

# Investigation into the dynamic relationships between global economic uncertainty and price volatilities of commodities, raw materials, and energy

Global  
economic  
uncertainty

23

Received 12 June 2023  
Revised 27 August 2023  
5 October 2023  
Accepted 10 October 2023

Malihe Ashena and Hamid Laal Khezri  
*Accounting Department, Faculty of Humanities,  
Bozorgmehr University of Qaenat, Qaen, Iran, and*

Ghazal Shahpari  
*Department of Management and Economics, Tarbiat Modares University,  
Tehran, Iran*

## Abstract

**Purpose** – This paper aims to deepen the understanding of the relationship between global economic uncertainty and price volatility, specifically focusing on commodity, industrial materials and energy price indices as proxies for global inflation, analyzing data from 1997 to 2020.

**Design/methodology/approach** – The dynamic conditional correlation generalized autoregressive conditional heteroscedasticity model is used to study the dynamic relationship between variables over a while.

**Findings** – The results demonstrated a positive relationship between commodity prices and the global economic policy uncertainty (GEPU). Except for 1999–2000 and 2006–2008, the results of the energy price index model were very similar to those of the commodity price index. A predominant positive relationship is observed focusing on the connection between GEPU and the industrial material price index. The results of the pairwise Granger causality reveal a unidirectional relationship between the GEPU – the Global Commodity Price Index – and the GEPU – the Global Industrial Material Price Index. However, there is bidirectional causality between the GEPU – the Global Energy Price Index. In sum, changes in price indices can be driven by GEPU as a political factor indicating unfavorable economic conditions.

**Originality/value** – This paper provides a deeper understanding of the role of global uncertainty in the global inflation process. It fills the gap in the literature by empirically investigating the dynamic movements of global uncertainty and the three most important groups of prices.

**Keywords** Global economic policy uncertainty, Commodity prices, Industrial raw materials prices, Energy prices, DCC-GARCH model, Granger causality

**Paper type** Research paper

© Malihe Ashena, Hamid Laal Khezri and Ghazal Shahpari. Published in *Applied Economic Analysis*. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) licence. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial and non-commercial purposes), subject to full attribution to the original publication and authors. The full terms of this licence maybe seen at <http://creativecommons.org/licenses/by/4.0/legalcode>

**JEL classification** – C22, D81, E31, E60



## 1. Introduction

Uncertainty is a complex phenomenon that influences various aspects of the economy, including supply and demand dynamics, production decisions, consumer behavior and other economic agents' decisions (Junttila and Vataja, 2018). During uncertain situations, economic agents cannot predict a disturbance's conditional volatility (Jurado *et al.*, 2015; Azimli, 2022).

Uncertainty can cause changes in macroeconomic variables, for example, industrial production and employment (Baker *et al.*, 2016), the unemployment rate (Caggiano *et al.*, 2017), asset prices (Brogaard and Detzel, 2015; Bilgin *et al.*, 2018) and financial markets (Pástor and Veronesi, 2013; Bordo *et al.*, 2016).

In recent decades, the concept of globalization and increasing interactions between countries have made the occurrence of uncertainty in one country, or one region of the world spread to other areas and even the entire globe (Civcir and Varoglu, 2019; Nyakurukwa and Seetharam, 2023). For instance, the advent of the coronavirus in late 2019 in China increased uncertainty in other Asian nations, which then spread to Europe and the USA (Sharma *et al.*, 2020). Although economic policy uncertainty has cross-border effects (Sen and Wesselbaum, 2022), global economic policy uncertainty (GEPU) is considered in this research for an accurate analysis of price volatilities at a global level.

Economic uncertainty shocks can influence commodity prices through financial, supply and demand channels. Uncertainty shocks will change the investment decisions of economic agents, thereby causing financial channels to cause changes in commodity prices (Huang *et al.*, 2021). Moreover, economic uncertainty results in changes in decisions about production, consumption and savings which in turn affects the demand and supply channels, the price level, and the price elasticity of commodities over time (Bakas and Triantafyllou, 2020).

In recent years, some studies concentrating on the empirical and theoretical relationship between global economic uncertainty and the prices of different markets have been enhanced (Baker *et al.*, 2016; Antonakakis *et al.*, 2014; Balcilar *et al.*, 2017; Bilgin *et al.*, 2018; Huang *et al.*, 2021). According to previous studies, economic policy uncertainty and price changes in different markets are interrelated (Salisu *et al.*, 2017; Qin *et al.*, 2020). Because the change of economic decisions in production, consumption and investment due to economic uncertainty may lead to changes and price fluctuations, there may be a spillover effect of fluctuations. Moreover, as changes in commodity prices can provide immediate and valuable insight into broader economic conditions, it is worthwhile to investigate commodity prices to obtain useful information and signals for future uncertainty (Wang *et al.*, 2015).

This study hypothesizes that there is a dynamic bidirectional relationship between global economic uncertainty and price volatility. So, the dynamic conditional correlation generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model is used to investigate the variables' dynamic behavior. An advantage of using the DCC-GARCH model is that it analyzes the direct link between the changing behavior of inflation volatility and economic uncertainty.

In addition to commodity prices, this study investigates industrial material prices and energy prices. Changes in the price of energy affect the input costs for most goods (Saddique *et al.*, 2022), which can lead to inflation and a variety of alterations in the decisions made by economic agents. Furthermore, global market uncertainty may be prevalent in manufacturing sectors. Energy and basic material price fluctuations can destabilize supply chains. On the contrary, the production of other economic sectors is affected by the rising prices of industrial materials. Therefore, it is crucial to study the effect of uncertainty on the price of industrial raw materials in light of its consequences.

This study applied Davis's (2016) GEPU index, computed based on Baker *et al.*'s (2016) index. Accordingly, the GEPU index is measured as the GDP-weighted average of the

---

national economic policy uncertainty (EPU) indices of selected countries (constituting two-thirds of global output).

This paper aims to provide a comprehensive understanding of the relationship between GEPU and price changes, thereby offering valuable insights for policymakers. Existing literature lacks a consensus on the effects of global economic uncertainty on price fluctuations at the global level, as this relationship is dynamic and fluctuates over time. Although some studies have examined the impact of uncertainty on commodity price volatility at the national level, there is a significant gap in understanding the dynamic movements of global uncertainty and its effects on price levels in global markets. To address this gap, the DCC-GARCH model is applied to empirically investigate the relationship between global uncertainty and prices of commodities, industrial materials and energy (as determinants of global inflation) from 1997 to 2020. Moreover, by examining the causal connection between global economic uncertainty and price indices at the global level, this study can help to enrich the inflation and uncertainty literature and clarify the related socioeconomic policies and strategies.

The remainder of this paper is organized as follows. Following a concise review of related studies in Section 2 is a description of the methodology in Section 3. Section 4 discusses the data and summarizes the empirical results. Finally, Section 5 closes the paper with some concluding remarks.

## 2. Literature review

In times of economic uncertainty, the behaviors of both producers and consumers change, which in turn causes changes in prices and price elasticity. Changes in price elasticities of supply and demand, referring to how the producers and consumers react to the changes in the price, would result in shifts in market equilibrium and influence the overall pricing dynamics (Bakas and Triantafyllou, 2020).

When uncertainty occurs, supply chains may be disrupted, leading to an increase in the prices of commodities. Moreover, production processes and methods may be adjusted in response to uncertain market conditions (Huang *et al.*, 2021). Conversely, in some cases, increased uncertainty may lead to decreased demand from consumers who become more cautious with their spending. This decrease in demand can result in price reductions (Karabulut *et al.*, 2020; Bakas and Triantafyllou, 2020). However, there may be an asymmetric relationship between uncertainty and price indices depending on the different responses of economic agents to uncertain situations (Ashena and Shahpari, 2022).

