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Time-varying partial-directed coherence approach to forecast global energy prices with stochastic volatility model

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Abstract

For investors and policymakers, forecasting energy prices with accuracy is essential and plays a major role in the global bulk commodity markets. The current study proposes a novel hybrid forecasting model to predict global energy prices, namely, time-varying partial-directed coherence with stochastic volatility. The proposed method combines partial-directed coherence analysis and stochastic volatility models. Accordingly, this study attempts to provide an in-depth understanding of the relationship between energy markets and global economic conditions as well as the causality pathway between the underlined markets. Monthly data from January 1982 to July 2022 is used in this study. The results show a strong causality between global economic conditions, European oil, and natural gas prices and have profound implications for policymakers. For completeness, we extend the analysis to the forecasting ability of global economic conditions for oil and natural gas prices. The out-of-sample results show that the autoregressive model incorporating the global economic conditions index can significantly improve the accuracy of oil and gas price forecasts. In addition, our results are strongly robust over a variety of time horizons for forecasting, and they provide valuable insights into the forecasting choices to guide investment strategies in the energy and financial market.

KEYWORDS

European energy prices, forecasting, global economic conditions, partial-directed coherence, stochastic volatility

1 | INTRODUCTION

Since the Russian invasion of Ukraine, there has been a significant deterioration of the global geopolitical outlook. Investors, market participants, and policymakers all have anticipated that the conflict would have a negative effect on the global economy, driving up inflation, resulting in a significant increase in both the degree of uncertainty and the likelihood of highly unfavorable outcomes (IMF, 2022). Due to the conflict and sanctions placed on Russia, not only the Russian and Ukrainian but global economy is also adversely affected. Moreover, commodity markets have been in chaos, and financial markets have been extremely volatile. As an example of these concerns, the EU imports a significant portion of its energy from Russia, including natural gas (35%) and crude oil (20%), and the price of European natural gas gained a historical high of 70.04 USD in August 2022 (World Bank, 2022). Given these developments, a key question is: How much do the deteriorating global economic conditions (GECON) may affect energy such as oil and natural gas prices?

The world's energy market is determined by a number of factors, such as demand, supply, speculation, macroeconomic conditions, and investor sentiment, among others (Lv & Wu, 2022; Salisu et al., 2022). A major factor influencing energy demand is the outlook of the global economy. Recently, Baumeister et al. (2022) has developed a new indicator of global economic activity (GECON) based on 16 elements such as actual economic activity, commodity prices, financial indicators, transportation, uncertainty measures, expectations indicators, weather, and energy-related measures. The level of economic activity throughout the world may have an impact on the demand for crude oil, which in turn can have an impact on the price volatility of crude oil. Guo et al. (2022) stated that the GECON is built using real-time joint density predictions that are produced from models of oil consumption and oil prices. These models have the ability to reflect future market demand and estimate oil prices within the next two years. According to Bakas and Triantafyllou (2020), a growing global economy always drives up the overall demand for commodities, which in turn drives up the price of energy markets. Salisu et al. (2022) investigated the role of GECON in the predictability of gold market volatility. The authors found that the volatility of the gold market is substantially influenced by economic situations throughout the world. Moreover, Lv and Wu (2022) explored whether GECON can successfully forecast the oil price. Their empirical findings indicate that the global economic circumstances index may significantly increase the accuracy of oil price forecasting in terms of univariate and bivariate analysis. Using the GECON index, Guo et al. (2022) examined the predictive power of five indicators of global economic activity for the volatility of West Texas Intermediate (WTI) crude oil prices and found that among the five global economic proxy models, GECON had the best predictive ability. Wang et al. (2022) investigated the volatility of natural gas and clean energy prices and found that uncertainty indices and GECON are both useful predictors of realized volatility in clean energy markets. Moreover, using mixed-frequency models, Baumeister and Guorin (2021) assessed the predictive potential of a collection of alternative monthly indicators of global economic activity for nowcasting and predicting quarterly global real GDP growth. The authors claimed that GECON offers useful data for determining the present and future economic conditions of a number of individuals and nations groups of countries. Salisu et al. (2021) evaluate the predictive power of six indicators of global economic activity in forecasting crude oil market volatility using the GARCH-MIDAS approach. The newly developed indicator of global economic activity, based on a set of 16 variables, consistently outperforms other indicators, and accounting for inherent asymmetry improves forecast accuracy. More recently, Salisu et al. (2023) examine the predictive power of global economic conditions in forecasting daily return volatility of international Real Estate Investment Trusts (REITs) indices. The results show that improvements in global economic conditions lead to the lower risk associated with REITs, particularly in the US and emerging markets. Gupta and Pierdzioch (2023) investigated whether aggregate and state-level economic conditions can predict the subsequent realized volatility of oil price returns in the United States using HAR-RV models. The study suggests that incorporating economic conditions in volatility forecasts can be useful for risk management and trading strategies in the oil market.

Recently, most studies predicting volatility have only dealt with crude oil, whereas natural gas has received very less attention. The aim of this paper is to conduct an extensive analysis on the causality and price predictability of fossil fuels and natural gas based on the global economic conditions. In fact, the capacity to effectively estimate and anticipate natural gas volatility is crucial for investors and researchers in order to mitigate energy market risks, promote green and sustainable economic growth, and ensure the long-term viability of the energy market (Balsalobre-Lorente et al., 2019). For example, Lu et al. (2022) used macroeconomic factors and economic indicators are used in this research to anticipate natural gas volatility. The authors revealed that the forecasting performance of the macroeconomic variables outperforms the economic indices. Following, Guo et al. (2022) and Baumeister et al. (2022), we employ the autoregressive (AR) as the baseline model for this research, which has been frequently used in financial market volatility predictions. Second, we combine the GECON with the AR. We found that constructing a combined indicator of global economic conditions (AR-GECON) helps improve the prediction accuracy for petroleum prices considerably.

Volatility, which measures how much the price of the underlying asset fluctuates, is a popular risk indicator. Stochastic volatility models are robust and flexible, and among the many models suggested for volatility modeling and prediction, they are particularly useful since the volatility of asset returns varies with time (Le et al., 2022; Yu, 2012). There is a large body of empirical evidence that demonstrates the important role of the time-varying parameter vector autoregressive (TVP-VAR) models in financial econometrics, for example, Chan (2022). In many cases, the estimation process of causal relationships between economic variables often exhibits coefficients that drift and stochastic volatility shocks (e.g., partial-directed coherence method). In such situations, using a model that has time-varying coefficients but constant volatility leads to the question of whether the estimated time-varying coefficients could be biased due to the potential disregarding of any fluctuations in disturbance volatility. To address this misspecification, stochastic volatility is assumed in the partial-directed coherence method model. On the other hand, relationships between variables that change over time can be modeled using the time-varying parameters (TVP) methodology. Compared to conventional models with constant parameters, the TVP methodology provides greater modeling flexibility and can produce more precise predictions. Additionally, this technique is a powerful tool for better fitting and modeling time-varying interactions between variables, resulting in more precise projections and a deeper understanding of underlying economic or social processes (Koop & Korobilis, 2013). The question arises as to whether partial-directed coherence under stochastic can be done with TVP-VAR.

