Return Volatility, Correlation, and Hedging of Green and Brown Stocks: Is there a Role for Climate Risk Factors?

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Abstract

We examine the effects of three monthly climate risk factors, climate policy uncertainty (CPU), climate change news (CCN), and negative climate change news (NCCN) on the long-run volatilities and correlation of daily green and brown energy stock returns, and perform a hedging analysis. Given that our dataset combines daily and monthly data, we rely on mixed data sampling models such as GARCH-MIDAS and DCC-MIDAS in standard and asymmetric forms with a bivariate skew-t distribution, which also allows us to deal with volatility clustering, asymmetric effects, and negative skewness in innovation which characterize our dataset. Firstly, the results of the GARCH-MIDAS models show evidence that climate risk contains information useful to improve the prediction of return volatility of brown energy stocks. Secondly, the results of the DCC-MIDAS model indicate that climate risk reduces the green-brown returns correlation, suggesting a negative effect and hedging opportunities. Thirdly, the results of the hedging analysis show that incorporating a climate risk factor, especially NCCN, into the long-run component of dynamic correlation significantly improves the hedging performance between green and brown energy stock indices, and this are robust to an out-of-sample analysis under various refitting window sizes. These results matter to portfolio and risk managers for energy transition and portfolio decarbonization.

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Keywords: Conditional volatility, dynamic correlation, GARCH-MIDAS, DCC-MIDAS, climate change news (CCN), Climate policy uncertainty (CPU), hedging

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Highlights

- We extend the symmetric DCC-MIDAS model to an asymmetric DCC-MIDAS model with bivariate skew-t to include negative skewness in innovation.
- The long-run volatilities of brown stock significantly increase with the climate risk factors, but the green do not.
- The negative climate change news index has a larger effect on the long-run volatilities of brown stock.
- The long-run correlation between brown and green stock index returns decreases significantly with an increase in climate risk factors, especially the negative climate change news index.
- The hedging performance between the two stock indices can be significantly improved by inserting the climate risk factor into the long-run component of dynamic correlation.

1 Introduction

The deteriorating conditions of the earth's climate in response to accumulating and rising greenhouse gas emissions are set to have an important economic impact and cause damage at a global scale. This has led to the adoption of the UN Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol, and the Paris Agreement. The Climate Change Conferences (COPs) constantly review these frameworks to ensure that the necessary decisions and actions plans are made for smooth and timely implementations. On the financial scene, a major theme in capital markets and investments is the transition to eco-friendly and green assets. This particularly targets the polluting brown energy sector, making investment in green and clean energy companies gain significant ground, and related stock indices, such as the WilderHill energy index, have emerged as a major benchmark in the area of clean energy stock investment.

In parallel, the academic literature has experienced huge growth in the field of the relationship between green and clean assets (Ferrer et al., 2018; Maghyereh et al., 2019; Fahmy, 2022; Saeed et al., 2020a, b; Dutta et al., 2020; Yousaf et al., 2022; Gauthier et al., 2023)[1] and the portfolio implications, but less evidence exists regarding the pricing of these assets and their interrelationships under the impact of climate risk. On the one hand, some studies argue that firms' decisions to reduce greenhouse gas emissions are

[1] Ferrer et al. (2018) show that the frequency-based spillovers of return and volatility across crude oil, and green, brown, and conventional stock markets occur in the short term and that the performance of green energy stocks is driven by crude oil prices. Maghyereh et al. (2019) also apply wavelets and consider conditional correlation models, and their results indicate the presence of long-term return and volatility linkages between crude oil and clean energy stocks. However, Fahmy (2022) finds that the return linkages ease after the Paris Agreement. Saeed et al. (2020a) show that clean energy stocks serve to hedge the risk of brown energy, notably crude oil prices, more effectively than green bonds. Saeed et al. (2020b) provide evidence of tail dependence among clean energy stocks, green bonds, and brown energy (e.g., crude oil and energy exchange-traded funds), which is affected by crude oil market uncertainty. Dutta et al. (2020) provide evidence that energy sector volatility has an impact on clean energy stock returns that differs between the volatility levels of the energy sector. Furthermore, changes in the level of energy sector volatility matters to the volatility of clean energy stocks. Yousaf et al. (2022) consider the hedging of green assets against conventional stock markets, indicating their hedging role, especially during the pandemic. Gauthier et al. (2023) examine the scale-based co-movement between crude oil prices and various renewable stock indices covering solar, wind, bio, and geothermal energy, showing that the co-movement is nonlinear and varies across time and investment horizons.

driven by the uncertainty surrounding climate policy regulation (Lopez et al., 2017) and that investors move away from brown companies to green companies when uncertainties about climate change increase (Pástor et al., 2021). In this regard, Choi et al. (2020) indicate that retail investors drop their investments in carbon-intensive companies when the temperature rises to very high levels. Hsu et al. (2020) find that uncertainty in environmental policies and regulations have a significant impact on the cross-section of emission portfolio returns. Engle et al. (2020) construct monthly climate change measures and argue that climate risk can affect firms' investment decisions. On the other hand, some studies consider the impact of the climate policy uncertainty index. For example, Bouri et al. (2022) show that the ratio of green over brown energy stock prices is impacted by the level of climate policy uncertainty, and that during periods of high climate policy uncertainty green energy stocks outperform their brown counterparts because of the switch of investors from brown to green energy investment. A quite similar conclusion is reported by Dutta et al. (2023) who find that high levels of climate policy uncertainty make investment in green energy more appealing and thus their prices increase and their volatility decreases, which might be associated with the safe-haven property of green assets, as argued by Bouri et al. (2019). Dutta et al. (2023) further show that green energy investments can hedge the downside risk of crude oil returns. Sarker et al. (2022) examine the impact of climate policy uncertainty on clean energy stocks in a non-linear autoregressive distributed lags (ARDL) model. They find an impact that differs between the short and long term, which points to an asymmetry and provides evidence that changes in climate policy uncertainty have a stronger impact on the volatility than the return of clean energy stocks in the long term[2].

While the above studies are useful and point to the importance of climate policy uncertainty on the returns of green and brown energy assets, they leave room for extension on at least two fronts. Firstly, most studies consider the monthly climate policy uncertainty (CPU) index only, covering exclusively news about climate policy

[2] Shang et al. (2022) show that CPU reduces the demand for non-renewable energy whereas it increases the renewable energy demand in the long term.

uncertainty and thus overlooking all other news related to climate change, including physical climate risk such as natural disasters and negative climate change sentiment. Interestingly, the availability of other monthly indices such as the Climate Change News (CCN) index and the negative climate change news (NCCN) index proposed by Engle et al. (2020) offers an opportunity for researchers to assess the multifaceted characteristics of climate risks for the price dynamics of green and brown energy stocks more comprehensively. In this regard, these two climate change news indices and the CPU index differ but are somewhat complementary, which enriches our analysis and allows us to detect potential heterogeneity in their impact within our methodological framework, extending studies that tend to consider only one aspect of climate risk covering policy uncertainty (Bouri et al., 2022; Sarker et al., 2022; Dutta et al., 2023). In fact, the correlation between the CPU and CCN indices is low (0.41), as shown by Gavriilidis (2021). Specifically, the CPU covers exclusively news about climate policy uncertainty, whereas CCN and NCCN cover news related to climate change, including natural disasters, and climate change sentiment. Secondly, the related literature remains silent on how climate policy uncertainty and climate change news indices affect the volatility, correlation, and hedging of green and brown energy stocks. This is important, given that these two energy assets are often found in the portfolios of global institutional investors, which makes any granulated information on the climate risk factors' effect on their volatility or correlation highly appreciated by investors and policymakers who are worried about long-term climate risks and their impact on the hedging role of clean against brown energy investment strategies. Specifically, addressing this research gap has potential implications for volatility modelling and forecasting, portfolio allocation, sector rotation, derivative pricing, risk management, and financial stability under energy transition.

In this paper, we examine the impact of various climate risks on the volatility and correlation of green and brown energy stocks and their inferences for hedging possibilities.

