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Carbon trading amidst global uncertainty: The role of policy and geopolitical uncertainty[☆]

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ABSTRACT

Economic policy uncertainty (EPU) and geopolitical uncertainty (GPU) can fuel speculation, flood the carbon trading market with excess allowances, and undermine the scheme's efficacy in tackling climate change. While the existing literature documents the adverse effects of uncertainty on macroeconomic and financial variables, the impact on the carbon trading risk remains unclear. This paper analyses the effects of EPU and GPU on the volatility and other risk levels in the carbon market using daily European Union Emissions Trading Scheme data (February 2, 2009 to 8/31/2022) and monthly data on the uncertainty indicators (2009M2–2022M8). The findings reveal that unstable policies and geopolitical tensions heighten carbon market risk since global uncertainty increases information asymmetry and risk premium and causes a delay in investment decisions. Future deliberation among the Cooperation of Parties under the United Nations Framework Convention on Climate Change should incorporate measures to mitigate global uncertainty while pushing for decarbonization and transition to clean technology.

1. Introduction

Carbon emission trading is a market-based approach that emanates from the Kyoto Protocol of the United Nations Framework Convention on Climate Change (UNFCCC) to combat climate change and greenhouse gas (GHG) emissions (Bekun et al., 2021a).[1] The carbon trading market exists as an arrangement for trading carbon emission allowances and offers a cost-effective, market-based solution to mitigate the existential threat posed by GHG emissions to the environment (Kabir et al., 2021). Among several carbon pricing mechanisms, the European Union Emissions Trading Scheme (EU-ETS) is the most developed and largest international carbon allowance market for trading in carbon allowances (Feng, 2015; Tian et al., 2016; Limei et al., 2020); therefore, it offers a suitable framework for analyzing the effectiveness of carbon trading for climate action. The motivation to focus on carbon emission trading more than other GHGs is because carbon emissions account for more than 70% of GHGs, and approximately three-quarters of carbon emissions are attributed to the unabated use of non-renewable energies and fossil fuels, such as crude oil, natural gas, and coal (Balcılar et al., 2015; Bekun et al., 2021b). This reality creates an avenue for carbon to be traded as an investment asset and enables investors to benefit from opportunities for portfolio diversification (Narayan and Sharma, 2015).

Given the financial nature of the market, this study models trading risks associated with the international carbon allowance market. Our analysis examines the carbon market's response to two classes of uncertainties that affect financial markets and highlights the practical implications of the research: economic policy uncertainty (EPU) and geopolitical uncertainty (GPU). This study provides two important contributions. First, it explores the response of the carbon market to the twin uncertainty of macroeconomic policy and security threats; see Wang et al. (2022) for a similar oil market analysis. Research on the effects of uncertainty stems from related evidence associating high policy uncertainty with stock market volatility (Dogah, 2021) and, as such, contributes to a similar analysis of the carbon trading market. Dou

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[1] The Kyoto Protocol led to three emission reduction implementation strategies. Two are project-based (clean development mechanism and joint implementation), while one currently under review (international emissions trading) is market based.

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et al. (2022) describe the carbon market as a complex volatility model in which market fundamentals (carbon allowance price and volatility) can be influenced by factors that shape the global macroeconomic environment, such as the price of oil and macroeconomic uncertainty. Thus, this study considers twin uncertainty (EPU and GPU) through a comprehensive analysis of the role of uncertainty. The two types are interlinked so that economic uncertainty increases during political tensions and upheavals, such as 9/11, the two Gulf Wars, and the war in Ukraine, among others (Wang et al., 2022).

Second, we provide empirical contributions involving extracting carbon trading risks using two approaches and different variants of EPU and GPU indices. We also adopt alternative approaches to examine the predictive content of the uncertainty indicators as predictors of carbon trading risk. The first is a model-based approach with which we extracted the realized volatility series as a measure of carbon trading risk using the generalized autoregressive conditional heteroscedasticity mixed data sampling (GARCH-MIDAS) approach (Ghysels et al., 2006; Engle et al., 2013). The second is the value at risk (VaR) approach (Best, 1998; Lian et al., 2020; Li et al., 2021), which uses the tail distribution of carbon price returns (as a measure of the potential loss of investors due to downside risk) to gage the systemic risk of the carbon allowance market. We use the conditional autoregressive value at risk (CAViaR) approach (Engle and Manganelli, 2004) to compute the carbon trading risk following Feng et al. (2012), who argued that exceptional circumstances, such as energy price crashes and macroeconomic uncertainty, could cause extreme tail movements in the carbon market. For robustness, we compare the effects of EPU and GPU on carbon price risk using global, European Union (EU), and American (US) uncertainty indicators.

This research is motivated by important policy and investment considerations. First, volatile carbon allowance prices could encourage speculation, lead to excess carbon allowances, and reduce the incentive for parties to participate in climate change agreements requiring a switch to clean technology. An unstable carbon price could also weaken the carbon trading market's ability to promote decarbonization (Dou et al., 2022) effectively. Second, increased and frequent uncertainty could exacerbate carbon price volatility and heighten speculation in the carbon market, possibly leading to the failure of the carbon allowance market to act as an effective decarbonization strategy. With higher market risks, investors may overreact by employing risk-hedging techniques to hold more commodity assets rather than carbon allowances to hedge the risk resulting from uncertainty, leaving the market with an excess supply of carbon allowances, which is detrimental to the drive to switch to cleaner technologies.

Based on extensive data analysis, this study's findings provide robust evidence of a strong and positive relationship between uncertainty and carbon trading risk. The results support the theory that macroeconomic uncertainty exacerbates volatility and risk in the carbon trading market. The findings of this research can be of interest to policymakers—particularly those involved in global discussions on climate change—that must be informed on the uncertainty that affects macroeconomic performance. Policymakers should realize that uncertainty could jeopardize the success of carbon trading as a market-based environmental sustainability strategy if left unchecked. The forecasting analysis in this study can also interest researchers and investors who should be aware that uncertainty indicators, especially EPU, provide valuable information about forecasting carbon market fundamentals.

The remaining sections of the paper are structured as follows. Section 2 discusses several underlying theoretical and empirical issues related to the macroeconomic impacts of uncertainty; more specifically, this section introduces and explains the nexus between carbon trading risk and uncertainty. Section 3 outlines the methodology for estimation and forecasting evaluation used in the study. Section 4 presents the results, and Section 5 is the conclusion.

2. Motivation

2.1. Macroeconomic effects of uncertainty

The extant theoretical and empirical literature appears to unanimously agree that macroeconomic uncertainty is linked to lower economic performance in many countries as uncertainty increases information asymmetry and credit risk and reduces investment (Bloom, 2009; Kang and Ratti, 2013; Phan et al., 2020; Demir and Danisman, 2021). Because increased information asymmetry is attributable to uncertainty, lenders find it difficult to distinguish between good and bad credit risk and hesitate to lend money, reducing investment and economic activity. An increase in uncertainty leads investors to adopt more conservative approaches while making investment decisions; they either retain their cash holdings as a precautionary measure or demand higher expected rates of returns, thereby slowing investment, production, and employment. Firms also tend to freeze hiring under these conditions (Handley and Limão, 2015; Al-Thaqeb and Algharabali, 2019; Phan et al., 2019; Dogah, 2021; Kim et al., 2021; Kisswani and Elian, 2021). Additionally, as businesses delay investment decisions due to uncertainty, consumers purchase fewer durable goods, such as automobiles, houses, and home appliances, waiting until the macroeconomic outlook improves (Yilanci and Kilci, 2021).

Shafiullah et al. (2021) presented a strong and comprehensive argument from the investor angle, suggesting that investors need policy stability to make long-term investment decisions that often involve significant capital outlays. Investors only commit vast resources if they see the prospect of positive net present value. The net current value of investment outlays depends on the discounting rate and future cash flow; however, uncertainty can influence both factors. For instance, EPU can affect the discount rate, so investment fund providers require higher discounting rates for projects in high-EPU environments. Moreover, EPU makes evaluating risks associated with an investment project challenging and complicates the estimation of expected future cash flows, explaining why investment decisions are usually put on hold due to heightened uncertainty.

For investors, EPU also constitutes a high-investment risk in equities because the uncertainty affects investor behavior and response, making it difficult for regulators to anticipate effective monetary policy (Tsai, 2017; Dash and Maitra, 2021). Higher uncertainty prompts investors to switch from riskier to hedge/diversifier assets and transfer investments from markets/regions with more significant uncertainty risks to markets/regions perceived as more stable (Yilanci and Kilci, 2021). A literature review by Al-Thaqeb and Algharabali (2019) proposes that EPU affects developing and developed economies worldwide. The overall expected impact of EPU is low economic growth, deterioration of capital investment, and reduced global spending by households, which decreases stock performance. Similarly, GPU in the geopolitical index is usually priced according to the equity options market structure. GPU can also lead firms to postpone or cancel investments as investor confidence diminishes; correspondingly, consumers decrease or delay the purchase of durable goods.

The literature has provided empirical evidence on the macroeconomic effect of uncertainty on key economic and corporate fundamentals. For instance, Gulen and Ion (2015) establish that macroeconomic uncertainty negatively impacts corporate decisions on capital investment, finding that a higher EPU index reduced corporate capital investment by about one-third during the global financial crisis. This reduction was especially true for firms that relied too much on government contracts and were dependent on irreversible investments. Bordo et al. (2016) show that uncertainty regarding future policies has adverse effects on bank credit and that this is a significant way in which uncertainty hampers investment (Demir and Danisman, 2021). Phan et al. (2020) conducted an empirical analysis in 23 countries, attributing the 7% rise in financial instability to a standard deviation increase in uncertainty. The results of Manrique-de-Lara-Penate et al. (2022) show that EPU and GPU limit the growth effect of the global tourism sector by roughly 14.3%.

Empirical evidence on the financial markets, such as that from Das et al. (2019), indicates that uncertainty increases volatility in conventional stock markets by raising the risk premium in the market. Kannadhasan and Das (2019) show that EPU and GPU pose threats to conventional stock markets, indicating that both consistently negatively affect emerging market stocks. Al Mamun et al. (2020) show that geopolitical and economic uncertainty raises the Bitcoin market's risk premium and that investors cannot hedge portfolio risks with conventional financial assets during high EPU. The extant literature has extensively studied the impact of macroeconomic uncertainty on macroeconomic fundamentals and conventional financial markets, including stock markets, the crude oil market, and the cryptocurrency market; however, similar consideration of the carbon allowance market has only recently been investigated. Based on quantile regression analysis, Dou et al.'s study (2022) showed that EPU negatively affects carbon futures price returns and cannot predict the volatility series. With the existing result of no predictability, this present study contributes to the literature by formulating a better approach than quantile regression (which has proven unproductive) to distinguish between high and low uncertainty. Additional contributions include analyzing several indicators of twin uncertainty and an extensive analysis of ETS market risk measures.

