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Impacts of COVID-19 outbreak, macroeconomic and financial stress factors on price spillovers among green bond

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ABSTRACT

We examine the impacts of the COVID-19 pandemic and global risk factors on the upside and downside price spillovers of MSCI global, building, financial, industrial, and utility green bonds (GBs). Using copulas, CoVaR, and quantile regression approaches, we show symmetric tail dependence between MSCI global GB and both building and utility GBs. Moreover, the upper tail dependence between MSCI global GB and financial GB intensified during COVID-19. We find asymmetric risk spillovers from MSCI global GB to the remaining GBs. Finally, the COVID-19 spread, the Citi macro risk index, and the financial condition index contribute positively to the quantiles' risk spillovers. The spillover index method shows significant dynamic volatility spillovers from global GB to GB sectors that intensify during the pandemic outbreak, except for financial GB. The causality-in-mean and in-variance from COVID-19, Citi macro risk index, and US financial condition index to the downside and upside spillover effects are sensitive to quantiles

1. Introduction

Green bonds (GBs) are a new financial asset. They aim to enhance environmental projects and social welfare. Like non-green bonds, companies can issue GBs to raise capital and finance their environment-friendly projects (reducing CO2 emissions and fighting pollution). The various purposes funded by green bonds (MSCI Global GBs, Building GBs, Industrial GBs, Financial GBs, and Utility) have expanded beyond alternative energy to green building and sustainable transportation projects. The investment in GBs shows increasing growth since 2015 (see Fig. 1) despite the fact that clean energy finance represents a small fraction of the financial markets (Le, Le, & Taghizadeh-Hesary, 2020; Pham & Huynh, 2020). The creation of this new financial product is to fund environmentally sustainable projects.[1] Investors are interested in this new asset class due to its low correlations with other financial assets (Reboredo, 2018; Rehman, 2020). Thus, GB may serve as a potential diversifier asset. In addition, investors are interested in understanding the dependence and spillover effects among GBs in order to check whether they can build a portfolio composed of different GB assets. In theory, the fundamentals-based hypothesis stipulates that the spillovers among financial assets result in fundamental changes (Ng, 1990; Karolyi & Stulz, 1996; King, Sentana, & Wadhwani, 1994). For example, the way that managers handle the corporation may alter the stock prices, generating time-varying spillover among different markets. The investor-induced hypothesis assumes that the behavior of international investors drives the spillover among markets. Herding behavior is the source of contagion effects (Boyer, Kumagai, & Yuan, 2006). Correlations between market returns are stronger during market downturns than during market upturns. This result suggests that contagion may be asymmetrical. Therefore, the spillover size and directions may affect the hedging demand during bearish and bullish market scenarios. Thus, the spread of crisis and information from one country to another may influence the portfolio structure during different market conditions. Kodres and Pritsker (2002) developed a theoretical model of financial contagion through cross-market portfolio rebalancing. Investors become aware of climate change for government policies and climate-related risks for companies.

However, the recent COVID-19 pandemic outbreak caused a significant shift in the world's economic and financial markets (Hanif, Mensi, & Vo, 2021; Mensi, Rehman, & Vo, 2021). Causing more than 196

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[1] For more information on GB markets, see the Climate Bonds Initiative https://www.climatebonds.net/resources/reports/2019

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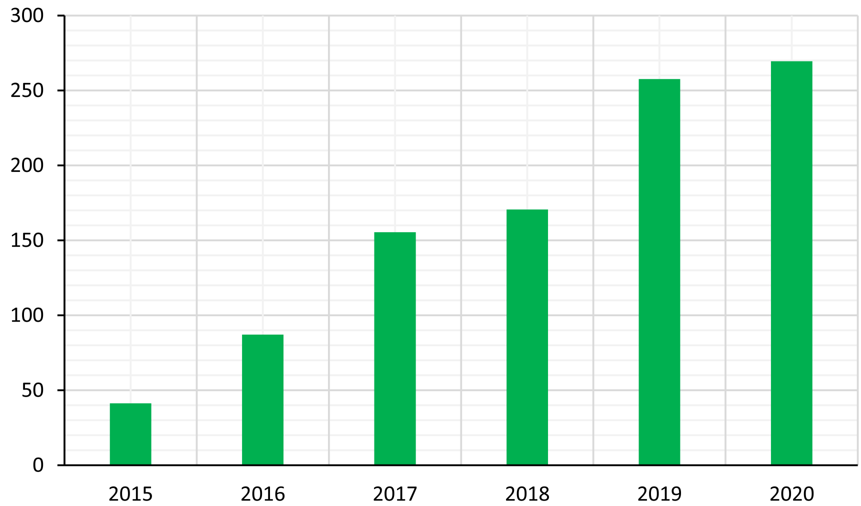


Fig. 1. Evolution of global GB issuance (in USD bn) between 2015 and 2020.
Source (https://www.climatebonds.net).

million confirmed cases and 4.2 million deaths in July 2021, this unprecedented pandemic crisis increased risks, uncertainties, fear, and volatility in financial markets of both developed and emerging economies. On the one hand, the massive rise in the number of confirmed cases pushes governments to impose strict containment measures, such as suspending business operations, locking down cities, restricting people's activities, and social distancing, all of which result in significant economic development slowdown. Moreover, the critical declines in consumer spending, supply chain disruptions, along with workforce shortages have led many businesses to cease operations. Therefore, the ongoing COVID-19 crisis has significantly increased the uncertainty and volatility of financial markets, leading to a strong economic recession (Elgammal, Ahmed, & Alshami, 2021). According to the IMF, global economic growth fell by 3.2% in 2020 due to the health crisis. Besides, international trade declined by 8.2% in 2020. The contingent effects of the health crisis have altered the fear, the preference, the risk appetite, and the herding behaviors of investors (Truelove, Carrico, Weber, Raimi, & Vandenbergh, 2014). This has intensified the exposure to cross-country spillovers, and the chaos seems to have spread across overall markets. The contingent effects of the global health crisis have augmented the fear and the herding behaviors as well as bidirectional shock spillovers. This has increased the contagion and spillovers among markets. According to Rizwan, Ahmad, and Ashraf (2020), banking risk has risen sharply in the world's eight major countries, including China, Canada, France, Italy, Germany, Spain, the US, and the UK. Similarly, Albulescu (2020) highlights the substantial impact of COVID-19 on the volatility index of the world's major financial markets. Ashraf (2020) concludes that equity market returns decrease as the number of confirmed cases increases, indicating a negative relationship between stock market returns and the COVID-19 pandemic growth. Lucey, Vigne, Yarovaya, and Wang (2021) show that the COVID-19 crisis intensifies the cryptocurrency index's price and policy uncertainty (UCRY). This UCRY index has predictability power in cryptocurrency markets during the COVID-19 pandemic spread.

Only a few studies have examined the relationships between GB prices and other financial assets (Ferrer, Shahzad, & Soriano, 2021; Reboredo, 2018; Reboredo & Ugolini, 2020). To the best of our knowledge, our research is the first to examine the dependence structure and risk spillovers among main GBs, as well as the determinants of spillovers under bear and bull market status. We augment our analysis with popular robustness tests. Specifically, we examine the evolving volatility spillovers between global GBs and their main GB sectors using the spillover index of Diebold and Yilmaz (2012). Moreover, we test the presence of quantile causality from both the COVID-19 crisis, the Citi Macro risk index, and the US financial condition index for upside/downside spillovers. For this purpose, we use the causality-in-mean and in-variance methods of Balcilar, Bekiros, and Gupta (2017). This study is informative for individual and institutional investors interested in clean energy finance.

This paper contributes to the limited empirical literature on GB in three ways. First, it examines the dependence structure between MSCI Global GB and Building, Utility, Financial, and Industrial GB price returns under bear, tranquil, and bull market conditions. Second, it investigates the asymmetric risk spillovers from MSCI Global GB to Building, Utility, Financial, and Industrial GB price returns. Third, we examine the determinants of the up/down risk spillovers by relying on the CITI Macro risk index, US Financial condition index, and COVID-19 outbreak under bear and bull market conditions. Our paper applies a battery of symmetric, asymmetric, time-invariant, and time-varying copula functions to examine the lower and upper tail dependence among markets under study. Our paper considers Normal copula, Student-t copula, Clayton copula, rotated Clayton copula, Gumbel, rotated Gumbel, and Symmetrized Joe-Clayton (SJC) copulas. In addition, we use the Value at Risk (VaR) and the conditional Value at Risk (CoVaR). The CoVaR captures the systemic risk from one market to another. More precisely, CoVaR identifies the presence of risk spillovers between assets by providing information on the VaR of an asset i, conditional on the fact that another market j is in financial distress. The quantile regression approach (QRA) provides valuable insights on the effects of the market i on the market j under different market statuses, including bearish (lower quantile) and bullish (upper quantile) markets (Mensi, Hammoudeh, Reboredo, & Nguyen, 2014). Baur (2013) argues for using the QRA to study the structure and degree of dependence as it can reveal information on the asymmetric and nonlinear effects of conditional variables on the dependent variables.

For robustness purposes, we examine the time-varying volatility spillovers between global GB and sectoral GBs before and during the COVID-19 pandemic spread using the spillover index by Diebold and Yilmaz (2012). This approach predicts the size and the net directional volatility spillovers among GB markets. It determines the percentage of risk received and transmitted for each market in the system. It is, therefore, able to capture the source of valuable contagion for portfolio risk management and asset allocations. It helps market participants determine whether the price transmissions from one market to another are time-varying and crisis sensitive. On the other hand, we explore whether the control variables cause the spillover strengths across different quantiles using the quantile causality test. The causality-in-mean and in-variance allow one to determine whether global GB has

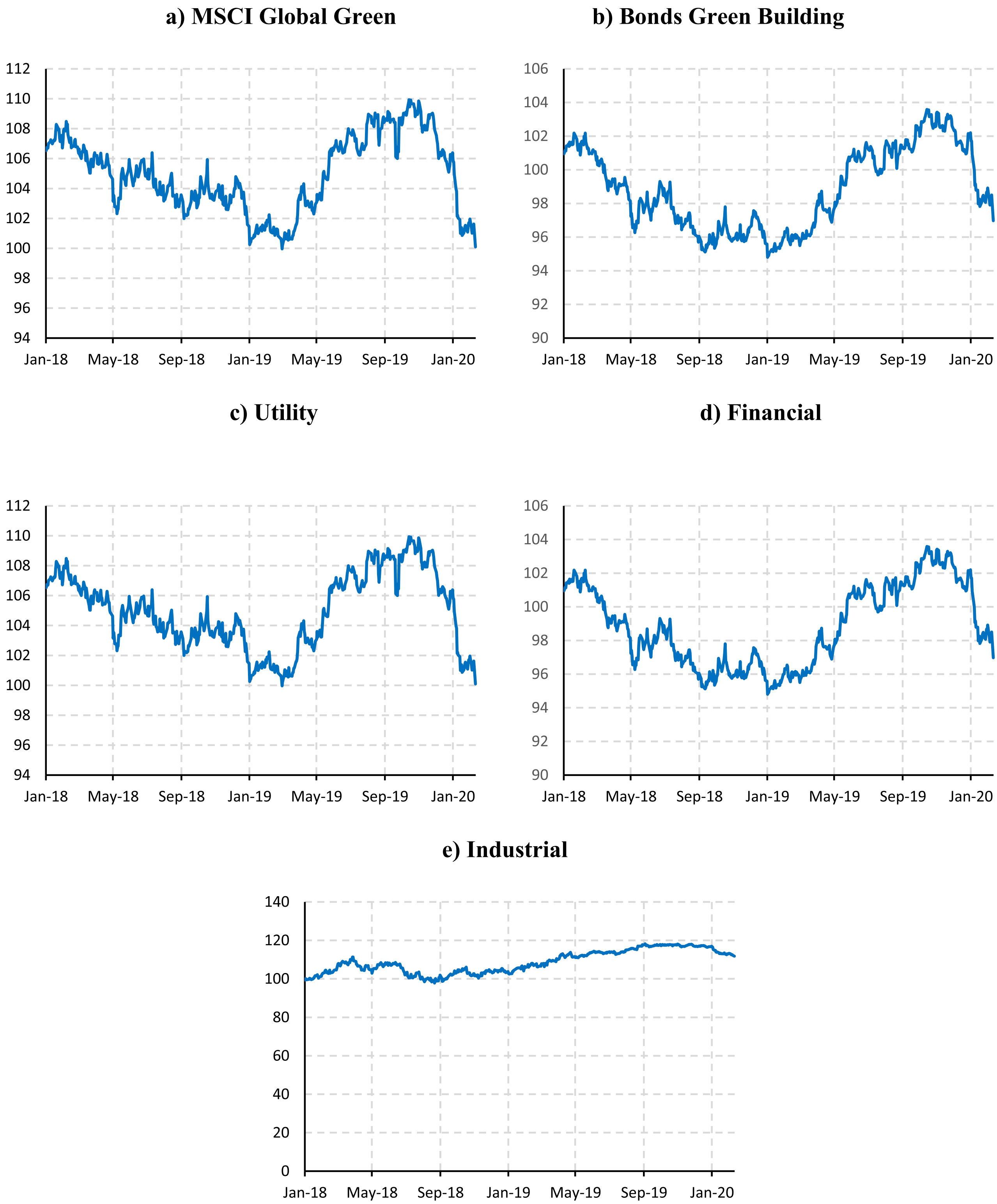


Fig. 2. Dynamic of GB daily prices.

predictive power for GB sectors. The nonparametric causality-in-quantiles test examines the predictability of the mean and variance of GB sectors through global GB. This method provides valuable information on the interactions among GB markets as it accounts for all market conditions jointly (e.g., bubbles, crashes, crises, and low/high volatility). Overall, the adopted methodology improves our understanding of the evolving volatility connectedness and informs investors about potential diversification benefit opportunities.

