, Gumbel, Frank, and Clayton copulas to examine their effectiveness in risk modelling. The tail dependence coefficient describes the association between the upper right and lower left part (tail) of two or more random variables (Schmidt, 2005). One significant difference among different types of copulas is the upper (lower) tail connotation they represent.

First, this study used Gaussian Copula, assuming that the data is upper (lower) tail independent, indicating that the extreme values from the different random variables occur independently, regardless of their correlation (AghaKouchak et al., 2013). The Gaussian copula function is defined as:

$$C_G(a, b) = \int_{-\infty}^{U^{-1}(a)} da \int_{-\infty}^{U^{-1}(b)} db \frac{1}{2\pi\sqrt{1-\delta^2}} \exp \left\{ -\frac{a^2 - 2\delta ab + b^2}{2(1-\delta^2)} \right\} = \Phi_\delta(U^{-1}(a), U^{-1}(b)) \quad (10)$$

where  $U$  represents a univariate standard normal distribution and  $\Phi_\delta$  is a bivariate standard normal distribution with the correlation coefficient  $-1 \leq \delta \leq 1$ . The Gaussian Copula is easy to compute, but the bivariate normality assumption limits its effectiveness in exploring the comovement dynamics between financial time series data and neglects the crucial dimension of tail dependence.

Based on the results of the Gaussian Copula, we estimated the t-student copula to measure the dependence structure at both sides of the tails due to its bivariate asymmetrical assumption. The t-student copula, proposed by Huang et al. (2009), is based on the multivariate t distribution and can be described as follows:

$$C_T = (u_1, u_2; \rho, d) = t_{d,\rho}(t_d^{-1}(u_1), t_d^{-1}(u_2)) \quad (11)$$

where,  $u_1, u_2$  and  $t_d$  are Gaussian distributions and  $t_{d,\rho}$  is the joint probability distribution with correlation coefficient  $\rho$ . The t-student copula is one of the most widely used copulae to measure tail dependence due to flexibility in changing the degree of freedom. To measure the upper tail dependency or heavy tail at the upper side of the distribution, Gumbel copula (Gumbel, 1960) is used and defined as:

$$C_{GU}(a, b) = \exp \left\{ -[( -\ln(a) )^\delta + ( -\ln(b) )^\delta]^\frac{1}{\delta} \right\}, \delta \geq 1 \quad (12)$$

In the above equation,  $\delta$  denotes the degree of dependence between  $a$  and  $b$  (no upper tail dependence for  $\delta = 1$  and minimum; upper tail dependence for the maximum value of  $\delta$ ).

The results of the Gumbel copula are used to estimate the Clayton copula (Clayton, 1978) to measure the lower tail dependence between  $a$  and  $b$ . The Clayton copula is described as below:

$$C_{LA}(a, b) = \max \left[ (a^{-\delta} + b^{-\delta} - 1)^{-\frac{1}{\delta}}, 0 \right], 0 < \delta \leq \infty \quad (13)$$

whereas  $\delta$  in the equation shows the extent of dependence between  $a$  and  $b$  ( $\delta = 0$  depicting no tail dependence). The increase in the value of  $\delta$  indicates an increase in lower tail dependency up to  $\infty$ , which is the maximum point of lower tail dependence.

Finally, Frank copula (Frank, 1979) is estimated based on the values of Clayton copula to calculate the greatest range of dependence, as it allows the modelling of positive and negative dependence in the data.

The Frank copula to measure the tail dependence between closed intervals  $a$  and  $b$  can be written as:

$$C_F = (a, b; \lambda) \quad (14)$$

$$= \frac{-1}{\lambda} \log \left( \frac{\lambda(1 - e^{-\lambda}) - (1 - e^{-\lambda a})(1 - e^{-\lambda b})}{1 - e^{-\lambda}} \right)$$

where,  $\lambda = \varepsilon(-\infty, 0) \cup (0, +\infty)$ .

### 3.2.3. Copula-VaR

For risk modelling of GBs and IFMs, VaR is employed, which is easy for a single asset portfolio but becomes challenging for a multiple asset portfolio. Computational problems arise with an increase in the number of assets in a portfolio due to a joint multivariate distribution enlargement. Such distributions do not provide appropriate results due to the asymmetry and excess financial data. Moreover, another challenge in estimating the VaR of a multiple series portfolio is to model the dependence structure of the FMs, particularly since VaR is associated with the tail of the distribution (Hotta et al., 2008).

Following Bianchi et al. (2010), we estimated the CoVaR model based on the Sklar (1959) theorem and created a multivariate normal distribution function to estimate the combined series's VaR. Mathematically, the CoVaR model for  $n$  endogenous variables is given as:

$$\mathcal{M}_{1,t} = \omega_1 + \sum_{i=1}^n \sum_{l=1}^p \varphi_{1,i,l} X_{i,t-l} + \sqrt{\hat{h}_{1,t}} \gamma_{1,t}$$

$$\mathcal{M}_{n,t} = \omega_n + \sum_{i=1}^n \sum_{l=1}^p \varphi_{n,i,l} X_{i,t-l} + \sqrt{\hat{h}_{n,t}} \gamma_{n,t} \quad (15)$$

where  $X_{i,t-1}$  is defined in terms of intercept  $\omega_j$  and autoregressive terms of order  $p$  and error term  $\hat{h}_{n,t} \gamma_{n,t}$ .  $\gamma_{n,t}$  is the standard innovation with zero mean and unit variance. In addition, the standardized error term has the conditional joint probability distribution  $\mathcal{H}_t(\gamma_{1,t}, \dots, \gamma_{n,t}; \theta)$  with parameter  $\theta$  that can be explained according to Sklar (1959).

