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Modelling economic policy issues

Frequency spillovers between green bonds, global factors and stock market before and during COVID-19 crisis[☆]Walid Mensi^{a,b}, Xuan Vinh Vo^c, Hee-Un Ko^d, Sang Hoon Kang^{e,*}^a Department of Economics and Finance, College of Economics and Political Science, Sultan Qaboos University, Muscat, Oman^b Institute of Business Research, University of Economics Ho Chi Minh City, Vietnam^c Institute of Business Research and CFVG, University of Economics Ho Chi Minh City, Vietnam^d Korea Housing & Urban Guarantee Corporation, Busan, South Korea^e PNU Business School, Pusan National University, Busan, South Korea

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ABSTRACT

This paper examines frequency dynamic spillovers in return and volatility and the hedging ability of Green Bonds, gold, silver, oil, the US dollar index, and volatility index against downside US stock prices before and during the COVID-19 pandemic outbreak and for the short and long run. To do so, we use the Diebold and Yilmaz (2014), the TVP-VAR model, and the frequency spillover index by Baruník and Křehlík (2018). We show that the short-term volatility spillovers dominate their long-term counterparts. Green Bond is net transmitters of spillovers in the system at the short term and net receivers at the long term. S&P500 and silver (USDIX and oil) are net transmitters (receivers) of short- and long-term spillovers. Gold and VIX are net receivers of short-term spillovers and net transmitters of long-term spillovers. COVID-19 crisis has more effects on the short-term spillover, which reaches its highest level early 2020. COVID-19 and time horizons lead the direction and the magnitude of spillovers. The Quantile-on-Quantile regression analysis shows significant nonlinear relationships between markets under study. More interestingly, we show that green bonds and gold are safe haven assets for US equity investors during COVID-19. On the other hand, a mixed portfolio offers higher diversification benefits. Finally, hedging effectiveness is dependent on COVID-19 and time horizon.

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1. Introduction

The new coronavirus disease (COVID-19) is a severe pandemic that struck the world in early 2020. Its spectacular spread has forced governments to undertake strict measures (e.g., locking down cities, suspending business operations, restricting the movements of people, and requiring social distancing). This has led to significant slowdowns of most economies. The uncertainty related to COVID-19, doubt about the vaccine's efficacy, and the sharp surge in the number of

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confirmed cases and deaths has increased investors' fears and changed their decision processes about investments. During the 2020 global health crisis (GHC) from the COVID-19 pandemic, the S&P 500 loses 34% of its value as of August 2020. The West Texas Intermediate oil prices record a negative value for the first time in history on April 20, 2020 (−\$37.63 per barrel). Conversely, GBs (Green Bonds) and gold prices demonstrate their robustness during the pandemic, and their prices go up. Specifically, the issuance of GBs has increased since the start of 2020. [Cheong and Choi \(2020\)](#) claim that stock market reacts the GB issuance. Despite the growth of GBs during the last few years, the role as a hedging instrument is often overlooked. Moreover, since GBs were first issued in 2013, there have not been many empirical studies of the spillovers between GBs and other major asset classes, the exceptions being [Mokni et al. \(2022\)](#), [Reboredo \(2018\)](#), [Reboredo et al. \(2020\)](#) and [Reboredo and Ugolini \(2020\)](#). Recent studies examine the effects of COVID-19 on the performance of stock markets ([Ashraf, 2020](#); [Harjoto et al., 2021](#); [He et al., 2020](#)). Another strand of literature investigates the ability of Catastrophe bonds as a diversifier during the spread of COVID-19 ([Drobtetz et al., 2020](#)).

Spillover between markets remains a hot topic for speculators, traders, hedgers, and portfolio managers during episodes of economic slowdown including the COVID-19 pandemic. Such a spillover effect intensifies the contagion risk across different assets and markets. Market participants during crises are more concerned about limiting damages than increasing the expected returns of their investments. The primary mission of market participants is seeking refuge assets to hedge risk exposure at different investment horizons. Therefore, the COVID-19 pandemic provides a unique opportunity to measure the time–frequency spillover, connectedness network and risk management at different time horizons.

This study is the first attempt to examine the dynamic and frequency spillovers and asymmetric connectedness between GB, Brent crude oil futures, gold futures, silver futures, Volatility index (VIX), the US dollar index (USDx), and the S&P 500 index (SP500) before and during the COVID-19 outbreak. It also investigates the impacts of COVID-19 and time investment horizons on the hedging property of the major asset classes against risk exposure of US stock prices.

Our results show evidence of time–frequency connectedness between those markets. Furthermore, the short-run spillovers are higher than their long-run counterpart and are influenced more by COVID-19 early in 2020. The pandemic and frequencies are key drivers of the spillover size and direction among the considered markets. Using the Quantile-on-Quantile regression, we find nonlinear relationships between markets under study. Moreover, green bonds and gold are a safe haven asset for stock markets during COVID-19 pandemic. Finally, the diversification benefits and hedging effectiveness vary across frequencies and are influenced by the spread of COVID-19.

This study contributes to the existing literature in different fronts. First, it examines the frequency spillovers in returns and volatility between the SP500, SP GBs, Brent oil futures, gold futures, and silver futures, the VIX and the USDx. The analysis of spillover strengths and directions allows market participants to identify the source of contagion. Moreover, the reaction of investors differs in the time investment horizons. The frequency factor is a key driver of the spillovers among markets ([Mensi et al., 2021b](#)). Specifically, arbitrage traders, short-term hedgers, and speculators are interested with spillovers in the short run whereas the mutual and hedge funds focused on the spillovers in the long run. Thus, accounting for asymmetric connectedness and time varying risk transfer from one market to another is useful for financial risk management. We therefore analyze the asymmetric connectedness at short (1–8 trading days) and long term (8–256 trading days) for the entire sample period. On the other hand, the geopolitical tensions, the COVID-19, and the 2022 Russian invasion of Ukraine have amplified the uncertainty in global markets, making the investment decision more complex. The rise in volatility in both financial and commodity markets increase the demand of hedging instruments which lead to large price swings of these instruments. In addition, the portfolio management is sensitive to bearish and bullish market statuses as the investor behaviors, expectations and risk appetite different during extreme downward and upward markets. Therefore, understanding the spillovers in first and second moments, the dependence structure as well as the possibility of hedging against extreme negative price movements is vital for portfolio managers to optimize fund allocations and monitor the portfolio risk.

Empirically, we use the recent methodology by [Barunik and Krehlik \(2018\)](#) to identify the frequency directional and magnitude of spillovers between markets under study. Interestingly, we analyze the network directional and magnitude connectedness before and after the COVID-19 epidemic spread in the short and long terms. For robustness, we use the time-domain spillover index of [Diebold and Yilmaz \(2012, 2014\)](#) as well as the time-varying parameter vector autoregression (TVP-VAR) model. The TVP-VAR model overcomes the drawbacks of time-domain spillover index. It does not require an arbitrarily chosen window size. Besides, we will not lose observations using the TVP-VAR model. This model is less sensitive to outlier and adjusts better to parameter changes. For a deepen analysis, we examine the quantile dependence between markets under study using the Quantile-on-Quantile (QQ) regression. This method provides useful insights on the nonlinear relationships between the quantiles of endogenous and exogenous variables. Unlike the panel model, QQ examines the impacts of quantile exogenous variables on the quantile of endogenous variable. Therefore, it explores the relationship over the entire conditional distribution of the considered variables. More interestingly, this method studies the relationships between variables during different market scenarios including bearish (lower quantiles), normal (median quantiles), bullish (higher quantiles) market conditions. It is able therefore to identify whether an asset plays as a diversifier or safe-haven asset.

Second, to make this study helpful for short-term and long-term equity investors, we analyze the hedging ability of Brent oil, gold, GB, silver, VIX, and USDx to equity portfolio. We carry the risk management in the short and long term as well as before and during COVID-19. More precisely, we analyze the optimal portfolio weights by cutting the portfolio risk without losing its returns. Furthermore, we analyze whether the hedging is expensive or cheap at the short and long

terms and before and during the pandemic spread. Finally, we investigate the hedging effectiveness at both short- and long-terms as well as before and during the pandemic period. This analysis is different to the study of [Bouri et al. \(2019\)](#) which investigates the safe-haven property of gold and crude oil in clean energy markets. They find that the two strategic commodities are a weak safe-haven asset against extreme downside prices of clean energy markets.

The remainder of this paper is organized as follows. Section 2 provides a review of the literature. Section 3 presents the data and the descriptive statistics. Section 4 describes the methodology. Section 5 discusses the results. Section 6 concludes the paper.

2. Literature review

An emerging empirical literature has addressed the effects of COVID-19 pandemic crisis on the relationships between different asset classes. [Hanif et al. \(2021\)](#) investigate the dependence structure and systemic risk between US and Chinese stock sectors before and during COVID-19. Using copula and conditional Value at Risk, the authors find that the strengths of risk spillovers from US to Chinese stock sectors is higher than those from China to US before COVID-19. In contrast, the risk transfer from China to US stock sectors is higher than those from US to Chinese sectors during COVID-19. Moreover, the degree of spillovers is intensified during the pandemic crisis. [Yarovaya et al. \(2021\)](#) analyze the impact of the COVID-19 spread on the spillover between Islamic and conventional stock and bond markets. The results show a spillover jump between conventional and Islamic stock markets during COVID-19 period. Moreover, the authors find that Sukuk is a safe haven asset during the pandemic and that COVID-19 pandemic and commodity assets (oil and gold) are key predictors of the spillovers between conventional and Islamic markets. Using the spillover index by [Diebold and Yilmaz \(2012\)](#), [Laborda and Olmo \(2021\)](#) examine the volatility spillovers among US stocks and show that Banking & Insurance, Biotechnology, Energy, and Technology are the important shock transmitter to the remaining industry sectors. Furthermore, the authors conclude that spillovers show capability to predict times of high volatility for the US stock market being useful as early financial crisis indicators.

Using high frequency data, [Shahzad et al. \(2021\)](#) show asymmetric spillovers among Chinese stock sectors where the bad volatility spillover shocks dominate good volatility spillover shocks during the COVID-19 period. [Ahmad et al. \(2021\)](#) show that VIX index has stronger effects of the spillover strengths on the US stock sector returns than the oil volatility index. Moreover, the pandemic crisis has intensified the level of spillover effect of the US equity sectors on the equity and oil volatility index. [Mensi et al. \(2021a\)](#) analyze the asymmetric spillovers between two strategic commodity futures (crude oil and gold) and Chinese stock sector returns (positive and negative returns). The author find that bad return spillovers dominate the good return spillovers. In addition, the global financial crisis, European crisis, oil price crash and COVID-19 outbreak intensify the spillovers among markets as well the hedging strategies. Using the spillover index and wavelet coherence methods, [Vo and Hung \(2021\)](#) examine the dynamic spillovers between strategic commodity and US stock markets before and during COVID-19 outbreak. The result shows different patterns in the spillovers between markets under investigation. [Ferrer et al. \(2021\)](#) investigate the multiscale spillovers between GB, financial and energy markets using the frequency spillover index of [Barunik and Krehlik \(2018\)](#). The authors find strong short-term connectedness between energy, financial, and GB markets.

[Andreasson et al. \(2016\)](#) find nonlinear causality between commodity futures and both the US stock returns and VIX. Moreover, the authors find unidirectional linear causality from commodity returns to excess speculation. [Bouri et al. \(2022\)](#) show that the climate policy uncertainty (CPU) index is a good predictor instrument to the performance of green energy stocks as well as the brown energy equity markets. Using a time-varying optimal copula method, [Naeem et al. \(2021\)](#) examine the tail dependence between energy and green bonds and find positive tail dependence between natural gas and green bonds, while the tail dependence is negative for coal, crude oil, gasoline, and heating oil. [Saeed et al. \(2021\)](#) examine the return spillovers at lower and upper quantiles between clean/green and dirty energy markets. The results show a high return connectedness at extreme tails than in the median between the considered markets. In addition, the return connectedness is negative and asymmetric as it differs between times of extreme negative returns and times of extreme positive returns. Using GARCH-based quantile regression model, [Dutta et al. \(2021\)](#) show strong spillovers from oil, gold, silver markets to Indian green stock market. Besides, the commodity market VIX has a strong impact on green stock index during bearish than bullish market conditions.