Our study contributes to the available literature as follows. First, we propose a new method based on the use of time-varying partial-directed coherence under stochastic volatility (PDC-SV). The PDC-SV allows us to capture possible changes in time and the frequency domain of the time series in a flexible and robust manner using the time-varying parameter vector autoregressive (TVP-VAR) model with stochastic volatility (for some applications of a linear model with stochastic volatility, see Dhifaoui, 2022). The TVP method is adaptable to a variety of models, including nonlinear models and those with nonstationary variables. Furthermore, TVP models are capable of capturing economic or policy structural changes that impact the correlation between variables (Huber et al., 2021). The behavior of macroeconomic time series has a tendency to change over time, particularly during times of periods of severe shocks such as COVID-19 and the Russia-Ukraine conflict. Significantly, these time-varying approaches are able to effectively and precisely capture the dynamic aspects of the linking effects across markets over time, which is urgently essential and extremely advantageous for investors and regulators. Second, this study provides new empirical insights into the relationship between the GECON index and oil and natural gas prices, including data related to the Russia-Ukraine war, and considers geopolitical risk, growth in transportation, oil price uncertainty, and weather-related factors. Third, we extend the limited literature on the GECON–energy price causal nexus. Our study has the advantage of simultaneously examining the causal nexus over the time and frequency domains within the study period, which provides a lot of more precise estimates and analysis. Fourth, we extend the available literature in forecasting oil and gas prices, including the Russian-Ukrainian conflict. Through extensive forecasting testing, we show that AR-GECON provides more important information than other AR or VAR models. Several robustness tests have confirmed the accuracy of these predictions.

The remainder of the paper is structured as follows. Section 2 introduces the new approach and describes the dataset. Section 3 presents the empirical results of PDC-SV and the out-sample predictive analyses. Section 4 discusses the findings and offers theoretical and managerial implications. Section 5 provides conclusions.

2 | DATA AND METHODOLOGY

2.1 | Data

We extracted monthly pricing data from the World Bank on Brent and WTI crude oil, US natural gas (USGAS), and European natural gas (EURGAS). The GECON of Baumeister et al. (2022) can be extracted from Baumeister's website. The monthly dataset covers the period from January 1982 to July 2022 (1982M1–2022M7), for a total of 486 observations. Table 1 depicts the descriptive statistics, and Figure 1 shows the evolution of the first difference in the studied time series.

2.2 | Time-varying partial-directed coherence under stochastic volatility

The first step in our proposed methodology was to estimate TVP-VAR model with stochastic volatility using the Markov chain Monte Carlo method (Nakajima, 2011). Second, we computed the PDC from time-varying parameters for different frequencies. Finally, significant PDC was obtained using the proposition of Takahashi et al. (2007). Let the bivariate process $Z_t = \{X_{1,t}, X_{2,t}\}_{t=1,\ldots,T-1}$, and the TVP-VAR model under stochastic volatility is given by

$$Z_t = c_t + \sum_{k=1}^{p} A_k(t) Z_{t-k} + \varepsilon_t \qquad (1)$$

TABLE 1 Summary statistics.

	GECON	USGAS	EURGAS	WTI	Brent
Min	3.471	−4.166	−10.188	190.73	3152.52
Max	4.559	3.4	17.772	418.01	6843.73
Std. dev	0.372	0.621	1.511	55.244	952.247
Skewness	2.142	−0.297	5.319	−0.221	−0.241
Kurtosis	60.361	11.263	71.822	2.028	1.837
Jarque-Bera test	74,793.26***	2603.006***	107,666.7***	869.802***	803.864***
ADF test	−10.753***	−8.732***	−7.271***	−8.479***	−8.365***

Abbreviations: ADF, augmented Dickey–Fuller; GECON, global economic condition; EURGAS, European natural gas; USGAS, US natural gas; WTI, West Texas Intermediate.
***The value is statistically significant for 5%.

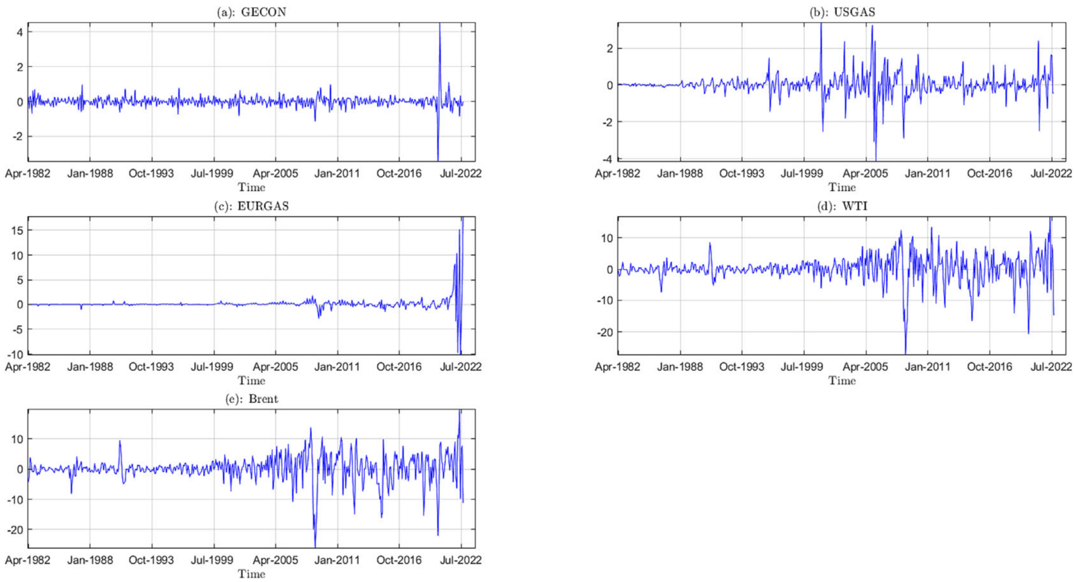

FIGURE 1 Visualization of the dynamics of the first difference in the time series. EURGAS, European natural gas; GECON, global economic condition; USGAS, US natural gas; WTI, West Texas Intermediate.

where $\varepsilon_t \sim N(0,\sigma_t^2)$, $\sigma_t^2 = \alpha \exp(h_t)$, $h_{t+1} = \beta h_t + \eta_t$ and $\eta_t \sim N(0,\sigma_\eta^2)$. Furthermore, c_t is the intercept, p is the order of the model, and $A_k(t), k = 1,...,p$ are (2×2) matrices of time-varying coefficients, where each component verifies $A_{i,j}(t+1) = A_{i,j}(t) + \mu_t$ with $\mu_t \sim N(0,\varphi)$.