It is important to consider that economic uncertainty can appear at different levels, ranging from a specific country's economic policies to global economic conditions. One country's EPU may have little effect on the commodity markets of other countries, whereas global uncertainty can have more widespread impacts on economies worldwide (Andreasson *et al.*, 2016; Gu and Liu, 2022).

Wang *et al.* (2015) emphasized commodity price fluctuations as a primary indicator of EPU, whereas other studies, such as those by Salisu *et al.* (2017) and Qin *et al.* (2020), demonstrated the relationship between elevated energy prices and higher inflation rates, highlighting the complex interplay between uncertainty and prices.

There are some studies about the relationship between uncertainty and energy prices. For instance, Antonakakis *et al.* (2014) studied the influence of EPU on international oil prices, revealing limited spillover effects from EPU to global energy prices. Su *et al.* (2018) used wavelet coherence analysis and identified oil prices as crucial to long-term uncertainty. In another study, Ringim *et al.* (2022) demonstrated robust interconnections between energy prices and economic EPU in Russia, using the DCC-MGARCH method.

Some studies have also investigated the relationship between EPU and other markets. [Jones and Olson \(2013\)](#) explored the dynamic correlations among uncertainty, inflation and output, indicating that the correlation shifted from negative to positive in the 1990s. [Bakas and Triantafyllou \(2020\)](#) demonstrated the significant negative impact of the pandemic on commodity market volatility and highlighted the vulnerability of petroleum oil markets to uncertainty. Meanwhile, [Ghosh et al. \(2022\)](#) using the DCC-GARCH model, revealed that EPU significantly impacted macroeconomic variables such as imports, exports and inflation rates following the outbreak of COVID-19. Similarly, [Yin et al. \(2023\)](#), using the SV-TVP-FAVAR model, revealed that during the COVID-19 period, commodity prices exhibited a fluctuating increasing trend.

Further studies examined the effects of global uncertainty shocks on global inflation and other related variables. [Kang et al. \(2020\)](#) showed that global uncertainty shocks sharply declined global inflation, economic growth and interest rates. Furthermore, [Dai et al. \(2022\)](#) used GARCH-MIDAS models and demonstrated that GEPU is an effective predictor for future market volatility of crude oil prices. In their study, [Liu and Chen \(2022\)](#), using a monthly data set from 2007 to 2021, revealed a short-term relationship between crude oil prices and GEPU. In a recent study, [Raza et al. \(2023\)](#), using the GARCH-MIDAS model indicate that any increase in uncertainty regarding GEPU leads to escalated price volatility of gold, palladium, platinum and silver. Besides, [Long et al. \(2023\)](#) revealed a positive and asymmetric association between GEPU and international grain prices based on the NARDL model.

Regarding oil pricing, [Khan et al. \(2021\)](#) observed a discernible relationship between GEPU and oil prices in the medium term. [Lyu et al. \(2021\)](#) discovered that GEPU shocks substantially amplified crude oil price volatility. [Ozcelebi \(2021\)](#) found that increasing GEPU led to decreased global economic activity and lower oil prices using the quantile regression model. Using a time-varying parameter VAR framework, [Lin and Bai \(2021\)](#) found that economic policy uncertainty reveals fluctuating responses to oil price shocks, and also, showed that oil-exporting nations are more vulnerable to oil price shocks than oil-importing nations.

Despite the considerable efforts made by researchers to analyze the consequences of GEPU, this study represents a comprehensive and precise understanding of the dynamic relationship between global uncertainty and global inflation by comparing three different price indices.

### 3. Methodology

#### 3.1 *Dynamic conditional correlation generalized autoregressive conditional heteroscedasticity model*

The GARCH model can be used to investigate the temporal correlation between economic variables. Compared with other estimation models, the DCC-GARCH models have some advantages ([Engle and Sheppard, 2001](#); [Engle, 2002](#)). This model detects changes in conditional correlations over time and enables the identification of the dynamic behavior of target variables in response to changes in economic variables ([Rajwani and Kumar, 2015](#)). In addition, this model allows for considering additional explanatory variables in the mean equation ([Chittedi, 2015](#)). The advantages of using this model are summarized below:

- By showing possible changes in conditional correlations over time, the dynamic behavior of variables can be followed by this model. So, DCC-GARCH can detect the market volatilities during different periods.

- The dynamic conditional correlations model addresses heteroscedasticity, because it estimates the correlation coefficients of the standardized residuals (Chittedi, 2015).
- Referring to continuously adjusting the correlations for time-varying, the DCC-GARCH model can be considered a superior correlation measure (Cho and Parhizgari, 2008).

To characterize volatility and time-varying dynamic conditional correlations between variables, this study uses DCC-MGARCH (1, 1) proposed by Engle (2002) and Tse and Tsui (2002). So, the following model is considered:

$$Y_t = \mu_t + \sigma_t \varepsilon_t \quad \varepsilon_t \sim (0, H_t) \quad (1)$$

where  $Y_t = (Y_{1,t}, Y_{2,t}, \dots, Y_{M,t})'$  and  $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \dots, \varepsilon_{M,t})$  are the  $(M \times 1)$  vector of the variables and zero mean residuals. The preceding model is assumed to be normally distributed with a zero mean and conditional variance-covariance matrix ( $H_t$ ).

$$H_t = \Gamma_t R_t \Gamma_t \quad (2)$$

where  $H_t$  represents the conditional variance-covariance matrix,  $\Gamma_t$  is a  $(k \times k)$  diagonal matrix, and  $R_t$  is a  $(k \times k)$  dimensional conditional correlation matrix. Based on a univariate GARCH ( $p, q$ ) process, the time-varying standard deviation matrix is calculated as follows:

$$\Gamma_t = \text{diag} \left\{ \sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \dots, \sqrt{h_{MM,t}} \right\} \quad (3)$$

$$h_{ii,t} = w_i + \beta_i h_{ii,t-1} + \alpha_i \varepsilon_{i,t-1}^2, \quad i = 1, 2, \dots, M \quad (4)$$

where  $h_{ii,t}$  is the conditional variance,  $\alpha$  and  $\beta$  are nonnegative parameters ( $\alpha \geq 0, \beta \geq 0$ ) that must satisfy  $\alpha + \beta < 1$  for defining the conditional correlation matrix by the standard GARCH restriction on the nonnegativity of variances. As Engle (2002) proposed a dynamic correlation structure, matrix  $R_t$  is defined following a multivariate GARCH ( $p, q$ ) process as follows:

$$R_t = (\text{diag}\{Q_t\})^{-1/2} Q_t (\text{diag}\{Q_t\})^{-1/2} \quad (5)$$

$$Q_t = (1 - \alpha - \beta) (\bar{Q} + \alpha u_{t-1} u_{t-1} + \beta Q_{t-1}) \quad (6)$$

where  $Q_t$  is a symmetric time-varying covariance matrix, and  $\bar{Q}$  is an unconditional variance matrix of  $u_{it}$ .

Then, the dynamic conditional correlation coefficient,  $\rho_{i,ii}$  is defined as follows:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}, \quad i, j = 1, 2, \dots, n, \quad \text{and } i \neq j \quad (7)$$

The correlation coefficients can be estimated by maximizing the log-likelihood function in a two-stage approach (Prabheesh *et al.*, 2020).

### 3.2 Granger causality tests

The Granger causality examines whether the lag of a variable ( $x$ ) can significantly explain the current values of another variable ( $y$ ). Recently, some studies have considered causality tests focusing on the quantile Granger causality approach (Chuang *et al.*, 2009; Troster *et al.*, 2018; Ahmed *et al.*, 2022). Because it is applicable to identify the causes of price volatility, this study applies standard Granger causality, time-varying causality and causality in quantiles to show more details about the relationship between policy uncertainty and price indices. Time-varying causality test can be examined based on the lag augmented VAR (LA-VAR) model. Different procedures including the forward expanding window, rolling window and the recursive evolving methods are usually applied to obtain test statistics of causal effects.

