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Unravelling green bond reactions to energy price volatility amid rising policy uncertainty

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Abstract
This paper investigates the impact of energy, oil, natural gas, and coal price volatility on green bond performance. It also explores how two types of policy uncertainty, economic, and climate-related, influence this relationship. Using Fourier-augmented autoregressive distributed lag and mixed-data sampling methods, the findings reveal that energy price volatility, as well as oil and natural gas price volatility, weakens green bond performance in the short run. In contrast, coal price volatility shows a positive impact. The results further show that both economic and climate policy uncertainty soften these short-run effects, with economic policy uncertainty having the stronger influence. This suggests that investors are more vulnerable to the instability of macroeconomic policies due to their direct impact on financial well-being. In the long run, while the impact of energy, oil, and natural gas price volatility remains negative, the impact of coal price volatility turns negative. This indicates the absence of effective government intervention in the coal market. The results further reveal that economic and climate policy uncertainties are the main drivers of the adverse impact of energy, oil, natural gas, and coal price volatility on green bond performance. Overall, this paper demonstrates that whether energy price volatility acts as a barrier or catalyst depends on the type of energy and the stability of economic and climate-related policies.

Keyword Energy price volatility, Green bonds, Policy uncertainty

1 Introduction

Over the past century, substantial efforts have been made to combat climate change, from the Kyoto Protocol, and the Paris Agreement to the recent Baku Climate Unity Pact. These policy initiatives have led to the emergence and rapid expansion of the green bond (GB) market as a pivotal instrument for financing green projects worldwide [1, 2]. GB can be defined as a financial instrument in which the proceeds will be used in financing or refinancing green projects [3]. Since the first issuance of GB in 2007, this market has experienced unprecedented growth [4]. Such rapid expansion can be attributed to its benefits, including lower financing costs [5], reduced capital availability risk [1] and greater effectiveness and innovativeness in financing climate change mitigation [6].

Despite this growth and popularity, GB has been noted, to have failed to bridge the financing gap in the energy transition [7]. United Nations [8] attributed this failure to energy price volatility. Such volatility induces the inefficiency within the green investment market, heightens investors' concern, and ultimately discourages green investment [9]. What is more concerning is that the global economy's continued dependency on fossil fuels has exacerbated the influence of energy price volatility. Although so, the World Economic Forum presents a contrasting discussion by highlighting the potential favourable role of energy price volatility in stimulating green investment, especially in GB [10]. This could be attributed to the stable market value [11] and hedging benefits of GB [12], which make them become more attractive during periods of highly volatile energy prices. Such contradictions underscore the need for further investigation to help policymakers formulate stable and credible policies that enhance investor confidence and ensure the effectiveness of GB in financing energy transition. For investors, addressing these contradictions is equally important in assessing risk exposure and the resilience of GB to energy price volatility, while enabling issuers to structure GB in ways that attract investors even when confronted with highly volatile energy prices.

Coinciding with persistent energy price volatility, recurrent political turbulence has sparked academic interest in policy uncertainty. Such turbulence creates ambiguity about the future direction of economic and climate policies by threatening abrupt shifts in regulatory priorities, subsidy frameworks, and long-term government commitments. The particular concern is the fact that frequent policy changes are having cross-border impacts due to the growing number of international initiatives aimed at supporting sustainable development in other countries, such as the China–Pakistan Economic Corridor and the Just Energy Transition Partnerships. This unpredictability undermines investors' and firms' ability to make informed decisions and thus results in greater hesitation in investment planning [13]. More importantly, policy uncertainty is claimed to exacerbate energy price volatility [14], suggesting that it may indirectly impede the GB performance by introducing additional uncertainty into the GB market and may further encourage investors to reduce their investment in it. Nevertheless, a contrasting discussion has emerged, suggesting that policy uncertainty might instead encourage investment in the GB market. This could be ascribed to the hedging benefit of GB against both energy price volatility and policy uncertainty [15–17]. Thus, the objective of this study is to examine the impact of energy, oil, natural gas, and coal price volatility, on GB performance, with particular focus on the moderating role of policy uncertainty in this relationship.

In particular, energy is the lifeblood of modern economic development; yet extant studies mainly rely on oil or coal price volatility to represent the entire energy market [18]. However, each energy market has a distinct market structure. While the oil market is highly globalised, the natural gas and coal markets are more regionalised and policy-driven, respectively [19, 20]. Such an approach may therefore yield biased policy implications [21] and lack insightful understanding of overall energy price volatility [18]. Hence, this paper not only examines the impact of energy price volatility but also the impact of oil, natural gas and coal price volatility, which account for most of global energy consumption.

This study contributes to the literature in several ways. Firstly, this study enriches the irreversible investment theory and real options theory by demonstrating how the presence of policy uncertainty influences the investors' willingness to include GB as hedging asset against energy price volatility. Secondly, it examines the impact of energy, oil, natural gas, and coal price volatility to account for heterogeneity across energy sources, which has important implications for portfolio management, risk management and energy transition policies. Third, unlike previous country-specific studies, this paper adopts a global perspective to ensure that the findings remain relevant to countries at different stages of development. Fourthly, this study incorporates policy uncertainty as a moderator to shed new light on how macroeconomic and climate policy-related risk shapes the energy price volatility-GB nexus and to demonstrate that this relationship is conditional on the political environment. Lastly, the application of the Mixed-Data Sampling (MIDAS) method differentiates this paper by accommodating mixed-frequency data. This approach avoids the information loss that commonly occurs when data are aggregated and thus yield more accurate results.

The remaining structure of this paper is as follows: Sect. 2 reviews the literature; Sect. 3 presents the variables and methodology employed; Sect. 4 presents the empirical findings; and Sect. 5 concludes with policy recommendations.

2 Literature review and hypothesis development

The relationship between energy price volatility and GB performance is rooted in irreversible investment theory and real options theory. Based on these theories, most investments are at least partially irreversible due to firm- or industry-specific characteristics [22]. Thus, an increase in uncertainty will, in turn, increase the value of waiting and induce investors to reduce or postpone investment until more information becomes available [23]. This hesitation arises because committing to an investment eliminates the option to wait for new information that could potentially improve the quality of the investment decision [24]. Even so, in light of investment flexibility, investors may also pursue an invest-and-see strategy, which enables them to gain greater access to information and reap first-mover advantages [25]. This argument is also supported by [26], who underscores that uncertainty offers opportunities to identify new products by exercising the option to expand. Collectively, these theories provide a comprehensive understanding of how energy price volatility and policy uncertainty affect GB performance.

2.1 Impact of energy price volatility

According to irreversible investment theory and real options theory, uncertainty arising from energy price volatility might encourage investors to reduce or defer their investment in the GB market by generating uncertainty in future cash flows and increasing investment risk [27, 28]. This, in turn, shifts investors' preference from long-term investments, like GB, to short-term investments [29]. In addition, energy price volatility also hinders GB performance by affecting interest rates, foreign direct investment risk, exchange rates, and returns on investment [30].