Considering time index t is fixed, the PDC from the process X_j to the process X_i at frequency f is defined from the Fourier transform of matrices $A_k(t)$ as

$$\mathrm{PDC}_{(X_i,X_j)}(f) = \frac{\overline{A}_{ij}(f)}{\sqrt{\overline{a}_j^H(f)\overline{a}_j(f)}} \tag{2}$$

where H denotes the transpose and complex conjugate operations. $\overline{A}(f) = \overline{a}_1(f), \overline{a}_2(f)$ represents the difference between the identity matrix I_2 and the matrix $A(f)$, where each element is given by

$$A_{i,j}(f) = \sum_{k=1}^{p} A_{i,j}(k) \exp(-i2\pi kf). \tag{3}$$

Thus,

$$\overline{A}_{i,j}(f) = \begin{cases} 1 - \sum_{k=1}^{p} A_{i,j}(k) \exp(-i2\pi kf), \text{if i} = j \\ -\sum_{k=1}^{p} A_{i,j}(k) \exp(-i2\pi kf), \text{ if i} \neq j. \end{cases} \tag{4}$$

According to Equation (1), we propose a time-varying PDC as the PDC given by Equation (2) for each time index t. Therefore, we have the following:

$$\mathrm{PDC}_{(X_i,X_j)}(t,f) = \frac{\overline{A}_{ij}(t,f)}{\sqrt{\overline{a}_j^H(t,f)\overline{a}_j(t,f)}}$$

and the significant values of $\left|\mathrm{PDC}_{(X_i,X_j)}(t,f)\right|^2$ are obtained based on the proposition given by Takahashi et al. (2007). In addition, we propose the time-varying causality as the sum of $\left|PDC_{(X_i,X_j)}(t,f)\right|^2$ for the band of frequencies $[f_1,f_2]$ as follows:

$$PDC_t = \sum_{f=f_1}^{f_2} \left|PDC_{(X_i,X_j)}(t,f)\right|^2, \tag{5}$$

and the frequency-varying causality as the sum of $\left|PDC_{(X_i,X_j)}(t,f)\right|^2$ for all time index t, thus

$$PDC_f = \sum_t \left|PDC_{(X_i,X_j)}(t,f)\right|^2.$$

2.3 | Out-of-sample prediction performance

Following Paye (2012), the classical autoregressive model (AR) is employed to predict time series, defined as

$$\Delta X_t = \alpha_0 + \sum_{\ell=1}^{p} \alpha_\ell \Delta X_{t-\ell} + \varepsilon_t \tag{6}$$

where p is the lag order, $X_{t-\ell}$ is the lag of X_t, and ε_t is the error term. Here, X_t can be EURGAS, USGAS, Brent, or WTI time series, and Δ denotes the symbol of the first difference. We extend the AR model with the globaleconomic condition index to explore its predictability on ΔX_t, then the AR-GECON model can be expressed as

$$\Delta X_t = \gamma_0 + \sum_{\ell=1}^{q} \gamma_\ell \Delta X_{t-\ell} + \beta \Delta \mathrm{GECON}_{t-1} + \varepsilon_t. \tag{7}$$

In the other hand, in order to explore the impact of some bidirectional interaction between ΔX_t and $\Delta GECON_{t-1}$ on the prediction of ΔX_t, we test the forecasting performance of the following VAR model

$$\begin{cases} \Delta X_t = \alpha_{1,0} + \sum\limits_{\ell=1}^{p_1} \alpha_{1,\ell} \Delta X_{t-\ell} + \sum\limits_{k=1}^{p_2} \beta_{1,k} \Delta \mathrm{GECON}_{t-k} + \varepsilon_{1,t} \\ \Delta \mathrm{GECON}_t = \alpha_{2,0} + \sum\limits_{\ell=1}^{p_3} \beta_{2,\ell} \Delta \mathrm{GECON}_{t-\ell} + \sum\limits_{k=1}^{p_4} \alpha_{2,k} \Delta X_{t-k} + \varepsilon_{2,t} \end{cases} \tag{8}$$

where $p_i, i=1,\ldots,4$ are lag orders and $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are the error terms.

According to Welch and Goyal (2007) and Wang et al. (2018), the out-of-sample R^2 test (R^2_{OOS}) is used to evaluate the forecasting quality. R^2_{OOS} assesses the percent reduction of the mean squared prediction error (MSPE) for predictive regression model i ($MSPE_{model_i}$) compared to MSPE of regression model j ($MSPE_{model_j}$, $j \neq i$), which can be expressed as

$$R^2_{OOS} = 1 - \frac{MSPE_{model_i}}{MSPE_{model_j}} \tag{9}$$

where

$$\begin{aligned} MSPE_{model_i} &= \frac{1}{h}\sum_{t=1}^{h}\left(\Delta X_t - \widehat{\Delta X}_{model_i,t}\right)^2 \text{and} \\ MSPE_{model_j} &= \frac{1}{h}\sum_{t=1}^{h}\left(\Delta X_t - \widehat{\Delta X}_{model_j,t}\right)^2 \end{aligned} \tag{10}$$

$\widehat{\Delta X}_{model_i,t}$ is the forecasting value of ΔX_t by model i, $\widehat{\Delta X}_{model_j,t}$ is the forecasting value of ΔX_t by the model j and h is the length of forecasting window. The model i can be AR-GECON model given by Equation (7) or VAR model given by Equation (8) whereas $model_j$ can be AR model given by Equation (6) or VAR model. In addition, to examine statistical difference between forecasting performance of model i and model j, we consider the MSPE-Adjusted (MSPE-Adj) statistics of Clark and West (2007). When R^2_{OOS} is positive, the model i outperforms the model j due to its lower MSPE.

For forecasting of EURGAS, USGAS, Brent, or WTI time series, we adopt the recursive window method for different windows length ($h=3$ months, $h=6$ months and $h=9$ months) where the prediction for the prior time step is used as input for making a prediction on the following time step. On the other hand, the AIC criterion is used to searching the optimal orders p, q, and $p_i, i=1,\ldots,4$ for different models. We take the first 400 months as the forecast period (82.304% of the studied sample), and the first forecast was in May 2015. The evaluation results of out of sample prediction are reported in Tables 2, 3, and 4.

3 | EMPIRICAL RESULTS

3.1 | TVP-PDC

The time-varying causality between GECON and USGAS is shown in Figure 2. The timeline and period are shown on the left and right sides of the graph, respectively. High causality between variables is represented by yellow, whereas poor causality is represented by blue, and the

TABLE 2 Forecasting performance (forecasting horizon $h = 3$).

	R^2_{OOS} (%)	MSPE-Adj.	p-value
Panel A: EURGAS			
AR-GECON vs. AR	0.055	2.295**	0.010
VAR vs. AR	0.081	2.074**	0.019
VAR vs. AR-GECON	0.026	1.430*	0.076
Panel B: USGAS			
AR-GECON vs. AR	−0.470	−2.253	0.987
VAR vs. AR	0.366	1.310*	0.094
VAR vs. AR-GECON	0.569	1.888**	0.029
Panel C: Brent			
AR-GECON vs. AR	0.059	2.269**	0.011
VAR vs. AR	−0.783	−4.357	0.999
VAR vs. AR-GECON	−0.895	−4.199	0.999
Panel D: WTI			
AR-GECON vs. AR	0.066	2.231**	0.012
VAR vs. AR	−0.288	−3.610	0.999
VAR vs. AR-GECON	−0.379	−3.442	0.999

Abbreviations: AR, autoregressive; EURGAS, European natural gas; GECON, global economic condition; MSPE-Adj, mean squared prediction error–adjusted; USGAS, US natural gas; VAR, vector autoregressive; WTI, West Texas Intermediate.
*Statistical significance at 10%.
**Statistical significance at 5%.
***Statistical significance at 1%.

TABLE 3 Forecasting performance (forecasting horizon $h = 6$).