More recently, [Mensi et al. \(2022a\)](#) use both wavelet coherency approach and the frequency spillover index of [Barunik and Krehlik \(2018\)](#) to examine the return spillovers between S&P green bond, West Texas Intermediate (WTI) crude oil and G7 stock markets. The authors show that the short-term spillovers are higher than intermediate- and long-term spillovers. In addition, they find that green bond serves as a strong diversifier for G7 equity investors, while oil is a weak diversifier. [Mensi et al. \(2022b\)](#) analyze the upside and downside systemic risk among global, building, industrial, financial, and utility green bond markets and the effects of macroeconomic and financial stress factors on quantile spillovers. The results show evidence of asymmetric spillovers among green bonds. In addition, the financial condition index, Citi macro risk index, and COVID-19 increase the spillover size.

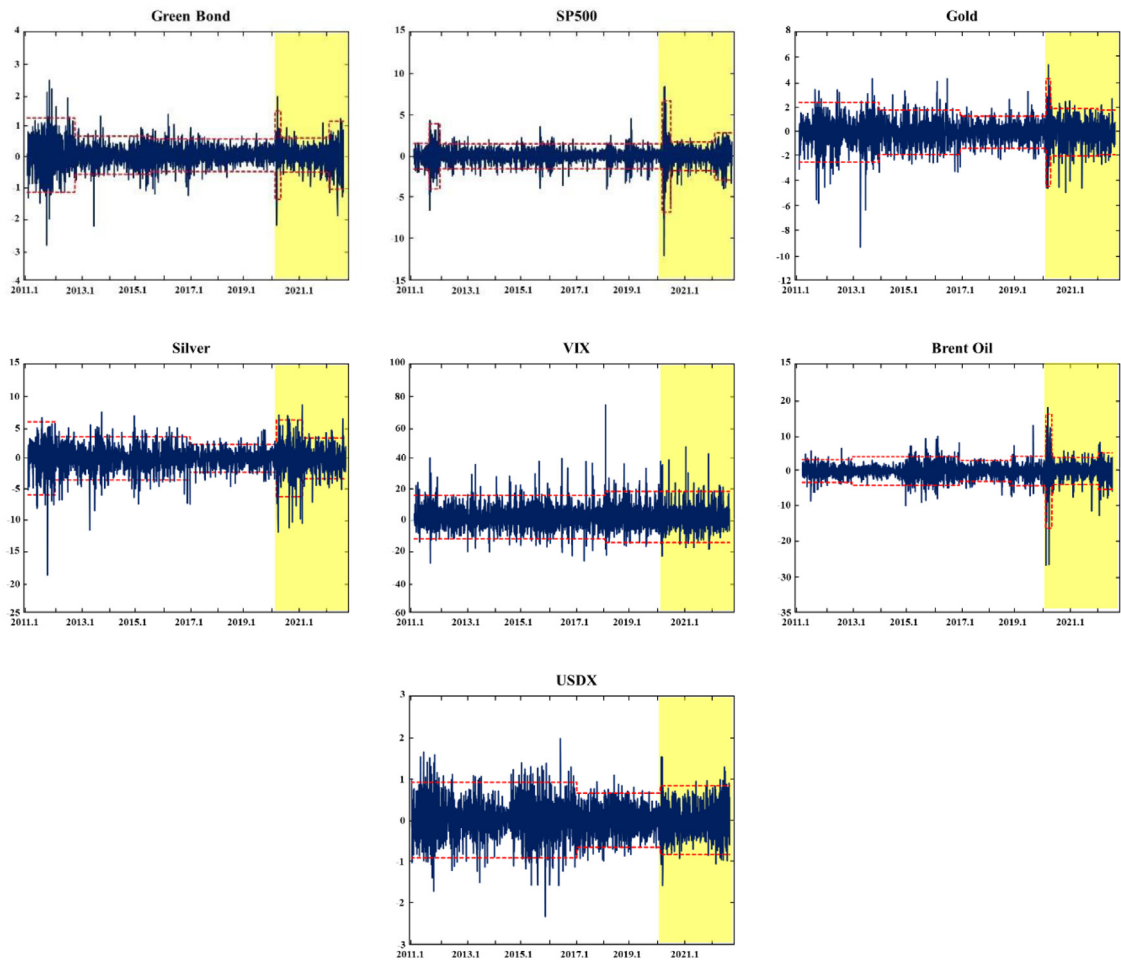


Fig. 1. Time-varying price returns.

Notes: Yellow shading indicates the period of the COVID-19 outbreak from January 2 to September 9, 2022. Bands ± 2 standard deviation (standard deviation in the unconditional volatility calculated for each period), structural breaks estimated using the modified ICSS algorithm of Inclán and Tiao (1994). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3. Data and descriptive statistics

3.1. Data

This paper uses daily closing price data for the S&P green bond (Green Bond), Brent oil, Standard & Poors 500 Index (SP500), gold, silver, Chicago Board Options Exchange Volatility Index (VIX), and US dollar index (USDX). The sample period spans from January 3, 2011 to September 9, 2022, which includes the European debt crisis, the Chinese economic slowdown, recent oil price fall, the COVID-19 pandemic, and the Russia–Ukraine war. All price series are extracted from the Datastream. We compute the continuously compounded daily returns by taking the difference in the natural log values of two consecutive daily prices. Fig. 1 plots the price returns of market under consideration, and it shows evidence of significant volatility clustering during the European crisis in 2012, the oil crisis in 2015, the Brexit referendum in 2016, and the COVID-19 outbreak in 2020.

Using the modified ICSS algorithm, we observe the presence of structural breaks in the return dynamics of all markets, mainly during the most turbulent periods of the global financial crisis and global food crisis. We detect six structural breaks in green bond and SP500 index, five for gold and silver, seven for oil, and two for VIX index. This reveals the presence of sudden jumps in returns and volatility. The regime shifts are due to the local and international economic and political shocks.

3.2. Descriptive statistics

Table 1 reports the basic statistics and unit root test of the return series. The average returns are positive for all markets, except for silver and Brent oil futures. SP500 shows the highest average returns. SP500 has the highest mean

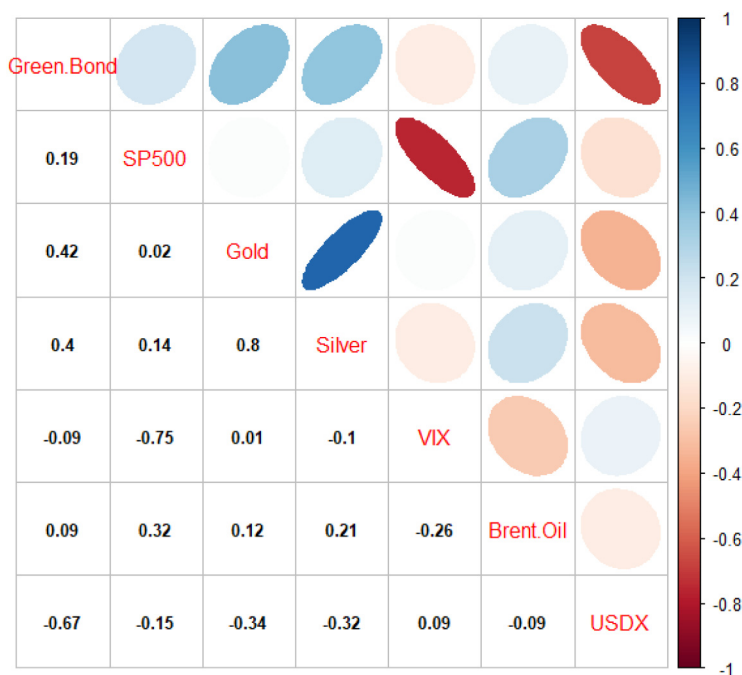


Fig. 2. Unconditional correlation matrix.

Notes: The colored disc stands for the extent of the correlation. The color represents the sign of the pairwise correlation (blue = positive and red = negative) . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Time-varying price returns.

	Green Bond	SP500	Gold	Silver	VIX	Brent Oil	USDX
Mean (%)	-0.0019	0.0395	0.0066	-0.0171	0.0087	-0.0009	0.0108
Max	2.572	8.968	5.775	7.708	76.82	19.07	2.032
Min	-3.078	-12.76	-9.810	-19.48	-31.41	-28.08	-2.398
Std. Dev.	0.397	1.109	1.027	1.940	7.972	2.377	0.429
Skewness	-0.368	-0.861	-0.625	-0.937	1.170	-1.034	0.084
Kurtosis	8.569	18.18	9.560	10.84	9.279	21.37	4.503
Jarque-Bera	3869.***	28628.***	5467.***	7970.***	5505.***	41928.***	280.6***
Q (20)	24.63	286.0***	27.99	33.41**	44.10***	56.87***	31.31**
ADF	-28.18***	-28.44***	-28.62***	-27.65***	-30.80***	-28.73***	-28.56***
KPSS	0.1201	0.0201	0.1793	0.1441	0.0098	0.0574	0.1278

Notes: *** indicates significance at the 1% level.

returns followed by gold and GB. The latter is the least volatile market, followed by the US dollar index. By contrast, VIX is the most volatile series. We note that silver is riskier than gold. All return series are left skewed except for the VIX variable, according to the skewness statistic. The kurtosis values indicate strong evidence of leptokurtic behavior and fat-tailed distribution. The results of Jarque-Bera test show evidence against normal distribution. According to the results of ADF unit root test of Dickey and Fuller (1979) and KPSS stationary test of the Kwiatkowski et al. (1992), stationarity characterizes all return series. Finally, the Ljung-Box statistics show significant serial correlations in the residuals.

Fig. 2 displays the heat map of the correlations between GB, US dollar index, VIX, stock, and commodity futures markets. The USDX is negatively correlated with all markets (except VIX). This result provides a preliminary insight on the ability of USDX as a diversifier asset. In contrast, Brent oil is positively correlated with all series, except for VIX. The SP500 is weakly or negatively correlated with other markets. Gold and silver are highly correlated. Besides, GB is negatively correlated with both USDX and VIX and positively correlated with the rest of the markets. This result indicates that GB may serve as a refuge asset during financial distress period.

4. Methodology

4.1. Spillover index approach

To measure the time–frequency connectedness, we extend the spillover method of (Diebold and Yilmaz, 2009, 2012, 2014, 2015) with the spectral representation of the variance decomposition method based on the frequency domain spillover method of Barunik and Krehlik (2018). Using the Fourier transform of the moving average coefficient Ψ with $i = \sqrt{-1}$, the frequency impulse response function can be defined as:

$$\Psi(e^{-ih\omega}) = \sum_{h=0}^{\infty} e^{-ih\omega} \Psi_h, \tag{1}$$

Following Barunik and Krehlik (2018), the generalized forecast error variance decompositions (FEVD) at a frequency band $d = (a, b) : a, b \in (-\pi, \pi)$ is derived as:

$$[\theta(d)]_{jk} = \frac{\sigma_{kk}^{-1} \int_a^b \left| [\Psi(e^{ih\omega}) \Sigma]_{jk} \right|^2 d\omega}{\int_{-\pi}^{\pi} \left[(\{\Psi e^{-ih\omega}\} \Sigma \{\Psi e^{+ih\omega}\})_{jj} \right] d\omega}, \tag{2}$$

where $[\theta(d)]_{jk}$ indicates the connectedness of the j th variable at a given frequency band due to shocks to the k th variable scaled by the variance of the j th variable. The total connectedness within the frequency band d is defined as:

$$C_{jk}^F(d) = 100 \left(\frac{\sum_{k=1, k \neq j}^n [\check{\theta}(d)]_{jk}}{\sum_{j,k} [\check{\theta}(g)]_{jk}} \right) \tag{3}$$

where $C_{jk}^F(d)$ represents the connectedness index within the frequency band d . In this paper we estimate the dynamic frequency-domain connectedness at three scales such as the short-, and long-term corresponding to period of 1 to 8 days, and 8 days to 256 days, respectively.

The time–frequency connectedness measures based on GFEVD are expressed as:

$$TO_{j \leftarrow * } = \sum_{k=1, k \neq j} [\check{\theta}(d)]_{jk} \tag{4}$$

$$FROM_{j \rightarrow * } = \sum_{k=1, k \neq j} [\check{\theta}(d)]_{kj} \tag{5}$$

$$NET_j = TO_j - FROM_j \tag{6}$$

where TO_j represents the aggregated impact of a shock in variable j on all other variables, whereas $FROM_j$ illustrates the aggregated influence of all other variables on variable j . NET_j indicates the difference between “TO” and “FROM”, where a positive value means a net transmitter, and a negative value refers to a net recipient from the other markets, respectively.