Nonetheless, the aforementioned discussions have overlooked the potential hedging role of GB against energy price volatility. Specifically, as GB is specifically designed to finance green projects, it tends to be more predictable than other financial instruments [17]. Besides, the stable cash flows and returns from green projects, combined with supportive government policies, collectively enhance the hedging effectiveness of GB [31]. Apart from this, the weak shift between GB and the energy market also provides GB with the ability to diversify the risks arising from energy price volatility [32]. Despite the ambiguous discussion regarding the impact of energy price volatility on GB performance, it is reasonable to hypothesise that:

H1: *Energy price volatility significantly impacts GB performance.*

2.2 Impact of oil, natural gas and coal price volatility

While the conventional view highlights the adverse impact of oil price volatility on green investment [11, 33] emphasises the hedging role of GB against oil price volatility. Supportive environmental policies also further enhance the resilience of GB to oil price volatility [34]. In this context, investors might increase their investment in GB. This argument is also aligned with real options theory, which postulates that the hedging benefits of GB against oil price volatility may encourage investors to exercise the option to switch or expand rather than contract [35].

In contrast, GB has been found to be ineffective in hedging against natural gas price volatility [36]. Similarly, [37] has also substantiated the adverse impact of natural gas price volatility on GB. Irreversible investment theory and real options theory attribute this negative impact to investors' pessimism about market conditions, which in turn casts a shadow over the GB market [37]. In the context of coal price volatility, [38] emphasise the hedging role of GB against such volatility. For this reason, coal price volatility is claimed to be able to enhance the attractiveness of GB among investors [38, 39]. These discussions lead to the following hypotheses:

H2a: *Oil price volatility significantly impacts GB performance.*

H2b: *Natural gas price volatility significantly impacts GB performance.*

H2c: *Coal price volatility significantly impacts GB performance.*

2.3 Moderating role of policy uncertainty

Real options theory suggests that EPU encourages the adoption of a "wait-and-see" approach, where investors postpone their investment until uncertainty is resolved. As a result, investors may redirect their funds from the GB market to shorter-term and safer assets [40], thereby dampening the progress of the energy transition. Furthermore, EPU can exacerbate energy price volatility by increasing financing costs and generating uncertainty regarding future energy demand [41]. The moderating role of EPU is also reflected by [42], who argues that EPU weakens the positive relationship between energy price volatility and economic performance. This is because EPU may generate unpredictable shifts in the business environment, weaken policy credibility, and raise the concern surrounding future regulatory direction [43, 44]. This heightened uncertainty can adversely affect investor expectations by reducing confidence in the long-term viability and returns of green investments, and thereby stimulating risk-averse behaviour among investors [17, 45].

In addition to energy price volatility, [46] underlines that EPU strengthens the adverse relationship between oil price volatility and stock return. This is because EPU introduces additional uncertainty into business operations, deteriorates the investment environment, reduces future cash flows, and thereby further impedes stock returns [47]. In contrast, while [46] also concludes that EPU exacerbates the natural gas price volatility by influencing market liquidity, [47] finds that EPU instead weakens natural gas price volatility. Geng [48] further attribute the reduction in investment to the inverse relationship between EPU and natural gas price volatility. Regarding coal price volatility, [49] argues that EPU can weaken coal price volatility, thereby making it easier for companies to manage cost uncertainty. Thus, this paper proposes the following hypothesis:

H3: *EPU moderates the impact of energy, oil, price volatility on GB performance.*

Apart from EPU, CPU is also claimed to affect energy price volatility through its influence on energy consumption [50]. On the one hand, the price advantage and convenience of fossil fuels make them more attractive during periods of high CPU. CPU, in turn, reduces renewable energy consumption and heightens vulnerability to energy price volatility. Moreover, CPU has been found to exacerbate energy price volatility by altering decisions related to energy efficiency, thereby generating uncertainty regarding future energy demand. This argument is also supported by [51], who posits that the CPU suppresses risk-taking behaviour and thus results in the postponement of investment in renewable energy projects. However, a recent study, [50], suggests that CPU may instead encourage renewable energy consumption as a precautionary response to frequent changes in climate policies.

While the aforementioned discussions have revolved around overall energy price volatility, [52] argues that the impact of CPU on oil price volatility tends to be more pronounced than EPU. This could be attributed to the introduction of the Paris Agreement, which encourages the formulation of climate policies [53]. Moreover, extant studies indicate that the relatively lower carbon emissions of natural gas have positioned it at the centre of global climate policies [54]. Consequently, CPU has been found to exacerbate natural gas price volatility [55]. Given that coal must be phased out to meet the goals of the Paris Agreement, its price has become increasingly sensitive to CPU [56]. Specifically, the CPU influences coal price volatility by affecting coal consumption and discouraging investment in the coal market [55, 56]. Accordingly, the following hypothesis is proposed:

H4: *CPU moderates the impact of energy, oil, natural gas, and coal price volatility on GB performance.*

3 Data and methodology

3.1 Data

This paper employs daily and monthly data spanning from December 1, 2008 to June 30, 2024. Following [57] and [58], GB performance is proxied by the Standard & Poor's (S&P) GB Index Total Return, as it reflects both price changes and coupon payments, allowing GB performance to be measured comprehensively [59]. In addition, based on [60], the performance of firms within the energy sector is closely connected to the energy market. This indicates that any change in the MSCI World Energy Index reflects uncertainty and volatility in the overall energy market. Thus, this index is used to measure the energy price volatility. In contrast, the Merill Lynch (MLCX) oil prices is used as the indicator for oil price due to the leading role of the U.S. in the global energy market [61], while the S&P GSCI Natural Gas Index, which is widely-recognised as a benchmark for assessing the performance of the natural gas market is used to measure natural gas prices. For coal price volatility, it is proxied by the global coal price. The Fractional Integrated Generalized Autoregressive Conditional Heteroscedasticity (FIGARCH) model is used to capture the volatility of these energy prices.

In terms of the EPU, the index developed by [60] is applied as it is able to measure the rate at which EPU increases over time [62]. In addition, the CPU index, which was introduced by [63], is used as the proxy for the CPU as it encompasses policies pertaining to global climate and weather changes [64]. In order to minimise the risk of omitted variables, three control variables are included in this paper. Stock market return is included as a control variable due to its influence on GB performance [65]. Similarly, the literature also underlines that an increase in the U.S. Treasury Bond index will enhance the attractiveness of GB [66]. In contrast, the USD index is claimed to be adversely correlated with the GB market due to its role as one of the safest financial instruments, which attracts investors more strongly during uncertainty [67]. Accordingly, these variables are included as control variables.

