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Can bonds hedge stock market risks? Green bonds vs conventional bonds☆

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ABSTRACT

Growing concerns about climate change have generated several ecofriendly investments, including green bonds. This study investigates the impacts of geopolitical, economic and climate policy risks (GPR, EPU and CPU, respectively) on the long-term conventional/energy stock and conventional/green bond correlations using the DCC-MIDAS-X model. We determine that GPR, EPU and CPU impact the correlations between these stock and bond markets differently. Both conventional and green bonds have a safe-haven function when GPR levels are high, while green bonds outperform conventional bonds as a safe haven when EPU and CPU levels are high. Moreover, incorporating green bond assets into diversified portfolios provides the best hedging effectiveness, particularly for assets with a high carbon footprint.

1. Introduction

Addressing climate change remains a global challenge. Massive capital is required to support large-scale transition projects in the transition to a low-carbon economy (Ferrer et al., 2021; Ye et al., 2021). Since their introduction by the European Investment Bank in 2007, green bonds have become increasingly popular as a promising method to fund low-carbon activities (Flammer, 2021; Nguyen et al., 2021; Pham and Cepni, 2022). Moreover, green bonds are beneficial to a low-carbon economy (Hammoudeh et al., 2020) as well as a safe haven against tail risks owing to their pro-environmental features (Guo and Zhou, 2021; Jin et al., 2020; Naeem et al., 2021).

Herein, we explore the hedging effects of conventional and green bonds on stock markets under various risks. Existing research had proved that conventional bonds such as government bonds can be an effective hedge against stock markets (Ma et al., 2021; Papadamou et al., 2021); however, some studies have found limited links between green bond and stock markets (Ferrer et al., 2021; Mensi et al., 2022; Reboredo and Ugolini, 2020). According to the signalling theory, green assets with low carbon footprint will gain more trading preference from individual and institutional investors because they send pro-environmental signals to the market (Engle et al.,

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2020; Pástor et al., 2021; Flammer, 2021), giving them relatively better yield performance in times of market turmoil. Moreover, green bonds actively disclose environmental information (Reboredo and Ugolini, 2020), and their transparency can solve the information asymmetry between managers and stakeholders to reduce risk exposure, especially the risk posed by climate and environmental uncertainty. Thus, green bonds may be more effective in hedging stock market risks than conventional bonds.

In recent years, black swan events have occurred more frequently, such as the subprime crisis in 2007 (Sanders, 2008), the global financial crisis in 2008, and the European sovereign debt crisis since late 2009 (Ureche-Rangau and Burietz, 2013; Wegener et al., 2019). Ureche-Rangau and Burietz (2013) find that government intervention policies such as capital injections and government guarantees are the reasons why the European sovereign debt crisis immediately followed the subprime crisis. Thus, unexpected economic policies and unsatisfactory economic fundamentals may induce black swan events. Given the current uncertainties in the global economy, researchers have focused on the impact of economic policy uncertainty on financial market risks (Fang et al., 2018; Dong and Yoon, 2019; Kundu and Paul, 2022; Dai et al., 2022). Recently, geopolitical risks such as the Russia–Ukraine war have adversely affected economic activities. Woo (2002) assesses the risks of terrorism and analyzes the losses caused by them. Arfaoui and Naoui (2022) indicate that terrorist attacks have negative effects on the British and the French stock market returns under extreme market conditions. Moreover, transition risks from climate change-related policies also have a huge impact on financial markets through investor sentiment and preferences (Naeem et al., 2021; Pástor et al., 2021). Hence, we explore the impacts of geopolitical, economic and climate policy risks on stock markets using the geopolitical risk (GPR) index (Caldara and Iacoviello, 2022), the economic policy uncertainty (EPU) index (Baker et al., 2016) and the climate policy uncertainty (CPU) index (Gavriilidis, 2021). The correlations among these three indices are quite small[1], proving that they can capture risk and uncertainty from different perspectives. Investors' behavioural decisions are likely to change when they face different risks.

This study contributes to the literature in at least two aspects. First, we analyse the impacts of GPR, EPU and CPU on long-term stock–bond correlations using the extended dynamic conditional correlation-mixed data sampling model (DCC-MIDAS-X) and find that these three risks influence the correlations between these markets in different ways. To our knowledge, no study simultaneously explores the stock–bond correlations under these three risks. Second, we evaluate the hedging effect of green bonds using three measures. The results show that including green bonds in diversified portfolios provides better hedging effectiveness than conventional bonds in terms of volatility and downside risk, particularly in stock markets with high carbon footprint.

The remainder of this study is organised as follows. The methodology and data are described in Section 2. The empirical findings are presented in Section 3. The conclusion is included in Section 4.