4.2. Quantile-on-quantile approach

Next, we examine the extreme dependence between S&P 500 and other financial assets (GB, Gold, Silver, VIX, Brent oil and USDX) using the quantile-on-quantile regression (QQR) of Sim and Zhou (2015). Unlike to the conventional quantile regression (QR) (Koenker, 2005), the QQR method measure the dependence at the different quantiles in the given distribution and help us to judge the quantile relationship across different time periods. The QQR method can be represented in the following non-parametric quantile regression equation:

$$R_t = \beta^\theta FA_t + \alpha^\theta R_{t-1} + \epsilon_t^\theta \tag{7}$$

where R_t denotes the S&P 500 returns at times t and FA denotes other financial asset returns (GB, Gold, Silver, VIX, Brent oil and USDX). ϵ_t^θ is the error term with a zero θ -quantile and $\beta^\theta(\cdot)$ is assumed to be an unknown function, respectively. We investigate this relationship over θ -quantiles of S&P 500 returns and τ -quantiles of other financial asset returns which is denoted by FA^τ . We linearize the function $\beta^\theta(\cdot)$ by taking a first-order Taylor expansion of $\beta^\theta(\cdot)$ around FA^τ , which can be expressed as:

$$\beta^\theta(FA_t) \approx \beta^\theta(FA^\tau) + \beta^{\theta'}(FA^\tau)(FA_t - FA^\tau), \tag{8}$$

where $\beta^{\theta'}$ is the partial derivative of $\beta^\theta(FA_t)$ for other financial asset returns, also known as the response (or marginal effect). Following Sim and Zhou (2015), $\beta^\theta(FA^\tau)$ and $\beta^{\theta'}(FA^\tau)$ can be redefined as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$, respectively. Eq. (8) can be rewritten as:

$$\beta^\theta(FA_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(FA_t - FA^\tau). \tag{9}$$

Table 2
Preliminary statistics of price returns.

Panel A: Returns								
	Green Bond	SP500	Gold	Silver	VIX	Brent Oil	USDX	FROM
Green Bond	41.91	5.71	11.98	9.18	4.18	3.84	23.19	58.09
SP500	4.87	45.67	3.43	2.86	31.58	6.7	4.89	54.33
Gold	11.48	3.13	42.44	28.95	2.87	3.03	8.1	57.56
Silver	8.82	3.13	29.93	44.47	3.15	3.98	6.51	55.53
VIX	3.79	33.54	2.77	2.46	48.12	5.36	3.96	51.88
Brent Oil	4.1	10.01	4.14	5.35	7.56	64.84	4	35.16
USDX	23.99	5.44	9.35	7.59	4.02	3.44	46.17	53.83
TO	57.05	60.96	61.61	56.38	53.38	26.35	50.65	366.38
ALL	98.97	106.63	104.05	100.85	101.49	91.19	96.82	52.34
NET	-1.03	6.63	4.05	0.85	1.49	-8.81	-3.18	
Panel B: Volatility								
	Green Bond	SP500	Gold	Silver	VIX	Brent Oil	USDX	FROM
Green Bond	65.42	4.07	6.7	4.5	1.54	2.05	15.74	34.58
SP500	2.84	57.83	2.74	1.97	27.9	3.86	2.85	42.17
Gold	5.82	3.42	57.73	26.22	1.44	2.06	3.31	42.27
Silver	4.41	2.81	27.25	59.74	1.18	2.46	2.14	40.26
VIX	1.43	29.29	1.54	1.22	62.45	2.13	1.93	37.55
Brent Oil	2.5	5.62	2.53	2.91	2.84	81.06	2.55	18.94
USDX	15.86	4.25	3.92	2.45	2.41	2.14	68.96	31.04
TO	32.86	49.46	44.69	39.27	37.31	14.7	28.51	246.8
ALL	98.28	107.29	102.42	99.01	99.76	95.76	97.48	35.26
NET	-1.72	7.29	2.42	-0.99	-0.24	-4.24	-2.52	

Notes: DY model is estimated with lag length criteria of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition

Upon substituting Eq. (9) into Eq. (7), the following equation is obtained:

$$R_t = \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(FA_t - FA^\tau) + \epsilon_t^\theta \tag{10}$$

Unlike the conventional QR method, the QQR model uncovers the true impacts of quantiles of *FA* on S&P 500 stock returns in every quantile since the coefficients β_0 and β_1 depend the value of quantiles θ and τ . Furthermore, the QQR model provides a more accurate information about the extreme dependence by taking into account the heterogeneity among the underlying relationships. Finally, the estimations are performed by selecting a bandwidth parameter of $h = 0.05$; this choice is consistent with Sim and Zhou (2015).

5. Results and analysis

5.1. DY spillover results

Table 2 presents the estimates of return (Panel A) and volatility (Panel B) spillovers using the time domain spillover index of DY12 method. The total return spillover is 52.3%. In addition, all markets are largely affected by their own-return shocks. Furthermore, we observe that green bond is a higher transmitter of returns to USDX by 24%, followed by gold (11.48%), silver (8.82%), SP500 (4.87%), Brent crude oil (4.1%). Among all markets, gold is the highest return transmitter (61.61%) in the system while green bond is the highest receiver of return spillover by 58%. More interestingly, we show that green bond, Brent oil, and USDX are net return receivers whereas US stock market, gold, silver, and VIX are net return transmitters. This result is consistent with the findings of Mensi et al. (2022a). As for volatility spillover, the average index reaches 35.26%. The US stock market is the highest contributor of volatility spillover and gold is the highest receiver of volatility in the system. Specifically, the US stock market (SP500) contributes respectively 29.29%, 5.62%, 4.25%, 4.07%, 3.42%, 2.81% on the forecasting variance for VIX, Brent oil, USDX, green bond, gold, and silver. In addition, all series are net receivers of volatility spillover with the exception of US stock and gold markets. An investor exploiting in a market with net transmitters can have hedge their assets against risks using assets of markets with negative net spillovers. Zhang and Hamori (2021) show that WTI crude oil is a net receiver of return and volatility spillover. In addition, the authors show that the news Headline Sentiment index is an important contributor of returns and volatility to the infectious disease equity market volatility tracker and economic index.

5.2. TVP-VAR connectedness results

For a deepen analysis, we conduct a time-varying spillover in returns and volatility by merging the DY spillover index and the time-varying parameter VAR (TVP-VAR) model by Koop and Korobilis (2014). This model does not require to

Table 3
DY connectedness in the returns and volatility.

Panel A: Returns								
	Green Bond	SP500	Gold	Silver	VIX	Brent Oil	USDX	FROM
Green Bond	46	4.95	10.61	8.24	3.24	2.39	24.58	59.59
SP500	3.86	50.45	1.73	1.45	33.01	5.89	3.6	70.02
Gold	10.31	1.69	46.9	30.7	1.25	2.11	7.03	71.46
Silver	8.3	1.78	31.1	47.69	1.5	3.62	6.02	69.49
VIX	2.93	34.67	1.3	1.18	52.42	4.32	3.19	68.04
Brent Oil	2.93	8.29	2.57	4.58	5.71	72.89	3.02	22.17
USDX	25.24	4.39	7.86	6.41	3.32	2.39	50.38	54.85
TO	66.66	69.47	69.53	65.6	60.16	25.13	59.06	415.62
ALL	99.56	106.22	102.09	100.24	100.46	93.61	97.83	TCI
NET	7.07	−0.54	−1.93	−3.89	−7.89	2.97	4.21	59.37
Panel B: Volatility								
	Green Bond	SP500	Gold	Silver	VIX	Brent Oil	USDX	FROM
Green Bond	61.65	4.82	6.99	6.29	1.55	2.53	16.17	39.98
SP500	3.73	57.1	3.49	2.63	25.52	4.76	2.77	54.38
Gold	6.81	4.49	56.14	25.78	1.37	2.19	3.22	54.59
Silver	7.11	4.02	25.71	56.88	1.12	2.77	2.38	53.54
VIX	1.48	28.73	1.38	1.05	62.88	2.67	1.81	49.75
Brent Oil	2.45	6.52	2.47	2.99	3.39	79.47	2.71	17.42
USDX	17.28	4.32	3.87	2.6	2.3	2.89	66.74	34.2
TO	45.52	61.85	51.31	48.44	41.64	20.89	34.2	303.86
ALL	100.51	109.99	100.06	98.22	98.13	97.29	95.8	TCI
NET	5.54	7.48	−3.29	−5.1	−8.11	3.48	0	43.41

Notes: The table is estimated based on TVP-VAR-based connectedness with 1 lag (BIC) and a 10 day forecast horizon.

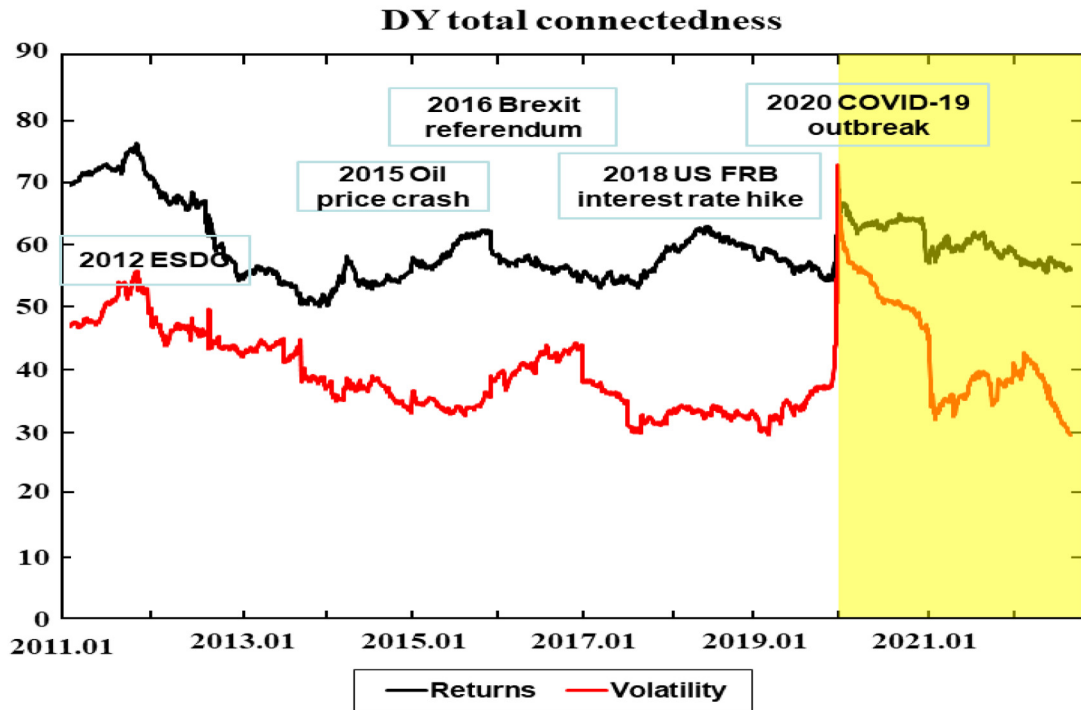
select the length period of the moving rolling window (Zhang and Hamori, 2021; Liu et al., 2022). In addition, the model is insensitive to the outliers. Table 3 summarizes the estimates of TVP-VAR connectedness in returns (Panel A) and volatility (Panel B). We select the optimal lag order of TVP-VAR model using the Bayesian information criteria. As we can see, the total connectedness index is 59.3% in returns and 43.4% in volatility. All markets are largely affected by their own shocks. Moreover, Green Bond, Brent oil, and USDX are net return transmitters, while other assets are net return spillovers. Gold is the largest transmitters of returns followed by SP500 and Green Bond, while Brent oil is the weakest return transmitter in the system. Green Bond transmits more return spillovers to USDX compared to the other assets. Among all markets, gold is the largest receiver of returns followed by SP500 and silver. Regarding the volatility spillovers, only the Green Bond and the SP500 markets are net transmitters in the system whereas the remaining markets are net receivers. We notice that the markets with negative net spillovers (SP500, gold, silver, and VIX) are less resilient compared to Green Bonds, USDX and Brent oil markets as they show strong capability to receive shocks from the other markets than they transmit. For net return transmitter markets, the values are lower for Brent oil and USDX than Green Bonds, indicating that investors exploiting in Green Bonds are more exposed to risk than those invested in oil. VIX transmits return and volatility spillovers to Green Bonds. These results confirm the findings of Long et al. (2022) who show significant spillovers from both VIX and OVX on the Green Bond market.