$$(\gamma_{1,t}, \dots, \gamma_{n,t}; \theta) \sim \mathcal{H}_t(\gamma_{1,t}, \dots, \gamma_{n,t}; \theta) \quad (16)$$

$$\mathcal{C}_t = (F_{1,t}(\gamma_{1,t}; \alpha_1), \dots, F_{1,t}(\gamma_{n,t}; \alpha_n); \gamma) \quad (17)$$

where,  $\mathcal{H}_t$  is the conditional joint probability distribution of the standardized error term or innovation, and  $\mathcal{C}_t(., \gamma)$  represent the copula's commutative distribution margin of the standardized error term or innovation's marginal, expressed in the above equation as  $F_{1,t}(\gamma_{1,t}; \alpha_1), \dots, F_{1,t}(\gamma_{n,t}; \alpha_n)$ . Where  $\gamma$  denotes the copula, and the marginal parameter is expressed as  $\alpha_1, \dots, \alpha_n$ . However, a copula function connects two or multiple marginal distributions to construct a multivariate joint probability distribution for measuring the dependence structure between different variables flexibly without needing identical marginal distributions.

### 3.2.4. Hedge ratios and optimal weights

The academicians and practitioners consider hedging a central strategy to risk management. In the optimal portfolio combination, the investor takes a long position in the assets to safeguard their returns against market fluctuations (Chen et al., 2004). This study uses the hedge ratio and optimal portfolio weights method frequently employed in the finance literature by many researchers (Ahmad et al., 2018; Beckmann et al., 2015; Mensi et al., 2021; Naeem et al., 2021) to minimize risk. The exercise of hedging critically depends on the estimation of the hedge ratio and optimal portfolio weights for investment at the minimum and maximum levels. The development of an optimal portfolio based on portfolio allocation decisions and risk management depends on the accurate calculation of conditional variance estimates (Antonakakis et al., 2018; Mensi et al., 2021).

Following Antonakakis et al. (2018), we apply a dynamic conditional correlation-GARCH model to calculate hedge ratios, optimal weights, and hedging effectiveness. The main benefits of the DCC-GARCH model are the positive conditional covariance matrices and the parameterized dynamic conditional volatilities and correlations (Yousaf and Ali, 2020). Practically, Investors take a precautionary measure for hostile volatility movements by hedging their long and short positions. The asset's long (short) position is taken when the future volatility is expected to be higher (lower) than the current volatility. To construct the optimal hedge ratios, we assume that investor takes a long position in green bonds  $gb_t$  and a short position in international financial markets,  $ifm_t$ . Following Kroner and Sultan (1993), we estimate the beta hedge ratio to minimize the risk of GBs and the IFM's volatility.

$$\beta_{gbt, ifmt} = \frac{Cov(r_{gbt}, r_{ifmt})}{var(r_{ifmt})} = \frac{\lambda_{gbt, ifmt}}{\lambda_{ifmt}} \quad (18)$$

where,  $\lambda_{gbt, ifmt}$  is the non-negative conditional covariance of GBs and IFMs, and  $\lambda_{ifmt}$  is the conditional variance of the IFMs at time  $t$ . The conditional volatilities are used to calculate the optimal portfolio weights comprising GBs and IFMs (Kroner and Ng, 1998) as follows:

$$w_{gbifmt} = \frac{\lambda_{ifmt} - \lambda_{gbt}}{\lambda_{gbt} - 2\lambda_{gbt, ifmt} + \lambda_{ifmt}} \quad (19)$$

With

$$w_{gbifmt} = \begin{cases} 0, & \text{if } w_{gbifmt} < 0 \\ w_{gbifmt}, & \text{if } 0 \leq w_{gbifmt} \leq 1 \\ 1, & \text{if } w_{gbifmt} > 1 \end{cases} \quad (20)$$

where,  $w_{gbifmt}$  is the weight of the GBs volatility in a one-dollar portfolio of GBs volatility and one of the FM's volatility at time  $t$ .

Lastly, we estimate the constructed portfolios' hedging effectiveness (HE), using the optimal weights and hedge ratios to compare the realized hedging errors (Antonakakis et al., 2018; Mensi et al., 2021). The HE is computed as follows:

$$HE = \frac{\sigma^2_{unhedged} - \sigma^2_{hedged}}{\sigma^2_{unhedged}} \quad (21)$$

where,  $\sigma^2_{unhedged}$  is portfolio variance of either the GBs or FM's volatility, which is estimated from the DCC model, and  $\sigma^2_{hedged}$  is the hedged portfolio variance from the optimal portfolio weights strategy. A higher HE value indicates better HE.

## 4. Results and discussion

### 4.1. Descriptive analysis

Before proceeding to further analysis, we begin with the descriptive analysis of the underlying series. We calculate the returns of GBs and other IFM indexes by first differencing their natural logs. Fig. 1 presents the time series plots of the GBs and IFMs returns. The equity markets (traditional and Islamic) and the oil market experience higher and more volatile returns than the GBs. On the other hand, the GB index experience more dramatic upward and downward movements than the Sukuk bond, the movement is quite similar to the conventional bonds.

Table 1 presents the comprehensive descriptive statistical analysis, including central tendency (mean, median) and variability (standard deviation, minimum, maximum, and skewness) of GBs and IFMs. The GBs and all IFMs have favourable returns on average, except for the oil market. The IE has the highest average return of 0.0313%, while the oil Index (O) offers the minimum average return of -0.0527%.