2. Methodology and data

The DCC-MIDAS model (Colacito et al., 2011) improves on the DCC model by allowing time-varying short- and long-term correlations to be distinguished. Similar to Conrad et al. (2014) and Ding et al. (2022), we extend the DCC-MIDAS model by including monthly GPR, EPU and CPU indices into the long-term correlation component, which can capture the influences of these different exogenous risks on the stock–bond correlations.

In the first step, consider a bivariate vector of returns on day t: $r_t = [r_{i,t}]$, where $i = 1$ and 2 follows the process $r_{i,t} = \mu_i + \sqrt{m_{i,\tau} \cdot g_{i,t}}\varepsilon_{i,t}$, with $\varepsilon_{i,t}|\phi_{t-1} \sim N(0,1)$. Here $g_{i,t}$ and $m_{i,\tau}$ are the short- and long-term variance components, respectively. In the GJR-GARCH-MIDAS model, $g_{i,t}$ is specified as

$$g_{i,t} = (1-\alpha_i-\beta_i-0.5\gamma_i) + \left(\alpha_i + 1_{\{r_{i-1,t}-\mu_i<0\}}\gamma_i\right)\frac{(r_{i-1,t}-\mu_i)^2}{m_{i,\tau}} + \beta_i g_{i,t-1} \tag{1}$$

where $\alpha_i > 0$, $\beta_i \geq 0$, $\gamma_i \geq 0$, $\alpha_i + \beta_i + 0.5\gamma_i < 1$ and $1_{\{\}}$ is an indicator function taking a value of one if the condition is satisfied; otherwise, it is zero. Moreover, $m_{i,\tau}$ fluctuates monthly and is defined as a slow varying function of lagged GPR (or EPU/CPU).

$$\log(m_{i,\tau}) = m_v^i + \theta_v^i \sum\nolimits_{k=1}^{K} \varphi_k(w_v^i) GPR_{\tau-k} \tag{2}$$

where m_v^i and θ_v^i are parameters to be estimated. θ_v^i captures the lag effect of three exogenous risks on the long-term variance component, and K is the number of lags for exogenous risks. Beta weight function φ_k is defined as

$$\varphi_k(w_v^i) = \frac{(1-k/K)^{w_v^i-1}}{\sum_{j=1}^{K}(1-j/K)^{w_v^i-1}}, \quad k = 1,\ldots,K \tag{3}$$

where the size of w_v^i controls the decaying pattern of this weighting function.

In the second step, the short-term correlations between stock and bond markets can be expressed as follows.

$$q_{ij,t} = (1-a-b)\bar{\rho}_{ij,\tau} + a\varepsilon_{i,t-1}\varepsilon_{j,t-1} + bq_{ij,t-1} \tag{4}$$

[1] During our sample period, the correlations of GPR, EPU and CPU are −0.219, 0.009 and 0.437, and the correlations of their change rates are −0.039, 0.021 and 0.192, respectively.

where $\varepsilon_{i,t-1}$ and $\varepsilon_{j,t-1}$ are the standardised residuals of two assets obtained from the univariate GJR-GARCH-MIDAS model. The long-term correlation component $\overline{\rho}_{ij,\tau}$ is driven by the exogenous risks and is defined by a Fisher-z transformation of the correlation coefficient as

$$\overline{\rho}_{ij,\tau} = \frac{\exp(2z_{ij,\tau}) - 1}{\exp(2z_{ij,\tau}) + 1} \tag{5}$$

with

$$z_{ij,\tau} = m_c + \theta_c \sum\nolimits_{k=1}^{K} \delta_k(w_c) GPR_{t-k} \tag{6}$$

where θ_c denotes the effect of three exogenous risks on the long-term correlation component. The weighting scheme $\delta_k(w_c)$ is defined similarly to $\varphi_k(w_v^i)$. Since we find that the choice of lag order significantly affects the results, following Bai et al. (2021) and Wei et al. (2022), the number of MIDAS lags in two-step procedure is set to 6, 12 and 24 periods, ensuring the robustness of the results obtained.

Herein, we combine the daily U.S. stock and conventional/green bond return series with monthly risks and uncertainty indices. The estimation period chosen is from 1 March 2012 to 31 March 2022. For the daily data, we consider the S&P 500 index, the S&P equity commodity energy index, the U.S. 10-year government bond price index and the S&P green bond index. The S&P 500 and equity commodity energy indices represent conventional and carbon-intensive stock assets, respectively. All the daily data are converted into logarithmic percentage return series, i.e. $r_t = 100 \times \ln(P_t / P_{t-1})$. To measure risk and uncertainty, we consider the GPR, EPU and CPU indices, respectively. These three indices are provided by EPU (www.policyuncertainty.com) and converted into the difference in logarithms, i.e. $\Delta risk_t = \ln(risk_t / risk_{t-1})$. Table 1 shows the descriptive statistics for all variables.