Our results show significant temporal and symmetric tail dependence between MSCI Global GB and Building and Utility GB during bear and bull market conditions. Moreover, an upper tail dependence is identified between MSCI Global GB and Financial GB. A Symmetrized JC copula reveals that Industrial GB has asymmetric tail dependence on MSCI Global. Furthermore, we find significant asymmetric risk

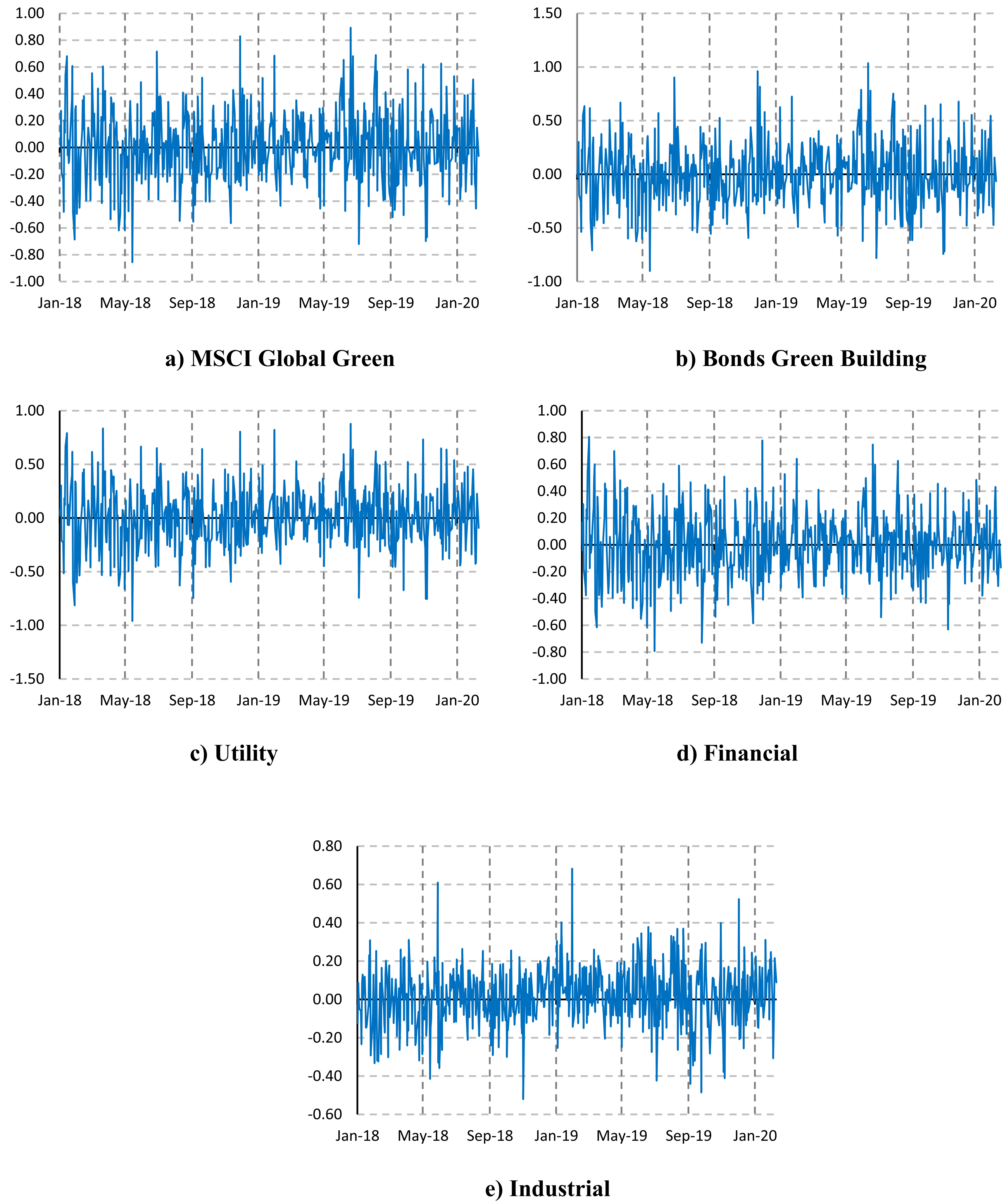


Fig. 3. Dynamics of GB daily price returns.

spillovers from MSCI Global GB to sectoral GBs intensified during the global health crisis. More importantly, the Citi Macro risk index positively impacts the upside risk spillover of Utility and Financial GBs across different quantiles. However, the Macro risk index contributes to the upside risk spillovers of Building at lower quantiles but has an insignificant impact on the upside risk spillovers of Industrial GB. The financial condition index affects negatively the upside spillovers of Industrial GB at low and high quantiles. The COVID-19 crisis influences the upside and downside spillover effects, with the exception of Industrial GB. The volatility spillover between global GB and sectoral GBs is time-varying and shows a significant jump during the pandemic. Finally, we find substantial causality in-mean and in-variance between markets under investigation, which is asymmetric and sensitive to quantiles.

The remainder of this paper is organized as follows. Section 2

Table 1
Descriptive statistics of GB price returns.

Statistics	MSCI Global	Building	Utility	Financial	Industrial
Mean	0.0051	0.0070	0.0077	0.0054	0.0203
Std. Dev.	0.3294	0.3275	0.3531	0.2905	0.4221
Kurtosis	1.6251	1.1550	3.4190	1.5767	5.7124
Skewness	−0.1597	−0.1223	−0.2779	−0.1033	−0.3839
Minimum	−1.6023	−1.4714	−2.1350	−1.5708	−2.5279
Maximum	1.6000	1.2426	2.1083	1.3321	1.9122
Jarque-Bera	155.226***	78.723***	680.814***	143.058***	1886.84***
Observations	550	550	550	550	550
ADF	−38.5393***	−38.6542***	−37.9844***	−37.4757***	−43.4832***
PP	−38.6736***	−38.6891***	−38.1323***	−37.5699***	−43.6627***
ARCH (20)	2.2112***	2.1826***	3.1330***	1.9373***	21.1771***
Q (20)	30.029*	33.372**	17.646	15.111	84.928***
Q^2(20)	64.321***	56.921***	64.331***	51.863***	1728.6***

Notes: This table reports the preliminary statistics of global and sectoral GB price returns. ADF and PP indicate Augmented Dickey Fuller and Phillips and Perron, respectively. The ARCH(20) test verifies the presence of ARCH effects. Q(20) and Q^2(20) refer to the empirical statistics of the Ljung-Box test for autocorrelation and squared autocorrelation, respectively. The asterisks *, **, and *** represent the rejection of the null hypothesis at the 10%, 5%, and 1% significance levels.

presents a review of the literature. Section 3 discusses the data and methodology. The empirical results are reported and discussed in Section 4, and a conclusion is presented in Section 5.

2. Literature review

There is limited empirical literature studying the relationships between GBs and financial markets. Reboredo (2018) shows that spillovers from conventional bonds influence GBs and that GB assets provide significant diversification gains for stock and energy markets. Reboredo and Ugolini (2020) examine the price spillovers between GBs, global government bond markets, global graded fixed-rate corporate debt, global high-yield debt markets, global stock markets, and USD currency markets. They find that GBs are net receivers of price spillovers. Ferrer et al. (2021) use the frequency dynamic spillover index of Baruník and Křehlík (2018) to show significant short-term spillovers between GBS and conventional financial and energy markets in the short term. Tiwari, Abakah, Gabauer, Adjei, and Dwumfour (2022) have recently investigated the return spillovers between S&P Green Bond, Solactive Global Solar, Solactive Global Wind, S&P Global Clean Energy, and Carbon price indexes. Using the TVP-VAR approach, the authors show that the total connectedness is time-varying and influenced by major events. Clean energy is a net transmitter of shocks in the system, whereas Green Bonds and Solactive Global Wind are net receivers of shocks in the system. Pham and Huynh (2020) examine the relationships between investor attention and GB markets. They show that investor attention can influence GB returns and volatility. Moreover, the authors find strong short-term interdependence between investor attention and GB market returns and volatility. Naeem, Mbakri, Altharthi, Omri, and Shahzad (2021) examine the impacts of the COVID-19 crisis on the frequency of spillovers between GBs and other financial and commodity markets (global stock market, bond market, oil, USD index, gold, and Bitcoin). Using both Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) methodologies, the authors find evidence of bi-directional spillovers between the USD index and GBs that intensified during the pandemic crisis. The authors also find a strong connection between GB and conventional bonds. Weak short- and long-term linkages between GBs and Bitcoin market are identified. Zamojska, Mosionek-Schweda, and Golab (2020) find that GBs are integrated with other financial markets. Hachenberg and Schiereck (2018) show that financial and corporate GBs trade tighter than their comparable non-green bonds, and government-related bonds, on the other hand, trade marginally wider. Tang and Whang (2020) show that GB issuance contributes positively to stock prices and liquidity. Moreover, the lower cost of debt does not fully explain the positive stock returns around green bond announcements. More importantly, institutional ownership rises after the firm issues GBs. Flammer (2021) confirms the findings of Tang and Whang (2020). The author shows a positive reaction from investors to GB issuance, especially for bonds certified by third parties and first-time issuers. Guo and Zhou (2021) show that GB was a good hedge asset during the COVID-19 crisis for US and Chinese financial markets. Other studies have examined the relationships between GB and other financial assets (Glomsrød & Wei, 2018; Hammoudeh, Ajmi, & Mokni, 2020).

Our study contributes to the literature by examining the lower and upper tail dependence between MSCI Global Green and both Building GBs, Industrial GBs, Financial GBs, and Utility GBs, using a variety of copula functions. Moreover, we analyze the downside and upside spillovers from MSCI Global Green and GB sectors (Building, Industrial, Financial, and Utility) using a conditional Value at Risk measure. For robustness, we investigate the volatility spillovers from global GBs to sector GBs using the spillover index by Diebold and Yilmaz (2012). For robustness, we analyze the drivers of spillovers. More precisely, we use the quantile causality in-mean and in-variance and test the causality from the COVID-19 pandemic crisis, the Financial condition index, and the Citi Macro risk index to upside/downside GB risk spillovers. Our empirical methods offer great flexibility and provide new insights into the linkages among GB markets.

3. Data and methodology

3.1. Data and summary statistics

We use daily closing spot prices of primary green bonds, namely MSCI Global GB, Building, Industrial, Financial, and Utility GBs. We select daily data in order to provide robust results in our estimations. Specifically, daily data evaluates the immediate market response to news announcements (Pastor & Veronesi, 2012). The use of low-frequency data (weekly, monthly, and quarterly) makes detecting an announcement shock and its immediate effects more difficult (Ferrari, Kearns, & Schrimpf, 2016). In addition, low-frequency data fails to deal with holidays and lead-lag relationships. Therefore, daily data is adequate for short-term and medium-term tactical forecasting. We notice that different days of the week have different patterns, which can be identified at this level. The sample period starts from January 2, 2018, to April 30, 2020 (550 daily observations). The data was compiled by Bloomberg. The selection period begins on January 2, 2018, to highlight the changing behavior of price spillover between GBs from tranquil to financially turbulent periods. This also provides us a baseline for a better understanding of the changes during the COVID-19 crisis. Fig. 2 depicts the evolution of GB prices and shows a similar trend among all GBs except the industrial GB. We observe that GB prices declined in 2018 because rising interest rates weighed on all debt issuance and during the COVID-19 outbreak. It is worth noting that GB prices experienced an upside trend in 2019. This is explained by the fact

Table 2
Unconditional correlation matrix among GB price returns.

	MSCI global	Building	Utility	Financial	Industrial
MSCI Global	1				
Building	0.9869***	1			
Utility	0.9654***	0.9279***	1		
Financial	0.9366***	0.8890***	0.9389***	1	
Industrial	0.6660***	0.6688***	0.6775***	0.5166***	1

Notes: This table reports the linear unconditional correlations among leading GB price returns. *** stands for significance level at 1%.

that investor demand has increased. Fig. 3 illustrates the time-varying GB price returns and shows evidence of volatility clustering and fat tails. This indicates evidence of a non-linear process.