As depicted in Table 1, O is much more volatile with a standard deviation of 0.0162 than the rest of the markets, possibly due to wild price-swings of oil in the last few years. Among all, the market offers the

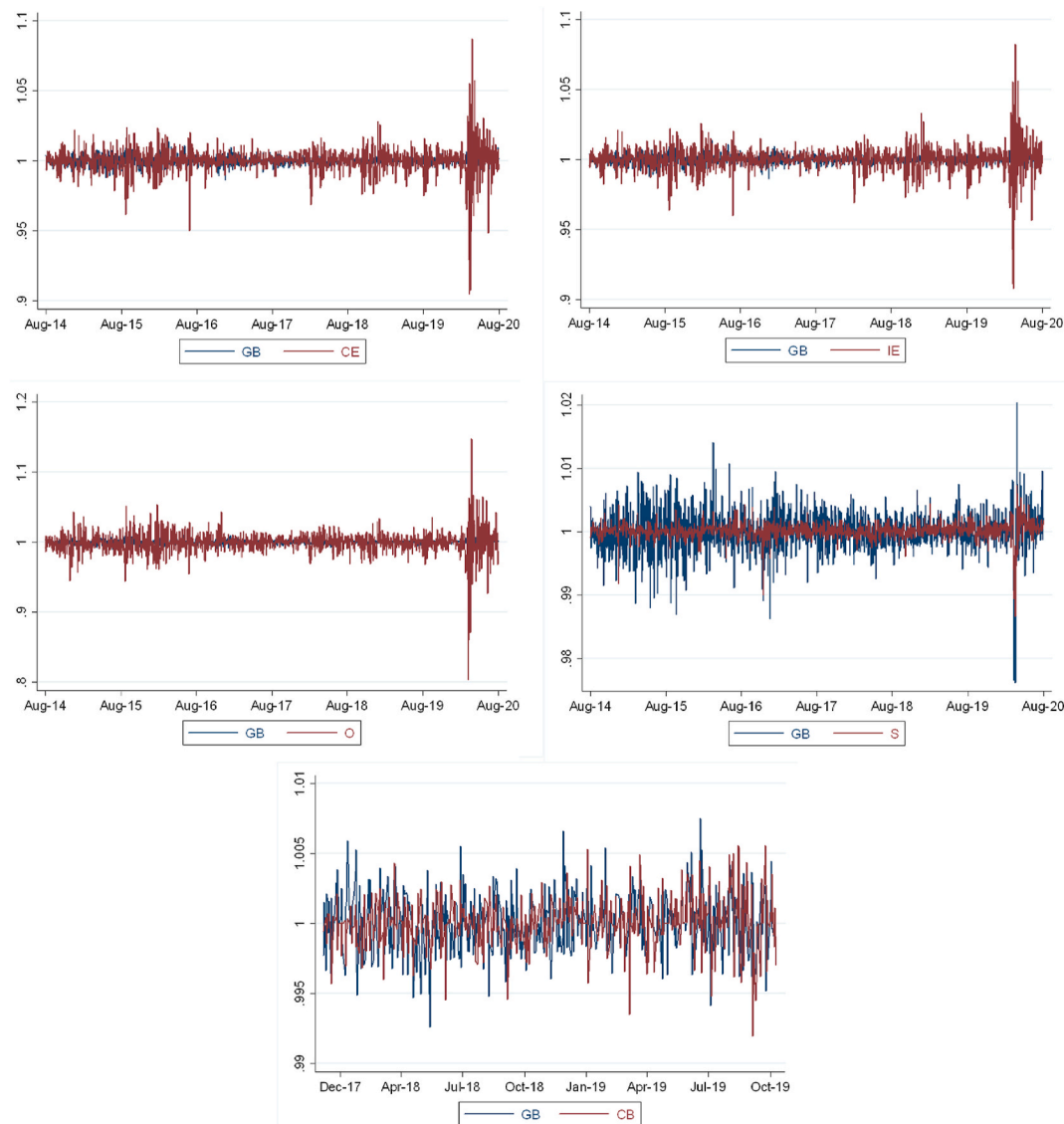


Fig. 1. Time series plots of GBs and IFMs Index returns.

**Table 1**  
Descriptive statistics.

| Variables | Mean (%) | Min (%)  | Max (%) | Median (%) | Std. Dev. | Skewness |
|-----------|----------|----------|---------|------------|-----------|----------|
| CE        | 0.0186   | −9.9758  | 8.3703  | 0.0459     | 0.0096    | −1.4876  |
| IE        | 0.0313   | −9.6386  | 7.9159  | 0.0546     | 0.0094    | −1.2489  |
| CB        | 0.0023   | 0.8060   | 0.5561  | 0.0000     | 0.0010    | −0.2052  |
| S         | 0.0172   | −1.3398  | 0.7293  | 0.0184     | 0.0013    | −2.0229  |
| GB        | 0.0056   | −2.4100  | 2.0130  | 0.0070     | 0.0032    | −0.5876  |
| O         | −0.0527  | −21.8646 | 13.7969 | −0.0259    | 0.0162    | −2.1856  |

This table displays the descriptive statistics of GBs and IFMs. Whereas CE = Logged returns of S&P Global 1200 (Gross Total Return), IE = Log returns of Dow Jones Islamic Market World Index, CB = Logged returns of FTSE World Government Bond Index, S = Logged returns of Dow Jones Sukuk Total Return Index (ex-Reinvestment), GB = Logged returns of S&P Green Bond Index, O = Logged returns of S&P Global Oil Index.

maximum return of 13.7969% and a minimum loss of −21.8646% in one day. The conventional bond (CB) volatility is considerably lower (0.0010) than other IFMs. The skewness coefficient is negative for all the series, suggesting that they are left-skewed and have a long-tail distribution on the left side.

