Uncertainty effects on European carbon prices and efficiency: A time-varying SVAR-SV Analysis

Abstract

Using the TVP-SVAR-SV analysis, this paper studies the effect of economic policy, financial, and geopolitical uncertainties on European carbon prices and efficiency at different time horizons and different time points. Based on the European carbon market data from January 2016 to October 2022, we consider three key events: The Brexit crisis, COVID-19, and the Russo-Ukrainian war. Moreover, we apply a structural threshold vector autoregressive (TVAR) model to study the asymmetric responses of carbon prices and corporate carbon efficiency to uncertainty shocks under different regimes. Our findings show; Firstly, economic policy uncertainty (EPU) and financial uncertainties (FSI) negatively impact the European carbon market more than geopolitical uncertainty (GPR). Secondly, significant events and crises increase the negative impact of uncertainty shocks on carbon prices and corporate carbon efficiency. Thirdly, we found that the impact of EPU, FSI, and GPR shocks on carbon prices and corporate carbon efficiency significantly differs across high and low regimes. For robustness, our findings are generally robust using both daily and weekly data. Our aim is to provide helpful insight for policymakers, investors, and European companies.

Keywords: SUncertainty, Carbon prices, carbon efficiency, time-varying SVAR-SV, Structure threshold VAR.

1 Introduction

The recent amplification of climate change, due to a rise in global warming gases, is a fact that severely affects both human health and economies. Temperature hikes are preceded by extreme meteorological conditions, including sea level rise, high risk of catastrophic flooding, periods of drought, storms, and wildfires, which are getting more severe and regular and threatening the world on a massive scale. In the face of global warming and increasing serious greenhouse gas emissions, the vision of carbon neutrality has grown stronger. Several countries have taken action to combat climate change and steer capital flows into greener technologies, announcing successively the goal of carbon neutrality, and sparking a wave of global carbon reduction initiatives.

Among European Union climate change policies, the EU Carbon Emission Trading System ETS is considered a critical component of regulating and mitigating the emission of greenhouse gases through the use of market mechanisms (Bing et al., 2015). Over the course of many years, the European Emission Trading System has been through four key commitment phases[1], which have all shown an important increase in terms of supporters number, trading volume, liquidity, and flexibility in the European carbon market. Nowadays, it is the world's largest carbon market using the cap-and-trade trading system (Ibikunle et al., 2016) and has considerably contributed to the reduction of carbon emissions in Europe (Ibikunle et al, 2016; Karpf et al, 2018). Many studies have found that the EU ETS affects electricity prices by changing the additional cost of generating power (Kara et al., 2008; Zachmann and Hirschhausen, 2008), influencing power-producing companies' profits and investing in limiting emissions (Bonenti et al., 2013). Furthermore, researchers believe that the establishment of the carbon market plays a consequential and powerful role in supporting the expansion of the renewable energy industry as new energy gradually replaces traditional energy (Hobbie et al., 2019).

However, recently, the price volatility of EUAs has been varying in parallel with the carbon market's quick expansion. Therefore, the realization of the EU's emission reduction targets will be directly impacted by the severity of the carbon price's fluctuations since it is the primary driving force behind the operation of an emissions trading system, which is not advantageous for the sustainable development of society (Fleschutz et al. 2021). According to Dou et al. (2022), unstable carbon prices affect carbon market performance, potentially reducing the impact of carbon emission reductions. Furthermore, significant changes in the value of carbon assets could stimulate speculative activity within the carbon market, increasing carbon price volatility. As a result of this vicious cycle, carbon prices will continue to deviate from the market's primary supply and demand levels, which is not ideal for the market's efficient operation. Regarding this matter, it is crucial to investigate factors that influence carbon prices to keep a reliable system for pricing carbon

[1] The project consisted of four phases. Phase I, which was the pilot period, took place between 2005 and 2007. Phase II, which covered the full operation, took place between 2008 and 2012. Phase III, which focused on the "Climate Change Package 2020," occurred from 2013 to 2020. Currently, phase IV is in effect, and it spans from 2021 to 2030.

assets, and ultimately establish a successful carbon market. Overall, the drivers of carbon prices are complex and interconnected, and understanding them is important for developing effective strategies to reduce greenhouse gas emissions. In line with this, researchers have investigated the factors that affect carbon price fluctuations, including the macroeconomic outlook, energy use, oil, coal, and electricity prices (e.g., Hammoudeh et al., 2014; Zhu et al., 2019; Zheng et al., 2021). Nevertheless, a larger body of research has concentrated on the influence of factors related to policies as an element in the pricing mechanism of carbon trades, contending that the impacts of policy may even exceed the influence of economic factors (Wang and Guo, 2018; Zhu et al., 2019). The theoretical explanations of Christiansen et al. (2005) that link carbon prices to policy regulation measures are confirmed by Benz and Trück's (2009) demonstration, proving that modifications to rules or policies can result in abrupt increases in carbon prices.

Despite the extensive literature on carbon price drivers, the effect of uncertainty on the carbon market and corporate carbon efficiency remains largely unexamined. Our research fills the gap in the relationship between uncertainty and the European Carbon market by exploring, for the first time, the time-varying response of the spot, future1, future4, and future6 carbon prices and corporate carbon efficiency index in the European market to different uncertainty indexes. In reality, the management of carbon market risk is crucial for firms to improve their carbon emission efficiency and mitigate associated risks. Hence it is important to examine the reaction of corporate carbon efficiency to uncertainty shocks. This study enriches the existing literature with several important contributions.

Firstly, the present study includes three types of uncertainty; EPU, financial stress index, and geopolitical uncertainty. In Fact, after the construction of the economic policy index (EPU) by Baker et al. (2016), researchers, investors, and policymakers become all interested in how political and economic instability affects economic activity (Bloom, 2009; Castelnuovo and Tran, 2017; Moore, 2017). A few years later, the concept of uncertainty is regarded as a fundamental principle when analyzing the changes and patterns in global economic growth (Dai et al., 2021b; Foglia and Dai, 2021). In addition to the economic development impact of EPU, it has been proved that EPU influences financial assets such as crude oil, gold, stock, and green assets (Karnizova and Li, 2014; Ko and Lee, 2015; Li et al., 2020; Su et al., 2021a; Sun et al., 2021). Since the carbon market is a financial asset, examining the effects of EPU on carbon price volatility and corporate carbon efficiency is essential. To date, limited studies investigated the relationship between EPU and European futures carbon prices (Gao et al., 2023, Dou et al., 2022, Ye et al., 2021). They confirmed that EPU can affect the European carbon market.
Besides the environmental impact of EPU, financial market uncertainty might influence the carbon market (Yuan et Yang., 2020). In fact, it is reasonable to suppose that there is a constant link between carbon market efficiency and financial market uncertainty due to the critical position that financial markets play in representing economic growth. According to Bloom (2009), uncertainty in the financial market is

not only clearly different from other uncertainties but also extremely interconnected with the real economy. In their research, Yuan and Yang (2020) examined how the uncertainty in the financial market is linked to the carbon market, by analyzing the uncertainty of the stock market and crude oil market. Their findings confirmed the existence of significant risk spillover from the stock market and crude oil market uncertainty to the carbon market. As a result, the goal of our research is to shed more light on the impact of financial market uncertainty shocks on carbon prices and carbon efficiency using the OFR Financial Stress Index (OFR FSI) which incorporates five categories of indicators: credit, equity valuation, funding, safe assets, and volatility.
Moreover, geopolitical uncertainty becomes among the most significant elements in determining investment strategies, along with EPU and financial uncertainty (Ding et al., 2021). Investor panic during extreme geopolitical risk events can result in abnormal market fluctuations, ultimately impacting returns and market volatility (Tiwari et al., 2021). Furthermore, geopolitical developments offer possibilities for significant changes in governmental strategy which impact investors' behavior in the financial market (Asai et al., 2020). Given that geopolitical risk influences changes in oil prices through supply and demand channels (Demirer et al.2019), if there is an initial positive effect on the price of carbon allowances due to a rise in crude oil prices, it is possible that GPR could have a substantial impact on carbon prices (Hammoudeh et al.2014). Although the important effect of geopolitical risk, the relationship between geopolitical uncertainty and the European carbon markets has not been studied. To our knowledge, no previous study has explored the responses of spot and futures carbon prices and corporate carbon efficiency to geopolitical uncertainties, which complements the current research on the effect of uncertainty on the carbon market.

Secondly, the relationship between uncertainty and fluctuations in carbon prices and carbon efficiency is anticipated to change over time in response to each significant event since unprecedented pandemics and financial crises increased risks, uncertainties, fear, and volatility in financial markets. Thus, the second contribution that this paper brings to the current body of literature is using the Bayesian TVP-SVAR-SV model to study the impact of EPU, GPR, and financial uncertainty on carbon prices and carbon efficiency in a time-varying framework during three different significant events. In fact, shocks and crises have long been recognized as major drivers of political processes by political scientists. The "multiple streams" hypothesis, which proposes that policy change happens when perceptions of issues, solutions, and politics converge around specific legislation, is one of the most often used ideas for explaining when and why certain policies change. The so-called "focused event" is a high-profile event that draws people's attention and forces them to focus on a particular dimension of a particular problem and a major component in the policy-making approach. Extraordinary events may also have an impact on politics and governments. As a result, these shocks might open up a "window of opportunity" for policymakers to address an issue that has been present for some time. Our study offers a new dynamic perspective for analyzing changes in the prices of carbon and corporate carbon efficiency by considering the differences in effects at various time points. As part of the identified key events, we consider the changes in the underlying structure caused by the recent Russo-Ukrainian crisis, Covid-19, and Brexit crisis. Dou et al. (2022) explored the linkage between EPU and the carbon future market before and after covid19. Their results confirm that the pandemic outbreak has an impact on the spillover and interdependence of EPU and carbon futures price return by affecting their short- and medium-term performance. This raises the question about the impact of significant events on the relationship between uncertainty and the carbon market. To fill this gap in the literature, our paper is the first study that reveals the time-varying response of carbon spot and futures prices and corporate carbon efficiency to EPU, financial uncertainty, and GPR during the Brexit crisis, covid19, and the Russo-Ukrainian crisis..

Thirdly, we use the structural threshold VAR model (STVAR) of Balke (2000) to examine the contemporaneous relation between the European carbon market and uncertainties spanning two regimes. Evidence from prior research shows a nonlinear link between uncertainty and the Chinese carbon market (Li et al, 2022, Zhang et al,2021). Furthermore, such an effect might be explained by changes in financial market conditions. Unfortunately, little attention has been devoted to the varying asymmetric impact of uncertainty on the European carbon market, and researches on this subject is still restricted to a few working papers (Gao et al,2023; Yuan et al,2020). To this, our study analyzes the varying effects of EPU, FSI, and GPR shocks on carbon price and corporate carbon efficiency across different uncertainty regimes. Overall, our study contributes to the literature by employing a TVAR model to explore the threshold impact that is induced by changes in uncertainty situations. To the best of our knowledge, this is the first study to examine the asymmetric impact of EPU, FSI, and GPR on carbon pricing and corporate carbon efficiency over different regimes.

This paper is structured as follows: Section 2 outlines the methodology and data used, Section 3 details the empirical results, Section 4 presents the robustness tests, and Section 5 summarizes the policy implications and conclusions.

2 Methodology

2.1 Construction of the TVP-SVAR-SV model

In most research examining the impact of uncertainty shocks on financial and commodity markets, the vector autoregression (VAR) or structural vector autoregression (SVAR) techniques with constant coefficients have been utilized (Bakas and Triantafyllou, 2018; Ding et al, 2021). The economic structure and the impacts of uncertainty shocks on the commodity market are both implicitly assumed to be constant in such models. However, the impact of uncertainty shocks varies based on macroeconomic circumstances and is not constant due to the complexity of the current global economic situation (Lyu et al., 2021). External shocks like financial crises or significant unpredictable events can cause structural changes in the financial sector and the economy as a whole (Nasir et al., 2018, Nasir et al.,2019).

