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Climate policies, energy shocks and spillovers between green and brown stock price indices

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ABSTRACT

This paper examines the effects of climate policies and energy shocks on mean and volatility spillovers between green and brown stock price indices in five countries (Canada, India, Japan, the UK and the US). More specifically, bivariate GARCH-BEKK models including dummy variables controlling for these shocks are estimated using weekly series with start dates ranging from March 13, 2009 to August 24, 2012 (depending on data availability for the green index) and an end date of December 29, 2023. Significant dynamic linkages between green and brown indices are found when climate policy and oil shocks are considered jointly. Some common patterns emerge, such as shifts in spillover dynamics between green and brown assets, but also country-specific effects of the climate policy shocks which reflect differences in regulatory frameworks and policies. By contrast, energy shocks tend to have a more uniform impact. Further, the interaction between climate policy and energy shocks weakens cross-market linkages, enhancing portfolio diversification opportunities for green investors. The conditional correlation analysis confirms this finding, suggesting that green stocks can be used as an effective hedge. These results highlight the benefits of incorporating green assets into diversified portfolios, particularly in financial centers where, in recent years, they have offered higher returns and lower volatility.

1. Introduction

Climate change has become a key issue for policy-makers and financial investors – this is because of the risks it generates and the consequent need to adopt policies to achieve the transition to a low-carbon economy by promoting renewable energy and sustainable investments. This process is expected to have significant effects on financial markets by reallocating capital toward sustainable sectors, driving innovation in renewable technologies, and altering risk profiles across industries. These changes are expected to create new opportunities in green sectors while increasing volatility and adjustment costs in traditional industries reliant on fossil fuels (Hanif et al., 2023). The shift toward a green economy drives changes in infrastructure and technology, opening new opportunities for some industries while posing challenges for others. Moreover, it reinforces the critical role of financial markets in channeling capital toward sustainable development. Venturini (2022) highlighted that accurately accounting for firms' exposure to climate risks in return

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forecasts makes expected returns more closely with actual outcomes, which raises important issues for investors. In their comprehensive review of the impact of climate change on financial markets, which focused especially on microeconomic evidence, de Bandt et al. (2024) showed that the cumulative effects are difficult to estimate, owing to the multifaceted nature of risks and their varying impact on markets and portfolios. The recent literature argues that increased stock markets volatility and uncertainty related to the green transition depends on exogenous shocks, such as new climate policies or commodity price fluctuations, particularly in the case of crude oil (see Al-Thaqeb & Algharabali, 2019; Dutta et al., 2020; among others).

Climate policies have become a key driver of volatility in environmentally focused financial markets owing to the significant changes they entail. The Paris Agreement (PA), signed on December 12, 2015 by 195 countries at the UNFCCC COP21 (United Nations Framework Convention on Climate Change, Convention of the Parties 2015), represented a turning point, as it required its signatories to adopt long-term strategies to reduce greenhouse gas emissions specifying targets for 2030 and 2050. Since its announcement, international and national climate-financial initiatives have grown, along with the need for investors to understand climate policies and their impact on stock returns (Monasterolo & De Angelis, 2020; D'Orazio & Thole, 2022; Raza et al., 2024). The existing literature provides evidence on the different effects of climate policies on market uncertainty. For instance, the 2019 violation of the Clean Air Act under the Trump administration was linked to increased market volatility, which reflected the destabilizing influence of weakened environmental regulations. By contrast, supranational initiatives such as the European Green Deal (European Commission, 2021) have proven effective at mitigating market uncertainties, especially in comparison to the case of Asian regions where the absence of appropriate climate policies has contributed to greater instability (Albanese et al., 2024; Husain et al., 2022).

Another strand of the literature has investigated the role of crude oil, as a primary energy resource, for stock markets. According to Ouyang et al. (2022), understanding the link between crude oil prices and financial risk is crucial for maintaining financial stability and fostering economic growth. Increasing oil prices may provide an incentive to invest in renewable energy, particularly in oil-importing economies (Azhgaliyeva et al., 2022). Such a shock may have a different impact on green relative to brown stock prices and thus on optimal investment strategies. Green companies prioritize sustainability, utilizing renewable energy and adopting eco-friendly practices to reduce emissions and enhance their ESG (environmental, social, and governance) scores. They are found in sectors such as renewable energy, organic agriculture, and sustainable transportation, among others. By contrast, brown companies operate in industries with environmentally harmful practices, often giving priority to profit over sustainability. Examples include fossil fuel production, deforestation, and the use of toxic chemicals (Hartzmark & Shue, 2022).

Global indices tracking green and brown stocks are often employed to monitor the performance of these energy sectors. Examples include the MAC Global Energy Index, the ISE Global Wind Energy Index, and the S&P 500 Global Clean Energy Index for green stocks. Brown indices typically focus on fossil fuel-related sectors such as crude oil, coal, and natural gas (Caporale et al., 2023). However, the global nature of such indices means that they are not informative about country-specific factors.

By contrast, the present paper uses weekly series with start dates ranging from March 13, 2009 to August 24, 2012 (depending on data availability for the green index) and an end date of December 29, 2023 for five major economies, namely Canada, India, Japan, the UK and the US, which allows to analyze spillovers between green and brown stock price indices and the possible impact of climate policy as well as energy shocks *at the national level*. The country selection is primarily driven by the availability of sufficiently long time series for the green indices to obtain robust estimates. The fact that such indices in most cases have only been introduced in recent years limits the analysis to the selected group. However, the findings will still be highly informative as the countries in our sample have adopted different climate policies, whose effects can be compared.

Therefore, the first contribution of this study is to investigate within-country spillover effects among green and brown stock price indices rather than focusing on global indicators. The second one is to assess the impact of exogenous shocks using independent climate change measures. In particular, the analysis uses the Climate Policy Index, a component of the Climate Change Performance Index (Germanwatch, 2022), which is a reliable benchmark for assessing country-specific climate policies (detailed in Section 3). Furthermore, following Kilian and Zhou (2022), Baumeister and Kilian (2016), and Gazzani et al. (2024), the effects of global energy shocks resulting from fluctuations in oil prices are also investigated. More precisely, bivariate VAR-GARCH-BEKK models are used to estimate simultaneously both the conditional mean and variance spillovers and the effects of shocks on those spillovers within each country. Note that the BEKK functional form not only ensures the positive definiteness of the variance–covariance matrix but also captures the transmission of shocks and volatility between indices, making it the most suitable empirical framework for our purposes.

The layout of the paper is the following: Section 2 briefly reviews the literature on the impact of climate change on financial markets; Section 3 describes the data used for the analysis; Section 4 outlines the empirical framework and the hypotheses tested; Section 5 discusses the empirical results; Section 5 offers some concluding remarks.

2. Literature review

The effects of climate risks, both physical and transition-related (Ardia et al., 2023; Bua et al., 2022; Campiglio et al., 2018), on financial markets have been extensively investigated in the recent literature, with a particular focus on market volatility linkages during stable and turbulent periods and their implications for investors. This is particularly important for the green and brown energy sectors, given the shift from fossil fuels towards renewable energy, which requires a thorough understanding of how information is transmitted between markets (Bouri, 2023). The literature has analyzed spillovers between green and brown market returns, often using global indicators to track the performance of "green" industries such as renewable energy, clean energy, solar, and wind, and "brown" ones such as oil, coal, and gas. For instance, Liu and Hamori (2020) analyzed US and European data and found that spillovers from fossil fuel to renewable energy stocks are slightly more pronounced in the US. Further, crude oil price shocks appear to have a stronger impact than natural gas ones, and volatility spillovers are more sizeable in the US, especially during financial crises, when investor uncertainty is higher.

Another study by Cepni et al. (2022) estimated an ADCC model using data on various green assets and found that green bonds are the most effective safe-haven against physical and transition risks and to manage climate risk exposures in investment portfolios. Caporale et al. (2024) focused on Germany, a leader in green investment within the EU, where sustainable growth is a priority. Their study provides new insights into the properties of green and traditional (brown) stock prices respectively by employing fractional integration techniques to analyze their persistence, which has implications for market efficiency. Using daily data from representative green and brown stock indices, their analysis shows that green stock returns exhibit higher volatility persistence than brown ones.

2.1. Climate policy shocks

One important issue when assessing the impact of climate change on stock markets is how to obtain accurate measures of climate risk. Textual analysis methods are often used for this purpose (Ardia et al., 2023; Bua et al., 2022; Engle et al., 2020). For example, Gavriilidis (2021) developed the Climate Policy Uncertainty (CPU) index by searching for articles in eight major US newspapers that included terms such as “uncertainty” “climate risk” “greenhouse gas emissions” “climate change” “regulation” and “policies”. The CPU has since become a widely used metric in the climate policy literature. Ren et al. (2023) carried out time-varying Granger tests to examine the dynamic bi-directional causality between CPU and both brown (coal, oil, natural gas) and green energy markets (clean energy, green bonds, carbon trading) in the US. Using monthly data, they considered various types of shocks including the sharp decline in crude oil prices in 2014. Their study showed evolving bi-directional causality patterns, suggesting that both energy price volatility and climate policy uncertainty influence traditional and green energy stocks. Also, Bouri et al. (2022) provide evidence that the Climate Policy Uncertainty (CPU) index is a key driver of the relative performance of green versus brown energy stocks, and highlight its prediction properties.

Husain et al. (2022) followed instead a cross-quantilogram approach to show that CPU affects green markets, especially during periods of high uncertainty. Pham (2019) analyzed the performance of the green bond market under uncertainty, and detected more sizeable spillovers during periods characterized by higher Economic Policy Uncertainty (EPU), stock market uncertainty and crude oil price volatility. Ehrenbergerová et al. (2023) examined how climate policies, COP meetings, and the COVID-19 pandemic affected green and brown firms' securities, using a difference-in-differences regression. Their findings indicate that these policies significantly influence securities, with policy makers generally providing greater support to green firms after major climate events as well as during pandemics. Diaz-Rainey et al. (2021) found that both Trump's election in 2020 and the Paris Agreement had negative effects on the oil and gas sectors. Finally, Bogmans et al. (2024) showed that, during the early stages of the energy transition, climate policy uncertainty negatively affects investments in the oil and gas sectors. Their analysis uses the transcripts of earnings calls from publicly-listed firms as a proxy for measuring climate policy uncertainty. Li et al. (2023) examined the effects of three climate risk factors, including the CPU, on the long-run volatility and correlation between green and brown stocks in the US, and found that climate risks have a significant impact only on the long-run volatility of brown stocks, while they tend to reduce the correlation between green and brown stocks. Specifically, their stydy employs four GARCH-type models, including GARCH, GJR-GARCH, EGARCH, or APARCH; however, those frameworks cannot capture cross-market linkages. By contrast, as explained in Section 4, in this paper we use a VAR-GARCH model (1, 1), which enables us to shed light on market interactions.

While textual analysis provides valuable insights, it has limitations, such as its reliance on a selected sample of news and reports. Moreover, indices as such CPU are global measures and therefore studies using it do not capture country-specific factors. For these reasons, the current study uses instead the Climate Policy Index from the Climate Change Performance Index (CCPI), calculated by GermanWatch, which provides a country-specific assessment of climate policies. Therefore, our analysis is based on country-specific indicators of climate change risk rather than the global metrics used in most existing studies. Thus, an important contribution to the literature of the present study is represented by our analysis of climate policy-related risks using a country-specific measure, rather than relying solely on a US-based index.

2.2. Energy shocks

Concerning the effects of energy price shocks, Wu et al. (2024) reported that spillovers between green finance and traditional energy markets peaked during periods of turmoil such as the 2016 oil price crash, the 2020 pandemic, and the Russia-Ukraine war, when traditional energy markets, particularly oil, tend to transmit more risk owing to supply uncertainty and regulatory pressures. Bouoiyour et al. (2023) employed wavelet decomposition to investigate directional causality between oil and renewable energy indices, and found strong but not long-lived linkages corresponding to key events such as the Paris Agreement and the COVID-19 pandemic. Dutta et al. (2020) and Kilian and Zhou (2022) analyzed oil price shocks and their effects on green investments, highlighting the critical role of oil market volatility as one of their drivers. Finally, Ferrer et al. (2018) examined interconnectedness between clean energy stock prices and crude oil, and found bigger spillovers during crisis periods. Hanif et al. (2023) investigated connectedness between oil shocks and green stocks and showed that this relationship becomes stronger in the long term, particularly within the green market and during financial crises, including the oil crisis. Finally, Liu and Hamori (2020) analyzed US and European data and found that spillovers from fossil fuel to renewable energy stocks are slightly more pronounced in the US. Further, crude oil price shocks have a stronger impact than natural gas ones, and volatility spillovers are more sizeable in the US, especially during financial crises, when investor uncertainty is higher. Bulding on such studies, we make a second contribution to the literature by jointly considering oil crises and climate policy shocks at the national level, as illustrated in Table 2.