#### 4.2. VaR estimation

For risk management, market risk measurement is crucial, as it

provides a fundamental approach to decision making. VaR is one of the standard risk measurement tools for estimating the systematic risk of an asset, financial security, or portfolio. This section measures the market risk of GBs and the IFMs by using VaR and CoVaR. For estimating VaR, Monte Carlo simulation is used, an enhanced VaR estimation method that allows for the joint distribution of the asset returns. It is one of the most widely and practically used methods in the financial risk management industry due to its high accuracy rate (Liyanage et al., 2017).

The VaR and CoVaR values determined by the Monte Carlo

simulation method for GBs and IFMs, at both the 95% and 99% levels, are presented in Table 2. Both values are higher at the 99% level than the equivalent values at the 95% level for all the series. Among all, the oil market (O) risk is higher than the GB and other IFMs. This could be attributed to the fact that there is wild fluctuation in the oil prices due to repetitive stormy and extreme events, e.g., oil price plunges of 2014–2016 and 2020, extreme declines in the oil prices since World War II. The maximum losses that the investor can bear in one day for O are  $-2.13\%$  and  $-3.01\%$ , at the 95% and 99% confidence intervals, respectively. Likewise, for O, the average expected losses represented by CoVaR are higher ( $-3.03\%$  and  $-3.96\%$ ), at both 95% and 99% levels, respectively. Our results reveal that the Islamic stock indices are less risky than conventional stocks. The results are consistent with Al-Khazali et al. (2014) and Jawadi et al. (2014), who found that Islamic stocks are less volatile than their conventional counterparts. These results could be attributed to less volatile Islamic stocks, probably due to the conservative nature of Sharia-compliant investments and companies' extra financial screening criteria (Akhtar and Jahromi, 2017; Al-Zoubi and Maghyereh, 2007).

The S&P Green Bond Index (GB) appears less risky than equity and oil markets. Amid all, the VaR ( $-0.51\%$  and  $-0.71\%$ ) and CoVaR ( $-0.75\%$  and  $-1.08\%$ ) values for GB are not too high, at both 95% and 99% levels, respectively. We found that the environmentally friendly GBs are more volatile than conventional and Islamic bonds. Although they belong to the same asset class, there are specific risks associated with the GBs; high corresponding environmental project risks, the high-risk profile of GBs issuers, relatively less mature and less orientation, uncertainty for the development of green technologies, e.g., investment only in the renewable energy sector or clean technology development (Elsayed et al., 2022; Löffler et al., 2021). Besides, this nexus of green label risk could reduce the greenium, a premium for GBs (Gianfrate and Peri, 2019), penalizing investors for going green (Karpf and Mandel, 2018). The Sukuk bond (S) appears to be less riskier among all, with the VaR values of  $0.20\%$  and  $0.28\%$ , respectively, at 95% and 99% levels. Moreover, the average expected losses are lower ( $-0.36\%$  and  $-0.53\%$ ) than other markets, respectively, at the 95% and 99% levels. Our results are consistent with the argument that the Sukuk, one of the most successful financial products, is ideal for investors requiring a fixed investment return with low risk (Bhuiyan et al., 2018; Godlewski et al., 2013).

#### 4.3. Estimation of copula models

We estimated Copulas to measure the degree and structure of the dependence between GBs and IFMs, as they accurately measure the asymmetric structure and nonlinear relationship among multiple risk factors. We employed the pseudo-maximum likelihood technique for calculating initial and final parameters to estimate Copulas. We used a large set of copula models (Gaussian, t-student, Gumbel, Frank, and Clayton copulas) to find the best fit. We used the output of one copula as an input of the next copula to measure the overall behaviour of markets across the tail distribution. After estimating all the Copulas, we select the most appropriate one based on the lower value of Akaike information criterion values (AIC).

**Table 2**  
VaR estimation.

| Series | Single Series |           |           |           |
|--------|---------------|-----------|-----------|-----------|
|        | VaR 95%       | VaR 99%   | CoVaR 95% | CoVaR 99% |
| CE     | $-1.29\%$     | $-1.82\%$ | $-2.15\%$ | $-2.63\%$ |
| IE     | $-1.28\%$     | $-1.80\%$ | $-2.10\%$ | $-2.60\%$ |
| CB     | $-0.29\%$     | $-0.41\%$ | $-0.40\%$ | $-0.48\%$ |
| S      | $-0.20\%$     | $-0.28\%$ | $-0.36\%$ | $-0.53\%$ |
| GB     | $-0.51\%$     | $-0.71\%$ | $-0.75\%$ | $-1.08\%$ |
| O      | $-2.13\%$     | $-3.01\%$ | $-3.03\%$ | $-3.96\%$ |

#### 4.4. Dependence structure of GBs and IFMs

The computational results of the marginal tail distribution of GBs and other IFMs for all Copulas are presented in Table 3. The table reports AIC, BIC (Bayesian Information Criterion), and upper and lower tail dependence for all Copulas. This paper uses the AIC to select the most suitable copula function from five alternative copulas.

The results show that the dependency structures vary from market to market. For the pairs of GBs and equity markets, CE and IE, the t-student copula is selected based on the lower value of AIC. The results indicate the existence of symmetric non-zero tail dependence characteristics between GBs and equity markets, with the upper (lower) tail dependence values of  $0.094$  and  $0.098$  for CE and IE, respectively. The t-student dependency model indicates that both good and bad information in the GB market similarly impacts returns. Similarly, the most suitable copula for the pairs of GB with S and O is the t-student copula. The results indicate asymmetric marginal tail distribution with the upper (lower) tail dependence values of  $0.198$  and  $0.096$  for S and O, respectively. Subsequently, the Clayton copula is selected for the CB as it has the lowest value of AIC. This copula is an asymmetric Archimedean copula that exhibits greater dependence in the negative tail than in the positive.