To better represent the changing effects of explanatory factors and to account for possible modifications in the structural relationships, we enhance the SVAR model by introducing time-varying parameters. We expand on Primiceri (2005) multivariate time-varying parameter vector autoregressive (TVP-VAR) model by including random time-varying volatilities inspired by Omori et al. (2007) and Nakajima (2011) innovations. Thus, the heteroskesticity property of structural innovations as well as the time variation of the simultaneous transmission of uncertainty shocks to carbon spot/futures price and carbon efficiency are both expected to be detected by our TVP-SVAR-SV model. These characteristics enable us to develop multiple insights into the effects of various uncertainty shocks on the carbon market over time. The SVAR model used in this paper is expressed as follows :

$$Ay_t = F_1 y_{t-1} + \ldots + F_s y_{t-s} + \mu_t, \quad t = s+1, \ldots, n \tag{1}$$

where y_t is a $k \times 1$ vector of observed variables. For instance, the vector $y_t = (\Delta uncertainty_t, \Delta carbon\ prices_t, \Delta Car\ eff_t)$ is used to investigate the impact of uncertainty (TEU or FSI or GEO) on the carbon prices (spot or futures1 or futures4 or futures6) and corporate carbon efficiency. Our empirical strategy consists of analyzing the response of carbon prices and corporate carbon efficiency to different uncertainty types (TEU or FSI or GEO). We also take into account multiple carbon price measures (spot or futures1 or futures4 or futures6).
The $F_1, \ldots, F_t$ and A denote the 3×3 matrices of the coefficients and μ_t represents a 3×1 column vector of structural shocks, where

$$A = \begin{pmatrix} 1 & 0 & \ldots & 0 \\ a_{21} & \ddots & & \vdots \\ \vdots & & \ddots & 1 \\ a_{k1} & \ldots & a_{kk-1} & 1 \end{pmatrix} \tag{2}$$

The reduced form of the SVAR model in Eq. (1) is given by :

$$y_t = B_1 y_{t-1} + \ldots + B_s y_{t-s} + A^{-1} \sum \varepsilon_t = X_t \beta + A^{-1} \sum \varepsilon_t \tag{3}$$

Where β is the $(k^2 s \times 1)$ vector derived from B_i. $X_t = I_k \otimes (y_{t-1}, \ldots, y_{t-i})$, where $\otimes$ denotes the Kronecker product. Based on a consistent literature body, we set the following variables order to identify the structural shocks; indeed, according to Baker et al. (2016), and Huang and Luk (2020), uncertainty variables are placed in the first order assuming that uncertainty shocks (emanating from economic policy or financial stress or geopolitical risk) are supposed to have an immediate impact on carbon price and carbon efficiency, while non-uncertainty shocks cannot immediately affect uncertainty. In addition, by placing carbon efficiency variable in the last order we assume that carbon efficiency instantly react to uncertainty and carbon price shocks, while the reverse does not hold true.

If we introduce a stochastic volatility (SV) process into the Eq.(3), we can express the TVP-SVAR-SV model as follows:

$$y_t = X_t\beta_1 + A_{-1}^{t}\sum_{t}\varepsilon_t, \quad t \;=\; s \;+\; 1, \;\cdots, \; n \tag{4}$$

As noted by Primiceri (2005) and Nakajima et al. (2011), the parameters are presumed to conform to a random walk process described as follows:

$$\begin{cases} \beta_{t-1} = \beta_t + \mu_{\beta t} \\ \alpha_{t+1} = \alpha_t + \mu_{\alpha t} \\ h_{t+1} = ht + \mu_{ht} \end{cases}$$

Where $t \;=\; s \;+\; 1, \;\ldots, \; n, \; \beta_{s+1} \;\sim\; N(\mu_{\beta 0}, \; \sum_{\beta 0}\,), \; \alpha_{s+1} \;\sim\; N(\mu_{\alpha 0}, \; \sum_{\alpha 0}), \; h_{s+1} \;\sim\; N(\mu_{h0}, \; \sum\,_{h0})$

and $\begin{pmatrix} \epsilon_t \\ \mu \\ \mu \\ \mu_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \sum_\beta & 0 & 0 \\ 0 & 0 & \sum_\alpha & 0 \\ 0 & 0 & 0 & \sum_h \end{pmatrix}\right)$

where $\sum_\beta$, $\sum_\alpha$, and $\sum_h$ are assumed to be diagonal matrices.

To estimate the TVP-SVAR-SV, we utilize Bayesian inference and carry out the estimation process with the Markov chain Monte Carlo (MCMC) technique. The Markov Chain Monte Carlo (MCMC) method, which is based on the entire set of available data, can offer smooth estimates of the parameters of interest. Therefore, in the context of Bayesian inference, we adopt the MCMC simulation algorithm to estimate the TVP-SVAR-SV model (Koop et al., 2009). We use the Gibbs sampling algorithm to obtain 10000 samples after discarding the first 1000 as burn-in in order to obtain valid samples from the estimated posterior (Primiceri, 2005).

2.2 Data and preliminary analysis

We analyze data from January 2016 to October 2022, encompassing a range of significant global financial market events, including the Brexit crisis, the United States departure from the Paris Agreement, trade conflicts between the US and China, and the COVID-19 pandemic, and the Russo-Ukrainian war.

Our data was extracted from several distinct sources. Starting with carbon prices, we used spot, futures 1, futures 4, and futures 6 carbon prices (car pri spot, car pri 1, car pri 4, and car pri 6) from the Thomson Reuteurs database. We utilized the SP Europe 350 Carbon Efficient Index from the Dow Jones database for corporate carbon efficiency (Car Eff). This index is intended to assess the performance of companies in the SP Europe 350 by assigning greater or lesser weightings to companies with lower or higher carbon emissions per unit of revenue. Regarding uncertainty indexes, our paper selects multiple types of uncertainty to analyze from a broader perspective. Firstly, we utilized the Twitter-based Economic Uncertainty (TEU) index, which measures the number of daily English tweets containing uncertainty and economy-related terms. This index, extracted from the Economic Policy Uncertainty website, generally reflects the level of economic policy uncertainty. Secondly, to measure financial uncertainty, we used the Financial Stress Index (FSI) from the Office of Finance Research database which incorporates five categories of indicators: credit, equity valuation, funding, safe assets, and volatility. The Financial Stress Index provides a daily assessment of stress in worldwide financial markets based on market indicators such as interest rates, valuation measures, and yield spreads. This index, developed by the Office of Financial Research (OFR), yields a positive value when stress levels exceed the average, and a negative value when stress levels are below average. Lastly, our study includes the Geopolitical Risk Index (GEO) developed by Caldara and Iacoviello (2022) (https://www.matteoiacoviello.com/gpr.htm). The GPR index is based on a text-search algorithm that takes into account 11 top newspapers in the United States, United Kingdom, and Canada. Hence, the index is built by tracking publications that contain phrases like "war," "military," "geopolitics," "terrorist," and other comparable terms. According to Caldara and Iacoviello (2018), the GPR index captures events that are exogenous to business and financial cycles better than the EPU index. This newly formed index is better than other individual indicators since it incorporates terrorism, political conflicts, and wars into a single measure. Furthermore, the index incorporates both present and expected risks that are associated to geopolitical events, as determined by monthly media data reports.

We employ the Kapetanios (2005) unit root test with structural breaks to examine the integration properties of the variables, which appears to be appropriate when taking into account structural changes impacting the stationarity of the underlying components. The results of the unit root tests with multiple structural breaks are presented in Table 1. As we can notice from Table 1, the results indicate that all the considered variables are found to be stationary in first difference. The graph in Fig. 1 shows how the carbon price and carbon efficiency change in relation to TEU, FSI, and GEO. It is evident that carbon efficiency and carbon price are linked to uncertainty indexes.

3 Empirical results

3.1 Estimation of selected parameters

Based on Akaike's information criterion (AIC) and the Hannan-Quinn information criterion (HQ), We set the lag length to 1 when estimating our TVP-SVAR-SV model. Table 2 provides a summary of the estimated results for the chosen param-

Table 1: Table 1. Kapetanios (2005) unit root tests with structural breaks.

	Level			1st Diff		
	k=1	k=2	k=3	k=1	k=2	k=3
Carbon Eff	-3,22018 2020:10:00	-3,22541 2017:05:00 2020:10:00	-3,51984 2017:05:00 2019:01:00 2020:10:00	-9,18422*** 2020:03:00	-9,18422*** 2018:12:00 2020:03:00	-9,18422*** 2017:08:00 2018:12:00 2020:03:00
Car pri (Spot)	-2,63806 2021:08:00	-3,1581 2020:02:00 2021:08:00	-3,30584 2018:02:00 2020:02:00 2021:08:00	-9,17919*** 2020:05:00	-9,47068*** 2017:12:00 2020:05:00	-9,47068*** 2017:12:00 2019:02:00 2020:05:00
Car pri (Futures1)	-2,64668 2021:08:00	-3,1412 2020:02:00 2021:08:00	-3,28453 2018:02:00 2020:02:00 2021:08:00	-9,16062*** 2020:05:00	-9,44674*** 2017:12:00 2020:05:00	-9,44674*** 2017:12:00 2019:02:00 2020:05:00
Car pri (Futures4)	-3,12219 2021:08:00	-3,12219 2020:02:00 2021:08:00	-3,12219 2018:02:00 2020:02:00 2021:08:00	-8,79027*** 2020:11:00	-9,01827*** 2017:12:00 2020:11:00	-9,01827*** 2017:12:00 2019:03:00 2020:11:00
Car pri (Futures6)	-3,30085 2020:07:00	-3,90166 2018:02:00 2020:07:00	-4,12737 2018:02:00 2019:04:00 2020:07:00	-8,43219*** 2021:02:00	-8,43219*** 2017:12:00 2021:02:00	-8,43219*** 2017:12:00 2019:12:00 2021:02:00
TEU	-3,85303 2020:07:00	-3,85303 2019:04:00 2020:07:00	-3,85303 2017:04:00 2019:04:00 2020:07:00	-8,93669*** 2020:05:00	-8,93669*** 2020:05:00 2021:08:00	-8,93669*** 2019:01:00 2020:05:00 2021:08:00
FSI	-4,69709 2020:07:00	-4,69709 2019:05:00 2020:07:00	-4,69709 2018:01:00 2019:05:00 2020:07:00	-7,50817*** 2020:05:00	-7,55411*** 2018:12:00 2020:05:00	-7,55411*** 2017:04:00 2018:12:00 2020:05:00
GEO	-4,94584 2021:05:00	-5,22746 2020:01:00 2021:05:00	-5,24837 2017:09:00 2020:01:00 2021:05:00	-9,54706*** 2021:07:00	-9,54959*** 2018:02:00 2021:07:00	-9,56935*** 2018:02:00 2020:04:00 2021:07:00

Note: Car Eff, Car pri, TEU, FSI, and GEO refer respectively to corporate carbon efficiency, carbon price, Economic policy uncertainty, financial uncertainty, and geopolitical uncertainty