Specifically, all variables are measured on a daily basis except for coal price volatility, EPU, and CPU, which are only available at a monthly frequency. The details of the variables are summarised in Table 1. In view of the emergence of numerous large GB issuers worldwide [68], this paper examines the relationship between the variables from a global perspective rather than country-specific.

3.2 Model specification and methodology

The methodology framework for this study is presented in Fig. 1. In order to confirm the stationarity of the variables, unit root tests with and without the structural breaks are conducted in this study. To begin with, the Augmented Dickey Fuller (ADF) unit root test is applied in this study together with the Philips-Perron (PP) unit root test. However, the unit root test without considering structural breaks might lead to spurious results

Table 1 Data and data sources

	Variable	Descriptions	Indicators	Frequency	Sources
Dependent variable	GB	Green Bond Performance	S&P Green Bond Index	Daily	Refinitiv Eikon Datastream
Independent variable	EPV	Energy Price Volatility	MSCI World Energy Index	Daily	Refinitiv Eikon Datastream
Independent variable	OPV	Oil Price Volatility	Merrill Lynch Crude Oil Spot Index	Daily	Refinitiv Eikon Datastream
Independent variable	NGV	Natural Gas Price Volatility	S&P GSCI Natural Gas Index	Daily	Refinitiv Eikon Datastream
Independent variable	CPV	Coal Price Volatility	Coal Price Index	Monthly	Refinitiv Eikon Datastream
Moderator	EPU	Economic Policy Uncertainty	Economic Policy Uncertainty Index	Monthly	policyuncer-tainty.com
Moderator	CPU	Climate Policy Uncertainty	Climate Policy Uncer-tainty Index	Monthly	policyuncer-tainty.com
Control variable	$SP500$	Stock Market Return	S&P 500 Index	Daily	Refinitiv Eikon Datastream
Control variable	UST	Bond Yield	U.S. 10-year Treasury Interest Rate	Daily	Refinitiv Eikon Datastream
Control variable	EX	USD Exchange Rate	USD Index	Daily	Yahoo Finance

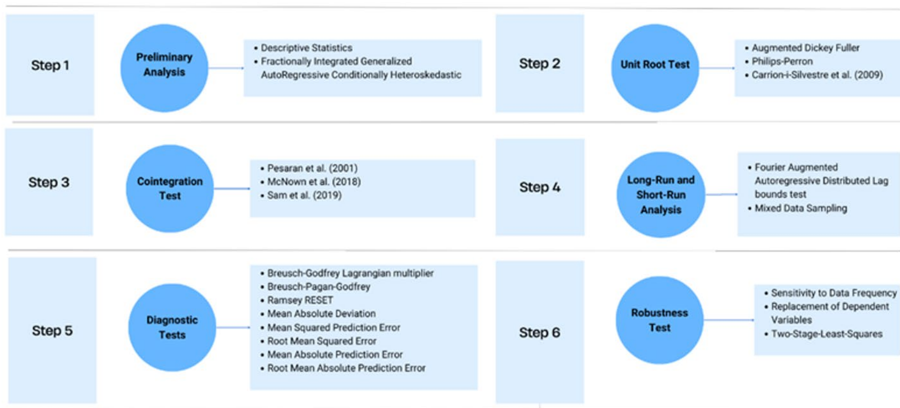

Fig. 1 Flowchart of methodology

[69]. Thus, the unit root test, which was introduced by [68], is applied in this paper, as it can detect up to five structural breaks at both the level and slope.

Following the unit root tests, the fractional integrated generalized autoregressive conditional heteroscedasticity (FIGARCH) is applied due to its ability to capture the persistence of volatility [70] and its superior performance compared to GARCH and IGARCH methods [71]. The FIGARCH model can be defined as follow:

$$\phi(L)(1-L)^{d}\varepsilon_t^2 = \alpha_0 + [1-\beta(L)]v_t \quad (1)$$

where $0 < d < 1$, and all the roots of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit circle.

In order to examine the impact of energy, oil, natural gas, and coal price volatility on GB performance, following [70], the following models are defined as follow:

Energy price volatility:

$$\text{Model (1a)}: GB_t = \alpha_0 + \sum_{j=1}^{p}\beta_{1j}GB_{t-j} + \beta_{11}EPV_t + \beta_{21}SP500_t + \beta_{31}UST_t + \beta_{21}EX_t + \theta_t \quad (2)$$

Oil price volatility:

$$\text{Model (1b)}: GB_t = \alpha_1 + \sum_{j=1}^{p}\alpha_{1j}GB_{t-j} + \varphi_{11}OPV_t + \varphi_{21}SP500_t + \varphi_{31}UST_t + \varphi_{41}EX_t + \omega_t \quad (3)$$

Natural gas price volatility:

$$\text{Model (1c)}: GB_t = \alpha_1 + \sum_{j=1}^{p}\alpha_{1j}GB_{t-j} + \xi_{11}NGV_t + \xi_{21}SP500_t + \xi_{31}UST_t + \xi_{41}EX_t + \phi_t \quad (4)$$

Coal price volatility:

$$\text{Model (1d)}: GB_t = \alpha_1 + \sum_{j=1}^{p}\alpha_{1j}GB_{t-j} + \psi_{11}CPV_t + \psi_{21}SP500_t + \psi_{31}UST_t + \psi_{41}EX_t + \lambda_t \quad (5)$$

where θ, ω, ϕ and λ denote the error terms.

Next, the EPU and CPU are incorporated as additional variable into model (1)–(4) to examine their moderating effect on this relationship. The rationale behind is to examine how policy uncertainty affects GB performance directly and indirectly by moderating the energy price volatility-GB nexus.

$$\text{Model (2a)}: GB_t = \alpha_1 + \sum_{j=1}^{p} \alpha_{1j} GB_{t-j} + \delta_{11} EPV_t + \delta_{21} EPU_t + \delta_{31}(EPV_t * EPU_t) + \delta_{41} SP500_t + \delta_{51} UST_t + \delta_{61} EX_t + \vartheta_t \tag{6}$$

$$\text{Model (2b)}: GB_t = \alpha_1 + \sum_{j=1}^{p} \alpha_{1j} GB_{t-j} + j_{11} OPV_t + j_{21} EPU_t + j_{31}(OPV_t * EPU_t) + j_{41} SP500_t + j_{51} UST_t + j_{61} EX_t + \ell_t \tag{7}$$

$$\text{Model (2c)}: GB_t = \alpha_1 + \sum_{j=1}^{p} \alpha_{1j} GB_{t-j} + x_{11} NGV_t + x_{21} EPU_t + x_{31}(NGV_t * EPU_t) + x_{41} SP500_t + x_{51} UST_t + x_{61} EX_t + \beth_t \tag{8}$$