2.2. Carbon market–uncertainty nexus

The trading market for carbon emission allowance has roots in the Kyoto Protocol, in which the international community decided on international emissions trading as a market-based strategy to tackle climate change and reduce GHG emissions. The Kyoto Protocol is a legally binding agreement on emission targets ratified by numerous countries in the UNFCCC in 1997 and effective as of 2005. The Protocol placed the bulk of the responsibility on advanced, industrialized, and transition economies as the primary sources of GHG emissions. Between 2008 and 2012, the first period of commitment, participating countries were required to aim to reduce emission levels by 5% against 1990 levels.

In the second commitment period (2013–2020), countries were required to reduce emissions by 18% against 1990 levels. Furthermore, the Paris Agreement (COP-21), effective in November 2016, targeted a reduction in global warming of 1.5 °C (34.7 °F) and the attainment of a climate-neutral global economy by 2050. COP-21 adopts a more inclusive approach; all of the countries presented their plans concerning reduced GHG emissions through what is known as nationally determined contributions. Overall, the Kyoto Protocol specifies the primary strategies for GHG emission reduction to specified targets through nationally developed measures, proposing three emission-reduction implementation strategies: two project-based approaches (clean development mechanism and joint implementation) and a market-based mechanism (international emissions trading).

The EU-ETS is a carbon emission allowance market that emerged as the EU's cost-effective, market-based response to the Kyoto Protocol's mandate. Feng (2015) provided a detailed description of the carbon trading market, suggesting that the market is a mechanism in which players buy and sell carbon emission allowances as a strategy to mitigate climate change; thus, the price of emission allowances indicates the actual cost of climate change. Market players (usually firms or industries) have a defined emission goal consistent with their country's national allocation plan. The market players are expected to work toward achieving the emission goal and must buy carbon emission allowances in the carbon market if they fail to achieve the emission target within the required timeframe (i.e., the marginal cost of emission reduction exceeds the price of emission allowances). In contrast, by meeting their targets for the period, players with superfluous emission allowances can sell the excess allowances on the carbon market. This process is the general idea behind carbon trading.

This study explores the connection between uncertainty and market risk levels in the carbon trading market. The motivation for adopting uncertainty as a predictor in the carbon trading risk predictive model suggests that the carbon market faces significant uncertainty; it is subject to intense international politicking and multilateral negotiations and regulations among advanced and emerging economies (Feng et al., 2012; Balcılar et al., 2015; Feng, 2015). Therefore, higher uncertainty should precede higher (risk) volatility in the financial market, and, as such, macroeconomic uncertainty should predict future volatility (Liu et al., 2017). Empirical evidence suggests that EPU matters in the volatility forecasting of stock returns, economic activity, and energy markets (Liu et al., 2017; Junttila and Vataja, 2018; Yu and Song, 2018; Rakpho and Yamaka, 2021; Yu and Huang, 2021).

Dai et al., 2021 also showed that global EPU could be a good predictor of carbon market-realized volatility; however, they only analyzed realized volatility as a measure of carbon market risk. In contrast, the present study explores various measures, including the market-based measure of carbon price risk. Therefore, it considers the role of twin uncertainty—including uncertainties stemming from unstable policies and geopolitical risk—which cuts across global indices and uncertainty emanating from the EU and the US. Regarding methodology, in addition to using carbon market risk as the realized long-run volatility of the international carbon market from the GARCH-MIDAS framework, this study also improves on Dai et al., 2021. We use a different measure of carbon trading risk obtained from the VaR models and Westerlund and Narayan's (2012, 2015) approach, which is estimated with a feasible quasi-generalized least squares estimator (FQGLS)[2] to explore the impact of uncertainty on carbon trading risk.

In addition, this study improves on extant research on the carbon market with a forecasting analysis of alternative measures of carbon trading risk. Previously, Hammoudeh et al. (2015) used the nonlinear (asymmetric) autoregressive distributed lag technique, indicating that energy prices (crude oil, coal, natural gas, and electricity prices) are key predictors of carbon allowance prices. A similar study (in terms of methodology) by Wen et al. (2020) shows the hedging potential between the carbon market and the Chinese stock market, given the evidence of a negative relationship between the two. The forecast analysis by Narayan and Sharma (2015) indicated that the carbon futures market could predict carbon spot market returns, demonstrating that the preferred model's forecasts allow investors to profit. In sum, the previously-mentioned studies necessitate further analysis of the uncertainty–carbon risk nexus that encompasses impact and predictability analyses, given the topic's theoretical, empirical, and policy appeal.

2.3. Twin uncertainty indicators

This study contributes to the literature that effectively quantifies different economic, political, and geopolitical forms of uncertainty. Complex and significant events in the 21st century, such as the global financial crisis, the Arab Spring, Russia's annexation of Crimea, Russia's war on Ukraine, and various refugee crises, have affected global political and economic uncertainty, heightening political and economic instability and global macroeconomic uncertainty (Al-Thaqeb and Algharabali, 2019).[3] Baker et al.'s (2016) descriptions of monetary and fiscal policy uncertainty and Caldara and Iacoviello's (2018) index of geopolitical risks were helpful for our study. Demir and Danisman (2021) show that macroeconomic uncertainty has been a significant concern

[2] The model is advantageous due to its capability to deal simultaneously with multiple econometric problems (endogeneity bias, persistency, and conditional heteroscedasticity) (Sharma, 2021).

[3] A recent source of uncertainty beyond this study's scope is the COVID-19 pandemic, which has increased the international spill of uncertainty shocks (Kumar et al., 2021).

since the global financial crisis; therefore, many monetary and fiscal regulatory authorities now more closely monitor the aspects of risk, such as EPU and GPU-related factors, as they develop policy approaches.

The EPU measures the economic risk associated with the indeterminate monetary and fiscal policy actions of governments and regulatory frameworks. Regarding measurement, the EPU index is a news-based index obtained through the text mining of related keywords from digital archives of 11 US-based and international newspapers; it was created by Baker et al. (2016) and has been subsequently updated (http://www.policyuncertainty.com/). The resulting global EPU index comprises 20 emerging and advanced economies: Brazil, Chile, China, Greece, India, Ireland, Mexico, Russia, South Korea, Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Spain, Sweden, the UK, and the US. The EPU index covers issues relating to economic policies, covering a combination of keywords, including "uncertainty," "uncertain," "economy," "economic," "deficit," "regulation," "Federal Reserve, " "Congress," "legislation," and "White House."

The GPU captures the actual occurrences and threats related to political instability, outbreaks or escalation of wars, terror-related activities, and other such incidents. The geopolitical risk index devised by Caldara and Iacoviello (2018) is similar to the EPU index in methodology, as both are based on a text-search algorithm. The geopolitical risk index is also text-based, and keywords related to conflicts can be used to search for information from several American and international media outlets, such as the Washington Post, the New York Times, the Chicago Tribune, the Los Angeles Times, the Guardian, the Daily Telegraph, the Financial Times, the Boston Globe, the Wall Street Journal, the Times, and the Globe and Mail. The geopolitical risk index captures war, war-related, and political tension risk components, such as military threats, political tensions, acts and threats of war, conflicts, nuclear threats, and similar tensions that could affect the normal course of international relations (Gupta et al., 2019). Data on geopolitical risk are obtained from newspaper articles using keywords such as "war," "terrorism," "military," and "geopolitics" (https://www.matteoiacoviello.com/gpr.htm).

High uncertainty events were recorded during the global financial crisis, the 9/11 attacks, the two Gulf Wars, the Ukraine–Russia conflict, the chaos in the Middle East, and, most recently, the coronavirus pandemic. Theoretically, as uncertainty increases the risk of premia in financial markets, the discount rate rises; hence, the net present value of future profitability falls, and stock prices decrease (Bijsterbosch and Guérin, 2013). These economic realities capture the need to separate high levels of EPU and GPU from low levels of uncertainty. Previously, Bijsterbosch and Guérin (2013) identified high uncertainty events via a regime-switching model of macroeconomic and financial variables, finding that high uncertainty events are associated with a decline in inflation, weakened economic activities, weaker growth performance, and sharp declines in stock prices.[4] A similar attempt by Dou et al. (2022) concerning the carbon market did not prove worthwhile, as the quantile method to distinguish between high and low uncertainty failed to predict the carbon price return. Our study uses Shin et al.'s (2014) approach to the partial sum decomposition, where the positive partial sums of uncertainty indices represent high uncertainty, and negative partial sums represent low uncertainty.

3. Methodology

3.1. Carbon trading risk: the GARCH-MIDAS approach

We adopted two approaches to measure carbon trading risk. The first is the mixed data sampling variant of the GARCH-MIDAS approach (Ghysels et al., 2006; Engle et al., 2013) to model the volatility of the EU-ETS return series as a measure of carbon trading risk. The MIDAS regression is useful in deploying data in their natural frequencies of occurrence, such that carbon price returns (which occur at a daily frequency) and uncertainty indicators (occurring at a monthly frequency) can be used. The MIDAS approach allows the two frequencies to be combined within the same modeling framework. Furthermore, the GARCH-MIDAS approach helps extract realized volatility as a measure of carbon allowance market risk, which helps circumvent using a special technique to distill market risk. Therefore, use the GARCH-MIDAS approach to determine and estimate the volatility of carbon returns.[5] Furthermore, we obtained the predictability and forecasting results from the GARCH-MIDAS model for EU-ETS for various variants of EPU and GPU, namely, EU, US, and global EPUs and GPUs, which were obtained at a monthly frequency.

We specified the conditional mean equation for the carbon allowance returns based on the carbon price observed on day i for each period t as follows:

$$cr_{i,t} = E_{i-1,t}(cr_{i,t}) + \sqrt{\sigma_{i,t}^2} * v_{i,t}; \forall i = 1, 2, ..., N_t \tag{1}$$

Here, $cr_{i,t}$ denotes daily carbon returns computed as $cr_{i,t} = \log(cp_{i,t}/cp_{i-1,t})$, and $cp_{i,t}$ are the daily carbon prices at period t, innovations are distributed as $v_{i,t}|\varphi_{i-1,t} \sim N(0,1)$. $\varphi_{i,t}$ represents the information set available on day $i-1$ at period t.