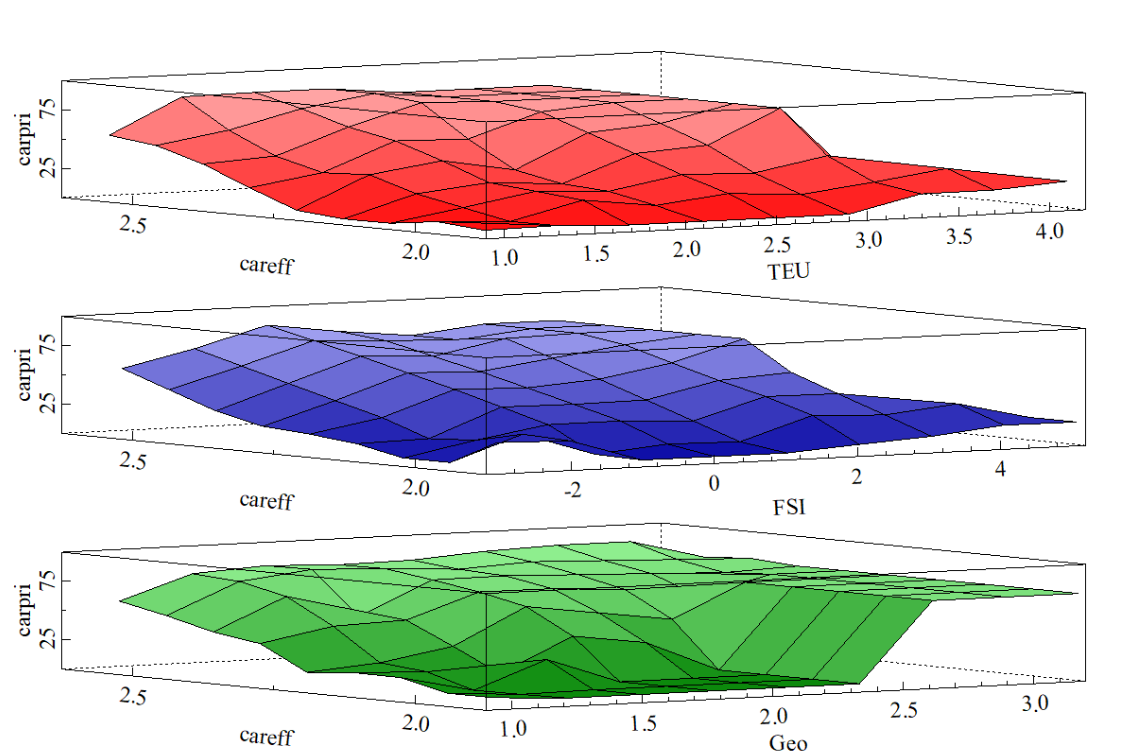


Figure 1: Evolution of carbon price and carbon efficiency as functions of uncertainty.

eters, including posterior means, standard deviations, intervals of 95% confidence, diagnostic statistics for Geweke convergence, and inefficiency. These findings demonstrate that the parameter estimates' posterior means are within the 95% confidence interval. The results suggest that there is no evidence of rejecting the null hypothesis of convergence to the posterior distribution for all parameters at a significance level of 5%, according to Geweke statistics. Additionally, almost all parameters have very low inefficiency factors. The posterior draws are efficiently produced by the MCMC algorithm.

The sample autocorrelations, sample paths, and posterior densities are shown in Fig.2. We discover that sample autocorrelations rapidly decrease and that sample paths typically remain stable. The findings suggest that posterior samples are effectively generated through the use of the MCMC sampling method.

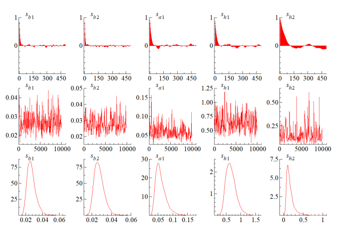
3.2 Stochastic volatility estimation

Fig.3 shows the dynamics of the estimated stochastic volatilities of the structural shocks originating from our variables as time progresses $\sigma it\ 2 = exp(hit)$, based on the posterior mean and 95% credible intervals. This figure demonstrates how volatility varies significantly over time, supporting the use of the TVP-SVAR model with stochastic volatility to prevent biased estimation given the importance of posterior estimates of stochastic volatilities.

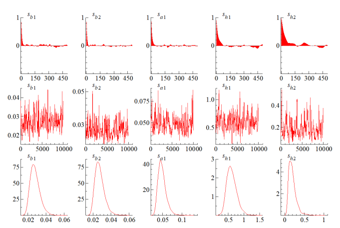
Table 2: Estimation of selected parameters in the TVP-SVAR-SV model

Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef.	Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef.	Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef.
TEU - spot							FSI - spot							GEO - spot						
$(\sum\beta)1$	0.0272	0.0052	0.0192	0.0394	0.008	14.50	$(\sum\beta)1$	0.0279	0.0053	0.0195	0.0404	0.671	17.79	$(\sum\beta)1$	0.0249	0.0042	0.0182	0.0345	0.105	12.77
$(\sum\beta)2$	0.0275	0.0051	0.0194	0.0390	0.229	10.18	$(\sum\beta)2$	0.0275	0.0053	0.0195	0.0399	0.847	14.84	$(\sum\beta)2$	0.0274	0.0051	0.0194	0.0397	0.731	14.52
$(\sum$a$)1$	0.0596	0.0176	0.0353	0.1044	0.599	22.73	$(\sum$a$)1$	0.0491	0.0104	0.0332	0.0736	0.165	15.49	$(\sum$a$)1$	0.0739	0.0221	0.0427	0.1291	0.324	21.35
$(\sum$h$)1$	0.6640	0.1710	0.3935	1.0574	0.027	29.43	$(\sum$h$)1$	0.6102	0.1583	0.3522	0.9702	0.077	34.65	$(\sum$h$)1$	0.4504	0.1534	0.2065	0.8023	0.364	43.77
$(\sum$h$)2$	0.1662	0.0971	0.0621	0.4421	0.976	68.03	$(\sum$h$)2$	0.1960	0.0967	0.0732	0.4378	0.308	71.25	$(\sum$h$)2$	0.1600	0.1160	0.0555	0.4933	0.297	108.09
TEU - Future1							FSI - Future1							GEO - Future1						
$(\sum\beta)1$	0.0274	0.0054	0.0192	0.0403	0.629	13.01	$(\sum\beta)1$	0.0280	0.0057	0.0196	0.0415	0.025	22.04	$(\sum\beta)1$	0.0252	0.0044	0.0183	0.0358	0.008	10.69
$(\sum\beta)2$	0.0274	0.0053	0.0194	0.0398	0.720	12.16	$(\sum\beta)2$	0.0274	0.0054	0.0192	0.0399	0.213	11.91	$(\sum\beta)2$	0.0277	0.0053	0.0196	0.0404	0.361	10.98
$(\sum$a$)1$	0.0602	0.0177	0.0363	0.1025	0.124	21.89	$(\sum$a$)1$	0.0510	0.0109	0.0333	0.0756	0.698	15.61	$(\sum$a$)1$	0.0714	0.0204	0.0413	0.1206	0.593	15.81
$(\sum$h$)1$	0.6505	0.1672	0.3945	1.0577	0.101	33.41	$(\sum$h$)1$	0.6096	0.1468	0.3603	0.9326	0.538	28.74	$(\sum$h$)1$	0.4483	0.1646	0.1710	0.8305	0.802	50.38
$(\sum$h$)2$	0.1535	0.0840	0.0569	0.3798	0.061	77.71	$(\sum$h$)2$	0.2116	0.1171	0.0736	0.5106	0.142	72.28	$(\sum$h$)2$	0.1395	0.0777	0.0566	0.3375	0.013	97.27
TEU - Future4							FSI - Future4							GEO - Future4						
$(\sum\beta)1$	0.0275	0.0055	0.0193	0.0402	0.767	13.47	$(\sum\beta)1$	0.0282	0.0056	0.0198	0.0423	1.000	18.82	$(\sum\beta)1$	0.0250	0.0043	0.0183	0.0351	0.295	10.72
$(\sum\beta)2$	0.0274	0.0055	0.0192	0.0402	0.887	8.27	$(\sum\beta)2$	0.0280	0.0055	0.0196	0.0413	0.007	14.39	$(\sum\beta)2$	0.0272	0.0052	0.0191	0.0394	0.005	12.40
$(\sum$a$)1$	0.0596	0.0167	0.0363	0.1003	0.184	23.38	$(\sum$a$)1$	0.0519	0.0116	0.0336	0.0785	0.275	21.54	$(\sum$a$)1$	0.0739	0.0215	0.0424	0.1245	0.154	27.94
$(\sum$h$)1$	0.6475	0.1697	0.3851	1.0380	0.151	29.61	$(\sum$h$)1$	0.6090	0.1746	0.3280	1.0183	0.228	46.00	$(\sum$h$)1$	0.4500	0.1668	0.1907	0.8301	0.665	59.04
$(\sum$h$)2$	0.1569	0.0823	0.0573	0.3678	0.000	44.78	$(\sum$h$)2$	0.1939	0.0913	0.0678	0.4077	0.901	61.34	$(\sum$h$)2$	0.1517	0.0941	0.0552	0.4031	0.623	55.74
TEU - Future6							FSI - Future6							GEO - Future6						
$(\sum\beta)1$	0.0271	0.0051	0.0192	0.0390	0.000	17.45	$(\sum\beta)1$	0.0277	0.0054	0.0195	0.0403	0.029	9.47	$(\sum\beta)1$	0.0260	0.0048	0.0186	0.0375	0.861	11.68
$(\sum\beta)2$	0.0278	0.0057	0.0195	0.0414	0.214	12.44	$(\sum\beta)2$	0.0271	0.0051	0.0193	0.0389	0.201	15.49	$(\sum\beta)2$	0.0275	0.0055	0.0192	0.0407	0.060	13.06
$(\sum$a$)1$	0.0562	0.0146	0.0352	0.0924	0.667	22.14	$(\sum$a$)1$	0.0514	0.0120	0.0332	0.0791	0.058	24.05	$(\sum$a$)1$	0.0609	0.0168	0.0367	0.1008	0.004	23.03
$(\sum$h$)1$	0.6453	0.1614	0.3881	1.0236	0.482	25.97	$(\sum$h$)1$	0.6507	0.1642	0.3779	1.0212	0.937	24.67	$(\sum$h$)1$	0.4662	0.1627	0.2050	0.8344	0.020	55.68
$(\sum$h$)2$	0.2750	0.1973	0.0700	0.7881	0.036	136.62	$(\sum$h$)2$	0.4132	0.2320	0.1088	0.9895	0.664	115.08	$(\sum$h$)2$	0.5312	0.3033	0.0773	1.2490	0.113	120.19

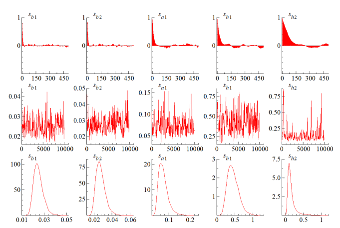
Note: “mean” refers to the posterior means, “95%L”: 95% lower credible interval limit, “95%U”: 95% upper credible interval limit, “Stdev”: standard deviations, “Inef”.: inefficiency, and “Geweke”: Geweke convergence diagnostics statistics.