$$\text{Model (2d)}: GB_t = \alpha_1 + \sum_{j=1}^{p} \alpha_{1j} GB_{t-j} + \Gamma_{11} COPV_t + \Gamma_{21} EPU_t + \Gamma_{31}(CPV_t * EPU_t) + \Gamma_{41} SP500_t + \Gamma_{51} UST_t + \Gamma_{61} EX_t + \mathcal{B}_t \tag{9}$$

$$\text{Model (3a)}: GB_t = \alpha_1 + \sum_{j=1}^{p} \alpha_{1j} GB_{t-j} + \gamma_{11} EPV_t + \gamma_{21} CPU_t + \gamma_{31}(EPV_t * CPU_t) + \gamma_{41} SP500_t + \gamma_{51} UST_t + \gamma_{61} EX_t + \tau_t \tag{10}$$

$$\text{Model (3b)}: GB_t = \alpha_1 + \sum_{j=1}^{p} \alpha_{1j} GB_{t-j} + h_{11} OPV_t + h_{21} CPU_t + h_{31}(OPV_t * CPU_t) + h_{41} SP500_t + h_{51} UST_t + h_{61} EX_t + \gimel_t \tag{11}$$

$$\text{Model (3c)}: GB_t = \alpha_1 + \sum_{j=1}^{p} \alpha_{1j} GB_{t-j} + o_{11} NGV_t + o_{21} CPU_t + o_{31}(NGV_t * CPU_t) + o_{41} SP500_t + o_{51} UST_t + o_{61} EX_t + o_t \tag{12}$$

$$\text{Model (3d)}: GB_t = \alpha_1 + \sum_{j=1}^{p} \alpha_{1j} GB_{t-j} + \mho_{11} COPV_t + \mho_{21} CPU_t + \mho_{31}(CPV_t * CPU_t) + \mho_{41} SP500_t + \mho_{51} UST_t + \mho_{61} EX_t + \mathcal{H}_t \tag{13}$$

where $\vartheta, \ell, \beth, \mathcal{B}, \tau, \gimel, \mathscr{g}$ and $\mathcal{H}$ represent the error terms; $EPV * EPU$ and $EPV * CPU$ are the interaction terms between energy price volatility and EPU (CPU) which aim at investigating the moderating effect of policy uncertainty.

In order to address the multiple structural breaks and prevent the overfitting issues [72], the Fourier Augmented Autoregressive Distributed Lag (FAARDL) bounds test was applied by incorporating the Fourier terms into the models. The Fourier approximation can be defined as follows:

$$d(t) = \sum_{k=1}^{n} \alpha_k \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} b_k \cos\left(\frac{2\pi kt}{T}\right) \tag{14}$$

where n denotes the frequencies presented in the Fourier function; T represents the sample size; t is the trend; π is 3.1415. Following [73] and [72], the single frequency in the Fourier function is defined as follows:

$$d(t) = \gamma 1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma 2 \cos\left(\frac{2\pi kt}{T}\right) \tag{15}$$

Accordingly, the following equations are defined:

$$\Delta GB_t = \rho + \sum_{i=1}^{y} \varphi_i \Delta GB_{t-i} + \sum_{i=0}^{p} \Omega_i \Delta EPV_{t-i} + \sum_{i=0}^{q} \Psi_i \Delta SP500_{t-i} + \sum_{i=0}^{m} \ell_i \Delta UST_{t-i} + \sum_{i=0}^{m} \Phi_i \Delta EX_{t-i} + \pi_1 GB_{t-1} + \pi_2 EPV_{t-1} + \pi_3 SP500_{t-i} + \pi_4 UST_{t-i} + \pi_5 EX_{t-i} + \gamma 1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma 2 \cos\left(\frac{2\pi kt}{T}\right) + \upsilon_t \quad (16)$$

$$\Delta GB_t = \rho + \sum_{i=1}^{y} \varphi_i \Delta GB_{t-i} + \sum_{i=0}^{p} \Omega_i \Delta OPV_{t-i} + \sum_{i=0}^{q} \Psi_i \Delta SP500_{t-i} + \sum_{i=0}^{m} \ell_i \Delta UST_{t-i} + \sum_{i=0}^{m} \Phi_i \Delta EX_{t-i} + \pi_1 GB_{t-1} + \pi_2 OPV_{t-1} + \pi_3 SP500_{t-i} + \pi_4 UST_{t-i} + \pi_5 EX_{t-i} + \gamma 1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma 2 \cos\left(\frac{2\pi kt}{T}\right) + \upsilon_t \quad (17)$$

$$\Delta GB_t = \rho + \Delta GB_{t-i} + \sum_{i=0}^{p} \Omega_i \Delta NGV_{t-i} + \sum_{i=0}^{q} \Psi_i \Delta SP500_{t-i} + \sum_{i=0}^{m} \ell_i \Delta UST_{t-i} + \sum_{i=0}^{m} \Phi_i \Delta EX_{t-i} + \pi_1 GB_{t-1} + \pi_2 NGV_{t-1} + \pi_3 SP500_{t-i} + \pi_4 UST_{t-i} + \pi_5 EX_{t-i} + \gamma 1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma 2 \cos\left(\frac{2\pi kt}{T}\right) + \upsilon_t \quad (18)$$

where $\gamma 1$ and $\gamma 2$ denote amplitude and displacement of the frequency component, respectively.

Given that converting high frequency data (i.e. $GB, EPV, OPV, NGV, SP500, UST$ and EX) into low-frequency may lead to a loss of valuable information and inaccurate results [74], the mixed-data sampling (MIDAS) method was employed to model the variables with different frequencies. Based on [75], the simple linear MIDAS model can be expressed as follows:

$$Y_t = \beta_0 + \beta_1 B\left(L^{\frac{1}{m}}; \theta\right) X_{t-1}^{(m)} + \varepsilon_t^{(m)} \quad (19)$$

where $B\left(L^{\frac{1}{m}}; \theta\right) = \sum_{j=0}^{j^{max}} B\left(j; \theta\right) L^{j/m}$ is the polynomial of length j^{max} in the $L^{\frac{1}{m}}$ operator; $L^{j/m}\chi_t = \chi_{t-j/m}$, meaning that $L^{j/m}$ operator generates the X_t value lagged by j/m periods.