3. Empirical results

3.1. GJR-GARCH-MIDAS model analysis

The empirical results for the GJR-GARCH-MIDAS-GPR model are presented in Table 2.[2] Most of the parameters α and β are statistically significant. Large and significant β values indicate the persistence of volatility. The sum of the parameters (α + β + 0.5γ) is close to 1, suggesting stability of the model. The coefficients γ, which measure the leverage effect, are positive and significant for the S&P 500, energy and government bond markets, implying that negative shocks have a larger influence on volatility than positive shocks in these three markets.

The coefficients θ_v depict the response of long-term volatility to GPR shocks. Parameters θ_v for the S&P 500 and green bond markets are significantly negative when GJR lags 6–24 months. For the energy market, they are significantly negative when GJR lags 12 months, which means that GJR has a negative influence on the long-term volatility of the S&P 500, energy and green bond markets.

3.2. DCC-MIDAS-X model analysis

The empirical results for the DCC-MIDAS-GPR model are presented in Table 3. The coefficients θ_c capture the impacts of GPR on the long-term correlations between conventional/energy stock and conventional/green bond markets. Most of the parameters θ_c are significantly negative, indicating that the increase in GPR results in a decrease in long-term correlations between these markets. According to Baur and McDermott's (2010) definition of safe-haven assets, both conventional and green bonds can serve as a strong safe haven against the S&P 500 and energy stock markets when GPR levels are high.

Table 4 shows that parameters θ_c are significantly negative in one out of six cases for the conventional/energy stock–conventional bond correlations and four out of six cases for the conventional/energy stock–green bond correlations using different lags. These findings suggest that when the EPU levels are high, the safe-haven feature of green bonds outperforms conventional bonds. In Table 5, most of the parameters θ_c are significantly negative for the conventional/energy stock–green bond correlations and significantly positive for the conventional/energy stock–conventional bond correlations. Hence, only green bonds can act as a safe haven against S&P 500 and energy stock markets, while both conventional/energy stock and conventional bonds face serious downward pressure during periods of high CPU.

Overall, geopolitical risks such as the Paris terrorist attacks in 2015, the U.S.–Iran tensions in 2020 and the recent Russia–Ukraine war are both accidental and sudden. Such circumstances have the typical characteristics of black swan events. Bekiros et al. (2017) suggest that the quest for diversification benefits is particularly strong in recent years due to frequent black swan events, and find that gold can act as a diversifier in both normal and bear markets for emerging stock markets. In this study, we believe that unpredictable geopolitical risks lead to investors quickly seeking to substitute stock with relatively safe assets as per the 'flight-to-quality' effect (Dong et al., 2021; Papadamou et al., 2021). Thus, both conventional and green bonds show a safe-haven function during periods of high GPR. However, compared to geopolitical risks, there are certain expectations about implementing economic and climate policies,

[2] Most of the coefficients θ_v are insignificantly negative in the results of the GJR-GARCH-MIDAS-EPU/CPU model. The results for α, β and γ are similar whether GPR, EPU or CPU are considered in the model. To save space, the GJR-GARCH-MIDAS-EPU/CPU model results are not reported and are available on request.

Table 1
Descriptive statistics.

Variable	Mean	SD	Skew	Kurt	ADF	KPSS	ARCH(10)
S&P 500	0.047	1.049	−0.949	23.454	−16.057***	0.035	181.81***
Energy	−0.004	1.695	−1.248	27.095	−16.686***	0.095	87.81***
Bond	0.006	3.034	0.080	26.104	−20.832***	0.081	220.48***
Green bond	0.000	0.326	−0.448	8.492	−33.851***	0.117	26.48***
GPR	0.009	0.203	0.318	3.904	−14.561***	0.210	
EPU	0.002	0.215	0.046	4.159	−14.443***	0.309	
CPU	0.010	0.590	0.123	4.298	−13.226***	0.150	

Note: ***, ** and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Table 2
Empirical results for GJR-GARCH-MIDAS-GPR model.