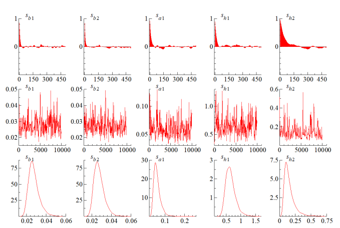
(a) TEU-Spot



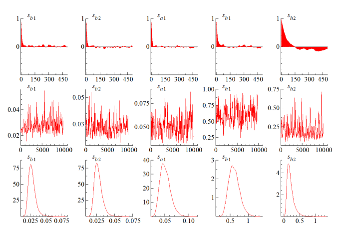
(b) FSI – Spot



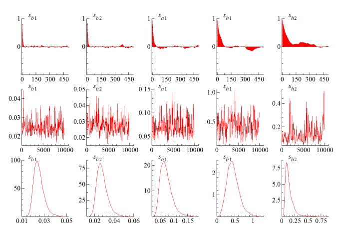
(c) GEO – Spot



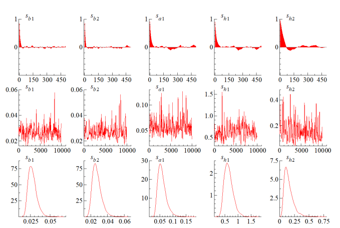
(d) TEU - Futures1



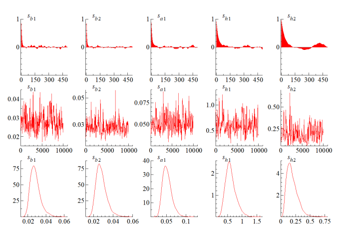
(e) FSI - Futures1



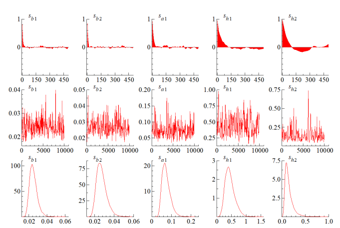
(f) GEO - Futures1



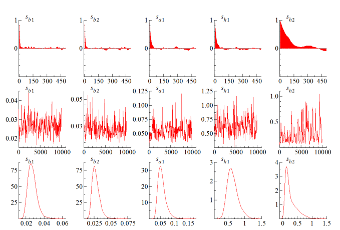
(g) TEU - Futures4



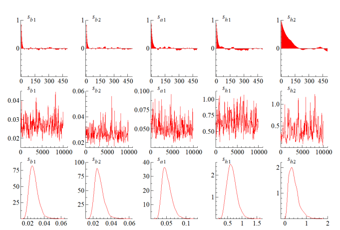
(h) FSI - Futures4



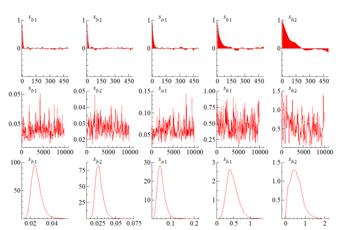
(i) GEO - Futures4



(j) TEU - Futures6



(k) FSI - Futures6

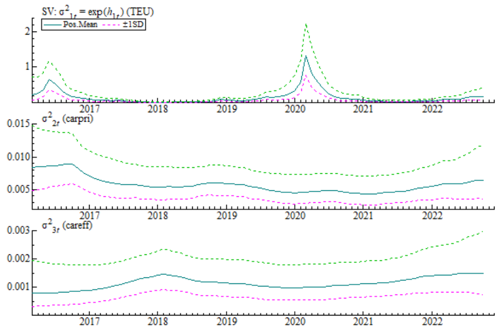


(l) GEO - Futures6

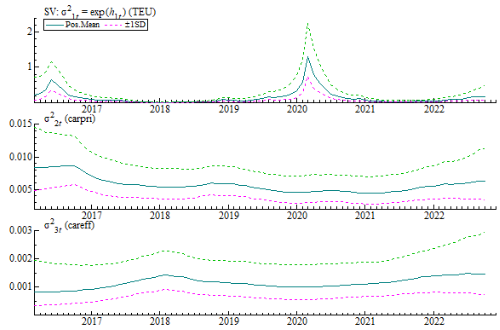
Figure 2: Sample autocorrelation, sample paths, and posterior densities for selected parameters

Three significant dates—2016, 2020, and 2022—as well as cyclical ups and downs are depicted on the plots of each estimated stochastic volatility. Starting with TEU, we note periods of high volatility in 2016, which reflects the Brexit crisis, 2020, which aligns with the time frame of the COVID-19 outbreak, and early in 2022, during the Russo-Ukrainian war. Additionally, fig.3 shows a high level of FSI volatility in 2020 and a slight increase in volatility in 2022. We discovered a significant increase in GEO stochastic volatility in 2022, which reflects the effect of the Russo-Ukrainian crisis on geopolitical uncertainty. These results encourage us to investigate the time-varying effect of uncertainty during the Brexit crisis, Covid19 pandemic, and the Russo-Ukranian war. Moreover, our findings demonstrate that the volatility shocks caused by economic, financial, and geopolitical uncertainty are not always the same over time, which supports the use of three different uncertainty indexes in our study.

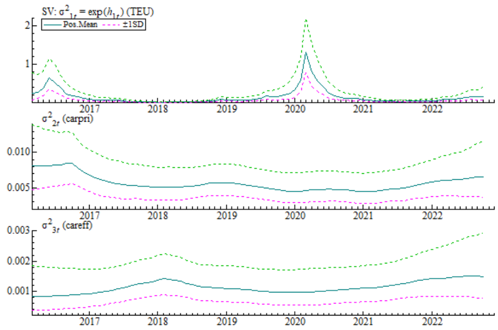
Regarding carbon price and carbon efficiency, our analysis revealed that the trend patterns and cyclic fluctuations of carbon spot, futures 1, and futures 4 prices' stochastic volatilities exhibit similar trajectories. Furthermore, compared to Covid19 pandemic, a higher level of volatility is reached during the Brexit and the Russo-Ukrainian crisis. This might be explained by the fact that these two crises are very related to the European carbon market. For corporate carbon efficiency stochastic volatility, the results confirm generally high volatility during 2016, 2020, and 2022. In addition, according to Fig. 3, carbon spot and futures prices are relatively stable during Phase III and Phase IV, except, in 2016, 2020, and 2022. The stability of the European carbon market is not only limited to carbon spot and futures prices but also to the stochastic volatility of the corporate carbon efficiency index. Our analysis provides guidance for investors and policy-makers to avoid the volatility of the European carbon market, especially during high uncertainty periods.



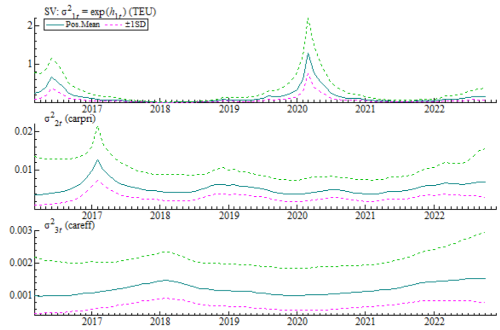
(a) TEU - Spot - CarEff



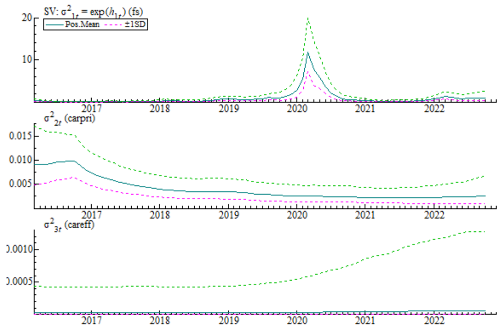
(b) TEU - F1 - CarEff



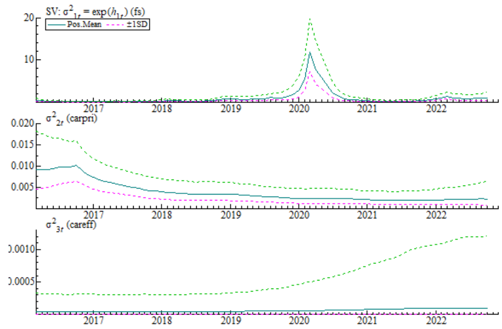
(c) TEU – F4 – CarEff



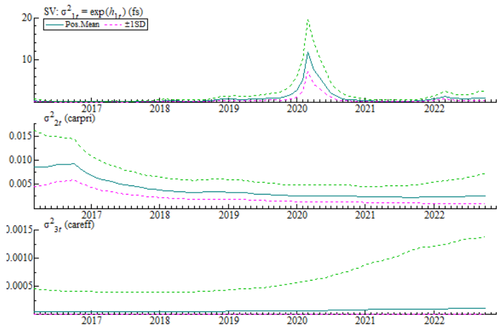
(d) TEU – F6 – CarEff



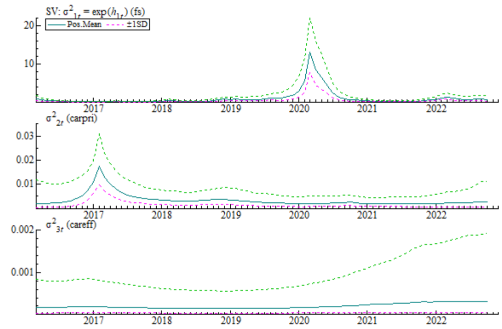
(e) FSI – Spot – CarEff



(f) FSI – F1 – CarEff

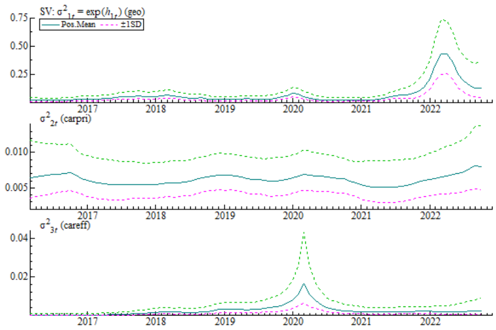


(g) FSI – F4 – CarEff

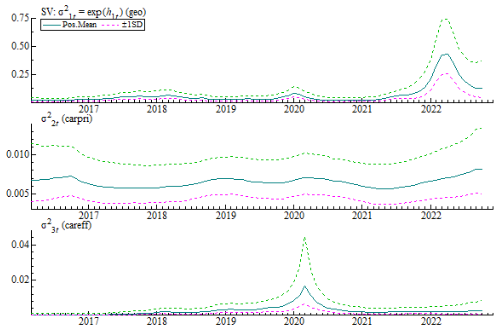


(h) FSI – F6 – CarEff

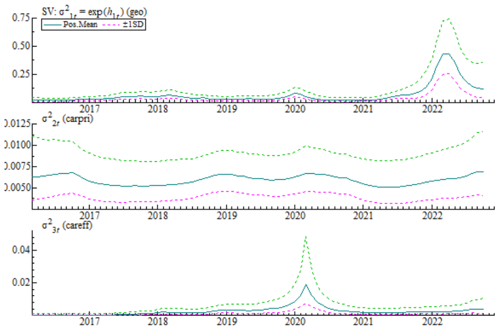
Figure 3: Posterior estimates for stochastic volatility of structural shocks (Spot and Futures prices)



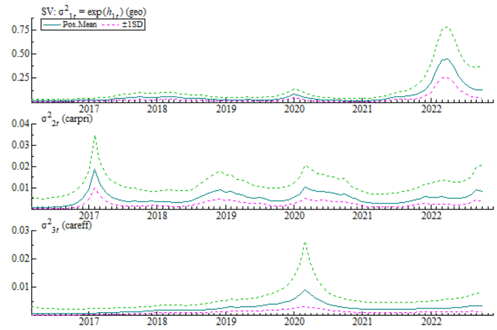
(i) GEO – Spot – CarEff



(j) GEO – F1 – CarEff



(k) GEO – F4 – CarEff



(l) GEO – F6 – CarEff

Figure 3: Posterior estimates for stochastic volatility of structural shocks (Spot and Futures prices) (continued)

3.3 Time-varying impacts of uncertainty shocks on carbon price and carbon efficiency at different time horizons

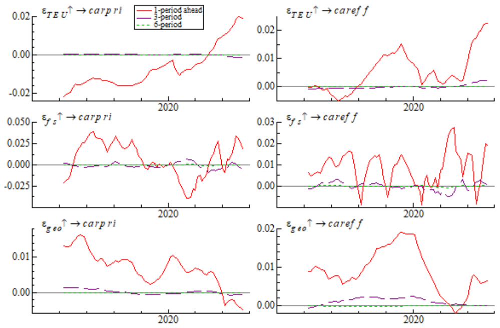
Fig. 4 displays the time-varying reactions of carbon spot and futures price, as well as corporate carbon efficiency, to TEU, FSI, and GEO. The short-, medium-, and long-term reactions should, in order, be reflected through the impulse responses observed at 1-month, 3-month, and 6-month intervals. Each variable's standardized response to shocks is shown on the vertical axis, while the horizontal axis shows the number of months following a shock. Given that our empirical model is time-varying, the impulse responses must be constructed using the estimated time-varying coefficients at every point in time during the sample period. In order to compute the impulse responses, Nakajima et al. (2011) recommend that the initial shock size be set to be equal to the time-series average of stochastic volatility over the sample period, followed by the use of simultaneous relations at each point in time.
As shown in Fig. 4, the effect of TEU, FSI, and GEO shocks on carbon prices and carbon efficiency varies over time. We notice that generally spot and different futures carbon prices react similarly to different uncertainty shocks.