Table 1 presents the descriptive statistics, correlation degree, unit root test, and Ljung Box test of GB price returns. The results show positive average price returns for all GBs. Industrial GB exhibits the highest average returns, while MSCI Global GB shows the opposite; Industrial GB has the highest risk, but Financial GB has the lowest. The hypothesis of the normal distribution is rejected according to the skewness, kurtosis, and Jarque Bera test. According to the Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) unit root tests, all GB price returns show stationary behavior. The results of the Ljung-Box test statistics of the residuals reject the null hypothesis of the white noise process (i.e., an i.i.d. process). Similarly, the results of the ARCH test of Engle (1982) reject the null of no ARCH effects. The preliminary analysis of GB price returns supports the presence of stylized facts (fat-tails, clustering volatility, persistence for the GB price returns).

Table 2 reports the results of the unconditional correlation matrix among GB price returns. The correlation between MSCI Global GB with Building, Financial, and Utility GBs is high (above 0.93), limiting the diversification benefits and indicating a recoupling between these assets. In contrast, we find a low correlation between MSCI Global GB and Industrial GB (0.66), suggesting a diversification opportunity. In addition, we observe that the correlation degree between Financial GB and Utility GB is high (0.93) and is 0.88 for Utility GB. The Industrial GB exhibits less correlation with the rest of the GBs as it ranges from 0.51 for Financial GB to 0.67 for Utility GB.

3.2. Methodology

3.2.1. Copula modeling

Copula provides great flexibility in separating the marginal distributions from the dependence structure and independently modeling these distributions. In contrast to the unconditional linear correlation coefficient, the copula does not require that price series follow a Gaussian distribution. Thus, copulas assess the temporal and non-linear dependence between the marginal distributions of the random variables instead of focusing directly on the dependency between the random variables themselves (Kakouris & Rustem, 2014; Luo, Liu, & Wang, 2021). It explored the monotonic relationships among the margins. Accurate modeling of financial risk contagion and extreme dependence are crucial for financial risk management. Copula is flexible enough to evaluate the financial contagion among markets as it happens. The copula approach offers valuable, useful information not only on average dependence but also on the likelihood that two variables will jointly experience extreme downside or upside movements. The Copula allows investors and portfolio managers to identify the property of an asset as a hedge or a safe haven. We select Elliptical copula, including Normal and Student-t copulas, as well as Archimedean copulas such as Clayton, Rotated Clayton, Gumbel, Rotated Gumbel Copula, and SJC Copula. Elliptical copulas assess the symmetric dependence by assuming similar relationships between variables during bearish and bullish market conditions. Conversely, the Archimedean copula assumes asymmetric dependence during market slumps and expansion.

We test the time-varying average and tail dependence between global green bonds and green bonds of the building, utility, financial, and industrial sectors using a set of time-varying copulas.[2] The underlying theory behind copulas is based on the Sklar theorem, stating that the joint distribution function, i.e. $F_{XY}(x,y)$ based on two continuous random variables, X and Y under copula specification $C(u,v)$ can be expressed as appended below.

$$F_{XY}(x,y) = C(u,v) \tag{1}$$

In Eq. (1), $u = F_X(x)$ and $v = F_Y(y)$ represent marginal distribution functions of random variables, suggesting that the copula is a multivariate function comprising uniform marginals describing dependence between two random variables. Such dependence is determined based on $RanF_x$ * $RanF_y$ for continuous margins, where $RanF_x$ and $RanF_y$ represent marginal distribution functions of random variables.

The joint probability density function of two series X and Y obtained from the copula density function, $c(u,v) = \frac{\partial^2 C(u,v)}{\partial u \partial v}$ is as follows.

$$f_{XY}(x,y) = c(u,v) f_Y(y) f_X(x) \tag{2}$$

where $f_Y(y)$ and $f_X(x)$ denote marginal densities of series Y and X, respectively. The information about marginal and copula densities is required to determine the joint densities of two variables, X and Y. Expressions for both the upper (right) and lower (left) tail dependence is below.

$$\lambda_U = lim_{u \to 1} Pr\left[X \geq F_X^{-1}(u) \,|\, Y \geq F_Y^{-1}(u)\right] = lim_{u \to 1} \frac{1 - 2u + C(u,u)}{1 - u} \tag{3}$$

$$\lambda_L = lim_{u \to 0} Pr\left[X \leq F_X^{-1}(u) \,|\, Y \leq F_Y^{-1}(u)\right] = lim_{u \to 0} \frac{C(u,u)}{u} \tag{4}$$

where λ_U, $\lambda_L \in [0,1]$, which suggests a non-zero probability of an extremely small (large) value for one series with an extremely small (large) value for another series. Our work employs seven different time-varying copulas consisting of Normal, Clayton, rotated Clayton, Gumbel, rotated Gumbel, Symmetrized Joe Clayton, and student t copulas.[3]

3.2.2. CoVaR measure

After identifying the best copula, we use this information on dependence structure to compute the Conditional Vvalue at Rrisk (CoVaR). One of the main advantages of CoVaR compared to bivariate dynamic condition correlation GARCH models is its ability to evaluate the extreme risk spillovers between markets during radical negative and positive price movements. CoVaR metric measure presents itself as an important methodological aspect of our work because of its ability to quantify the financial risk contagion from Global GBs towards the US sectoral GBs during periods of distress rather than the median state (Adrian & Brunnermeier, 2016; Lee & Long, 2009; Samarakoon, 2011). Since our study samples the COVID-19 period and aims to measure dependence between global and US sectoral GBs, applying CoVaR is the center of our methodology in measuring spillover from global to US sectoral green bonds during this distressing period. Systemic risk may be asymmetric due to the heterogeneous driving variables of financial risk spillovers. For this purpose, we quantify the upside and downside risk spillovers (Yang, Chen and Xie, 2018; Sun, Liu, Wang, & Li, 2020).

The copulas estimates are used to quantify the downside and upside risk spillover from global green bonds towards green bonds of the Building, Utility, Financial, and Industrial sectors. Under a confidence interval of 1 – α, the downside (upside) VaR at time t is given by $Pr(r_t \leq$

[2] Our copula estimations are based on the residuals from the ARMA-GARCH model.

[3] Details about the specification of these models are explained by Reboredo, Rivera-Castro, and Ugolini (2016) and Shahzad et al. (2017).

$VaR_{\alpha,\ t}) = \alpha\ (Pr(r_t \geq VaR_{1-\alpha,\ t}) = \alpha)$, where r_t represents GB price returns. The expressions for upside and downside VaR extracted from the marginal models are appended below.

$$VaR^{upside}_{\alpha,t} = \mu_t + t^{-1}_{\upsilon,\eta}(1-\alpha)\sigma_t \tag{5}$$

$$VaR^{downside}_{\alpha,t} = \mu_t + t^{-1}_{\upsilon,\eta}(\alpha)\sigma_t \tag{6}$$

where $t_{\upsilon,\ \eta}{}^{-1}(\alpha)$ denotes αth quantile of the skewed Student-t distribution and μ_t and σ_t represent the conditional mean and standard deviation of the return series, respectively, estimated from the ARMA-GARCH model. To measure the effect of extreme return movements in global green bonds on the green bond market of Building, Utility, Financial, and Industrial sectors, we apply the CoVaR[4] methodology proposed by Adrian and Brunnermeier (2016). We assume r_t^{sgb} and r_t^{gbb} which represents the returns of sectoral green bonds (i.e. Building, Utility, Financial and Industrial sectors) and global GBs, respectively. For a confidence level of 1 − β and the β-quantile of the conditional distribution of r_t^{sgb}, the downside and upside $CoVaRs$ for any given green bond sectoral returns due to an extreme downward and upward global green bond market are shown as:

$$Pr\left(r_t^{sgb} \leq CoVaR^{c,downside}_{\beta,t} | r_t^{gbb} \leq VaR^{gbb,downside}_{\alpha,t}\right) = \beta \tag{7}$$

$$Pr\left(r_t^{sgb} \geq CoVaR^{sgb,upside}_{\beta,t} | r_t^{gbb} \geq VaR^{gbb,upside}_{1-\alpha,t}\right) = \beta \tag{8}$$

In the above equations, $VaR_{\alpha,\ t}{}^{ggb}$ represents α-quantile of the global green bonds return distribution. $r(r_t^{ggb} \leq VaR_{\alpha,\ t}{}^{ggb}) = \alpha$ quantifies potential loss for global green bonds for a specific time horizon under the confidence interval 1 – α where $VaR_{1-\alpha,\ t}{}^{ggb}$ is the potential loss during a short position in global green bonds for a specific period under the confidence interval of 1 – α. We follow Reboredo and Ugolini (2015) for estimating CoVaR using a two-step method. The first step is to calculate the dependence parameter as the best copula fit between global green bonds and each green bond sectoral markets. The second step involves the estimation of conditional mean and variance parameters obtained from the dependence model (ARMA-GARCH in our case). These two steps are then used to estimate the conditional value at risk (CoVaR) between global and sectoral green bond markets.

Following VaR and CoVaR estimations, we apply the Kolmogorov-Smirnov (KS) bootstrapping test proposed by Abadie (2002) to investigate asymmetry in risk spillover. More specifically, this test measures the difference between two cumulative quantile functions without considering any underlying distribution function. Expression for the resultant KS test is as follows.

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{1/l} sup_x |F_m(x) - G_n(x)| \tag{9}$$

where $F_m(x)$ and $G_n(x)$ represent cumulative $CoVaR$ and VaR distribution functions, respectively. On the other hand, m and n represent two sample sizes. The expression for null hypotheses to test equalities and asymmetries between VaR and CoVaR between green sectoral market and global green bond returns is as follows.

$$H_0 : CoVaR^{sgb}_{\beta,t} = VaR^{sgb}_{\beta,t}, \text{and} \tag{10}$$

$$H_0 : \text{CoVaR(D)}/\text{VaR(D)} = \text{CoVaR(U)}/\text{VaR(U)} \tag{11}$$

3.2.3. Quantile regression approach

We apply quantile regression QRA to examine the effects of different explanatory variables (Citi Macro risk index, US Financial condition index, and COVID-19 crisis) on the upside and downside risk spillovers resulting from Global GB towards US sectoral GBs. The QRA is more informative than the linear ordinary least square regression (Koenker & Bassset, 1978; Lee, 2021). Under QRA, the risk spillover (dependent variable) covers the entire distribution (different quantiles) conditional on a set of explanatory variables. QRA, therefore, accounts for the heterogeneity and extreme outliers (Fattouh, Scaramozzino, & Harris, 2005). The QRA captures the non-linear effects of external risk factors and variables on the extreme risk spillovers under different return distributions. In this way, the sensitivity of downside and upside risk spillover to various external factors can be examined under extreme spillover phenomena. Therefore, the application of QRA to measure sensitivity to the nonlinearities of spillover towards US sectoral green bonds and risk factors (or explanatory variables) provides superior results and deeper insights to investors compared with the conventional OLS method.

We proceed by assuming that the θ quantile of the conditional distribution of spillover towards US sectoral green bonds y_{it} is linear in x_{it}, the resultant expression of which is appended below.

$$y_{it} = x_{it}{}'.\beta_0 + u_{\theta it}$$

$$Quant_\theta(y_{it}|x_{it}) \equiv inf\ \{y : F_{it}(y|x)\theta\} = x_{it}{}'.\beta_0 \tag{12}$$

$$Quant_\theta(u_{\theta it}|x_{it}) = 0$$

where $Quant_\theta(y_{it} \mid x_{it})$ represents the θth conditional quantile of y_{it} on the independent variables (external risk factors in our case) x_{it}, β_0 represents the unknown parameter vector which needs to be estimated for different θ values in (0,1), $u_{\theta it}$ represents error term extracted from the continuously differentiable distribution function $F_{u\theta}(.|x)$ and the density function $f_{u\theta}(.|x)$. Conditional distribution of the spillover index conditional on external risk factors is denoted by $F_{it}(.|x)$. The entire distribution of the spillover index conditional on external risk factors is represented by values ranging between 0 and 1. We can get the estimator for β_0 as

$$min \sum_{it:u_{\theta it}>0} \theta \times |u_{it}| + \sum_{it:u_{\theta it}<0} (1-\theta) \times |u_{it}|$$

$$= \sum_{it:y_{it}-x_{it}{}'.\beta_\theta>0} \theta \times |y_{it} - x_{it}{}'.\beta_\theta| + \sum_{it:y_{it}-x_{it}{}'.\beta_\theta<0} (1-\theta) \times |y_{it} - x_{it}{}'.\beta_\theta| \tag{13}$$

The estimators presented in the above equation lack any explicit form. However, we can solve the resulting minimization problem through the linear programming technique. The application of quantile regression in our work enables us to trace the entire distribution of spillover towards US sectoral green bonds condition due to external risk factors, i.e., the Citi Macro risk index, the US Financial condition index, and the COVID-19 outbreak. We present an expression for estimating the vector of β using the ordinary least square optimization technique as follows.

$$min \sum_i (u_{it})^2 = \sum_i (y_{it} - x_{it}{}'.\beta)^2 \tag{14}$$

On comparing the last two equations, we find one prominent feature of the quantile regression technique that the value of the estimator vector of β_θ, varies with θ. By making a comparison of behaviors based on changing values of θ, we can characterize dynamic estimator vector β_θ, for different quantile regions.