3. Data sources and variables description

For our analysis we use weekly green and brown stock price indices obtained from Refinitiv, as well as several climate change indicators built by Germanwatch (2022), for five countries (Canada, India, Japan, the UK and the US). The model also includes two control variables, namely: (i) a proxy for global stock markets uncertainty, specifically changes in the Chicago Board Options Exchange volatility index, known as VIX, which is a measure of implied volatility (Zhen et al., 2025) and is calculated using option prices on the S&P 500 index; this allows us to control for any effects of stock market global uncertainty on the linkages between green and brown indices; short-term interest rates (the 3-month policy rates) to control for country-specific macroeconomic developments (Priya and Sharma, 2025). The source for both series is again Refinitiv.[1]

As already mentioned, the selection of these countries is mainly driven by the availability of data on the green index and the need to ensure a comparable sample size for all of them. More precisely, for Japan, the US and the UK the series used is the FTSE Environmental Opportunity Index starting on March 13, 2009, whilst for Canada and India it is the S&P TSX Renewable Energy Index and the S&P BSE GREENEX respectively, the corresponding start dates being April 2, 2010 and August 24, 2012. In all cases the end date is December 29, 2023. The estimation period is set accordingly.

For each index, the corresponding rate of return is calculated as follows: $\text{Returns}_t = [(\text{Prices}_t - \text{Prices}_{t-1}) \ / \ \text{Prices}_{t-1}] \times 100.$

Table 1 provides definitions of each of the green and brown stock indices considered. We selected the Energy Price Return Index from Refinitiv, based on the Refinitiv Business Classification, as our measure for brown indices. This classification system categorizes global companies by industry. In detail, for Canada, the index includes 64 companies; for India, 30 companies; for Japan, 20 companies; for the UK, 11 companies; for the US, 117 companies. For the green stock indices, we employ instead the FTSE Environmental Opportunities Index Series, which evaluates the performance of global companies significantly involved in environmental activities, such as renewable and alternative energy, energy management, water infrastructure, and waste and pollution control. To qualify for inclusion, companies must obtain at least 20 % of their revenues from environmental products and services. In our sample, this index is not available for Canada and India, for which we use instead the S&P TSX Renewable Energy Index, which tracks Canadian companies listed on the TSX with core activities in green technologies and sustainable infrastructure solutions,[2] and for India the S&P BSE GREENEX, which measures the performance of the top 25 "green" companies based on GHG emissions, market capitalization, and liquidity.

To capture the role of climate policies, we use the Climate Change Performance Index (CCPI) constructed by Germanwatch (2022). This is an independent measure that evaluates countries' efforts in climate protection, promoting transparency in global climate policies and enabling cross-country comparisons (Albanese et al., 2025). The climate policy component of the CCPI is derived from an annual questionnaire that assesses both national and international policies. Experts from NGOs, universities and think tanks rate governments' performance in key areas on a scale from 1 (weak) to 5 (strong). The questionnaire focuses on assessing national and international policies related to greenhouse gas (GHG) emissions reduction, energy transition, and climate strategies. It specifically examines the effectiveness of national strategies for GHG emission reductions, the promotion of renewable energy, and energy sector management, with particular emphasis on the gradual phase-out of fossil fuels and incentives for sustainable energy sources. The section on energy supply and renewable energy evaluates the implementation of policies aimed at phasing out coal, gas, and oil, as well as the financial support for renewable energy sources such as sustainable biofuels. Also, the questionnaire discusses the significance of biomass in the national energy mix, addressing potential environmental justice issues and impacts on ecosystems associated with its use. In the energy use category, the questionnaire investigates decarbonization policies for the transport and industrial sectors, focusing on low-emission technologies and regulations aimed at improving energy efficiency. Progress towards more energy-efficient buildings is also assessed. The questions regarding future targets concentrate on national emission reduction goals for 2030, compatibility with international climate agreements, and ambition relative to the country's capabilities, while evaluating the integration of renewable energy. The section on non-energy sectors explores policies related to forestry, peatlands, and agriculture, assessing the level of support for sustainable practices and efforts to reduce deforestation. It also addresses the phase-out of fossil fuels, focusing on national efforts to ban extraction and halt subsidies for fossil fuel production. Finally, the international performance of a country is analyzed in relation to its participation in climate negotiations and forums, such as the UNFCCC, considering both progressive and regressive actions. The questionnaire also examines participation in global climate initiatives and the country's position in international climate negotiations (Germanwatch, 2022). In this paper we use scores associated to both the national and international climate policy components.

3.1. Dummy variables

To measure the impact of climate policies on stock returns, we define two sets of dummy variables, each including two dummies corresponding to national and international climate policies respectively. In the first (second) set these variables take a value of 1 when the climate policy score, national or international, exhibits a positive (negative) change from one year to the next and 0 otherwise. In addition, to capture global energy prices shocks, following the works of Kilian and Zhou (2022), Baumeister and Kilian (2016), and

[1] Given the weekly frequency of our data, it would not be feasible to include other macroeconomic variables, such as GDP growth or inflation, which are only available at a lower frequency.

[2] The constituents are screened by Sustainalytics, one of the world's leading providers of environmental, social, and governance research and analysis.

Table 1
Brown and green stock indices definitions.

Country	Brown index	Definition	Green Index	Definition
Canada	Canada Energy Price Stocks Index	Composed of 64 companies across sectors like uranium mining, oil services, natural gas exploration, oil refining, and unconventional oil production.	S&P/TSX Renewable Energy and Clean Technology Index	Measures companies focused on green technologies and sustainable infrastructure solutions, screened by Sustainalytics.
India	India Energy Price Stocks Index	Includes 30 companies in sectors such as oil drilling, petroleum refining, wind systems, coal mining, and LNG transportation.	S&P BSE GREENEX	Tracks the performance of the top 25 ″green" companies based on GHG emissions, market capitalization, and liquidity.
Japan	Japan Energy Price Stocks Index	Comprises 20 companies, including coal wholesale, petroleum refining, and oil-related services.	FTSE Environmental Opportunities	It measures global companies significantly involved in renewable energy, pollution control, energy efficiency and water infrastructure.
United Kingdom	U.K. Energy Price Stocks Index	Consists of 11 companies in oil exploration, integrated oil and gas services, and stationary fuel cells.	FTSE Environmental Opportunities	
United States	U.S. Energy Price Stocks Index	Tracks 117 companies in sectors such as uranium, coal, oil exploration, and renewable energy services.	FTSE Environmental Opportunities	

Notes: The source for all indices is Refinitiv.

Gazzani et al. (2024), we introduce a fifth dummy variable which takes a value of 1 when an oil price shock occurs and 0 otherwise.

To analyze the combined effects of climate policy shocks and energy shocks, we also include interaction dummies between them. These allow us to assess whether the simultaneous occurrence of the two types of shocks considered enhances or mitigates their impact on the dynamic linkages between green and brown assets. Table 2 specifies the periods when climate policy shocks and oil price ones occurred simultaneously, with the corresponding interaction dummy taking a value of 1. This modelling approach provides deeper

Table 2
Climate policy and oil price shocks - interaction dummies.

Country	National pos. + Oil	National neg. + Oil	International pos. + Oil	International neg. + Oil
Canada	May 30, 2014 to December 19, 2014; June 17, 2016; March 23, 2018; September 24, 2021 to October 22, 2021	May 21, 2010; July 29, 2011 to September 09, 2011; May 25, 2012; May 17, 2019 to May 24, 2019; August 02, 2019; February 14, 2020; May 29, 2020; February 25, 2022 to March 25, 2022	July 29, 2011 to August 05, 2011; September 09, 2011; June 17, 2016; March 23, 2018; February 25, 2022 to March 25, 2022	May 25, 2012; May 30, 2014 to December 19, 2014; May 17, 2019 to May 24, 2019; August 02, 2019; February 14, 2020; May 29, 2020; September 24, 2021 to October 22, 2021
India	June 17, 2016; May 17, 2019 to May 24, 2019; August 02, 2019; February 14, 2020; May 29, 2020	May 30, 2014 to December 19, 2014; March 23, 2018; September 24, 2021 to October 22, 2021; February 25, 2022 to March 25, 2022	June 17, 2016; March 23, 2018; February 14, 2020; May 29, 2020; February 25, 2022 to March 25, 2022	May 30, 2014 to December 19, 2014; May 17, 2019 to May 24, 2019; August 02, 2019; September 24, 2021 to October 22, 2021
Japan	April 17, 2009; May 28, 2010; August 05, 2011; September 16, 2011; June 01, 2012; March 30, 2018; May 24, 2019 to May 31, 2019; October 01, 2021 to October 29, 2021; March 04, 2022 to April 01, 2022	June 06, 2014 to December 26, 2014; June 24, 2016; 2102/ 2020; June 05, 2020	May 28, 2010; May 24, 2019 to May 31, 2019; August 09, 2019; October 01, 2021 to October 29, 2021; March 04, 2022 to April 01, 2022	April 17, 2009; August 05, 2011 to August 12, 2011; September 16, 2011; June 01, 2012; June 06, 2014 to December 26, 2014; June 24, 2016/; March 30, 2018; February 21, 2020; June 05, 2020
United Kingdom	May 21, 2010; May 25, 2012; May 30, 2014 to December 19, 2014; June 17, 2016; March 23, 2018; May 17, 2019 to May 24, 2019; February 14, 2020; May 29, 2020; May 19, 2020; 25/ 02/20222 to March 25, 2022	July 29, 2011 to August 05, 2011; September 09, 2011; September 24, 2021 to October 22, 2021	May 21, 2010; May 25, 2012; May 30, 2014 to December 19, 2014; June 17, 2016; March 23, 2018; May 17, 2019 to May 24, 2019; August 02, 2019; February 25, 2022 to March 25, 2022	July 29, 2011 to August 05, 2011; September 09, 2011; September 24, 2021 to October 22, 2021
United States	September 10, 2010; November 18, 2011 to November 25, 2011; December 30, 2011; September 14, 2012; October 07, 2016; January 14, 2022 to February 11, 2022; June 17, 2022 to July 15, 2022	September 19, 2014 to April 10, 2015; July 13, 2018; June 05, 2020; September 18, 2020	July 31, 2009; September 10, 2010; September 14, 2012; September 19, 2014 to April 10, 2015; October 07, 2016	November 18, 2011 to November 25, 2011; December 30, 2011

Note: The reported dates correspond to periods when climate policy shocks and oil price shocks were observed. Climate policy shocks are identified using the CCPI index, while oil price shocks are based on Kilian and Zhou (2022), Baumeister and Kilian (2016), and Gazzani et al. (2024). These shocks are represented by a value of 1 when they occur and 0 otherwise.

insights into how the interplay between policy-driven environmental changes, at country level, and exogenous energy market disruptions influence financial markets and asset diversification.

We also include a set of control variables. Global stock markets uncertainty is proxied by the changes in the Chicago Board Options Exchange volatility index, known as VIX, which is a measure of implied volatility and is calculated using option prices on the S&P 500 index (this series is also obtained from Refinitiv). In addition, we control for monetary policy country-specific effects by including short-term interest rates (the 3-month policy rates).

3.2. Descriptive statistics

Table 3 reports some descriptive statistics for all variables used in our empirical analysis. Green stock returns are, on average, twice as high as brown stock returns in Japan, the UK, and the US, whilst in Canada and India brown stocks have been more profitable. This suggests that investors in green assets tend to prefer more liquid markets, particularly in major financial centers, where green investment opportunities are more developed. On the contrary, in smaller financial markets such as Canada and India, green assets appear less attractive to financial investors, leading to a stronger demand for conventional brown stocks.

Concerning the second moment, it can be seen that green stock returns exhibit lower volatility compared to brown ones in all the countries in our sample. This evidence, combined with the significantly higher returns observed in Japan, the UK, and the US, highlights the important role of green stocks in portfolio diversification and profit-making strategies, particularly in well-established financial markets.

4. Empirical model

In this section, we describe the multivariate setup we use to estimate simultaneously the first and second moments of green and

Table 3
Descriptive statistics.