Beginning with TEU, the response of spot and futures carbon prices to a shock in economic policy uncertainty is mostly negative but there are substantial differences with different lag periods. For the short term, we detect a negative impact of

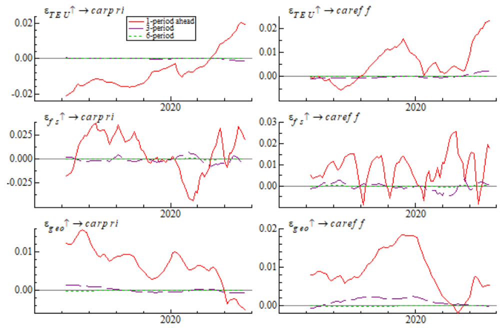
TEU shocks on carbon spot, futures1, futures4, and futures6 prices from 2016 until 2022, by contrast, the impact is mostly positive from 2022. Moreover, the response is slightly negative, especially during 2022 in the medium-term, but almost negligible in the long-term. Our result, for the short-term impact, is confirmed by Gao et al (2023) who studied the impact of EPU on China and European carbon futures prices. According to them, because of the growing level of uncertainty, the economic foundations in the future are expected to decline, production will decline, and prices for carbon emission allowances will also decline as a result. Nevertheless, the process of financialization in the carbon emissions trading market has led to the emergence of several financial market features. Increasing uncertainty means increased market risk causing traders to reduce their financial asset holdings. As a result, there is less demand for carbon emission allowances, which drives down prices. Furthermore, our results imply that TEU shocks have a negative effect on corporate carbon efficiency in the short term from 2016 to 2018. However, the response turns out to be positive from 2018 to 2022 with a significant drop after the COVID-19 pandemic. These findings are in line with the extremely fluctuating level of the Economic Policy Uncertainty Index in 2019 and 2020, indicating that economic risks during the covid crisis led to decreases in corporate carbon efficiency. In fact, Tee et al. (2023) examined how EPU affected corporate carbon footprint in 2019 and found that when EPU was higher than average, there were fewer incentives for businesses to make investments in the environment. As a result, rising EPU would encourage firms to postpone comparable investments to survive. In conclusion, reducing investment in renewable energy would increase CO2 emissions and influence corporate carbon efficiency. Moreover, increased EPU discourages businesses' desire to minimize pollution through green behavior and innovation (Hou et al., 2022; Lou et al., 2022). In general, rising EPU introduces higher risks and influences managers' motivation for innovative investment. As a result, there is a negative relationship between EPU and corporate carbon efficiency. Nevertheless, the positive impact of TEU shocks on carbon efficiency after 2018 might be explained by the fact that recently, the climate change effect is more visible, investors are aware of the negative impact of climate change and start paying more attention to corporate sustainability and carbon efficiency which encourage firms to reduce their carbon emission even during high economic uncertainty. Also, for the medium term, we detect that TEU has a marginally negative effect on corporate carbon efficiency, which is consistent with the real options theory that holds that uncertainty at the national level discourages companies from making long-term investments (e.g., investment in corporate sustainability). The firm's cash flows are unstable in uncertainty times, and because green technology takes so long to develop, it is hard to predict future risks. Firms may delay future investments in green technology until economic uncertainty subsides because its expenses are significant and irreversible. Our result is confirmed by Jia et al (2020).

We next conduct the time-varying impulse responses of carbon spot and futures prices and carbon efficiency to FSI shocks. Regarding the impact of FSI shocks on carbon spot and futures prices, the differences in the magnitudes of the fluctuations are evident. With a lag of 1 period, the responses of carbon prices to FSI shock are mainly positive except in 2016, 2019, 2020, and at the beginning of 2022 which reflect respectively the Brexit crisis, the COVID-19 pandemic, and the Russo-Ukrainian war. In fact, after a financial crisis, the effects of financial stress on time variation in carbon market volatility became more evident. This suggests that the carbon market is more vulnerable to financial market volatility and instability during periods of high uncertainty or crisis compared to periods of relative stability or economic growth. These findings further confirm the procyclical nature of the carbon market. Our findings support in part those of Ji et al. (2018) which show that the dynamic correlations between carbon prices and financial instability are mostly negative indicating that the price of carbon tends to decline as financial uncertainty rises. According to economic theory, the carbon price rises when the economy is strong and falls when the economy is weak (Jiao et al., 2018). However, the magnitudes and the fluctuations of both spot carbon price and futures carbon price are lower in lag2 and almost negligible in lag3 indicating the ability of the European carbon market to absorb the negative impact of financial shocks and return stable after a few months. Furthermore, our results confirm that corporate carbon efficiency reacts, generally, positively to financial uncertainty shocks but negatively only during the Sino-US trade disputes in 2018, the covid19 pandemic in 2019 and 2020, and the Russo-Ukrainian war in February 2022 and became negligible in the medium and long term. These findings confirm that high financial stress and uncertainty due to different crises lead managers and investors to invest in projects that can generate profits at the expense of the environment and profit becomes their only motive to invest, which, subsequently, affects negatively firms' carbon efficiency.

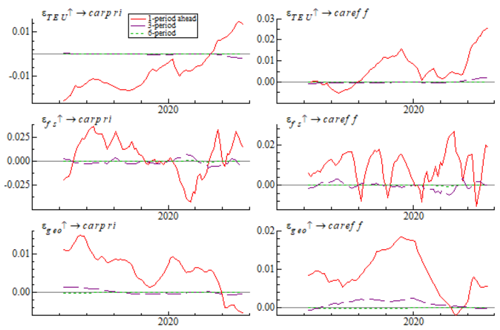
The impact of GEO shocks on carbon prices (spot and futures) is mostly positive at 1- month and 3-month horizons except during the Russo-Ukrainian war. This result is possibly due to the fact that oil and carbon markets are close substitutes. Given that oil prices are acutely responsive to geopolitical uncertainty, carbon prices, which demonstrate similar trends to conventional energy prices, could experience substantial fluctuations in response to changes in levels of geopolitical risk. Also, as geopolitical risk rises, consumers of crude oil - a commodity highly susceptible to such risk - tend to view renewable energy sources as a viable alternative to conventional sources. This leads to an increase in energy and carbon prices. This causes growth in energy prices and carbon prices. In addition, the negative impact during 2022 might be caused by the Russo-Ukrainian war and explained by the fact that this crisis is very related to the European market. Our results indicate also a positive impact of GEO on the European corporate carbon efficiency index. Extreme geopolitical events, such as political upheavals, terrorist attacks, and geopolitical risks, are taken into consideration while making investing decisions. On the other hand, geopolitical uncertainties might alter how investors perceive the future supply of oil, which would modify oil prices and increase corporate carbon efficiency. According to Dutta et al (2020), the motivation and interest in green investments will decline when the crude oil market faces significant negative fluctuation. But, when oil prices rise due to a high level of uncertainty, the incentives will rise as well, driving up the equity price of these kinds of green products (Bondia et al, 2016; Xia et al, 2019). Consequently, due to the growth in GPR over the past few years, several firms start investing more in renewable energy. Such initiatives are also reflected in corporate carbon efficiency.



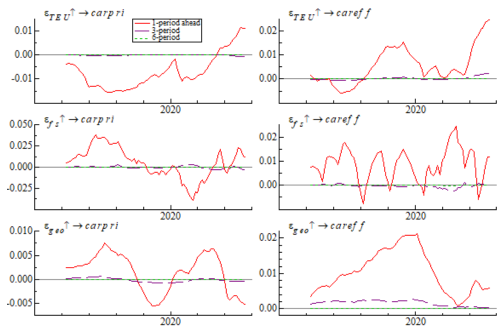
(a) Uncertainty, spot carbon price, and carbon efficiency



(b) Uncertainty, futures (1) carbon price, and carbon efficiency



(c) Uncertainty, futures (4) carbon price, and carbon efficiency



(d) Uncertainty, futures (6) carbon price, and carbon efficiency

Figure 4: Impact of uncertainty shocks on carbon price and carbon efficiency at different time horizons

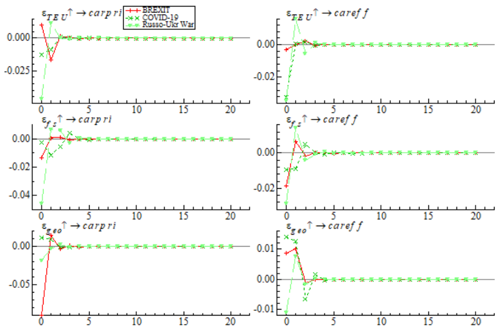
3.4 The impact of uncertainty shocks on carbon price and corporate carbon efficiency at different time points.

The impact of uncertainty shocks on carbon price and corporate carbon efficiency at different time horizons confirmed structural changes following specific periods related to some major events during 2016, 2019, and 2022. Thus, to supplement the dynamic impulse findings, we also conduct separate analyses for multiple time periods in order to examine changes in the impacts of uncertainties on carbon prices and corporate carbon efficiency during various uncertainty-related events. We consider three key events: The Brexit crisis in June 2016, the covid19 in April 2020, and the Russo-Ukrainian war in February 2022. As indicated in fig3, the Brexit crisis marks the starting of a boom cycle of EPU and the rise in carbon price volatility. April 2020 marks the Covid pandemic, with high financial and economic policy uncertainty reaching their highest levels. However, the recent Russo-Ukrainian in 2022 war is closely related to high geopolitical risk.

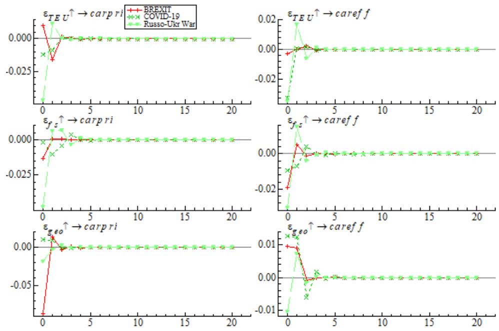
As demonstrated in Fig.5, similarities are detected in the responses of the spot and the three-futures carbon prices (futures1, futures4, and futures6) to the different uncertainty shocks during the Brexit crisis, Covid19 pandemic, and the Russo-Ukrainian war which confirm that generally, carbon spot and futures prices react with the same way to TEU, FSI, and GEO shocks. We also observe that the effect of the uncertainties shocks at different time points is found to be only significant for the short term and negligible for the medium and long term confirming the results of Fig. 4. Moreover, fig.5 confirms that the negative immediate effects of Covid19 pandemic in April 2020 lasted more than the other crisis, indicating that covid19 has a severe effect on both carbon price and carbon efficiency. Global economic and financial markets experienced an enormous change as a result of the recent COVID-19 pandemic outbreak (Hanif et al, 2021; Mensi et al, 2021). Risks, uncertainty, panic, and volatility in the financial markets of developed and emerging economies all heightened as a result of this unprecedented pandemic catastrophe. The sharp increase in confirmed cases forces governments to enact stringent containment measures, which slow down economic growth significantly. These measures include suspending commercial operations, isolating cities, limiting people's activities, and social isolation. Our result is confirmed by Dou et al (2022), who studied the relationship between EPU and futures carbon prices and found that the short- and medium-term performance of both EPU and carbon futures prices has been affected by the COVID-19 pandemic, which in turn has had an impact on the spillover and connectedness between them.