The total conditional variance (volatility), $\sigma_{i,t}^2$ can be decomposed into short-run $(h_{i,t})$ and long-run (g_t) volatility components as follows:

$$\sigma_{i,t}^2 = g_t * h_{i,t} \tag{2}$$

$$h_{i,t} = (1-a-b) + a\frac{(cr_{i-1,t}-\mu)^2}{g_t} + bh_{i-1,t} \tag{3}$$

$$g_t = \alpha + \theta \sum_{k=1}^{K} \delta_k(\varpi) RV_{t-k} \tag{4}$$

Here, $\mu = E_{i-1,t}(cr_{i,t})$, a and b are the ARCH and GARCH terms, respectively. These are defined by $a > 0$, $b \geq 0$, and $a + b < 1$, such that the higher the "b" parameter, the greater the volatility clustering in the carbon market. RV_t is the realized volatility defined as $RV_t = \sum_{1=1}^{N_t} cr_{i,t}^2$, g_t is the smoothed realized volatility (hence, it results in monthly observations), K is the period when the RV_t is smoothed, and N_t represents the number of trading days in the carbon market for each month.

We defined the two-parameter beta polynomials employed as the weighting scheme for the GARCH-MIDAS, $\delta_k(\varpi)$, as follows (Engle et al., 2013; Conrad et al., 2018):

$$\delta_k(\varpi) = \delta_k(\varpi_1, \varpi_2) = \frac{[k/(K+1)]^{\varpi_1-1}[1-k/(K+1)]^{\varpi_2-1}}{\sum_{j=1}^{K}[j/(K+1)]^{\varpi_1-1}[1-j/(K+1)]^{\varpi_2-1}} \tag{5}$$

The combination of equations (1) and (5) describes the GARCH-MIDAS model for obtaining the realized volatility required for this study; however, we documented the predictability results from the model with uncertainty (UNC), which can be subdivided into EPU and GPU as the low (monthly) frequency predictors. We augmented the equation for the long-run volatility as follows:

[4] Dogan et al. (2021) compared the impacts of geopolitical risk and economic policy uncertainty on natural resource rents of developing countries, finding that economic uncertainty decreases natural resource rents at higher quantiles.

[5] The GARCH-MIDAS technique has been applied to forecast the volatility of various financial markets, including stock markets (Asgharian et al., 2013; Fang et al., 2020; Wang et al., 2020; Salisu and Gupta, 2021), oil markets (Salisu et al., 2021), and foreign exchange rate markets (You and Liu, 2020; Zhou et al., 2020; Salisu et al., 2022a,b,c).

$$g_t = \alpha + \theta \sum_{k=1}^{K} \delta_k(\varpi) UNC_{t-k} \tag{6}$$

Here, the other equations, including the weighting scheme, remain defined, and UNC_t represents any of the EU, US, and global EPUs and GPUs obtained monthly. The θ in equations (4) and (6) signifies the impact (or predictability) of realized volatility or uncertainty on the measure of carbon trading risk (long-run volatility of carbon return).

3.2. Carbon trading risk: conditional autoregressive value at risk (CAViaR) approach

Alternatively, we measured the carbon trading risk with CAViaR (Engle and Manganelli, 2004) due to its suitability in measuring portfolio risk in various financial markets. The approach is appropriate for measuring the downside market risk of financial series as it is computed from the tail distribution of the market return series. For a method to measure stock market risk, see Salisu et al. (2022a,b,c); to measure oil price risk, see Salisu et al. (2022a,b,c); to measure exchange rate risk, see Adediran (2021). Unlike standard VaR models, CAViaR incorporates time variation in estimating the conditional quantile distribution rather than the entire distribution of portfolio values. The baseline model proceeds as follows:

$$f_t(\beta) = \beta_0 + \sum_{j=1}^{p} \beta_j f_{t-j}(\beta) + \sum_{i=1}^{q} \beta_i \ell(z_{t-i}) \tag{7}$$

Here, $f_t(\beta) \equiv f_t(z_{t-1}, \beta_\vartheta)$ is the ϑ th quantile (either 1% or 5%) distribution of carbon returns at time "t" but formed at time "t–1." $\beta_j f_{t-j}(\beta); j = 1, 2, \ldots p$ are autoregressive terms/parameters included to ensure smoothness in the time variation, $(p + q + 1)$ represents the dimension of β, ℓ is a function of lagged observables (z_t), and $\ell(z_{t-i})$ helps link the quantile distribution to the observables in the available information set.

Four alternative specifications of the CAViaR from which we selected the optimal one across the 1% or 5% quantile distributions are presented as follows:

Adaptive model:

$$f_t(\beta_1) = f_{t-1}(\beta_1) + \beta_1 \left\{ [1 + \exp(G[x_{t-1} - f_{t-1}(\beta_1)])]^{-1} - \vartheta \right\} \tag{8}$$

Symmetric absolute value model:

$$f_t(\boldsymbol{\beta}) = \beta_1 + \beta_2 f_{t-1}(\boldsymbol{\beta}) + \beta_3 |x_{t-1}| \tag{9}$$

Asymmetric slope model:

$$f_t(\boldsymbol{\beta}) = \beta_1 + \beta_2 f_{t-1}(\boldsymbol{\beta}) + \beta_3 (x_{t-1})^+ + \beta_4 (x_{t-1})^- \tag{10}$$

Indirect GARCH model:

$$f_t(\boldsymbol{\beta}) = \left(\beta_1 + \beta_2 f_{t-1}^2(\boldsymbol{\beta}) + \beta_3 x_{t-1}^2\right)^{1/2} \tag{11}$$

The symmetric, asymmetric, and indirect GARCH are mean reverting, whereas the adaptive model is not, since the coefficient of the autoregressive term is not restricted to 1 in the previous models. The asymmetric model also differs from the others as it distinguishes between positive and negative portfolio returns. For further robustness, we computed the 1% and 5% conditional VaRs from the carbon return series for the four CAViaR alternative specifications. We determined the optimal model for each quantile distribution using a combination of diagnostic tests: the Dynamic Quantile (DQ) test, the %Hits test, and the Regression Quantile test.

3.3. Predictability models and forecast evaluation measures

To explore the research objective centered on the role of two classes of uncertainty indicators as predictors of carbon trading risk, we used the two carbon risks computed from CAViaR specifications. These risks are used to model the predictability of the international carbon trading risk in the econometric model structured according to Westerlund and Narayan's (2012, 2015) estimation approach. The technique has been widely applied to various financial market series, given its ability to simultaneously incorporate suspected endogeneity bias, conditional heteroscedasticity, and persistency in the series (Bannigidadmath and Narayan, 2015; Salisu and Isah, 2018; Salisu et al., 2019; Sharma, 2021; Adediran et al., 2021).

The Westerlund and Narayan (2012, 2015) model is estimated with the FQGLS estimator. It can be specified so that the carbon trading risk (CTR_t) (measured with CAViaR at 1% and 5%, respectively) is modeled with uncertainty (UNC_t), EPU (EPU_t), and GPU (GPU_t) as alternative regressors:

$$CTR_t^{CAVaiR1\%} = \alpha^{CAVaiR1\%} + \beta^{CAVaiR1\%} UNC_{t-1} + \varphi^{CAVaiR1\%} \left(UNC_t - \rho^{CAVaiR1\%} UNC_{t-1}\right) + \varepsilon_t^{CAVaiR1\%} \tag{12}$$

$$CTR_t^{CAVaiR5\%} = \alpha^{CAVaiR5\%} + \beta^{CAVaiR5\%} UNC_{t-1} + \varphi^{CAVaiR5\%} \left(UNC_t - \rho^{CAVaiR5\%} UNC_{t-1}\right) + \varepsilon_t^{CAVaiR5\%} \tag{13}$$

Here, α is the constant term, β is the bias-adjusted slope coefficient that shows the impact of the respective uncertainty indicator series on the carbon trading risk. The superscripts $CAViaR1\%$ and $CAViaR5\%$ help differentiate between either of the VaR measures of carbon risks, and ε_t denotes the *iid* error term.[6]

For the out-of-sample forecast evaluation, we compared the predictive accuracies of our preferred models, containing EPU and GPU as the predictors of alternative carbon trading risk, against the benchmark model. The benchmark model for comparison incorporates the international crude oil price (West Texas Intermediate or the UK Brent crude oil benchmarks) as the predictor series.

$$CTR_t^{CAVaiR1\%} = \alpha^{CAVaiR1\%} + \beta^{CAVaiR1\%} OIL_{t-1} + \varphi^{CAVaiR1\%} \left(OIL_t - \rho^{CAVaiR1\%} OIL_{t-1}\right) + \varepsilon_t^{CAVaiR1\%} \tag{14a}$$

[6] We included the $\varphi^{CAVaiR1\%}(UNC_t - \rho^{CAVaiR1\%} UNC_{t-1})$ and $\varphi^{CAVaiR5\%}(UNC_t - \rho^{CAVaiR5\%} UNC_{t-1})$ terms in each model to resolve potential endogeneity bias, and ρ addresses the persistence effect. The endogeneity test is conducted with the following null hypothesis ($\varphi = 0$ i.e., no endogeneity bias) against the alternative ($\varphi \neq 0$ i.e., presence of endogeneity bias). If the models exhibited endogeneity and persistence effects, we estimated the bias-adjusted coefficient, β as follows: $\beta = b - \varphi(\rho - 1)$, where b is the coefficient of the original specification $CTR_t = \alpha + bUNC_{t-1} + e_t$. The in-sample predictability test evaluates the null, $\beta = 0$, against the alternative, $\beta \neq 0$. Furthermore, the bias-adjusted generalized least squares estimator is suitable if conditional heteroscedasticity is present in the model, where the error follows the ARCH process, $\sigma_{\varepsilon,t}^2 = \varpi_t + \sum_{i=1}^{k} \varpi_i \varepsilon_{t-1}^2$. This is done by pre-weighting the series with the quantity.

$$CTR_t^{CAVaiR5\%} = \alpha^{CAVaiR5\%} + \beta^{CAVaiR5\%} OIL_{t-1} + \varphi^{CAVaiR5\%} \left(OIL_t - \rho^{CAVaiR5\%} OIL_{t-1}\right) + \varepsilon_t^{CAVaiR5\%} \tag{14b}$$

We use the oil price because crude oil accounts for approximately 45% of GHG emissions and is a significant contributor to the adverse effects of carbon emissions, such as the increase in heat waves and rising sea levels (Shafiullah et al., 2021). In addition, Hammoudeh et al. (2015) suggest that oil (and other energy) prices could contain some predictive content for carbon allowance prices. Therefore, we selected a benchmark model in which crude oil prices are the predictor.