Testing Granger causality based on the quantile method can be applied as a nonparametric approach to check the relationship between variables across quantiles of the conditional distribution (Ozcebe and Tevfik Izgi, 2023).

Considering a rolling-window procedure and following Jeong *et al.* (2012) and Balcilar *et al.* (2017), the quantile model is specified as follows, which implies  $x_t$  does not cause  $y_t$  in  $\tau$ th quantile:

$$Q_\tau(y_t|y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) = Q_\tau(y_t|y_{t-1}, \dots, y_{t-p}) \quad (8)$$

where  $Q_\tau(y_t|\cdot)$  is  $\tau$ th quantile of  $y_t$  depending on  $t$ , and  $p$  is the lag order.

Considering  $Y_{t-1}$  and  $Z_{t-1}$  as the vector of variable lags of  $y_t$  and  $x_t$ , respectively,  $V_t \equiv (Z_t, Y_t)$ , the conditional distribution functions of  $y_t$  given  $V_{t-1}$  and  $Y_{t-1}$  are denoted as  $F_{(y_t|V_{t-1})}(y_t|V_{t-1})$  [1] and  $F_{(y_t|Y_{t-1})}(y_t|Y_{t-1})$  [2].

The  $H_0$  hypothesis of no Granger causality running from  $x$  to  $y$  in the  $\tau$ th quantile is equal to  $H_0 = P\{F_{(y_t|V_{t-1})}\{Q_\tau(V_{t-1})|V_{t-1}\} = \tau\} = 1$ .

Jeong *et al.* (2012) applied a distance function ( $J$ ), based on which  $H_0$  can be tested ( $J \geq 0$  implying  $H_0$  is true). By estimating the test statistic for  $J$  the above hypothesis can be examined. [3]

To conduct causality test in quantile, lag order  $P$  (based on Schwarz information criterion under a VAR model), the bandwidth  $h$  and Gaussian-type kernels  $K(\cdot)$  must be defined.

## 4. Data and empirical results

### 4.1 Data

This study uses monthly data from January 1997 to December 2020 for the Global Energy Price Index (RGEP), Global Commodity Price Index (RGCP), Global Industrial Material Price Index (RGIMP) and GEP index. The GEP data is obtained from economic policy uncertainty website [4], whereas the other data is collected from the International Monetary Fund. During this time period, there have been numerous fluctuations in uncertainty, including the crisis of 2007–2009 and the crisis of the spread of COVID-19 disease, which began in 2019 (Bhar and Malliaris, 2021; Singh *et al.*, 2022). Every price index is converted into growth rates.

Regarding the fact that time series may be dominated by stochastic processes, the unit root test is necessary to ensure the results' validity. The augmented Dickey–Fuller statistics show that all series are stationary.

### 4.2 Empirical results

4.2.1 *Dynamic conditional correlations.* The matrices of the variables' unconditional correlations are displayed in Table 1. The results indicate that the correlation between

GEPU and other variables is negative and equals  $-0.17$ ,  $-0.19$  and  $-0.13$ , respectively. A conditional correlation model is estimated for a more precise examination of the correlation between GEPU and price indices.

First, the average equation is estimated using autocorrelation functions, partial autocorrelation functions and Akaike and Schwarz–Bayesian criteria (based on which the number of autoregression terms and the number of moving average terms are determined). Based on the results from these criteria, the AR (1) process is the best model for all three indicators among the different models. Table 2 indicates that three-time series exhibit strong autocorrelations and significant ARCH effects. To confirm the ARCH effect, the Lagrange Multiplier test (ARCH-LM) is used to assess variance heteroscedasticity in the residual components of the mean equation.

Various GARCH models were examined based on confirming the ARCH effect and using Akaike and Schwarz–Bayesian criteria. The GARCH (1,1) model was selected as the optimal model for the volatility of RGIMP and RGCP variables, whereas the GARCH (1,0) model was chosen for RGEP (Table 3). All estimation parameters are statistically significant. The ARCH-LM test results indicate a variance in homoscedasticity. Therefore, the GARCH model is well-defined, and the DCC-MGARCH model can be used for analysis.

4.2.2 *Dynamic conditional correlation generalized autoregressive conditional heteroscedasticity model results.* The estimation of the dynamic conditional correlation model is based on two steps. First, a GARCH model is selected for the conditional variance, followed by calculating the conditional correlation matrix based on the conditional variance. Considering the Akaike and Schwarz–Bayesian criteria, the optimal mean and variance equations are chosen. The DCC-GARCH results are displayed in Table 4.

Based on the results,  $\alpha$  and  $\beta$  parameters are nonnegatively significant. The  $\alpha + \beta$  value is close to 1, indicating the variables’ sustainability is significant.

If the parameter  $\alpha$  is positive, a shock in the series of variables may increase the conditional correlation for the next period. The parameter  $\beta$  in the model indicates the

Variable	GEPU	RGEP	RGCP	RGIMP
GEPU	1.000	-0.178	-0.197	-0.132
RGEP	-0.178	1.000	0.940	0.451
RGCP	-0.197	0.940	1.000	0.621
RGIMP	-0.132	0.451	0.621	1.000

**Table 1.**  
Unconditional  
correlation between  
variables

Source: Authors’ own work

Variable	Statistic test	Statistic value	Prob.
RGEP	<i>F</i> -statistic	30.695	0.000
	Obs* <i>R</i> -squared	27.851	0.000
RGCP	<i>F</i> -statistic	6.811	0.009
	Obs* <i>R</i> -squared	6.696	0.009
RGIMP	<i>F</i> -statistic	7.903	0.005
	Obs* <i>R</i> -squared	7.741	0.005