Using three climate risk indices, CPU, CCN, and NCCN, covering the transitional and physical dimensions of climate risk, we rely on mixed data sampling models, namely the GARCH-MIDAS model of Engle et al. (2013) and the asymmetric and symmetric DCC-MIDAS models of Colacito et al. (2011). Notably, we extend the asymmetric DCC-MIDS model by considering the bivariate skew-t to include negative skewness in innovation. These models are suitable for our case, because: (1) the GARCH-MIDAS model allows us to directly examine how the long-run volatilities of green and brown energy stocks are affected by climate risks; (2) the DCC-MIDAS model helps us examine the effect of climate risks on the correlation between green and brown energy stocks while decomposing the correlation into long- and short-run components; (3) both models combine daily returns of green and brown energy stocks with monthly levels of climate risk indices; and (4) these models are extended from symmetric to asymmetric form to account for the leverage effect often found in energy stocks. Importantly, the asymmetric DCC-MIDAS model is employed with bivariate skew-t to include negative skewness in innovation, which constitutes a methodological extension to previous studies.

Our current study is related to a growing strand of literature on environmental firms (Huang, 2021) and climate finance, highlighting the impact of climate risk on asset pricing (e.g. Choi et al., 2020; Engle et al., 2020; Bolton & Kacperczyk, 2021; Pástor et al., 2021) and the co-movement between assets such as commodities and their financial stability (Flori et al., 2021). It is related to the study of Liang et al. (2022), who apply a GARCH-MIDAS model and show that CPU has a significant predictive power for the long-term volatility of renewable energy. However, our current study differs in both the scope and methods applied, given that we use three climate risk measures, consider the impact of climate risk on the correlation between green and brown energy stocks, and make hedging inferences. Equally, our analysis differs from that of Dutta et al. (2023), who consider monthly data, use one dimension of climate risk, and overlook the correlation between green and brown stocks and the portfolio and hedging implications.

Our main results offer evidence from a new perspective, showing that all the climate risk indices used in the study contain useful information for improving the prediction of the return volatility of brown stock, reducing the green-brown returns correlation, and making the hedging between brown and clean energy stocks cheaper and more effective, especially when negative climate change news is incorporated into the long-run component of dynamic correlation.

The rest of the paper is divided into four sections. Section 2 describes the research design, including the GARCH-MIDAS and DCC-MIDAS models. Section 3 provides the dataset on green and brown energy stock indices and the climate risk factors. Section 4 presents and discusses the results on the conditional volatility and conditional correlation. Section 5 assesses the hedging performance under the impact of climate risk factors. Section 6 concludes with some policy implications.

2 Methodology

We model the green and brown energy stock index returns using four GARCH-type models, standard GARCH, GRJGARCH, EGARCH, and APARCH. For the exogenous shocks from climate risk factors, we choose the Wall Street Journal (WSJ) climate change news (CCN) index and Crimson Hexagon (HE) negative climate change news index (NCC) proposed by Engle et al. (2020), and the Climate Policy Uncertainty index (CPU) of Gavriilidis (2021).

Specifically, the impact of various climate risks as exogenous shocks on the long-run volatility and dynamic correlation of brown and green energy stock returns is examined in a multistep approach. In the first step, we insert each of the three climate risk measures into the long-run component of GARCH-MIDAS specification on the volatility of brown and green energy stock index returns. We extend the conditional distribution to include non-zero skewness and excess kurtosis of innovation. The results of this step show the impact of various climate risks on the long-run volatilities of brown and green stock returns by assuming the index returns follow univariate time-varying processes. In the second step, we insert each of the three climate risk measures into the long-run component of the DCC-MIDAS specification of the correlation of brown and green energy stock index returns. We extend the standard DCC-MIDAS to include the non-zero skewness and excess kurtosis of the innovation distribution, and asymmetric effect of innovation on short- and long-run correlations. The results of this step show the impact of various climate risks on the long-run correlations of brown and green stock returns by assuming the two indices' returns follow bivariate time-varying processes. The third step consists of proposing a portfolio strategy to hedge brown energy with green energy accounting for the impact of climate on the correlation estimation.

2.1 GARCH models

The standard univariate GARCH and its generalized specifications are used as basic specifications for the volatilities of the green and brown energy stock index returns. The GARCH (1,1) model has the most concise form. Based on the same frequency data, it is described as:

$$r_t - \mu_t = \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sqrt{\sigma_t^2 z_t} \tag{2}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{3}$$

where r_t is the natural logarithmic rate of returns from the green or brown energy stock index; the conditional mean is $\mu_t = E_{t-1}(r_t) = \mu - \rho r_{t-1}$ as commonly used in the literature; ε_t is the innovations that are standardized to be z_t by σ_t, the conditional standard deviation; ω, α, and β are the estimated coefficients. $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$ are used to ensure the nonnegativity and stationarity of the variance process.

The GJRGARCH is widely used to describe the "leverage effect", the asymmetric shock by positive and negative innovation to the volatilities, where negative return shocks exert a larger impact on future conditional volatility than positive return shocks:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I_{t-1}^{-}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{4}$$

where $I_{t-1}^{-} = 1$ if $\varepsilon_{t-1} < 0$, otherwise $I_{t-1}^{-} = 0$.

Exponential GARCH (EGARCH), proposed by Nelson (1991), is also a commonly used model to describe the asymmetric volatility:

$$\ln \sigma_t^2 = \omega + \alpha(|z_{t-1}| - E|z_{t-1}|) + \gamma z_{t-1} + \beta \ln \sigma_{t-1}^2 \quad (5)$$

Following Ding et al. (1993), we include the asymmetric power GARCH (APARCH) for long memory property:

$$(\sqrt{\sigma_t})^\delta = \omega + \alpha(|\,\varepsilon_{t-1}\,| - \gamma\varepsilon_{t-1})^\delta + \beta(\sqrt{\sigma_{t-1}})^\delta \quad (6)$$

For the conditional distribution of the standardized innovations, we introduce Hansen's (1994) skewed t distribution:

$$\text{Skew-t}(z_t|\lambda,\eta) = BC\left(1 + \frac{1}{\eta-2}\left(\frac{Bz_t + A}{1 + \text{sgn}(\,z_t + \frac{A}{B})\lambda}\right)^2\right)^{-(\eta+1)/2}$$

where λ and η are the coefficient of skewness and degree of freedom, $\text{sgn}(x)$ is the sign function of x; and the constants A, B, and C are given by:

$$A = 4\lambda C\frac{\eta-2}{\eta-1}, \quad B = \sqrt{1 + 3\lambda^2 - A^2}, \quad C = \frac{\Gamma(\frac{(\eta+1)}{2})}{\sqrt{\pi(\eta-2)}\Gamma(\frac{\eta}{2})}$$

where $\lambda > 0$ and $\lambda < 0$ indicate that the distribution is positively and negatively skewed, respectively. The larger $|\lambda|$, the larger the skewness. When $\lambda = 0$, the distribution is symmetric and thus reduced to a standard *t* distribution. The degree of freedom, η, captures the excess kurtosis, which is consistent with the tail heaviness. Besides these two distributions, we also consider a normal distribution in the standard way.

2.2 GARCH-MIDAS models

Compared to the GARCH model based on the same frequency data, the GARCH-MIDAS model decomposes the volatility into short- and long-run components. In practice, the short-run volatility component of the GARCH-MIDAS model is assumed to be temporarily shocked by innovations (in high frequency), while the long-run component is more likely to be related to fundamental/microeconomic factors that are usually low frequency, such as climate risk in the present work.