The preferred and benchmark models are non-nested (that is, the oil-based model is not a subset of uncertainty-based models). Therefore, we employed the modified Diebold and Mariano (DM) pairwise test (Diebold and Mariano, 1995; Harvey et al., 1997) to evaluate the out-of-sample forecast performance of EPU and GPU in the predictability of carbon trading risks by comparing the forecast errors of the competing models. We subsequently compare the two uncertainty indicators. The traditional and modified DM test equations are specified as follows in equations (15) and (16), respectively:

$$DM = \frac{diff^*}{\sqrt{V(diff)/T}} \sim N(0,1) \tag{15}$$

$$MDM = \left(\sqrt{T + 1 - 2h + T^{-1}h(h-1)/T}\right) DM \tag{16}$$

Here, $diff = l(\varepsilon_{CTR}) - l(\varepsilon_{AR})$, $l(\varepsilon_{CTR})$ is the loss function of the alternative carbon risk models. $l(\varepsilon_{AR})$ is the loss function of the autoregressive (baseline) model, $diff^*$ and $V(diff)$ are the mean and variance of the loss differentials, respectively, and h is the forecast horizon.

We tested the null $E(diff) = 0$ against the alternative $E(diff) < 0$ (negative DM statistics), which suggests that the carbon risk-based models with either EPU or GPU are preferred to the oil-based baseline models if the former results in a lower error and proves more accurate than the latter. Other possibilities exist, such as $E(diff) > 0$, where the reverse holds, and $E(diff) = 0$, which shows no difference in forecast accuracies.

3.4. Data issues

This study obtained data on the daily price of emissions allowances EU-ETS spot carbon allowance trading prices from February 2, 2009 to 8/31/2022 from the DataStream database. We ignored data before 2009 due to breaks in EU-ETS during the pilot period before 2008. For the predictor series in our model, we used the most robust monthly EPU series available from http://www.policyuncertainty.com. The EPU indicator is a GDP-PPP-weighted composite index of individual countries' EPU for 21 advanced and emerging countries: the US, Canada, Italy, Australia, France, Germany, Ireland, the UK, Sweden, the Netherlands, Japan, Spain, South Korea, India, Colombia, China, Greece, Chile, Mexico, Brazil, and Russia. Implementing the EPU index as a predictor of carbon trading risk is further underscored because of its global appeal emanating from text-mined EPU of all the countries mentioned above, comprising over 70% of the global PPP-adjusted GDP and representing the world's major financial markets. The monthly EPU data cover 2009M2–2022M8 (163 months) for global EPU, EU EPU, and US EPU. As extensively argued and for comprehensive analysis, we use similar indicators of GPU (https://www.matteoiacoviello.com/gpr.htm) that include global GPU, EU GPU, and US GPU. The oil price proxies were also obtained monthly across the same period. They were sourced from the US Energy Information Administration (https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm) to estimate the baseline model for forecasting evaluation.

4. Results

4.1. Preliminaries

This section presents relevant descriptive statistics, including the mean and standard deviation values in rows 2 and 3 of the upper and lower panels in Table 1, exploratory analyses using graphs in Figs. 1–4, and pre-tests in rows 3 to 7 of the two panels in Table 1. The statistics reveal some salient features of the data (skewness, kurtosis, persistence, and conditional heteroscedasticity) useful for commenting on the analysis of carbon trading risks. We further analyzed carbon trading risks using the four alternative market risk (CAViaR) models provided by Engle and Manganelli (2004): the adaptive model (Model 1), symmetric absolute value model (Model 2), asymmetric slope model (Model 3), and the indirect GARCH model (Model 4). We chose the optimal model among the competing models for each of the 1% and 5% tail risks based on the Hits% statistics and the DQ probability values. Hits% should be close to 1 for CAViaR 1% and 5 for CAViaR 5%, and the DQ statistic should be statistically insignificant (Table 2). Therefore, the closer to 1 or 5 the Hits% and the more insignificant the DQ statistic, the better the selected CAViaR model.

The average price of emissions allowances (carbon price) in the EU-ETS is about EUR 18.30 per ton, with the average returns over the daily data frequency at approximately 0.06. Compared with the mean, the standard deviation values are high, suggesting that market volatility (and risk) could be high. Additionally, the average market return is negatively skewed and exhibits heavy-tailed (leptokurtic) distribution based on excess kurtosis, suggesting the possibility of the market being susceptible to risk. This could explain the position of Dou et al. (2022), describing the carbon market as a complex volatility model predisposed to factors that shape macroeconomic outlook and fundamentals, such as macroeconomic uncertainty. The preceding information could also suggest that the carbon market is prone to extreme events. Therefore, the market informs the choice of the VaR (tail risk) measures to obtain the carbon trading risk and the predictive role of EPU and GPU as contributors to extreme market events in the international financial space.

Fig. 1 shows that the carbon price was unstable from mid-2018 until 2022, unlike earlier periods of relative stability. Intuitively, unstable prices may give room for market speculation and excessive carbon allowances. Fig. 2 renders the carbon price return, and the carbon trading risk constructed from the same data via the VaR is presented together in Fig. 3. CAViaR 1% and CAViaR 5% track each other well and should produce robust results. Fig. 3 also graphs the two carbon trading risk data points against the three EPU indices in Fig. 3 and the three GPU indices in Fig. 4. The graphs show visible co-movements between the carbon risk proxies and the uncertainty indicators. This suggests that we expect a positive nexus between the two and that EPU could better predict carbon trading risk than GPU because the former commoves more with the carbon risk measures than the latter.

This study uses two techniques to analyze the predictability of carbon market risk with uncertainty. The first is the GARCH-MIDAS, which is informed by the difference in the frequency of the carbon market risk (predictand) and predictors (EPU and GPU indicators). This technique enables us to use the volatility of the carbon return series to measure carbon trading risk. The second technique is the Westerlund and Narayan (2012, 2015) model, estimated using the FQGLS estimator. This is justified by the evidence of persistence in the dependent variable (1% and 5% carbon risk measures) and the predictor series (global, EU, and US EPU and global, EU, and US GPU at a monthly frequency).

Furthermore, all of the variables exhibit the problem of conditional heteroscedasticity, as shown by the ARCH-LM test conducted with 5 and 10 lags (Table 1). Before estimating the Westerlund and Narayan (2012, 2015) model, we determined the optimal carbon trading risks among competing CAViaR models and the choice of Model 1 (adaptive model) for CAViaR 1% and Model 2 (symmetric absolute value model) for

Table 1
Descriptive statistics & pre-tests.

Statistics	EU-ETS (price)	EU-ETS (returns)	Carbon risk (1%)	Carbon risk (5%)	Oil price (WTI)	Oil price (Brent)
Mean	18.3010	0.0579	7.6198	4.4499	70.4522	76.3595
Std. Dev.	19.6956	3.1716	3.3501	1.8848	22.5124	26.2290
Skewness	2.2460	−0.9797	2.0217	1.8413	0.0441	0.1730
Kurtosis	7.4902	18.9176	10.3631	8.8286	2.0604	1.8863
Persistence	1.0004***	−0.0005	0.9361***	0.9698***	0.9959***	0.9980***
	(0.0008)	(0.0171)	(0.0060)	(0.0041)	(0.0015)	(0.0010)
ARCH(5)	74,568.1***	19.2658***	1789.54***	3907.24***	4252.96***	29,174.6***
ARCH(10)	39,148.1***	9.9875***	908.46***	1958.51***	2126.93***	14,728.3***
NOBS	3390	3390	3390	3390	3390	3390
Data freq.	Daily	Daily	Daily	Daily	Daily	Daily
Statistics	**EPU (Global)**	**EPU (EU)**	**EPU (US)**	**GPU (Global)**	**GPU (EU)**	**GPU (US)**
Mean	179.6385	206.0070	122.3608	95.3714	4.3021	2.1567
Std. Dev.	74.2151	65.9820	84.3769	29.3417	3.5599	0.6902
Skewness	0.9860	1.0387	2.3891	3.9241	4.8526	2.9352
Kurtosis	3.2775	4.3366	11.6714	27.548	33.4953	18.2804
Persistence	0.8928***	0.7356***	0.7598***	0.6706***	0.8072***	0.6375***
	(0.0362)	(0.0555)	(0.0111)	(0.0588)	(0.0469)	(0.0613)
ARCH(5)	30.2067***	10.7298***	1152.07***	6.8578***	14.652***	6.1863***
ARCH(10)	16.4319***	5.9781***	589.583***	3.8597***	7.0645***	3.4389***
NOBS	163	163	163	163	163	163
Data freq.	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly

Note: EU-ETS implies European Union Emissions Trading Scheme, the largest carbon trading market in the world. Prices & returns are the EU-ETS market prices and returns. Carbon risks 1% & 5% are measures of carbon allowance trading risks obtained as the optimal 1% and 5% Value at Risks from the Conditional Autoregressive Value at Risk approach. WTI & Brent are global crude oil price proxies considered in this study as baseline predictors of carbon trading risk. The economic policy uncertainty (EPU) and geopolitical uncertainty (GPU) are the global, EU, & US uncertainty indices. ARCH is the test for conditional heteroscedasticity with 5 & 10 lags. NOBS is the number of observations. "***" indicates statistical significance at 1% significance level.

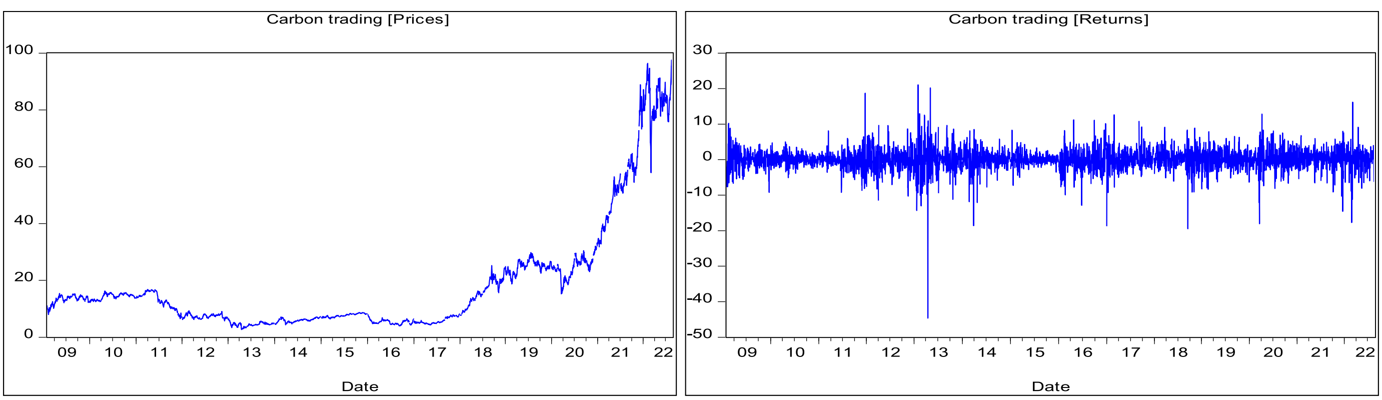

Fig. 1. EU-ETS carbon trading [Prices & returns].