Regarding the Brexit crisis effect, we found a negative impact of uncertainty shocks especially on carbon prices (spot and futures). The price of carbon emissions in the EU has decreased since the Brexit news came, plunging more than 15%, to €4.88 from its peak of surpassing €8 (The highest level since 2012). Following the vote, the price of carbon decreased in part as a "reflection of where all commodity prices" had fallen, but it also did so as a result of traders' anxiety about the future of the ETS, who were previously buying and selling carbon permits. This uncertainty resulted from "the fact that the UK was a big player in the carbon market.

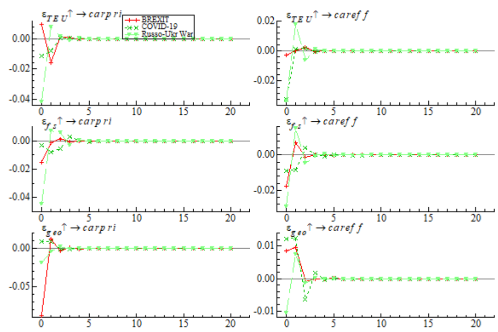
Lastly, we examined the impact of uncertainties on carbon prices and corporate carbon efficiency during the Russo-Ukrainian war. Our results reveal significant immediate negative responses of both carbon prices and corporate carbon efficiency to TEU, FSI, and GEO shocks. Undoubtedly, the conflict between Russia and Ukraine represents the most significant upheaval in Europe since World War II and has had a considerable impact on financial markets worldwide. The consequences of the conflict have already begun to affect the European clean markets. Santorsola et al. (2022) claimed that the financial markets in Europe and the United Kingdom were impacted by the crisis. Moreover, the global economy has been greatly affected by the energy market fluctuations resulting from the geopolitical conflict between Russia and Ukraine. This has caused significant disruption to both the world energy and carbon price markets, leading to considerable difficulties in ensuring energy security. Bedowska-Sójka et al. (2022) examined how current Russia-Ukraine tensions affected financial markets. According to their results, the conflict disrupted the link between asset prices and geopolitical risk. However, our results indicate that the negative impact of uncertainty shocks on carbon prices and corporate carbon efficiency starts to decrease after a few days and becomes positive. This might be explained by the fact that the conflict between Russia and Ukraine is of crucial to both energy and carbon markets due to Russia's position as the world's largest supplier of oil and gas. It is worth noting that Europe depends on Russia for one-third of its oil and gas needs. Also, the Russian traditional energy markets have increased the desire for alternative sources of energy, the clean energy markets, which explains the increases in carbon prices. Furthermore, firms that promote and implement renewable energy sources have been gaining investors since they take into account the demand for alternative energy sources.



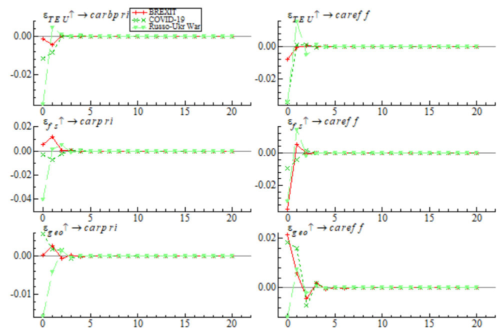
(a) Uncertainty, spot carbon price, and carbon efficiency



(b) Uncertainty, futures (1) carbon price, and carbon efficiency



(c) Uncertainty, futures (4) carbon price, and carbon efficiency



(d) Uncertainty, futures (6) carbon price, and carbon efficiency

Figure 5: Impact of uncertainty shocks on carbon price and carbon efficiency at different time points

4 Robustness test

4.1 Daily and weekly data

To confirm the robustness of our findings, we use weekly and daily data of TEU, FSI, GEO, carbon price, and carbon efficiency. For the carbon price, we use only the carbon future1 price since the previous results confirmed a similarity in the reaction of carbon spot and futures prices to different uncertainties shocks. Table 3 demonstrates that the parameter estimates' posterior means are within the 95% confidence interval. The results suggest that, at the 5% level of significance, there is no evidence to reject the null hypothesis that all parameters converge to the posterior distribution, according to Geweke statistics. Additionally, almost all parameters have very low inefficiency factors. The posterior draws are efficiently produced by the MCMC algorithm. According to Fig 6, the sample autocorrelations rapidly decrease and the sample paths typically remain stable. The findings suggest that posterior samples are effectively generated through the use of the MCMC sampling method.

Table 3: Estimation of selected parameters in the TVP-SVAR-SV model

Weekly							**Daily**						
Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef.	Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef.
TEU							**TEU**						
$(\sum\beta)1$	0.0205	0.0028	0.0159	0.0268	0.23	23.14	$(\sum\beta)1$	0.0346	0.0062	0.0242	0.0481	0.844	184.99
$(\sum\beta)2$	0.0245	0.0040	0.0181	0.0339	0.965	37.71	$(\sum\beta)2$	0.0307	0.0038	0.0239	0.0382	0.118	107.39
$(\sum$a$)1$	0.0326	0.0048	0.0252	0.0440	0.334	21.75	$(\sum$a$)1$	0.0170	0.0012	0.0149	0.0197	0.073	49.42
$(\sum$h$)1$	0.6217	0.0846	0.4622	0.7923	0.515	51.14	$(\sum$h$)1$	0.6067	0.0449	0.5202	0.6957	0.208	73.79
$(\sum$h$)2$	0.2735	0.0436	0.2002	0.3698	0.547	47.18	$(\sum$h$)2$	0.4551	0.0346	0.3935	0.5297	0.219	51.80
FSI							**FSI**						
$(\sum\beta)1$	0.0220	0.0034	0.0167	0.0302	0.895	21.43	$(\sum\beta)1$	0.0140	0.0014	0.0116	0.0168	0.333	54.29
$(\sum\beta)2$	0.0247	0.0041	0.0183	0.0345	0.092	24.97	$(\sum\beta)2$	0.0200	0.0025	0.0160	0.0263	0.578	102.90
$(\sum$a$)1$	0.0340	0.0050	0.0258	0.0451	0.358	24.89	$(\sum$a$)1$	0.0209	0.0018	0.0178	0.0246	0.215	43.04
$(\sum$h$)1$	0.5235	0.0757	0.3869	0.6807	0.384	35.88	$(\sum$h$)1$	0.4531	0.0318	0.3945	0.5195	0.137	30.81
$(\sum$h$)2$	0.2917	0.0461	0.2131	0.3927	0.487	60.30	$(\sum$h$)2$	0.4186	0.0303	0.3601	0.4790	0.843	53.96
GEO							**GEO**						
$(\sum\beta)1$	0.0207	0.0028	0.0159	0.0270	0.235	27.66	$(\sum\beta)1$	0.0229	0.0030	0.0171	0.0289	0.115	101.01
$(\sum\beta)2$	0.0246	0.0041	0.0179	0.0338	0.930	33.21	$(\sum\beta)2$	0.0289	0.0044	0.0216	0.0381	0.039	124.07
$(\sum$a$)1$	0.3904	0.0050	0.0256	0.0454	0.012	27.53	$(\sum$a$)1$	0.0165	0.0011	0.0145	0.0189	0.000	29.10
$(\sum$h$)1$	0.3904	0.0716	0.2630	0.5386	0.166	48.63	$(\sum$h$)1$	0.3625	0.0305	0.3069	0.4257	0.019	53.89
$(\sum$h$)2$	0.2898	0.0442	0.2131	0.3856	0.183	52.62	$(\sum$h$)2$	0.4666	0.0392	0.3977	0.5536	0.749	63.45

Note: "mean" refers to the posterior means, "95%L": 95% lower credible interval limit, "95%U": 95% upper credible interval limit, "Stdev": standard deviations, "Inef".: inefficiency, and "Geweke": Geweke convergence diagnostics statistics.

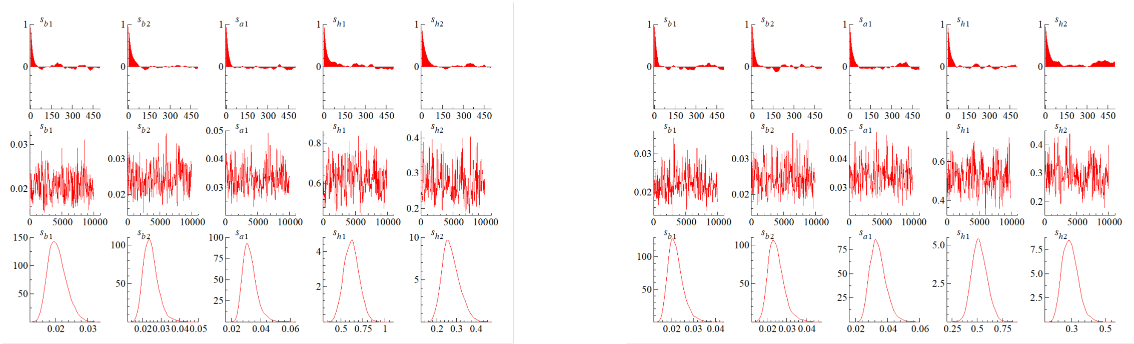


Figure 6: Sample autocorrelation, sample paths, and posterior densities for selected parameters

The time-varying responses of the daily and weekly carbon price and corporate carbon efficiency to different uncertainties shocks are presented in Fig 7 and Fig 9. Our results are robust and show a significant variation of the reactions of the carbon price and corporate carbon efficiency to the three types of uncertainty shock over time. However, the responses of the daily carbon price and corporate carbon efficiency to uncertainties shocks at various time horizons change severely, are not constant, and largely depend on the economic situation, confirming that the stability of the carbon market price and carbon efficiency is threatened by the policy environment, financial market conditions, and geopolitical risk. In general, we confirm that the magnitudes and the fluctuations of both carbon price and carbon efficiency are lower in lag2 and almost negligible in lag3 indicating the importance of examining how uncertainty and the carbon market are connected across time and proving that the impact of the unexpected event can be rapidly and effectively absorbed by the European carbon market, and fluctuations may be smoothed out, allowing a quick return to stability. Moreover, we notice that, for the medium term, the magnitude of GEO shocks was the highest, followed by financial uncertainty and TEU. We also confirm that the relationship between TEU, FSI, and GEO and the European carbon market is mostly negative during the Brexit crisis, COVID-19, Sino-US trade disputes, and the Russo-Ukrainian war.

Fig 8 and Fig 10 represent the time-varying impulse responses of carbon price and corporate carbon efficiency uncertainties shocks at different time points. Our findings indicate that crises affect the impact of uncertainty shocks on carbon market efficiency for the short and medium term. In other words, shocks from GEO, FSI, and TEU have a more considerable effect on carbon price and corporate carbon efficiency during the Brexit crisis, COVID pandemic, and Russo-Ukrainian war, which again verifies our principal results. In addition, we detect some differences between daily and weekly results regarding the reaction of the carbon price and corporate carbon efficiency to uncertainties shocks at different time points. This result is quite reasonable and can be explained by the fact that using daily and weekly data allows us to discover in detail the response of our variables to uncertainty during global crises.