**Table 2.**  
Results of the  
heteroscedasticity  
test: ARCH

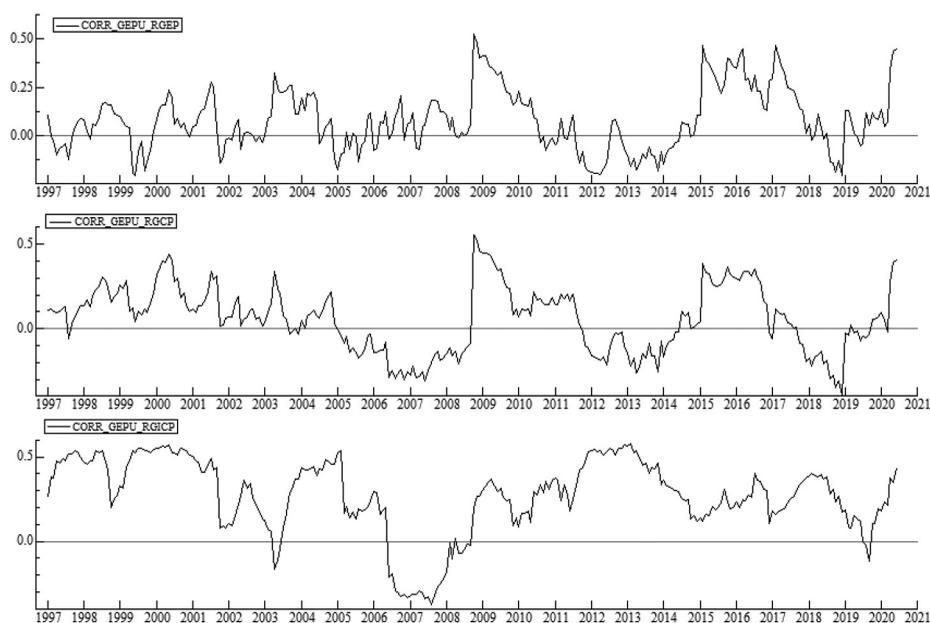
Source: Authors’ own work

AEA 32,94	Variable	Coefficient	Std. error	Z-statistic	Prob.
	<i>GARCH(1, 0) for RGEP</i>				
	C	0.011	0.005	2.292	0.021
	AR(1)	0.237	0.063	3.722	0.000
	<i>Variance equation</i>				
	C	0.002	0.000	8.180	0.000
	RESID(-1) <sup>2</sup>	0.435	0.102	4.232	0.000
	ARCH-LM test				
	F-statistic			0.066 (0.796)	
	Obs*R-squared			0.067 (0.795)	
	<i>GARCH(1, 1) for RGCP</i>				
	C	0.002	0.003	0.698	0.484
	AR(1)	0.320	0.058	5.474	0.000
	<i>Variance equation</i>				
	C	0.000	0.000	1.135	0.256
	RESID(-1) <sup>2</sup>	0.151	0.056	2.679	0.007
	GARCH(-1)	0.757	0.125	6.038	0.000
	ARCH-LM test				
	F-statistic			0.0022 (0.962)	
	Obs*R-squared			0.0022 (0.961)	
	<i>GARCH (1, 1) for RGIMP</i>				
	C	0.001	0.002	0.385	0.699
	AR(1)	0.328	0.057	5.699	0.000
	<i>Variance equation</i>				
	C	0.001	0.000	1.45	0.147
	RESID(-1) <sup>2</sup>	0.064	0.028	2.244	0.024
	GARCH(-1)	0.918	0.035	25.665	0.000
	ARCH-LM test				
	F-statistic			0.005(0.941)	
	Obs*R-squared			0.005(0.941)	
<b>Table 3.</b> Results of GARCH estimation	<b>Source:</b> Authors' own work				

	Variable	GEPU	LVOLRGEP	LVOLRGCP	LVOLRGIMP	DCC-GARCH
	ARCH ( $\alpha$ )	0.190 (0.000)	0.317 (0.012)	0.336 (0.004)	0.314 (0.000)	0.086 (0.003)
	GARCH ( $\beta$ )	0.762 (0.000)	0.287 (0.034)	0.530 (0.000)	0.612 (0.000)	0.820 (0.000)
	$\alpha + \beta$	0.952	0.605	0.867	0.926	0.906
<b>Table 4.</b> DCC-GARCH (1, 1) results	<b>Source:</b> Authors' own work					

conditional correlation effect of the previous period on the current period. For larger values of  $\beta$ , closer to one, it is anticipated that, for each pair of calculated correlations, the conditional correlations of the current period approach those of the previous period.

The trend of the dynamic conditional correlation between the GEPU index and the growth rate of various price indices is presented in [Figure 1](#). Clearly, dynamic conditional correlation coefficients vary considerably over time. The fluctuating range of the dynamic relationship between the GEPU index and price indices is between  $-0.3$  and  $0.5$ . The



**Figure 1.**  
Dynamic conditional  
correlation between  
the GEPU and price  
indices

**Source:** Authors' own work

dynamic conditional correlation between GEPU and RGCP was positive and weak until the end of 2005. In contrast, the dynamic conditional correlation between GEPU and RGEP is positive and negative until 2005. Then, the RGCP index increased by the end of 2005 due to policy uncertainty. During 2005–2009, the dynamic conditional correlation between GEPU–RGEP and GEPU–RGCP declined and demonstrated a downward trend. In 2008, concurrent with the onset of the financial crisis, the correlation between GEPU and three other price indices rose and eventually reached its maximum value. The relationship between GEPU–RGEP and GEPU–RGCP exhibited substantial positive and negative fluctuations until the end of the period beginning in 2009.

Until 2006, the dynamic correlation between GEPU and RGIMP was nearly a very strong positive correlation. The relationship then demonstrates a three-year decline. After 2009, the relationship between GEPU and RGIMP is consistently positive, except for the year 2020, indicating that as GEPU increases, the global price index of industrial products increases.

Generally, the relationships between GEPU and price indices are volatile and exhibit downward and upward trends throughout the period. Given the significant correlation between the GEPU index and the growth rate of the prices, these findings are consistent with the findings of [Jones and Olson \(2013\)](#) and [Karabulut \*et al.\* \(2020\)](#), which demonstrate a positive correlation between uncertainty and inflation. According to the study by [Kang \*et al.\* \(2020\)](#), the responses of inflation rates in various economies to the uncertainty index depend on macroeconomic conditions and the characteristics of inflation cycles.

As explained in the review literature, the performance of two channels determines the change in price indices of various commodities following a shock of uncertainty. According to the aggregate demand channel, increased uncertainty leads to decreased consumption

and inflation. On the contrary, the supply channel, through higher levels of economic activity profitability, results in increased inflation (Fernandez-Villaverde *et al.*, 2011).

The analysis of the results indicates that prices respond negatively and significantly to an acute uncertainty, such as a financial crisis or pandemic shock, for approximately one year after the initial shock. In other words, the relationship’s volatility in the present study confirms Bloom’s (2009) findings that inflationary reactions are temporary and typically vanish within three to five periods.

Although the DCC-GARCH results indicate the existence of relationships between GEPU and price indices, the direction of causality cannot be determined. To evaluate the reliability of the results, directional causal relationships between variables are also investigated.

*4.2.3 Results of testing causality.* Table 5 displays the results of the traditional Granger causality test. The standard Granger causality estimation results demonstrate causality from GEPU to all three price indices. In addition, the results indicate the presence of a bidirectional causal relationship between energy price indices and GEPU. More causality tests can be applied to investigate the causal links of variables more accurately in the time domain and in the target variable’s percentiles.

The BDS test on the residuals of the regression model, based on Broock *et al.* (1996), is performed to examine the nonlinear relationship between variables. This test is conducted on the residuals of the VAR (1) model regarding GEPU and price indices. Based on the results presented in Table 6, the null hypothesis is not rejected at all embedding dimensions (m), implying that nonlinear models are not appropriate to investigating the relationship between variables.

Time-varying causality can exhibit changes in the causality relationship over time. Therefore, this study uses the time-varying form of the causality test following Ozcelebi and Tevfik Izgi (2023) and Yilanci and Kilci (2021). The results of the time-varying causality

Variable	F-statistics	Direction of causality
RGEP → GEPU	3.26*	Bidirectional
GEPU → RGEP	6.68***	
RGCP → GEPU	1.27	Unidirectional
GEPU → RGCP	4.86***	
RGIMP → GEPU	0.32	Unidirectional
GEPU → RGIMP	5.80***	