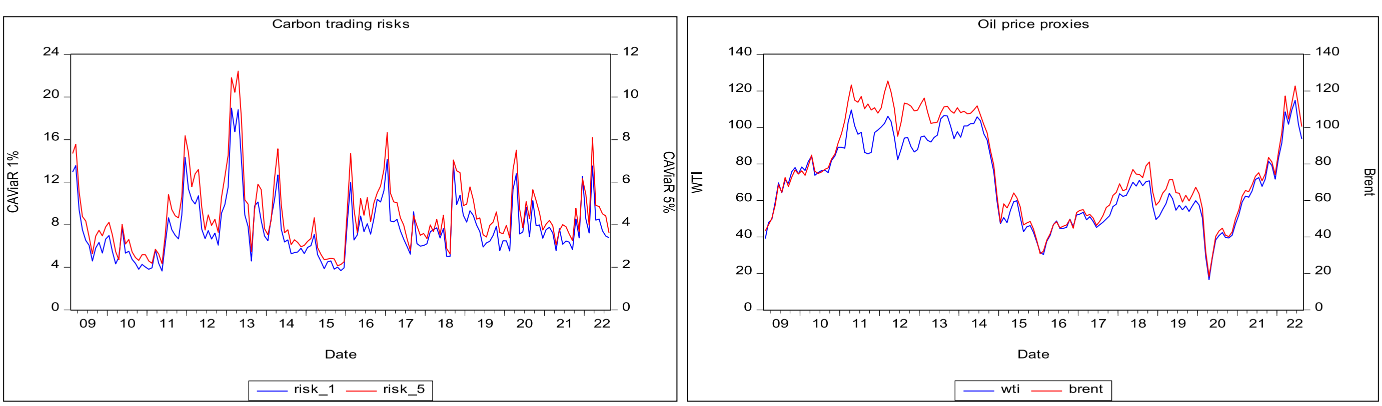

Fig. 2. Carbon trading risk and oil proxies.

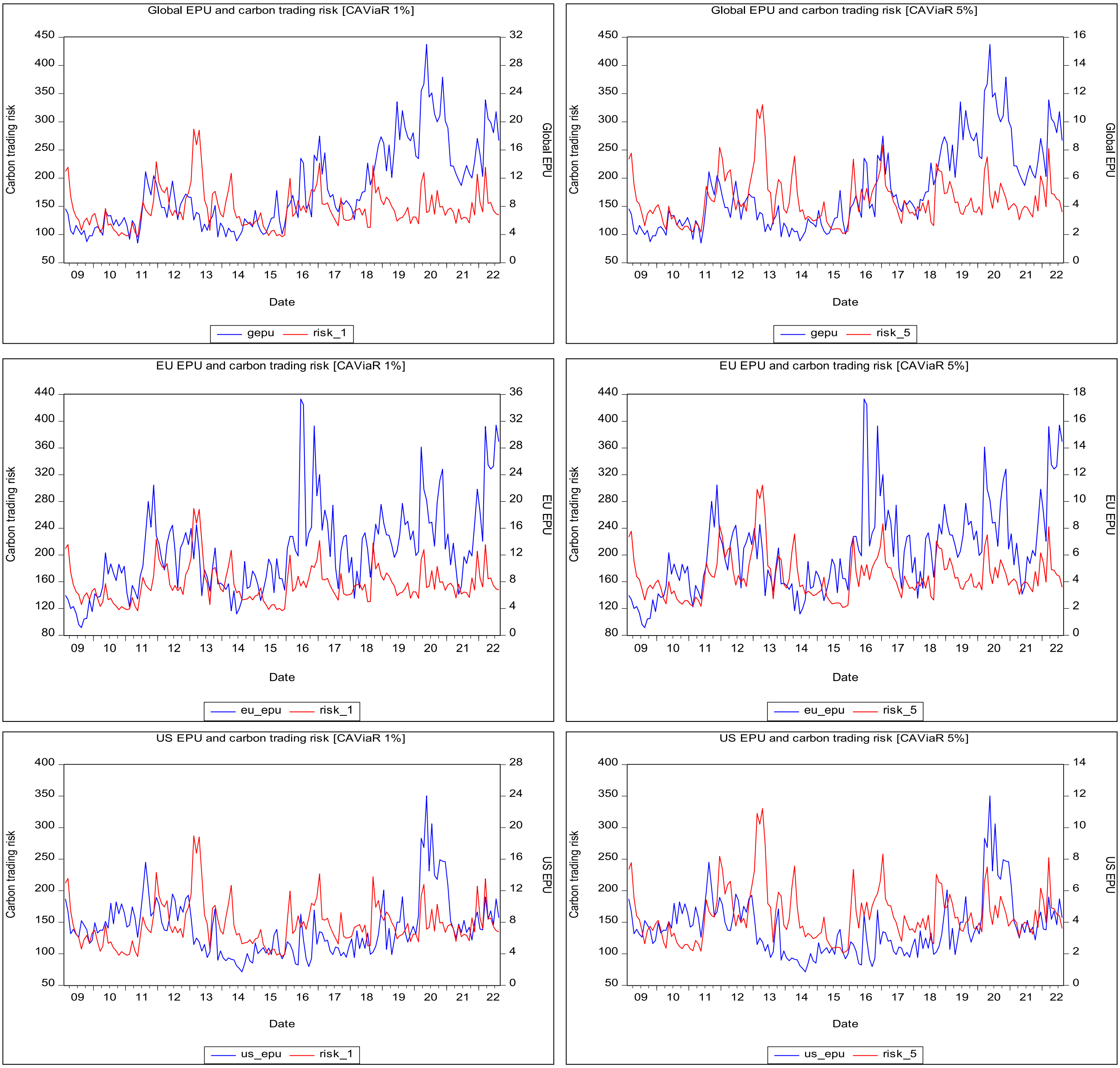

Fig. 3. Carbon trading risk and economic policy uncertainty.

CAViaR 5% (Table 2). This decision is based on the out-of-sample Hits% values and the out-of-sample DQ p-values. The chosen models, in the family of three other competitors, have the closest Hits% values to 1 and 5 and the most statistically insignificant DQ p-values.

4.2. Main results

We begin the results section with the predictability and out-of-sample forecast evaluation of the GARCH-MIDAS model for the EU-ETS carbon trading risk based on EPU and GPU. We considered three variants of the two uncertainty indicators: global EPU and GPU (which comprise the GDP-PPP-weighted composite index of 21 advanced and emerging countries), EU EPU and GPU, and US EPU and GPU for robust analysis. We expected a priori the coefficient of interest—i.e., theta (θ)—to be positively signed to indicate a positive impact of EPU on the carbon trading risk. This study's theoretical framework suggests that higher EPU and GPU could precede higher risk levels and volatility in the carbon trading market because complex negotiations and regulations among global players across many economies influence the market. Additionally, unstable carbon allowance prices and returns could increase speculation in the market and flood it with excess allowances, resulting in potential implications related to discouraging substituting dirty technologies for clean alternatives due to surplus allowances.

Table 3 presents the results of the GARCH-MIDAS regressions (GARCH-MIDAS-Global-EPU, GARCH-MIDAS-EU-EPU, and GARCH-MIDAS-US-EPU) compared with (GARCH-MIDAS-Global-GPU, GARCH-

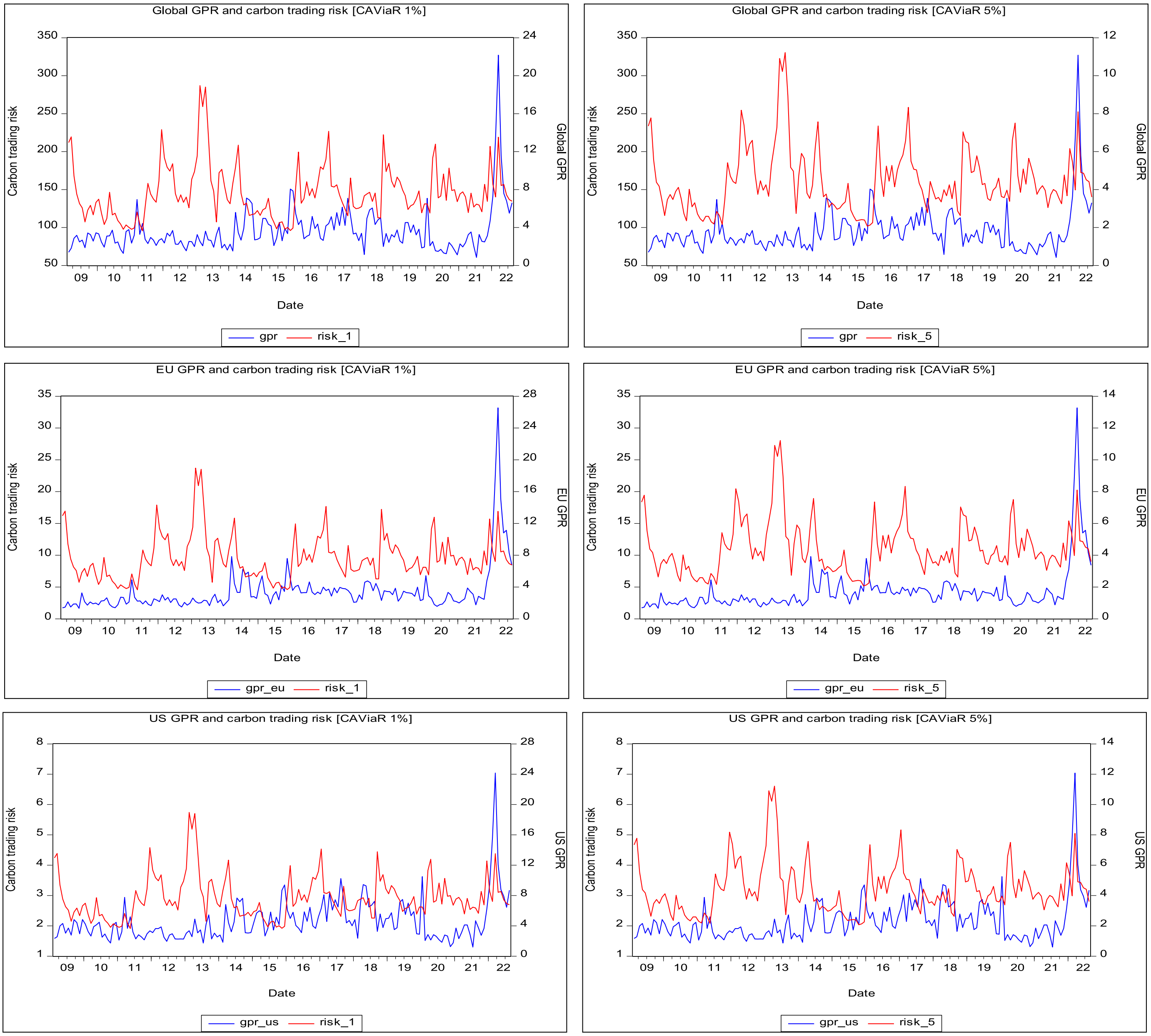

Fig. 4. Carbon trading risk and geopolitical uncertainty.