Country		Green	Brown	Interest Rate
Canada	Mean	0.05	0.09	1.13
	S.D.	2.46	3.26	1.19
	Min.	−15.77	−26.16	0.03
	Max.	11.97	13.56	5.16
	Obs.	717	717	717
India	Mean	0.20	0.30	6.40
	S.D.	2.01	3.28	1.86
	Min.	−11.09	−17.35	3
	Max.	14.40	14.84	11.75
	Obs.	592	592	592
Japan	Mean	0.24	0.12	−0.04
	S.D.	2.95	3.46	0.14
	Min.	−13.73	−20.21	−0.47
	Max.	13.90	15.31	0.28
	Obs.	772	772	772
United Kingdom	Mean	0.19	0.11	0.80
	S.D.	2.20	3.58	1.18
	Min.	−14.01	−29.77	−0.09
	Max.	10.86	18.59	5.58
	Obs.	757	757	757
United States	Mean	0.29	0.15	0.91
	S.D.	2.76	3.76	1.45
	Min.	−17.68	−24.31	−0.05
	Max.	15.37	15.48	5.51
	Obs.	772	772	772

Global Control Variable		**VIX**
	Mean	18.90
	S.D.	7.31
	Min.	9.14
	Max.	66.04
	Obs.	772

Notes: for Japan, the US and the UK the green index used is the FTSE Environmental Opportunity Index starting on March 13, 2009, whilst for Canada and India it is the S&P TSX Renewable Energy Index and the S&P BSE GREENEX respectively, the corresponding start dates being April 2, 2010 and August 24, 2012. In all cases the end date is December 29, 2023. The sample period is set accordingly for all series.

brown stock returns as well as the corresponding spillovers within each country. We model the joint process governing green and brown stock returns using a bi-variate BEKK-GARCH(1,1) framework based on the representation proposed by.Engle and Kroner (1995). The choice of this model is motivated by the properties of its functional form. In particular, it is a multivariate framework which allows to examine mean and volatility transmission across markets, while ensuring the positive definiteness of the associated variance–covariance matrix. In its most general specification, the model takes the following form:

$$x_t = \alpha + \beta x_{t-1} + \phi\, z_{t-1} + u_t \tag{1}$$

where $x_t =$ (Green Stock Returns$_t$, Brown Stock Returns$_t$). The parameter vectors of the mean equation (1) are the constant $\alpha = (\alpha_{11}, \alpha_{22})$ and the autoregressive term $\beta = (\beta_{11}, \beta_{12} + \beta^*_{12} \,|\beta_{21} + \beta^*_{21}, \beta_{22})$, x_{t-1} is the corresponding vector of lagged returns,[3] and $z_{t-1} = = (IR_{\ t-1}, VIX_{\ t-1})$ is a vector containing the 3-month policy rate, to capture country-specific macroeconomic effects, as well as the *VIX* to control for global financial uncertainty.

To account for the potential effect of climate policies and/or energy shocks, we include, in turn, the dummy variables, discussed in section 3.1, and denoted by *. The residual vector u_t is bivariate and normally distributed $u_t \mid I_{t-1} \sim (0, H_t)$ with its conditional variance-covariance matrix given by:

$$H_t = \begin{bmatrix} \mathrm{h}_{11,\mathrm{t}} & \mathrm{h}_{12,\mathrm{t}} \\ \mathrm{h}_{21,\mathrm{t}} & \mathrm{h}_{22,\mathrm{t}} \end{bmatrix} \tag{2}$$

The parameter matrices for the variance equation (2) are defined as C, which is restricted to be upper triangular, and two unrestricted matrices, A_{11} and G_{11}, whose elements are the a and g coefficients, respectively. Therefore, the second moment will take the following form:

$$H_t = C'C + A'_{11} \begin{bmatrix} u^2_{1,t-1} & u_{1,t-1}u_{2,t-1} \\ u_{2,t-1}u_{1,t-1} & u^2_{2,t-1} \end{bmatrix} A_{11} + G'_{11} H_{t-1} G_{11}, \tag{3}$$

where

$$A'_{11} = \begin{bmatrix} a_{11} & a_{12} + a_{12}{}^* \\ a_{21} + a_{21}{}^* & a_{22} \end{bmatrix}'; \; G'_{11} = \begin{bmatrix} g_{11} & g_{12} + g_{12}{}^* \\ g_{21} + g_{21}{}^* & g_{22} \end{bmatrix}'.$$

Equation (3) models the dynamic process of H_t as a linear function of its own past values H_{t-1} and past values of the innovations ($u_{1,t-1}$, $u_{2,t-1}$), allowing for own-market and cross-market influences in the conditional variances. The off-diagonal parameters in the latter two matrices capture the volatility spillovers (causality-in-variance) among the two indices under investigation. Given a sample of T observations, a vector of unknown parameters[4] θ, and a 2×1 vector of variables x_t, the conditional density function for the model (1)–(2) is:

$$f(x_t|I_{t-1};\theta) = (2\pi)^{-1}|H_t|^{-1/2}\, exp\left(-\left[u_t{}'(H_t{}^{-1})u_t\right]/2\right) \tag{4}$$

The log-likelihood function is:

$$Log - Lik = \sum_{t=1}^{T} log\, f(x_t|I_{t-1};\theta) \tag{5}$$

In recent years, other types of models have also been used to investigate cross-country co-movements. Among those, copula models have become increasingly popular. A comprehensive discussion of the pros and cons of using them rather than DCC and GARCH models can be found in Al Rahahleh and Bhatti (2017), Nguyen et al. (2017) and Bhatti and Do (2019). Given the nature of our research question and the relatively small number of variables considered, we have chosen to estimate reduced-form VAR models including a GARCH component because of their suitability to analyze both co-movement and spillover effects within the same econometric framework. Furthermore, the adopted BEKK representation guarantees by construction the positive-definiteness of the variance-covariance matrix.

4.1. Hypotheses tested

We examine mean and volatility spillovers, as well as possible shifts in the cross parameters, by incorporating dummy variables into the model specification (see Section 3). Specifically, we test the following null hypotheses:

Test for No Structural Shifts in the Conditional Mean and Variance.

H01. No shift in the conditional mean: $a^*_{11} = a^*_{22} = 0$

[3] Note that the dummy variables are used to model shifts in the cross-parameters only, not in the autoregressive terms.

[4] P-values are calculated using the quasi-maximum likelihood method of Bollerslev and Wooldridge (1992), which is robust to the distribution of the underlying residuals.

Table 4
Estimated GARCH(1,1)-BEKK models for Canada.

	Benchmark	Energy shock	Climate policy shocks				Oil and Climate Policy Shocks Interaction			
			Nat. Pos.	Nat. Neg	Int. Pos.	Int Neg.	Oil + Nat. Pos.	Oil + Nat. Neg	Oil + Int. Pos.	Oil + Int. Neg
Conditional mean equation										
α_{11}	−0.03	−0.01	−0.16	−0.02	−0.02	−0.02	−0.00	0.12	0.11	−0.02
	(0.878)	(0.980)	(0.666)	(0.929)	(0.929)	(0.923)	(0.990)	(0.556)	(0.579)	(0.898)
α^*_{11}	–	0.01	0.14	−0.14	−0.13	0.15	−0.11	**0.97**	0.25	0.06
		(0.959)	(0.315)	(0.372)	(0.372)	(0.201)	(0.574)	**(0.003)**	(0.541)	(0.755)
β_{11}	0.01	0.00	0.02	0.02	0.02	0.02	0.01	0.01	0.03	0.02
	(0.532)	(0.868)	(0.742)	(0.623)	(0.623)	(0.597)	(0.848)	(0.633)	(0.408)	(0.616)
β_{12}	0.02	0.01	−0.00	0.04	0.04	−0.00	0.01	0.01	0.00	0.01
	(0.532)	(0.809)	(0.928)	(0.259)	(0.259)	(0.917)	(0.625)	(0.713)	(0.948)	(0.608)
β^*_{12}	–	0.03	0.04	−0.03	−0.04	0.03	0.01	0.16	0.18	−0.04
		(0.686)	(0.395)	(0.376)	(0.376)	(0.365)	(0.853)	(0.253)	(0.263)	(0.566)
IR	−0.12	−0.12	**−0.18**	**−0.17**	**−0.18**	**−0.17**	−0.13	**−0.19**	**−0.19**	**−0.13**
	(0.108)	(0.098)	**(0.023)**	**(0.023)**	**(0.022)**	**(0.002)**	(0.597)	**(0.008)**	**(0.011)**	**(0.028)**
VIX	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.01	0.02
	(0.146)	(0.404)	(0.175)	(0.121)	(0.121)	(0.245)	(0.146)	(0.351)	(0.245)	(0.136)
α_{22}	−0.52	−0.43	**−1.10**	**−0.75**	**−0.75**	−0.52	−0.48	−0.56	**−0.62**	−0.50
	(0.093)	(0.414)	**(0.007)**	**(0.012)**	**(0.012)**	(0.067)	(0.125)	(0.061)	**(0.037)**	(0.096)
α^*_{22}	–	−0.09	**0.35**	−0.35	0.03	0.11	0.10	−0.26	0.75	0.00
		(0.829)	**(0.045)**	(0.099)	(0.591)	(0.476)	(0.762)	(0.637)	(0.263)	(0.991)
β_{22}	0.04	0.05	0.04	0.05	0.05	0.03	0.05	0.05	0.05	0.04
	(0.258)	(0.279)	(0.208)	(0.175)	(0.175)	(0.236)	(0.149)	(0.106)	(0.156)	(0.140)
β_{21}	0.06	0.07	0.08	0.03	0.03	0.05	0.07	0.03	0.01	0.07
	(0.265)	(0.241)	(0.348)	(0.590)	(0.590)	(0.555)	(0.147)	(0.546)	(0.821)	(0.145)
β^*_{21}	–	**−0.24**	−0.05	0.05	0.04	0.04	−0.28	0.02	0.22	**−0.44**
		(0.045)	(0.627)	(0.626)	(0.626)	(0.648)	(0.142)	(0.905)	(0.295)	**(0.019)**
IR	−0.02	−0.01	−0.05	−0.04	−0.05	−0.01	−0.02	−0.03	−0.02	−0.02
	(0.718)	(0.889)	(0.565)	(0.572)	(0.572)	(0.821)	(0.616)	(0.662)	(0.832)	(0.723)
VIX	0.04	0.03	**−0.06**	**0.06**	**0.06**	0.03	0.03	**−0.05**	**−0.04**	**−0.04**
	(0.065)	(0.335)	**(0.002)**	**(0.001)**	**(0.001)**	(0.084)	(0.091)	**(0.025)**	**(0.011)**	**(0.045)**
Conditional variance equation										
c_{11}	**−0.18**	0.07	**0.76**	**0.32**	**0.39**	−0.00	0.16	**0.37**	0.32	**0.19**
	(0.002)	(0.961)	**(0.008)**	**(0.040)**	**(0.040)**	(0.998)	(0.144)	**(0.004)**	(0.079)	**(0.019)**
c^*_{11}	-	−0.35	−0.37	0.37	**0.37**	0.14	−0.39	**−0.37**	−0.33	**−0.19**
		(0.765)	(0.103)	(0.087)	**(0.087)**	(0.304)	(0.222)	**(0.016)**	(0.103)	**(0.045)**
g_{11}	**−0.92**	**0.92**	**0.90**	**0.90**	**0.94**	**−0.42**	**0.91**	**0.94**	**0.96**	**0.90**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
g_{12}	**−0.09**	−0.10	**0.32**	0.17	**0.16**	**0.94**	**−0.10**	**0.23**	**0.29**	**−0.09**
	(0.000)	(0.113)	**(0.000)**	(0.082)	**(0.082)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
g^*_{12}	-	0.10	−0.16	0.16	0.16	**−0.12**	**0.26**	**−0.61**	**−0.71**	−0.08
		(0.711)	(0.120)	(0.124)	(0.124)	**(0.000)**	**(0.000)**	**(0.018)**	**(0.000)**	(0.107)
a_{11}	**0.3**	**0.38**	**0.43**	**0.49**	**0.49**	**0.18**	**0.39**	**0.38**	**0.39**	**0.41**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
a_{12}	**−0.10**	**0.35**	−0.10	**0.02**	0.03	**0.48**	**0.36**	−0.15	**−0.19**	**0.29**
	(0.000)	**(0.051)**	(0.493)	**(0.006)**	(0.854)	**(0.000)**	**(0.000)**	(0.138)	**(0.055)**	**(0.000)**
a^*_{12}	-	−0.02	0.13	0.16	−0.13	0.07	**−0.41**	**0.91**	**0.63**	**0.60**
		(0.974)	(0.434)	(0.124)	(0.448)	(0.191)	**(0.036)**	**(0.009)**	**(0.006)**	**(0.013)**
c_{22}	**0.59**	−0.49	0.30	**0.86**	**0.86**	**0.85**	**0.49**	**0.66**	**0.68**	**0.56**
	(0.000)	(0.283)	(0.841)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.001)**	**(0.001)**	**(0.000)**	**(0.005)**
c^*_{22}	-	0.04	0.57	−0.56	**−0.56**	−0.27	**−0.48**	**−0.70**	**−0.72**	0.07
		(0.962)	(0.695)	(0.690)	**(0.690)**	(0.413)	**(0.023)**	**(0.013)**	**(0.002)**	(0.833)
c_{21}	**0.37**	−0.42	0.7	0.07	0.07	**0.29**	**0.40**	−0.05	−0.09	**0.40**
	(0.000)	(0.167)	(0.728)	(0.735)	(0.735)	**(0.000)**	**(0.000)**	(0.734)	(0.607)	**(0.000)**
g_{22}	**0.92**	**0.93**	**0.82**	**0.82**	**0.82**	**0.31**	**0.93**	**0.83**	**0.79**	**0.94**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
g_{21}	**−0.02**	−0.01	**−0.08**	−0.07	−0.07	**0.76**	−0.01	**−0.06**	**−0.08**	−0.03
	(0.035)	(0.583)	**(0.027)**	(0.148)	(0.148)	**(0.000)**	(0.167)	**(0.000)**	**(0.000)**	(0.238)
g^*_{21}	-	−0.02	0.01	−0.01	−0.01	**0.11**	0.04	−0.06	−0.00	0.02
		(0.257)	(0.681)	(0.689)	(0.689)	**(0.000)**	(0.111)	(0.480)	(0.954)	(0.292)
a_{22}	**0.23**	**0.22**	**0.28**	**0.29**	**0.29**	**0.11**	**0.21**	**0.33**	**0.35**	**0.20**
	(0.000)	**(0.031)**	**(0.000)**	**(0.006)**	**(0.006)**	**(0.001)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
a_{21}	0.01	0.01	−0.04	**−0.00**	−0.00	**0.11**	−0.00	0.03	0.04	0.02
	(0.064)	(0.882)	(0.662)	**(0.908)**	(0.908)	**(0.000)**	(0.977)	(0.507)	(0.430)	(0.573)