Practically, Almon polynomial function and Beta function are always employed to reduce the parameter space. For Almon polynomial function, it can be defined as:

$$B\left(j; \theta\right) = \frac{\exp(\theta_1 j + \theta_2 j^2 + \cdots + \theta_q j^q)}{\sum_{j=0}^{J} exp(\theta_1 j + \theta_2 j^2 + \cdots + \theta_q j^q)} \quad (20)$$

whereas Beta function is defined as:

$$B\left(j; \theta\right) = \frac{f(j/J, \theta_1, \theta_2, \ldots, \theta_q)}{\sum_{j=1}^{J} f(j/J, \theta_1, \theta_2, \ldots, \theta_q)} \quad (21)$$

where $f\left(x, a, b\right) = \frac{x^{a-1}(1-x)^{b-1}T(a+b)}{T(a)+T(b)}, T\left(a\right) = \int_0^\infty e^{-x} x^{a-1} dx$

4 Empirical results

4.1 Descriptive statistics

The descriptive statistics of the variables are presented in Table 2. GB has a mean score of 4.6436, standard deviation of 0.1023, whereas the mean and standard deviation for energy price volatility are 5.3572 and 0.2056, respectively. In contrast to natural gas and coal price volatility, oil price volatility surprisingly has the lowest standard deviation, suggesting that it exhibits the least variation compared to the other three variables. Apart from these, EPU and CPU are having the mean scores of 4.8858 and 5.1439, respectively.

Table 2 Descriptive statistics

Variable	Mean	Minimum	Maximum	Median	Standard deviation
GB	4.6436	4.3343	4.8227	4.6520	0.1023
EPV	−0.0004	−0.2129	0.1403	−6.87E−0.5	0.0155
OPV	1	0.8776	1.0938	1.0001	0.0052
NGV	−0.0009	−0.1869	0.1731	−0.0008	0.0310
CPV	−0.0038	−0.4150	0.2900	−0.0074	0.0839
EPU	5.1439	4.4585	6.0676	5.1145	0.3774
CPU	4.8858	3.6400	6.0193	4.8468	0.4678
$SP500$	7.7087	6.5170	8.6101	7.6796	0.4951
UST	1.0101	0.1823	1.5913	1.0543	0.3171
EX	4.6633	4.4481	4.8556	4.085	0.1113

4.2 Unit root test

The results of the unit root tests are presented in Table 3. Based on the results of the ADF and PP unit root tests, the null hypothesis for NGV, EPU, CPU, and $SP500$ are rejected, suggesting that these variables are integrated of order 0, that is I(0). In contrast, the null hypothesis for GB, EPV, UST, and EX cannot be rejected, indicating that these variables contain a unit root. Thus, this paper proceeds to take the first difference of these variables and notices that the null hypothesis is then rejected, implying that these variables are stationary at first difference, that is I(1). However, given that these methods might lead to misleading results due to their failure to capture structural breaks [76], following [77], this paper proceeds to conduct the unit root test with structural breaks.

According to the results of the [68] unit root test, EPU and $SP500$ are found to be stationary at first difference rather than at level, while EPV and CPV are stationary at level instead of first difference. The unit root test results for the other variables remain unchanged. Based on [76], failing to account for structural breaks will limit the reliability of the unit root test, suggesting that the results of the [68] unit root test is more reliable than ADF and PP unit root tests.

4.3 Results of cointegration test

Prior to examine the relationship between the variables, the cointegration tests, which were recommended by [78–80], are employed in this study. The results of the cointegration test are presented in Table 4. The results reveal that all of the variables are cointegrated with each other. Thus, this study proceeds to examine the relationship between the variables.

4.4 Empirical results and discussions

The results for the impact of energy, oil, natural gas, and coal price volatility are presented in Table 5. Given that the results of the Breusch-Pagan-Godfrey (BP) test indicate the presence of heteroscedasticity in Models (1)–(3), this study proceeds to estimate robust standard error. In doing so, it is found that the volatility of energy, oil and natural gas prices dampens GB performance in the short-run, indicating that H1, H2a, and H2b are supported. This may be explained by investors' and companies' sensitivity to uncertain cost structure and future cash flows. However, the negative impact becomes stronger over time, revealing that persistent volatility raises investor concern in the long-term economic viability of the underlying green projects. Theoretically, these findings align

Table 3 Results of unit root tests

	Without structural breaks				With structural breaks									
	ADF		PP		Carrion-i-silvestre									
	Level	1st difference	Level	1st difference	Level					1st difference				
					Pt	MPt	MZa	MSB	MZt	Pt	MPt	MZa	MSB	MZt
GB	−2.772	−62.401***	−2.777	−62.395***	16.041	13.903	−17.354	0.170	−2.942	0.214***	0.202***	−1149.263***	0.021***	−23.971***
EPV	−2.700	−60.927***	−2.676	−60.928***	7.492*	6.353**	−40.027**	0.111**	−4.442**					
OPV	−2.743	−30.645***	−2.617	−62.417***	12.285	10.633	−23.413	0.146	−3.416	3.778***	3.157***	−77.712***	0.080***	−6.233***
NGV	−3.212*		−3.331*		7.742*	7.167**	−25.020**	0.140**	−3.506*					
CPV	−1.803	−13.205***	−2.185	−13.400***	8.267*	7.723*	−30.317*	0.128*	−3.888					
EPU	−5.083***		−4.919***		14.349	13.163	−21.009	0.154	−3.237	3.607***	3.362***	−82.299***	0.078***	−6.414***
CPU	−8.162***		−8.502***		6.285***	5.863***	−71.142***	0.084***	−5.960***					
SP500	−4.280***		−4.519***		13.237	11.003	−40.220	0.111	−4.479	4.522***	4.392***	−100.204***	0.071***	−7.078***
UST	−1.857	−47.487***	−1.683	−63.833***	9.394	8.971	−27.601	0.134	−3.706	1.409***	1.365***	−322.702***	0.039***	−12.702***
EX	−2.934	−62.527***	−2.983	−62.543***	12.413	11.715	−25.956	0.138	−3.593	1.453***	1.402***	−217.891***	0.048***	−10.434***

***, ** and * denote significant at 1%, 5% and 10% level, respectively

Table 4 Results of cointegration test

Model	1a	1b	1c
	Energy	**Oil**	**Natural gas**
F-test(1)	114.30	53.55	76.18
t-test	−4.40	−4.58	−4.72
F-test(2)	89.32	66.01	104.9
	K=4		
F-test(1)	1%	5%	10%
I(0)	3.74	2.86	2.45
I(1)	5.06	4.01	3.52
t-test	1%	5%	10%
I(0)	−3.43	−2.86	−2.57
I(1)	−4.60	−3.99	−3.66
F-test(2)	1%	5%	10%
I(0)	3.33	2.39	1.96
I(1)	5.47	4.18	3.58

The threshold value for F-test(1) and t-test are obtained from [80] while the critical values for F-test(2) are obtained from [81]

with irreversible investment and real options theories, which postulate that uncertainty arising from energy price volatility can increase the value of waiting and thereby induce investors to reduce or postpone their investment in the GB market [82].

In the context of coal price volatility, it is found to be conducive to GB performance in the short-run, reflecting investor optimism that coal market instability will spur supportive policies to phase out coal and accelerate the energy transition [83]. However, this positive impact reverses in the long-run. This might be due to the persistent volatility, which signals the absence of effective government intervention and increases the risk premium for GB. This, in turn, undermines investor confidence and discourages investment in the GB market. The findings indicate that H2c is supported, as the significant impact effect is observed in both short-run and long-run.