MIDAS-EU-GPU, and GARCH-MIDAS-US-GPU). The coefficient of major interest was the theta (θ),[7] which indicates the predictability of EPU and GPU for carbon risk. The results show that the three EPU and GPU indices heighten risk levels in the EU-ETS market, in line with the underlying theoretical intuition of the study. This is reflected in the positive and statistically significant values of the θ coefficients for the global, EU, and US EPU; however, none of the three positive GPU coefficients was statistically significant. The exception is the US GPU index. Among the three EPU indices, EU EPU shows the biggest impact, followed closely by global EPU and US EPU, which is a very distant third; however, global GPU has a greater impact on carbon trading risk than EU GPU. The coefficient of US GPU is insignificant. The results show that returns in the EU-ETS market exhibit stronger responses to EPUs in European countries than other uncertainties in other countries. These findings indicate wider market inefficiencies in the European carbon emission market (Rammerstorfer and Wagner, 2009; Borges, 2010).

Table 4 shows that additional results involve distilling the high uncertainty series from the EPU and GPU series obtained as the positive partial sums (Shin et al., 2014) of the uncertainty variables from their level forms; these sums are used as predictors of carbon trading risk.[8] This is more consistent with the body of theoretical constructs that largely present arguments about how increased uncertainty affects macroeconomic and financial variables, including carbon market fundamentals (Bijsterbosch and Guérin, 2013; Kisswani and Elian, 2021;

[7] The ARCH and GARCH terms are theoretically expected to be positive ($a > 0$) and strictly positive ($b \geq 0$),respectively, and the sum less than 1 (i.e., $a + b < 1$). The two terms fulfill all of the necessary conditions across the models, and the respective statistics are all statistically significant.

[8] The mathematics behind the decompositions are as follows: high EPU, $\sum_{j=1}^{t} \Delta EPU_j^{+} = \sum_{j=1}^{t} \max(\Delta EPU_j^t, 0)$; low EPU, $\sum_{j=1}^{t} \Delta EPU_j^{-} = \sum_{j=1}^{t} \min(\Delta EPU_j^t, 0)$; high GPU, $\sum_{j=1}^{t} \Delta GPU_j^{+} = \sum_{j=1}^{t} \max(\Delta GPU_j^t, 0)$; and low GPU, $\sum_{j=1}^{t} \Delta GPU_j^{-} = \sum_{j=1}^{t} \min(\Delta GPU_j^t, 0)$.

Table 2
The Conditional Autoregressive Value at Risk [CAViaR] results.

Statistic	CAViaR 1%				CAViaR 5%			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
β_1	0.5741	0.8636	0.8729	1.0300	0.2142	0.1044	0.3775	1.1394
Standard errors	0.2925	0.4026	1.0791	0.2110	0.0640	0.0464	0.1849	0.0907
P values	0.0248	0.0160	0.2093	0.0000	0.0004	0.0122	0.0206	0.0000
β_2	0.8039	0.7295	0.8124	0.0000	0.8753	0.8909	0.8728	0.0000
Standard errors	0.0498	0.0666	0.0567	0.0000	0.0263	0.0398	0.0143	0.0000
P values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
β_3	0.5459	0.3728	1.3318	0.0000	0.2036	0.1133	0.2702	0.0000
Standard errors	0.1413	0.1361	2.6360	0.0000	0.0382	0.0634	0.0835	0.0000
P values	0.0001	0.0031	0.3067	0.0000	0.0000	0.0370	0.0006	0.0000
β_5	0.0000	0.7494	0.0000	0.0000	0.0000	0.2442	0.0000	0.0000
Standard errors	0.0000	0.1240	0.0000	0.0000	0.0000	0.0944	0.0000	0.0000
P values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0048	0.0000	0.0000
RQ	330.46	327.15	324.81	370.40	1009.0	1002.1	1005.3	1041.8
Hits in-sample (%)	1.0333	1.0000	1.0333	0.9667	5.1000	5.0667	5.1667	4.8333
Hits out-of-sample (%)	2.3136	3.0848	2.8278	2.0566	6.4267	6.4267	6.1697	5.3985
DQ in-sample (P-values)	0.0000	0.0263	0.0001	0.0002	0.0052	0.0921	0.0049	0.0000
DQ out-of-sample (P-values)	0.1728	0.0004	0.0084	0.0106	0.6125	0.5704	0.8974	0.6142

Note: The statistics presented are the Value at Risks obtained from the Conditional Autoregressive Value at Risk (CAViaR) approach detailed in Engle and Manganelli (2004). Model 1 = Adaptive model, Model 2 = Symmetric absolute value model, Model 3 = Asymmetric slope model, Model 4 = Indirect GARCH model. The optimal CAViaR models are Model 1 for 1% CAViaR and Model 2 for 5% CAViaR judging by the Hits% and statistical insignificance of the DQ statistics.

Table 3
Uncertainty-carbon trading risk [GARCH-MIDAS].

	Economic policy uncertainty			Geopolitical uncertainty		
	EPU (Global)	EPU (EU)	EPU (US)	GPU (Global)	GPU (EU)	GPU (US)
Theta (θ)	0.0010***	0.0017***	0.0006***	0.0436***	0.0089**	0.0206
	(0.0002)	(0.0002)	(0.0002)	(0.0022)	(0.0042)	(0.0141)
ARCH term	0.1216***	0.1293***	0.1199***	0.0502***	0.1165***	0.1162***
	(0.0070)	(0.0077)	(0.0071)	(0.0025)	(0.0066)	(0.0066)
GARCH term	0.8613***	0.8449***	0.8636***	0.9004***	0.8694***	0.8701***
	(0.0075)	(0.0092)	(0.0078)	(0.0043)	(0.0071)	(0.0070)
ϖ	1.0046**	1.0391***	39.402	5.0000***	49.899	23.456
	(0.4321)	(0.1759)	(46.026)	(0.0008)	(54.787)	(31.072)
Mu	0.0012***	0.0012***	0.0012***	0.0014**	0.0013***	0.0012***
	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0004)	(0.0004)
Constant	−0.0004	−0.0020***	0.0005*	−0.0322***	0.0009***	0.0009***
	(0.0003)	(0.0003)	(0.0002)	(0.0015)	(0.0002)	(0.0004)

Note: The table presents the results of the mixed data sampling (GARCH-MIDAS) estimation of the economic policy uncertainty-carbon trading risk model and the geopolitical uncertainty-carbon trading risk model. Carbon trading risk here is measured with realized volatility obtained from the GARCH-MIDAS model of the EU-ETS returns. The carbon trading risk (realized volatility of EU-ETS returns) is the high frequency (daily) variable while the uncertainty series (EPU & GPU) are of lower (monthly) frequency. Theta is the key parameter of interest which measures the impacts of the uncertainty indicators on the carbon trading risk. The values in round brackets are standard errors. ***,**, & * indicates statistical significance at 1 percent, 5 percent, & 10 percent respectively.

Table 4
High uncertainty-carbon trading risk [GARCH-MIDAS].

	High economic policy uncertainty			High geopolitical uncertainty		
	EPU (Global)	EPU (EU)	EPU (US)	GPU (Global)	GPU (EU)	GPU (US)
Theta (θ)	0.0190***	0.0149***	0.0161***	0.0166***	0.0168***	0.0143***
	(0.0051)	(0.0040)	(0.0044)	(0.0047)	(0.0027)	(0.0039)
ARCH term	0.1190***	0.1188***	0.1184**	0.1180***	0.1492***	0.1172***
	(0.0063)	(0.0063)	(0.0063)	(0.0067)	(0.0061)	(0.0063)
GARCH term	0.8681***	0.8679***	0.8682***	0.8691***	0.8345***	0.8702***
	(0.0066)	(0.0067)	(0.0066)	(0.0069)	(0.0055)	(0.0065)
ϖ	36.657	31.405	39.912	6.8114	3.5156	24.881
	(130.1)	(119.28)	(142.86)	(36.65)	(4.378)	(89.797)
Mu	0.0013***	0.0012***	0.0012***	0.0012***	0.0025***	0.0012***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)
Constant	0.0004**	0.0005***	0.0005***	0.0004**	−0.0004***	0.0005***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.00007)	(0.0002)

Note: The table presents the results of the GARCH-MIDAS estimation where the predictors of carbon trading risk are high economic policy uncertainty and high geopolitical uncertainty. Carbon trading risk here is measured with realized volatility obtained from the GARCH-MIDAS model of the EU-ETS returns. The carbon trading risk (realized volatility of EU-ETS returns) is the high frequency (daily) variable while the uncertainty series (EPU & GPU) are of lower (monthly) frequency. Theta is the key parameter of interest which measures the impacts of the uncertainty indicators on the carbon trading risk. The values in round brackets are standard errors. ***,**, & * indicates statistical significance at 1 percent, 5 percent, & 10 percent respectively.

Table 5
Low uncertainty-carbon trading risk [GARCH-MIDAS].

	Low economic policy uncertainty			Low geopolitical uncertainty		
	EPU	EPU	EPU	GPU	GPU	GPU
	(Global)	(EU)	(US)	(Global)	(EU)	(US)
Theta (θ)	−0.2214	−0.0977	−0.0219***	−0.0322**	−0.0043	−0.0283***
	(0.3184)	(0.1091)	(0.0082)	(0.0131)	(0.5627)	(0.0127)
ARCH term	0.1054***	0.1040***	0.1034***	0.1084***	0.0745***	0.1084***
	(0.0056)	(0.0056)	(0.0068)	(0.0063)	(0.0034)	(0.0068)
GARCH term	0.8936***	0.8938***	0.8885***	0.8840***	0.9254***	0.8842***
	(0.0052)	(0.0053)	(0.0065)	(0.0061)	(0.0035)	(0.0062)
ϖ	6.5561	49.851	7.8234	1.3177	5.0565	46.911
	(20.128)	(106.57)	(67.28)	(8.2102)	(30.173)	(239.87)
Mu	0.0011**	0.0011**	0.0011**	0.0010**	0.0011**	0.0011**
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)
Constant	−0.0022	−0.0008	0.0003	0.0004	0.0024	0.0002
	(0.0031)	(0.0011)	(0.0003)	(0.0006)	(0.0026)	(0.0002)

Note: The table presents the results of the GARCH-MIDAS estimation where the predictors of carbon trading risk are low economic policy uncertainty and low geopolitical uncertainty. Carbon trading risk here is measured with realized volatility obtained from the GARCH-MIDAS model of the EU-ETS returns. The carbon trading risk (realized volatility of EU-ETS returns) is the high frequency (daily) variable while the uncertainty series (EPU & GPU) are of lower (monthly) frequency. Theta is the key parameter of interest which measures the impacts of the uncertainty indicators on the carbon trading risk. The values in round brackets are standard errors. ***,**, & * indicates statistical significance at 1 percent, 5 percent, & 10 percent respectively.