(*continued on next page*)

Table 4 (*continued*)

	Benchmark	Energy shock	Climate policy shocks				Oil and Climate Policy Shocks Interaction			
			Nat. Pos.	Nat. Neg	Int. Pos.	Int Neg.	Oil + Nat. Pos.	Oil + Nat. Neg	Oil + Int. Pos.	Oil + Int. Neg
a^*_{21}	-	0.02 (0.882)	0.03 (0.722)	**−0.01** **(0.689)**	−0.03 (0.716)	−0.00 (0.983)	−0.08 (0.278)	**0.37** **(0.008)**	0.20 (0.181)	**0.11** **(0.057)**
LogLik	3218.47	3212.53	3227.05	3227.05	3227.05	3216.61	3209.99	3223.87	3226.43	3212.34
$LB_{Green(7)}$	8.41 (0.297)	8.89 (0.260)	8.78 (0.268)	8.78 (0.268)	7.68 (0.361)	7.58 (0.371)	8.15 (0.319)	7.56 (0.372)	7.56 (0.372)	8.45 (0.294)
$LB_{Brown(7)}$	8.40 (0.297)	8.84 (0.355)	7.51 (0.377)	7.51 (0.377)	8.67 (0.276)	8.86 (0.262)	8.04 (0.328)	8.15 (0.318)	8.34 (0.303)	8.71 (0.274)

Notes: Statistically significant parameters at 5 % are shown in bold. Parameters β_{12} and a_{12} measure the spillover effect of brown on green stock returns and brown on green stock returns volatility, respectively. Whereas, β_{21} and a_{21} capture the spillover effect of green on brown stock returns and brown on green stock returns volatility, respectively. The asterisk (*) denotes dummy variables corresponding to each climate policy shock (national and international; positive and negative), energy (oil) shocks, and their respective interactions. P-values (in brackets) are computed using the quasi-maximum likelihood method of Bollerslev and Wooldridge (1992), which is robust to the distribution of the underlying residuals. The first column presents the benchmark model without the inclusion of dummy variables. $LB_{Green(7)}$ and $LB_{Brown(7)}$ are the Ljung-Box test (1978) of significance of no autocorrelations of seven lags in the standardized residuals for green and brown returns, respectively. The covariance stationarity condition is satisfied by all the estimated models, all the eigenvalues of $A11 \otimes A11 + G11 \otimes G11$ being less than one in modulus.

H02. No shift in the conditional variance: $c^*_{11} = c^*_{22} = 0$

Test for No Mean Spillovers Between Green and Brown Stock Returns.

H03. No mean spillovers between green and brown stock returns: $\beta_{12} = \beta_{21} = 0$

H04. No mean spillovers between green and brown stock returns as a result of exogenous shocks (climate policy and/or oil): $\beta^*_{12} = \beta^*_{21} = 0$

Test for No Volatility Spillovers Between Green and Brown Stock Returns.

H05. No volatility spillovers between stock returns: $a_{12} = a_{21} = 0$

H06. No volatility spillovers between stock returns as a result of exogenous shocks (climate policy and/or oil): $a^*_{12} = a^*_{21} = 0$

Testing empirically these hypotheses allows us to assess the extent to which market linkages and risk transmission between green and brown assets are influenced by country-specific climate change shocks and global energy shocks.

5. Empirical results

We determine the optimal lag length for the mean equation using the Schwarz Information Criterion, which suggests that only one lag should be included in all cases. To assess the adequacy of the models, we conduct Ljung–Box portmanteau tests on the standardized residuals. The pairwise estimates of the dependence between green and brown indices in both the conditional mean and variance exhibit variations in both size and direction. The estimated GARCH(1,1)-BEKK models with the associated robust p-values and likelihood function values are presented in Tables 4–8. Given the extensive set of results presented, we focus only on the most relevant coefficients in our discussion.

The model specification allows us to explore the shift in the conditional mean value and conditional variance, and causality in mean and in variance between green and brown stock returns. The main findings emerging from Tables 4–8 can be summarized as follows.

First, we reject the null hypothesis (H_{01}) of no shift in the conditional mean in some cases. Specifically, we find a shift in green stock returns in Japan corresponding to positive changes in national climate policy scores ($a^*_{11} = -0.44$), in the UK during periods associated to energy shocks ($a^*_{11} = -0.88$) and in Canada when negative changes in the national climate policy score interact with oil shocks ($a^*_{11} = 0.97$). Furthermore, there is a positive shift in the conditional mean of brown stock returns corresponding to negative changes in the national climate policy score in the UK ($a^*_{22} = 0.44$), an a negative shift in India and the US when positive changes in the international climate policy score interact with energy shocks ($a^*_{22} = -3.15$ and $a^*_{22} = -0.60$, respectively).

The shift in the conditional variance (H_{02}) instead is more pronounced and occurs in both green and brown stock returns in several cases. Specifically, we find it in Canada in correspondence with positive changes in the international climate policy score ($c^*_{11} = 0.59$ and $c^*_{22} = 1.31$, respectively), in Japan when there is a significant interaction between negative changes in the international climate policy score and energy shocks ($c^*_{11} = 1.12$), and in India for brown stock returns when positive changes in the national climate policy score interact with energy shocks ($c^*_{11} =$ -0.22).

Table 5
Estimated GARCH(1,1)-BEKK models for India.

	Benchmark	Energy shock	Climate policy shocks				Oil and Climate Policy Shocks Interaction			
			Nat. Pos.	Nat. Neg	Int. Pos.	Int Neg.	Oil + Nat. Pos.	Oil + Nat. Neg	Oil + Int. Pos.	Oil + Int. Neg
Conditional mean equation										
a_{11}	−0.06	−0.30	−0.32	−0.34	−0.29	−0.62	**0.38**	−0.02	**0.19**	0.07
	(0.895)	(0.549)	(0.522)	(0.511)	(0.383)	(0.305)	**(0.000)**	(0.954)	**(0.000)**	(0.875)
a^*_{11}	–	0.03	−0.01	0.01	−0.30	**0.34**	**−0.59**	0.05	**−1.53**	0.38
		(0.909)	(0.926)	(0.926)	(0.083)	**(0.042)**	**(0.000)**	(0.826)	**(0.000)**	(0.201)
β_{11}	**0.13**	**0.14**	**0.12**	**0.12**	**0.15**	**0.13**	**0.12**	**0.12**	**0.12**	**0.10**
	(0.005)	**(0.06)**	**(0.002)**	**(0.002)**	**(0.000)**	**(0.004)**	**(0.000)**	**(0.006)**	**(0.000)**	**(0.002)**
β_{12}	**−0.07**	**−0.07**	−0.05	−0.07	−0.09	−0.10	−0.05	−0.07	**−0.05**	−0.05
	(0.058)	**(0.029)**	(0.206)	(0.171)	(0.252)	(0.097)	(0.250)	(0.060)	**(0.002)**	(0.175)
β^*_{12}	–	0.07	−0.01	0.01	0.05	0.02	0.03	0.14	**0.08**	0.06
		(0.345)	(0.775)	(0.779)	(0.252)	(0.679)	(0.601)	(0.156)	**(0.002)**	(0.347)
IR	0.01	0.02	0.02	0.02	0.01	0.02	**−0.06**	0.09	**−0.03**	0.02
	(0.839)	(0.740)	(0.688)	(0.688)	(0.642)	(0.679)	**(0.000)**	(0.839)	**(0.000)**	(0.763)
VIX	0.01	0.02	0.02	0.02	**0.03**	0.030	**0.01**	0.01	**0.01**	0.00
	(0.401)	(0.146)	(0.178)	(0.178)	**(0.048)**	(0.118)	**(0.000)**	(0.521)	**(0.000)**	(0.788)
a_{22}	0.55	0.04	−0.08	0.10	0.13	−0.22	**0.30**	0.03	−0.06	0.31
	(0.464)	(0.939)	(0.935)	(0.920)	(0.790)	(0.807)	**(0.021)**	(0.968)	(0.511)	(0.615)
a^*_{22}	–	−0.43	0.18	−0.18	−0.25	0.27	**−1.21**	−0.51	**−3.15**	0.02
		(0.297)	(0.369)	(0.402)	(0.297)	(0.210)	**(0.000)**	(0.122)	**(0.000)**	(0.967)
β_{22}	**−0.10**	**−0.11**	−0.09	−0.09	**−0.13**	**−0.13**	**−0.13**	−0.11	**−0.14**	**−0.09**
	(0.049)	**(0.015)**	(0.079)	(0.079)	**(0.028)**	**(0.031)**	**(0.000)**	(0.122)	**(0.000)**	**(0.032)**
β_{21}	0.16	**0.21**	**0.17**	0.14	**0.15**	**0.23**	**0.23**	**0.19**	**0.25**	**0.16**
	(0.063)	**(0.006)**	**(0.047)**	(0.774)	**(0.053)**	**(0.025)**	**(0.000)**	**(0.048)**	**(0.000)**	**(0.009)**
β^*_{21}	–	−0.02	−0.03	0.03	0.14	−0.08	−0.18	0.03	**−0.79**	−0.23
		(0.188)	(0.767)	(0.532)	(0.122)	(0.431)	(0.586)	(0.830)	**(0.000)**	(0.132)
IR	−0.05	−0.01	−0.02	−0.02	−0.01	−0.00	**−0.07**	0.00	**−0.03**	−0.01
	(0.457)	(0.763)	(0.669)	(0.669)	(0.823)	(0.956)	**(0.000)**	(0.989)	**(0.005)**	(0.616)
VIX	0.01	0.03	0.03	0.03	0.02	0.02	**0.03**	0.01	**0.03**	0.10
	(0.698)	(0.178)	(0.532)	(0.532)	(0.995)	(0.397)	**(0.002)**	(0.439)	**(0.000)**	(0.616)
Conditional variance equation										
c_{11}	0.00	0.00	0.00	0.00	−0.000	**0.37**	0.22	0.00	−0.32	−0.00
	(0.999)	(0.999)	(0.999)	(0.999)	(0.995)	**(0.001)**	(0.130)	(0.999)	(0.459)	(0.999)
c^*_{11}	-	**−1.00**	−0.00	−0.00	**0.60**	−0.18	**−0.22**	−0.00	0.32	0.31
		(0.015)	(0.999)	(0.999)	**(0.021)**	(0.587)	**(0.117)**	(0.999)	(0.456)	(0.257)
g_{11}	**0.94**	**0.81**	**0.90**	**0.90**	**0.88**	**0.86**	**0.75**	**1.00**	**0.74**	**0.76**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
g_{12}	**0.11**	**1.36**	0.02	**−0.12**	**1.59**	−0.18	**0.12**	0.21	**0.19**	**−0.35**
	(0.031)	**(0.000)**	(0.592)	**(0.029)**	**(0.000)**	(0.183)	**(0.000)**	(0.315)	**(0.002)**	**(0.000)**
g^*_{12}	-	**0.50**	**0.05**	**0.14**	−0.21	0.01	**0.79**	0.17	**0.18**	**−0.35**
		(0.002)	**(0.003)**	**(0.007)**	(0.171)	(0.863)	**(0.000)**	(0.094)	**(0.002)**	**(0.000)**
a_{11}	0.00	0.13	−0.06	−0.06	**0.13**	−0.12	**0.17**	−0.03	**0.12**	0.12
	(0.999)	(0.189)	(0.598)	(0.598)	**(0.059)**	(0.331)	**(0.000)**	(0.743)	**(0.000)**	(0.298)
a_{12}	**−0.31**	−0.19	**−0.41**	−0.31	**0.07**	**−0.50**	**−0.35**	−0.43	**−0.04**	**0.52**
	(0.007)	(0.062)	**(0.021)**	(0.188)	**(0.559)**	**(0.022)**	**(0.000)**	(0.105)	**(0.000)**	**(0.000)**
a^*_{12}	-	−0.06	−0.09	−0.09	**−0.29**	0.12	**0.14**	−0.02	**−0.02**	**0.66**
		(0.808)	(0.441)	(0.188)	**(0.000)**	(0.427)	**(0.005)**	(0.904)	**(0.000)**	**(0.000)**
c_{22}	**0.83**	**1.28**	**1.21**	**1.51**	**0.98**	**1.78**	**2.27**	**1.22**	**2.13**	**0.88**
	(0.008)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.001)**	**(0.025)**	**(0.000)**	**(0.000)**
c^*_{22}	-	−0.58	0.30	−0.30	0.01	−0.14	**−1.96**	−0.62	**−2.00**	**−0.88**
		(0.242)	(0.592)	(0.186)	(0.972)	(0.503)	**(0.000)**	(0.241)	**(0.000)**	**(0.011)**
c_{21}	**0.71**	**0.82**	**0.80**	**0.80**	**0.68**	**0.87**	0.25	0.56	**0.08**	0.00
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.139)	(0.063)	**(0.000)**	(0.980)
g_{22}	**0.87**	**−0.93**	**0.84**	**0.84**	**−1.00**	**0.78**	**0.53**	**0.75**	**0.53**	**1.02**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
g_{21}	**−0.10**	**0.51**	**−0.11**	**−0.06**	**−0.03**	−0.03	**0.17**	−0.17	**0.18**	**0.20**
	(0.000)	**(0.002)**	**(0.002)**	**(0.052)**	**(0.005)**	(0.469)	**(0.000)**	(0.094)	**(0.000)**	**(0.000)**
g^*_{21}	-	−0.08	**0.05**	**−0.05**	−0.05	−0.12	**0.27**	0.04	**0.19**	**−0.10**
		(0.308)	**(0.003)**	**(0.003)**	(0.110)	(0.331)	**(0.000)**	(0.486)	**(0.000)**	**(0.001)**
a_{22}	**0.32**	**0.35**	**0.44**	**0.44**	**0.24**	**0.53**	**0.37**	**0.42**	**0.49**	−0.05
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.010)**	**(0.000)**	(0.669)
a_{21}	**0.28**	**0.24**	**0.32**	**0.32**	**0.19**	**0.35**	**0.19**	**0.31**	**0.21**	0.12
	(0.000)	**(0.002)**	**(0.000)**	**(0.000)**	**(0.006)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.142)