**Table 5.**  
Results of Granger  
causality tests

**Note:** \*\* and \*denote significant level at 1 and 5% respectively  
**Source:** Authors’ own work

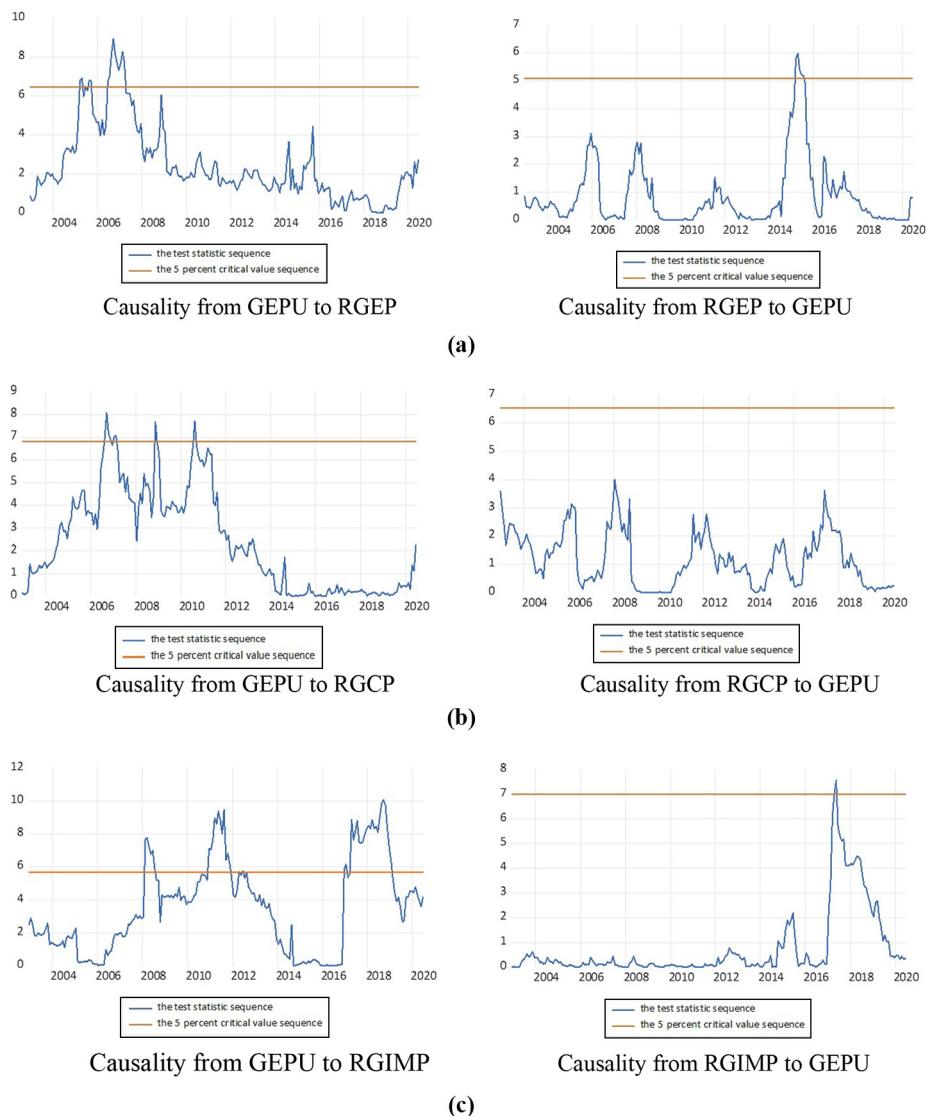
Variables	Dimension				
	m = 2	m = 3	m = 4	m = 5	m = 6
RGEP	0.004 (0.318)	0.010 (0.120)	0.017 (0.032)	0.015 (0.070)	0.016 (0.043)
RGCP	0.003 (0.478)	0.008 (0.199)	0.014 (0.068)	0.012 (0.136)	0.013 (0.087)
RGIMP	0.000 (0.847)	0.006 (0.356)	0.011 (0.153)	0.008 (0.314)	0.009 (0.243)

**Table 6.**  
BDS test for  
nonlinearity

**Note:** p-Values are presented in the parentheses  
**Source:** Authors’ own work

tests (based on the rolling window procedure) are reported in Figure 2 at a 5% significance level.

It is found that the inflation of energy and industrial materials led to changes in GEPU only in 2015 and 2017, respectively. On the contrary, it can be interpreted that during global



**Notes:** (a) GEPU–RGEP relationship; (b) GEPU–RGCP relationship; (c) GEPU–RGIMP relationship

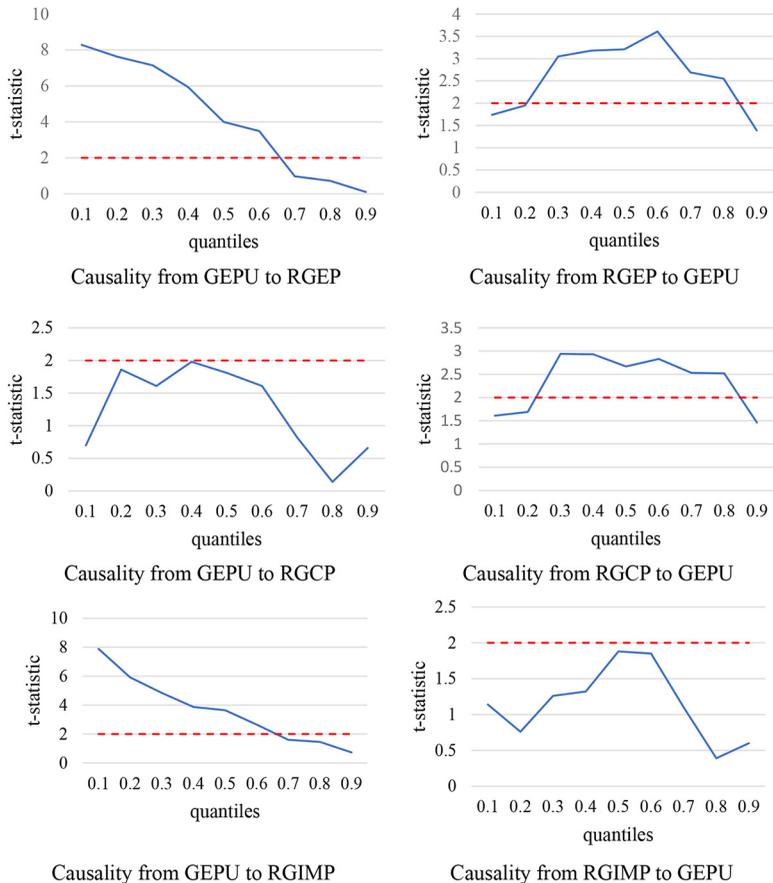
**Source:** Authors' own work

**Figure 2.**  
Results of time-varying causality between variables

financial crisis (2007–2009), GEPU caused changes in all price indices. Time-varying causality is dominant for the commodity price index during 2007–2011. Considering the prices of industrial materials, it is found that GEPU has a causal effect in more time. In summary, the results of the time-varying causality test confirm the effect of GEPU on global inflation, which is consistent with the studies of [Karabulut et al. \(2020\)](#) and [Huang et al. \(2021\)](#). Moreover, a time-dependent causality relationship is not found from price indices to GEPU except in 2015 and 2017.

The causal relationship at different quantiles of the conditional distribution can provide a more accurate understating of the relationship between variables. The results of the Granger causality test in quantiles are presented below. The unit-root test reveals that all variables are stationary, so all variables are used at the level. [Figure 3](#) shows the causality tests between variables across quantiles regarding test statistics and critical values.

The null hypothesis of noncausality between GEPU and RGEP cannot be rejected at the 5% significance level in most quantiles and a two-way relationship is confirmed. The



**Figure 3.**  
Results of Granger  
causality in quantiles

Source: Authors' own work

---

bidirectional causality observed between GEPU and energy price accentuates the intricate interplay between economic uncertainty and energy markets.

Considering causality from GEPU to RGCP, the  $H_0$  test of the noncausality test is not rejected in all quantiles. However, in the opposite direction, the  $H_0$  test is not rejected just in extreme quantiles. This result implies that there is unidirectional causality between global uncertainty and commodity prices.

The results of the noncausality test from GEPU to RGIMP indicates that GEPU leads to shocks to the prices of industrial materials. Moreover, the noncausality test in the opposite direction is not rejected across all quantiles, indicating unidirectional causality from GEPU to RGIMP. In summary, causal independence was observed in most quantiles from GEPU to RGEP and RGIMP.

A unique facet of our study is its departure from the findings of [Kang et al. \(2020\)](#), which discovered a negative effect of global uncertainty shocks on prices in several economies. Contrarily, our results align more closely with studies such as those by [Jones and Olson \(2013\)](#), [Karabulut et al. \(2020\)](#), [Liu and Chen \(2022\)](#) and [Long et al. \(2023\)](#) highlighting the nuanced variability of the relationship between uncertainty and inflation. As highlighted by [Mumtaz and Theodoridis \(2015\)](#), this variation leads to divergent inflation impacts in different regions.