Shafiullah et al., 2021; Yilanci and Kilci, 2021). Considering the high uncertainty series, all three EPU and GPU indices have positive and significant coefficients, as expected. This further reinforces the results in Table 3, showing the uncertainty–carbon risk nexus as positive; however, to demonstrate the consistency of the result, we also show that a reduction in the uncertainty indices reduces carbon trading risk (Table 5) and the higher the uncertainty, the higher the carbon trading risk.

The above description suggests that EPU and GPU indices could have predictive content for the EU market carbon trading risk. The results largely corroborate Dai et al.'s study results (2021), although these include an additional EPU index and comparison between EPU and GPU indicators. The results are similar to other research data that show that uncertainty indices can be exploited to forecast other financial markets, including stock and energy markets (Liu et al., 2017; Junttila and Vataja, 2018; Yu and Song, 2018; Rakpho and Yamaka, 2021; Yu and Huang, 2021). We examined the predictive power of twin uncertainty compared with the oil price as the baseline predictor of the carbon price. The underlying results in Table A1 affirm that the two oil price proxies also contribute to higher carbon price volatility; hence, the oil price-based model can be a benchmark for forecast evaluation (Hammoudeh et al., 2015; Shafiullah et al., 2021). We subsequently considered a forecast evaluation based on models that include oil price proxies as a benchmark to evaluate the predictive content of our uncertainty-based predictive models of carbon trading risks.

To make the analysis more robust and extensive, we also estimated the carbon trading predictive model designed according to the Westerlund and Narayan (2012, 2015) model, calculated with the FQGLS estimator. This estimation is preceded by obtaining the carbon trading risks via the VaR approach, which produces two carbon market risk measures (CAViaR 1% and CAViaR 5%). These are considered alternative carbon risk measures in the predictive models that contain either EPU (global EPU, EU EPU, and US EPU) or GPU (global GPU, EU GPU, and US GPU) as alternative predictors of carbon risk.

Table 6
Uncertainty-carbon trading risk [Westerlund & Narayan].

	Economic policy uncertainty			Geopolitical uncertainty		
	EPU (Global)	EPU (EU)	EPU (US)	GPU (Global)	GPU (EU)	GPU (US)
Carbon trading risk [CAViaR 1%]						
Constant	5.5524***	4.1625***	5.6007***	5.9205***	6.7357***	6.1875***
	(0.0436)	(0.1249)	(0.0996)	(0.0789)	(0.0231)	(0.0032)
Beta-adjusted	0.0104***	0.0159***	0.0125***	0.0145***	0.0955***	0.4632***
	(0.0004)	(0.0005)	(0.0012)	(0.0012)	(0.0066)	(0.0018)
RMSE	2.7050	2.6029	2.7617	2.8015	2.7894	2.8047
DM	−1.8780*	−3.0303***	−1.4512	−0.3698	−0.6768	−0.4146
MDM	−1.8719*	−3.0206***	−1.4466	−0.3686	−0.6746	−0.4133
	EPU (Global)	**EPU (EU)**	**EPU (US)**	**GPU (Global)**	**GPU (EU)**	**GPU (US)**
Carbon trading risk [CAViaR 5%]						
Constant	3.0942***	2.3937***	2.9580***	3.2635***	3.7678***	3.3419***
	(0.0260)	(0.0754)	(0.0675)	(0.0395)	(0.0103)	(0.0309)
Beta-adjusted	0.0059***	0.0076***	0.0071***	0.0094***	0.0633***	0.3612***
	(0.0001)	(0.0003)	(0.0004)	(0.0004)	(0.0024)	(0.0176)
RMSE	1.6503	1.6336	1.7190	1.7025	1.7068	1.7085
DM	−3.2806***	−3.5147***	−1.7320*	−1.5116	−1.5529	−1.5495
MDM	−3.2700***	−3.5034***	−1.7264*	−1.5067	−1.5479	−1.5445

Note: The table presents the results of the Westerlund & Narayan estimation of the economic policy uncertainty-carbon trading risk model and the geopolitical uncertainty-carbon trading risk model. Carbon trading risk here is measured with CAViaR 1% and CAViaR 5% obtained from the Conditional Autoregressive Value at Risk. Beta-adjusted is the key parameter of interest which measures the impacts of the uncertainty indicators on the carbon trading risk. RMSE represents the root mean square error of the models. DM and MDM are the Diebold & Mariano and Modified Diebold & Mariano test statistics for in-sample forecast evaluation. The values in round brackets are standard errors. ***,**, & * indicates statistical significance at 1 percent, 5 percent, & 10 percent respectively.

Table 7
High uncertainty-carbon trading risk [Westerlund & Narayan].

	High economic policy uncertainty			High geopolitical uncertainty		
	EPU (Global)	EPU (EU)	EPU (US)	GPU (Global)	GPU (EU)	GPU (US)
Carbon trading risk [CAViaR 1%]						
Constant	5.6299***	5.7665***	5.8464***	6.0876***	5.9183***	5.7159***
	(0.0154)	(0.1452)	(0.0231)	(0.0864)	(0.1615)	(0.0175)
Beta-adjusted	0.2310***	0.1592***	0.1923***	0.1757***	0.0964***	0.1913***
	(0.0068)	(0.0144)	(0.0046)	(0.0114)	(0.0130)	(0.0038)
RMSE	2.7745	2.7568	2.7792	2.7896	2.8102	2.8245
DM	−0.1879	−0.4607	−0.1184	0.0599	0.4678	0.6639
MDM	−0.1873	−0.4592	−0.1180	0.0597	0.4663	0.6617
	EPU (Global)	**EPU (EU)**	**EPU (US)**	**GPU (Global)**	**GPU (EU)**	**GPU (US)**
Carbon trading risk [CAViaR 5%]						
Constant	3.2336***	3.2436***	3.2929***	3.2765***	3.1172***	3.3064***
	(0.0086)	(0.0055)	(0.0095)	(0.0219)	(0.0088)	(0.0435)
Beta-adjusted	0.1181***	0.1227***	0.1323***	0.1155***	0.0857***	0.0960***
	(0.0021)	(0.0004)	(0.0017)	(0.0033)	(0.0032)	(0.0044)
RMSE	1.7179	1.7169	1.7217	1.7337	1.7348	1.7352
DM	−1.0427	−1.0642	−0.9497	−0.6319	−0.5698	−0.6075
MDM	−1.0393	−1.0608	−0.9466	−0.6299	−0.5680	−0.6055

Note: The table presents the results of the Westerlund & Narayan estimation where the predictors of carbon trading risk are high economic policy uncertainty and high geopolitical uncertainty. Carbon trading risk here is measured with CAViaR 1% and CAViaR 5% obtained from the Conditional Autoregressive Value at Risk. Beta-adjusted is the major parameter of interest which measures the impacts of the uncertainty indicators on the carbon trading risk. RMSE represents the root mean square error of the models. DM and MDM are the Diebold & Mariano and Modified Diebold & Mariano test statistics for in-sample forecast evaluation. The values in round brackets are standard errors. ***,**, & * indicates statistical significance at 1 percent, 5 percent, & 10 percent respectively.

Table 8
Low uncertainty-carbon trading risk [Westerlund & Narayan].

	Low economic policy uncertainty			Low geopolitical uncertainty		
	EPU (Global)	EPU (EU)	EPU (US)	GPU (Global)	GPU (EU)	GPU (US)
Carbon trading risk [CAViaR 1%]						
Constant	5.7216***	6.4873***	5.8942***	6.0676***	6.0919***	5.7745***
	(0.0589)	(0.0916)	(0.0922)	(0.0797)	(0.0399)	(0.0102)
Beta-adjusted	−0.2621***	−0.1335***	−0.1988***	−0.2061***	−0.1113***	−0.1970***
	(0.0079)	(0.0087)	(0.0104)	(0.0093)	(0.0028)	(0.0027)
RMSE	2.8263	2.7536	2.7943	2.7848	2.7712	2.8151
DM	0.6019	−0.9332	0.1618	−0.0290	−0.3686	0.5246
MDM	0.6000	−0.9302	0.1688	−0.0289	−0.3674	0.5229
	EPU (Global)	**EPU (EU)**	**EPU (US)**	**GPU (Global)**	**GPU (EU)**	**GPU (US)**
Carbon trading risk [CAViaR 5%]						
Constant	3.2189***	3.3105***	3.2673***	3.3363***	3.4345***	3.3747***
	(0.0098)	(0.0064)	(0.0008)	(0.0225)	(0.0196)	(0.0303)
Beta-adjusted	−0.1445***	−0.1185***	−0.1277***	−0.1211***	−0.0650***	−0.1059***
	(0.0025)	(0.0035)	(0.0004)	(0.0028)	(0.0026)	(0.0020)
RMSE	1.7351	1.7457	1.7315	1.7214	1.6992	1.7159
DM	−0.5942	−0.2916	−0.6961	−1.0627	−1.8498*	−1.2140
MDM	−0.5923	−0.2906	−0.6939	−1.0593	−1.8438*	−1.2101

Note: The table presents the results of the Westerlund & Narayan estimation where the predictors of carbon trading risk are low economic policy uncertainty and low geopolitical uncertainty. Carbon trading risk here is measured with CAViaR 1% and CAViaR 5% obtained from the Conditional Autoregressive Value at Risk. Beta-adjusted is the major parameter of interest which measures the impacts of the uncertainty indicators on the carbon trading risk. RMSE represents the root mean square error of the models. DM and MDM are the Diebold & Mariano and Modified Diebold & Mariano test statistics for in-sample forecast evaluation. Values in round brackets are standard errors. ***,**, & * indicates statistical significance at 1 percent, 5 percent, & 10 percent respectively.