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Table 5 (*continued*)

	Benchmark	Energy shock	Climate policy shocks				Oil and Climate Policy Shocks Interaction			
			Nat. Pos.	Nat. Neg	Int. Pos.	Int Neg.	Oil + Nat. Pos.	Oil + Nat. Neg	Oil + Int. Pos.	Oil + Int. Neg
α^*_{21}	-	−0.08	0.00	0.00	0.07	0.00	**0.14**	**−0.44**	**0.20**	**−0.45**
		(0.380)	(0.972)	(0.972)	(0.138)	(0.978)	**(0.005)**	**(0.000)**	**(0.000)**	**(0.000)**
LogLik	2634.15	2637.65	2629.70	2629.70	2626.82	2627.17	2631.77	2627.74	2630.85	2634.54
$LB_{Green(7)}$	7.62	6.85	7.93	7.93	9.45	9.62	7.97	7.50	9.95	5.36
	(0.366)	(0.444)	(0.259)	(0.338)	(0.221)	(0.211)	(0.334)	(0.378)	(0.190)	(0.616)
$LB_{Brown(7)}$	6.44	6.53	6.22	6.22	6.26	7.28	6.47	6.26	6.94	7.02
	(0.488)	(0.478)	(0.514)	(0.514)	(0.532)	(0.400)	(0.486)	(0.509)	(0.434)	(0.426)

Notes: Please refer to the notes in Table 4.

Table 6
Estimated GARCH(1,1)-BEKK models for Japan.

	Benchmark	Energy shock	Climate policy shocks				Oil and Climate Policy Shocks Interaction			
			Nat. Pos.	Nat. Neg	Int. Pos.	Int Neg.	Oil + Nat. Pos.	Oil + Nat. Neg	Oil + Int. Pos.	Oil + Int. Neg
Conditional mean equation										
α_{11}	0.01	0.12	0.19	−0.25	0.18	0.12	0.20	−0.16	0.03	−0.11
	(0.945)	(0.627)	(0.442)	(0.362)	(0.667)	(0.637)	(0.461)	(0.585)	(0.890)	(0.679)
α^*_{11}	–	0.25	**−0.44**	**0.44**	−0.27	0.22	−0.33	0.40	**−1.08**	0.23
		(0.450)	**(0.015)**	**(0.018)**	(0.155)	(0.153)	(0.631)	(0.481)	**(0.032)**	(0.577)
β_{11}	0.03	0.01	0.01	0.01	0.05	0.04	0.06	0.02	0.04	0.01
	(0.447)	(0.764)	(0.798)	(0.787)	(0.273)	(0.277)	(0.085)	(0.503)	(0.213)	(0.699)
β_{12}	−0.02	−0.03	−0.05	0.00	−0.00	−0.02	−0.03	−0.01	−0.02	−0.01
	(0.532)	(0.214)	(0.276)	(0.949)	(0.891)	(0.662)	(0.247)	(0.582)	(0.371)	(0.542)
β^*_{12}	–	0.12	0.05	−0.05	−0.02	0.00	0.09	**0.27**	0.22	**0.33**
		(0.298)	(0.309)	(0.314)	(0.716)	(0.872)	(0.628)	**(0.053)**	(0.219)	**(0.004)**
IR	−0.29	−0.08	0.25	0.25	−0.34	**−0.28**	−0.07	−0.53	−0.26	−0.32
	(0.691)	(0.887)	(0.719)	(0.687)	(0.703)	**(0.677)**	(0.916)	(0.464)	(0.708)	(0.643)
VIX	0.01	0.01	**0.02**	0.02	0.01	0.00	0.00	0.02	0.01	0.02
	(0.263)	(0.360)	**(0.056)**	(0.073)	(0.522)	(0.851)	(0.593)	(0.107)	(0.281)	(0.090)
α_{22}	−0.01	0.15	0.04	0.04	0.18	0.13	0.25	−0.02	0.25	0.01
	(0.968)	(0.606)	(0.888)	(0.892)	(0.508)	(0.678)	(0.414)	(0.926)	(0.937)	(0.976)
α^*_{22}	–	−0.00	0.00	−0.00	−0.10	0.06	1.04	**−0.74**	0.93	**−0.92**
		(0.976)	(0.985)	(0.984)	(0.711)	(0.672)	(0.122)	**(0.052)**	(0.221)	**(0.014)**
β_{22}	**−0.09**	**−0.09**	**−0.08**	**−0.08**	**−0.07**	**−0.08**	**−0.10**	**−0.08**	**−0.10**	**−0.08**
	(0.008)	**(0.005)**	**(0.001)**	**(0.009)**	**(0.023)**	**(0.011)**	**(0.000)**	**(0.004)**	**(0.002)**	**(0.010)**
β_{21}	**0.27**	**0.26**	**0.37**	**0.18**	**0.20**	**0.32**	**0.28**	**0.27**	**0.29**	**0.26**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.029)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
β^*_{21}	–	−0.18	**−0.19**	**0.19**	0.09	−0.14	0.11	−0.11	−0.08	−0.08
		(0.216)	**(0.013)**	**(0.007)**	(0.285)	(0.103)	(0.498)	(0.358)	(0.607)	(0.388)
IR	−0.61	−0.39	−0.54	−0.54	−0.81	−0.95	−0.06	0.62	−0.57	−0.35
	(0.435)	(0.589)	(0.485)	(0.434)	(0.279)	(0.225)	(0.429)	(0.457)	(0.500)	(0.676)
VIX	0.01	0.00	0.00	0.00	0.02	−0.00	−0.01	0.01	0.00	0.01
	(0.657)	(0.907)	(0.700)	(0.714)	(0.882)	(0.991)	(0.631)	(0.642)	(0.835)	(0.597)
Conditional variance equation										
c_{11}	0.00	0.00	0.29	0.00	**0.97**	0.00	0.56	0.00	0.73	0.00
	(0.999)	(0.999)	(0.729)	(0.999)	**(0.040)**	(0.999)	(0.493)	(0.999)	(0.081)	(0.999)
c^*_{11}	-	−0.00	−0.29	0.29	0.31	**0.79**	−0.56	**1.12**	**−0.73**	**1.09**
		(0.999)	(0.713)	(0.721)	(0.435)	**(0.000)**	(0.514)	**(0.043)**	**(0.054)**	**(0.032)**
g_{11}	**0.89**	**0.99**	**0.97**	**0.97**	**0.80**	**0.85**	0.06	**0.89**	**0.82**	**0.92**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.002)**	**(0.000)**	(0.663)	**(0.000)**	**(0.000)**	**(0.000)**
g_{12}	**0.66**	**0.71**	**0.69**	**0.72**	0.07	−0.10	**0.79**	**0.57**	**0.59**	**0.60**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	(0.744)	(0.147)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
g^*_{12}	-	−0.00	0.03	−0.03	−0.07	0.06	−0.14	**−0.29**	**−0.63**	**−0.33**
		(0.977)	(0.681)	(0.682)	(0.305)	(0.331)	(0.507)	**(0.050)**	**(0.052)**	**(0.023)**
a_{11}	**0.27**	**0.19**	**0.24**	**0.24**	0.05	0.02	**0.11**	**0.27**	**0.32**	**0.25**
	(0.000)	**(0.002)**	**(0.001)**	**(0.002)**	(0.804)	(0.750)	**(0.016)**	**(0.000)**	**(0.000)**	**(0.000)**
a_{12}	**−0.39**	**−0.45**	**−0.54**	**−0.27**	**−0.42**	**0.32**	**−0.45**	**−0.41**	**−0.31**	**−0.44**
	(0.000)	**(0.000)**	**(0.002)**	**(0.005)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.003)**	**(0.000)**

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Table 6 (*continued*)

	Benchmark	Energy shock	Climate policy shocks				Oil and Climate Policy Shocks Interaction			
			Nat. Pos.	Nat. Neg	Int. Pos.	Int Neg.	Oil + Nat. Pos.	Oil + Nat. Neg	Oil + Int. Pos.	Oil + Int. Neg
a^*_{12}	-	**1.14**	0.27	−0.27	−0.13	0.05	−0.04	**0.74**	0.11	**0.90**
		(0.000)	(0.215)	(0.213)	(0.236)	(0.572)	(0.806)	**(0.000)**	(0.415)	**(0.000)**
c_{22}	**1.61**	**1.95**	**1.56**	**2.00**	**1.34**	**1.29**	**1.38**	**1.68**	**1.64**	**1.73**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.001)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
c^*_{22}	-	−1.10	0.43	−0.43	−0.24	0.22	**0.36**	**−2.29**	**2.06**	**−2.32**
		(0.323)	(0.125)	(0.169)	(0.663)	(0.079)	**(0.761)**	**(0.000)**	**(0.023)**	**(0.000)**
c_{21}	**−0.91**	**−0.59**	**−0.69**	**−0.69**	0.11	**1.10**	−0.45	**−0.79**	**−0.76**	**−0.79**
	(0.000)	**(0.003)**	**(0.031)**	**(0.053)**	(0.937)	**(0.002)**	(0.077)	**(0.000)**	**(0.008)**	**(0.000)**
g_{22}	**0.34**	0.15	0.29	0.20	**0.81**	**0.86**	**0.21**	**0.41**	**0.41**	**0.36**
	(0.002)	(0.279)	(0.274)	(0.311)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.009)**	**(0.000)**
g_{21}	−0.02	−0.13	−0.11	−0.10	0.08	**−0.09**	**0.78**	0.03	0.06	−0.01
	(0.867)	(0.173)	(0.543)	(0.630)	(0.776)	**(0.038)**	**(0.000)**	(0.715)	(0.581)	(0.981)
g^*_{21}	-	**−0.48**	0.01	−0.01	−0.03	0.07	**0.27**	0.04	**0.19**	**−0.10**
		(0.000)	(0.843)	(0.846)	(0.672)	(0.124)	**(0.000)**	(0.486)	**(0.000)**	**(0.001)**
a_{22}	**0.36**	**0.29**	**0.32**	**0.32**	0.04	−0.01	**0.00**	**−0.74**	0.14	**−0.62**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	(0.448)	(0.746)	**(0.989)**	**(0.000)**	(0.403)	**(0.000)**
a_{21}	**0.08**	**0.11**	**0.06**	**0.11**	**−0.37**	**0.22**	**−0.30**	0.06	0.05	0.07
	(0.055)	**(0.000)**	**(0.100)**	**(0.052)**	**(0.003)**	**(0.001)**	**(0.000)**	(0.272)	(0.361)	(0.078)
a^*_{21}	-	**0.43**	0.04	−0.04	0.15	0.07	−0.22	0.13	**−0.41**	0.22
		(0.007)	(0.540)	(0.538)	(0.147)	(0.350)	(0.082)	(0.537)	**(0.007)**	(0.207)
LogLik	3786.94	3778.86	3777.23	3777.23	3764.26	3757.87	3765.52	3772.12	3778.32	3768.66
$LB_{Green(7)}$	0.96	0.63	1.56	1.56	1.34	1.17	3.04	1.03	1.26	0.79
	(0.995)	(0.998)	(0.980)	(0.980)	(0.987)	(0.991)	(0.880)	(0.994)	(0.989)	(0.997)
$LB_{Brown(7)}$	4.78	4.43	3.61	3.64	4.74	4.54	5.01	4.96	4.84	5.05
	(0.686)	(0.729)	(0.820)	(0.820)	(0.692)	(0.715)	(0.658)	(0.664)	(0.679)	(0.654)

Notes: Please refer to the notes in Table 4.