	lag	μ	α	β	γ	m_v	θ_v	ω_v
S&P 500	6	0.042***	0.074*	0.731***	0.296***	0.090	−3.139*	1.319***
		(0.014)	(0.042)	(0.035)	(0.061)	(0.369)	(1.908)	(0.316)
	12	0.044***	0.067*	0.736***	0.291***	−0.015	−7.902**	1.662***
		(0.014)	(0.039)	(0.035)	(0.057)	(0.250)	(3.671)	(0.302)
	24	0.041***	0.072*	0.729***	0.310***	0.127	−20.22**	1.262***
		(0.015)	(0.042)	(0.036)	(0.066)	(0.340)	(9.730)	(0.457)
Energy	6	0.010	0.027***	0.924***	0.084***	0.784***	−0.597	18.818***
		(0.023)	(0.010)	(0.014)	(0.018)	(0.283)	(0.381)	(6.263)
	12	0.017	0.026***	0.925***	0.081***	0.664**	−0.633*	64.459***
		(0.026)	(0.010)	(0.014)	(0.017)	(0.298)	(0.373)	(18.218)
	24	0.016	0.028***	0.920***	0.084***	0.762***	−0.636	82.763***
		(0.030)	(0.011)	(0.015)	(0.018)	(0.283)	(0.411)	(31.628)
Bond	6	−0.006	0.026*	0.948***	0.049***	2.297***	−0.455	1.001
		(0.038)	(0.015)	(0.019)	(0.014)	(0.362)	(1.318)	(1.799)
	12	−0.002	0.026	0.947***	0.047***	1.917***	−0.226	37.658**
		(0.027)	(0.017)	(0.023)	(0.014)	(0.282)	(0.253)	(15.291)
	24	−0.016	0.029	0.939***	0.054***	1.780***	9.671	1.000
		(0.058)	(0.048)	(0.064)	(0.024)	(0.683)	(12.74)	(1.274)
Green bond	6	0.004	0.055***	0.938***	−0.001	−1.937**	−0.412*	45.046***
		(0.006)	(0.021)	(0.017)	(0.017)	(0.784)	(0.223)	(7.273)
	12	0.003	0.052**	0.935***	0.002	−2.266***	−0.413**	89.263***
		(0.006)	(0.022)	(0.019)	(0.017)	(0.236)	(0.233)	(13.715)
	24	0.003	0.053**	0.932***	0.002	−2.350***	−0.390**	237.93***
		(0.006)	(0.022)	(0.021)	(0.017)	(0.199)	(0.235)	(52.899)

Notes: The standard errors are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

which usually give investors more time to adjust their investment strategies. The predictability of EPU and CPU makes investors show more preference for green bonds with a low carbon footprint than conventional bonds, especially during periods of high CPU.

Figs. 1 and 2 present dynamic correlations (blue line) and long-term correlations (red line) between S&P 500/energy stock and conventional/green bond markets considering different risks and uncertainties.[3] We find that the mean of correlations between conventional/energy stock and green bond markets is relatively smaller than those between conventional/energy stock and conventional bond markets[4], indicating that green bonds are better hedging instruments than conventional bonds during regular market periods. Moreover, correlations between conventional/energy stock and green bond markets show a downward trend in early 2020, which means that the outbreak of COVID-19 pandemic strengthened the safe-haven role of green bonds (Mensi et al., 2022).

3.3. Risk management analysis

To manage conventional/energy stock and conventional/green bond assets more efficiently, we compute the optimal portfolio weight and hedge ratio for building investment strategies based on the results of the DCC-MIDAS-X model. Following Kroner and Ng (1998), we design diversified portfolios; the portfolio weight of conventional/green bond assets is given by

$$w_t^B = \frac{h_t^S - h_t^{S,B}}{h_t^S - 2h_t^{S,B} + h_t^B} \tag{7}$$

[3] The dynamic correlation results of other lags are similar to those of 12 lags. The trends for long-term correlations are also the same, except that their fluctuation varies according to the lag period.

[4] The mean of conventional/energy stock–conventional bond correlations is almost equal to 0.3, the mean of conventional/energy stock–green bond correlations is almost equal to 0.

Table 3
Empirical results for DCC-MIDAS-GPR model.