	R^2_{OOS} (%)	MSPE-Adj.	p-value
Panel A: EURGAS			
AR-GECON vs. AR	0.042	3.238***	0.0006
VAR vs. AR	0.154	1.556*	0.059
VAR vs. AR-GECON	0.117	1.266	0.102
Panel B: USGAS			
AR-GECON vs. AR	0.013	0.290	0.385
VAR vs. AR	0.151	0.845	0.198
VAR vs. AR-GECON	0.139	1.152	0.124
Panel C: Brent			
AR-GECON vs. AR	0.059	1.959**	0.025
VAR vs. AR	−0.721	−1.546	0.938
VAR vs. AR-GECON	−0.831	−1.593	0.944
Panel D: WTI			
AR-GECON vs. AR	0.068	1.818**	0.034
VAR vs. AR	−0.287	−1.684	0.954
VAR vs. AR-GECON	−0.381	−1.793	0.963

Abbreviations: AR, autoregressive; EURGAS, European natural gas; GECON, global economic condition; MSPE-Adj, mean squared prediction error–adjusted; USGAS, US natural gas; VAR, vector autoregressive; WTI, West Texas Intermediate.
*Statistical significance at 10%.
**Statistical significance at 5%.
***Statistical significance at 1%.

thick red contour indicates significant causality at 5%. The PDC-SV map in Figure 2a from GECON to EUGAS reveals that there is no causality between this pair from the beginning of the study period (January 01, 1982) until the end of March 2005. However, there is significant causality with the in-phase relation from the beginning of January 2020 until the end of the study period (July 01, 2022), as indicated by the significant red-colored, which corresponds to the COVID-19 pandemic and Russia-Ukraine War. The PDC-SV shown on the right (Figure 2b) depicts causality from USGAS to GECON. The time-varying (Figure 2c) and frequency-varying causality (Figure 2d) quantified the directional information transfer between GECON and EURGAS, respectively. Consistent with our findings, high information runs from GECON to USGAS, specifically during the COVID-19 and Russia-Ukraine War periods.

The causality between GECON and EURGAS is depicted in Figure 3. As seen in the PDC-SV heat map, there is a significant connection between the two variables over the various periods of our sample (e.g., April 1982, 2005, and 2008) and at the end of the period (the period covering 2022). This highest causality is likely to be related to the COVID-19 pandemic and Russia-Ukraine War's effects at the medium- (10-month frequency band) and long-term (50- to 60-month frequency band) investment horizons. A stronger information transfer from GECON to EURGAS can be observed on both the timeline and frequency lines (Figure 3c,d), surpassing the transfer from EURGAS to GECON. This result highlights the dependence of the EU on Russian natural gas and reveals the rising uncertainty that contributes to the further deterioration of GECON. According to Baumeister et al. (2022), GECON closely monitors recognized events of global contractions and expansions, including the current downturn caused by the Russia-Ukraine War.

Figure 4a presents the PDC-SV between the GECON index and the WTI. We can observe several periods of significant coherence, mainly in the 8- to 10-month and 50- to 60-month frequency bands. Shortly before the beginning of 2022, there was a strong connection between GECON and WTI in the long-term horizon. The heat map of the GECON-WTI pair in Figure 4b shows many hot-colored yellow, suggesting a significantly strong causality from WTI to GECON. We note that remarkable consistency occurs at various scales and timeframes for the 30-month frequency bands. As agreed in

TABLE 4 Forecasting performance (forecasting horizon $h = 9$).

	R^2_{OOS} (%)	MSPE-Adj.	*p*-value
Panel A: EURGAS			
AR-GECON vs. AR	3.447e−02	4.232e+00***	1.155e−05
VAR vs. AR	0.171	2.621***	0.004
VAR vs. AR-GECON	0.141	2.255**	0.012
Panel B: USGAS			
AR-GECON vs. AR	0.012	0.332	0.369
VAR vs. AR	0.130	0.944	0.172
VAR vs. AR-GECON	0.119	1.095	0.136
Panel C: Brent			
AR-GECON vs. AR	0.048	2.197**	0.013
VAR vs. AR	−0.611	−1.751	0.960
VAR vs. AR-GECON	−0.693	−1.760	0.960
Panel D: WTI			
AR-GECON vs. AR	0.059	1.576**	0.057
VAR vs. AR	−0.411	−2.347	0.990
VAR vs. AR-GECON	−0.500	−2.348	0.990

Abbreviations: AR, autoregressive; EURGAS, European natural gas; GECON, global economic condition; MSPE-Adj, mean squared prediction error–adjusted; USGAS, US natural gas; VAR, vector autoregressive; WTI, West Texas Intermediate.
*Statistical significance at 10%.
**Statistical significance at 5%.
***Statistical significance at 1%.

previous studies (Wang et al., 2022), oil price fluctuations may have a significant influence on the real economy, financial markets, and macroeconomic conditions.

Figure 5a shows the PDC-SV between GECON and Brent prices. The former generally reveals more co-movements during 2020 and later in 2022, particularly during the war period. This may indicate that under contraction conditions, GECON is highly associated with Brent price in the medium term (5- to 10-month frequency bands). Figure 5 shows the PDC-SV heat map for the Brent-GECON pair. As seen in the PDC-SV scalogram, at different scales and times, there is a significant yellow island on the 30-month frequency band, indicating a strong connection between Brent and GECON in the long-term horizon. Furthermore, there is stronger information transfer from Brent to GECON on both the time and frequency lines (Figure 5c,d, respectively). This finding aligns with that of Baumeister et al. (2022), who indicated that GECON are a key driver of energy market prices.

3.2 | Out-of-sample prediction

According to Table 2, which shows the results for $h = 3$, when the forecasted time series is EURGAS, we can see that the GECON can provide a positive result of 0.055, implying that the GECON may minimize the 0.055% MSPE compared to the historical return of the EURGAS time series. Also, the VAR model outperforms the AR and AR-GECON models using the associated R^2_{OOS} that are 0.081 and 0.026, respectively; these results are confirmed by the significant MSPE-Adj values. When the forecasted time series is USGAS, the VAR model outperforms the AR and AR-GECON models using the associated R^2_{OOS} that are 0.366 and 0.569, respectively. However, when the forecasted time series are Brent or WTI time series, we can see that the GECON can produce positive values of 0.059 and 0.066, respectively, noting that the GECON can decrease the 0.059% and 0.066% MSPE, respectively, relative to the historical return of Brent and WTI, respectively.