#### 4.5. Estimation of Copula-VaR

For an accurate description of the dependence between GBs and IFMs, we choose copula models with different tail characteristics and then estimate CoVaR using the best-fit copula model. The CoVaR model is used to overcome the shortcoming of the VaR for multiple asset portfolios to capture the VaR of portfolios (Huang et al., 2009). In this model, the portfolio's VaR is computed using the mixed GARCH-based model and copula, hence, also commonly known as the conditional Copula-GARCH model. We used normal distribution along with Student-t copula to incorporate both assumptions of tail distribution, i.e., symmetry or asymmetry of data for the tail distribution selection.

**Table 3**  
Dependence structure between GBs and IFMs.

|       | Copula   | AIC        | BIC        | Lower tail dep. | Upper tail dep. |
|-------|----------|------------|------------|-----------------|-----------------|
| GB-CE | Gaussian | 0.751      | 6.107      | 0.000           | 0.000           |
|       | t-       | $-47.054$  | $-36.342$  | 0.094           | 0.094           |
|       | Student  |            |            |                 |                 |
|       | Gumbel   | $-9.924$   | $-4.568$   | 0.000           | 0.053           |
|       | Clayton  | $-0.907$   | 4.450      | 0.000           | 0.000           |
| GB-IE | Frank    | 0.581      | 5.937      | 0.000           | 0.000           |
|       | Gaussian | $-2.730$   | 2.626      | 0.000           | 0.000           |
|       | t-       | $-50.168$  | $-39.455$  | 0.098           | 0.098           |
|       | Student  |            |            |                 |                 |
|       | Gumbel   | $-14.669$  | $-9.312$   | 0.000           | 0.000           |
| GB-CB | Clayton  | $-0.907$   | $-4.450$   | 0.000           | 0.000           |
|       | Frank    | $-2.963$   | 2.393      | 0.000           | 0.000           |
|       | Gaussian | 1.998      | 7.354      | 0.000           | 0.000           |
|       | t-       | 4.476      | 15.189     | 0.078           | 0.078           |
|       | Student  |            |            |                 |                 |
| GB-S  | Gumbel   | 2.000      | 7.356      | 0.000           | 0.000           |
|       | Clayton  | $-0.907$   | 4.450      | 0.000           | 0.000           |
|       | Frank    | 1.964      | 7.321      | 0.000           | 0.000           |
|       | Gaussian | $-172.460$ | $-167.104$ | 0.000           | 0.000           |
|       | t-       | $-225.874$ | $-215.161$ | 0.198           | 0.198           |
| GB-O  | Student  |            |            |                 |                 |
|       | Gumbel   | $-181.333$ | $-175.977$ | 0.000           | 0.262           |
|       | Clayton  | $-0.907$   | 4.450      | 0.000           | 0.000           |
|       | Frank    | $-152.507$ | $-147.151$ | 0.000           | 0.000           |
|       | Gaussian | $-0.241$   | 5.115      | 0.000           | 0.000           |
| GB-O  | t-       | $-38.879$  | $-28.166$  | 0.096           | 0.096           |
|       | Student  |            |            |                 |                 |
|       | Gumbel   | $-6.116$   | $-0.759$   | 0.000           | 0.050           |
|       | Clayton  | $-2.729$   | 2.627      | 0.000           | 0.000           |
|       | Frank    | $-0.149$   | 5.207      | 0.000           | 0.000           |

**Table 4**  
Tail distribution selection.

| Series | Marginal  | Marginal's AIC | Marginal's BIC | Selected  |
|--------|-----------|----------------|----------------|-----------|
| GB-CE  | Normal    | -13566.63      | -13555.92      | T-student |
|        |           | -10114.31      | -10103.6       |           |
|        | T-student | -13777.16      | -13761.09      |           |
| GB-IE  | Normal    | -10912.85      | -10896.78      | T-student |
|        |           | -13566.63      | -13555.92      |           |
|        | T-student | -10176.46      | -10165.74      |           |
| GB-CB  | Normal    | -13777.16      | -13761.09      | T-student |
|        |           | -10885.99      | -10869.92      |           |
|        | T-student | -13566.63      | -13555.92      |           |
| GB-S   | Normal    | -17145.11      | -17134.4       | T-student |
|        |           | -13777.16      | -13761.09      |           |
|        | T-student | -10912.85      | -10896.78      |           |
| GB-SPG | Normal    | -13566.63      | -13555.92      | T-student |
|        |           | -16398.49      | -16387.78      |           |
|        | T-student | -13777.16      | -13761.09      |           |
|        | Normal    | -10912.85      | -10896.78      |           |
|        |           | -13566.63      | -13555.92      |           |
|        | T-student | -8462.061      | -8451.348      |           |
|        | Normal    | -13777.16      | -13761.09      |           |
|        |           | -9050.389      | -9034.32       |           |
|        | T-student | -13761.09      | -13750.32      |           |

Table 4 presents the marginal AIC and BIC results for the pairs of GBs and IFMs. For VaR calculation, the best-fitted copula is selected based on the lower value of AIC and BIC. The results indicate that the t-student copula best describes the dependence structure of all the series, indicating the asymmetry of financial data and fatter tails of series.

We estimated the CoVaR of the GB with each IFM for all five copula models and selected the best fit with the lower value of AIC. To accurately examine the portfolio VaR, we estimated the changes in the VaR for both normally and non-normally distributed data. The comparative results of VaR and CoVaR for the market risk of single and paired (GB-IFMs) series, respectively, are presented in Table 5. The table shows the maximum expected losses, VaR and average expected losses, conditional VaR, that an investor could bear at the 95% and 99% confidence intervals.