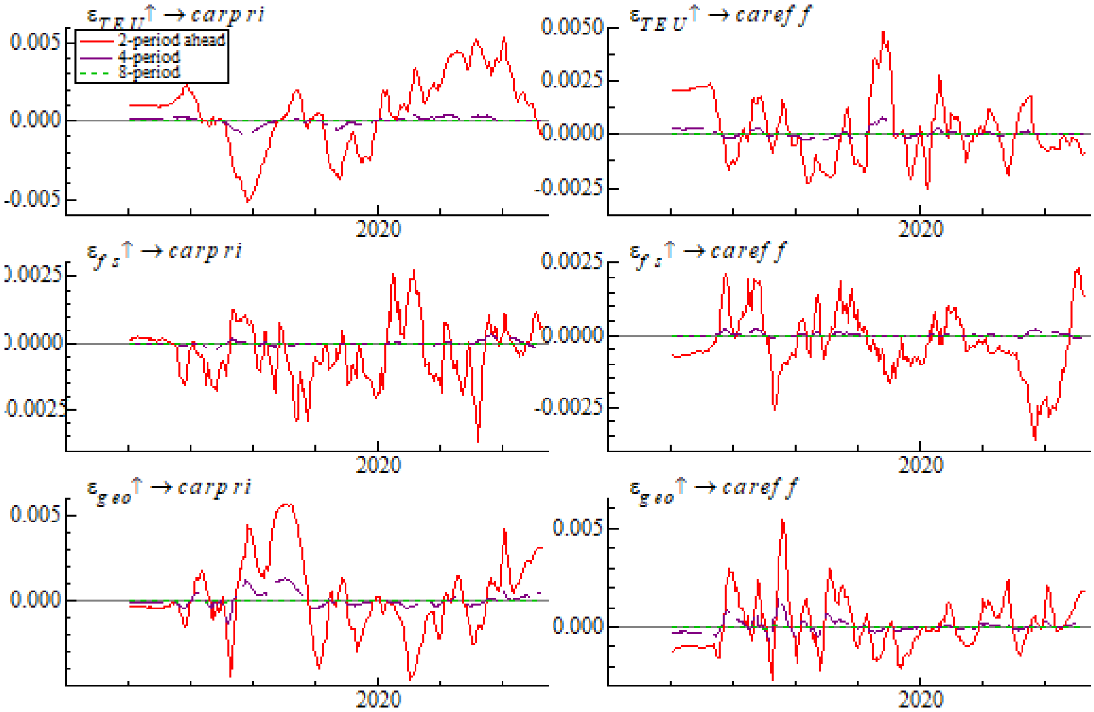


Figure 7: Impact of uncertainty shocks on weekly carbon price and carbon efficiency at different time horizons.

4.2 Nonlinear Impulse-response Analysis

Using the threshold SVAR, we studied the asymmetric impact of uncertainty shocks on carbon price and carbon efficiency. The Threshold SVAR model has numerous distinct characteristics that make it an adaptive tool for capturing some of the potential nonlinearities resulting from regime change, multiple equilibria, and asymmetrical responses to shocks (Atanasova, 2003; Ferraresi et al., 2015). The testing of a linear VAR against a threshold alternative is shown in Table 4. As demonstrated, the P-values for all three Wald tests (sup-Wald, avg-Wald, and exp-Wald) reject linearity and support the presence of two different regimes. Figs. 11, 12, and 13 provide a summary of the nonlinear impulse response functions. We simulate the reactions by allowing each structural shock to enter the model with a different sign (positive or negative) and varying magnitude (one- or two-SDs) in order to reveal the potential asymmetry.

Starting with TEU, fig.1 shows the response of carbon price and corporate carbon efficiency to TEU shocks in low and high regimes. Our result indicates that corporate carbon efficiency and carbon price reacts more to both positive and negative shocks in the low TEU regime than in the high TEU regime. This may acknowledge the presence of asymmetries. As seen in Figure 11, the response of both carbon

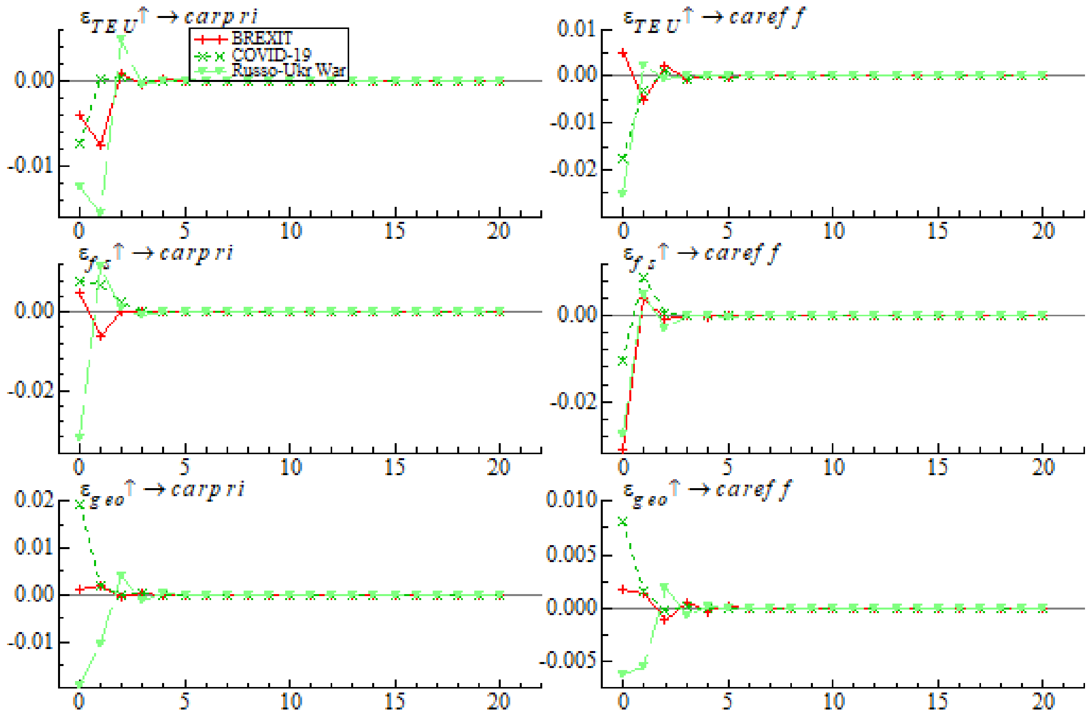


Figure 8: Impact of uncertainty shocks on weekly carbon price and carbon efficiency at different time points.

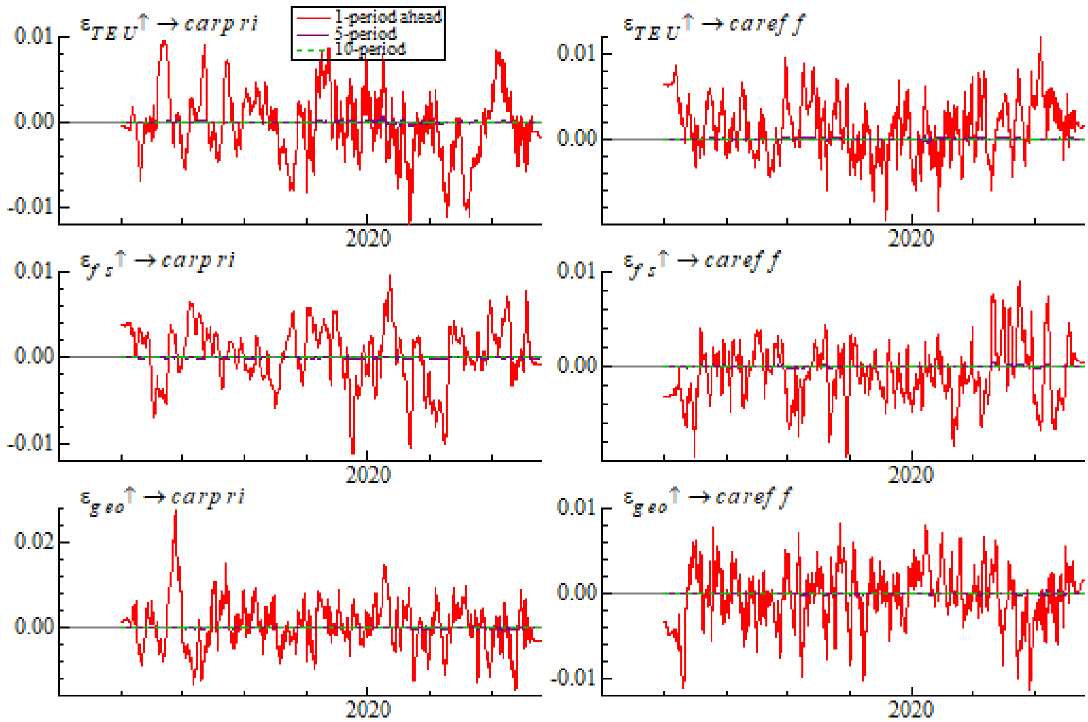


Figure 9: Impact of uncertainty shocks on daily carbon price and carbon efficiency at different time horizons.

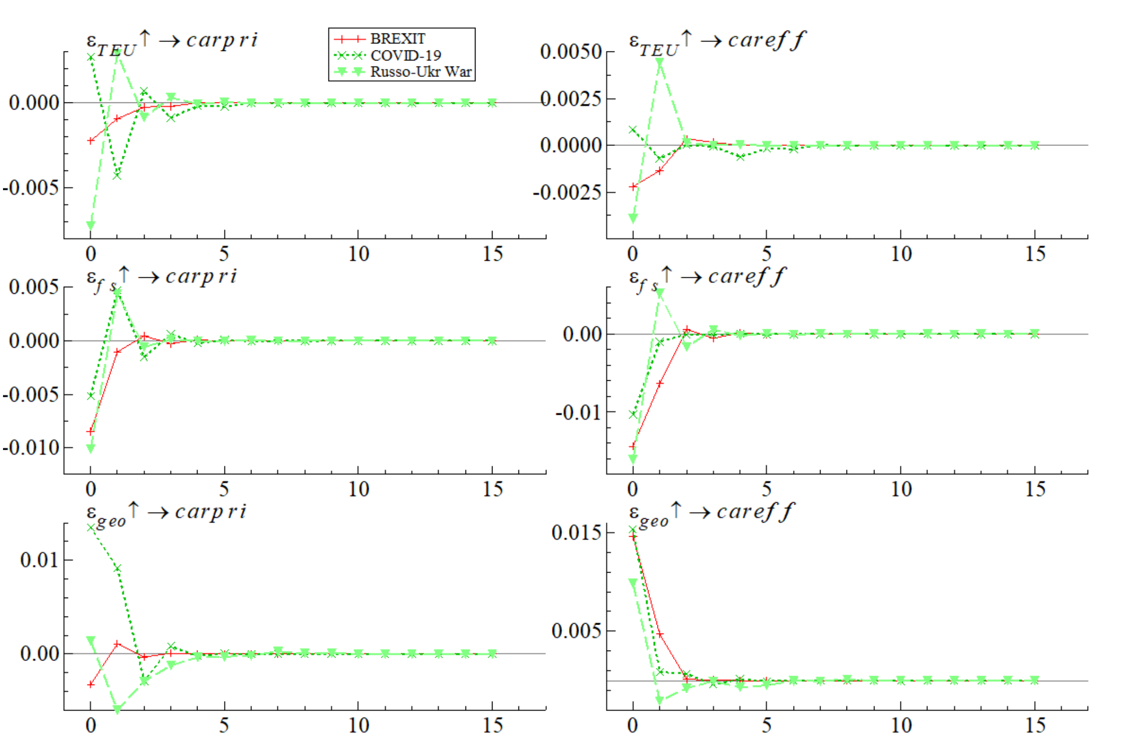


Figure 10: Impact of uncertainty shocks on daily carbon price and carbon efficiency at different time points.