The forecasting performance when $h = 6$, as reported in Table 3, shows that the GECON index provides a positive value of 0.042, suggesting that the GECON index diminish the 0.042% MSPE related to the historical return when the forecasted time series is EURGAS. Also, the GECON index can yield a positive value of 0.059, which implies that the GECON index can reduce the 0.059% MSPE relative to the historical return when the forecasted time series is Brent. Whereas when the time series is WTI, the GECON index has the potential to provide a

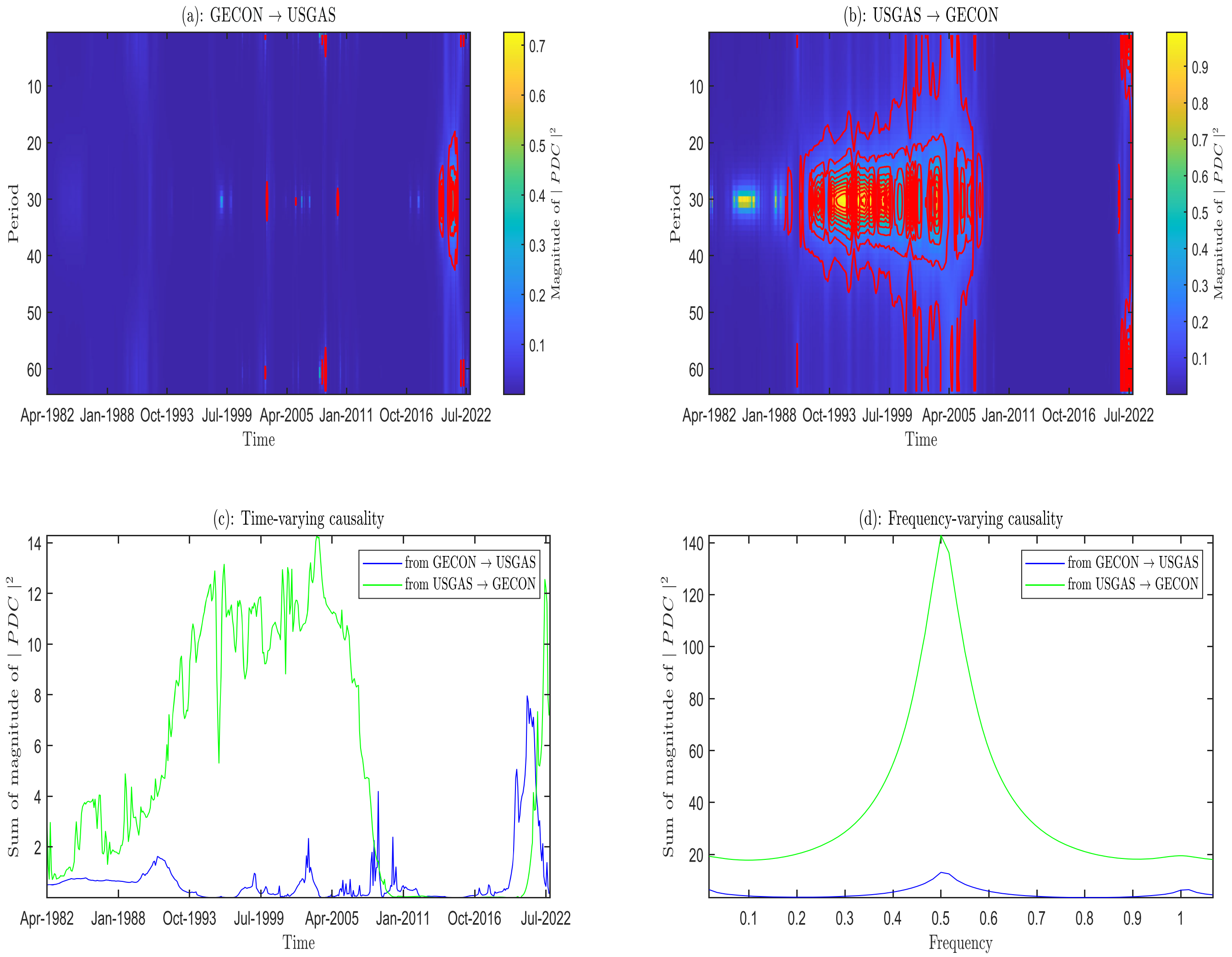

FIGURE 2 Bidirectional causality between GECON and USGAS. (a) The PDC-SV causality from GECON to USGAS; (b) PDC-SV causality from USGAS to GECON: the color code spans from blue (low intensity) to yellow (high intensity), and the red contour denotes regions in which causality is significant at the 5% level; (c) time-varying (left) and (d) frequency-varying (right) directional information transfer (denoted by $|\mathrm{PDC}|^2$) are shown. GECON, global economic condition; PDC, partial-directed coherence; PDC-SV, partial-directed coherence under stochastic volatility; USGAS, US natural gas.

positive value of 0.068, indicating that it has the potential to lower the MSPE compared to the historical return by 0.068%.

As depicted in Table 4 ($h=9$), when Brent is used as the projected time series, the GECON index may provide a positive result of 0.048, indicating that it can lower the MSPE compared to the historical return by 0.048%. Comparatively, when the projected time series is WTI, the GECON index provides a positive result of 0.059, indicating that the GECON index can lower the 0.059% MSPE compared to the historical return.

Two major results can be concluded from Tables 2, 3, and 4. The first result is that the GECON time series cannot be used to explain the future evolution of the USGAS time series, seeing that for $h=3$, $h=6$, and $h=9$, the R^2_{OOS} is negative or MSPE-Adj is not statistically significant. The second result is that the AR-GECON model outperforms the AR model when the forecasted time series are EURGAS, Brent, and WTI, as R^2_{OOS} is positive and MSPE-Adj is statistically significant.

Since the AR-GECON model outperforms the AR model in the out-of-sample examination, we employ the cumulative mean squared forecasting error (CumMSFE) to observe the forecasting performance of the GECON index over time. CumMSFE can be expressed as

$$\mathrm{CumMSFE}_{i,t} = \frac{1}{t}\sum_{\ell=1}^{t}\left(\left(\widehat{\Delta X}^{i}_{AR,t} - \Delta X^{i}_{t}\right)^2 - \left(\widehat{\Delta X}^{i}_{AR-GECON,t} - \Delta X^{i}_{t}\right)^2\right), t = 1,\ldots,M \tag{11}$$