4. Empirical results

4.1. Dependence analysis during bear and bull market conditions

Before carrying the copula, we estimate the appropriate marginal

[4] The CoVaR for an asset i represents VaR for asset i conditional on extreme movement in asset j.

model using different lag orders and the Akaike information criteria (AIC). We find that ARMA-GARCH (1,1) fits our data.[5]

To select the best copula function, we estimate different time-invariant and time-varying copulas and use the AIC to choose the best function. The results show that the time-varying copula outperforms the time-invariant copula, suggesting a temporal dependence between MSCI Global and sectoral GBs. To save space, we report in Table 3 the results of the time-varying copula. As we can see, we find a symmetric tail dependence between MSCI Global GB and both Building and Utility GB as given by the time-varying parameter (TVP) student-t copula. This result shows that the dependence is symmetric during bear and bull markets. This also indicates that investors have the same behavior during extremely agitated market conditions (both downside and upside trends). As modeled by Gumbel copula, Financial GB is dependent on MSCI Global GB in the upper tail (bull market) and independent in the lower tail (bear market). This result shows that Financial GB was a safe haven asset for MSCI Global GB during the financial crisis. A Symmetrized JC copula reveals that Industrial GB has a symmetric tail dependence on MSCI Global GB.

Fig. 4 displays the evolving dependence between MSCI Global GB and Building, Utility, Financial, and Industrial GB price returns. As we can see, the dependence varies over time and shows different patterns. This result indicates the heterogeneous responsiveness of Building, Utility, Financial, and Industrial GB returns to MSCI Global GB return shocks. We note that the dependence between MSCI Global GB and Industrial GB is more stable than the remaining cases. Moreover, the visual evidence shows that the COVID-19 has weak effects on the dependence between Global and Industrial GBs. For Financial GB, the dependence has gradually increased since May 2019 and intensified during the COVID-19 outbreak period. This result shows increasing integration and financial contagion between these two markets. For Utility and Building GBs, the dependence is more volatile, indicating that investors often restructure their portfolios. This is due to the fact that Building GB is the most widely used sector for green bond investment. The market capitalization of US Green Buildings will reach $103.08 billion by 2023.[6] Moreover, the increasing dependence in early 2020 is driven by the global health crisis.

Overall, the increasing dependence between GB markets shows the surge of green finance in the last few years. Different factors may influence the dependence between Global GB and sectoral GBs. The various degrees of development and ratings of Building, Financial, Industrial, and Utility GBs may explain their different dependence and responsiveness to Global GB returns. In addition, investors' awareness of climate, inappropriate institutional arrangements, economic policy instability, and energy price shocks may be the key factors affecting GB markets' performance.

Table 4 reports the descriptive statistics of up/down VaR and CoVaR. As shown in the table, the average and standard deviations of upside/downside CoVaR values are superior to those of upside/downside VaR values of Building and Utility GBs. This result shows that Global GB has a systemic risk to the sectoral GBs. More interestingly, we discover that Utility GB has the highest risk spillovers, followed by Financial and Industrial GBs. In contrast, Building is the most negligibly affected by the Global GB shocks. This result supports evidence of financial contagion between the markets under study. Besides, we show that green Utility has the highest upside and downside risk as measured by the VaR values, whereas green Building exhibits the least one. This result can be explained by the fact that the Building GB market is more developed than the Utility GB.

The visual evidence reported in Fig. 5 is consistent with the findings in Table 3. In more detail, the risk spillover trajectories differ from one market to another. In addition, we find that upside/downside CoVaR is superior (inferior) to upside/downside VaR over the sample period for Building and Utility (Financial and Industrial) GBs. The magnitude of risk spillovers is higher for Utility than Building GB, indicating that the information transmitted in MSCI Global GB has more effect on Utility GB than Building GB prices. The results of risk spillovers for Financial GB are in line with the findings of the dependence structure where the markets present lower tail independence during the bearish market condition. We note that the COVID-19 outbreak has a moderate effect on risk spillovers.

We augment our analysis with the robustness of the Kolmogorov–Smirnov (KS) test to check whether the VaR values are statistically different from the CoVaR values. We also test the asymmetric effects of the CoVaRs on the upside and downside. The results are reported in Table 5 and show that the values of both VaR and CoVaR are statistically significant at a 1% level of significance, suggesting the presence of systemic risk from Global GB to sectoral GB. This result also indicates the validity and robustness of our analysis. In addition, we find that the upside CoVaR values are statistically different from the downside CoVaR values. This result reveals that portfolio risk management differs during upside and downside trends. Identifying the appropriate short and extended positions requires investors and portfolio managers to consider the asymmetric risk spillovers among GBs during downturns and upturns in markets.

4.2. Determinants of volatility spillovers

The presence of risk spillovers motivates us to study the determinants of spillovers during downturn and upturn market trends. Three main variables are considered in this study to examine their ability to explain the time variations of risk spillovers. They are the Citi Macro risk index, the US Financial condition index, and the COVID-19 crisis.[7] The choice of these variables is motivated by their potent effects on economic development (the creation of wealth) and financial stability. More specifically, we test the determinants of spillover effects in GB markets under nine different quantiles to account for diverse risk spillover levels. We use the quantile regression approach to test the nonlinearity in the relationships.

Table 6 summarizes the empirical results of the upside and downside risk spillover determinants. Therein, the dependent variable is a time-varying series of upside and downside risk spillovers estimated from the CoVaR model[8], i.e. Eqs. (7) and (8). It is also plotted in Fig. 5 and is regressed on external risk factors, i.e., the Citi Macro risk index, the US Financial condition index, and the COVID-19 crisis indicator. The downside and upside spillover values are extracted from the CoVaR estimation of Global GBs towards sectoral GBs. These spillover series are then regressed against Citi Macro risk, Financial condition index, and the COVID-19 crisis. According to Panel A, we find that the Citi Macro risk index positively impacts the upside risk spillover of Utility and Financial GBs across different quantiles. The Citi Macro risk index contributes to the upside risk spillovers of Building at lower quantiles (lower risk spillover level). Still, it has an insignificant impact on the upside risk spillovers of Industrial GB. This indicates that risk aversion in global financial markets influences the dynamic of GB prices. With the

[5] The results of this model are available upon request.

[6] https://seedscientific.com/green-building-statistics.

[7] The Citi Macro risk and Financial condition index data are sourced from Bloomberg. COVID-19 is a dummy variable that takes the value of one during the pandemic period and zero otherwise. The breakpoint is December 1, 2019 and onwards.

[8] In order to measure risk spillover, we apply the CoVaR measure proposed by Adrian and Brunnermeier (2016). The measurement of CoVaR uses dependence coefficients extracted from the copulas model, and the best fitted copulas are used as inputs in estimating the CoVaR values. The output from CoVaR estimations is in the form of time-varying series. Table 4 presents the results of these upside and downside risk spillover series in the form of descriptive statistics, whereas these series are plotted in Fig. 5.

Table 3
Time varying copula dependencies between MSCI GB and sectoral series.

	Building	Utility	Financial	Industrial
1. Normal				
$\dot{\omega}$	0.3684***	4.9994***	4.9990***	−0.6207***
	(2.1514)	(20.5062)	(95.7371)	(0.1801)
A	−0.1084***	−0.4221***	0.1925***	0.0485***
	(0.1481)	(8.1533)	(2.4121)	(0.0405)
B	4.9398***	−0.4759***	−1.7817***	3.3198***
	(2.1688)	(28.0539)	(104.3676)	(0.2975)
AIC	−2017.2415	−1507.0531	−1177.6893	−346.6468
2. Clayton				
Ψ_0	1.0000***	1.0000***	1.0000***	1.8543***
	(1.0000)	(1.0000)	(1.0000)	(2.2667)
Ψ_1	−1.0000***	−1.0000***	−1.0000***	−0.9758
	(1.0000)	(1.0000)	(1.0000)	(15.0586)
Ψ_2	0.0000	0.0000	0.0000	0.1285
	(1.0000)	(1.0000)	(1.0000)	(13.7079)
AIC	2E+08	2E+08	2E+08	−202.9589
3. Rotated clayton				
$\dot{\omega}$	1.0000***	1.0000***	1.0000***	1.8632***
	(1.0000)	(1.0000)	(1.0000)	(4.4056)
A	−1.0000***	−1.0000***	−1.0000***	−1.0097**
	(1.0000)	(1.0000)	(1.0000)	(10.1389)
B	0.0000	0.0000	0.0000	0.0551
	(1.0000)	(1.0000)	(1.0000)	(2.2647)
AIC	2E+08	2E+08	2E+08	−163.2813
4. Gumbel				
$\dot{\omega}_u$	1.7366***	1.3460***	1.8194	0.6180***
	(0.1429)	(0.1043)	(251.3107)	(0.5059)
α_u	0.1391***	0.1729***	0.0958	0.2487***
	(0.0085)	(0.0093)	(47.3562)	(0.2212)
β_u	−4.7346***	−3.0624***	−4.9971	−0.8958***
	(1.9878)	(0.9628)	(690.0103)	(0.6160)
AIC	−1977.8175	−1505.2495	**−1224.7566**	−332.9853
5. Rotated Gumbel				
$\dot{\omega}_L$	1.6778***	1.2394***	1.7718	0.6861***
	(0.1336)	(1.2047)	(78.3998)	(0.3385)
α_L	0.1423***	0.1815***	0.0987	0.2008***
	(0.0085)	(0.1131)	(14.1861)	(0.1768)
β_L	−3.8187***	−2.0732***	−4.9946	−0.7405***
	(1.6942)	(12.0377)	(304.9231)	(0.2508)
AIC	−1977.0272	−1465.5011	−1171.0654	−342.5105
6. Symmetrized JC				
$\dot{\omega}_U$	1.9546***	1.9201***	1.6843***	−1.9853***
	(1.3213)	(0.8437)	(0.8482)	(0.0394)
β_U	0.0000	−0.0029	0.0000	−0.2545***
	(1.0010)	(1.0046)	(1.1298)	(0.1481)
α_U	0.0000	0.0094	0.0000	4.0650***
	(1.2777)	(0.9484)	(0.0003)	(0.0591)
$\dot{\omega}_L$	1.9528***	1.8777***	1.3980***	0.3779***
	(1.4714)	(1.0798)	(0.9221)	(0.2151)
β_L	0.0000	−0.0032	0.0000	−2.1757***
	(1.0007)	(0.9451)	(1.1049)	(0.6552)
α_L	0.0000	−0.0301	0.0000	0.0917***
	(1.7153)	(0.9435)	(1.3870)	(0.3022)
AIC	−1774.7651	−1431.8524	−1162.6763	**−364.5105**
7. Student's t				
Ψ_0	0.7145	−0.4683	−1.2886***	0.9290***
	(5336.1556)	(0.1085)	(1.1996)	(1.7670)
Ψ_1	−0.0631	−0.1402	0.0798***	0.0676***
	(1608.8858)	(0.0652)	(0.5043)	(0.0878)
Ψ_2	4.5869	4.9973	4.9957***	0.9910***
	(2119.3992)	(0.1213)	(2.2770)	(2.6457)
υ	4.9985***	4.9998	4.7605***	4.9999***
	(1.9833)	(2.2373)	(5.0620)	(1.3075)
AIC	**−2035.0111**	**−1530.5111**	−1212.9466	−359.0732

Notes: The table presents the estimates and standard errors (in brackets) for the different time-varying bivariate copula models between MSCI GB and Building, Financial, Industrial, and Utility price returns. The Akaike information criterion (AIC) values adjusted for small-sample bias are provided for the different copula models. We note that the minimum AIC values (in bold) indicate the best copula fit. The A parameter stands for the average dependence (or zero tail-dependence) as given by the TVP normal copula. Ψ_1 and A measure the lower tail dependence as defined by the Clayton copula and the upper tail dependence modeled by the rotated Clayton copula, respectively. The α_u and α_L parameters refer to the lower tail independence and upper tail dependence defined by the Gumbel and rotated Gumbel copulas. ϑ stands for degrees of freedom. β_U and $\beta_L$measure the lower and upper tail dependence as defined by the SJC copula. The Ψ_0, Ψ_1, and Ψ_2 parameters determine the dependence, persistence, and adjustment for Student-t copula. *** indicates the significance of the parameters at the 1% level.

exception of Industrial GB, the increase in Macro uncertainty contributes to the risk of spillovers. As for the downside risk spillovers (Panel B), the relationship is negative across quantiles. The rise in Citi Macro risk uncertainty index decreases the downside risk spillovers. The effect of the Financial condition index on the upside spillovers is mixed. It positively affects the upside spillovers of Utility at intermediate quantiles, Financial GB across all quantiles. In contrast, the Financial condition index affects the upside spillovers of Industrial GB negatively at low and high quantiles. This indicates that the increase in the financial condition index reduces the upside spillover level at low and high quantiles. The results for downside spillover are pretty similar, with the exception of the Financial condition index, which affects the downside spillover of Industrial GB across all quantiles. Overall, the financial stress in the US bond, equity, and money markets constitutes vital information to predict the relationships between Global and sectoral GBs.

Table 4
Descriptive statistics of VaR and CoVaR.