	lag	α	β	ω_c	m_c	θ_c
S&P 500-Bond	6	0.056***	0.888***	9.657	0.371***	−1.084***
		(0.015)	(0.038)	(13.639)	(0.051)	(0.249)
	12	0.055***	0.882***	19.112***	0.349***	−1.067**
		(0.015)	(0.033)	(0.057)	(0.045)	0.440
	24	0.060***	0.872***	35.802***	0.363***	−0.906*
		(0.015)	(0.032)	(0.107)	(0.047)	(0.468)
S&P 500-Green bond	6	0.050***	0.874***	1.001	0.013	−0.829*
		(0.019)	(0.062)	(0.737)	(0.039)	(0.498)
	12	0.053**	0.830***	2.470	−0.005	−0.576
		(0.022)	(0.096)	(2.225)	(0.036)	(1.880)
	24	0.065***	0.805***	1.402**	−0.028	−2.896**
		(0.021)	(0.087)	(0.676)	(0.037)	(1.255)
Energy-Bond	6	0.030***	0.928***	6.307***	0.337***	−1.139**
		(0.010)	(0.025)	(0.452)	(0.041)	(0.536)
	12	0.027***	0.930***	12.041	0.314***	−1.116***
		(0.010)	(0.027)	(7.976)	(0.039)	(0.271)
	24	0.030**	0.892***	2.114***	0.330***	−4.284***
		(0.012)	(0.040)	(0.512)	(0.036)	(1.309)
Energy-Green bond	6	0.029***	0.945***	1.042	0.085*	−1.145**
		(0.010)	(0.023)	(0.956)	(0.045)	(0.584)
	12	0.026**	0.938***	4.600***	0.051	−0.358
		(0.011)	(0.034)	(0.355)	(0.038)	(0.509)
	24	0.032**	0.911***	1.463	0.023	−0.798*
		(0.014)	(0.056)	(1.353)	(0.037)	(0.487)

Note: See note of Table 2.

Table 4
Empirical results for DCC-MIDAS-EPU model.

	lag	α	β	ω_c	m_c	θ_c
S&P 500-Bond	6	0.062***	0.867***	1.001	0.354***	0.970
		(0.016)	(0.036)	(1.102)	(0.045)	(0.749)
	12	0.064***	0.852***	1.553	0.333***	1.460
		(0.018)	(0.060)	(8.569)	(0.044)	(5.738)
	24	0.065***	0.858***	1.022***	0.357***	−2.019***
		(0.017)	(0.038)	(0.348)	(0.049)	(0.610)
S&P 500-Green bond	6	0.047**	0.872***	4.885***	0.009	−0.473***
		(0.019)	(0.064)	(1.412)	(0.038)	(0.123)
	12	0.047**	0.836***	8.436***	−0.009	−0.527*
		(0.021)	(0.085)	(0.262)	(0.034)	(0.318)
	24	0.068*	0.769*	1.001	−0.047	3.771
		(0.037)	(0.406)	(2.019)	(0.046)	(2.809)
Energy-Bond	6	0.031***	0.924***	1.001	0.331***	1.285
		(0.013)	(0.032)	(1.104)	(0.040)	(1.357)
	12	0.030**	0.911***	1.561	0.310***	1.703
		(0.012)	(0.034)	(1.207)	(0.037)	(2.280)
	24	0.030**	0.891***	1.716**	0.320***	2.366
		(0.013)	(0.038)	(0.740)	(0.036)	(1.620)
Energy-Green bond	6	0.028***	0.950***	1.001	0.081*	−0.503*
		(0.009)	(0.018)	(0.689)	(0.046)	(0.303)
	12	0.023***	0.942***	1.215***	0.041	−1.721
		(0.010)	(0.024)	(0.323)	(0.038)	(2.022)
	24	0.028**	0.925***	1.001***	0.030	−1.917***
		(0.013)	(0.039)	(0.243)	(0.037)	(0.682)

Note: See note of Table 2.

$$w_t^{*B} = \begin{cases} 0, & if\ w_t^B < 0 \\ w_t^B, & if\ 0 \le w_t^B \le 1 \\ 1, & if\ w_t^S > 1 \end{cases} \tag{8}$$

where h_t^S and h_t^B refer to the conditional variance of two stock and two bond markets, respectively, and $h_t^{S,B}$ refers to the conditional covariance between these markets.

Moreover, we design the hedging portfolios based on a hedging strategy that involves holding a long position in one unit of

Table 5
Empirical results for DCC-MIDAS-CPU model.