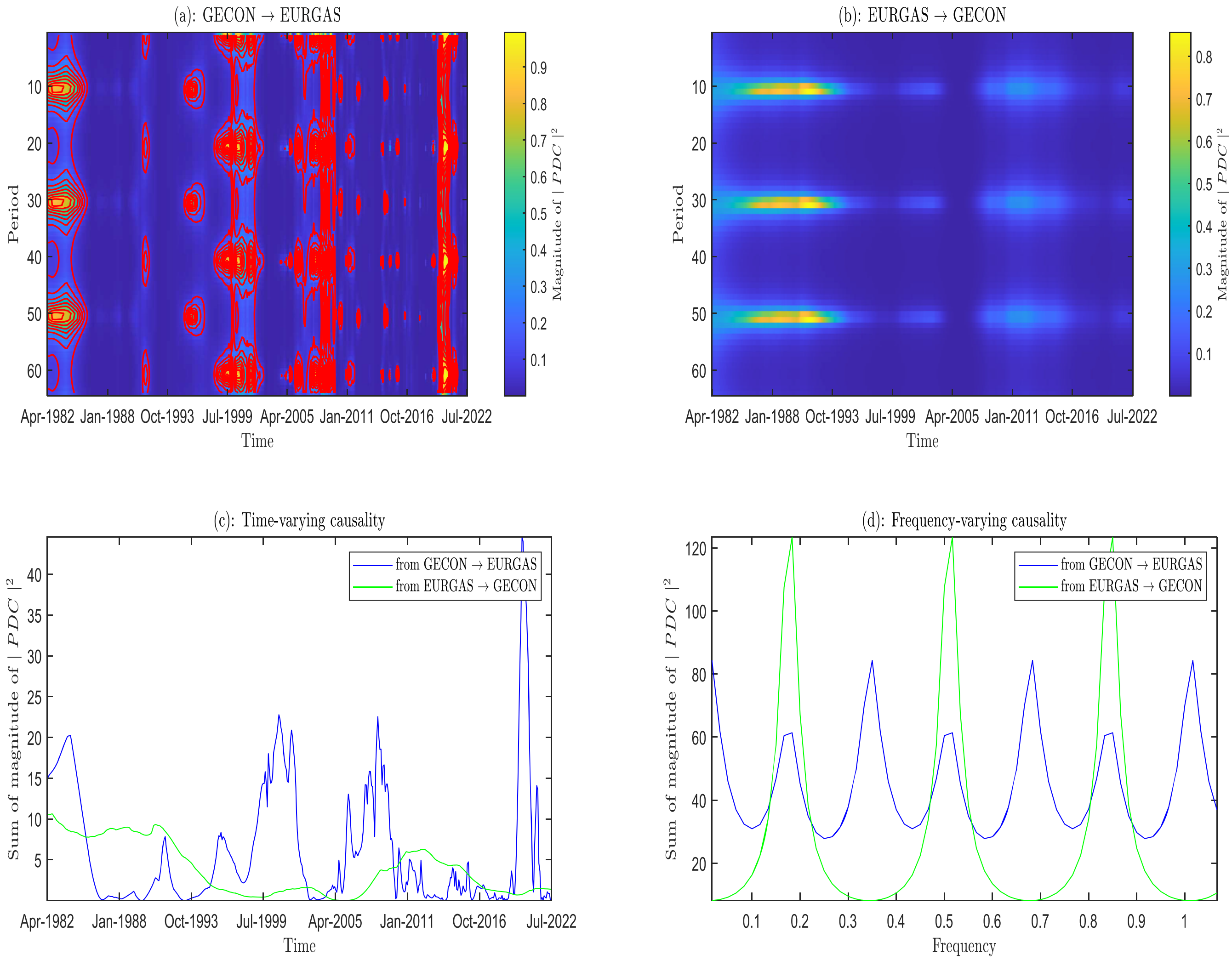

FIGURE 3 Bidirectional causality between GECON and EURGAS. EURGAS, European natural gas; GECON, global economic condition.

where $\widehat{\Delta X}^{i}_{AR-GECON,t}$ and $\widehat{\Delta X}^{i}_{AR,t}$ are the out of sample prediction of the time series i by AR-GECON model and AR model, respectively, M is the length of out-of-sample prediction window and $i=$(EURGAS, Brent, WTI). If CumMSFE is positive, this indicates that the forecasting performance of the GECON index is superior to that of the historical return of the forecasted time series. The evolution over time for CumMSFE when the predicted time series is EUROGAS, USGAS, Brent, and WTI is shown in Figure 6.

According to the time evolution of CumMSFE for the EURGAS time series, we can see that the AR-GECON model continues to outperform the AR model, suggesting that the connection between the GECON index and EURGAS time series detected by PDC-SV continues in the out of sample. Throughout half of 2021, the CumMSFE was negative, which implies that the AR model outperforms AR-GECON due to the high volatility of the GECON index in this period. The evolution of CumMSFE over time for the USGAS time series reveals that there are some periods in which the AR-GECON model outperformed the AR model (CumMSFE is positive), for example, from the beginning of 2021 to the end of the studied period, where the GECON index and the USGAS time series were characterized by a similar evolution. This result was confirmed by the information flow from the GECON index to the USGAS time series detected by PDC-SV. There were also other time periods in which the AR model outperformed the AR-GECON model (CumMSFE is negative), for example, in 2021, which corresponds to the high volatility of the GECON index. For the out-of-sample predicted time series Brent and WTI, we can remark that, based on the evolution of CumMSFE over time, the AR-GECON model continues to outperform the AR model. This is because the Brent and WTI time series had, globally, the same evolution in

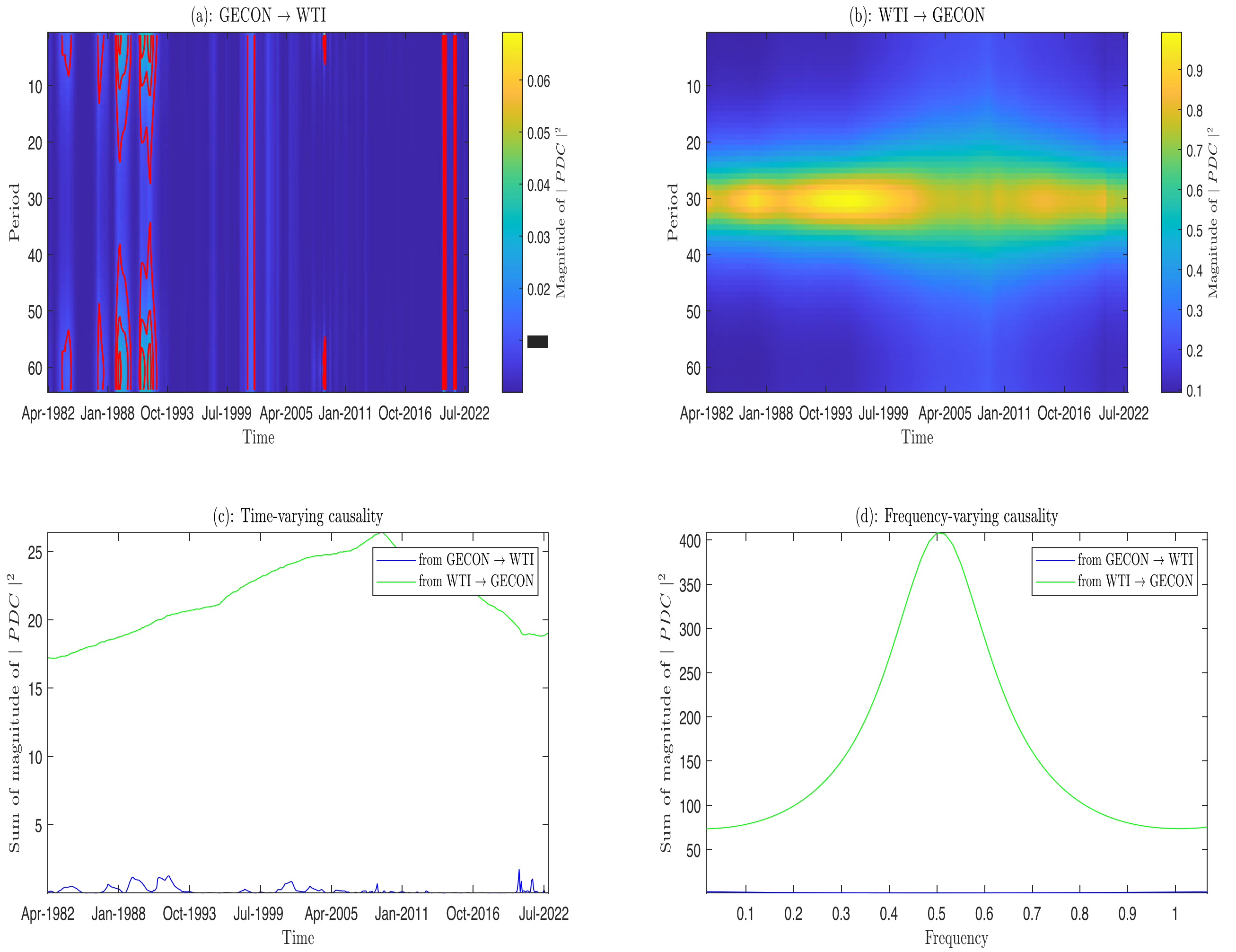

FIGURE 4 Bidirectional causality between GECON and WTI. GECON, global economic condition; WTI, West Texas Intermediate.

the studied period, and there was a transfer of information from the GECON index to the WTI time series captured by PDC-SV. This finding implies that global economic activity can perform well in forecasting EURGAS, Brent, and WTI time series, as demonstrated by the historical return of these time series in this examination.