	Upside VaR	Downside VaR	Upside CoVaR	Downside CoVaR
Building	0.1810 (0.0132)	−0.1799 (0.0129)	0.2209 (0.0160)	−0.2048 (0.0147)
Utility	0.5543 (0.0531)	−0.5312 (0.0565)	0.6767 (0.0616)	−0.6121 (0.0616)
Financial	0.4645 (0.0556)	−0.4590 (0.0586)	0.4221 (0.0525)	−0.3979 (0.0529)
Industrial	0.3256 (0.0300)	−0.2891 (0.0276)	0.2629 (0.0255)	−0.3099 (0.0276)

Notes: This table presents the mean and the standard deviation (in parenthesis) of the upside and downside VaR and CoVaR of GBs.

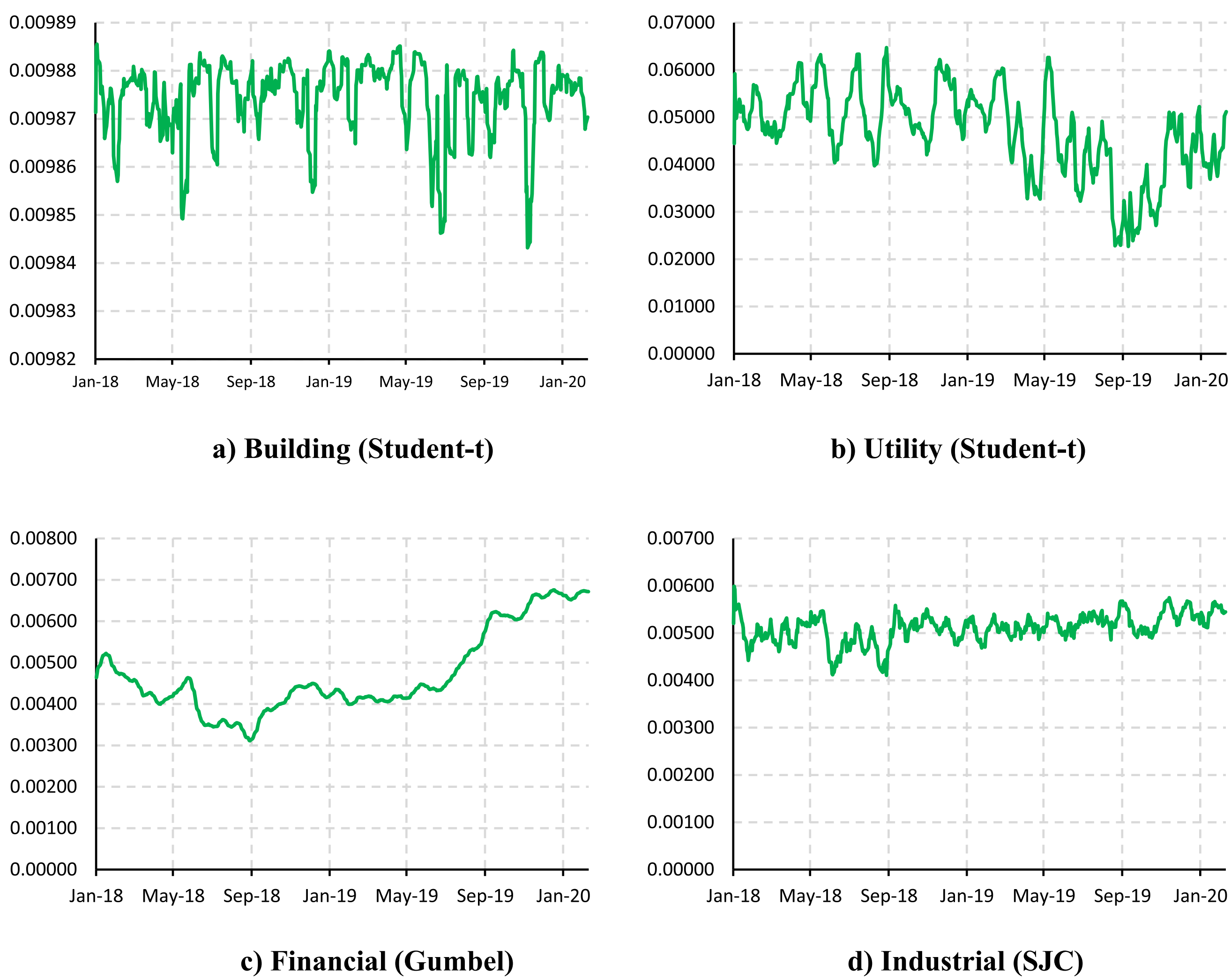


Fig. 4. Best fitted time-varying copulas between global GB and GB sectors.
Note: The time-varying dependence structure is based on the best-fitted copulas (see Table 3). We find that the dependence structure between global GBs and sectoral GBs is best suited for student t copula in the case of Building and Utility sectors. For Financial sector, we report Gumbel copula as best fitted. In contrast, in the case of Industrial sector, Symmetrized JC appears as the best-fitted copula based on the least corresponding AIC values.

Fig. 5. Time variations of VaR and CoVaR.

Table 5
Tests of equalities and asymmetries between VaR and CoVaR.

	Building	Utility	Financial	Industrial
Test of equalities				
H0: CoVaR (D) = VaR (D)	0.7782	0.5833	0.3881	0.3414
H1: CoVaR (D) ≠ VaR (D)	[0.0000]	[0.0000]	[0.0000]	[0.0000]
H0: CoVaR (U) = VaR (U)	0.9237	0.7506	0.2971	0.8398
H1: CoVaR (U) ≠ VaR (U)	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Test of asymmetries				
H_0: CoVaR(D)/VaR(D) = CoVaR (U)/VaR(U)	0.6958	0.7250	0.3424	0.8251
H_a: CoVaR(D)/VaR(D) < CoVaR (U)/VaR(U)	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Notes: This table reports the results of the Kolmogorov–Smirnov (KS) test. The KS tests the null hypothesis of no systemic impact between Global GB and sectoral GB price returns. The values in squared brackets stand for *p*-values for the KS statistic.

Regarding the effects of the global health crisis on the quantile spillovers, we find an asymmetric dependence between the COVID-19 outbreak and upside/downside spillovers for Building GB under extreme quantiles. COVID-19 intensifies (reduces) the downside (upside) risk spillovers for Financial GB regardless of quantiles. In contrast, the pandemic outbreak reduces (increases) the downside (upside) spillovers for Utility GB at both intermediate and upper (only lower and medium) quantiles. The lockdown, the increasing uncertainty, and the operating chain's disruption have put the brakes on the GB issuance and, therefore, on the magnitude of risk spillovers. On the other hand, we show insignificant quantile dependence for the case of Industrial GB.

4.3. Robustness tests: Quantile causality test and spillover index method

We notice that robustness tests enhance our findings' relevance and reliability. It also confirms or infirms the quality and strength of the used models. In our study, we apply two robustness measures to our principal analysis, namely volatility spillover, based on the work of Diebold and Yilmaz (2012), and causality in quantiles, following Balcilar et al. (2017). The former measure helps examine the volatility spillover between global and US sectoral green bonds. The results of this methodology support our earlier findings as we can see a significant increase in volatility transmission during the COVID-19 period, marked by a red line. Our second robustness measure supports the quantile regression results by estimating the coefficient of causal relationship running from external risk factors to the upside and downside risk spillover. This test helps measure causality across extreme and median distributions of spillover, which is similar to quantile regression, in which we examine the effect of external risk factors on upside and downside risk spillover towards US sectoral GB. Nevertheless, the quantile regression results are based on a multivariate regression model, which is later confirmed by the bivariate causality test across different quantiles.

The expression to measure causality in quantiles running from risk

Table 6
Results of QRA for CoVaR.

Panel A: Determinants of upside risk spillovers									
Building	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
C	**0.2016*** **	**0.2018*** **	**0.2073*** **	**0.2125*** **	**0.2197*** **	**0.2203*** **	**0.2242*** **	**0.2304*** **	**0.2605*** **
	(0.0026)	**(0.0031)**	**(0.0038)**	**(0.0046)**	**(0.0051)**	**(0.0057)**	**(0.0061)**	**(0.0069)**	**(0.0126)**
Macro Risk	**0.0068***	**0.0105***	0.0060	0.0022	−0.0029	0.0025	0.0044	0.0038	−0.0195
	(0.0040)	**(0.0046)**	(0.0055)	(0.0066)	(0.0072)	(0.0084)	(0.0092)	(0.0104)	(0.0173)
Financial	0.0006	0.0023	0.0010	−0.0006	−0.0037	−0.0031	−0.0034	−0.0043	**−0.0157***
	(0.0014)	(0.0017)	(0.0022)	(0.0028)	(0.0032)	(0.0036)	(0.0036)	(0.0043)	**(0.0083)**
COVID-19	0.0025	**0.0036***	**0.0041** **	0.0031	0.0009	0.0010	−0.0021	−0.0016	**−0.0139*** **
	(0.0020)	**(0.0020)**	**(0.0020)**	(0.0021)	(0.0022)	(0.0024)	(0.0026)	(0.0034)	**(0.0043)**
Pseudo R-squared		0.0021							
Utility	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**
C	**0.5534*** **	**0.5331*** **	**0.5755*** **	**0.5659*** **	**0.5879*** **	**0.6084*** **	**0.6318*** **	**0.6583*** **	**0.6609*** **
	(0.0485)	**(0.0337)**	**(0.0198)**	**(0.0196)**	**(0.0169)**	**(0.0177)**	**(0.0194)**	**(0.0196)**	**(0.0213)**
Macro Risk	0.1124	**0.1727*** **	**0.1311*** **	**0.1662*** **	**0.1500*** **	**0.1476*** **	**0.1586*** **	**0.1473*** **	**0.1858*** **
	(0.0770)	**(0.0506)**	**(0.0313)**	**(0.0315)**	**(0.0279)**	**(0.0273)**	**(0.0265)**	**(0.0265)**	**(0.0312)**
Financial	−0.0249	0.0035	0.0070	**0.0188** **	**0.0208** **	0.0105	−0.0125	−0.0160	−0.0026
	(0.0268)	(0.0167)	(0.0106)	**(0.0093)**	**(0.0085)**	(0.0119)	(0.0130)	(0.0142)	(0.0152)
COVID-19	0.0714***	**0.0576*** **	**0.0369*** **	**0.0297*** **	**0.0189*** **	0.0083	0.0014	**−0.0128***	**−0.0181***
	(0.0077)	**(0.0094)**	**(0.0076)**	**(0.0080)**	**(0.0073)**	(0.0074)	(0.0079)	**(0.0076)**	**(0.0105)**
Pseudo R-squared		0.0594							
Financial	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**
C	**0.3349*** **	**0.2853*** **	**0.2714*** **	**0.2632*** **	**0.2568*** **	**0.2678*** **	**0.2840*** **	**0.2976*** **	**0.3716*** **
	(0.0171)	**(0.0188)**	**(0.0133)**	**(0.0120)**	**(0.0111)**	**(0.0119)**	**(0.0132)**	**(0.0197)**	**(0.0297)**
Macro Risk	**0.0728*** **	**0.1795*** **	**0.2226*** **	**0.2512*** **	**0.2768*** **	**0.2777*** **	**0.2697*** **	**0.2662*** **	**0.1930*** **
	(0.0279)	**(0.0302)**	**(0.0211)**	**(0.0189)**	**(0.0174)**	**(0.0181)**	**(0.0197)**	**(0.0288)**	**(0.0415)**
Financial	−0.0063	**0.0317** **	**0.0428*** **	**0.0497*** **	**0.0557*** **	**0.0582*** **	**0.0538*** **	**0.0577*** **	**0.0330** **
	(0.0150)	**(0.0142)**	**(0.0093)**	**(0.0078)**	**(0.0071)**	**(0.0070)**	**(0.0078)**	**(0.0102)**	**(0.0138)**
COVID-19	**−0.0205*** **	**−0.0222*** **	**−0.0225*** **	**−0.0166*** **	**−0.0189*** **	**−0.0229*** **	**−0.0312*** **	**−0.0405*** **	**−0.0734*** **
	(0.0054)	**(0.0059)**	**(0.0062)**	**(0.0056)**	**(0.0057)**	**(0.0060)**	**(0.0062)**	**(0.0084)**	**(0.0116)**
Pseudo R-squared		0.2791							
Industrial	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**
C	**0.2389*** **	**0.2523*** **	**0.2575*** **	**0.2595*** **	**0.2660*** **	**0.2757*** **	**0.2860*** **	**0.2940*** **	**0.3292*** **
	(0.0075)	**(0.0061)**	**(0.0065)**	**(0.0073)**	**(0.0088)**	**(0.0091)**	**(0.0095)**	**(0.0114)**	**(0.0220)**
Macro Risk	−0.0027	−0.0125	−0.0131	−0.0085	−0.0085	−0.0112	−0.0150	−0.0131	−0.0463
	(0.0107)	(0.0092)	(0.0097)	(0.0109)	(0.0123)	(0.0130)	(0.0140)	(0.0171)	(0.0330)
Financial	−0.0031	**−0.0080** **	**−0.0061*** **	−0.0057	−0.0076	−0.0094	**−0.0152*** **	**−0.0182** **	**−0.0233***
	(0.0039)	**(0.0033)**	**(0.0037)**	(0.0044)	(0.0060)	(0.0059)	**(0.0058)**	**(0.0074)**	**(0.0119)**
COVID-19	−0.0014	−0.0021	−0.0041	−0.0029	−0.0065	−0.0076	−0.0055	−0.0035	−0.0158
	(0.0035)	(0.0036)	(0.0036)	(0.0040)	(0.0043)	(0.0047)	(0.0053)	(0.0055)	(0.0100)
Pseudo R-squared		0.0044							