Suppose $r_{t,\tau}$ is the return on day *t* of period τ that is low frequency, such as monthly, quarterly or yearly, the short-run volatility changes at the daily frequency *t*, and long-run volatility changes at the period frequency τ. As suggested by Engle, Ghysels, and Sohn (2008), we assume the daily conditional variance in period τ to be $\sqrt{\sigma_{t,\tau}^2} = \sqrt{m_\tau \times g_{t,\tau}}$, where $g_{t,\tau}$ is the daily volatility (short-run component) and m_τ denotes the long-run component. Generalized from the standard GARCH as Eq. (3), $g_{t,\tau}$ is specified as:

$$g_{t,\tau} = \omega + \alpha \frac{{\varepsilon_{t-1,\tau}}^2}{m_\tau} + \beta g_{t-1,\tau} \tag{7}$$

where $\varepsilon_{t,\tau}$ is the innovation of the green or brown stock index returns as defined in Eq. (1) and Eq. (2). Engle et al. (2013) specify m_τ by smoothing the realized volatility or macroeconomic (exogenous) variable in the spirit of MIDAS regression:

$$\ln m_\tau = m + \theta \sum_{k=1}^{K} \varphi_k(w, 1) X_{\tau-k} \tag{8}$$

where $X_{\tau-k}$ is the low-frequency part, such as the climate risk index. Notably, we use the innovation of $X_{\tau-k}$ from the AR(1) regression as Engle et al. (2020) suggests, where *K* is the maximum lag. $\varphi_k(w_1, w_2)$ is a weight equation based on the beta function and described as:

$$\phi_k(w_1, w_2) = \frac{(k/K)^{w_1-1}(1-k/K)^{w_2-1}}{\sum_{j=1}^{K}(\frac{j}{K})^{w_1-1}(1-\frac{j}{K})^{w_2-1}} \tag{9}$$

where we set $w_2 = 1$ as suggested by Engle et al. (2008) and Colacito et al. (2011). Similar to Eq. (7), we also decompose the daily conditional volatility σ_t^2 as in GJRGARCH, EGARCH, and APARCH, into two components in the MIDAS regression. We omit the details here, but the reader can refer to the work of Amendola et al. (2019, 2021).

2.3 DCC-MIDAS models

The dynamic correlation model of mixed data sampling (DCC-MIDAS) is based on the DCC model of Engle (2002) and the GARCH-MIDAS model of Engle et al. (2008). Among them, the DCC-MIDAS model mainly examines the impact of the long-run components extracted by mixed data sampling on the long-run fluctuation and dynamic correlation of financial time series, in our case the returns of green and brown stocks.

Specifically, for each asset $i,j = 1,2$ to denote the green and brown stock indices. The univariate return series satisfies the GARCH-MIDAS process. The conditional correlation between them at daily frequency t is:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}}\sqrt{q_{j,j,t}}} \tag{10}$$

We adopt Colacito, Engle, and Ghysels' (2011) version of the multivariate DCC-MIDAS model in which the covariates directly affect the long-run component of green and brown stock index returns. That is, $q_{i,j,t}$ is given by:

$$q_{i,j,t} = \bar{\rho}_{i,j,\tau}(1 - a - b) + a\varepsilon_{i,t-1}\varepsilon_{j,t-1} + bq_{i,j,t-1} \tag{11}$$

where $\bar{\rho}_{i,j,\tau}$ is the long-run component of conditional correlation given by:

$$\bar{\rho}_{i,j,\tau} = \sum_{l=1}^{L} \varphi_l(w_c, 1)C_{\tau-l} \tag{12}$$

where C_τ is the averaged conditional correlation of $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ in period τ. To capture the effect of climate risk on the long-run correlation, we also introduce the effect directly into Eq. (12) following the spirit of Eq. (8). The difference is that a logistic transformation $\Lambda(x)$ is needed to make a valid definition of correlation:

$$\bar{\rho}_{i,j,\tau} = \Lambda(2x_\tau),\ \ x_\tau = m_c + \theta_c \sum_{l=1}^{L} \varphi_l(w_c, 1)X_{\tau-l} \tag{13}$$

where X_τ is the low-frequency part which is set to be climate risk index in our present work.

Motivated by the ADCC-GARCH model of Cappiello et al. (2006), we follow Amendola et al. (2019) and introduce an asymmetric term into the standard DCC model:

$$q_{i,j,t} = \bar{\rho}_{i,j,\tau}(1 - a - b) - g\bar{n}_{i,j,\tau} + a\varepsilon_{i,t-1}\varepsilon_{j,t-1} + gn_{i,t-1}n_{j,t-1} + bq_{i,j,t-1} \tag{14}$$

where $n_{i,t} = \min(\varepsilon_{i,t}, 0)$, and $\bar{n}_{i,j,\tau}$ is the average of $n_{i,t-1}n_{j,t-1}$ in period τ.

In addition to the multivariate normal distribution, we introduce the bivariate skew-t distribution (*bskew-t*) proposed by Bauwens and Laurent (2005) to accommodate the leptokurtosis and non-zero skewness in the standardized innovations z_i. The density function is:

$$bskew - t(z|\nu, \lambda_1, \lambda_2) = C\left(\prod_{i=1}^{2} \frac{2b}{\lambda_i + \frac{1}{\lambda_i}}\right)\left(1 + \frac{{z^*}'z^*}{\nu - 2}\right)^{\frac{\nu+2}{2}}$$

where λ_1, λ_2 are the skewness parameters, ν is the degrees of freedom parameter, $z^* = \left(z_i^*, z_j^*\right)'$, $z_i^* = (b_i z_i + a_i)\lambda_i^{I_i}$, the indicator function $I_i = 1$ if $z_i < a_i/b_i$, otherwise, $I_i = -1$; and the constants a_i, b_i and C are:

$$a_i = \frac{\Gamma\left(\frac{v-1}{2}\right)\sqrt{v-2}}{\sqrt{\pi}\Gamma\left(\frac{v}{2}\right)}\left(\lambda_i - \frac{1}{\lambda_i}\right)\ ,\ b_i^2 = \left(\lambda_i + \frac{1}{\lambda_i} - 1\right) - a_i^2\ ,\ C = \frac{\Gamma\left(\frac{v+2}{2}\right)}{\pi(v-2)\Gamma\left(\frac{v}{2}\right)}$$

With this density function, the log-likelihood function is directly equivalent to that of Cappiello et al. (2006).

3 Data

We combine daily brown and green energy stocks data with monthly observations of climate risk data. Our sample period ends in March 2021 when we coded the models in Section 2. The final sample period relies on the merging of results when we apply the GARCH-MIDAS and DCC-MIDAS models. For example, when we use GARCH-MIDAS with CCN, the final sample period ends in June 2017 because of the availability of CCN. However, when we use GARCH-MIDAS with CPU, the final sample period ends in March 2021[3].

3.1 Green and brown energy stock indices

We measure the performance of green energy stocks using the WilderHill clean energy index which has a varied scope covering the universe of businesses that are

[3] Although updated data is now available, at the time of writing the paper and model estimation, data were available till June 2017 for CCN and March 2021 for CPU.

positioned to benefit from a transition to cleaner energy from wind, solar, biofuels, and geothermal companies. These companies belong to various sectors such as industrials, technology, consumer discretionary, materials, and utilities. Their selection is dictated by their contribution to the progress of clean energy in an ecological and economic manner. For the performance of brown energy stocks, we use the S&P500 Energy Sector Index, which covers the energy sector of the S&P 500 Index, represented by companies belonging to the oil, gas and consumable fuel, energy equipment and services industries, such as Exxon Mobil Corporation, Chevron Corporation, and ConocoPhillips. Data on both indices are USD-denominated. They are collected from DataStream. The sample period begins from January 1, 2001 when both indices' data are available, and ends on March 31, 2021, when we began the present work.

3.2 Climate risk data

We consider three climate risk measures, the Climate Policy Uncertainty (CPU) index of Gavriilidis (2021)[4], and the Wall Street Journal Climate Change News (CCN) index and Negative Climate Change News (NCCN) index proposed by Engle et al. (2020)[5].

The CPU index is developed in *Measuring Climate Policy Uncertainty* (Gavriilidis, 2021), in which the author searches for articles in eight leading US newspapers containing the terms {"uncertainty" or "uncertain"} and {"carbon dioxide" or "climate" or "climate risk" or "greenhouse gas emissions" or "greenhouse" or "CO2" or "emissions" or "global warming" or "climate change" or "green energy" or "renewable energy" or "environmental"} and ("regulation" or "legislation" or "White House" or "Congress" or "EPA" or "law" or "policy"} from January 2000 to March 2021. The eight newspapers are the Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and Wall Street Journal. For each newspaper, Gavriilidis (2021) scales the number of relevant articles per month to the total number of articles during the same month. The eight series are standardized to

[4] CPU data are extracted from http://policyuncertainty.com/climate_uncertainty.html.
[5] Data on CCN and NCCN indices are shared by Engle et al. (2020).

have a unit standard deviation and averaged across newspapers by month. Finally, the averaged series are normalized to have a mean value of 100 for the period January 2000 to March 2021.