Our study further underscores the global implications of uncertainty on commodity and energy markets. In light of these observations, it becomes evident that the impact of economic uncertainty resonates across various sectors and demands comprehensive attention from business investors, policymakers and global institutions. Crafting targeted policy interventions to mitigate the adverse effects, particularly in economically vulnerable nations, becomes paramount.

## 5. Conclusion and policy recommendation

This study investigates the dynamic movements of GEPU and prices in different markets and examines the causal relationship. So, we harnessed the power of DCC-GARCH to delve into the intricate landscape of the time-varying dynamic relationship between global policy uncertainty and global price indices. The period from 1997 to 2020 was scrutinized to reveal insights into these complex dynamics. A salient revelation is the oscillation in the correlation between uncertainty and price indices, transitioning from negative to positive and back again. The dual dynamics of the aggregate demand channel, leading to decreased inflation during heightened uncertainty, and the profitability enhancement channel, fueling higher inflation, can explain volatile relationships ([Fernandez-Villaverde et al., 2011](#)).

Time-varying and quantile causality results also show the two-way causality between GEPU and energy price in different quantiles and periods. At the same time, the GEPU and price of commodities and raw materials show a one-way causality relationship.

To summarize the findings:

- Energy price and global uncertainty relationship: In uncertain periods, economic agents tend to be risk averse. Therefore, through production and consumption channels, energy prices can change. Furthermore, an increase in uncertainty can lead to a recession. Thus, industries that are the main energy consumers such as manufacturing, transportation and construction can reduce their energy consumption and lead to energy price changes ([Adedoyin and Zakari, 2020](#)). Fluctuations in energy prices can increase in production costs by affecting producers' expenditure and varying their decisions ([Alqaralleh et al., 2021](#)), which cause uncertainty in the economy.

- Commodity price and global uncertainty relationship: Severe fluctuations in the prices of one or more key commodities can increase societies' worries about inflation. Therefore, consumers will change their expenditure patterns, leading to uncertain situations.
- Industrial materials price and global uncertainty relationship: Uncertainty can change and delay decisions on business plans. Therefore, demand for industrial inputs will decrease. This can change input prices (Ercolani and Natoli, 2020). The volatility stemming from the uncertainty of raw material supply further compounds the challenges, necessitating strategic decisions in cost management and pricing strategies.

The insights unveiled here form a critical stepping stone for informed decision-making, as the global community collectively navigates the complexities of economic uncertainty and its far-reaching impacts. Economic agents including investors, producers, and policymakers, should consider global uncertainty changes when analyzing and predicting the prices of different markets, especially oil and industrial materials. The rising cost of energy and raw materials impacts numerous industries and sectors. In other words, uncertainty affecting the supply of energy and raw material contributes to commodity price volatility. Therefore, in uncertain conditions, producers must decide whether to endure additional costs by reducing other expenses or pass on price increases to customers.

Despite addressing the valuable issue provided, some limitations can be considered for future recommendations. First, it is important to acknowledge that the scope of variables considered is not exhaustive. Incorporating additional variables and exploring their interactions could enhance future analyses. Moreover, the study focusses on the period of 1997–2020, which may not fully consider the market developments and fluctuations. Therefore, expanding the study to encompass a broader array of economic factors and using a more diverse set of analytical tools is recommended. Furthermore, given the ever-evolving global economic landscape, periodic updates to the research would facilitate real-time relevance and foster a more accurate depiction of contemporary realities.

### Notes

1. It is absolutely continuous for almost all  $V_{t-1}$ .
2. Denoting  $Q_\tau(V_{t-1}) \equiv Q_\tau(y_t|V_{t-1})$  and  $Q_\tau(Y_{t-1}) \equiv Q_\tau(y_t|Y_{t-1})$ , then  $F_{(y_t|V_{t-1})}\{Q_\tau(V_{t-1})|V_{t-1}\} = \tau$  with the probability of 1.
3.  $\hat{J}_t = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^T \sum_{s=p+1}^T k\left(\frac{V_{t-1}-V_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s$
4. [www.policyuncertainty.com/global\\_monthly.html](http://www.policyuncertainty.com/global_monthly.html)

### References

- Adedoyin, F.F. and Zakari, A. (2020), "Energy consumption, economic expansion, and CO<sub>2</sub> emission in the UK: the role of economic policy uncertainty", *Science of the Total Environment*, Vol. 738, p. 738, doi: [10.1016/j.scitotenv.2020.140014](https://doi.org/10.1016/j.scitotenv.2020.140014).
- Ahmed, A., Granberg, M., Troster, V. and Uddin, G. (2022), "Asymmetric dynamics between uncertainty and unemployment flows in the United States", *Studies in Nonlinear Dynamics and Econometrics*, Vol. 26 No. 1, pp. 155-172, doi: [10.1515/snde-2019-0058](https://doi.org/10.1515/snde-2019-0058).
- Alqaralleh, H.S., Al-Saraireh, A. and Canepa, A. (2021), "Energy market risk management under uncertainty: a VAR based on wavelet approach", *International Journal of Energy Economics and Policy*, Vol. 11 No. 5, pp. 130-137, doi: [10.32479/ijeeep.11404](https://doi.org/10.32479/ijeeep.11404).

- Andreasson, P., Bekiros, S., Nguyen, D.K. and Uddin, G.S. (2016), "Impact of speculation and economic uncertainty on commodity markets", *International Review of Financial Analysis*, Vol. 43, pp. 115-127.
- Antonakakis, N., Chatziantoniou, I. and Filis, G. (2014), "Dynamic spillovers of oil price shocks and economic policy uncertainty", *Energy Economics*, Vol. 44, pp. 433-447.
- Ashena, M. and Shahpari, G. (2022), "Policy uncertainty, economic activity, and carbon emissions: a nonlinear autoregressive distributed lag approach", *Environmental Science and Pollution Research*, Vol. 29 No. 34, pp. 52233-52247, doi: [10.1007/s11356-022-19432-3](https://doi.org/10.1007/s11356-022-19432-3).
- Azimli, A. (2022), "The impact of policy, political and economic uncertainty on corporate capital investment in the emerging markets of Eastern Europe and Turkey", *Economic Systems*, Vol. 46 No. 2, p. 100974, doi: [10.1016/j.ecosys.2022.100974](https://doi.org/10.1016/j.ecosys.2022.100974).
- Bakas, D. and Triantafyllou, A. (2020), "Commodity price volatility and the economic uncertainty of pandemics", *Economics Letters*, Vol. 193, p. 109283, doi: [10.1016/j.econlet.2020.109283](https://doi.org/10.1016/j.econlet.2020.109283).
- Baker, S.R., Bloom, N. and Davis, S.J. (2016), "Measuring economic policy uncertainty", *The Quarterly Journal of Economics*, Vol. 131 No. 4, pp. 1593-1636.
- Balcilar, M., Bekiros, S. and Gupta, R. (2017), "The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method", *Empirical Economics*, Vol. 53 No. 3, pp. 879-889, doi: [10.1007/s00181-016-1150-0](https://doi.org/10.1007/s00181-016-1150-0).
- Bhar, R. and Malliaris, A.G. (2021), "Modeling U.S. monetary policy during the global financial crisis and lessons for Covid-19", *Journal of Policy Modeling*, Vol. 43 No. 1, pp. 15-33, doi: [10.1016/j.jpolmod.2020.07.001](https://doi.org/10.1016/j.jpolmod.2020.07.001).
- Bilgin, M.H., Gozgor, G., Chi, K.M.L. and Xin, S. (2018), "The effects of uncertainty measures on the price of gold", *International Review of Financial Analysis*, Vol. 58, pp. 1-7, doi: [10.1016/j.irfa.2018.03.009](https://doi.org/10.1016/j.irfa.2018.03.009).
- Bloom, N. (2009), "The impact of uncertainty shocks", *Econometrica*, Vol. 77 No. 3, pp. 623-685.
- Bordo, M.D., Duca, J.V. and Koch, C. (2016), "Economic policy uncertainty and the credit channel: aggregate and bank level U.S.S. evidence over several decades", *Journal of Financial Stability*, Vol. 26, pp. 90-106.
- Brogaard, J. and Detzel, A. (2015), "The asset-pricing implications of government economic policy uncertainty", *Management Science*, Vol. 61 No. 1, pp. 3-18.
- Broock, W.A., Scheinkman, J.A., Dechert, W.D. and LeBaron, B. (1996), "A test for independence based on the correlation dimension", *Econometric Reviews*, Vol. 15 No. 3, pp. 197-235, doi: [10.1080/07474939608800353](https://doi.org/10.1080/07474939608800353).
- Caggiano, G., Castelnuovo, E. and Figueres, J.M. (2017), "Economic policy uncertainty and unemployment in the United States: a nonlinear approach", *Economics Letters*, Vol. 151, pp. 31-34.
- Chittedi, K.R. (2015), "Financial crisis and contagion effects to Indian stock market: 'DCC-GARCH' analysis", *Global Business Review*, Vol. 16 No. 1, pp. 50-60.
- Cho, J.H. and Parhizgari, A.M. (2008), "East Asian financial contagion under DCC-GARCH", *International Journal of Banking and Finance*, Vol. 6 No. 1, pp. 17-30.
- Chuang, C.-C., Kuan, C.-M. and Lin, H.-y (2009), "Causality in quantiles and dynamic stock return-volume relations", *Journal of Banking and Finance*, Vol. 33 No. 7, pp. 1351-1360.
- Civcir, I. and Varoglu, D.E. (2019), "International transmission of monetary and global commodity price shocks to Turkey", *Journal of Policy Modeling*, Vol. 41 No. 4, doi: [10.1016/j.jpolmod.2019.02.004](https://doi.org/10.1016/j.jpolmod.2019.02.004).
- Dai, P.-F., Xiong, X., Zhang, J. and Zhou, W.-X. (2022), "The role of global economic policy uncertainty in predicting crude oil futures volatility: evidence from a two-factor GARCH-MIDAS model", *Resources Policy*, Vol. 78, p. 102849.
- Davis, S.J. (2016), "An index of global economic policy uncertainty", *Becker Friedman Institute for Research in Economics*, Working Paper, No. 2016-24, available at: SSRN: <https://ssrn.com/abstract2852531>