When climate policies and energy shocks are not accounted for, causality-in-mean and causality-in-variance are observed; concerning the former, the mean spillovers run from brown to green stock returns in India and in the US and volatility spillovers in the same direction in Japan ($a_{12} = -0.31$), and in the UK ($a_{12} = 0.12$). As for spillovers from green to brown stock returns, the mean equation provides supporting evidence only in the case of Japan ($\beta_{21} = 0.27$), but not for Canada, India, Japan and the US. Therefore, for Japan we reject the null hypothesis of no spillovers between green and brown stock returns (H_{03}). Conversely, we reject the null hypothesis of spillovers in the conditional volatility (H_{05}) for India ($a_{21} = 0.28$), Japan ($a_{21} = 0.08$), and the US ($a_{21} = 0.18$). Therefore, on the whole we find statistically significant spillover effects in the second moment regardless of the inclusion of the climate policies and energy shock dummies, whereas the mean spillovers appear to be significant only for the UK. Finally, in general the exogenous control variables are statistically significant. In particular, the estimated coefficients indicate that monetary policy, measured by the domestic 3-month policy rate, has a negative effect on asset returns, as one would expect. By contrast, global financial markets uncertainty, measured by the VIX, tends to affect negatively brown stock returns but positively green ones, though not in all cases. These differences in the behaviour of green vis-a-vis brown stock returns make them a possible hedge during periods of heightened uncertainty to mitigate exposure to market turbulence.

5.1. Climate policy shocks

As mentioned before, the impact of climate policy shocks is measured using four appropriately defined dummies for the cases of positive and negative changes in the national and international scores respectively. The null hypothesis (H_{04}) of no mean spillovers between green and brown stock returns resulting from those shocks is rejected for the UK ($\beta^*_{12} = 0.12$), and the US ($\beta^*_{12} = -0.07$). Specifically, in the case of a positive national climate policy shock spillovers are positive in the UK (Table 7), but negative in the US (Table 8). The corresponding spillovers are negative in Japan, but positive in response to a negative policy shock (Table 6).

As for the volatility spillovers, we find that in the UK and the US these run from brown to green stock returns in correspondence with increases in the international climate policy score ($a^*_{12} = -0.29$; $a^*_{12} = -0.32$, and $a^*_{12} = 0.67$, respectively). They also run from green to brown stock returns in the US when there is a positive change in the national climate policy score ($a^*_{21} = 0.11$). The latter findings are consistent with those of Banerjee et al. (2024), who detected volatility spillovers varying in both sign and magnitude in response to economic shocks.

5.2. Energy shocks

The second set of exogenous shocks, also modelled using dummy variables, captures energy price uncertainty as identified by Kilian and Zhou (2022), Baumeister and Kilian (2016), and Gazzani et al. (2024). The conditional mean equation results are largely

Table 7
Estimated GARCH(1,1)-BEKK models for the United Kingdom.

	Benchmark	Energy shock	Climate policy shocks				Oil and Climate Policy Shocks Interaction			
			Nat. Pos.	Nat. Neg	Int. Pos.	Int Neg.	Oil + Nat. Pos.	Oil + Nat. Neg	Oil + Int. Pos.	Oil + Int. Neg
Conditional mean equation										
a_{11}	−0.15	−0.13	−0.27	−0.28	0.07	−0.12	−0.10	−0.09	−0.00	−0.30
	(0.503)	(0.553)	(0.151)	(0.240)	(0.766)	(0.619)	(0.673)	(0.683)	(0.984)	(0.255)
a^*_{11}	–	**−0.88**	**−0.23**	0.16	−0.19	0.19	−0.10	−1.87	−0.32	−1.92
		(0.028)	**(0.052)**	(0.215)	(0.134)	(0.156)	(0.732)	(0.312)	(0.293)	(0.342)
β_{11}	−0.00	−0.04	0.01	−0.02	0.00	0.00	0.00	−0.02	0.00	−0.02
	(0.930)	(0.340)	(0.695)	(0.577)	(0.940)	(0.839)	(0.908)	(0.513)	(0.929)	(0.473)
β_{12}	−0.00	0.00	**−0.07**	0.00	−0.02	0.01	−0.03	−0.01	−0.03	0.00
	(0.932)	(0.946)	**(0.004)**	(0.949)	(0.734)	(0.616)	(0.195)	(0.612)	(0.209)	(0.946)
β^*_{12}	–	−0.07	**0.12**	−0.05	0.03	−0.03	0.05	**−0.43**	0.00	−0.11
		(0.663)	**(0.000)**	(0.314)	(0.568)	(0.618)	(0.531)	**(0.034)**	(0.953)	(0.435)
IR	−0.02	−0.09	−0.00	0.25	−0.02	−0.02	−0.05	−0.08	−0.06	−0.10
	(0.709)	(0.241)	(0.962)	(0.687)	(0.754)	(0.744)	(0.329)	(0.158)	(0.344)	(0.085)
VIX	0.02	**0.02**	**0.03**	**0.02**	0.01	0.01	0.02	0.02	0.01	**0.03**
	(0.070)	**(0.030)**	**(0.000)**	**(0.046)**	(0.271)	(0.182)	(0.142)	(0.068)	(0.293)	**(0.031)**
a_{22}	**−0.68**	−0.49	**−0.67**	**−0.87**	−0.37	**−0.71**	−0.31	−0.53	−0.25	−0.42
	(0.023)	(0.120)	**(0.014)**	**(0.015)**	(0.215)	**(0.040)**	(0.337)	(0.123)	(0.455)	(0.215)
a^*_{22}	–	−0.49	−0.30	**0.44**	−0.33	0.33	0.00	−3.46	−0.48	−1.83
		(0.433)	(0.075)	**(0.017)**	(0.153)	(0.173)	(0.993)	(0.073)	(0.156)	(0.610)
β_{22}	0.06	**−0.08**	**0.11**	**0.07**	**0.09**	0.09	0.05	0.03	0.03	**0.09**
	(0.133)	**(0.035)**	**(0.001)**	**(0.054)**	**(0.052)**	(0.089)	(0.146)	(0.326)	(0.370)	**(0.021)**
β_{21}	0.01	−0.05	−0.08	0.05	−0.02	0.02	−0.01	−0.01	−0.00	−0.04
	(0.855)	(0.423)	(0.130)	(0.354)	(0.699)	(0.734)	(0.851)	(0.851)	(0.982)	(0.427)
β^*_{21}	–	−0.25	0.11	−0.11	0.05	−0.05	−0.00	**−0.82**	−0.11	−0.63
		(0.356)	(0.082)	(0.135)	(0.553)	(0.624)	(0.993)	**(0.000)**	(0.578)	(0.175)
IR	−0.01	−0.11	−0.04	−0.05	0.00	0.00	−0.04	−0.09	−0.09	−0.08
	(0.811)	(0.332)	(0.545)	(0.454)	(0.967)	(0.965)	(0.619)	(0.233)	(0.351)	(0.407)
VIX	**0.04**	**0.04**	**0.05**	**0.04**	**0.03**	**0.03**	−0.02	**0.04**	0.03	0.03
	(0.007)	**(0.024)**	**(0.000)**	**(0.026)**	**(0.054)**	**(0.044)**	(0.211)	**(0.033)**	(0.141)	(0.131)
Conditional variance equation										
c_{11}	**0.27**	0.00	0.00	**0.33**	−0.16	0.37	0.00	0.00	0.00	0.00
	(0.002)	(0.999)	(0.999)	**(0.000)**	(0.573)	(0.078)	(0.999)	(0.999)	(0.999)	(0.999)
c^*_{11}	-	**1.13**	0.45	**−0.33**	−0.21	−0.53	−0.00	**−0.00**	0.00	**−3.10**
		(0.005)	(0.064)	**(0.019)**	(0.478)	(0.159)	(0.999)	**(0.999)**	(0.999)	**(0.000)**
g_{11}	**0.89**	**0.97**	**0.77**	**0.89**	**0.87**	**0.87**	**−0.70**	**0.45**	**0.44**	**−0.97**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.002)**	**(0.003)**	**(0.000)**
g_{12}	**0.09**	**0.57**	**1.77**	**−0.09**	**−0.14**	−0.05	**−1.16**	**−0.20**	**−0.15**	**−1.40**
	(0.003)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.026)**	(0.285)	**(0.000)**	**(0.124)**	**(0.460)**	**(0.000)**
g^*_{12}	-	−0.28	−0.07	0.03	0.09	−0.09	**−0.77**	0.58	−0.14	0.16
		(0.177)	(0.607)	(0.361)	(0.148)	(0.195)	**(0.000)**	(0.107)	(0.268)	(0.719)
a_{11}	**0.33**	−0.08	**0.32**	**0.37**	**0.38**	**0.38**	−0.08	0.02	0.02	−0.23
	(0.000)	(0.337)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.358)	(0.903)	(0.809)	(0.062)
a_{12}	**0.12**	0.29	**0.17**	**0.27**	**0.25**	**0.02**	**−0.16**	0.02	−0.08	**−0.25**
	(0.098)	(0.188)	**(0.010)**	**(0.017)**	**(0.019)**	**(0.800)**	**(0.014)**	(0.791)	(0.243)	**(0.009)**
a^*_{12}	-	−0.64	**−0.32**	−0.18	−0.23	0.23	−0.03	**0.82**	0.19	−0.06
		(0.177)	**(0.000)**	(0.123)	(0.048)	(0.099)	(0.782)	**(0.000)**	(0.130)	(0.695)
c_{22}	**0.75**	**0.01**	**0.51**	**0.60**	**0.71**	**0.80**	**−1.22**	**−0.94**	**0.88**	**0.80**
	(0.000)	**(0.970)**	**(0.001)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.028)**	**(0.000)**
c^*_{22}	-	**−2.28**	0.02	−0.04	0.09	−0.09	−0.28	−0.81	0.151	**3.29**
		(0.036)	(0.795)	(0.823)	(0.609)	(0.655)	(0.104)	(0.580)	(0.645)	**(0.000)**
c_{21}	**0.60**	**−0.71**	**0.52**	**0.55**	**0.59**	**0.59**	**−1.48**	**−1.59**	**1.64**	**0.64**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
g_{22}	**0.94**	**0.70**	**−0.83**	**0.96**	**0.95**	**0.95**	**1.06**	**0.94**	**0.94**	**1.01**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
g_{21}	0.00	**−0.18**	**0.14**	**0.01**	0.04	0.00	**0.13**	−0.00	0.06	−0.01
	(0.965)	**(0.000)**	**(0.000)**	**(0.434)**	(0.410)	(0.966)	**(0.000)**	(0.715)	(0.581)	(0.981)
g^*_{21}	-	0.07	−0.02	−0.01	−0.04	0.04	**0.27**	0.04	0.00	0.08
		(0.301)	(0.280)	(0.381)	(0.672)	(0.354)	**(0.000)**	(0.803)	(0.939)	(0.493)
a_{22}	**0.28**	0.08	**0.17**	**0.19**	**0.25**	**0.25**	0.05	**0.39**	**0.41**	**0.24**
	(0.000)	(0.626)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.271)	**(0.000)**	**(0.000)**	**(0.000)**
a_{21}	−0.01	**0.29**	−0.01	−0.06	0.09	−0.02	**−0.23**	**0.31**	**0.32**	0.00
	(0.872)	**(0.000)**	(0.582)	(0.124)	(0.211)	(0.724)	**(0.000)**	**(0.000)**	**(0.001)**	(0.979)

(*continued on next page*)

Table 7 (*continued*)

	Benchmark	Energy shock	Climate policy shocks				Oil and Climate Policy Shocks Interaction			
			Nat. Pos.	Nat. Neg	Int. Pos.	Int Neg.	Oil + Nat. Pos.	Oil + Nat. Neg	Oil + Int. Pos.	Oil + Int. Neg
a^*_{21}	-	−0.10 (0.487)	0.04 (0.322)	0.04 (0.398)	0.07 (0.472)	−0.07 (0.399)	0.11 (0.329)	**−0.95** **(0.000)**	−0.05 (0.711)	0.17 (0.313)
LogLik	3422.08	3434.01	3403.68	3414.55	3414.55	3414.55	3423.40	3424.18	3438.64	3412.79
$LB_{Green(7)}$	6.77 (0.452)	5.55 (0.489)	7.22 (0.405)	6.77 (0.453)	7.29 (00.399)	7.29 (0.399)	7.99 (0.333)	8.04 (0.328)	9.04 (0.249)	5.16 (0.640)
$LB_{Brown(7)}$	10.57 (0.158)	11.58 (0.115)	11.65 (0.112)	11.29 (0.126)	10.93 (0.141)	10.93 (0.141)	11.62 (0.113)	11.73 (0.109)	12.59 (0.082)	11.49 (0.118)

Notes: Please refer to the notes in Table 4.

insignificant except for a negative spillover from green to brown stock returns in Canada ($\beta^*_{21} = -0.24$), whereas there is evidence of significant bi-directional volatility spillovers in the case of Japan ($a^*_{12} = 1.14$ and $a^*_{21} = 0.43$). In all other cases, we fail to reject the null hypothesis (H_{06}), which implies that there are no significant shifts in volatility spillovers due to energy shocks.