Table 6 presents the in-sample predictability results demonstrating the impact of the uncertainty indicators on the carbon market risk. As seen in the modeling section, the major coefficient of interest is the beta-adjusted coefficient. The beta-adjusted coefficients are analogous to the theta coefficients obtained from the GARCH-MIDAS regression. Therefore, the predictability results are consistent as they also show that EPU and GPU and their variants heighten the carbon trading risks obtained from the tail risk measure. The beta-adjusted coefficients are positive and significant in the alternative models for CAViaR 1% and CAViaR 5%. The results are consistent in that high GPU and EPU indices obtained as positive partial sums of the level uncertainty series positively affect carbon market risk levels (Table 7). Interestingly, this positive relationship is consistent with the results in Table 8 since low uncertainty also reduces carbon trading risk. The findings further reinforce the evidence from the GARCH-MIDAS regression that carbon market risk can be tamed by paying adequate attention to the two primary drivers of macroeconomic uncertainty.

For the forecast evaluation, we compared the carbon trading risk (CAViaR 1%-based and CAViaR 5%-based) predictive models with a benchmark model that includes oil prices in place of the EPU and GPU index, as previously justified. Subsequently, we compared the two uncertainty-based models to comment on the predictive content of EPU and GPU. We used modified Diebold and Mariano (MDM) statistics for the forecasting evaluation. The MDM statistics should be negative and

Table 9
Out-of-sample forecast evaluation [Uncertainty vs. Baseline].

	Economic policy uncertainty			Geopolitical uncertainty		
	EPU (Global)	EPU (EU)	EPU (US)	GPU (Global)	GPU (EU)	GPU (US)
Out-of-sample forecast evaluation [CAViaR 1%]						
h = 3	−1.6663*	−3.5434***	−1.0555	0.9879	0.4203	0.9173
h = 6	−1.6447*	−3.4876***	−1.0440	1.1224	0.5588	0.9544
h = 9	−1.8758*	−3.4404***	−1.3571	−0.2911	−0.5767	−0.2926
h = 12	−1.8793*	−3.3872***	−1.3682	−0.3228	−0.6092	−0.3371
	EPU (Global)	**EPU (EU)**	**EPU (US)**	**GPU (Global)**	**GPU (EU)**	**GPU (US)**
Out-of-sample forecast evaluation [CAViaR 5%]						
h = 3	−3.8380***	−3.4397***	−1.2363	−1.1027	−1.1473	−1.0832
h = 6	−3.7934***	−3.4051***	−1.2333	−0.9961	−1.0358	−1.0188
h = 9	−3.1322***	−3.0588***	−1.5576	−1.3627	−1.3768	−1.3806
h = 12	−3.1263***	−3.0507***	−1.5465	−1.3693	−1.3902	−1.3928

Note: This table presents the results of Modified Diebold & Mariano out-of-sample forecast evaluation test. The test compares the preferred uncertainty-based model against the oil price-based predictive model as the baseline model. The forecast evaluation extends over 3-, 6-, 9-, & 12-month ahead forecasts. The preferred model is adjudged to better predict carbon trading risk than the baseline if the reported statistic is negative and significant. Otherwise, the oil price-based model outperforms the uncertainty-based model if the statistic is positive and significant. ***,**, & * indicates statistical significance at 1 percent, 5 percent, & 10 percent respectively.

Table 10
Out-of-sample forecast evaluation [Policy uncertainty vs. Geopolitical uncertainty].

	Global (EPU vs. GPU)	EU (EPU vs. GPU)	US (EPU vs. GPU)
Out-of-sample forecast evaluation [CAViaR 1%]			
h = 3	−2.1057**	−3.2776***	−1.2943
h = 6	−2.1485**	−3.2791***	−1.3030
h = 9	−1.8987*	−3.1702***	−0.9188
h = 12	−1.8704*	−3.0871***	−0.8910
	Global (EPU vs. GPU)	**EU (EPU vs. GPU)**	**US (EPU vs. GPU)**
Out-of-sample forecast evaluation [CAViaR 5%]			
h = 3	−2.6570***	−2.8051***	−0.1680
h = 6	−2.7113***	−2.8544***	−0.2243
h = 9	−2.2104**	−2.3384**	0.2716
h = 12	−2.1854**	−2.3033**	0.3004

Note: This table presents the results of Modified Diebold & Mariano out-of-sample forecast evaluation test. The test compares the economic policy uncertainty-based model against the geopolitical uncertainty-based model. The forecast evaluation extends over 3-, 6-, 9-, & 12-month ahead forecasts. The policy uncertainty model is adjudged to outperform the geopolitical uncertainty model if the reported statistic is negative and significant. The reverse holds if the statistic is positive and significant. ***,**, & * indicates statistical significance at 1 percent, 5 percent, & 10 percent respectively.

statistically significant to indicate that models with EPU or GPU as the predictor perform better than those using oil price proxies. For the out-of-sample forecast evaluation of the models, we considered an analysis with 75:25 data split over four forecast horizon periods (3 months, 6 months, 9 months, and 12 months ahead).

The out-of-sample forecast evaluation conducted with the modified MDM test in Table 9 suggests that only global EPU and EU EPU consistently outperform the West Texas Intermediate and Brent crude oil price-based predictive models. The associated MDM statistics were negative and statistically significant. Similar statistics for US EPU are negative but insignificant; however, most of the GPU indices are positive and insignificant; therefore, GPU cannot outperform the oil price as a better predictor of carbon price risk. This result does not mean that GPU cannot predict carbon price, but its predictive content is lower than the oil price. We probed further to confirm that our conclusion is consistent based on a comparison between the uncertainty series and oil price as a benchmark. To do so, we compared the out-of-sample forecast between EPU and GPU in Table 10. The results show that our conclusion is consistent in that EPU predicts carbon trading risk better than GPU; hence, better prediction of carbon trading risk can be achieved with the information contained in global and EU EPUs.

5. Conclusions and policy recommendations

As a strategy to fight climate change, trading carbon allowances is useful as a market-based approach to further the decarbonization agenda and ensure that the global economy completely disconnects economic growth from carbon emissions. The carbon trading system allows carbon emissions to be priced so parties can hold carbon emission allowances; thus, energy-intensive companies can transition from dirty to clean energy technologies. Parties with excess allowances can trade the surplus with those with shortages if the opportunity cost of decarbonization is higher than the holding of allowances; however, the financialization of the market makes it challenging to separate trading from speculative activities and other factors that drive financial markets. When the macroeconomic outlook is uncertain, economic agents become hesitant and investment decreases, increasing the risk levels of the financial market as investor sentiments heighten and equity prices destabilize.

The problems mentioned above are undesirable for the carbon trading market. Stable prices and relatively scarce allowances are vital to ensuring that the market continues to function effectively, enabling economic agents to abandon dirty technologies for cleaner alternatives. Therefore, this study examined the nexus between uncertainty and the risk levels of the carbon trading market and distinguished between two primary forms of macroeconomic uncertainty: EPU and GPU. To ensure that the analyses were robust, we used data related to the two uncertainty indicators at the global level: EU EPU and GPU indices and US EPU and GPU indices. In addition, we measured the carbon trading risk through the realized volatility and VaR approaches.

Specifically, this study utilized the GARCH-MIDAS modeling framework to address the inherent drawbacks of traditional aggregation/disaggregation methods that result in loss of information from mixed-frequency carbon prices/economic uncertainty series. Additionally, we used conditional autoregressive VaR to compute the tail distribution to evaluate the downside risk of the carbon return series and estimate the predictability of carbon trading risk with a modeling approach that accounts for the salient features of the data. This paper's empirical results are rendered as in-sample and multi-horizon out-of-sample predictability and forecast analysis, which were evaluated using the MDM tests.

This study's findings indicate that returns on EU-ETS markets exhibit a stronger response to EPUs in European countries than other countries. In line with our underlying theoretical intuition, the results show that the three EPU and GPU indices heighten risk levels in the EU-ETS market, as illustrated by the coefficients' positive and statistically significant values across the explored estimation approaches. The forecast evaluation conducted with the modified MDM tests indicates that EPU—primarily global EPU and EU EPU—better predict the carbon trading risk than their GPU counterparts, global GPU and EU EPU. Generally, policymakers, specifically the Cooperation of Parties under the UNFCCC, should understand that macroeconomic uncertainty is inimical to the carbon-free economy goal. Researchers and investors wishing to minimize downside risk should also pay attention to macroeconomic uncertainty—specifically EPU—as a significant indicator of whether or not to hold carbon allowances in an investment portfolio.

Since no study is entirely exhaustive, future research could focus on a burgeoning area of research: the connection between climate risk and fundamentals in the carbon allowance market, such as carbon prices, returns, volatility, and risk. Prospective researchers interested in this area could construct (daily) climate risk indices or use available climate data, e.g., temperature anomaly data from the NASA Goddard Institute for Space Studies (https://data.giss.nasa.gov/gistemp/) or climate policy uncertainty data (https://www.policyuncertainty.com/climate_uncertainty.html). For background information on the indices mentioned above for macroeconomic analysis, see Oloko et al. (2022) and Adediran et al. (2023).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

Table A1
Oil price-carbon trading risk nexus

	Full data sample		75% data sample	
	WTI	Brent	WTI	Brent
Theta (θ)	0.0009**	0.0634***	0.0011**	0.0013***
	(0.0004)	(0.0037)	(0.0005)	(0.0005)
ARCH term	0.1228***	0.0502***	0.1151***	0.1161***
	(0.0076)	(0.0025)	(0.0079)	(0.0081)
GARCH term	0.8586***	0.9002***	0.8731***	0.8719***
	(0.0086)	(0.0077)	(0.0082)	(0.0084)
ϖ	5.4846	5.0000***	4.7389	4.0337
	(7.0059)	(0.0031)	(5.8452)	(3.4936)
Mu	0.0013***	0.0012**	0.0011**	0.0011**
	(0.0005)	(0.0006)	(0.0005)	(0.0005)
Constant	0.0007***	−0.0264***	0.0005*	0.00032
	(0.0003)	(0.0016)	(0.0003)	(0.0003)

Note: The table presents the results of the baseline model where the oil price proxies serve as the predictors of carbon trading risk in the GARCH-MIDAS framework. Carbon trading risk here is measured with realized volatility obtained from the GARCH-MIDAS model of the EU-ETS returns. The carbon trading risk (realized volatility of EU-ETS returns) is the high frequency (daily) variable while the oil price series (WTI & Brent) are of lower (monthly) frequency. Theta is the key parameter of interest which measures the impacts of the uncertainty indicators on the carbon trading risk. The values in round brackets are standard errors. ***,**, & * indicates statistical significance at 1 percent, 5 percent, & 10 percent respectively.

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