Panel B: Determinants of downside risk spillovers									
Building	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
C	**−0.2328*** **	**−0.2171*** **	**−0.2074*** **	**−0.2054*** **	**−0.2003*** **	**−0.1969*** **	**−0.1908*** **	**−0.1875*** **	**−0.1872*** **
	(0.0099)	**(0.0081)**	**(0.0061)**	**(0.0049)**	**(0.0046)**	**(0.0042)**	**(0.0035)**	**(0.0028)**	**(0.0023)**
Macro Risk	0.0092	−0.0023	−0.0031	−0.0005	−0.0012	−0.0026	−0.0079	−0.0094	**−0.0057** **
	(0.0140)	(0.0118)	(0.0092)	(0.0073)	(0.0066)	(0.0060)	(0.0050)	(0.0042)	**(0.0036)**
Financial	0.0101	0.0075	0.0021	0.0036	0.0008	0.0008	−0.0015	−0.0015	−0.0011
	(0.0063)	(0.0048)	(0.0034)	(0.0031)	(0.0028)	(0.0026)	(0.0021)	(0.0017)	(0.0013)
COVID-19	**0.0067*** **	0.0036	0.0003	−0.0025	−0.0029	−0.0023	**−0.0040** **	**−0.0033***	−0.0015
	(0.0038)	(0.0032)	(0.0026)	(0.0024)	(0.0022)	(0.0022)	**(0.0020)**	**(0.0018)**	(0.0018)
Pseudo R-squared		0.0020							
Utility	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**
C	**−0.6260*** **	**−0.5738*** **	**−0.5523*** **	**−0.5127*** **	**−0.4995*** **	**−0.4875*** **	**−0.4724*** **	**−0.4265*** **	**−0.5092*** **
	(0.0286)	**(0.0193)**	**(0.0185)**	**(0.0179)**	**(0.0189)**	**(0.0193)**	**(0.0216)**	**(0.0303)**	**(0.0594)**
Macro Risk	**−0.1378*** **	**−0.1751*** **	**−0.1771*** **	**−0.1827*** **	**−0.1800*** **	**−0.1855*** **	**−0.1907*** **	**−0.2406*** **	−0.0732
	(0.0370)	**(0.0265)**	**(0.0254)**	**(0.0283)**	**(0.0306)**	**(0.0310)**	**(0.0334)**	**(0.0447)**	(0.0979)
Financial	0.0237	0.0012	−0.0049	**−0.0328*** **	**−0.0339*** **	**−0.0274*** **	**−0.0217** **	**−0.0298** **	0.0363
	(0.0186)	(0.0126)	(0.0129)	**(0.0097)**	**(0.0085)**	**(0.0085)**	**(0.0102)**	**(0.0158)**	(0.0317)
COVID-19	0.0226**	0.0037	−0.0032	**−0.0171** **	**−0.0229*** **	**−0.0313*** **	**−0.0424*** **	**−0.0554*** **	**−0.0574*** **
	(0.0101)	(0.0086)	(0.0080)	**(0.0081)**	**(0.0085)**	**(0.0086)**	**(0.0086)**	**(0.0093)**	**(0.0097)**
Pseudo R-squared		***0.0617***							
Financial	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**

(*continued on next page*)

Table 6 (*continued*)

Panel B: Determinants of downside risk spillovers									
Building	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
C	**−0.3398***** **(0.0287)**	**−0.2690***** **(0.0207)**	**−0.2423***** **(0.0111)**	**−0.2304***** **(0.0106)**	**−0.2234***** **(0.0109)**	**−0.2234***** **(0.0118)**	**−0.2260***** **(0.0140)**	**−0.2424***** **(0.0222)**	**−0.2955***** **(0.0190)**
Macro Risk	**−0.2054***** **(0.0397)**	**−0.2759***** **(0.0281)**	**−0.2886***** **(0.0163)**	**−0.2898***** **(0.0156)**	**−0.2837***** **(0.0167)**	**−0.2692***** **(0.0186)**	**−0.2490***** **(0.0224)**	**−0.2038***** **(0.0361)**	**−0.0949***** **(0.0305)**
Financial	**−0.0278**** **(0.0141)**	**−0.0568***** **(0.0116)**	**−0.0660***** **(0.0068)**	**−0.0704***** **(0.0073)**	**−0.0716***** **(0.0070)**	**−0.0675***** **(0.0074)**	**−0.0605***** **(0.0089)**	**−0.0458***** **(0.0151)**	−0.0086 (0.0142)
COVID-19	**0.0539***** **(0.0119)**	**0.0377***** **(0.0089)**	**0.0287***** **(0.0060)**	**0.0262***** **(0.0054)**	**0.0230***** **(0.0054)**	**0.0188***** **(0.0053)**	**0.0165***** **(0.0051)**	**0.0169***** **(0.0054)**	**0.0245***** **(0.0067)**
Pseudo R-squared		0.3016							
Industrial	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**
C	**−0.3818***** **(0.0198)**	**−0.3593***** **(0.0137)**	**−0.3482***** **(0.0132)**	**−0.3361***** **(0.0098)**	**−0.3269***** **(0.0086)**	**−0.3185***** **(0.0081)**	**−0.3164***** **(0.0080)**	**−0.3033***** **(0.0080)**	**−0.3069***** **(0.0066)**
Macro Risk	0.0355 (0.0327)	0.0253 (0.0199)	0.0296 (0.0186)	**0.0280**** **(0.0139)**	**0.0227***** **(0.0127)**	0.0191 (0.0119)	**0.0236**** **(0.0118)**	0.0173 (0.0114)	*0.0346**** *(0.0098)*
Financial	**0.0418***** **(0.0101)**	**0.0361***** **(0.0092)**	**0.0290***** **(0.0090)**	**0.0242***** **(0.0071)**	**0.0225***** **(0.0056)**	**0.0203***** **(0.0048)**	**0.0228***** **(0.0046)**	**0.0157***** **(0.0047)**	**0.0198***** **(0.0036)**
COVID-19	0.0012 (0.0088)	−0.0002 (0.0069)	0.0022 (0.0081)	0.0061 (0.0057)	0.0041 (0.0049)	0.0047 (0.0039)	0.0048 (0.0037)	−0.0004 (0.0034)	−0.0012 (0.0028)
Pseudo R-squared		0.0310							

Notes: *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

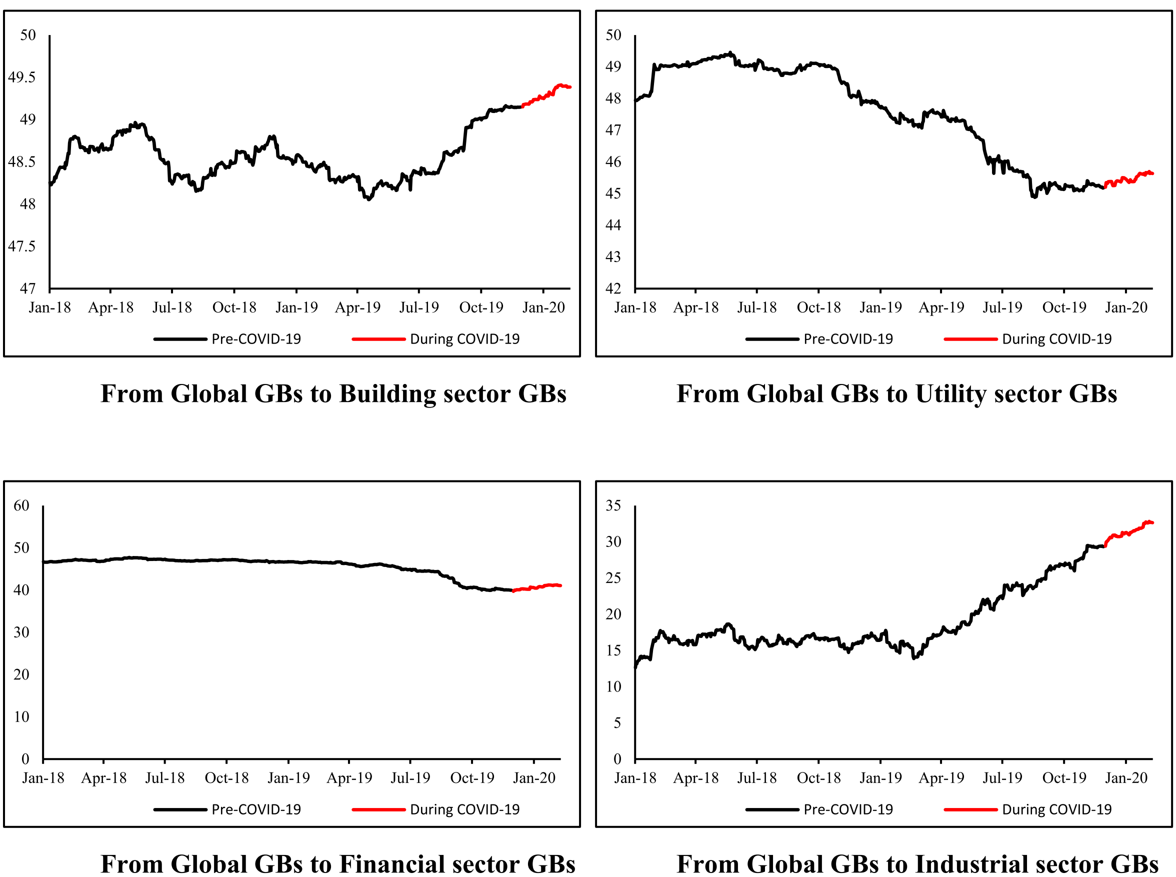


Fig. 6. Volatility spillover from Global GBs to sectoral GBs.

Building sector

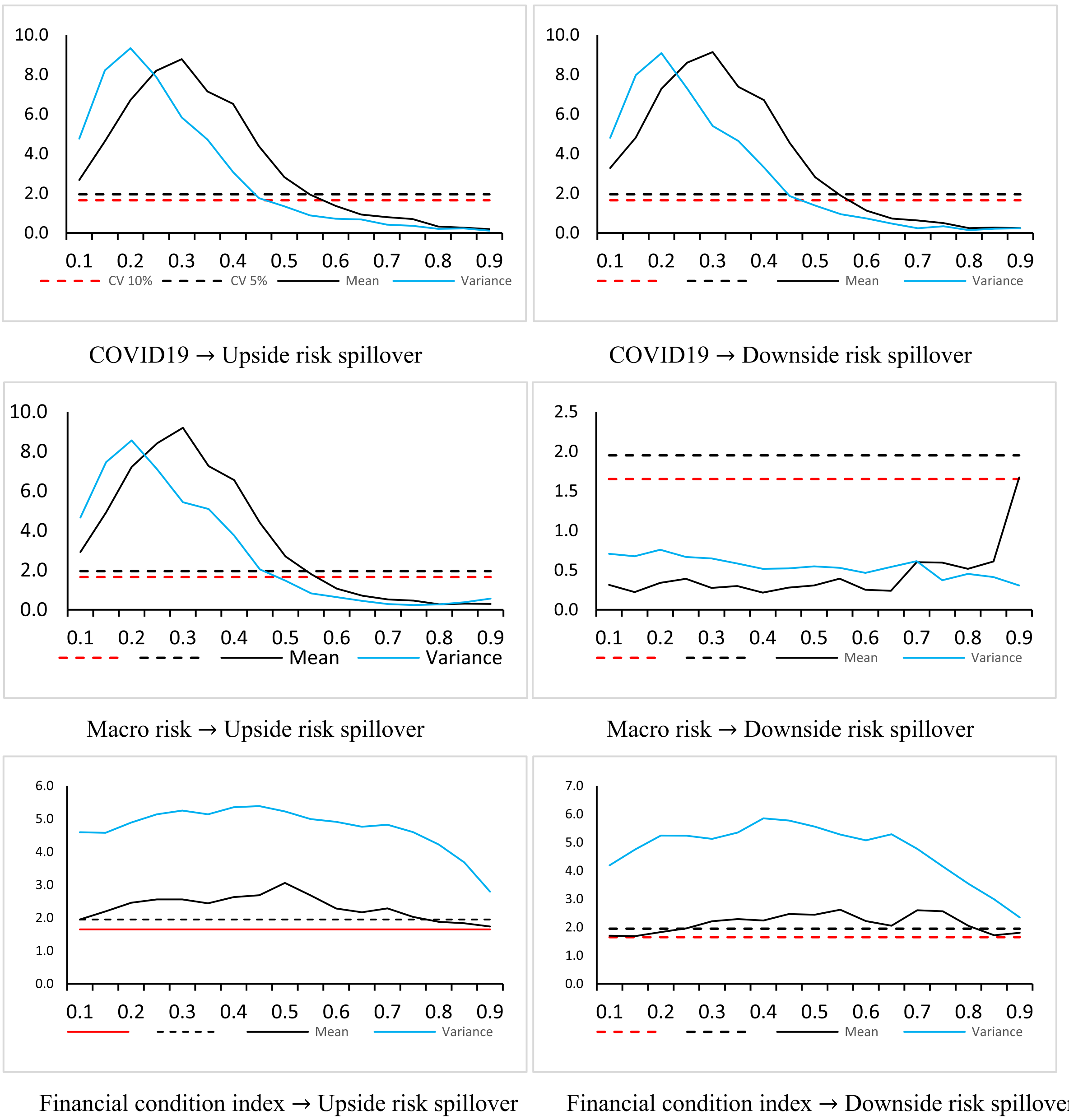
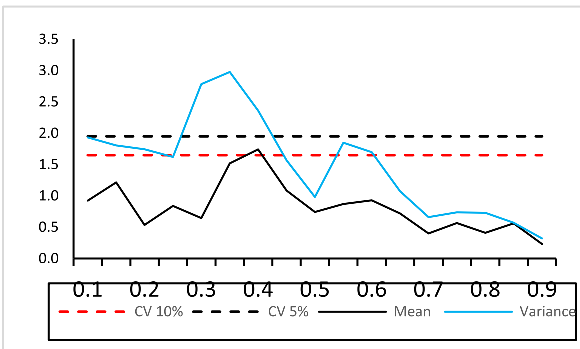
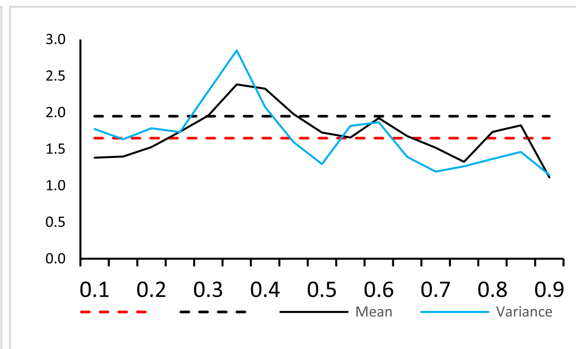