The CCN and NCCN indices are developed by Engle et al. (2020), who compare news content to a corpus of authoritative texts on the subject of climate change. In particular, they collect 19 climate change white papers from sources such as the Intergovernmental Panel on Climate Change (IPCC), and complement these with 55 climate change glossaries from sources such as the United Nations, NASA, IPCC, EPA, and others. They aggregate the seventy-four text documents into a “Climate Change Vocabulary” (CCV), which amounts to a list of unique terms (stemmed unigrams and bigrams) and the associated frequency with which each term appears in the aggregated corpus. They form an analogous list of term counts for the WSJ. Each (daily) edition of the WSJ is treated as a “document”, and term counts are tallied separately for each document. They convert the WSJ term counts into “term frequency-inverse document frequency”, or tf-idf, scores. Common terms that appear in most documents earn low scores because they are less informative about any individual document’s content (they have low idf), as do terms that are rare in a given article (they have low tf). The tf-idf transformation defines the most representative terms in a given document to be those that appear infrequently overall, but frequently in that specific document (see Gentzkow, Kelly, and Taddy, 2018). As with the WSJ, they convert the CCV term counts into tf-idf. They treat the aggregated CCV as a single document when calculating term frequencies, and apply the inverse document frequency calculation from the WSJ corpus. Finally, they construct the daily climate change index as the “cosine similarity” between the tf-idf scores for the CCV and each daily WSJ edition. Days in which the WSJ uses the same terms in the same proportion as the CCV earn an index value of one, while days in which the WSJ uses no words from the CCV earn an index value of zero. Approximately speaking, the raw WSJ Climate Change News Index describes the fraction of the WSJ dedicated to the topic of climate change each day, as defined by the texts that underlie the CCV. They scale this index by a factor of 10,000 to allow interpretation of the magnitudes of innovations in the index. Engle et al. (2021) define the NCCN index as the share of all news articles from the rich Crimson Hexagon (CH) database that are both about "climate change" and that have been assigned to the "negative sentiment" category. The WSJ CCN covers January 1984 to June 2017 and CH NCCN covers the period July 2008 to May 2018.

3.3 Descriptive statistics

As stated in Section 3.1 and 3.2, the sample periods of the climate risk factors vary because of data availability. Therefore, we show the summary statistics with the sample period determined after merging the related variables used in our empirical work. Specifically, the sample period covers January 2001 to June 2017 for CCN, July 2008 to May 2018 for NCCN, and January 2001 to March 2021 for CPU. For the brown and green stock indices, we report the summary statistics with the largest sample period according to the climate risk factors, that is January 1, 2001 to March 31, 2021.

Table 1 Descriptive statistics

	Panel A: Brown and green energy				Panel B: Climate risks					
	Brown energy stock returns		Green energy stock returns		CCN index		NCCN index		CPU index	
	Raw	GARCH	Raw	GARCH	Raw	AR1	Raw	AR1	Raw	AR1
mean	0.01	-0.04	0.00	-0.03	0.64	0.04	0.21	0.00	1.04	-0.00
std	1.77	1.77	2.07	2.07	0.21	0.19	0.12	0.07	0.83	14.99
min	-22.42	-22.63	-16.24	-16.52	0.34	-0.62	0.08	-0.31	0.04	-4.6E2
Q(5%)	-2.64	-2.70	-3.24	-3.26	0.39	-0.20	0.10	-0.08	0.15	-1.55
Q(10%)	-1.79	-1.85	-2.35	-2.37	0.42	-0.14	0.11	-0.06	0.23	-1.38
Q(20%)	-1.03	-1.07	-1.34	-1.36	0.48	-0.09	0.12	-0.04	0.37	-1.14
Median	0.00	-0.02	0.02	0.01	0.61	0.03	0.17	-0.01	0.88	-0.28
Q(80%)	1.10	1.06	1.36	1.33	0.77	0.15	0.29	0.04	1.57	0.96
Q(90%)	1.76	1.72	2.11	2.08	0.89	0.22	0.37	0.08	2.04	1.92
Q(95%)	2.41	2.37	3.00	2.98	0.99	0.34	0.45	0.14	2.63	3.16
max	16.96	16.67	14.52	14.27	1.94	1.09	0.71	0.31	6.29	4.89E2
Skew	**-0.67**	**-0.73**	**-0.37**	**-0.32**	**2.17**	**1.54**	**1.90**	**0.51**	**2.00**	**1.25**
Kurt	**16.23**	**16.26**	**5.68**	**5.68**	**8.97**	**7.32**	**4.13**	**4.5**	**6.87**	**418.46**
JB-stats	**5.82E3**	**5.86E3**	**7.2E3**	**7.2E3**	**1.8E4**	**1.1E4**	**3.4E4**	**2.3E3**	**1.3E4**	**3.85E7**
Sample Period	Jan. 1 2001-Mar. 31 2021 (Daily #obs.: 5283)				Jan. 2001-Jun. 2017 (Monthly #obs.: 198)		Jul. 2008-May. 2018 (Monthly #obs.: 108)		Jan. 2001-Mar. 2021 (Monthly #obs.: 243)	

Note: We report the descriptive statistics of the raw returns of brown and green stock index, and their innovations filtered by GARCH(1,1). AR1 denotes the first-order autoregression. Climate risk factors include the CCN and

NCCN (negative change counterpart of WSJ) shared by Engle et al. (2020), and CPU from Gavriilidis (2021). We present the statistical significance of skewness and excess kurtosis (kurtosis minus 3) with the assumption of normality, that is, zero-mean and $\sqrt{6/T}$ and $\sqrt{24/T}$ standard deviation respectively. JB-stats indicates the Jarque-Bera test result for the assumption of normality. The results in bold are statistically significant at the 5% level.

Panel A of Table 1 provides summary statistics for the energy stock return series. While the sample mean of the returns is positive for both the green and brown energy stock indices, the unconditional standard deviation of the green energy stocks returns (2.054) is higher than that of the brown energy stock returns (1.782). Panel B of Table 1 provides the descriptive statistics for the climate risk data, where the mean of CPU is the largest and has the highest standard deviation.