4 | DISCUSSION

Energy price fluctuations not only have an immediate impact on consumers' wallets but also have an impact on the kind of automobiles people purchase and how near they choose to reside to their places of employment (Baumeister et al., 2017). According to Yellen (2011), central bankers are worried about the impact of rising fuel costs on inflation expectations, consumer spending, and consumer confidence. Forecasts of the price of gasoline play a significant part in both the microeconomic models used to study the car industry and the economic investigation of environmental legislation (Baumeister & Kilian, 2012). The pricing of derivatives, risk management, hedging techniques, and asset allocation all critically depend on accurate estimates of the volatility of crude oil and gas prices. Our findings are in line with those found under the high volatility regime (Figure 6), which suggests that increased volatility may be a contributing factor to the occurrence of recessions (Choudhry et al., 2016; Guo et al., 2022). The outstanding predicting forecasting performance of GECON is mainly reflected after 2022 because the Russia-Ukraine war led to a rapid increase in energy prices.

4.1 | Methodological implications

This study provides novel insights by examining how deteriorating global economic conditions may affect energy prices. First, we advance the understanding of the key drivers of world energy markets (e.g., Baumeister &

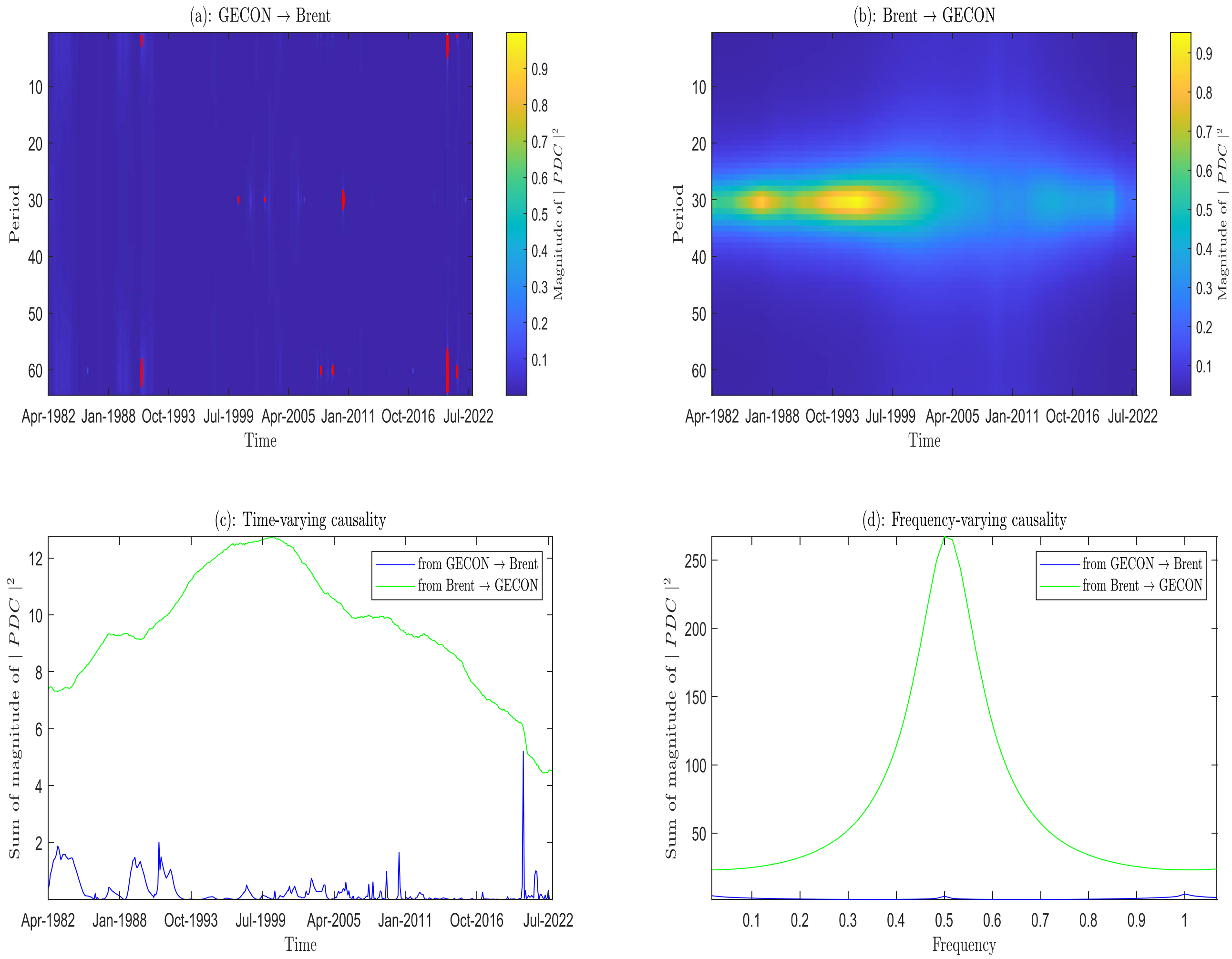

FIGURE 5 Bidirectional causality between GECON and Brent. GECON, global economic condition.

Peersman, 2013; Baumeister et al., 2022). Specifically, we propose a new technique to estimate the GECON–energy price causal nexus, namely, the time-varying partial-directed coherence under stochastic volatility. In fact, one of the most pressing challenges in contemporary economics and mathematics is the identification and quantification of causal relationships (Tian et al., 2021). Significant progress has been made in determining causation using theoretical statistical models like Granger causality and transfer entropy (Granger, 1969; Schreiber, 2000). In our study, we present a new partial-directed coherence method, a model metric of causality, to extract possible changes in time and the frequency domain of the time series. Our method effectively handles stationary processes and high-dimensional processes by providing an information-rich representation of time-varying latent causal links. Second, our empirical findings reveal that GECON can successfully predict oil and gas prices, which extends the existing literature. We support this evidence using more recent data that include the Russian-Ukrainian conflict. We found that constructing an indicator of global economic conditions enhances the reliability of petroleum consumption forecasts.