Fig. 7. Causality in quantiles from control variables to upside/downside risk spillovers.
Notes: The black and blue lines in the above figures represent causality in mean and variance, respectively, running from COVID-19, Macro risk, and Financial condition index towards upside/downside risk spillover (from global GBs to sectoral GBs). Dark blue and red dashed lines represent critical values at 5% and 10%, respectively.

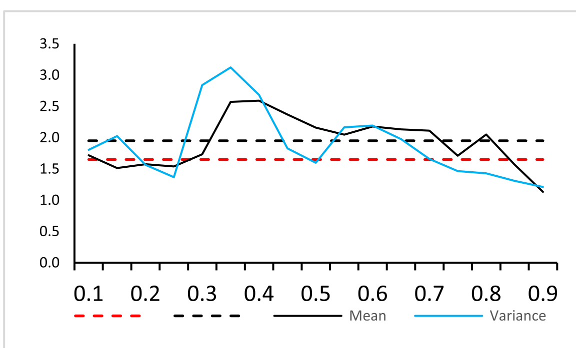
Utility sector



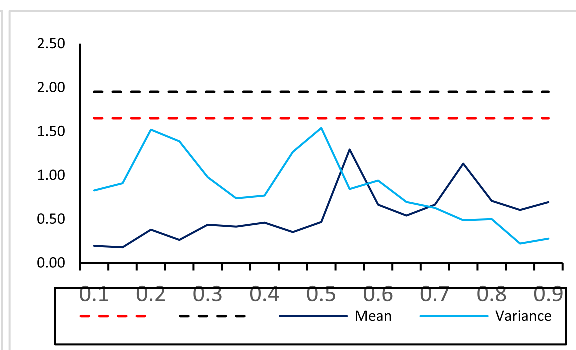
COVID19 → Upside risk spillover



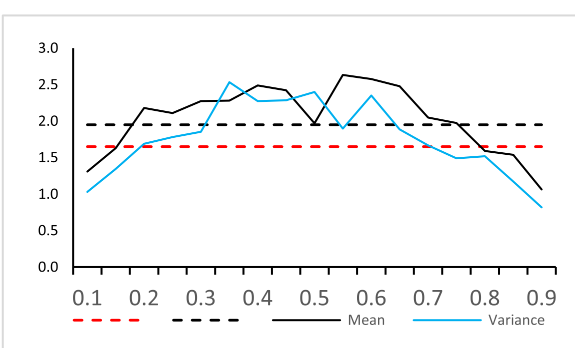
COVID19 → Downside risk spillover



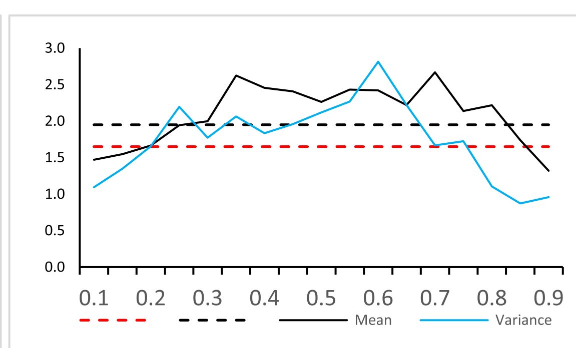
Macro risk → Upside risk spillover



Macro risk → Downside risk spillover



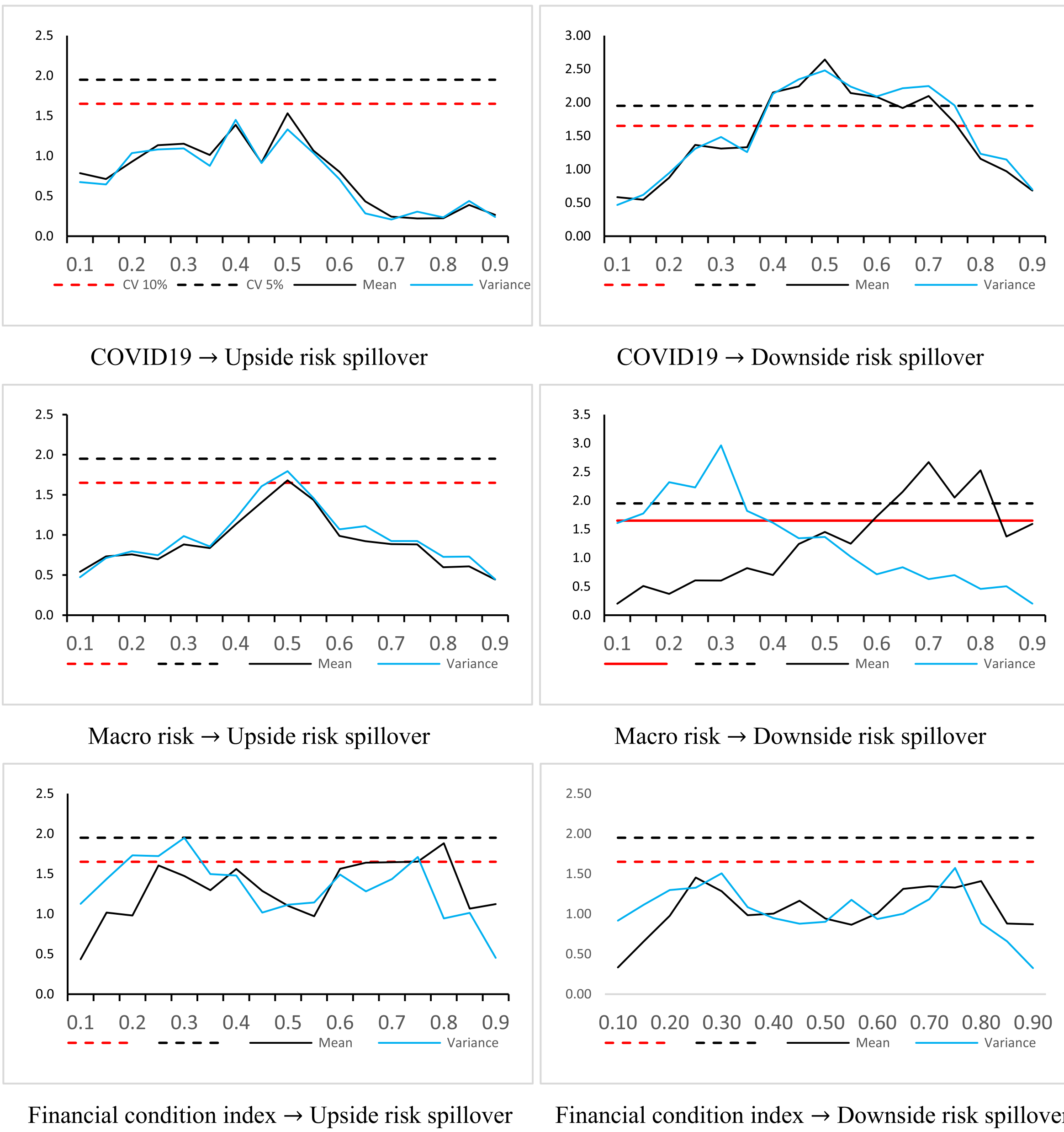
Financial condition index → Upside risk spillover



Financial condition index → Downside risk spillover

Fig. 7. (*continued*).

Financial sector



COVID19 → Upside risk spillover

COVID19 → Downside risk spillover

Macro risk → Upside risk spillover

Macro risk → Downside risk spillover

Financial condition index → Upside risk spillover

Financial condition index → Downside risk spillover

Fig. 7. (*continued*).

Industrial sector

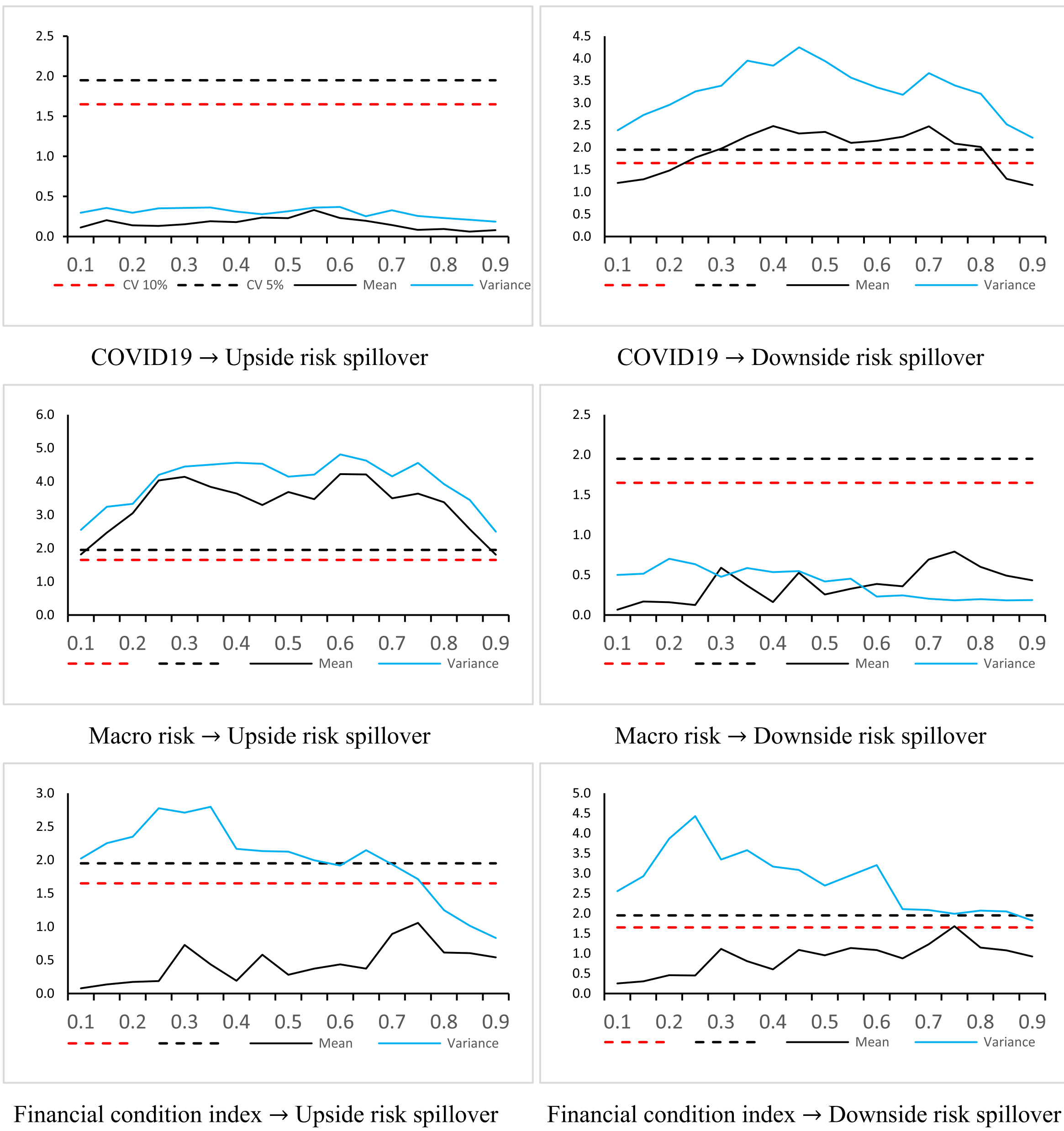


Fig. 7. (*continued*).