- Engle, R. (2002), "Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models", *Journal of Business and Economic Statistics*, Vol. 20 No. 3, pp. 339-350.
- Engle, R.F. and Sheppard, K. (2001), "Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH", *NBER Working Paper No. 8554*. 2001.
- Ercolani, V. and Natoli, F. (2020), "Forecasting US recessions: the role of economic uncertainty", *Economics Letters*, Vol. 193, p. 109302, doi: [10.1016/j.econlet.2020.109302](https://doi.org/10.1016/j.econlet.2020.109302).
- Fernandez-Villaverde, J., Guerron-Quintana, P., Rubio-Ramirez, J.F. and Uribe, M. (2011), "Risk matters: the real effects of volatility shocks", *American Economic Review*, Vol. 101 No. 6, pp. 2530-2561.
- Ghosh, R., Bagchi, B. and Chatterjee, S. (2022), "The effect of economic policy uncertainty index on the Indian economy in the wake of Covid-19 pandemic", *Journal of Economic and Administrative Sciences*, doi: [10.1108/JEAS-08-2021-0172](https://doi.org/10.1108/JEAS-08-2021-0172).
- Gu, R. and Liu, S. (2022), "Nonlinear analysis of economic policy uncertainty: based on the data in China, the US and the global", *Physica A: Statistical Mechanics and Its Applications*, Vol. 593, p. 126897, doi: [10.1016/j.physa.2022.126897](https://doi.org/10.1016/j.physa.2022.126897).
- Huang, J., Li, Y., Zhang, H. and Chen, J. (2021), "The effects of uncertainty measures on commodity prices from a time-varying perspective", *International Review of Economics and Finance*, Vol. 71, pp. 100-114.
- Jeong, K., Härdle, W. and Song, S. (2012), "A consistent nonparametric test for causality in quantile", *Econometric Theory*, Vol. 28 No. 4, pp. 861-887, doi: [10.1017/S0266466611000685](https://doi.org/10.1017/S0266466611000685).
- Jones, P.M. and Olson, E. (2013), "The time-varying correlation between uncertainty, output, and inflation: evidence from a DCC-GARCH model", *Economics Letters*, Vol. 118 No. 1, pp. 33-37.
- Junttila, J. and Vataja, J. (2018), "Economic policy uncertainty effects for forecasting future real economic activity", *Economic Systems*, Vol. 42 No. 4, pp. 569-583, doi: [10.1016/j.ecosys.2016.02.009](https://doi.org/10.1016/j.ecosys.2016.02.009).
- Jurado, K., Ludvigson, S.C. and Ng, S. (2015), "Measuring uncertainty", *American Economic Review*, Vol. 105 No. 3, doi: [10.1257/aer.20131193](https://doi.org/10.1257/aer.20131193).
- Kang, W., Ratti, R.A. and Vespignani, J. (2020), "Impact of global uncertainty on the global economy and large developed and developing economies", *Applied Economics*, Vol. 52 No. 22, pp. 2392-2407, doi: [10.1080/00036846.2019.1690629](https://doi.org/10.1080/00036846.2019.1690629).
- Karabulut, G., Bilgin, M.H. and Doker, A.C. (2020), "The relationship between commodity prices and world trade uncertainty", *Economic Analysis and Policy*, Vol. 66, pp. 276-281, doi: [10.1016/j.eap.2020.05.001](https://doi.org/10.1016/j.eap.2020.05.001).
- Khan, K., Tao, R. and Umar, M. (2021), "How often do oil prices and tanker freight rates depend on global uncertainty?", *Regional Studies in Marine Science*, Vol. 48, p. 102043, doi: [10.1016/j.rsma.2021.102043](https://doi.org/10.1016/j.rsma.2021.102043).
- Lin, B. and Bai, R. (2021), "Oil prices and economic policy uncertainty: evidence from global, oil importers, and exporters' perspective", *Research in International Business and Finance*, Vol. 56, p. 101357, doi: [10.1016/j.ribaf.2020.101357](https://doi.org/10.1016/j.ribaf.2020.101357).
- Liu, W. and Chen, X. (2022), "Natural resources commodity prices volatility and economic uncertainty: evaluating the role of oil and gas rents in Covid-19", *Resources Policy*, Vol. 76, p. 102581, doi: [10.1016/j.resourpol.2022.102581](https://doi.org/10.1016/j.resourpol.2022.102581).
- Long, S., Li, J. and Luo, T. (2023), "The asymmetric impact of global economic policy uncertainty on international grain prices", *Journal of Commodity Markets*, Vol. 30, p. 100273, doi: [10.1016/j.jcomm.2022.100273](https://doi.org/10.1016/j.jcomm.2022.100273).
- Lyu, Y., Tuo, S., Wei, Y. and Yang, M. (2021), "Time-varying effects of global economic policy uncertainty shocks on crude oil price volatility: new evidence", *Resources Policy*, Vol. 70, p. 101943, doi: [10.1016/j.resourpol.2020.101943](https://doi.org/10.1016/j.resourpol.2020.101943).
- Mumtaz, H. and Theodoridis, K. (2015), "The international transmission of volatility shocks: an empirical analysis", *Journal of the European Economic Association*, Vol. 13 No. 3, pp. 512-533.