As discussed earlier, the overall results of VaR indicate that the GB is a risky financial instrument and combining it with other asset classes makes them riskier at both quartiles. Generally, all the pairs show a similar pattern, an increase in individual risk of the series with the combination of GBs. When we look at the individual series, the results indicate that the VaR and CoVaR of the equity markets, CE and IE, are higher than GB, at 95% and 99% levels. CoVaR results show that combining GBs with the conventional equity market (GB-CE) increases the risk and tail-risk of the portfolio at both 95% and 99% confidence intervals. Similarly, combining GBs with the Islamic equity market (GB-IE) increased the risk from -1.28% to 2.74%, at a 95% confidence interval and from -1.80% to -7.406% at a 99% confidence interval. Moreover, the conditional VaR shows the same pattern of increment in risk from -2.10% to -4.79%, at a 95% level, and 2.60% to -12.77%, at a 99% confidence interval.

The conventional and Islamic bond markets, CB and S, are less risky than GB, as both are old and mature products with greater orientation and investors' confidence. Similar to the findings of equity markets, the combined risk of green and conventional bond series, GB-CB and GB-S,

**Table 5**  
Comparison of VaR and CoVaR.

| Series | Single Series |         |           |           | Series | Combined Series |         |           |           |
|--------|---------------|---------|-----------|-----------|--------|-----------------|---------|-----------|-----------|
|        | VaR 95%       | VaR 99% | CoVaR 95% | CoVaR 99% |        | VaR 95%         | VaR 99% | CoVaR 95% | CoVaR 99% |
| CE     | -1.29%        | -1.82%  | -2.15%    | -2.63%    | GB-CE  | -2.70%          | -7.17%  | -4.68%    | -12.33%   |
| IE     | -1.28%        | -1.80%  | -2.10%    | -2.60%    | GB-IE  | -2.74%          | -7.41%  | -4.79%    | -12.77%   |
| CB     | -0.29%        | -0.41%  | -0.40%    | -0.48%    | GB-CB  | -2.71%          | -7.07%  | -4.72%    | -11.89%   |
| S      | -0.20%        | -0.28%  | -0.36%    | -0.53%    | GB-S   | -2.88%          | -7.66%  | -4.93%    | -12.80%   |
| GB     | -0.51%        | -0.71%  | -0.75%    | -1.08%    | -      | -               | -       | -         | -         |
| O      | -2.13%        | -3.01%  | -3.03%    | -3.96%    | GB-O   | -3.33%          | -5.12%  | -4.10%    | -6.06%    |

increases at both 95% and 99% levels. This could be attributed to the strong relationship between green and non-green bonds due to macro-economic factors, e.g., economic activities, policy uncertainty, market volatility, news-based investors' sentiments, etc. (Broadstock and Cheng, 2019). Moreover, the GB market is interdependent and is strongly influenced by the CB markets, and there is a strong volatility spillover from GB to CB (Pham, 2016). Our findings confirm that the energy market is vulnerable and volatile (Azhgaliyeva et al., 2022; Reboredo and Ugolini, 2020; Saeed et al., 2021), possibly due to wild oil price fluctuation since 2014. The risk of the combined series, GB-O, is comparatively lower than other pairs, as both markets mutually affect each other prices, i.e., movement in oil prices leads to changes in GB prices and vice versa (Lee et al., 2021). Moreover, the price of GBs follows the trend of oil price; when there is an upward movement in the oil prices, the GB's interests also increase, resulting in higher incentives (Xia et al., 2019). When the oil market experiences large adverse fluctuations, the GBs incentives and interests also decrease (Dutta et al., 2020).

#### 4.6. Optimal weights and hedging ratios portfolio implications

Understanding how GB investors can hedge their investment is essential for risk management. As a final step of our analysis, we assess the importance of GBs as an effective hedger in investors' portfolios and help make optimal portfolio allocation decisions. Specifically, we estimate the hedge ratios and optimal portfolio weights using the DCC-GARCH model to identify minimum risk GB portfolios. GB is a new fixed-income sustainable-oriented financial instrument and can be very volatile (Pham, 2016); therefore, in this study, a long position is taken for the GBs and a short position for the rest of the portfolio assets.

Fig. 2(a-e) presents the levels of optimal hedge ratios estimated through GARCH models for the pairs of GB and each IFM. The hedge ratios of GB with all the markets show high variability, extreme upper tail's hedging for CE, IE, and O, while the lower tail's hedging for CB and S. The more detailed analysis, including summary statistics for hedge ratios and the values of optimal weight are reported in Table 6. For the sake of brevity, the interpretations here are only provided for the pairs where GB's position is long, as GB is considered a volatile asset in the long run (Naeem et al., 2021; Pham, 2016).

Panel A in Table 6 reports the summary statistics for hedge ratios. The results indicate that hedge ratios are not too high, indicating an effective hedge in GBs. For instance, the average hedge ratio between a long position in GB volatility and a short position in FM volatility ranged between \$0.01 to \$0.04, suggesting that the cheapest hedge for a \$1 long position in GB is obtained with a short position in S and O (\$0.01), while the most expensive with IE (\$0.04). Hence, IE is the least effective market to hedge against GB volatility. On the other hand, it is evident that among all IFMs, GB creates the most valuable hedge with S and O.