	lag	α	β	ω_c	m_c	θ_c
S&P 500-Bond	6	0.059***	0.874***	2.818***	0.346***	0.500
		(0.016)	(0.036)	(2.701)	(0.046)	(0.400)
	12	0.059***	0.846***	1.380***	0.313***	1.737***
		(0.016)	(0.045)	(0.357)	(0.042)	(0.650)
	24	0.062**	0.863***	19.087	0.342***	0.345**
		(0.028)	(0.082)	(83.705)	(0.054)	(0.152)
S&P 500-Green bond	6	0.046**	0.873***	2.263***	0.014	−0.607***
		(0.018)	(0.053)	(0.603)	(0.037)	(0.225)
	12	0.043*	0.830***	1.886***	−0.001	−1.453**
		(0.022)	(0.079)	(0.588)	(0.033)	(0.620)
	24	0.053**	0.832***	4.482***	−0.015	−1.234***
		(0.023)	(0.064)	(0.310)	(0.037)	(0.470)
Energy-Bond	6	0.032**	0.920***	2.641	0.321***	0.537
		(0.013)	(0.037)	(5.641)	(0.040)	(0.506)
	12	0.029**	0.906***	1.628***	0.293***	1.313**
		(0.011)	(0.031)	(0.281)	(0.035)	(0.545)
	24	0.028**	0.899***	6.099***	0.317***	0.660**
		(0.013)	(0.030)	(0.166)	(0.037)	(0.325)
Energy-Green bond	6	0.027***	0.946***	5.861***	0.087**	−0.552**
		(0.010)	(0.019)	(0.320)	(0.044)	(0.236)
	12	0.023	0.917***	2.969	0.048	−1.209
		(0.021)	(0.128)	(12.927)	(0.035)	(4.118)
	24	0.028**	0.897***	5.545***	0.031	−1.244***
		(0.014)	(0.040)	(0.396)	(0.032)	(0.364)

Note: See note of Table 2.

conventional/energy stock hedged by a short position of β_t^B conventional/green bonds (Kroner and Sultan, 1993) given by

$$\beta_t^B = \frac{h_t^{S,B}}{h_t^B} \tag{9}$$

This study evaluates these two portfolios using the following hedging effectiveness measures. The variance reduction of two portfolios relative to that of a single stock asset can be written as

$$VR\ Reduction = 1 - \frac{Var_{p,t}}{Var_{s,t}} \tag{10}$$

where $Var_{p,t}$ and $Var_{s,t}$ are the variance of two portfolios and single stock, respectively.

However, since investors are more concerned about downside risk than upside risk, we use the lower partial moment (LPM) and value-at-risk (VaR) to estimate downside risk; the decrease in LPM and VaR (Cotter and Hanly, 2012) is specified as

$$LPM\ Reduction = 1 - \frac{LPM_{1\ P}}{LPM_{1\ S}}\ and\ VaR\ Reduction = 1 - \frac{VaR_{1\%\ P}}{VaR_{1\%\ S}} \tag{11}$$

where LPM_{1P} and LPM_{1S} represent the average loss below a target return of zero in two portfolios and single stock, respectively.[5] $VaR_{1\%\ P}$ and $VaR_{1\%S}$ represent the maximum loss of two portfolios and single stock for a given time horizon at the 1% confidence level, respectively.

Table 6 reports the hedging effectiveness measures for these two portfolios.[6] The diversified portfolios that consider green bonds achieve higher values, and the hedging portfolios that consider conventional bonds achieve higher values. However, diversified portfolios that include green bonds exhibit a substantial improvement in hedging effectiveness, particularly for energy stock markets with high carbon footprint (Engle et al., 2020; Ding et al., 2022), which suggests that the inclusion of green bond assets in these portfolios can assist investors more effectively in reducing volatility and downside risk. According to the results from the DCC-MIDAS-X model, conventional/energy stock–green bond correlations are quite small. Hence, the portfolio strategies that are diversified with green bonds perform better than those hedged with green bonds.

4. Conclusions

This study investigates the influences of GPR, EPU and CPU on the long-term conventional/energy stock and conventional/green bond correlations using the DCC-MIDAS-X model. Our analysis confirms that GPR, EPU and CPU impact the correlations between these

[5] The order of LPM is 1, meaning that the investor is risk neutral.
[6] The hedging effectiveness results of other lags are similar to those of 12 lags.