The static analysis hides vital information on the spillover in terms of size and directions during major events. We use a rolling window approach and plot the DY return and volatility spillover in Panel A of Fig. 3. As we can see, the DY return and volatility spillovers are time varying and sensitive to financial and global health crises. Specially, the return spillover is higher than the volatility spillover along the sample period with the exception of early 2020, corresponding to the first wave of COVID-19 outbreak. We notice that the return spillover index varies from 52% in 2014 to 78% in 2012. The return spillover increases during the European crisis and decreases between 2012 until 2014 followed by another upside trend during the oil price crash. Between 2016 and 2017, the return spillover decreases and varies between 50% and 60% followed by an increase in 2018 and a decrease in 2019. We note that during the first quarter of 2020, the spillover index shows a jump followed by a decrease in 2021 and 2022. The volatility spillover shows a significant jump during the first phase of pandemic crisis (2020Q1) followed by a decline during the remaining sample period. Our result corroborates the results of Pham and Cepni (2022) who find asymmetric spillovers between green bond and investor attention at extreme tail of dependence. In addition, oil, stock, bond market volatility, and economic policy uncertainty influence the spillover effects. Panel B of Fig. 3 displays the dynamic TVP-VAR model estimates. We observe that the pathways of return and volatility spillovers are similar to those obtained in Panel A of Fig. 3 which confirms our findings.

5.3. Analysis of frequency connectedness

Table 4 reports the frequency connectedness at two bands: the short-term horizon (Panel A) and long-term horizon (Panel B). These correspond to frequency bands of 1~8 days and 8~256 days, respectively. A close inspection of this

(A)



(B)

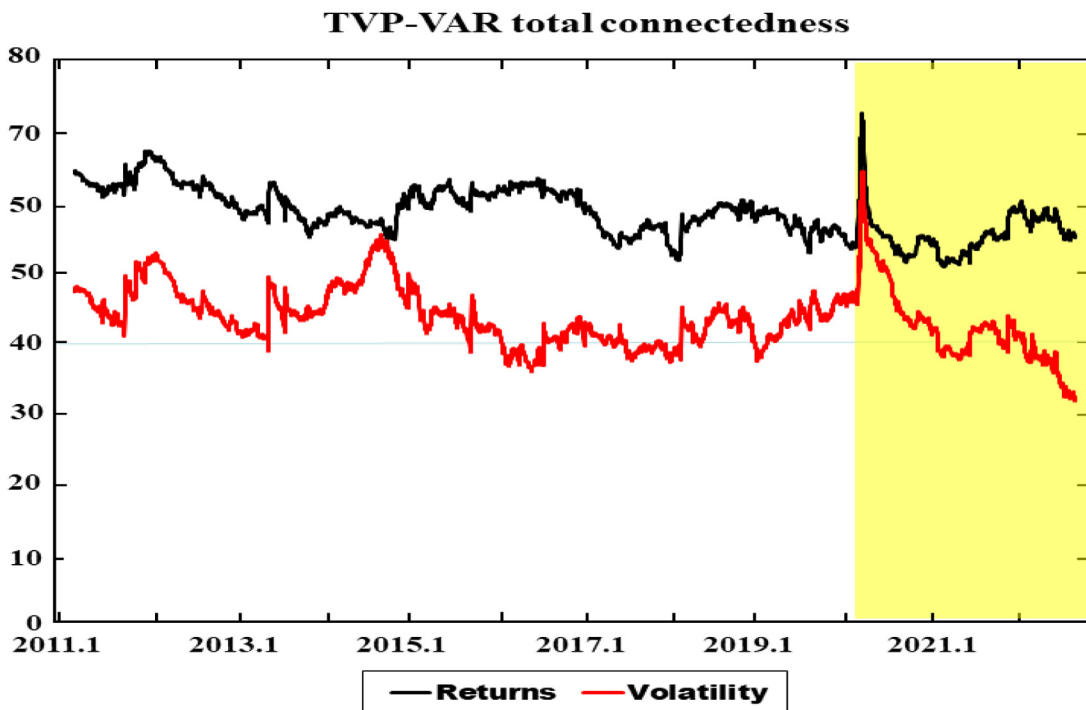


Fig. 3. Dynamics of total connectedness.

Note: This figure shows the dynamics of total return and volatility connectedness: (A) DY total connectedness; (B) TVP-VAR total connectedness..

Table 4
Connectedness at different frequencies.

Panel A: Short term connectedness									
	Green Bond	SP500	Gold	Silver	VIX	Brent Oil	USDX	FROM_ABS	FROM_WTH
Green Bond	43.19	2.94	7.3	6.41	1	0.51	20.63	5.54	6.36
SP500	2.56	49.21	0.27	1.01	28.09	5.83	1.77	5.65	6.49
Gold	7.92	0.29	44.58	28.71	0.23	0.77	5.53	6.21	7.13
Silver	6.81	1.06	27.96	43.7	0.74	1.98	4.54	6.16	7.07
VIX	0.9	32.52	0.03	0.71	52.99	4.08	0.75	5.57	6.4
Brent Oil	1.1	7.89	1.3	3.54	4.77	66.52	0.82	2.77	3.19
USDX	23.47	1.69	5.73	4.71	0.54	0.55	49.28	5.24	6.02
TO_ABS	6.11	6.63	6.08	6.44	5.05	1.96	4.86	37.13	
TO_WTH	7.02	7.61	6.99	7.4	5.8	2.25	5.59		42.65
NET	0.66	1.12	−0.14	0.33	−0.6	−0.94	−0.43		
Panel B: Long term connectedness									
	Green Bond	SP500	Gold	Silver	VIX	Brent Oil	USDX	FROM_ABS	FROM_WTH
Green Bond	6.74	1.16	1.71	1.79	0.41	0.3	4.5	1.41	11.79
SP500	0.37	5.18	0.04	0.27	3.6	0.78	0.17	0.75	6.25
Gold	0.99	0.01	5.65	3.54	0	0.15	0.79	0.78	6.55
Silver	0.99	0.3	3.85	5.74	0.23	0.48	0.61	0.92	7.71
VIX	0.04	2.48	0	0.06	4.58	0.33	0.01	0.42	3.5
Brent Oil	0.09	1.46	0.07	0.4	1.27	9.46	0.1	0.48	4.05
USDX	3.09	0.4	1.2	1.26	0.12	0.24	6.66	0.9	7.53
TO_ABS	0.8	0.83	0.98	1.05	0.8	0.32	0.88	5.66	
TO_WTH	6.66	6.94	8.2	8.75	6.73	2.71	7.39		47.37
NET	−5.13	0.69	1.65	1.04	3.23	−1.34	−0.14		

Notes: The abbreviations “ABS” and “WTH” stand for “absolute” and “within”, respectively.

table reveals that the total long-term spillovers (6%) is inferior to the short-term spillovers (38%). This result is in line with the findings of frequency spillovers between a news-based economic uncertainty index and three renewable energy stock indices namely European Renewable Energy Price Index, Wilder Hill Clean Energy Index, and Standard & Poor Global Clean Energy Index (S&P GCE). In addition, GB is a net contributor of short-term volatility (1–8 trading days), but it shifts to become a net receiver of spillover when there are more than eight trading days. The SP500 is a net contributor of spillover at different time horizons. The ability of the SP500 to transmit risk to other markets decreases in the long term. Silver exhibits the same result as the SP500, but its ability to transmit spillovers increases in the long term more than in the short term. Gold is a net receiver of short-term spillovers and switches to become a net transmitter of spillover when there are more than eight trading days. Brent oil and USDX are net receivers of spillovers irrespective of time horizon. Moreover, they receive more spillovers in the long term than in the short term. Gold is the largest receiver of short-term spillovers in the system, while GBs are the largest receiver in the long term. The SP500 is the largest contributor of spillover in the system in the short term, while and silver is the largest contributor of spillover in the system in the long term. All markets receive the largest proportion of spillovers from their own shocks which are sensitive to the time investment horizons. GB transmits the largest spillover to precious metals (gold and silver) and the USDX in both the short- and long-terms. The SP500 contributes to the spillovers of VIX and Brent oil. Gold and silver are interdependent markets, and the magnitude of their spillovers is higher in the short term than in the long term. SP500 receives weak spillovers from Green Bond, precious metals, and USDX, implying that these assets may serve as a hedge asset for US equity investors at both short and long terms. The high bidirectional spillovers between gold and precious metals indicate that the inability of gold/silver to hedge against the silver/gold. This result corroborates the findings of [Fasanya et al. \(2021\)](#). The results reported in [Table 4](#) are confirmed by [Fig. 4](#). The graphical evidence shows higher spillover in the short term than in the long term for the whole period. Specifically, spillover in the short-term varies between 45% and 85% whereas it is less than 10% in the long term. We observe that the spillover reaches its maximum in February 2020, where the first confirmed cases of COVID-19 are announced in the US. In addition, the spillover in the short term is higher than those at the long term. This result is consistent with the findings of [Fang et al. \(2023\)](#) who find a jump in risk spillovers between stock, bond, crude oil, and foreign exchange markets, mainly at the short term. The decreases in spillover during 2014 and 2015 may be due to the fall in oil prices during the same period. Another important observation is that the spillover decreases after the 2012 European crisis. This is because of the trade relationships between the US and the European Union (EU) in which the economic recovery of the EU stimulates economic growth in the US.

5.4. Connectedness network analysis

Identifying the source of contagion is important for optimal fund allocation and portfolio risk assessment. Panels A–F of [Fig. 5](#) display the network directional and magnitude connectedness before and during the spread of the COVID-19

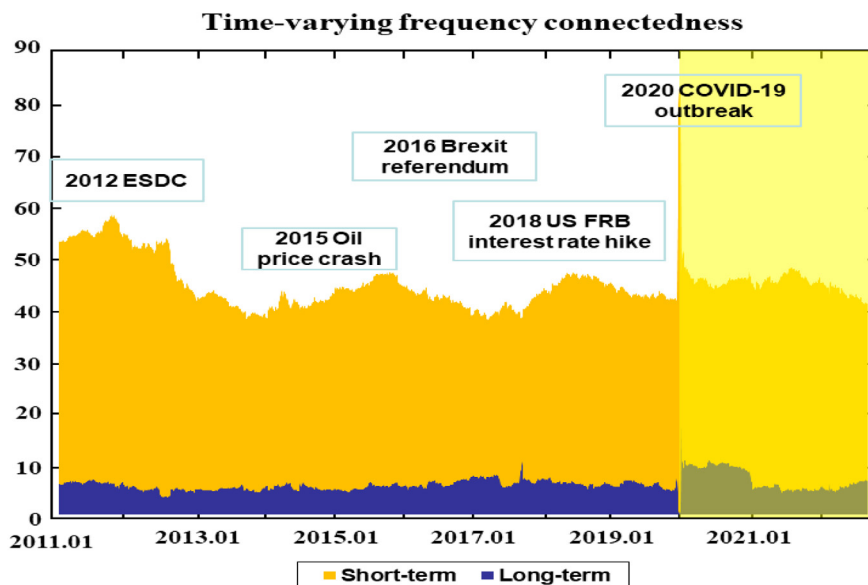


Fig. 4. Dynamics of frequency connectedness.

epidemic and under different investment horizons. In the short term (Panels A and B), we find that GB is the largest contributor of risk to USDX. In addition, the SP500 transmits a large portion of short-term spillover to Brent oil and VIX. Brent oil also receives spillover from silver, VIX, and GBs with different magnitudes. Gold, VIX, USDX, and Brent oil are net receivers of spillover. However, the results change in the long term (Panel B). Specifically, we show that USDX and Brent oil are the largest contributors of spillover to the other markets. Precious metals also contribute risk to the other markets. The SP500 receives more long-term shocks from USDX, Brent oil, and VIX. GBs become a receiver of spillover from the other markets in the long term, but with a low magnitude. This indicates that investors' anticipations and appetite for risk are related to the time horizon. It also shows that uncertainty is more pronounced in the long term than in the short term, making portfolio management more difficult.