Figure 1 The dynamics of brown and green stock indices with CCN, NCCN, and CPU

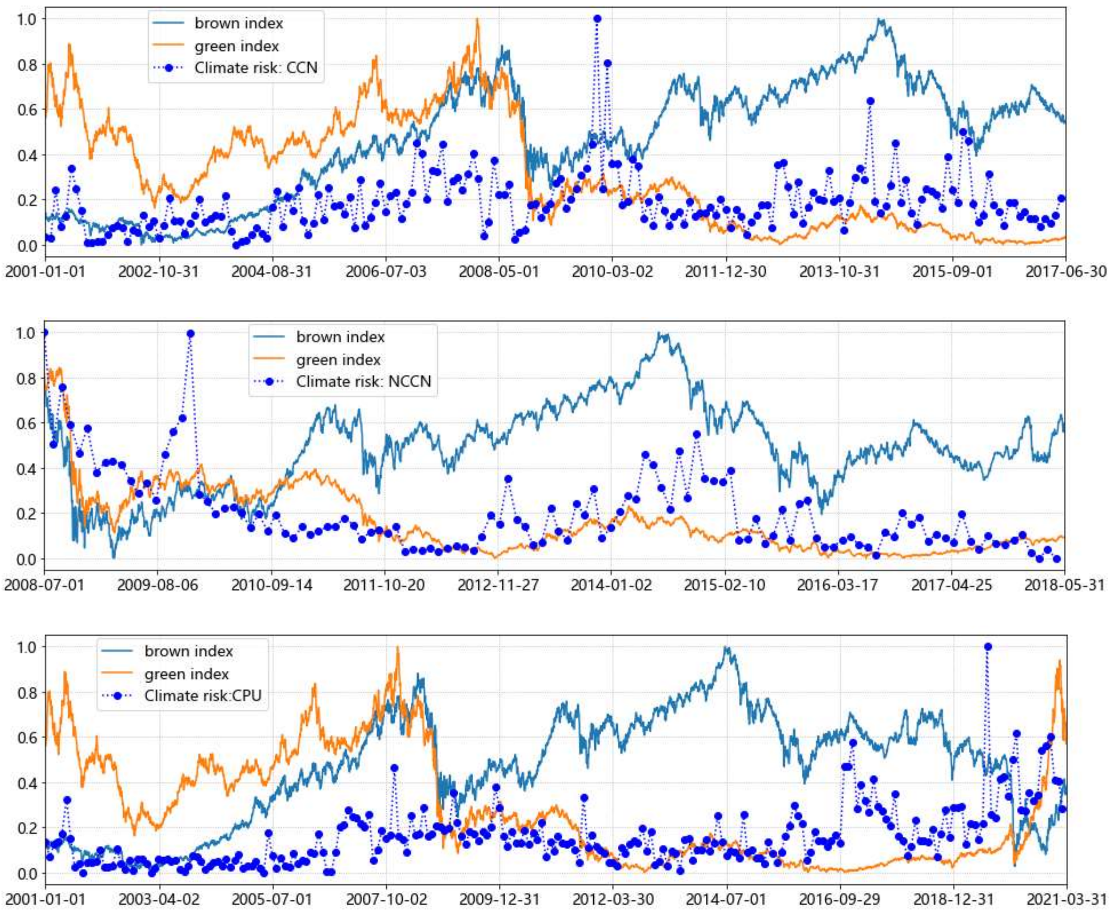

Figure 1 shows the dynamics of the brown and green stock indices with CCN, NCCN, and CPU. To make the data comparable, we scale each series to [0,1] and draw them in each panel relative to each climate risk factor. From Figure 1, we can see that the brown energy index fluctuates much more than the green energy index. Furthermore, CCN seems much more correlated with the two energy indices. Specifically, the monthly returns of the brown stock index are correlated to CCN, NCCN, and CPU with Pearson coefficients[6] of 0.049, -0.263 and 0.006, respectively, while the monthly returns of the green stock index are correlated by 0.100, -0.178 and 0.137, respectively.

4 The effect of climate risk on long-run volatility and correlation

We first present the long-run volatilities of the brown and green stock indices and how they relate to the climate risk factors based on GARCH-MIDAS with various specifications of structure and conditional distribution. We then show the relation of the climate risk factors to the long-run correlations between the brown and green stock index returns based on various DCC-MIDAS specifications.

4.1 The effect of climate risk on the long-run volatility of brown and green energy stock indices

Tables 2 and 3 present the estimated results of the impact of the WSJ climate risk factor on the brown and green stock index long-run volatilities based on GARCH-MIDAS, GJRGARCH-MIDAS, EGARCH-MIDAS and APARCH-MIDAS with the conditional distribution of standard t and skew-t. To ensure comparability across all specifications, we choose K = 12 for both returns. We see that the estimated α and β in Tables 2 and 3 are all significantly positive, and $\alpha + \beta$ is near to one for both energy stock returns. That is, the short-run volatility component for all specifications is mean-reverting to the long-run trend.

Both Table 2 and Table 3 show that the γ parameters in the GJRGARCH-MIDAS and APARCH-MIDAS models are significantly positive, and in the EGARCH-MIDAS model are significantly negative. That is, the "leverage effect" measured by γ is consistent with the common knowledge that a negative innovation leads to larger conditional volatility in the next period than a positive innovation of the same

[6] The coefficients are calculated based on all observations with each pair of series.

magnitude. The diagnostic statistics, LLF, AIC, and BIC, consistently show that the model fitness is better when we use the conditional distribution with skewness parameter (λ). All the estimated results of λ are significantly negative, implying that both energy stock returns are significantly and negatively skewed, which is consistent with common knowledge. Finally, all the diagnostic statistics suggest that EGARCH-MIDAS with skew-t distribution has the best fitting performance.

Table 2 Conditional volatility of brown energy stock index with the climate risk factor CCN

Coef.	GARCH-MIDAS		GJRGARCH-MIDAS		EGARCH-MIDAS		APARCH-MIDAS	
	Std-t	Skew-t	Std-t	Skew-t	Std-t	Skew-t	Std-t	Skew-t
ω	0.025***	0.024***	0.029***	0.030***	0.011***	0.012***	0.024***	0.025***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.003)	(0.003)	(0.006)	(0.006)
α	0.072***	0.074***	0.020**	0.019**	0.124***	0.123***	0.063***	0.063***
	(0.010)	(0.010)	(0.009)	(0.008)	(0.015)	(0.014)	(0.009)	(0.009)
β	0.918***	0.913***	0.912***	0.925***	0.986***	0.987***	0.919***	0.913***
	(0.356)	(0.335)	(0.290)	(0.358)	(0.003)	(0.003)	(0.306)	(0.333)
γ			0.083***	0.084***	-0.068***	-0.069***	0.535***	0.559***
			(0.015)	(0.015)	(0.010)	(0.010)	(0.110)	(0.110)
δ							1.314***	1.296***
							(0.204)	(0.188)
m	0.181***	0.176***	0.189***	0.167***	0.390***	0.336***	0.339***	0.347***
	(0.022)	(0.023)	(0.022)	(0.023)	(0.013)	(0.018)	(0.018)	(0.018)
θ	0.192***	0.240**	0.310***	0.233***	0.183***	0.220**	0.155**	0.197***
	(0.033)	(0.117)	(0.103)	(0.035)	(0.032)	(0.092)	(0.063)	(0.033)
w	7.032***	6.200***	6.536***	6.200***	8.152***	9.898***	6.321***	6.852***
	(2.126)	(1.760)	(2.365)	(1.729)	(2.384)	(3.582)	(1.819)	(2.030)
η	8.955***	9.868***	9.795***	10.813***	9.799***	10.812***	9.941***	10.979***
	(1.155)	(1.376)	(1.373)	(1.637)	(1.354)	(1.613)	(1.402)	(1.670)
λ		-0.098***		-0.107***		-0.108***		-0.110***
		(0.021)		(0.021)		(0.022)		(0.021)
LLF	-7375.96	-7365.49	-7355.00	-7342.64	-7350.93	**-7313.69**	-7353.98	-7340.86
AIC	14765.91	14746.97	14726.00	14703.27	14719.86	**14665.38**	14723.97	14699.72
BIC	14810.49	14797.91	14776.94	14760.58	14777.17	**14755.26**	14774.91	14757.03

Notes: This table shows the estimated results of the short- and long-run volatility of brown energy stock returns where the exogenous variable for long-run volatility is CCN. For robustness, we consider various models of GARCH-MIDAS, GJRGARCH-MIDAS, EGARCH-MIDAS, and APARCH-MIDAS with conditional distribution of standard-t (*Std-t*) and skewed t (Skew-t). LLF, AIC and BIC are diagnostic statistics that indicate log-likelihood function value, Akaike information criterion and Bayesian information criterion. Standard errors are presented in parentheses. *p <.1; **p <.05; ***p <.01.