The results further reveal the negative impact of stock market return on GB performance, which can be attributed to the substitution effect, where rising stock market returns redirect investment away from GB. Similarly, the U.S. Treasury Bond Index impedes GB performance by making the risk-free asset more attractive than GB. Lastly, the negative relationship between exchange rate and GB performance can be attributed to investors' intention to avoid high-risk projects like renewable energy projects [84]. However, the impact of these control variables becomes insignificant in Model (1d), implying that investors respond more strongly to coal price volatility than to other financial market signals.

In view of the significant direct impact of energy price volatility on GB performance, this study proceeds to examine the moderating role of EPU on this relationship. The results indicate that energy price volatility positively impacts GB performance, while EPU has a negative impact in the short-run. This suggests that investors are willing to use GB as a hedging asset against energy price volatility, but not against EPU. However, this favourable role declines as EPU increases, illustrating how policy-related risks can reduce the positive impact. In the long-run, the direct impact of energy price volatility becomes insignificant. One plausible explanation is that EPU leads to the suspension of green projects, which undermines the hedging effectiveness of GB [85]. Consequently, EPU will result in the net negative outcome on GB performance in the long-run. The absence of a direct impact and moderating role of EPU in the long-run can be attributed

Table 5 Empirical results

Model	1a	1b	1c	1d
	Energy	**Oil**	**Natural gas**	**Coal**
Panel A: Long-run analysis				
EPV	−0.182*** (0.000)			
OPV		−0.063*** (0.000)		
NGV			−0.126*** (0.000)	
CPV				−0.034*** (0.000)
$SP500$	−0.036*** (0.000)	−0.110*** (0.000)	−0.111*** (0.032)	−0.058 (0.607)
UST	−0.8663*** (0.0000)	0.1883 (0.115)	−0.0002*** (0.000)	−0.005 (0.358)
EX	−0.878*** (0.0000)	−0.078*** (0.0000)	−0.007*** (0.000)	0.157 (0.646)
Panel B: Short-run analysis				
EPV	−0.001* (0.072)			
OPV		−0.003* (0.078)		
NGV			−0.001** (0.020)	
CPV				0.273*** (0.000)
$SP500$	−0.002*** (0.000)	−0.005*** (0.000)	−0.005*** (0.000)	0.0102 (0.975)
UST	0.000 (0.357)	0.001 (0.4062)	−0.009 (0.3356)	−0.0013 (0.933)
EX	−0.050*** (0.002)	−0.032*** (7.681e-09)	−0.004*** (6.240e-14)	−0.5580 (0.567)
Panel C: Fourier terms				
$\gamma 1$	−177.700 (0.2810)	−18.110 (0.2711)	−16.380 (0.321)	
$\gamma 2$	27.460 (0.281)	27.990 (0.271)	25.320 (0.321)	
Panel D: Diagnostic tests				
BG-LM test	0.753	0.696	0.280	
Ramsey RESET	0.800	0.056	0.374	
BP test	0.000	0.000	0.000	
CUSUM	S	S	S	
MAD				0.125
MSPE				0.022
RMSE				0.148
MAPE				0.027
RMAPE				0.164

***, ** and * denote significant at 1%, 5% and 10% level, respectively. P-values are presented in parentheses

to policies implemented to stabilise the political environment and alleviate the influence of EPU [86].

Similarly, Table 6 also reveals a positive relationship between oil and natural gas prices volatility and GB performance in the short-run. This favourable role is weakened as EPU increases, underscoring the active role of government in stabilising the oil and natural gas market. However, both the direct impact of price volatility and the moderating role of EPU become insignificant in the long-run. These findings collectively demonstrate

Table 6 Moderating role of EPU and CPU

Model	2a	2b	2c	2d	3a	3b	3c	3d
	Energy	**Oil**	**Natural gas**	**Coal**	**Energy**	**Oil**	**Natural gas**	**Coal**
Panel A: Long-run analysis								
EPV	−0.225 (0.332)				0.059 (0.906)			
OPV		−0.003 (0.950)				−0.020 (0.682)		
NGV			−0.024 (0.614)				−0.026 (0.568)	
CPV				0.359*** (0.000)				0.070** (0.029)
EPU	−0.002 (0.908)	0.010 (0.127)	0.003 (0.715)	0.351*** (0.000)				
CPU					0.013 (0.317)	0.001 (0.698)	0.006 (0.191)	0.058** (0.029)
EPV* EPU	−0.021 (0.192)							
OPV* EPU		−0.001 (0.977)						
NGV* EPU			−0.001 (0.940)					
CPV* EPU				−0.080*** (0.000)				
EPV* CPU					−0.001 (0.971)			
OPV* CPU						−0.001 (0.571)		
NGV* CPU							−0.001 (0.675)	
CPV* CPU								−0.013** (0.028)
SP500	0.385 (0.252)	0.125 (0.211)	0.058 (0.616)	0.031 (0.746)	0.574 (0.382)	0.071 (0.519)	0.039 (0.779)	0.049 (0.525)
UST	−0.001 (0.937)	−0.005 (0.307)	−0.005 (0.385)	−0.001 (0.820)	−0.001 (0.997)	−0.003 (0.495)	−0.005 (0.459)	−0.001 (0.791)
EX	−0.111 (0.907)	0.118 (0.701)	0.197 (0.580)	0.138 (0.645)	−0.400 (0.825)	0.254 (0.209)	0.399 (0.349)	0.224 (0.352)
Panel B: Short−run analysis								
EPV	1.837*** (0.000)				1.556*** (0.003)			
OPV		1.555*** (0.000)				1.547*** (0.000)		
NGV			1.580*** (0.000)				1.484*** (0.000)	
CPV				0.310** (0.022)				0.114** (0.011)
EPU	−0.329*** (0.000)	1.784*** (0.000)	1.436*** (0.000)	−0.134* (0.050)				
CPU					1.788*** (0.000)	1.796*** (0.000)	1.361*** (0.000)	0.099*** (0.008)
EPV* EPU	−1.784*** (0.000)							
OPV* EPU		−0.301*** (0.000)						
NGV* EPU			−0.283*** (0.000)					
CPV* EPU				−0.032** (0.034)				

Table 6 (continued)