Hedgers adjust their portfolio allocation to maintain their target hedge ratios. Based on the hedge ratios discussed earlier, we calculated optimal portfolio weights to help investors create an effective hedge with GBs and other financial assets. Panel B of Table 6 shows that the optimal weights range between 0.83 and 0.84 for the conventional and Islamic equity markets. This result shows that for a \$1 budget, the

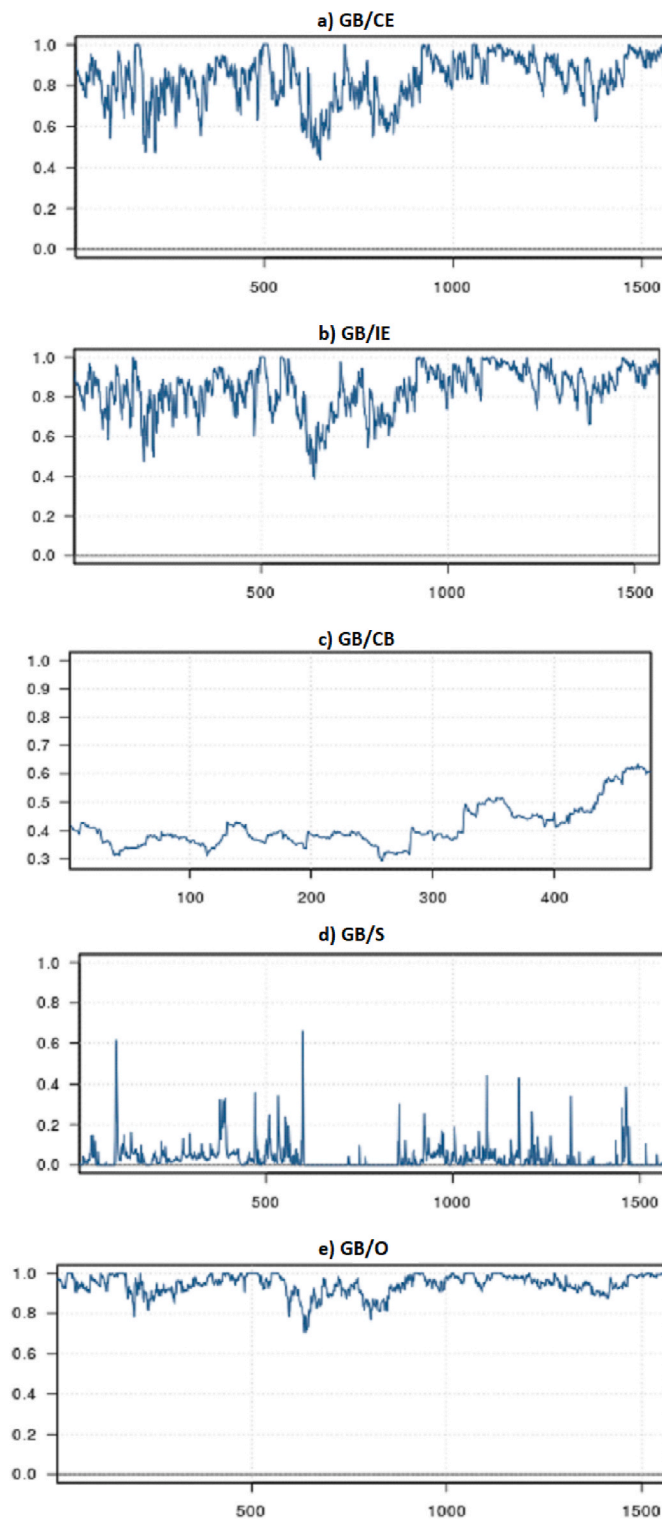


Fig. 2. (a–e): Optimal hedge ratios for GBs and IFMs.

investors should invest 83%–84% in GB and the remaining 17%–18% in CE and IE, respectively, to minimize risk. Concerning CB, the average weight is 0.40, indicating that for a \$1 portfolio, 40% should be invested in GB and the remaining 60% in CB to minimize risk without changes in the expected return. GB volatility assumes the lowest weight for both S and O, i.e., 0.06, indicating that for a \$1 budget, the investors should invest 6% in GB and the remaining 94% in each IFM, S, and O.

Table 7 reports the results of the HE; a higher value indicates greater

Table 6

Hedge ratios and portfolio weights: summary statistics.

|                                           | Mean | Std. dev | Min   | Max  |
|-------------------------------------------|------|----------|-------|------|
| <b>Panel A: Hedge ratios (long/short)</b> |      |          |       |      |
| GB/CE                                     | 0.02 | 0.07     | −0.09 | 0.15 |
| GB/IE                                     | 0.04 | 0.07     | −0.06 | 0.16 |
| GB/CB                                     | 0.03 | 0.00     | 0.02  | 0.04 |
| GB/S                                      | 0.01 | 0.04     | −0.05 | 0.09 |
| GB/O                                      | 0.01 | 0.04     | −0.05 | 0.09 |
| CE/GB                                     | 0.06 | 0.59     | −0.79 | 0.86 |
| IE/GB                                     | 0.16 | 0.51     | −0.57 | 0.85 |
| CB/GB                                     | 0.02 | 0.00     | 0.02  | 0.03 |
| S/GB                                      | 0.09 | 0.80     | −1.27 | 1.18 |
| O/GB                                      | 0.09 | 0.80     | −1.27 | 1.18 |
| <b>Panel B: Portfolio weights</b>         |      |          |       |      |
| GB/CE                                     | 0.83 | 0.12     | 0.61  | 0.99 |
| GB/IE                                     | 0.84 | 0.11     | 0.63  | 0.99 |
| GB/CB                                     | 0.41 | 0.07     | 0.32  | 0.59 |
| GB/S                                      | 0.06 | 0.05     | 0.00  | 0.16 |
| GB/O                                      | 0.06 | 0.05     | 0.00  | 0.16 |
| CE/GB                                     | 0.17 | 0.12     | 0.01  | 0.39 |
| IE/GB                                     | 0.16 | 0.11     | 0.01  | 0.37 |
| CB/GB                                     | 0.59 | 0.07     | 0.41  | 0.68 |
| S/GB                                      | 0.04 | 0.05     | 0.04  | 1.00 |
| O/GB                                      | 0.04 | 0.05     | 0.04  | 1.00 |