5.3. Interaction between climate policy and energy price shocks

The previous evidence concerning shifts in mean and volatility spillovers, following climate policy and energy shocks examined separately, is somewhat mixed. However, the introduction of interaction dummies produces a different scenario (Tables 4–8). Specifically, mean spillovers from brown to green stock returns are now found in all countries under examination except the US. In Canada, these are negative and significant in response to positive international climate policy and energy shocks $(\beta^*_{12} = -0.62)$, whereas in the UK they are negative in correspondence to negative national climate policy shocks $(\beta^*_{12} = -0.43)$. In India, positive spillovers are detected when positive international climate policy shocks occur $(\beta^*_{12} = 0.08)$, while in Japan significant positive spillovers are observed in the case of negative national and international climate policy shocks ($\beta^*_{12} = 0.27$ and $\beta^*_{12} = 0.33$, respectively).

There is also evidence of mean spillovers from green to brown stock returns, which are always negative. In Canada, for instance, in response to negative international climate policy and energy shocks, the links between the two markets become much weaker ($\beta^*_{21} = -0.44$), which is in line with the findings of Athari and Kirikkaleli (2024), who argue that fluctuations in oil prices significantly affect green energy companies. A similar pattern emerges for the UK, as shown in Table 7, and India when the latter is hit by positive international climate policy shocks ($\beta^*_{21} = -0.82$ and $\beta^*_{21} = -0.79$).

Volatility spillovers are generally more sizeable and statistically significant. They run from brown to green stock returns in Canada when negative national and international climate policy shocks occur ($a^*_{12} = 0.91$ and $a^*_{12} = 0.60$, respectively). Similar results are found for Japan ($a^*_{12} = 0.74$ and $a^*_{12} = 0.90$) and the US, where spillovers are significant only in response to negative national climate policy and energy shocks ($a^*_{12} = 0.52$). In a related study Bouri (2023) also reported that the total connectedness index for volatility exhibits significant spikes during the oil price crash from mid-2014 to January 2016 and the COVID-19 pandemic, with green stock indices typically being net volatility transmitters throughout the sample period.

Volatility spillovers from green to brown stock returns are generally significant. In India they shift in the presence of positive national and international climate policy shocks ($a^*_{21} = 0.14$ and $a^*_{21} = 0.20$, respectively). In Japan, they result from the interaction between positive international climate policies and oil price shocks ($a^*_{21} =$ -0.41), and in UK and Canada from the interaction between negative national climate policy and oil price shocks ($a^*_{21} = -0.95$ and $a^*_{21} = 0.37$, respectively). There is also a similar pattern in the US $\left(a^*_{21} = 0.12\right)$. These findings are in line with those of Guo et al. (2024), who reported that cross-country risk spillovers fluctuate over time since they are highly sensitive to major climate actions and financial shocks.

Finally, Figs. 1 and 2 display the green and brown stock return series, their conditional correlations and the dummy variable for the interaction between negative national climate policy and energy shocks. The predominantly positive correlations suggest that green and brown stocks tend to move in the same direction over the years, with some exceptions. In the case of Canada, for instance, the conditional correlation exhibits significant variability, frequently oscillating between negative and positive values, with more stable periods around 2015 and 2020. India and the UK stand out since their green and brown stock returns correlations are always positive over the period analyzed. In the case of the US, they are generally high and predominantly positive before 2018, but drop almost to zero in 2020. In Japan, the UK and the US they are lower post-2020 (Fig. 2). This suggests that in recent years green assets could have been used as a hedge against market turbulence, in line with the findings of Farid et al. (2023).

On the whole, the results indicate that effective climate policies, especially at the national level, can mitigate volatility spillovers and encourage stable investments in green markets. Regarding individual countries, Canada appears to be particularly exposed to energy shocks, which makes diversification across green and brown sectors essential.

With Canada's strong focus on hydro and wind power, long-term investments in renewable energy stocks could provide stable returns (Chen et al., 2023). In India, the responsiveness of brown stocks to positive climate policy shocks offers opportunities for

Table 8
Estimated GARCH(1,1)-BEKK models for the United States.

	Benchmark	Energy shock	Climate policy shocks				Oil and Climate Policy Shocks Interaction			
			Nat. Pos.	Nat. Neg	Int. Pos.	Int Neg.	Oil + Nat. Pos.	Oil + Nat. Neg	Oil + Int. Pos.	Oil + Int. Neg
Conditional mean equation										
α_{11}	−0.47	−0.28	**−0.44**	−0.46	−0.30	**−0.44**	−0.40	−0.06	−0.32	**−0.40**
	(0.061)	(0.198)	**(0.039)**	(0.091)	(0.247)	**(0.049)**	(0.061)	(0.214)	(0.147)	**(0.000)**
α^{*}_{11}	–	−0.52	−0.23	0.05	−0.01	0.10	−0.38	−0.29	−0.41	−1.58
		(0.186)	(0.771)	(0.709)	(0.936)	(0.504)	(0.640)	(0.523)	(0.084)	(0.607)
β_{11}	−0.00	0.02	0.04	0.03	0.02	0.028	0.03	0.17	0.02	0.03
	(0.941)	(0.564)	(0.216)	(0.256)	(0.482)	(0.460)	(0.415)	(0.713)	(0.438)	(0.079)
β_{12}	**−0.07**	**−0.07**	−0.03	**−0.08**	−0.04	**−0.06**	**−0.06**	−0.05	**−0.07**	**−0.07**
	(0.025)	**(0.003)**	(0.259)	**(0.002)**	(0.238)	**(0.026)**	**(0.024)**	(0.068)	**(0.001)**	**(0.004)**
β^{*}_{12}	–	0.05	**−0.07**	0.03	0.03	−0.07	−0.03	0.00	0.06	0.18
		(0.396)	**(0.057)**	(0.529)	(0.435)	(0.277)	(0.837)	(0.984)	(0.203)	(0.533)
IR	0.01	−0.02	−0.02	−0.01	−0.02	−0.00	−0.00	−0.02	−0.01	−0.00
	(0.814)	(0.631)	(0.581)	(0.809)	(0.649)	(0.888)	(0.861)	(0.658)	(0.674)	(0.875)
VIX	**0.04**	**0.04**	**0.05**	**0.04**	**0.04**	**0.04**	**0.04**	**0.04**	**0.04**	**0.04**
	(0.000)	**(0.001)**	**(0.000)**	**(0.000)**	**(0.002)**	**(0.000)**	**(0.000)**	**(0.005)**	**(0.001)**	**(0.000)**
α_{22}	**−1.10**	**−0.65**	**−0.88**	**−0.74**	**−1.01**	**−0.85**	**−0.83**	**−0.79**	**−0.71**	**−0.85**
	(0.000)	**(0.015)**	**(0.001)**	**(0.018)**	**(0.018)**	**(0.002)**	**(0.001)**	**(0.012)**	**(0.006)**	**(0.000)**
α^{*}_{22}	–	−0.72	0.13	−0.06	0.03	0.07	0.28	−0.84	**−0.60**	−4.03
		(0.168)	(0.421)	(0.749)	(0.885)	(0.769)	(0.817)	(0.225)	**(0.040)**	(0.275)
β_{22}	−0.07	−0.04	**−0.07**	**−0.06**	0.00	−0.06	−0.05	−0.02	**−0.05**	**−0.07**
	(0.091)	(0.257)	**(0.020)**	**(0.007)**	(0.947)	(0.105)	(0.169)	(0.433)	**(0.052)**	**(0.010)**
β_{21}	0.06	0.06	**0.14**	0.06	0.08	0.11	0.07	0.07	**0.07**	**0.08**
	(0.335)	(0.225)	**(0.003)**	(0.227)	(0.295)	(0.107)	(0.169)	(0.151)	**(0.053)**	**(0.000)**
β^{*}_{21}	–	0.02	−0.06	0.06	−0.00	−0.11	0.22	−0.41	−0.07	0.09
		(0.880)	(0.266)	(0.540)	(0.947)	(0.331)	(0.278)	(0.186)	(0.628)	(0.824)
IR	−0.03	−0.09	−0.08	−0.08	−0.10	−0.06	−0.07	**−0.11**	−0.08	−0.06
	(0.573)	(0.110)	(0.063)	(0.250)	(0.242)	(0.238)	(0.330)	**(0.045)**	(0.113)	(0.303)
VIX	**0.07**	**0.05**	**0.07**	**0.06**	**0.07**	**0.06**	**0.06**	**0.05**	**0.06**	**0.06**
	(0.007)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.001)**	**(0.000)**	**(0.000)**
Conditional variance equation										
c_{11}	−0.00	0.13	**0.258**	0.07	0.00	**0.20**	**0.22**	0.13	**0.149**	**0.18**
	(0.998)	(0.076)	**(0.031)**	(0.656)	(0.999)	**(0.000)**	**(0.000)**	(0.107)	**(0.008)**	**(0.023)**
c^{*}_{11}	-	−0.13	**−0.25**	**−0.33**	−0.39	**−0.20**	−0.22	−0.13	−0.15	−0.18
		(0.258)	**(0.029)**	**(0.046)**	(0.061)	**(0.004)**	(0.085)	(0.226)	(0.385)	(0.566)
g_{11}	**0.42**	**0.88**	**0.88**	**0.90**	**1.07**	**0.91**	**0.90**	**0.88**	**0.90**	**0.91**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
g_{12}	**1.56**	**−0.07**	−0.01	−0.07	**0.98**	−0.03	0.04	−0.08	−0.05	−0.03
	0.000)	**0.050)**	(0.705)	(0.482)	**(0.000)**	(0.351)	(0.173)	(0.176)	(0.116)	(0.234)
g^{*}_{12}	-	0.03	**−0.10**	0.06	−0.10	−0.02	0.02	**−0.90**	0.01	**0.63**
		(0.490)	**(0.011)**	(0.164)	(0.231)	(0.201)	(0.818)	**(0.016)**	(0.829)	**(0.000)**
α_{11}	**0.22**	**0.26**	**0.15**	0.17	**0.29**	0.19	**0.18**	0.31	**0.24**	0.14
	(0.014)	**(0.050)**	**(0.038)**	(0.177)	**(0.000)**	(0.070)	**(0.048)**	(0.141)	**(0.055)**	(0.073)
α_{12}	0.01	0.03	−0.21	0.00	**−0.68**	−0.07	−0.09	0.11	0.01	−0.12
	(0.898)	(0.803)	(0.099)	(0.999)	**(0.000)**	(0.507)	(0.375)	(0.649)	(0.928)	(0.190)
α^{*}_{12}	-	0.07	**0.28**	−0.15	**0.67**	0.11	0.23	**0.52**	0.00	0.09
		(0.625)	**(0.005)**	(0.175)	**(0.000)**	(0.201)	(0.103)	**(0.001)**	(0.972)	(0.538)
c_{22}	**0.53**	**0.54**	**0.50**	**0.579**	**2.31**	**0.59**	**0.577**	**0.59**	**0.568**	**0.61**
	(0.000)	**(0.000)**	**(0.000)**	**(0.003)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
c^{*}_{22}	-	−0.01	0.17	−0.08	**−0.90**	0.12	−0.23	0.19	0.30	−0.11
		(0.934)	(0.357)	(0.649)	**(0.000)**	(0.357)	(0.845)	(0.439)	(0.479)	(0.565)
c_{21}	**0.65**	**0.60**	**0.62**	**0.56**	−0.14	**0.56**	**0.55**	**0.62**	**0.59**	**0.57**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	(0.338)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
g_{22}	**−0.53**	**0.94**	**0.92**	**0.92**	−0.01	**0.91**	**0.92**	**0.93**	**0.93**	**0.91**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	(0.874)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
g_{21}	**1.57**	**−0.03**	−0.02	**−0.05**	**−0.21**	**−0.05**	**−0.04**	−0.03	**−0.04**	**−0.05**
	(0.000)	**(0.032)**	(0.098)	**(0.005)**	**(0.001)**	**(0.000)**	**(0.001)**	(0.148)	**(0.015)**	**(0.000)**
g^{*}_{21}	-	**−0.04**	**−0.03**	0.01	−0.08	−0.01	**−0.10**	−0.00	−0.01	**0.439**
		(0.020)	**(0.028)**	(0.343)	(0.068)	(0.061)	**(0.003)**	(0.907)	(0.827)	**(0.000)**
α_{22}	**0.44**	**0.39**	**0.46**	**0.45**	**0.56**	**0.44**	**0.44**	**0.37**	**0.41**	**0.46**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.007)**	**(0.000)**	**(0.000)**
α_{21}	**0.18**	**0.18**	**0.22**	**0.27**	**0.07**	**0.21**	**0.21**	**0.52**	**0.19**	**0.23**
	(0.000)	**(0.028)**	**(0.000)**	**(0.000)**	**(0.043)**	**(0.001)**	**(0.000)**	**(0.001)**	**(0.025)**	**(0.000)**

(continued on next page)

Table 8 (*continued*)

	Benchmark	Energy shock	Climate policy shocks				Oil and Climate Policy Shocks Interaction			
			Nat. Pos.	Nat. Neg	Int. Pos.	Int Neg.	Oil + Nat. Pos.	Oil + Nat. Neg	Oil + Int. Pos.	Oil + Int. Neg
a^{*}_{21}	-	0.09	**0.11**	−0.05	**0.18**	0.09	**0.23**	**0.12**	0.05	**0.239**
		(0.247)	**(0.009)**	(0.411)	**(0.002)**	(0.102)	**(0.008)**	**(0.050)**	(0.629)	**(0.000)**
LogLik	3513.02	3493.12	2116.98	2116.98	2116.98	2116.98	2116.98	2116.98	2116.98	2116.98
$LB_{Green(7)}$	9.71	8.33	7.51	7.97	7.28	8.73	8.16	6.75	7.90	7.62
	(0.205)	(0.401)	(0.378)	(0.334)	(0.400)	(0.272)	(0.318)	(0.455)	(0.333)	(0.367)
$LB_{Brown(7)}$	13.57	8.35	8.86	9.19	4.77	9.79	8.99	7.83	9.19	8.56
	(0.059)	(0.302)	(0.262)	(0.239)	(0.687)	(0.200)	(0.252)	(0.348)	(0.239)	(0.285)

Notes: Please refer to the notes in Table 4.