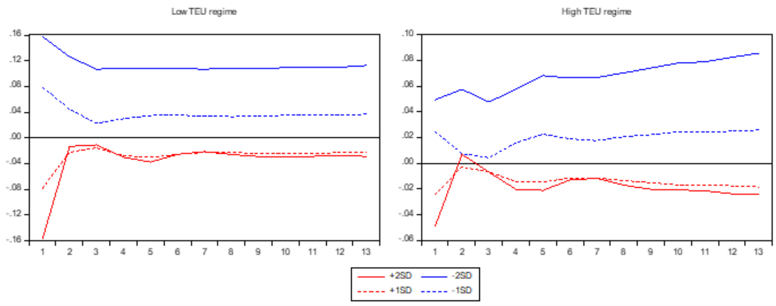
Table 4: Threshold estimations

Threshold Variable	Estimated Threshold	Sup-Wald Statistic	Avg-Wald Statistic	Exp-Wald Statistic	Obs. in High regime	Obs. in Low regime
TEU	$\hat{y}$ = 0.025722	73.91 (0.000)	53.54 (0.000)	34.67 (0.000)	35	44
FSI	$\hat{y}$ = 0.128105	57.95 (0.000)	43.17 (0.000)	26.23 (0.000)	26	53
GEO	$\hat{y}$ = -0.021376	54.11 (0.000)	34.48 (0.020)	24.10 (0.000)	46	33

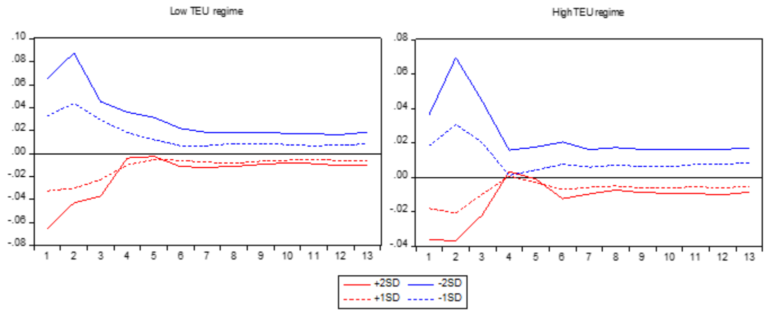
Note: Values in brackets are P-values. The delay parameter is set to 1 following Balke (2000) and each regime is restricted to contain at least 15% of the total observations price and corporate carbon efficiency to TEU shocks seems to be fairly symmetrical in both the high TEU regime as well as in the low TEU regime, i.e. positive and negative shocks seem to have roughly the same impact in both regimes. On average, carbon price and corporate carbon efficiency react negatively (positively) to a positive (negative) shock of TEU. Specifically, the influence of TEU shocks on carbon markets is most pronounced in the short and medium run but becomes less significant in the long term. Essentially, if there is an unexpected increase in TEU, this will likely result in a drop in carbon prices and corporate carbon efficiency in the short and medium term for both low and high regimes, rather than in the long term.

Secondly, we examined the response of carbon price and corporate carbon efficiency to financial uncertainty. Fig.12, confirm, for the low and high regime, a negative (positive) shock in FSI increases (decreases) carbon price and corporate carbon efficiency in the short and medium term, which is clearer for large (two-standard deviation) shocks and confirms our principal results. Furthermore, the impact of the impulse response remains only for a duration of four months and later becomes insignificant in the long term. We also found that corporate carbon efficiency reacts more to both positive and negative shocks in the high FSI regime than in the low regime.

Regarding geopolitical uncertainty, under the high-stress regime, carbon prices and corporate carbon efficiency are more sensitive to GEO shocks. Although carbon pricing and carbon efficiency instantly react negatively to a negative shock in the GEO in the low regime, it appears to initially react positively in the high regime before adopting negative figures lower than those obtained in the low regime. Moreover, for the low regime, a positive GEO shock has a positive influence on carbon price and carbon efficiency in the short and medium term before declining and becoming negative. We also discovered that, for the high regime, a positive GEO shock has an immediate negative influence on carbon price and corporate carbon efficiency in the short term, before decreasing in the medium and long term.
In conclusion, our findings demonstrate that the effects of TEU, FSI, and GEO shocks on carbon prices and efficiency differ significantly between high and low regimes, particularly in the short term, which confirms the robustness of our results.

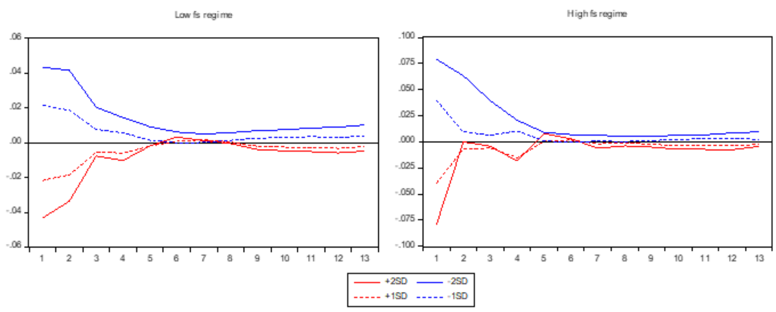


(a) Responses of carbon efficiency to TEU shocks



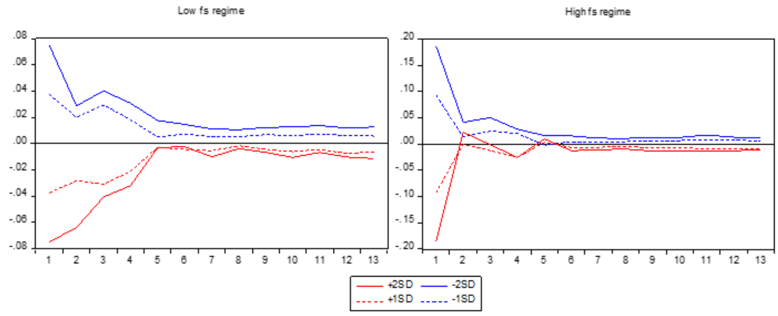
(b) Responses of carbon prices to TEU shocks

Figure 11: Response of carbon prices and carbon efficiency to TEU



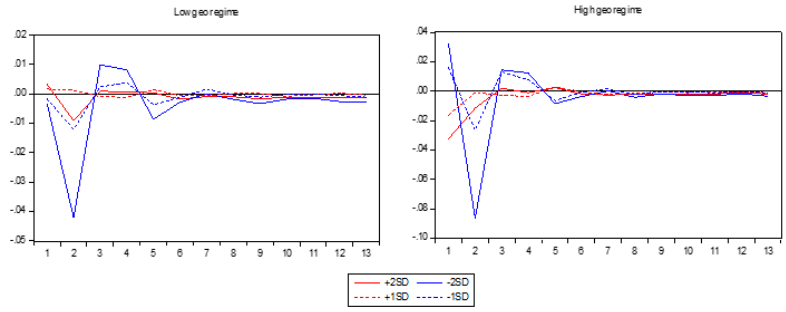
(a) Responses of carbon prices to FSI shocks

Figure 12: Response of carbon price and carbon efficiency to FSI

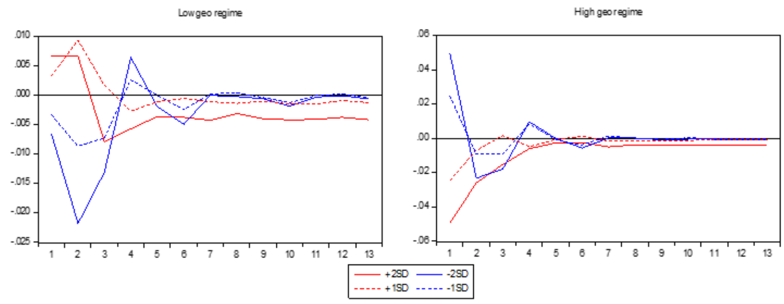


(b) Responses of carbon efficiency to FSI shocks

Figure 12: Response of carbon price and carbon efficiency to FSI (continued)



(a) Responses of carbon efficiency to GEO shocks



(b) Responses of carbon prices to GEO shocks

Figure 13: Response of carbon prices and carbon efficiency to GEO

5 Conclusion and policy implication

The effectiveness of Emissions Trading Schemes (ETS) is heavily reliant on market indicators such as the stability and predictability of prices, both of which can be negatively impacted by market uncertainty. Research reveals that the stability of the European carbon market price is threatened by uncertainty. Based on the discussions above, figuring out the relationship between carbon market and uncertainty can enhance our comprehension of the carbon pricing mechanism. This can further lead to the development of more precise and efficient policies to decrease carbon emissions and uncertainty. To this, our paper investigates how economic policy uncertainty, financial uncertainty, and geopolitical uncertainty may affect the European carbon price and corporate carbon efficiency under difficult crises and major social events. Using the Bayesian TVP-SVAR-SV model, we studied firstly the Time-varying impulse responses of spot and futures carbon prices and carbon efficiency to TEU, FSI, and GEO uncertainties shocks at different time horizons. Secondly, we selected three major crises which are the Brexit crisis on 23 June 2016, the covid19 on 22 April 2020, and the Russo-Ukrainian war on 24 February 2022 to examine the Time-varying impulse responses of spot and futures carbon prices and carbon efficiency to the three uncertainties shocks at different time points. Our results indicate, for the short term, that TEU and FSI uncertainties negatively impact the European carbon market more than GEO uncertainty. The negative impact decreased in the medium term and became negligible in the long term. Furthermore, significant events and crises increase the negative effect of uncertainty shocks on spot and futures carbon prices and corporate carbon efficiency. For robustness, our findings are generally robust using both daily and weekly data. Moreover, we applied the structural threshold VAR model (STVAR) to investigate the varying effects of TEU, FSI, and GEO shocks on carbon price and corporate carbon efficiency across different uncertainty regimes. We found that the impact of TEU, FSI, and GEO shocks on carbon price and carbon efficiency is significantly different across high and low regimes specifically in the short run, which confirms the robustness of our results.

Our study brings new analytical tools and several implications for managers, investors, and policymakers. As carbon pricing and carbon efficiency have overreacted to severe TEU, FSI, and GEO uncertainty shocks, policymakers need to pay attention to the impact of uncertainty changes on the European carbon market. To reduce it and stabilize market functioning, European policymakers should carefully investigate the causes of this overreaction. Additionally, while making dynamic changes to preserve price stability, policymakers should take into account many factors. For instance, financial and geopolitical issues should be taken into account in addition to economic concerns. In periods of low uncertainty or situations of high uncertainty, policymakers may require different strategies. To increase the predictability of policies and prices and to ensure price stability, rules should be explicitly adjusted to different uncertainty shocks. The government should also continue to promote economic growth and work to reduce the effect of uncertainty shocks. Even while facing significant risks, such as the Covid-19 epidemic, the Brexit crisis, and the Russo-Ukrainian conflict. Government should exert effort in its resolve to lower CO2 emissions. To reduce uncertainty and ensure policy transparency and sustainability, some supporting measures must be used, such as platforms for promoting innovation and expediting the energy transition. Investors might also use our findings to anticipate changes in carbon prices and to manage their investment decisions in order to minimize potential risks associated with TEU, FSI, and GEO volatility. Second, investors need to be aware of the characteristics of diverse types of uncertainty as the European market responds to the TEU, FSI, and GEO in different ways. Investors and traders must consider the effects of these various uncertainty increases, especially when trying to purchase or hold carbon allowances. Additionally, managers and directors benefit from understanding the elements affecting companies' sustainability performance, especially those out of their direct control. In this paper, we identify and investigate an important issue that affects the sustainability performance of their firms, namely uncertainty. The results of our study are expected to capture their attention or be noteworthy to them, as we give evidence that corporate carbon efficiency is sensitive and negatively impacted by uncertainty. Thus, firms should enhance their carbon emission management systems through market-based rules. Also, they should focus on promoting green technology, improving the management of fossil fuels, optimizing manufacturing, and ultimately turning these expenses for reducing carbon emissions into profits. Firms can only have sufficient incentives to reduce their carbon footprint during uncertain times in this way.

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