4.2 | Policy implications

This study offers useful insights for business and government planners. First, financial institutions, central banks, and organizations such as the International Monetary Fund (IMF), the International Energy Agency (IEA), and the U.S. Energy Information Administration (EIA) all devote significant resources to forecasting the future of energy production, consumption, and prices. Our main conclusion is that significant improvements in directional accuracy, as well as significant decreases in cumulative mean squared forecasting error (CumMSFE) of oil and gas price projections, are both attainable in real time at horizons up to 2 years, which is in line with the existing

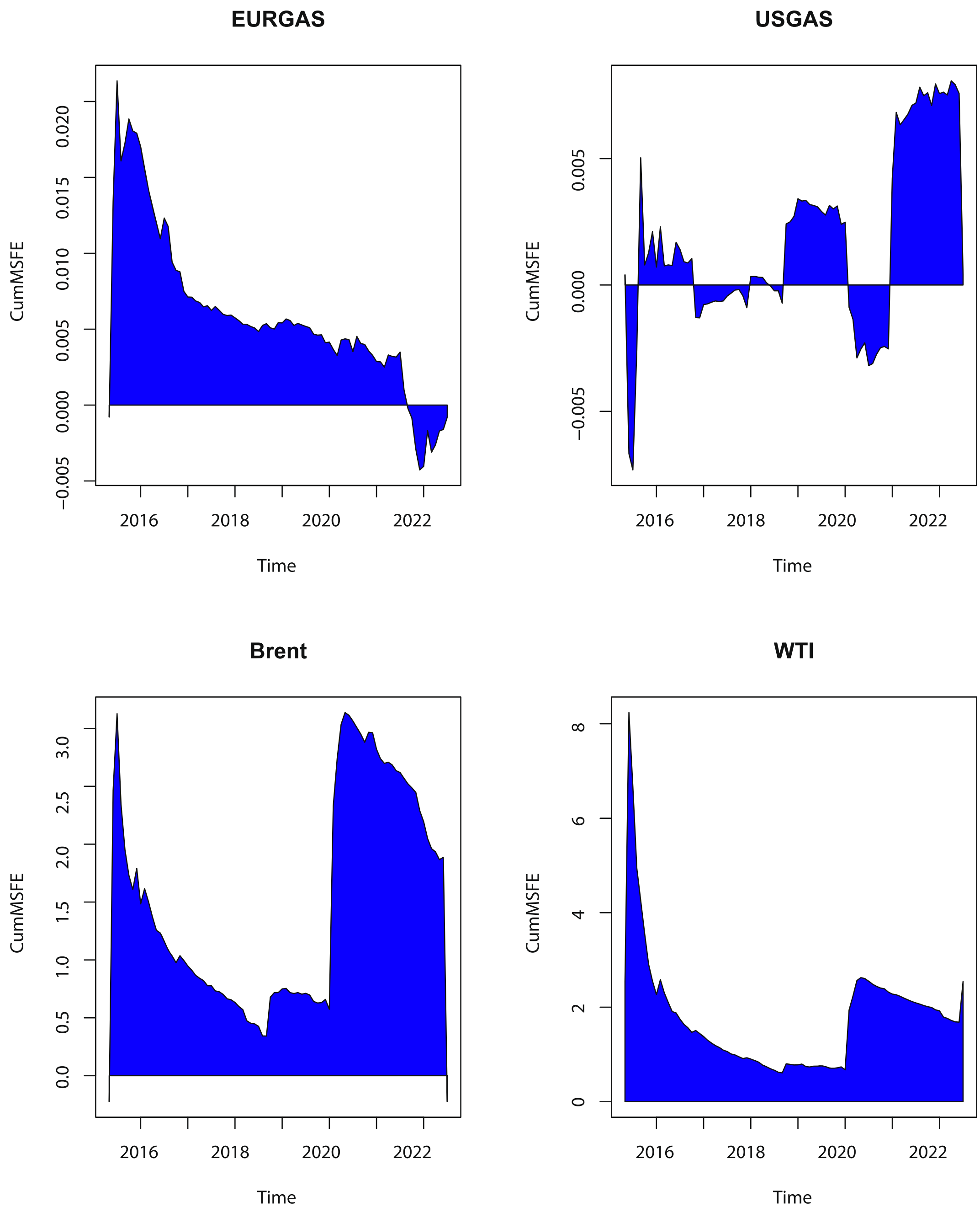

FIGURE 6 CumMSFE of EURGAS, USGAS, Brent, and WTI, respectively. CumMSFE, cumulative mean squared forecasting error; EURGAS, European natural gas; USGAS, US natural gas; WTI, West Texas Intermediate.

research of Lv and Wu (2022) and Salisu et al. (2022). Second, based on the findings of our research, these indicators may be of great assistance to analysts attempting to evaluate the consequences of recent events in energy markets for the purpose of making choices about budgeting and planning. An accurate prediction would offer information about the course that the macro economy is expected to take in the future, depending on how uncertainty evolves, as oil and gas price volatility reflect economic uncertainty. This information can be incorporated to quantify economic activity. This would enable policymakers to devise appropriate solutions to avert negative effects. Energy price projections may be used by governments to examine the anticipated effects of various policy alternatives as well as the effects of policies on energy production, consumption, and pricing. Policymakers may increase the effectiveness of energy programs and reduce unexpected effects by adopting more precise projections. Third, it is possible for international organizations, central banks, and financial institutions to collaborate in order to share data and best practices, as well as to develop more advanced forecasting models that take into account a variety of factors including geopolitical risks, technological advancements, and climate policies.

5 | CONCLUSION

In the context of the Russian invasion of Ukraine and the resulting deterioration of the economic and geopolitical outlook, we developed and employed a new technique to estimate the GECON–energy price causal nexus, namely, the time-varying partial-directed coherence under stochastic volatility (PDC-SV). We investigated the relationship between the new indicator of global economic conditions (GECON) and European energy prices, and our key findings lead us to conclude that the deterioration of global economic conditions can negatively influence European energy prices. Furthermore, we also conclude that the incorporation of the Global Economic Conditions Index (AR-GECON) that manifests the global economic outlook can significantly improve power the accuracy of oil and gas price volatility forecasts. Concomitantly, the decline in energy prices may release inflationary pressure to some degree and hence would have profound implications for the forward-looking monetary policy formulation and central banks as well as the stakeholder of economic and price stability. The findings provide valuable insights into the investment choices in the energy market and they also have profound implications for the household and firms that are facing increasing cost pressures.

This study provides novel insights by proposing a new technique to estimate the GECON–energy price causal nexus, and by demonstrating that global economic conditions can successfully predict oil and gas prices. The research offers valuable contributions to the understanding of the key drivers of world energy markets and extends the existing literature by including more recent data that includes the Russian-Ukrainian conflict. The study has significant policy implications, as it can improve the accuracy of energy price projections, assist in evaluating the consequences of recent events in energy markets, and help policymakers devise appropriate solutions to avert negative effects.

Despite the significant contributions of our study, our proposed methodology has not been tested against the presence of outlier observations and different types of noise that may exist in various studied time series. To overcome the issue of outlier observations and noise, different robust regression methods can be applied to obtain the time-varying parameters. Additionally, the results of predictions using AR, AR-GECON, and VAR models can be improved by using the rolling window method instead of the recursive approach, allowing for better comparison between the tested models. Future research could also explore the causal nexus between GECON and energy prices in other economies, particularly in emerging countries where probably the energy market may be more sensitive to global economic conditions.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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