- Nyakurukwa, K. and Seetharam, Y. (2023), "Cross-country categorical economic policy uncertainty spillovers: evidence from a conditional connectedness TVP-VAR framework", *Journal of Financial Economic Policy*, Vol. 15 No. 2, pp. 164-181, doi: [10.1108/JFEP-10-2022-0256](https://doi.org/10.1108/JFEP-10-2022-0256).
- Ozcelebi, O. (2021), "Assessing the impacts of global economic policy uncertainty and the long-term bond yields on oil prices", *Applied Economic Analysis*, Vol. 29 No. 87, pp. 226-244, doi: [10.1108/AEA-05-2020-0046](https://doi.org/10.1108/AEA-05-2020-0046).
- Ozcelebi, O. and Tefvik Izgi, M. (2023), "Assessing the impacts of economic policy uncertainty of the US on the exchange rates and stock returns of Korea, Mexico, Poland and Russia", *Eastern European Economics*, Vol. 61 No. 1, pp. 1-22, doi: [10.1080/00128775.2022.2107937](https://doi.org/10.1080/00128775.2022.2107937).
- Pástor, L. and Veronesi, P. (2013), "Political uncertainty and risk premia", *Journal of Financial Economics*, Vol. 110 No. 3, pp. 520-545, doi: [10.1016/j.jfineco.2013.08.007](https://doi.org/10.1016/j.jfineco.2013.08.007).
- Prabheesh, K.P., Anglingkusumo, R. and Juhro, S.M. (2020), "The dynamics of global financial cycle and domestic economic cycles: evidence from India and Indonesia", *Economic Modelling*, Vol. 94, pp. 1-41, doi: [10.1016/j.econmod.2020.02.024](https://doi.org/10.1016/j.econmod.2020.02.024).
- Qin, M., Su, C.-W., Hao, L.-N. and Tao, R. (2020), "The stability of U.S. economic policy: does it really matter for oil price?", *Energy*, Vol. 198, p. 117315, doi: [10.1016/j.energy.2020.117315](https://doi.org/10.1016/j.energy.2020.117315).
- Rajwani, S. and Kumar, D. (2015), "A dynamic conditional correlation analysis-based approach to test financial contagion in developing markets", *Managing in Recovering Markets*, Springer Proceedings in Business and Economics, New Delhi, pp. 1-13, doi: [10.1007/978-81-322-1979-8\\_1](https://doi.org/10.1007/978-81-322-1979-8_1).
- Raza, S.A., Masood, A., Benkraiem, R. and Urom, C. (2023), "Forecasting the volatility of precious metals prices with global economic policy uncertainty in pre and during the Covid-19 period: novel evidence from the GARCH-MIDAS approach", *Energy Economics*, Vol. 120, p. 106591, doi: [10.1016/j.eneco.2023.106591](https://doi.org/10.1016/j.eneco.2023.106591).
- Ringim, S.H., Alhassan, A., Güngör, H. and Bekun, F.V. (2022), "Economic policy uncertainty and energy prices: empirical evidence from multivariate DCC-GARCH models", *Energies*, Vol. 15 No. 10, p. 3712, doi: [10.3390/en15103712](https://doi.org/10.3390/en15103712).
- Saddique, T., Saleem, R., Ullah, A. and Amjad, M. (2022), "The moderating role of per capita income in energy consumption-poverty nexus: empirical evidence from Pakistan", *Journal of Asian and African Studies*, doi: [10.1177/00219096221106091](https://doi.org/10.1177/00219096221106091).
- Salisu, A.A., Isah, K.O., Oyewole, O.J. and Akanni, L.O. (2017), "Modelling oil price-inflation nexus: the role of asymmetries", *Energy*, Vol. 125, pp. 97-106, doi: [10.1016/j.energy.2017.02.128](https://doi.org/10.1016/j.energy.2017.02.128).
- Sen, A. and Wesselbaum, D. (2022), "On the international spillover effects of uncertainty", *Open Economies Review*, Vol. 34 No. 3, pp. 541-554, doi: [10.1007/s11079-022-09694-2](https://doi.org/10.1007/s11079-022-09694-2).
- Sharma, P., Leung, T.Y., Kingshott, R.P.J., Davcik, N.S. and Cardinali, S. (2020), "Managing uncertainty during a global pandemic: an international business perspective", *Journal of Business Research*, Vol. 116, pp. 188-192, doi: [10.1016/j.jbusres.2020.05.026](https://doi.org/10.1016/j.jbusres.2020.05.026).
- Singh, B., Chattu, V.K., Kaur, J., Mol, R., Gauttam, P. and Singh, B. (2022), "COVID-19 and global distributive justice: 'health diplomacy' of India and South Africa for the TRIPS waiver", *Journal of Asian and African Studies*, Vol. 58 No. 5, doi: [10.1177/00219096211069652](https://doi.org/10.1177/00219096211069652).
- Su, Z., Lu, M. and Yin, L. (2018), "Oil prices and news-based uncertainty: novel evidence", *Energy Economics*, Vol. 72, pp. 331-340, doi: [10.1016/j.eneco.2018.04.021](https://doi.org/10.1016/j.eneco.2018.04.021).
- Troster, V., Shahbaz, M. and Uddin, G.S. (2018), "Renewable energy, oil prices, and economic activity: a granger-causality in quantiles analysis", *Energy Economics*, Vol. 70, pp. 440-452, doi: [10.1016/j.eneco.2018.01.029](https://doi.org/10.1016/j.eneco.2018.01.029).
- Tse, Y.K. and Tsui, A.A. (2002), "Multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations", *Journal of Business and Economic Statistics*, Vol. 20 No. 3, pp. 351-362.
- Wang, Y., Bing, Z., Diao, X. and Wu, C. (2015), "Commodity price changes and the predictability of economic policy uncertainty", *Economics Letters*, Vol. 127, pp. 39-42, doi: [10.1016/j.econlet.2014.12.030](https://doi.org/10.1016/j.econlet.2014.12.030).

Yilanci, V. and Kilci, E.N. (2021), "The role of economic policy uncertainty and geopolitical risk in predicting prices of precious metals: evidence from a time-varying bootstrap causality test", *Resources Policy*, Vol. 72, p. 102039, doi: [10.1016/j.resourpol.2021.102039](https://doi.org/10.1016/j.resourpol.2021.102039).

Yin, H., Chang, L. and Wang, S. (2023), "The impact of China's economic uncertainty on commodity and financial markets", *Resources Policy*, Vol. 84, p. 103779, doi: [10.1016/j.resourpol.2023.103779](https://doi.org/10.1016/j.resourpol.2023.103779).

#### Further reading

Bakas, D. and Triantafyllou, A. (2018), "The impact of uncertainty shocks on the volatility of commodity prices", *Journal of International Money and Finance*, Vol. 87, pp. 96-111, doi: [10.1016/j.jimonfin.2018.06.001](https://doi.org/10.1016/j.jimonfin.2018.06.001).

Bobasu, A., Geis, A., Quaglietti, L. and Ricci, M. (2020), "Tracking global economic uncertainty: implications for global investment and trade", *ECB Economic Bulletin*, p. 1.

Economic Policy Uncertainty Index (2023), "Global economic policy uncertainty index", available at: [www.policyuncertainty.com/global\\_monthly.html](http://www.policyuncertainty.com/global_monthly.html) (accessed 5 May 2021).

International Monetary Fund (2021), "Global price of industrial materials index [PINDUINDEXM]", retrieved from FRED, Federal Reserve Bank of St. Louis, available at: <https://fred.stlouisfed.org/series/PINDUINDEXM>

Jégourel, Y. and Chalmin, P. (2017), "The dynamics of the price of raw materials and industrial strategies in African producer countries: what are the challenges?", *Revue Internationale de Politique de Développement*, Vol. 8 No. 8.1, p. 3290, doi: [10.4000/poldev.3290](https://doi.org/10.4000/poldev.3290).

#### Corresponding author

Malihe Ashena can be contacted at: [ashena@buqaen.ac.ir](mailto:ashena@buqaen.ac.ir)