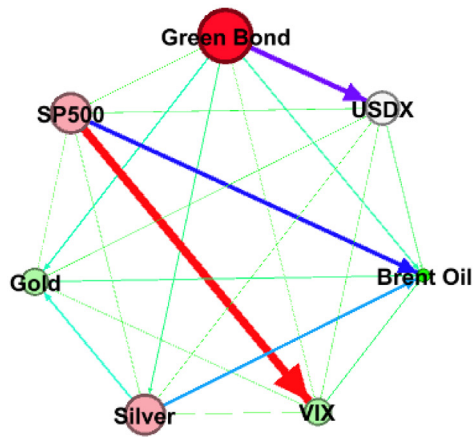
We deepen our analysis by showing the role of the spread of COVID-19 on network short-term connectedness (Panels C and D) and the long-term connectedness (Panels E and F). We observe that gold is a receiver of short-term shocks before the pandemic, but it switches to become a contributor of short-term shocks during the pandemic. This is consistent with the results of Akhtaruzzaman et al. (2021) where they show that gold loses his property as a safe haven asset from March 17, 2020 to April 24, 2020. In contrast, the VIX shifts from being a net contributor before COVID-19 to being a net receiver during COVID-19. Both gold and silver also have switching roles. This means that these metals are influenced by the pandemic. This result persists in the long term. A potential explanation is that there is a wide demand for gold, but the significant drop in the demand for silver might be due to production stoppages in some industry-based silver. The contribution of USDX to spillovers rises after the pandemic irrespective of time horizons. On the other hand, GBs and the SP500 are net receivers of spillovers irrespective of the effects of the pandemic. In the long term, the results change significantly, where the GBs become net contributors of spillover to the other markets, especially to USDX and gold before COVID-19 and to the SP500 and Brent oil during COVID-19. We notice that Brent oil is a net receiver of long-term spillover after the pandemic. This can be explained by the oil price shocks and the economic slowdown during the lockdowns in many states. VIX is a net receiver of spillover before and during COVID-19. This is the opposite of the result in the short term.

5.5. Robustness analysis using quantile-on-quantile

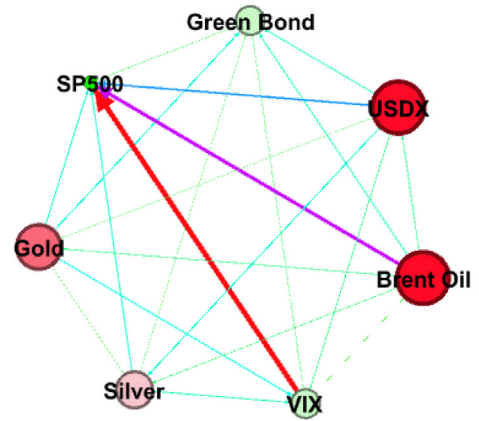
Now we use the quantile-on-quantile (QQ) method of Sim and Zhou (2015) to estimate the heterogeneous dependence between GBs, global factors, and US equity markets before and during COVID-19. One main advantage of QQ is its flexibility to assess the heterogeneous dependence structure at opposing return quantiles and explores the asymmetric return nonlinear relationships. More interestingly, QQ is able to identify the hedging potential of assets as well as their role to serve as a safe haven asset during crisis periods.

Panels A and B of Fig. 6 plots the QQ between U.S. stock market (SP500) and both gold, oil, GB, silver, VIX, and US dollar index before and during the COVID-19 period, respectively. The x-axis represents the quantiles of financial market returns and the y-axis represents the quantiles of US stock returns. Lower or higher quantiles of x-axis show the extreme conditions of the uncertainty level. For y-axis, the lower or higher quantiles for SP500 refer to how bearish or bullish market the markets are, respectively.

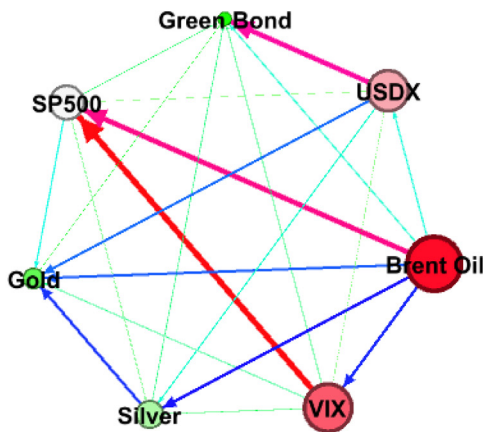
Panel A: Short-term frequency (1-8 days)



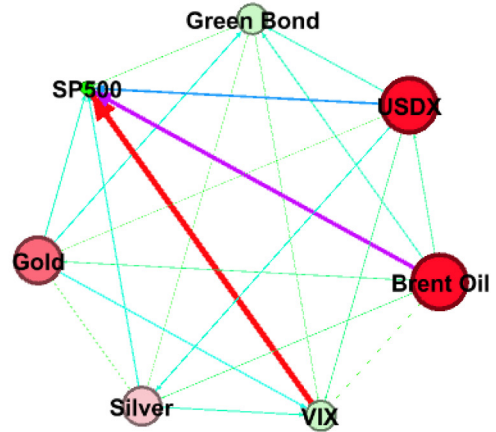
Panel B: Long-term frequency (≥ 8 days)



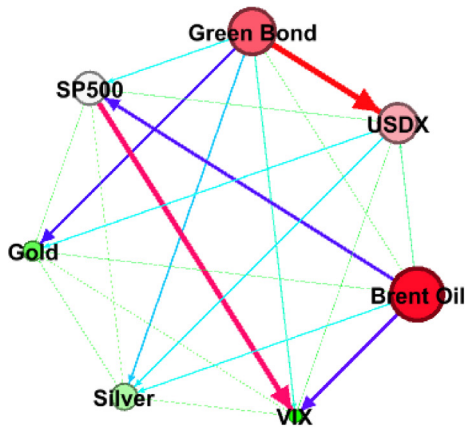
Panel C: Before COVID-19 with a short-term horizon



Panel D: COVID-19 pandemic with a short-term horizon



Panel E: Before COVID-19 with a long-term horizon



Panel F: COVID-19 pandemic with a long-term horizon

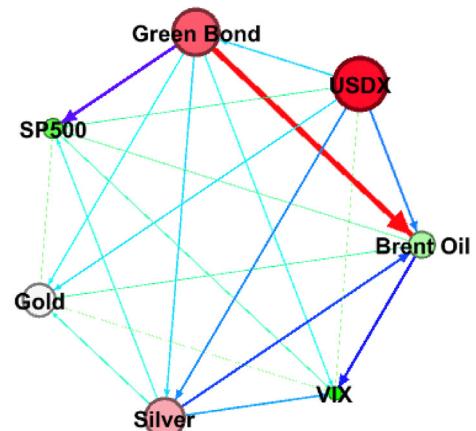


Fig. 5. Net pairwise directional connectedness at short- and long-terms.

As we can see, we find negative or zero correlations between GB and SP500 before and during the pandemic crisis during different market conditions. This result exhibits that GB is a safe haven asset during the COVID-19 period. Moreover,

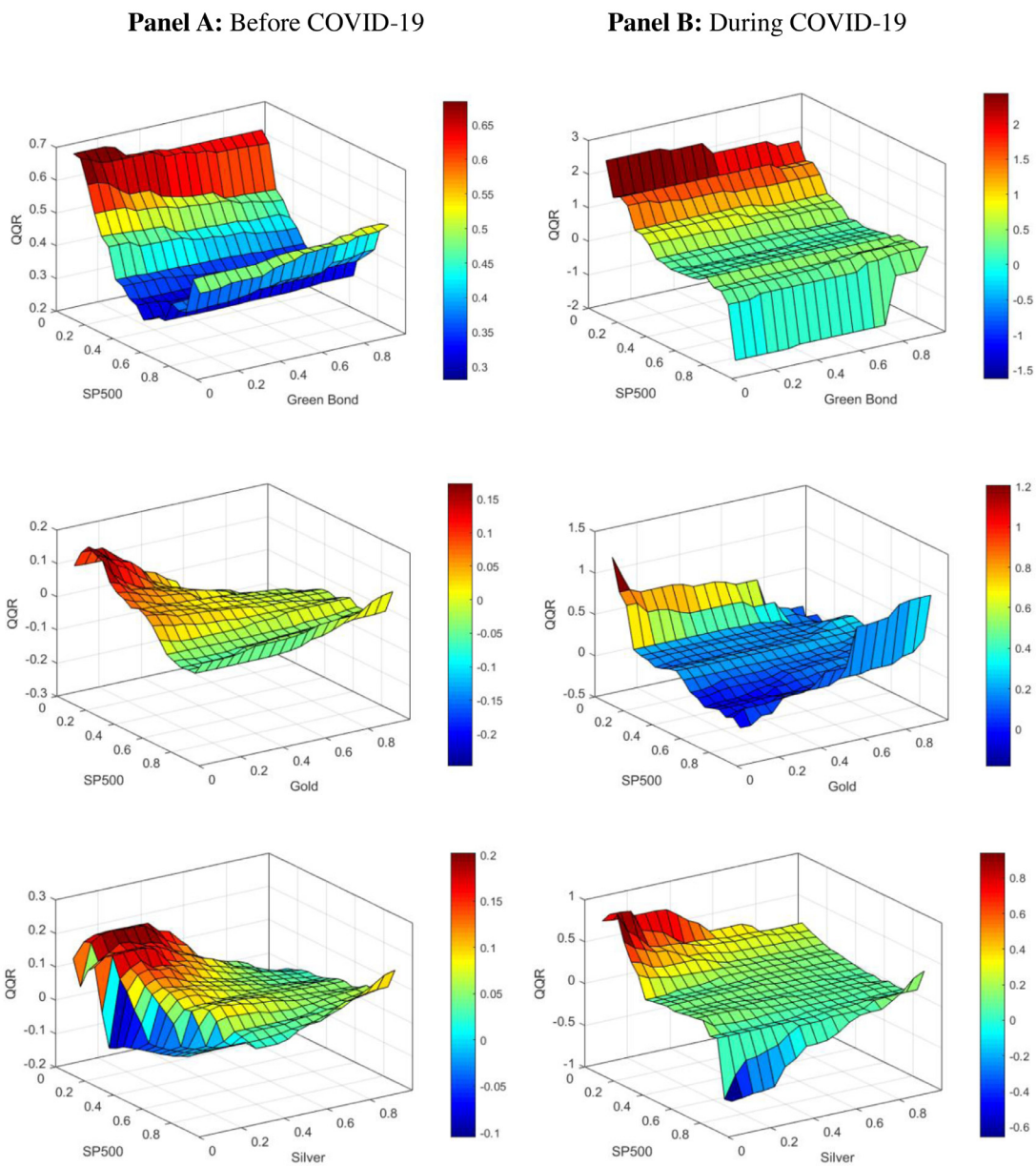


Fig. 6. Quantile on Quantile regression estimates slope of the coefficients.

the intensity of dependence rises a little bit during COVID-19 than before. Gold exhibits low or insignificant dependence with SP500 before and during the COVID-19, irrespective of market conditions. This result is in line with previous literature about the role of gold as a safe haven asset against extreme negative stock price movements (see [Baur and Lucey, 2010](#)). Silver shows negative correlations with SP500 before the pandemic. The correlation between SP500 and silver rises during COVID-19 but still weak (less than 0.2). This underscores that silver is a hedge asset for US equity investors. As for VIX, it presents a high positive correlation with SP500 during normal, bearish, and bullish market conditions. This result shows that VIX is a predictor indicator for US stock markets. Investors can therefore use the information embodied in VIX to predict future stock prices. Our result corroborates the results of [Wang et al. \(2020\)](#) where the authors find that VIX contains more important information than EPU to predict the stock markets' future volatility. Similarly, [Liang et al. \(2020\)](#) confirm the VIX's forecasting ability for international stock markets. Brent oil exhibits a negative dependence with SP500 during the pandemic period. This result may be explained by the decrease in the global oil demand during the crisis due to the lockdowns and travel restrictions. As for the USDX, we observe a shift from positive to negative or near-zero correlation with SP500. This shows that COVID-19 impacts the SP500-USDX nexus.