factors (x_t) to the US sectoral spillover (y_t) is presented below.[9]

$$H_0 : P\left\{F_{yt}|y_{t-1}\{Q_\theta|\,(Y_{t-1})\,|\,Z_{t-1}\} = \theta\right\} = 1 \quad (15)$$

$$H_1 : P\left\{F_{yt}|y_{t-1}\{Q_\theta|\,(Y_{t-1})\,|\,Z_{t-1}\} = \theta\right\}\langle 1 \quad (16)$$

For our work, we also estimate causality in variance as the second moment. This is because the rejection of the hypothesis of causality in moment m does not imply non-causality in moment k, for $m \leq k$. Therefore, for this purpose, we present causality in variance as follows

$$H_0 : P\left\{F_{yt}|y_{t-1}\{Q_\theta|\,(Y_{t-1})\,|\,Z_{t-1}\} = \theta\right\} = 1 \text{ for } k = 1, 2, \ldots K \quad (17)$$

$$H_1 : P\left\{F_{yt}|y_{t-1}\{Q_\theta|\,(Y_{t-1})\,|\,Z_{t-1}\} = \theta\right\}\langle 1 \text{ for } k = 1, 2, \ldots K \quad (18)$$

The second robustness test is the spillover index of Diebold and Yilmaz (2012). This spillover index is defined as the flow of information from one market towards the other by employing a generalized VAR model, as appended below.

$$C_{i\leftarrow *}(H) = \frac{\sum_{j=1,j\neq i}^{N}\widetilde{\theta}_{ij}(H)}{\sum_{ij=1}^{N}\widetilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{j=1,j\neq 1}^{N}\widetilde{\theta}_{ij}(H)}{N} \times 100$$

In the above spillover formula, the directional connectedness $C_{i\leftarrow *}(H)$ is directed from global GB towards other US sectoral GBs, where i denotes sectoral green bonds and j represents Global GB.

Fig. 6 displays the time variations of volatility spillovers between Global GB and sectoral GBs using the spillover index of Diebold and Yilmaz (2012). As we can see, the volatility spillovers between markets under investigation are time-varying and sensitive to the COVID-19 pandemic crisis. More specifically, the dynamic volatility spillovers between global GBs and Building GBs vary between 48.23% in January 2018 and 49.38% in February 2020. As for Industrial GB, the extent of spillovers ranges between 12.6% in January 2018 and 32.6% in February 2020. The spillover index between Global GB and the Financial sector GB is less volatile and shows a smooth evolution of around 42%. The spillovers between GBs and the Utility GB exhibit a downside trend during the COVID-19 pandemic crisis. More interestingly, the spillover index increases during the ongoing pandemic for both Building and Industrial GBs and decreases in the case of Utility and Financial GBs. Yi, Bai, Lyu, and Dai (2021) show that the spread of COVID-19 has had a significant impact on the GB market volatility. We notice that the spillover effects between global GBs and Financial GB are relatively stable at around 46% showing a decrease during the pandemic crisis (around 41% in February 2020). This result indicates that the responsiveness of GB sectors to Global GB prices is heterogeneous and asymmetric.

Fig. 7 displays the estimated results of quantile causality in-mean (black color curve) and in-variance (blue color curve) from the COVID-19 crisis, the Citi Macro Risk index, and the US financial condition index, the upside/downside spillovers as measured by CoVaR. Looking at the Building GBs, the visual evidence shows significant causality in-mean and in-variance from the COVID-19 crisis to upside/downside risk spillovers between global GB and Building GBs at lower and medium quantiles (from 0.1 to 0.5 for causality invariance and 0.6 for causality in mean). The result is similar when considering the causality of the Citi Macro Risk index to upside risk spillovers. In contrast, we observe insignificant causality at the upper quantiles of COVID-19 to upside/downside spillovers. Similarly, we find negligible quantile causality (in mean and invariance) from the Citi Macro Risk index to downside spillovers. In the case of Building GB, the financial condition index has a significant quantile causality on the upside/downside spillovers. Looking at the Utility GB, we observe insignificant causality from the COVID-19 crisis to the upside/downside spillovers of the Utility sector for most quantiles, with the middle quantile the exception. A similar result is obtained for the Citi Macro Risk index, where this variable causes the downside spillovers in mean (variance) at lower (upper) quantiles. The financial condition index has insignificant quantile causality of upside/downside spillovers. On the upside spillovers, the financial GB, COVID-19, macro risk, and financial condition index have insignificant causality-in-mean and in-variance. As for downside spillovers, the results of the causality-in-quantile test reveal that the COVID-19 spread shows significant effects in the median. However, we offer insignificant quantile causality from the financial condition index to the downside spillovers. The Citi Macro Risk index causes the downside spillovers of Financial GB at the upper (lower) quantiles. Finally, the COVID-19 pandemic spread has insignificant quantile causality on the upside spillovers, whereas it shows significant causality in-mean and in-variance on the downside spillovers at intermediate quantiles. On the other hand, the Citi Macro Risk index has only a significant impact on the upside spillovers across different quantiles. The financial condition index has insignificant causality-in-mean on upside and downside spillovers for all quantiles. In contrast, the financial condition index has significant causality-in-variance at the lower and intermediate quantiles. Overall, we observe that the causality in-mean and in-variance is asymmetric and sensitive to quantiles and the GB sectors.

5. Conclusion

This study is the first to examine the dependence structure and the asymmetric up/down risk spillovers between MSCI Global GB and both Building, Utility, Industrial, and Financial GB price returns. It also examines the impacts of the COVID-19 outbreak, the Citi Macro risk index, and the US financial condition index on up/down spillovers across different quantiles. To achieve our objectives, we use diverse copula functions, conditional Value at Risk (CoVaR), the spillover index of Diebold and Yilmaz (2012), the quantile causality test, and the quantile regression approach.

The results show a symmetric tail dependence between MSCI Global GB and Building, and Utility GB price returns. In contrast, we find an asymmetric tail dependence between MSCI Global GB and Industrial, and Financial GBs. The dependence between the markets understudy is time-varying and affected by COVID-19 for Financial, Utility, Building GBs, and it is relatively stable for Industrial GB. More interestingly, we show significant upside/downside risk spillovers from MSCI Global GB to Building and Utility GBs, whereas little spillover is found for Financial and Industrial GBs. On the other hand, we find minor effects of Citi Macro risk and US Financial condition indexes along with the COVID-19 pandemic crisis on both the downside (except highest quantiles) and upside (except lower quantiles) risk spillovers from global GBs towards the Building sector GBs. In contrast, Utilities and Financial sectors remain most vulnerable to the effects of the Citi Macro Risk index, Financial Condition index, and COVID-19 crisis on the downside and upside risk spillovers. Both upside and downside risk spillover in the Financial sector appear even more sensitive to changes in Macro risk and Financial Condition indexes together with the COVID-19 outbreak. The robustness test shows asymmetric risk spillovers. The Citi Macro Risk

[9] To measure causality in quantiles, the analysis uses the novel methodological approach proposed by Balcilar, Gupta, and Pierdzioch (2016). We follow the work of Jeong et al. (2012) to test that x_t does not cause y_t in the θ quantile for the lag vector of $\{y_{t-1}, \ldots y_{t-p}, x_{t-1}, \ldots x_{t-p}\}$ if: $Q_\theta\,(y_t, y_{t-1}, \ldots y_{t-p}, x_{t-1}, \ldots x_{t-p}) = Q_\theta\,(y_t, y_{t-1}, \ldots y_{t-p})$. However, we presume that causality exists between x_t and $y_{t.}$ in *θth* quantile with regards to:$\{y_{t-1}, \ldots y_{t-p}, x_{t-1}, \ldots x_{t-p}\}$ $\{y_{t-1}, \ldots y_{t-p}, x_{t-1}, \ldots x_{t-p}\}$ if $Q_\theta\,(y_t, y_{t-1}, \ldots y_{t-p}, x_{t-1}, \ldots x_{t-p}) \neq Q_\theta\,(y_t, y_{t-1}, \ldots y_{t-p})$. $Q_\theta\,(y_t^{\cdot})$ in the above equation represents the *θth* quantile of $y_{t.}$ The conditional quantiles of $Q_\theta\,(y_t^{\cdot})$ and y_t are dependent on *t* and range between zero and one, i.e. $0 < \theta < 1$. We define the vectors $y_{t-1} \equiv (y_{t-1}, \ldots y_{t-p})$, $(x_{t-1}, \ldots x_{t-p})$ and $Z_t = (X_t, Y_t)$. The functions $F_{yt|yt-1}\,(y_{t|}\; Y_{t-1})$ and $F_{yt|zt-1}\,(y_{t|}\; Z_{t-1})$ represent the conditional distribution functions of y_t conditional on the vectors Y_{t-1} and $Z_{t-1,}$ respectively. The distribution $F_{yt|zt-1}\,(y_{t|}\; Z_{t-1})$ is presumed to be continuous completely in y_t almost for all $Z_{t-1.}$ We define $Q_\theta\,(Z_{t-1}) \equiv Q_\theta\,(y_t|Z_{t-1})$ and $Q_\theta\,(Y_{t-1}) \equiv Q_\theta\,(y_t|Y_{t-1})$ $Q_\theta\,(Y_{t-1}) \equiv Q_\theta\,(y_t|Y_{t-1})$ which yields $F_{yt|zt-1}\{Q_{\theta|}\,(Z_{t-1})|\; Z_{t-1}\}$ holding probability to unit (one).

index, US Financial condition index, and the COVID-19 outbreak are critical determinants for risk spillovers. The relationship varies across various quantiles (or different levels of spillovers), indicating non-linear dependence. The spillover index analysis shows dynamic volatility spillover effects between MSCI global GB and sectoral GBs. More precisely, the spillover intensified during the COVID-19 pandemic crisis for all sectors except Financial GB, where the spillover index remains relatively stable. The nonparametric quantile causality test reveals that the COVID-19 crisis, the Citi Macro Risk index, and the US financial condition index cause the upside/downside spillovers invariance.

These findings have important policy implications for market participants. Investors exploiting sector GBs should pay attention to the effects of MSCI global GB price return shocks. Specifically, investors should be aware that Industrial GB is the least vulnerable market to Global GB shocks. Building and Utilities GB sectors are more sensitive to changes in global GB price movement (both upward and downward). The low CoVaR values of Financial and Industrial sector GBs highlight their common sensitivity to the increasing level of risk in global green bonds. Investors should be aware that consumer-oriented sectors are more sensitive to global GBs than the economy-oriented sectors. Despite the common aspect of GBs (i.e., investing in environmentally friendly initiatives and projects), they exhibit heterogeneous behavior in terms of risk spillover, which carries implications for individuals as well as institutional investors. Policymakers should be aware of the heterogeneity of spillovers between Global GB and GB sectors as well as of the critical drivers of spillovers that vary across quantiles. The cross-market information among GBs provides vital information to regulators to reduce the magnitude of shocks received by GB sectors to mitigate financial contagions during market downturns and stipulate the growth of GBs through more issues by mainstream companies. This may, therefore, motivate investors to consider the less vulnerable GBs in their investment strategies.

This paper can be extended by examining the role of the main GBs as hedges or safe-haven assets for the Cryptocurrency Environmental Attention Index (CEAI).[10] In addition, future research can examine the short- and long-term spillovers among GBs because these environmentally friendly assets provide more significant long-term benefits to investors.

Acknowledgement

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Appendix

A.1. Quantile regression

Under the quantile framework, dependence between two variables x and y remain unconditional in the absence of any exogenous variable however becomes conditional along with x. We can determine the dependence structure using values of $\beta(\tau)$ for $\tau \in [0,1]$. The dependence of y on an independent variable in vector x can be *i)* a constant for which the value of $\beta(\tau)$ remains unchanged for different values of τ, *ii)* symmetric (asymmetric) in the case when the value of $\beta(\tau)$ remains similar (dissimilar) under low and high quantile values, *iii)* monotonically increasing (decreasing) when the value of $\beta(\tau)$ increases (decreases) with the value of τ. We can measure coefficients of $\beta(\tau)$ for given τ values by minimizing the weighted absolute deviations between x and y as mentioned below.

$$\widehat{\beta}(\tau) = \text{argmin} \sum_{t=1}^{T} \left(\tau - 1_{\{y_t < x_t' \beta(\tau)\}} \right) |y_t - x_t' \beta(\tau)| \tag{A1}$$

Eq. (A1) contains $1_{\{yt<xt' \ \beta(\tau)\}}$ as an indicator function. Koenker and d'Orey (1987) proposed this usual indicator function solution using a linear programming algorithm.

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[10] See Wang, Lucey, Vigne, and Yarovaya (2021) for further information on CEAIx.

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