Table 3 Conditional volatility of green energy stock index with climate risk factor CCN

Coef.	GARCH-MIDAS		GJRGARCH-MIDAS		EGARCH-MIDAS		APARCH-MIDAS	
	Std-t	Skew-t	Std-t	Skew-t	Std-t	Skew-t	Std-t	Skew-t
ω	0.057***	0.057***	0.071***	0.073***	0.025***	0.026***	0.079***	0.082***
	(0.018)	(0.017)	(0.020)	(0.020)	(0.007)	(0.007)	(0.026)	(0.026)
α	0.077***	0.076***	0.041***	0.040***	0.151***	0.149***	0.065***	0.064***
	(0.013)	(0.012)	(0.010)	(0.010)	(0.024)	(0.023)	(0.014)	(0.014)
β	0.901***	0.907***	0.903***	0.904***	0.981***	0.980***	0.913***	0.921***
	(0.348)	(0.016)	(0.017)	(0.016)	(0.006)	(0.006)	(0.298)	(0.349)
γ			0.066***	0.066***	-0.048***	-0.048***	0.214***	0.222***
			(0.017)	(0.017)	(0.011)	(0.011)	(0.063)	(0.064)
δ							2.248***	2.243***
							(0.362)	(0.354)
m	0.445***	0.443***	0.448***	0.350**	0.397**	0.440**	0.429**	0.413***
	(0.018)	(0.018)	(0.019)	(0.150)	(0.187)	(0.198)	(0.191)	(0.140)
θ	0.150	0.149	0.142	0.130	0.386	0.360	0.346	0.367
	(0.190)	(0.116)	(0.172)	(0.115)	(0.391)	(0.335)	(0.338)	(0.269)
w	18.800*	18.607*	18.860**	16.552**	14.080**	16.619*	18.295***	15.106**
	(10.256)	(9.969)	(9.024)	(7.231)	(5.919)	(8.668)	(5.967)	(7.624)
η	10.055***	10.339***	10.360***	10.479***	9.632***	9.813***	10.426***	10.534***
	(1.487)	(1.575)	(1.589)	(1.619)	(1.343)	(1.394)	(1.616)	(1.642)
λ		-0.112***		-0.095***		-0.091***		-0.088***
		(0.038)		(0.036)		(0.035)		(0.032)
LLF	-8443.35	-8424.37	-8420.21	-8411.97	-8419.93	**-8411.70**	-8434.75	-8426.80
AIC	16910.71	16882.75	16874.41	16859.93	16875.86	**16858.40**	16903.50	16889.60
BIC	16987.10	16990.96	16982.63	16974.51	16990.43	**16981.34**	17011.71	17004.17

Notes: This table shows the estimated results of the short- and long-run volatility of green energy stock returns where the exogenous variable for long-run volatility is CCN. For robustness, we consider various models of GARCH-MIDAS, GJRGARCH-MIDAS, EGARCH-MIDAS, and APARCH-MIDAS with conditional distribution of standard-t (*Std-t*) and skewed t (*Skew-t*). LLF, AIC and BIC are diagnostic statistics that indicate log-likelihood function value, Akaike information criterion and Bayesian information criterion. Standard errors are presented in parentheses. *p <.1; **p <.05; ***p <.01.

The coefficient of interest, θ, measures how the climate risk factor (CCN) affects the long-run component of the energy stock indices' conditional volatility. The estimated results in Table 2 show that θ is significantly positive at various specifications, which implies that higher levels of climate change lead to a rise in long-run brown energy stock volatility. However, Table 3 shows that the estimated θ is insignificant at various specifications, implying that the climate risk factor of CCN does not significantly affect the long-run volatility of green stock index returns.

Table 4 presents the estimated results for the effect of the other two climate risk factors, NCCN and CPU, on the conditional volatilities of brown stock index returns. To save space, we omit the estimated coefficient results for the variance equations as indicated by Eqs. (4)-(6)[7]. That is, we only report the estimated results for the coefficients in the MIDAS regression on the long-run volatilities as in Eq. (8), which demonstrate how the climate risk factors NCCN and CPU affect the long-run volatilities of brown stock index returns. We also report the diagnostic statistics, LLF, AIC, and BIC, in Table 4. For the green stock index, Table 5 shows the estimated results in a similar way to Table 4.

The results in Table 4 show significantly negative skewness of the conditional distribution (in accordance with Table 2) and the fitness of the models with the skewness parameter is better, as suggested by the diagnostic statistics. All the diagnostic statistics suggest that EGARCH-MIDAS with skew-t distribution has the best fitting performance. The important result is that both of the two climate risk factors (NCCN and CPU) significantly increase the long-run volatility of the brown energy index. As far the economic size of the effect on brown energy stock is concerned, NCCN has larger effect than CCN and CPU, compared to the results in Table 2.

Table 4 Effect of NCCN and CPU on the long-run volatilities of the brown energy stock index

Coeff.	GARCH-MIDAS		GJRGARCH-MIDAS		EGARCH-MIDAS		APARCH-MIDAS	
	Std-t	Skew-t	Std-t	Skew-t	Std-t	Skew-t	Std-t	Skew-t
Panel A: MIDAS with NCCN								
m	0.113**	0.170***	0.186**	0.299***	0.429***	0.432***	0.576***	0.507***
	(0.044)	(0.061)	(0.078)	(0.114)	(0.142)	(0.147)	(0.215)	(0.165)
θ	0.475**	0.409***	0.389***	0.319**	0.483**	0.478***	0.411***	0.442***
	(0.199)	(0.137)	(0.145)	(0.141)	(0.204)	(0.165)	(0.153)	(0.150)
w	7.068***	8.895***	7.612**	8.630**	8.833***	9.131***	8.842*	9.870*
	(2.583)	(3.143)	(3.396)	(3.709)	(2.964)	(3.212)	(4.751)	(5.413)

[7] The detailed results are available on request.

η	10.511*** (3.906)	10.419*** (3.723)	9.173*** (2.695)	9.268*** (2.877)	10.527*** (3.449)	9.975*** (3.800)	10.440*** (3.844)	9.821*** (3.508)
λ		-0.103*** (0.019)		-0.102** (0.050)		-0.091** (0.039)		-0.087*** (0.018)
LLF	-7329.95	-7326.66	-7327.65	-7325.68	-7304.47	-7296.11	-7305.93	**-7290.81**
AIC	14740.70	14733.72	14727.83	14702.07	14713.89	14682.07	14718.59	**14643.48**
BIC	14821.11	14810.79	14818.30	14796.34	14776.98	14751.71	14767.25	**14755.15**
Panel B: MIDAS with CPU								
m	0.519*** (0.138)	0.364*** (0.118)	0.343*** (0.124)	0.535*** (0.202)	0.498*** (0.167)	0.386*** (0.144)	0.648*** (0.243)	0.340*** (0.114)
θ	0.179*** (0.050)	0.202*** (0.067)	0.289*** (0.110)	0.156*** (0.054)	0.248*** (0.089)	0.267*** (0.099)	0.247*** (0.084)	0.163*** (0.063)
w	9.613*** (3.705)	10.130** (4.867)	10.646** (4.286)	8.879** (4.104)	8.869** (3.689)	9.509*** (3.579)	10.018*** (3.780)	8.915*** (3.278)
η	8.011*** (2.593)	8.293*** (3.142)	10.301*** (3.862)	9.226*** (3.581)	8.127*** (3.152)	7.865*** (2.997)	9.615*** (3.693)	7.519*** (2.689)
λ		-0.122*** (0.002)		-0.119** (0.054)		-0.115*** (0.013)		-0.089*** (0.027)
LLF	-7321.71	-7308.68	-7315.34	-7308.31	-7297.22	-7288.17	-7293.03	**-7282.83**
AIC	14724.03	14714.51	14682.47	14695.70	14664.51	14678.03	14667.98	**14651.12**
BIC	14840.84	14831.82	14846.71	14828.56	14840.32	14795.71	14822.03	**14793.69**

Notes: This table shows the estimated results of the long-run volatility of brown energy stock returns where the exogenous variable for long-run volatility is NCCN in Panel A and CPU in Panel B. We omit the estimated results of the short-run components to save space. For robustness, we consider various models of GARCH-MIDAS, GJRGARCH-MIDAS, EGARCH-MIDAS, and APARCH-MIDAS with conditional distribution of standard-t (*Std-t*) and skewed t (*Skew-t*). LLF, AIC and BIC are diagnostic statistics that indicate log-likelihood function value, Akaike information criterion and Bayesian information criterion. Standard errors are presented in parentheses. *p <.1; **p <.05; ***p <.01.