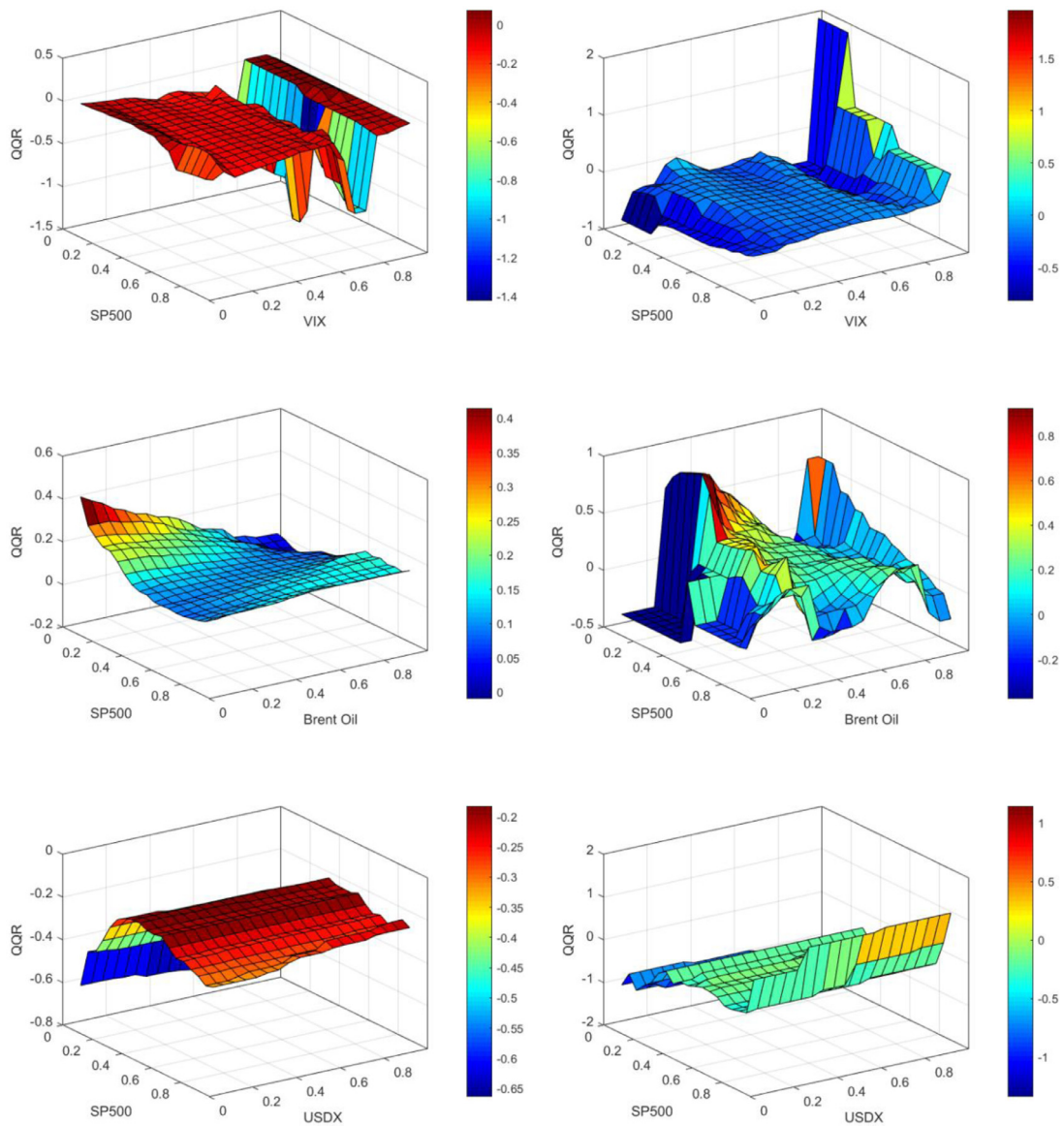


Fig. 6. (continued).

For robustness of the QQ method, we plot in Fig. 7 the relationships between SP500 and other series by comparing QQ and standard Quantile regression before and during the COVID-19 pandemic. The result shows similar trend between QR and QQR over different quantiles for all cases with the exception of gold, VIX, silver before COVID-19, and Brent oil during COVID-19. The graphical evidence confirms the results of QQ. Our result is in line with those of Shahzad et al. (2018) when they studied the relationships between industry-level U.S. credit and stock markets.

5.6. Portfolio management implications

Our results have important implications for holding efficiently diversified portfolios and conducting risk management. Thus, we analyze whether US equity investors can hedge their equity portfolio through GBs, gold, silver, oil, the US dollar index, and VIX.

To diversify the portfolio risk more efficiently, we calculate the optimal portfolio weights and the hedge ratios for designing optimal hedging strategies at both short- and long-terms using wavelet-based GARCH-DCC model.¹ First, we

¹ To save space, we do not report the results of the bivariate DCC-GARCH model. Upon request, we can provide these estimates.

Panel A: Before COVID-19

Panel B: During COVID-19

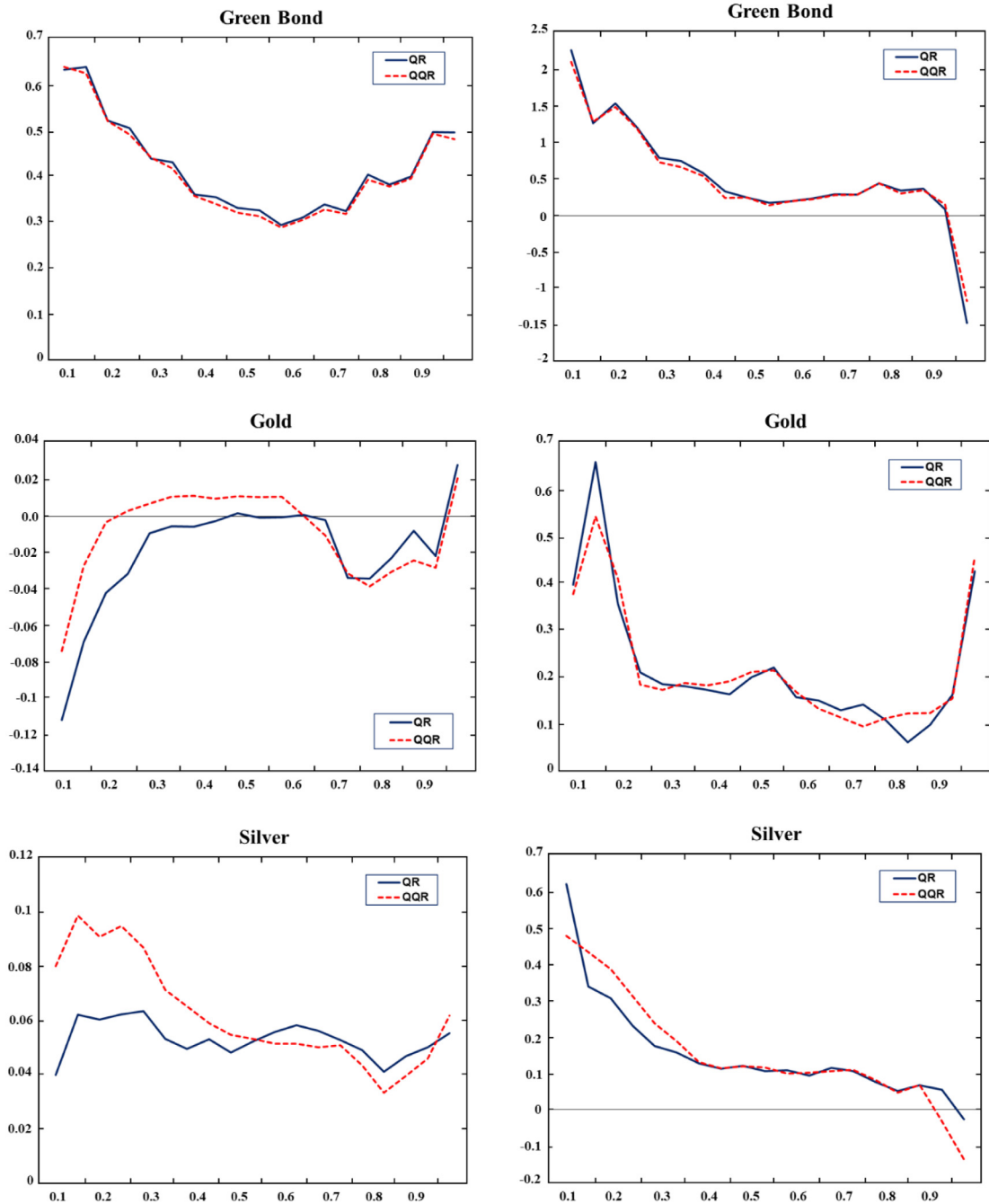


Fig. 7. Comparison between Quantile on Quantile and Quantile regression.

use the methodology of Kroner and Ng (1998) to determine the portfolio weight (w_t^S) of the US equity asset (SP500) holdings by:

$$w_t^S = \frac{h_t^O - h_t^{S,O}}{h_t^S - 2h_t^{S,O} + h_t^O}, \text{ with } w_t^S = \begin{cases} 0 & w_t^S < 1 \\ w_t^S & 0 \leq w_t^S \leq 1 \\ 1 & w_t^S > 1, \end{cases} \quad (11)$$

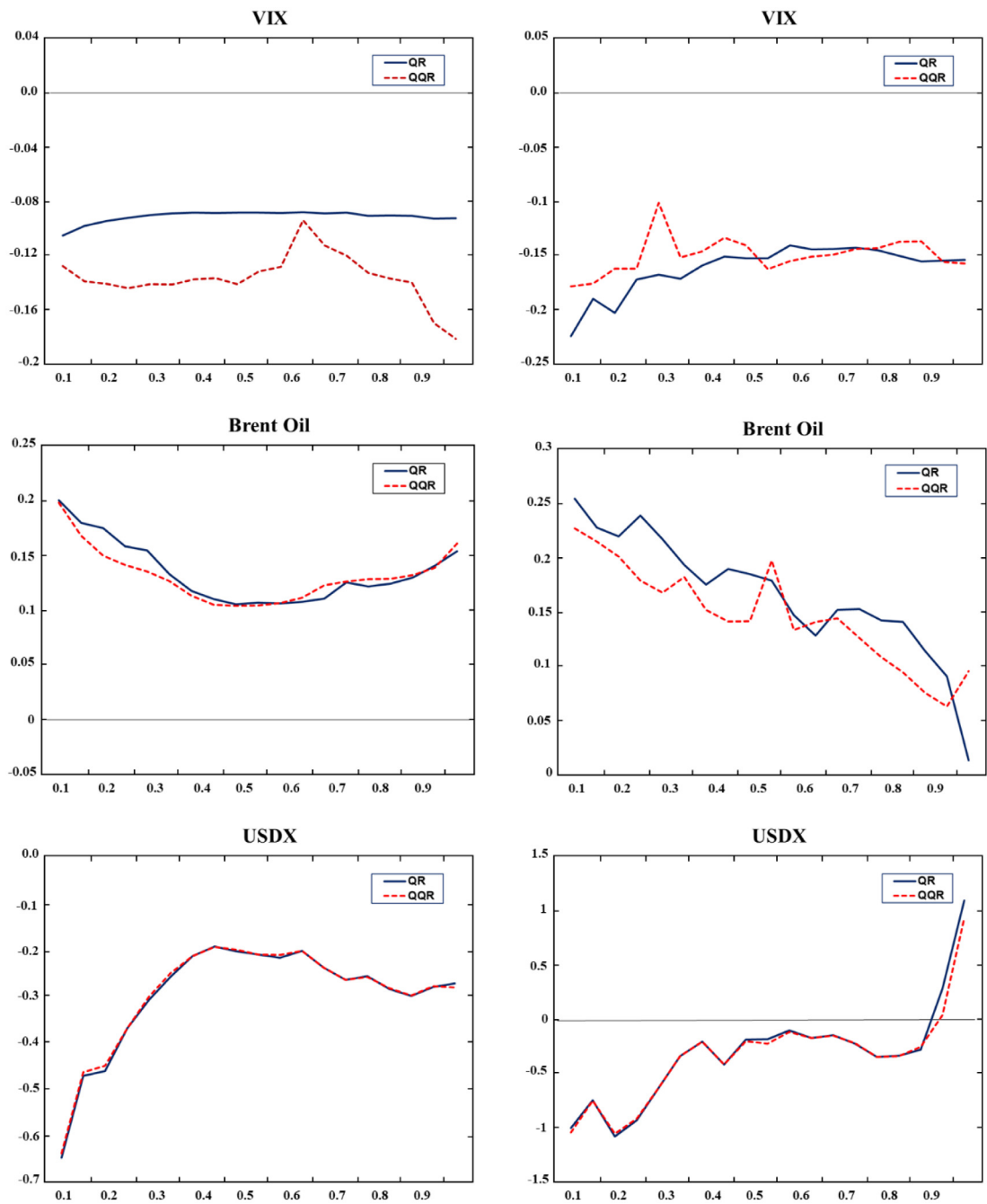


Fig. 7. (continued).

where h_t^S , h_t^O , and $h_t^{S,O}$ are the conditional volatility of the US equity market, the conditional volatility of the other assets (GBs, gold, silver, oil, the US dollar index, and VIX), and the conditional covariance between the US equity and the other assets at time t , respectively.

Using the methodology of Kroner and Sultan (1993), we calculate the hedging of a long position (purchase) of one dollar in the US equity by a short position (sell) of β_t^C dollar in other assets; that is:

$$\beta_t^S = \frac{h_t^{S,O}}{h_t^S}. \tag{12}$$

Table 5
Portfolio design in short- and long-terms.