Table 7

Performance of an optimal hedge ratio and portfolio weights strategies.

|       | $\beta_t$ | $w_t$ | HE     |
|-------|-----------|-------|--------|
| GB/CE | 0.02      | 0.83  | 0.15** |
| GB/IE | 0.04      | 0.84  | 0.12** |
| GB/CB | 0.03      | 0.41  | 0.58** |
| GB/S  | 0.01      | 0.06  | 0.96** |
| GB/O  | 0.01      | 0.06  | 0.96** |
| CE/GB | 0.06      | 0.17  | 0.91** |
| IE/GB | 0.16      | 0.16  | 0.9**  |
| CB/GB | 0.02      | 0.59  | 0.43** |
| S/GB  | 0.09      | 0.04  | 0.04   |
| O/GB  | 0.09      | 0.04  | 0.04   |

Note:  $\beta_t$  and  $w_t$  refer to hedge ratios and portfolio weights, respectively. \*, \*\* indicates significance at the 5% and 1% levels, respectively.

risk reduction. Generally, the HE is positive for all the markets. However, it is evident that among all IFMs, GB has the highest HE for S (0.96) and O (0.96), implying that the GB index is the best hedge against the market risk of S and O. Our results for the energy market, concurs with the findings of previous studies indicating that GBs offer diversification benefits against the risk of energy markets (Kuang, 2021; Naeem et al., 2021; Nguyen et al., 2021; Reboredo, 2018; Reboredo et al., 2020; Saeed et al., 2021).

## 5. Conclusion

Over the years, the GBs have become one of the most popular fixed-income green financial instruments to scale up the transition to a climate-resilient economy. The recent years' explosive growth of the GB market has escalated the researcher's interest in understanding their risk dynamics for optimal portfolio diversification. This study contributes to the increasing body of knowledge by examining the GB's market risk, dependence structure, hedge effectiveness, and portfolio diversification benefits with other IFMs (traditional equity, Islamic equity, conventional bond, Islamic bond, and oil markets).

The empirical results of market risk (VaR and CoVaR) revealed that the oil market is riskier among all IFMs, probably due to wild oil price fluctuations since 2014. On the contrary, the Islamic bond (Sukuk) is one of the less risky asset classes, ideal for risk-averse investors. The environment-friendly GBs are less risky than equity and oil markets,

while they appear riskier than conventional and Islamic bonds. Moreover, the market risk of the paired series (GB-IFM) increased at both quartiles due to the riskier nature of GBs. Hence, our findings confirm that GBs possess specific green label risks, including risky eco-friendly projects, issuer's profile, and uncertainty of new green technologies (Löffler et al., 2021). Investors could use these results to make informed investment decisions and selection of asset classes as per their risk appetite and tolerance.

The Copula estimates reveal the existence of symmetric upper and lower tail dependencies between GBs and other IFMs, except for the CB market. The findings imply zero tail dependence between GB-CB during extreme negative market conditions. Additionally, the maximum upper and lower tail dependence exists between GB-S, probably due to extra environmental and ethical responsibilities. Moreover, both asset classes protect investors with asset backing, extra financial screening, and investment criteria, hence experiencing a similar level of booms and busts. Similarly, there is symmetric tail dependence among GB-CE, GB-IE, and GB-O, suggesting that the investors should carefully use these combinations for portfolio construction and allocation of resources, especially for the upward and downward swings of the market. Overall, the findings suggest that all IFMs possess different risk profiles, and the investors should not treat them as homogenous assets while combining them with GBs. These findings are particularly important for investors during extreme market conditions. Further analysis reveals that the GB index has the highest hedging effectiveness for S and O, signifying that fund managers and traders could use both to maximize their returns. As the results unveil that GBs are a riskier asset class, the investors could adjust their portfolios according to the suggested optimal portfolio weights to hedge against the market volatility of GBs.

Our findings have several implications for investors and policymakers to strengthen the future sustainability of the GB market by directing financial resources toward green projects. Specifically, the hedging effectiveness of GBs with other IFMs will help investors safely invest in the GBs, which potentially aims to offer better liquidity, resilience, sustainability, transparency, and reputation (Reboredo, 2018; Naeem et al., 2021), thereby promoting energy-efficient, environmentally friendly projects. Moreover, Investors and fund managers can hedge their investments against their portfolio's revelation to long-term environmental controlling risks associated with the evolution of a climate-friendly economy. On the other hand, these findings would also lend credibility to policymakers' belief that GBs could be a feasible means to deal with the threats of climate and environmental challenges.

In addition, investors need to be critically aware of the possible shocks/news in the oil market to maximize return and minimize losses, as our results suggest that the GB and oil market mutually affect each other prices, and the risk of combining both is comparatively lower than other IFMs. Our overall results suggest that the GB market could be used to decrease climate-related financial instability and global warming by reducing the fiscal pressure on environmental protection and management.

This research has some limitations that provide inspiration for further research. This study found that each IFM possesses a different risk profile and behaves differently when combined with GBs. It would be interesting to determine the factors affecting the relationship between GBs and other IFMs during different investment timelines. Another unexplored research focuses on generalizing the results for other green asset classes, including green equities, exchange-traded funds, and mutual funds. These results will help those who wish to make the world greener by persuading IFMs to stabilize and increase eco-friendly economic activities.

#### CRediT authorship contribution statement

**Rimsha Ejaz:** Conceptualization, Methodology, Formal analysis. **Sumaira Ashraf:** Conceptualization, Methodology, Writing – original draft. **Arshad Hassan:** Supervision, Validation, Writing – review &

editing. **Ankit Gupta:** Visualization, Software, Writing – review & editing.

#### 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.

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