Table 5 presents the estimated coefficient, θ, for both NCCN and CPU, which does not significantly affect the long-run volatility of the green stock index. This implies that climate risk matters for the volatility of the polluting energy sector but not the clean energy sector. Specifically, under the energy transition, investors switch from the polluting brown energy sector, leading to an increase in its volatility, to green energy stocks, which seem not to experience any significant change in volatility, reflecting the rough movement of stock investments from brown energy and the smooth stock movement to green energy.

Table 5 Effect of NCCN and CPU on the long-run volatilities of the green energy stock index

Coeff.	GARCH-MIDAS		GJRGARCH-MIDAS		EGARCH-MIDAS		APARCH-MIDAS	
	Std-t	Skew-t	Std-t	Skew-t	Std-t	Skew-t	Std-t	Skew-t
Panel A: MIDAS with NCCN								
m	0.498***	0.601***	0.525***	0.568***	0.384***	0.521***	0.371***	0.644***
	(0.177)	(0.219)	(0.181)	(0.185)	(0.129)	(0.184)	(0.127)	(0.233)
θ	0.332	0.201	0.217	0.251	0.348	0.313	0.331	0.250
	(0.203)	(0.144)	(0.167)	(0.294)	(0.273)	(0.203)	(0.204)	(0.181)
w	16.784*	15.759**	13.797***	10.573*	14.102**	15.208***	17.247***	16.169***
	(8.699)	(7.650)	(4.498)	(5.880)	(6.118)	(5.514)	(6.593)	(5.703)
η	5.105**	5.701**	6.839**	8.950**	7.350**	8.017**	10.911***	10.796**
	(2.265)	(2.299)	(3.294)	(3.982)	(3.482)	(3.758)	(3.780)	(4.736)
λ		-0.124***		-0.122***		-0.094***		-0.086***
		(0.016)		(0.041)		(0.014)		(0.002)
LLF	-8446.68	-8436.95	-8442.20	-8433.80	-8448.15	-8436.95	-8432.00	**-8430.52**
AIC	17007.87	17005.88	17004.97	16995.93	16991.26	16984.67	16989.50	**16972.21**
BIC	17006.23	17002.18	17004.91	16990.57	16997.61	16988.76	16996.30	**16986.48**
Panel B: MIDAS with CPU								
m	0.520***	0.614***	0.271***	0.545***	0.525***	0.398***	0.322***	0.405***
	(0.163)	(0.226)	(0.099)	(0.189)	(0.164)	(0.150)	(0.108)	(0.156)
θ	0.165	0.214	0.303	0.221	0.194	0.276	0.203	0.301
	(0.156)	(0.168)	(0.333)	(0.163)	(0.199)	(0.266)	(0.230)	(0.337)
w	14.117***	17.144***	13.381***	16.928***	14.582**	16.371*	15.384**	16.193*
	(5.218)	(6.054)	(4.756)	(5.426)	(7.253)	(8.447)	(7.713)	(8.322)
η	7.285***	8.311***	9.640***	10.040***	10.293***	10.277***	10.375***	10.536***
	(2.725)	(2.732)	(2.973)	(3.002)	(3.843)	(3.838)	(3.915)	(3.780)
λ		-0.132***		-0.110***		-0.084*		-0.081**
		(0.040)		(0.039)		(0.044)		(0.038)
LLF	-8453.12	-8442.76	-8440.55	-8428.24	-8421.01	-8416.55	-8420.27	**-8411.46**
AIC	17011.99	17008.23	17003.34	16994.01	16995.76	16989.64	16996.69	**16987.67**
BIC	17008.18	17005.68	17008.43	16993.62	16991.65	16989.36	16990.45	**16980.09**

Notes: This table shows the estimated results of the long-run volatility of green energy stock returns where the exogenous variable for long-run volatility is NCCN in Panel A and CPU in Panel B. We omit the estimated results of the short-run components to save space. For robustness, we consider various models of GARCH-MIDAS, GJRGARCH-MIDAS, EGARCH-MIDAS, and APARCH-MIDAS with conditional distribution of standard-t (*Std-t*) and skewed t (*Skew-t*). LLF, AIC and BIC are diagnostic statistics that indicate log-likelihood function value, Akaike information criterion and Bayesian information criterion. Standard errors are presented in parentheses. *p <.1; **p <.05; ***p <.01.

4.2 The effect of climate risk on the long-run correlation between the brown and green energy stock indices

In this section, we analyse how the climate risk factor affects the long-run correlation between green and brown stock index returns. As Eq. (11) and Eq. (14) indicate, we introduce the symmetric and asymmetric innovation shock into the short-run correlation, denoted as DCC-MIDAS and ADCC-MIDAS. For the variance equation, before estimating the dynamic correlation, we adopt the suggestion from Tables 2 to 5 that the EGARCH-MIDAS with skew-t distribution has the best fitting performance. Therefore, we omit the other specifications for volatilities from the estimation of dynamic correlation. Similarly, we consider only the conditional distribution of the dynamic correlation *bskew-t* because of the significant and negative skewness in both the brown and green energy stock index returns. We include one lag year of climate risk factor into the MIDAS regression for the long-run correlation, i.e., $L = 12$ in Eq. (13), as for the long-run volatilities.

As Table 6 shows that the estimated coefficients a and b for DCC-MIDAS and ADCC-MIDAS have a sum near to one. This implies that the quasi-correlations are mean-reverted. The significant and positive estimation of g for ADCC-MIDAS suggests that the dynamic correlation increases much more with both negative innovations in brown and green stock index returns. The diagnostic statistics of AIC, BIC and LLF show that the models with asymmetric effects of returns innovation on the conditional correlation have the better fitting performance. The important result in Table 6 is that the estimated coefficients of θ are all significantly negative. This implies that the long-run conditional correlation between the brown and green stock index returns decreases with an increase in climate risk, irrespective whether the risk proxy is CCN, NCCN or CPU. Another interesting result is that the economic size of the effect is much larger when we use NCCN as the proxy of climate risk, suggesting that the correlation between the returns of brown and green energy stock indices are more sensitive to negative climate change news and sentiment (Engle et al., 2020). This result is not surprising given previous evidence for the tendency of investors to move away from brown energy to green and clean energy investments under high temperatures (Choi et al., 2020) and intensified climate risk (Pástor et al., 2021; Bouri et al., 2022), as captured by negative climate change news.

Table 6 Estimated results of (A)DCC-MIDAS for the brown and green energy stock indices with the effect of climate risk factors

Coef.	DCC-EGARCH-MIDAS			ADCC-EGARCH-MIDAS		
	CCN	NCCN	CPU	CCN	NCCN	CPU
a	0.107***	0.151**	0.104*	0.085**	0.098***	0.051***
	(0.015)	(0.075)	(0.054)	(0.043)	(0.027)	(0.019)
b	0.892***	0.875**	0.859*	0.895***	0.890*	0.916**
	(0.313)	(0.425)	(0.453)	(0.328)	(0.458)	(0.430)
g				0.068*	0.020**	0.031*
				(0.035)	(0.009)	(0.016)
m	1.569**	0.746*	1.317**	0.814**	1.751*	0.817**
	(0.624)	(0.381)	(0.542)	(0.393)	(0.989)	(0.340)
θ	-0.069*	-0.289***	-0.063*	-0.070**	-0.269*	-0.078*
	(0.040)	(0.106)	(0.034)	(0.035)	(0.157)	(0.045)
w_c	7.855***	3.495**	2.221*	3.257**	6.655**	5.153*
	(2.780)	(1.527)	(1.145)	(1.528)	(2.929)	(2.690)
λ_1	-0.102***	-0.165**	-0.138**	-0.078**	-0.127***	-0.216**
	(0.038)	(0.069)	(0.058)	(0.034)	(0.042)	(0.101)
λ_2	-0.073***	-0.211***	-0.162**	-0.167***	-0.220**	-0.208***
	(0.027)	(0.074)	(0.081)	(0.060)	(0.092)	(0.067)
ν	9.175***	10.896**	9.550***	9.907**	10.284***	10.811***
	(3.293)	(5.256)	(3.647)	(4.147)	(3.651)	(2.951)
AIC	11827.67	11775.95	11819.92	11750.27	11750.27	11780.73
BIC	11849.90	12230.00	15172.05	11818.49	12139.64	15081.19
LLF	-5899.30	-6094.24	-7574.07	-5882.88	-5966.75	-7519.29

Notes: This table shows the estimated results of the short- and long-run correlations of the brown and green energy stock returns, where the exogenous variable for the long-run component is CCN, NCCN and CPU. We consider only (A)DCC-EGARCH-MIDAS with conditional distribution of skewed t (*Skew-t*) according to the diagnostic results in Tables 2-5. LLF, AIC and BIC are diagnostic statistics that indicate log-likelihood function value, Akaike information criterion and Bayesian information criterion. Standard errors are presented in parentheses. *p <.1; **p <.05; ***p <.01.