Portfolio Pairs	w_t^S		β_t^S		HE (%)	
	Short term	Long term	Short term	Long term	Short term	Long term
Panel A: Before COVID-19						
Green Bond/SP500	0.1619	0.2044	0.0469	0.2403	6.344%	7.260%
Gold/SP500	0.5753	0.5672	0.0253	0.4334	60.39%	61.29%
Silver/SP500	0.8025	0.7411	0.1898	0.9323	80.41%	81.50%
VIX/SP500	0.9151	0.9753	-0.8913	-0.7298	99.71%	98.32%
Brent Oil/SP500	0.8725	0.7723	0.6994	0.8041	80.45%	76.52%
USDX/SP500	0.2521	0.3443	0.0081	0.2053	34.20%	27.63%
Panel B: During COVID-19						
Green Bond/SP500	0.0617	0.1097	0.0266	0.1365	0.233%	NA
Gold/SP500	0.4432	0.3801	0.0350	0.2608	21.77%	2.502%
Silver/SP500	0.7510	0.6561	0.2955	0.8173	63.49%	55.24%
VIX/SP500	0.8604	0.9617	-0.5376	-0.3022	98.42%	95.43%
Brent Oil/SP500	0.9129	0.7386	0.7717	0.8831	72.24%	81.10%
USDX/SP500	0.1356	0.2107	0.0027	0.1596	10.33%	NA

Notes: This table summarizes the results of the optimal weights, hedge ratios and hedging effectiveness before and during COVID-19 and at both short- and long-terms. NA stands for not available.

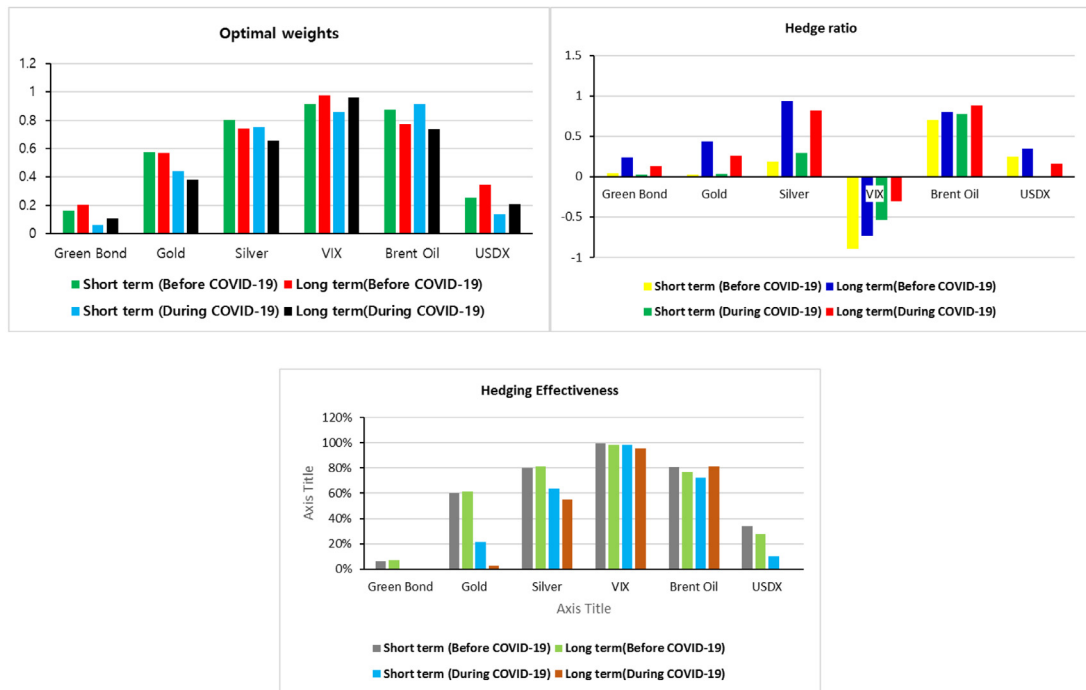


Fig. 8. Portfolio design under short and long term and before and during COVID-19.

Comparing the realized hedging errors (Ku et al., 2007), the hedging effectiveness (HE) of the constructed portfolios can be expressed as follows:

$$HE = 1 - \frac{Var_{hedged}}{Var_{unhedged}}, \tag{13}$$

where (Var_{hedged}) is the variance of portfolio of a US equity and each other asset and ($Var_{unhedged}$) is the variance of benchmark portfolio. A higher HE ratio implies a greater risk reduction.

Table 5 summarizes the results of optimal portfolio weight, hedge ratios and hedging effectiveness before and during COVID-19 and under different investment horizons. The results reveal that investors should hold more precious metals (gold and silver), VIX, and oil than equities irrespective of time horizons and before and during the pandemic. Moreover, the proportion invested in these potential hedge assets decreases during the COVID-19 outbreak in both the short and

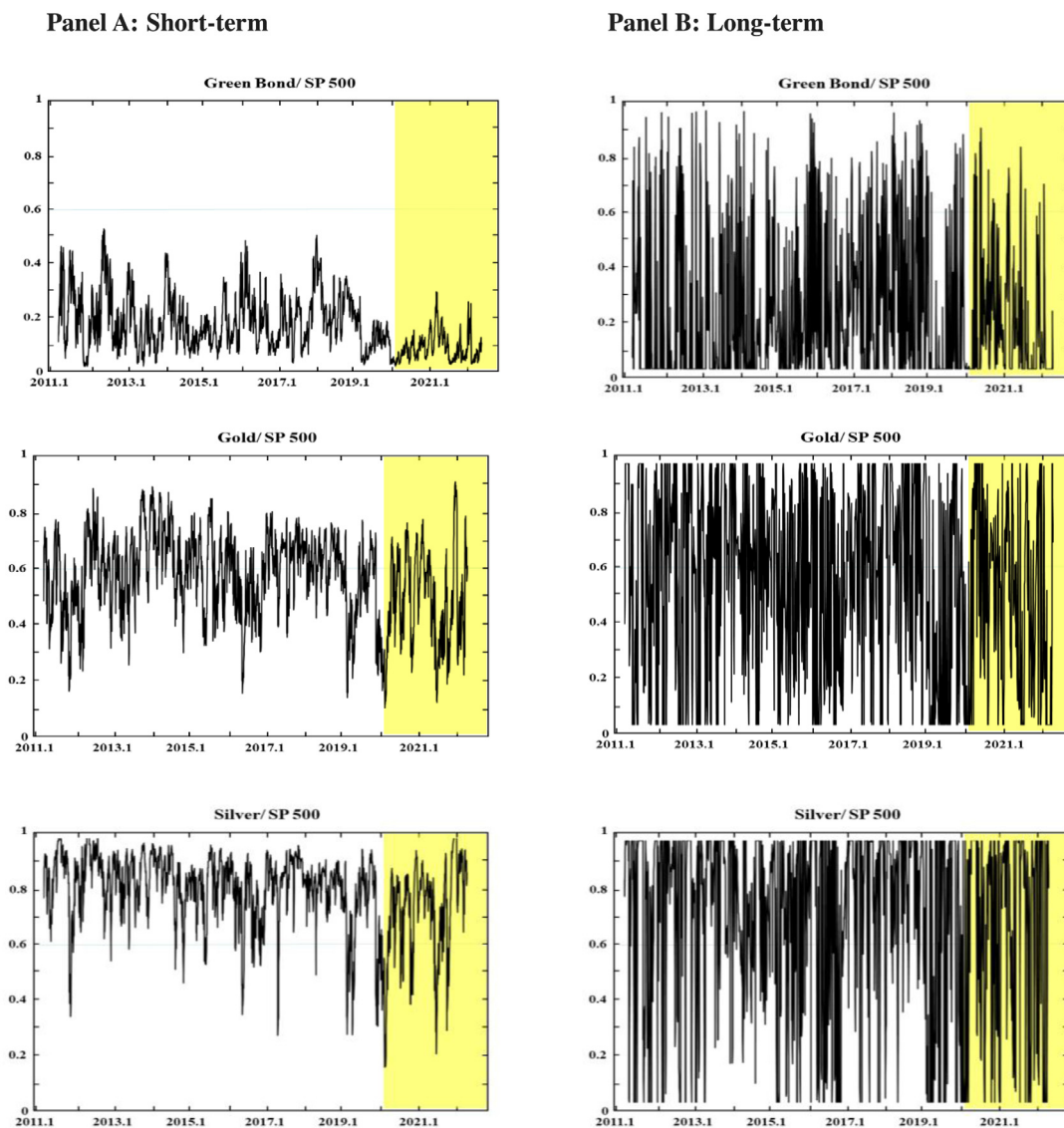


Fig. 9. The time varying optimal weights.

long terms, except for crude oil. This may be because of a sharp fall in oil prices and because equity investors prefer to hold oil futures in anticipation of an oil futures price increases in the near future. By comparing the investments in the short and long terms, we find that the optimal weight is higher in the long term for GBs, VIX, and USDX irrespective of the effects of the pandemic. The hedge ratios show that hedging is more expensive in the long term than in the short term for all cases. In addition, the hedging is cheaper during the COVID-19 outbreak, except for oil futures. Before COVID-19, GBs, gold, and silver offer more hedging effectiveness in the long term than in the short term. This result confirms the findings of Chai et al. (2022) who find that adding green bonds and clean energy to stock portfolio provide diversification gains. Our results are also consistent with the findings of Arif et al. (2022) who find that green bonds serve as diversifier and safe haven at the long term. Conversely, the HE is higher in the short term for VIX, oil, and USDX. During the pandemic, the HE is higher in the short term for all markets except oil.

Fig. 8 plots the portfolio design (optimal weight structure, hedge ratio, and hedging effectiveness) before and during COVID-19 as well as at short- and long-term horizons. We observe that equity investors should hold more VIX, oil, and precious metals than stock shares at both short and long terms and before and during the pandemic. As for VIX, investors have interest to hold a short position in VIX and long position in stock shares. The hedging is expensive for oil at long term than short term and during COVID-19 crisis than before. For precious metals (gold and silver) USDX and green bonds,

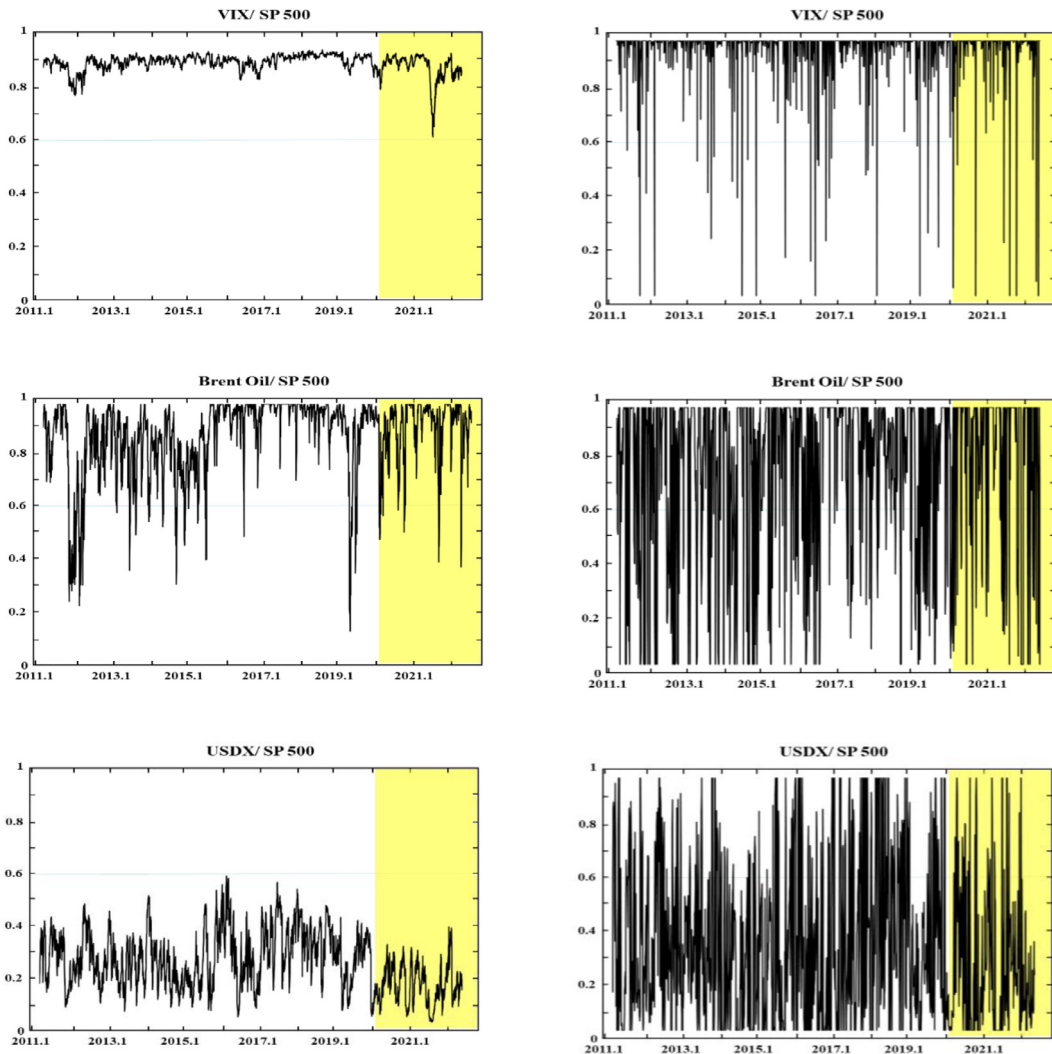


Fig. 9. (continued).

the hedging is cheaper during the pandemic crisis. This underlines the importance of these assets for hedging strategies and risk minimizing portfolios. VIX product offers the highest hedging effectiveness irrespective of time horizons and pandemic crisis.