Model	2a	2b	2c	2d	3a	3b	3c	3d
	Energy	**Oil**	**Natural gas**	**Coal**	**Energy**	**Oil**	**Natural gas**	**Coal**
EPV* CPU					−0.338***			
					(0.000)			
OPV* CPU						−0.298***		
						(0.000)		
NGV* CPU							−0.269***	
							(0.000)	
CPV* CPU								−0.022***
								(0.007)
SP500	−0.543	−0.222	0.124	−0.054	−0.673	−0.159	−0.068	−0.136
	(0.142)	(0.178)	(0.516)	(0.693)	(0.322)	(0.385)	(0.766)	(0.255)
UST	−0.010	−0.007	−0.008	−0.007	−0.008	−0.009	−0.009	−0.007
	(0.292)	(0.381)	(0.363)	(0.251)	(0.723)	(0.265)	(0.396)	(0.218)
EX	−0.927	−1.109**	−1.290**	−0.966**	−0.708	−1.375**	−1.796**	−1.327***
	(0.385)	(0.031)	(0.031)	(0.026)	(0.710)	(0.016)	(0.012)	(0.001)
Panel C: Diagnostic and stability tests								
MAD	0.034	0.037	0.045	0.023	0.040	0.042	0.053	0.024
MSPE	0.085	0.090	0.099	0.071	0.009	0.003	0.005	0.001
RMSE	0.007	0.008	0.010	0.005	0.051	0.054	0.068	0.032
MAPE	0.002	0.002	0.239	0.001	0.003	0.009	0.011	0.005
RMAPE	0.041	0.049	0.057	0.033	0.051	0.096	0.107	0.072

***, ** and * denote significant at 1%, 5% and 10% level, respectively. P-values are presented in parentheses

investors' stronger response to market volatility and policy unpredictability in the short-run. By comparing these results with Table 5, it is reasonable to infer that EPU is one of the main drivers of the overall negative impact on GB performance in the long-run.

Similarly, coal price volatility is also found to exert a positive impact on GB performance in the short-run, while EPU dampens it. This finding suggests the willingness of investors to incorporate GB to hedge against coal price volatility, but not against EPU. However, the analysis reveals the weakening effect of EPU on the positive relationship between coal price volatility and GB performance in both the short- and long-run. The discrepancy between Models (1d) and (2d) reveals that EPU is a driver of the adverse impact of coal price volatility by introducing additional uncertainty and stimulating risk-averse behaviour among investors [45, 87]. This, in turn, leads to an overall negative outcome for GB performance. Furthermore, the significant moderating impact of EPU in the long-run can be ascribed to the status of the coal market as a policy-driven market, which makes it more exposed to policy changes than oil and natural gas. These findings provide partial support for H3, as the moderating effect of EPU is observed in the short-run not in the long-run.

Table 6 reveals the weakening effect of the CPU on the positive relationship between energy, oil and natural gas prices volatility and GB performance in the short-run. This could be ascribed to the role of the CPU in promoting renewable energy consumption [88]. Furthermore, the positive impact of the CPU on the GB performance in Models (3a)–(3c) can be attributed to the hedging role of the GB against the CPU [89]. However, in the long-run, the positive impact of energy, oil, and natural gas prices volatility becomes insignificant. The variation in results between Tables 5 and 6 indicates that CPU is another main driver behind the adverse impacts of energy, oil, and natural gas price volatility on GB performance. The absence of direct and moderating impact of the CPU in the long-run is due to policymakers' intention in addressing the CPU [90].

Similarly, both coal price volatility and the CPU exert a positive impact on GB performance in the short-run. In addition, it is also found that CPU weakens the positive relationship between these variables by encouraging renewable energy consumption and reducing dependency on coal [91]. Given the positive impact of coal price volatility remaining significant in the long-run, the discrepancy between Models (1d) and (3d) indicates that CPU does not necessarily lead to reduced coal consumption in the long-run. Instead, it introduces additional uncertainty into the market, stimulates risk-averse behaviour among investors and thus results in an overall negative impact on GB performance. The persistent weakening effect of the CPU in the long-run further reveals that the coal market is more exposed to long-term environmental regulations due to its status as the most environmentally damaging fossil fuel [92]. The results suggest that H4 is partially supported, as the moderating effect of CPU on the impact of energy, oil and natural gas prices volatility is significant only in the short-run but not in the long-run.

Furthermore, the results also reveal that EPU has a stronger weakening effect than CPU. Specifically, while CPU is primarily concerned with climate-related policies, EPU raises concerns regarding political stability future cash flows, and energy transition costs [93]. This, in turn, increases the perceived risks of green investment and reduces investor confidence in the GB market [94]. Consequently, investors are more likely to reallocate their portfolios away from GB under high levels of EPU.

To confirm the results' accuracy, diagnostic tests are conducted for the FAARDL models, and the results are presented in Panel D of Table 5. The results show that Models (1a)–(1d) have passed the BG-LM test and Ramsey RESET test, suggesting that the null hypothesis of no serial correlation and correct specification are accepted. However, the result of the BP test shows that the null hypothesis of homoscedasticity cannot be rejected, as the p-value is significant at the 1% level. Thus, robust standard errors are estimated. In addition, the results of Cumulative Sum (CUSUM) test further confirm the results' stability. Furthermore, several diagnostic and stability tests are also employed to ensure the accuracy of the results derived from the MIDAS models. All computed values for Mean Absolute Deviation (MAD), Mean Squared Prediction Error (MSPE), Root Mean Squared Error (RMSE), Mean Absolute Prediction Error (MAPE) and Root MAPE (RMAPE) fall below 10%, thereby confirming the reliability of the results.

4.5 Robustness tests

4.5.1 Sensitivity to data frequency

To ensure the robustness of the results, this study proceeds to examine their sensitivity to data frequency by converting the main interest variables, EPV, OPV and NGV, into monthly data while, CPV is converted into daily data. The results are presented in Table 7. While the impacts of oil, natural gas, and coal price volatility remain to be negative and significant, the impact of energy price volatility becomes insignificant. The variation in the results could be ascribed to the loss of information during the conversion of data frequency. Overall, the results confirm the robustness of the findings of this study.

4.5.2 Replacement of dependent variable

Following [91], this paper also replaces the global GB index with GB issued in British pounds, and the results are presented in Table 8. Specifically, the results reveal that the

Table 7 Sensitivity to data frequency

Model	1a	1b	1c	1d
	Energy	**Oil**	**Natural gas**	**Coal**
Panel A: Long-run analysis				
EPV	−0.174 (0.321)			
OPV		−0.397*** (0.000)		
NGV			−0.643* (0.055)	
CPV				−3.177*** (0.010)
$SP500$	−0.189 (0.472)	0.144** (0.040)	−0.209 (0.245)	−0.008 (0.932)
UST	0.011 (0.811)	0.004 (0.811)	0.053 (0.316)	−0.001 (0.959)
EX	−0.304 (0.749)	−1.980*** (0.000)	−0.786 (0.141)	−0.632* (0.086)
Panel B: Short-run analysis				
EPV	−0.004 (0.496)			
OPV		−0.020*** (0.001)		
NGV			−0.016*** (0.000)	
CPV				−0.009*** (0.004)
$SP500$	−0.004 (0.209)	0.007 (0.126)	−0.005* (0.081)	−0.002 (0.931)
UST	0.001 (0.787)	0.001 (0.804)	0.001 (0.128)	−0.003 (0.959)
EX	−0.007 (0.792)	−0.100*** (0.005)	−0.019 (0.272)	−0.002 (0.221)

***, ** and * denote significant at 1%, 5% and 10% level, respectively

impacts of energy, oil, natural gas, and coal price volatility on GB performance remains to be negative and significant, further confirming the robustness of the findings.