5 Hedging performance with the effect of the climate risk factor

The significant negative effect of the climate risk factor on the dynamic correlation between the returns of brown and green energy stock indices suggests that including the climate risk factor may be helpful to improve the hedging performance of the two indices. Therefore, we test this implication by considering the hedge ratio and hedging effectiveness.

Firstly, we follow Kroner and Sultan (1993) and compute the optimal hedge ratio between the brown and green stock indices at day *t*:

$$\beta_t = \rho_t \cdot \frac{\sigma_t^b}{\sigma_t^g}$$

where σ_t^b and σ_t^g are the conditional volatility of the brown and green stock index returns on day *t*, and ρ_t is their time varying correlation, which are all extracted from EGARCH-ADCC-MIDAS with *bskew-t* distribution. We do one-day-ahead prediction for σ_t^b, σ_t^g and ρ_t using a rolling window scheme. As a robustness check, we choose window sizes of 10, 30 and 60 days. That is, we leave 2/3 of the sample (in-sample) to fit the model and do one-day-ahead prediction. Then, we fix the length of the in-sample but fit the model again, after the window size of the prediction has been done. We repeat such a procedure until the remaining 1/3 sample (out-of-sample) is used. With the help of the predicted σ_t^b, σ_t^g and ρ_t, we can easily compute the optimal hedge ratio (β_t) and thus the hedged portfolio returns as:

$$R_{H,t} = R_{b,t} - \beta_t R_{g,t}$$

where $R_{b,t}$ and $R_{g,t}$ are the out-of-sample daily returns of the brown and green stock indices.

Secondly, we measure the hedging effectiveness as:

$$HE = 1 - \frac{V^H}{V^U}$$

where V^H is the variance of hedged portfolio returns ($R_{H,t}$), and V^U is the variance of unhedged portfolio returns ($R_{b,t}$). HE measures how much the variance of the brown index returns is hedged out by the green stock index returns with the long-short ratio β_t. The higher the HE, the better the hedging effectiveness.

To highlight the gain of adding the climate risk factor, we estimate β_t by EGARCH-ADCC-MIDAS with and without the climate risk factors. We denote the hedging ratio without the climate risk factor as β_t-None, and the hedging ratio with the climate risk factors as β_t-CCN, β_t-NCCN and β_t-CPU. Similarly, we denote the hedging effectiveness based on the model without the climate risk factor as HE-None and the models with the climate risk factors of CCN, NCCN, and CPU as HE-CCN, HE-NCCN, and HE-CPU, respectively.

Table 7 Summary statistics of hedge ratios and hedging effectiveness (HE)

	Refitting window = 10			Refitting window = 30			Refitting window = 60		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Panel A: Hedge ratio									
β_t-None	0.411	-0.292	1.648	0.487	-0.214	1.691	0.431	-0.178	1.714
β_t-CCN	0.299	-0.414	1.206	0.257	-0.396	1.302	0.291	-0.379	1.371
β_t-NCCN	0.167	-0.528	0.965	0.159	-0.501	1.024	0.189	-0.517	1.079
β_t-CPU	0.232	-0.487	1.324	0.295	-0.422	1.330	0.276	-0.411	1.285
Panel B: Hedging effectiveness									
HE-None	0.036			0.056			0.042		
HE-CCN	0.117			0.128			0.113		
HE-NCCN	0.138			0.155			0.147		
HE-CPU	0.121			0.127			0.115		

Notes: This table presents the summary statistics of the dynamic optimal hedge ratio for the green and brown stock indices in Panel A and the hedging effectiveness in Panel B. For robustness, we consider refitting window sizes of 10, 30, and 60 days after one-day-ahead prediction. For the exogenous variable in MIDAS, we compare the results from four specification of no climate risk factor (None), CCN, NCCN, and CPU.

Table 7 presents the summary statistics of the optimal hedge ratios and hedging effectiveness (HE). The hedge ratio, β_t, with the climate risk factor has a lower mean than β_t-None, which does not include any climate risk factors, for all sizes of refitting window. This implies that the hedge ratio accounting for a climate risk factor is cheaper. The HE for β_t-None is smaller than all the β_t with the climate risk factors. These results are robust to out-of-sample analysis and under various refitting window sizes. They imply that the dynamic optimal hedge ratio with climate risk leads to better hedging effectiveness. Furthermore, β_t-NCCN has a lower mean than the other statistics for all sizes of refitting window, and its hedging effectiveness (HE-NCCN) is highest. This suggests that the model including NCCN is better at capturing the negative correlation between the brown and green stock indices and thus reflects more opportunities for hedging. Overall, these results show that the correlation between brown and green energy returns is more affected by negative climate news and sentiment, captured by the NCCN index, than CPU or regular climate news. This result reflects the importance of considering comprehensive climate risk measures including the physical aspects of (negative) climate news and climate disaster events, not just transitional measures such climate policy uncertainty. This is intuitive and further confirms our choice to move beyond the CPU index used by Bouri et al. (2022), Dutta et al. (2022), and Liang et al. (2022), to consider negative climate change news.

6 Conclusions

Significant risks associated with climate change and related policies have prompted concentrated research into potential solutions and action plans for the economic transformation toward net-zero emissions in alignment with the Climate Change Conferences. In this paper, we extend the academic literature on modelling the volatility and correlation of green and brown energy stock indices by relating them to various news-based climate risk measures reflecting not only climate policy uncertainty as in previous studies (e.g. Bouri et al., 2022; Sarker et al., 2022; Liang et al., 2022; Dutta et al., 2023) but both a climate change news index and a negative climate change news index.

Using mixed data sampling models combining daily returns on green and brown energy stock indices with monthly data on climate risks, we extend, for the first time, the symmetric DCC-MIDAS model to an asymmetric DCC-MIDAS model with bivariate skew-t, to include negative skewness in innovation. The main results are as follows. Firstly, CPU, the climate change index, and the news index contain information useful for improving the prediction of the volatility of the brown energy stock index returns, whereas the impact on the volatility of the green energy stock index returns is insignificant. Secondly, the three climate risk measures reduce the green-brown returns correlation, with the negative climate change news index having the most impact. Thirdly, the practical implications are highlighted by the results of the hedging analysis, which indicates that the hedging performance between the brown and green energy stock indices is significantly improved by inserting the negative climate change news index into the long-run component of dynamic correlation.

These findings concern both investors and policymakers. Investors can build on our analysis by considering the impact of climate risk on the volatility of the brown energy stock index, notably that of negative climate change news, within a volatility prediction model, and its implications for portfolio allocation and risk management. Furthermore, the hedging benefits arising from accounting for climate risk are highlighted, which is useful for portfolio decarbonization under the energy transition towards net-zero emissions. The findings are useful for policymakers, especially given their continuous efforts to green the economy and financial system and set green financial principles and disclosure requirements for funds and investment banks on climate-related risk assessments.

Although our current paper captures the impact of exogenous climate risk shocks on the long-term fluctuation and dynamic correlation of the stock index returns of brown and green energy firms, and the hedging strategy between brown and green energy stocks, accounting for the impact of climate risk, it does not regard this portfolio as a part of a hedging framework to deal with climate change risk and thus does not provide policies for reducing climate-related risk. Nevertheless, this paper takes this topic as a starting point in a research field which offers many valuable research directions for the future.

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