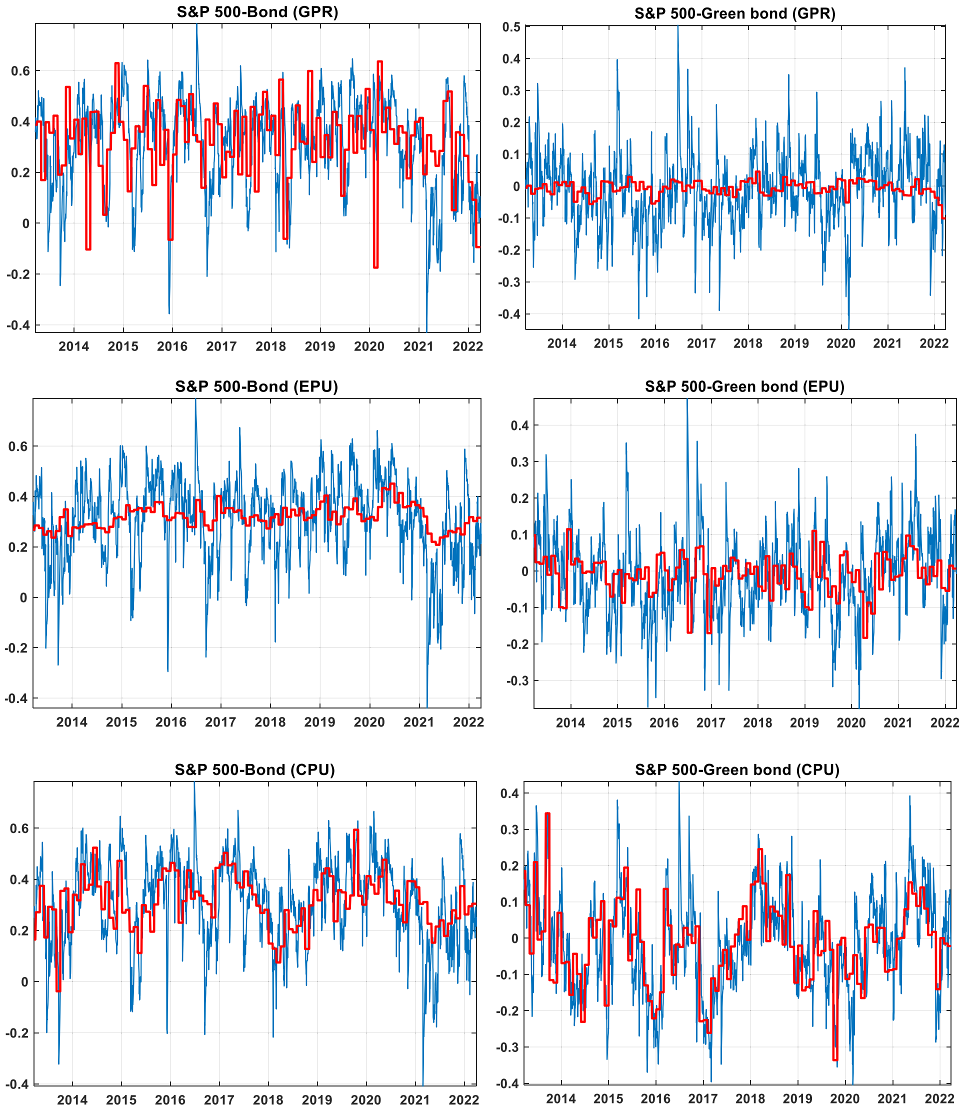

Fig. 1. Dynamic correlations (blue line) and long-term correlations (red line) between S&P 500 and conventional/green bond markets (lag = 12 months).

markets in distinct ways, leading to differences in the safe-haven role of conventional and green bonds. Both conventional and green bonds have a safe-haven feature when GPR levels are high; however, the safe-haven feature of green bonds is better than that of conventional bonds when EPU and CPU levels are high. Moreover, the conventional/energy stock–green bond correlations are relatively smaller than the conventional/energy stock–conventional bond correlations. Incorporating green bond assets into diversified portfolios provides the best hedging effectiveness, indicating that investors should retain more green bond assets to minimise overall losses.

These results have several important implications for investors and policymakers. Regardless of the geopolitical, economic and climate policy risks, green bonds are favoured by investors because of their pro-environmental properties, enabling them to hedge against tail risks. Furthermore, investors have different preferences for assets based on the nature and predictability of risks, and relevant media reports and policy announcements also affect investor sentiment and preferences, which can be good short-term predictors of stock price movements. Hence, investors could design sentiment/preference-based trading strategies, which will outperform other strategies in the short term (Karalevicius et al., 2018).

In our future study, we could consider incorporating structural changes and asymmetry effects into the DCC-MIDAS-X model due to the characteristics of financial markets, which can improve the accuracy of the model and provide more information. A further avenue for future research would be to construct portfolios composed of various low-carbon assets including green bonds, and examine whether these portfolios are superior to those composed of high-carbon assets in terms of hedging geopolitical, economic and climate policy risks.