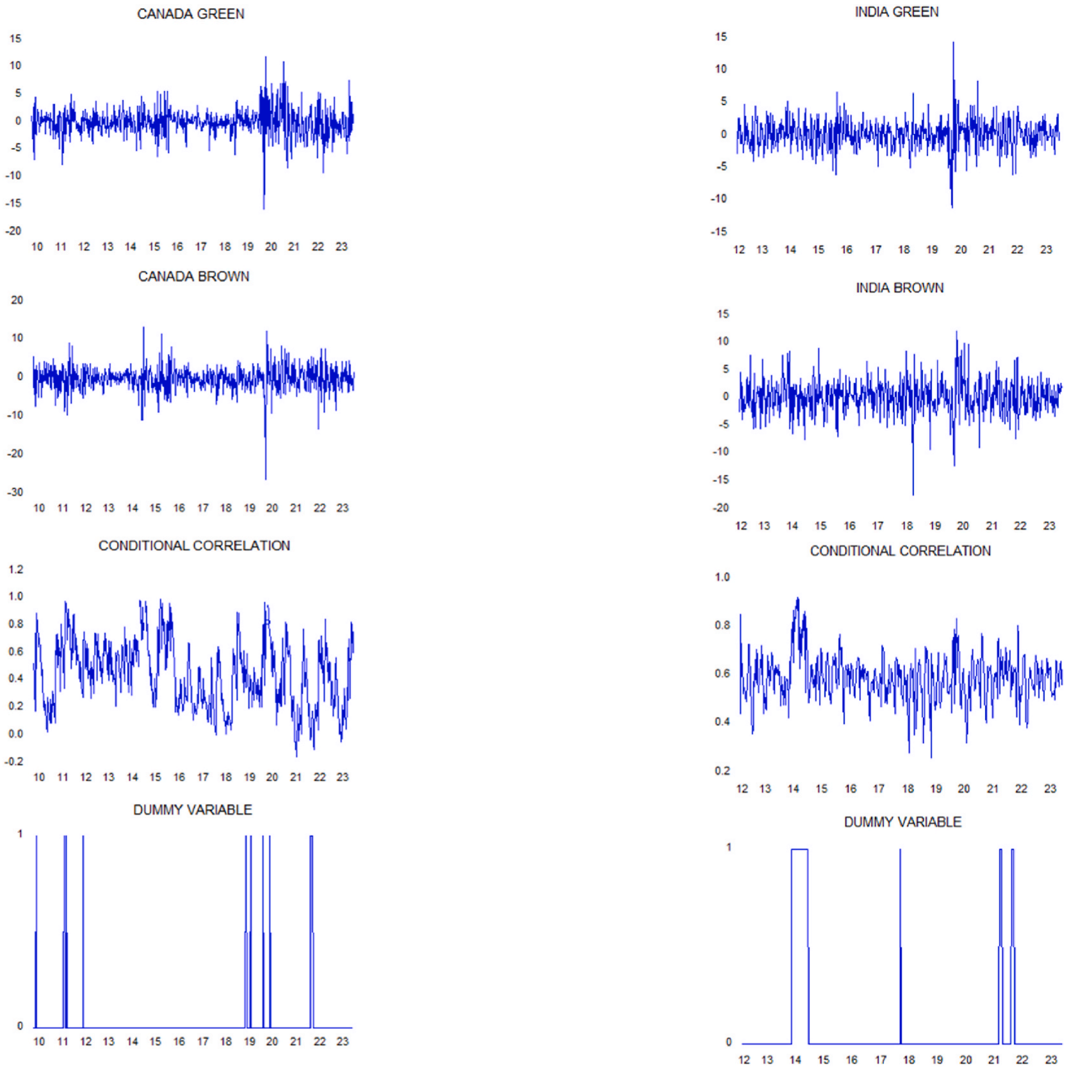

Fig. 1. Stock Returns and Conditional Correlations.

Notes: To examine the combined effects of climate policy shocks and energy shocks, we incorporate interaction dummies that account for the simultaneous occurrence of both types of shocks. Specifically, the figures at the bottom illustrate the interaction dummy representing instances where national climate policies in favour of a green transition coincide with oil shocks. Furthermore, the time-varying conditional correlation ($\rho_{12,t}=h_{12,t}/(\sqrt{h_{11,t}}\sqrt{h_{22,t}})$) is estimated using the multivariate GARCH(1,1)-BEKK model, which explicitly includes the interaction dummies discussed.

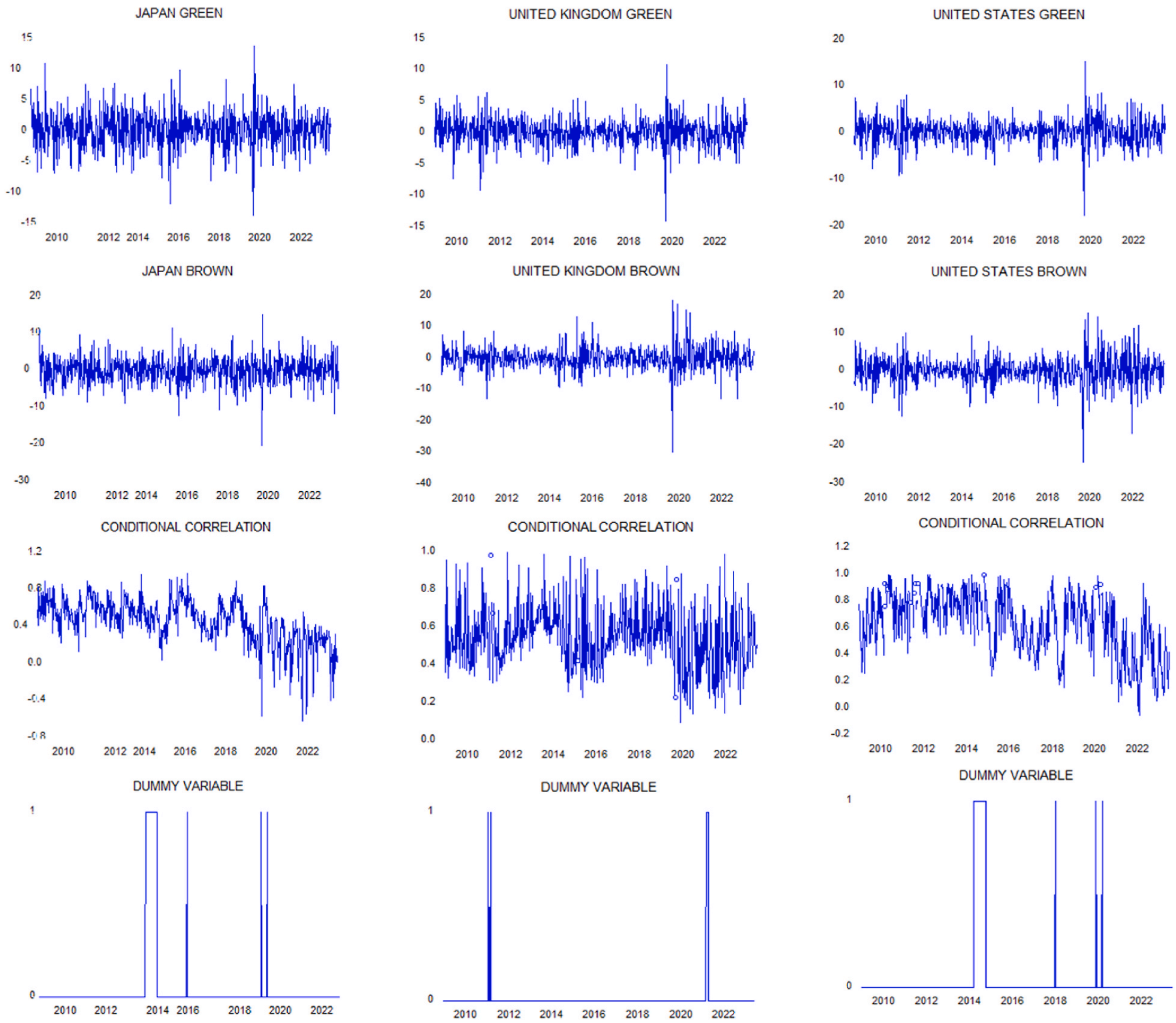

Fig. 2. Stock Returns and Conditional Correlations.
Notes: Please refer to the notes in Fig. 1.

short-term gains (Basu & Ishihara, 2023). However, with coal dominating the energy landscape, green investments are critical for long-term portfolio stability, especially as the country ramps up its renewable energy capacity. Investors in the Japanese markets appear to have benefited from the nation's decarbonization initiatives, which have strengthened the performance of green stocks in response to positive national as well as international climate policy shocks. However, as noted by Paramati et al. (2017), the Japanese economy is still strongly reliant on brown energy. In the UK, positive climate policy shocks enhance spillovers from brown to green stocks, which reflects a commitment to a well-defined framework for the transition to a low-carbon economy, as noted by Shah et al. (2018). Finally, in the US the lack of a consistent climate policy framework (Shah et al., 2018) appears to increase significantly volatility, especially in the case of brown stocks (Chen et al., 2025).

6. Conclusions

This paper provides comprehensive evidence on the behaviour of brown and green stock returns in response to both climate policy and energy shocks in five major economies, namely Canada, India, Japan, the UK and the US, with the sample start dates ranging from March 13, 2009 to August 24, 2012 and the end date being December 29, 2023 in all cases, the sample selection being driven by data availability on country-specific green energy indices. More specifically, a VAR-GARCH-BEKK framework is used to estimate simultaneously bivariate mean and volatility spillovers and the effects on those dynamic linkages of both (national and international) climate policy and energy shocks, which are modelled using dummy variables and are also allowed to interact. The former are measured using indices produced by GermanWatch, whilst the latter are captured using oil prices.

The findings reveal strong dynamic linkages between green and brown stock returns, which are significantly influenced by exogenous shocks, and expecially by the interaction between climate policy and oil price shocks, these effects varying across countries. The conditional correlations between stock returns are predominantly positive but appear to have turned negative in recent years. The detected dynamic linkages between green and brown stock markets highlight the need for diversified investment strategies that incorporate both asset types to mitigate risks arising from energy price uncertainty and climate policy shocks. In particular, our findings suggest that: i) investors should adopt region-specific strategies to optimize their portfolios; the reason is that long-term investments in renewables may offer superior returns in markets, such as the UK and Japan, where climate policies appear to have a stronger influence on green asset performance; by contrast, in oil-dependent economies, such as Canada, brown stocks may remain more resilient to energy shocks; and ii) international investors and asset managers can benefit from forward-looking climate risk assessments to identify opportunities in regions where green investments are actively promoted by policy interventions. These insights can guide capital allocation towards sustainable assets while managing exposure to conventional markets to balance risk-return trade-offs.

Policymakers clearly also play a crucial role in shaping the investment landscape by implementing measures that facilitate green market development and enhance financial stability. Governments should introduce incentives such as green bonds, tax breaks, and subsidies to encourage investment in sustainable sectors. and focus on transparent and stable regulatory environments that provide clear long-term signals to investors. Strategic investment in green infrastructure, coupled with retraining programmes for fossil fuel-dependent industries, can facilitate a smoother transition to a low-carbon economy. Finally, given the international nature of climate risks and financial markets, coordinated efforts among policymakers can enhance global green investment opportunities. Establishing regional climate investment funds and harmonizing carbon pricing mechanisms can improve capital flow into sustainable sectors.

On the whole, this study makes a novel contribution to the understanding of the linkages between climate risks, crude oil shocks, and the dynamics of green and brown stock returns. However, its limitations should be acknowledged. In particular, data availability constraints meant that the analysis could only be carried out for a limited set of countries. Furthermore, the low frequency of the climate policy indices implies that the analysis cannot shed light on the impact of short-term fluctuations in transition climate risk. Future research could also yield additional insights by using sectoral data to uncover industry-specific patterns, and by investigating the role of emerging technologies, such as carbon capture and storage or renewable energy innovations, as a driver of stock market spillover dynamics.

Declaration of competing interest

The authors have no interests to declare.

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Data availability

Data will be made available on request.

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