Although Table 5 provides a useful summary of mean optimal weights and hedge ratio, they do not exhibit the fluctuations taking place during our whole sample period. The static approach hides therefore a useful information on how the portfolio structure and hedge costs change over time and respond to shocks. To overcome this drawback, we use a dynamic rolling-sample analysis. Figs. 9 and 10 displays the dynamic optimal weights and hedge ratios estimated between stock markets and the potential hedge assets (Green Bond, gold, silver, Brent crude oil, US dollar index, and VIX) under short and long terms, respectively. As we can see in Fig. 9, the optimal portfolio weights evolve over time, underlying that equity investors change its position frequently. In addition, the optimal weight is different under short and long terms. This indicates the importance of relying on time investment horizon factor to build an optimal portfolio. This also reveals that the behaviors of short-term investors (speculators) are different to the long-term investors (institutional investors). Specifically, investors frequently change the capital structure weights of their portfolio in the long term than in the short term. Furthermore, the temporal changes of optimal portfolio weights are more pronounced during the COVID-19 crisis for gold, oil, and silver. This may be due to high demand of this products by investors to protect against extreme downward stock prices. The time-varying behavior of hedge ratio is explained by the information arrivals to stock markets. Besides, the hedge ratio for all pairs responds differently to shocks. For example, the Green Bond-stock pair exhibits a downside pattern under short term than in the long term. The decrease continues during the pandemic crisis period and at the

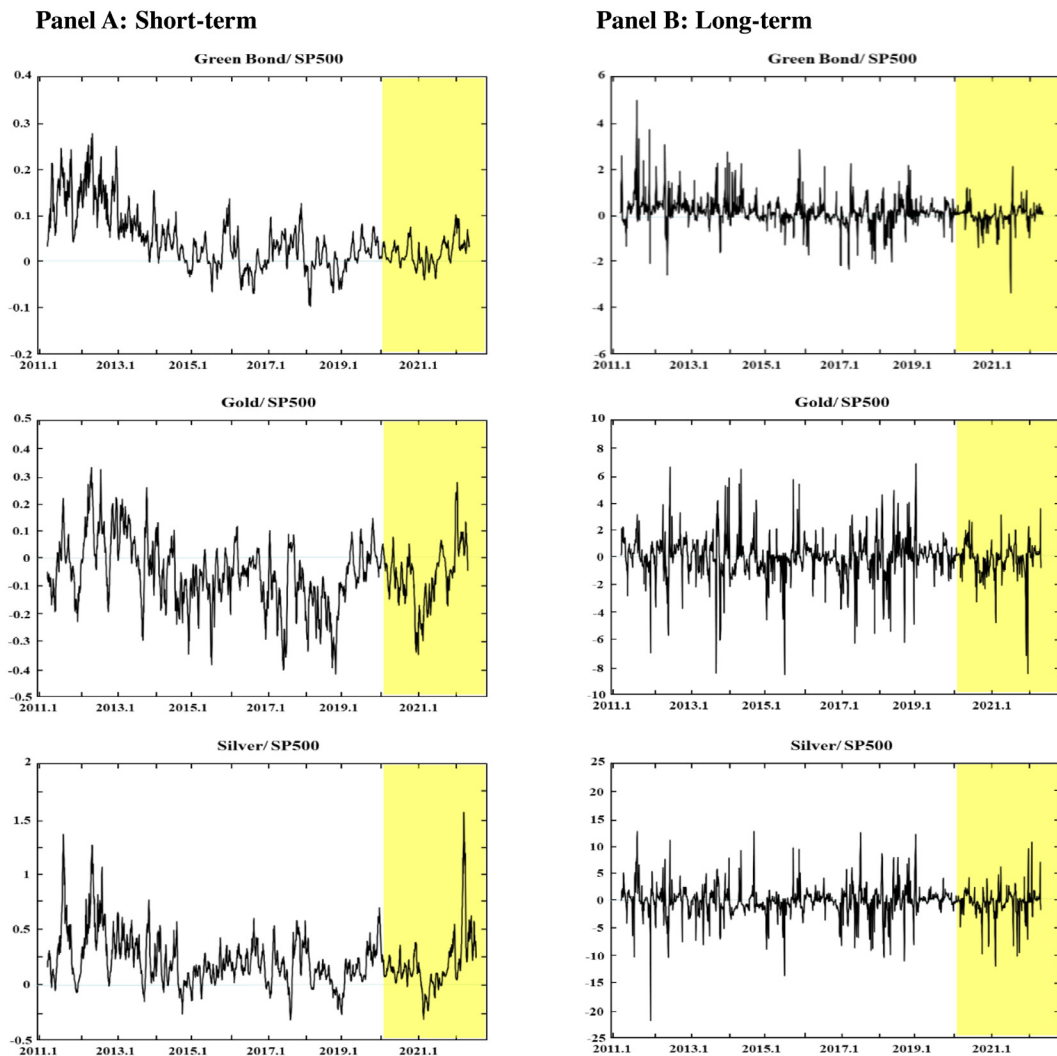


Fig. 10. Time-varying hedging ratios.

short term. This indicates that Green Bond is a cheap hedge asset at the short term than long term. This result confirms the results of Table 5. As for crude oil, we observe that the hedging is more turbulent at the short term than long term. The difference in hedge ratio before and during the pandemic shows that the markets respond to the severe government measures and plans to beat the virus. In sum, the portfolio capital structure and hedge ratio are time varying and event dependent.

6. Conclusion

This paper contributes in two ways to the emerging literature on the impacts of COVID-19 on spillovers between different asset classes. First, we apply the methodologies of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), the TVP-VAR model and the Quantile-on-Quantile regression method to examine the time and frequency dynamics of the connectedness between SP500 stock prices and the prices of GBs, gold, silver, Brent oil, US dollar index and VIX futures. Second, we also analyze the effects of COVID-19 on portfolio design across different frequencies.

Our empirical results show that the spillovers are lower in the long-term than in the short term along the sample period. The time-varying spillover is highest during the spread of the pandemic in early 2020. GBs are net receivers of spillover in the short term and source of spillover in the long term, independent of the effects of COVID-19. Gold and silver are net receivers of short- and long-term spillover before the pandemic and switch to be a source of spillover during the pandemic. VIX is a net contributor of short-term spillover before COVID-19, and it becomes a net receiver during the pandemic. The SP500 index is a net receiver of spillovers irrespective of the time frame or effects of COVID-19. We also

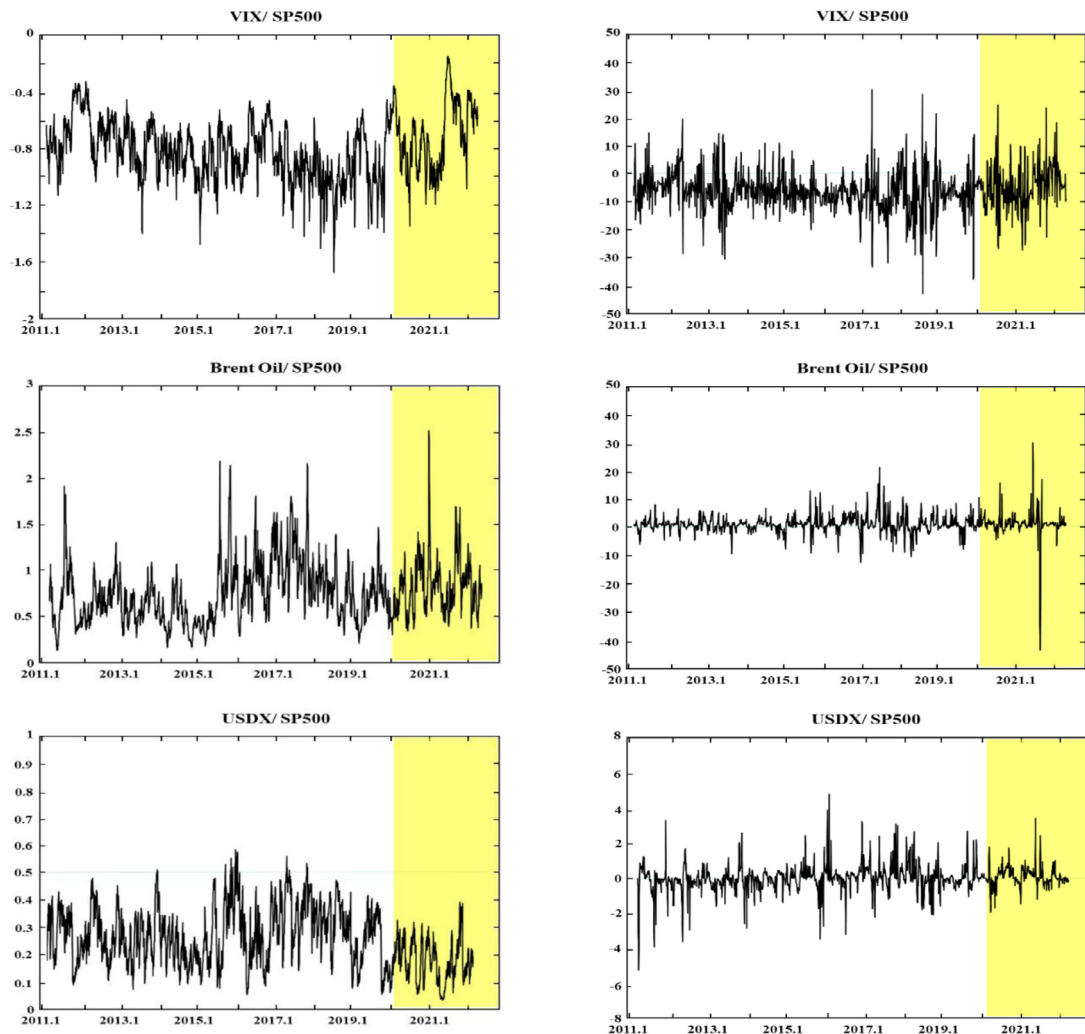


Fig. 10. (continued).

show a strong long-term spillover from GBs to USDX before COVID-19 and to oil during COVID-19. Brent oil is a source of spillover before the pandemic, but a net receiver of long-term spillover during COVID-19. The Quantile-on-Quantile regression method shows evidence of quantile relationships between US stock markets and green bonds, Brent oil, gold, silver and US dollar index, suggesting a nonlinear and asymmetric dependencies. More interestingly, GB and gold plays the role of safe haven asset during the COVID-19 period. A mixed portfolio offers gains from diversification. Before COVID-19, there is more HE in the long term than in the short term for GBs, gold, and silver, whereas it is stronger in the short term during COVID-19 for all cases except oil futures.

Our results offer new insights for investors, portfolio managers, and policy makers. Investors should rely on the time investment horizons to hedge their position against risk exposure. Moreover, not only financial crisis has impacts on market uncertainty but also global health crisis may alter the contagion and spillovers directions and size between markets. Investors should pay attention to the dependence among markets under bearish and bullish markets as market volatility and expectations are sensitive to market statuses. Investors should be familiar that GB is a safe-haven asset for US stock markets during times of financial distress. In addition to gold, portfolio managers should keep in mind that the inclusion of GBs in stock portfolios. VIX is a good predictor tool to forecast futures stock prices and reduces the uncertainty in stock markets. Our results may assist policy makers to detect the assets source of contagion (net transmitters) at different time investment horizons and to reduce the shocks emanating from these assets.

Our research can be extended by analyzing the spillovers in high-order moments (skewness, kurtosis, and jumps) between the considered markets before and during COVID-19 pandemic. This study can also be extended by investigation the time-varying and frequency spillovers between Green Bond, oil, gold, silver, USDX, and stock sectoral markets.

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