4.5.3 Endogeneity test

Given that the endogeneity issue has become a major concern in empirical study [95], following [93], this study then applies the Two-Stage Least-Squares (2SLS) method and replaces the endogenous variables with instrumental variables. All independent variables are lagged by one period and used as the instrumental variables to mitigate both endogeneity and reverse causality issues [96]. The results of the endogeneity test are presented in Table 9. The results further confirm the robustness of the previous findings by demonstrating that energy, oil, natural gas, and coal price volatility adversely impact GB performance. Besides, the computed Cragg–Donald F-statistic is greater than 10 across all models, indicating that the weak instrument problem is not a concern [97, 98].

5 Conclusion

This paper investigates the impact of energy, oil, natural gas, and coal price volatility on GB, with a particular focus on the moderating effects of policy uncertainty (EPU and CPU) from global perspective. The findings of this study empirically demonstrate that policy uncertainty weakens the positive impact of energy price volatility on GB

Table 8 Replacement of dependent variables

Model	1a	1b	1c	1d
	Energy	**Oil**	**Natural gas**	**Coal**
Panel A: Long-run analysis				
EPV	−0.018** (0.010)			
OPV		−0.012*** (0.003)		
NGV			−0.006** (0.040)	
CPV				−0.044** (0.029)
$SP500$	0.010 (0.176)	0.010 (0.180)	−0.007** (0.043)	−0.063 (0.779)
UST	−0.001 (0.599)	−0.002 (0.386)	−0.002 (0.319)	−0.003 (0.736)
EX	0.006*** (0.000)	0.006*** (0.000)	0.006*** (0.000)	0.807 (0.250)
Panel B: Short-run analysis				
EPV	−0.008** (0.039)			
OPV		−0.003** (0.020)		
NGV			−0.003** (0.014)	
CPV				−0.151*** (0.000)
$SP500$	−0.004 (0.369)	−0.005 (0.352)	−0.007 (0.141)	0.050 (0.886)
UST	−0.001 (0.609)	−0.002 (0.383)	−0.008 (0.341)	−0.006 (0.635)
EX	−0.002*** (0.002)	−0.004*** (0.000)	0.003*** (0.000)	−1.196 (0.275)

***, ** and * denote significant at 1%, 5% and 10% level, respectively

Table 9 Results of endogeneity test

Model	1a	1b	1c	1d
	Energy	**Oil**	**Natural gas**	**Coal**
EPV	−0.228*** (0.000)			
OPV		−0.058*** (0.000)		
NGV			−0.030*** (0.000)	
CPV				−0.792*** (0.000)
$SP500$	−0.115*** (0.000)	−0.124*** (0.000)	−0.132*** (0.000)	−0.337*** (0.000)
UST	−0.011 (0.519)	−0.0156 (0.499)	−0.015 (0.538)	−0.041*** (0.000)
EX	0.119*** (0.000)	0.081*** (0.000)	0.080*** (0.000)	1.508*** (0.000)
Cragg-Donald F-Statistic	20.050	25.852	14.893	20.801

***, ** and * denote significant at 1%, 5% and 10% level, respectively performance and makes the adverse impact more significant. Furthermore, the analysis reveals that policy uncertainty weakens the impact of energy, oil, and natural gas price volatility in the short-run, suggesting a stronger investor response to an unpredictable policy framework. In contrast, policy uncertainty is found to moderate the coal price volatility-GB performance nexus in both the short- and long-run, indicating that the coal market is more exposed to long-term environmental regulations than oil and natural gas.

Overall, this paper demonstrates that policy uncertainty is not merely a direct risk but also an important conditional factor determining the impact of energy price volatility on GB performance. Ultimately, the results indicate that the extent to which GB can attract investors through its hedging benefits is contingent upon the stability of macroeconomic and environmental policies. Collectively, these findings underline that the challenge for GB lies not in energy price volatility itself but also in the political and regulatory context in which it operates.

The findings of this study yield several policy implications. Firstly, a universally accepted GB standard should be established to enhance market resilience against both energy price volatility and policy uncertainty. Secondly, policymakers should ensure timely and transparent communication of policies and avoid abrupt policy changes to foster a stable and predictable political environment. Thirdly, investors, particularly those in the coal market, should incorporate policy-related risk assessments into their investment strategies to better align their portfolios with evolving regulations. Lastly, GB issuers should regularly disclose the environmental outcomes of GB and mitigate risks associated with policy uncertainty to strengthen credibility.

This paper is subject to a few limitations. First, this research is conducted from a global perspective. The findings may or may not capture country-specific conditions. Second, the energy price volatility is proxied by energy sector equity index, which reflects market-based energy sector uncertainty rather than direct energy price volatility. Third, the study uses the CPU, which was developed based on the United States, and may therefore not reflect the CPU in other countries due to the due to the unique characteristics of climate policy regulations and implementation strategies worldwide. Lastly, this paper overlooks other types of energy, like the renewable energy market, and thus might overstate the impact of traditional fossil fuels and fail to account for the role played by other energy sources.

Therefore, more country-specific studies should be conducted in the future, particularly in countries experiencing political turmoil. Such studies would enable researchers to provide policy implications that are more tailored to each country's situation and offer more regionalised insights for investors in managing their portfolios. Besides, future studies may consider incorporating aggregate energy price volatility to provide a more dynamic perspective on energy market risk. Furthermore, future studies are recommended to develop CPU index for specific countries to provide more accurate and actionable insights. If data are available, future studies should incorporate other types of energy to provide a more holistic understanding of how the energy market affects green investment. Lastly, potential mediating variables, such as investor sentiment or financial constraints, can be incorporated into future studies to better understand the mechanisms through which policy uncertainty affects the energy price volatility-GB nexus.

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Author contributions
Vanessa Ming Miin Chan conceived the work's original idea, conducted the literature search, drafted and revised the manuscript. Ramez Abubakr Badeeb, Poh Ling Ho and Ivy S.H. Hii supervised the overall research design and critically revise the manuscript.

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Data availability
The datasets generated during and/or analysed during the current study are available in the Refinitiv Eikon Datastream, policyuncertainty.com and https://finance.yahoo.com/quote/DX-Y.NYB/history/?period1=31813200&period2=1767624202.

Declarations

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