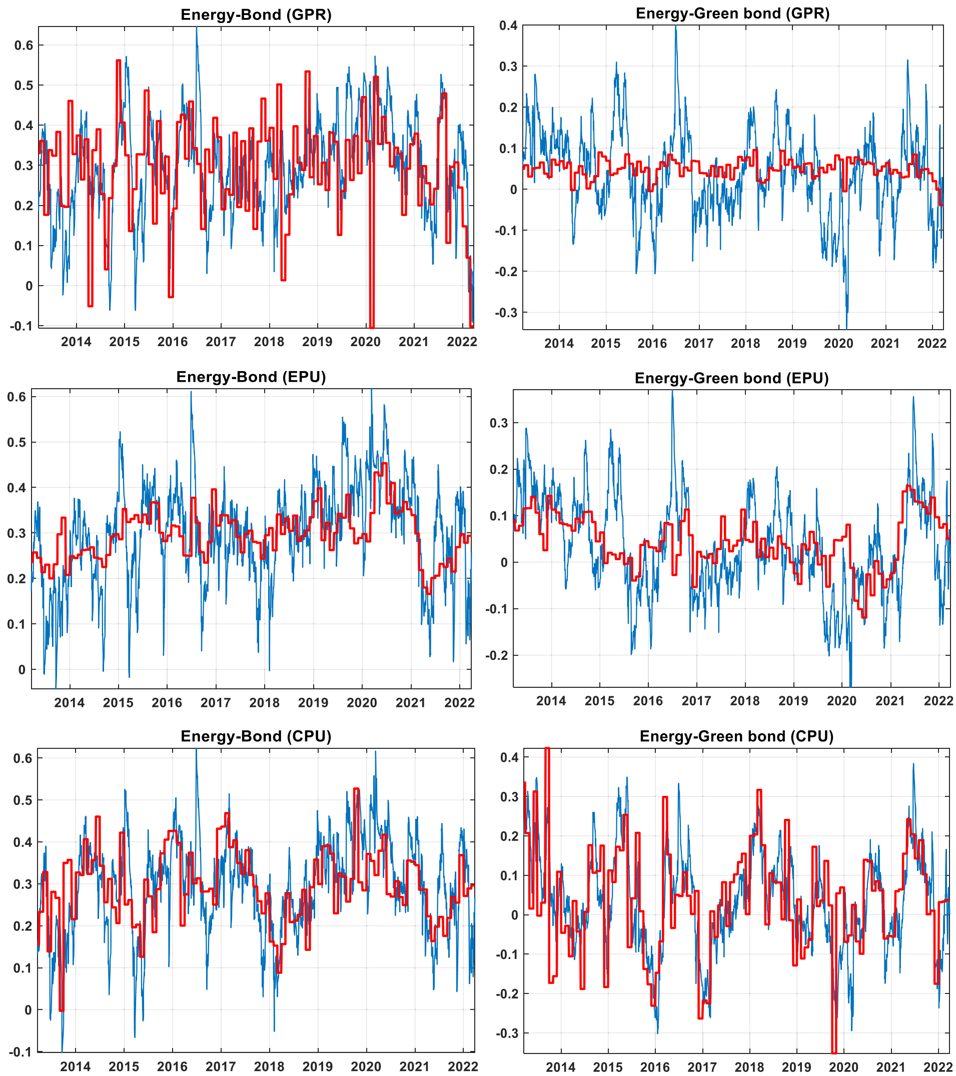

Fig. 2. Dynamic correlations (blue line) and long-term correlations (red line) between energy stock and conventional/green bond markets (lag = 12 months).

Table 6
Hedging effectiveness measures (lag = 12 months, unit = %).

	DCC-MIDAS-GPR			DCC-MIDAS-EPU			DCC-MIDAS-CPU		
	VR	LPM	VaR	VR	LPM	VaR	VR	LPM	VaR
Diversified portfolios									
S&P 500-Bond	−1.27	0.79	−1.16	−1.31	0.85	−0.80	−1.36	1.04	−0.86
S&P 500-Green bond	72.52	66.32	66.75	72.45	66.66	66.68	72.44	66.66	66.62
Energy-Bond	2.82	3.33	0.31	2.98	3.11	0.08	3.12	3.18	0.66
Energy-Green bond	82.22	80.00	76.08	82.21	79.94	76.17	82.24	79.99	76.18
Hedging portfolios									
S&P 500-Bond	7.28	8.03	2.64	6.88	8.03	3.44	6.87	8.31	4.06
S&P 500-Green bond	−3.17	0.66	0.35	−2.82	0.03	0.87	−2.52	0.08	0.87
Energy-Bond	5.69	7.39	−1.62	5.20	7.00	1.64	5.19	7.14	1.84
Energy-Green bond	−3.15	−0.95	−1.86	−3.11	−0.62	−1.91	−2.46	−0.39	−1.90

CRediT authorship contribution statement

Xiyong Dong: Conceptualization, Methodology, Software, Formal analysis, Investigation, Visualization, Writing – original draft, Funding acquisition. **Youlin Xiong:** Conceptualization, Data curation, Formal analysis, Resources, Writing – original draft, Validation. **Siyue Nie:** Formal analysis, Software, Validation, Visualization, Writing – review & editing. **Seong-Min Yoon:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

There are no conflicts of interest to declare.

Data availability

The authors do not have permission to share data.

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