

Assessing the impacts of global economic policy uncertainty and the long-term bond yields on oil prices

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Abstract

Purpose – Might the impact of the global economic policy uncertainty (GEPU) and the long-term bond yields on oil prices be asymmetric? This paper aims to consider the effects of the GEPU and the US long-term government bond yields on oil prices using quantile-based analysis and nonlinear vector autoregression (VAR) model. The author hypothesized whether the negative and positive changes in the GEPU and the long-term bond yields of the USA have different effects on oil prices.

Design/methodology/approach – To address this question, the author uses quantile cointegration model and the impulse response functions (IRFs) of the censored variable approach of Kilian and Vigfusson (2011).

Findings – The quantile cointegration test showed the existence of non-linear cointegration relationship, whereas Granger-causality analysis revealed that positive/negative variations in GEPU will have opposite effects on oil prices. This result was supported by the quantile regression model's coefficients and nonlinear VAR model's IRFs; more specifically, it was stressed that increasing/decreasing GEPU will deaccelerate/accelerate global economic activity and thus lead to a fall/rise in oil prices. On the other hand, the empirical models indicated that the impact of US 10-year government bond yields on oil prices is asymmetrical, while it was found that deterioration in the borrowing conditions in the USA may have an impact on oil prices by slowing down the global economic activity.

Originality/value – As a robustness check of the quantile-based analysis results, the slope-based Mork test is used.

Keywords Oil prices, Global economic policy uncertainty, Long-term government bond yields, Nonlinear VAR, Quantile-based analysis

Paper type Research paper

1. Introduction

After the recent global financial crisis (GFC), the relationship between monetary policy indicators and the oil market increased, and it has been acknowledged that this phenomenon is owing to the expansionary policies implemented by major central banks to revive economies. It should be noted that, although there are studies in the scientific literature focusing on the relationship between the US federal funds rate and the oil prices (Ansari and Sensarma, 2019; Rosa, 2014), the relevant analysis can also be enhanced through the



incorporation of monetary indicators that have a crucial role in the global economic activity (Belke *et al.*, 2010; Ratti and Vespignani, 2016). More specifically, Ratti and Vespignani (2016) stressed that, when considering the world price of oil, it is necessary to take into account the influence of macroeconomic variables, including those that also embody the monetary conditions in the major developing and developed countries. In this respect, the 10-year government bond yields of the USA have been regarded as an indicator that reflects the expectations of economic agents for future economic conditions. This indicator is also a barometer of the long-term monetary conditions in the USA, while 10-year US Treasury yields have been recognized as a safe-haven asset in times of negative macroeconomic expectations. Considering their strong relationship with other financial indicators, it can also be suggested that the relevant bond yields are an indicator that has a high representative capacity to evaluate the relationship between the bond market and the oil market (Balcilar *et al.*, 2020; Demirer *et al.*, 2020; Gormus *et al.*, 2018; Kang *et al.*, 2014; Lee *et al.*, 2017; Nazlioglu *et al.*, 2020; Shahzad *et al.*, 2017; Tule *et al.*, 2017).

On the other hand, the long-term government bond yields of the USA are under the influence of expectations regarding the course of the US economy, which are highly affected by economic policy decisions and thus economic policy uncertainty (EPU) [1]. More specifically, EPU is rapidly reflected in the pricing in the bond market while also activating the interest of researchers in investigating the impacts of global economic policy uncertainty (GEPU) on the commodity markets, given the importance of the uncertainties following the GFC. As shown in Figure 1, all the indicators had close values at the beginning of 2010, although considerable dynamics influenced the 10-year government bond yields, GEPU and oil prices. In this respect, it can be suggested that the developments after the GFC also had significant consequences. More specifically, as GEPU rose, it can be put forward that the relevant yields decreased, corresponding to the increase in demand for 10-year government bonds owing to investors' demand for safe-haven assets. Similarly, as a result of the increasing GEPU, the global economic activity was adversely affected and thus the oil prices decreased as a result of the falling oil demand. Thus, this study also conducts an empirical analysis in the light of the studies indicating a high level of interactions between EPU and oil prices (Antonakakis *et al.*, 2014; Degiannakis *et al.*, 2018; Hailemariam *et al.*, 2019; Kang and Ratti, 2013; Kang *et al.*, 2017; Kang *et al.*, 2019; Rehman, 2018; Yang, 2019).

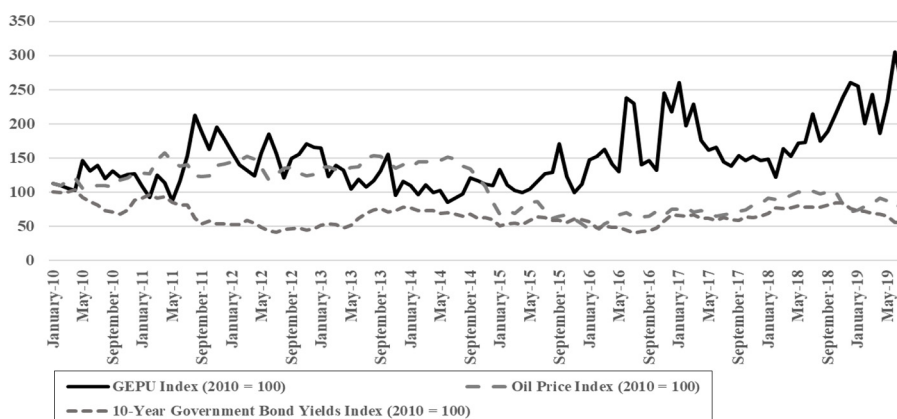


Figure 1. GEPU index, oil price index and 10-Year Government Bond Yields Index after the GFC

Source: The Federal Reserve Bank of St. Louis and Baker *et al.* (2016)

Additionally, it should be borne in mind that there are several macro variables that can affect oil prices while in turn interacting with bond yields. Although it is known that many macroeconomic and financial variables as well as interest rates have an effect on oil prices, this study excludes other possible factors owing to the close relationship between the long-term government bond yields of the USA and the economic policy uncertainty on the global scale. Moreover, studies in the literature have determined the model variables in line with their assumptions without controlling for the effects of all the possible macroeconomic and financial variables on oil prices. In this vein, this study is based on the indispensable interactions among the global bond market and oil markets by testing the asymmetric effects of the US long-term bond yields and the GEPU on oil prices. More specifically, this study assesses the asymmetric effects of the US long-term interest rates and GEPU on oil prices without including GEPU and the 10-year government bond yields of the USA in the vector of a VAR-type model at the same time. Thus, I incorporate the role of the asymmetry in the relationship between model variables using the impulse response functions (IRFs) and the Mork test on the basis of the nonlinear vector autoregression (VAR) model of [Kilian and Vigfusson \(2011\)](#) to compare the results with those of the quantile cointegration model and provide support for the robustness of the first approach.

The aim of this study is threefold:

- (1) to determine the long-run relationship among GEPU and oil prices and the long-term government bond yields of the USA and oil prices via the quantile cointegration test;
- (2) to explore the impacts of negative and positive changes in GEPU and the long-term government bond yields of the USA rates on oil prices via the quantile Granger-causality test; and
- (3) to specify the responsiveness of oil prices to the negative and positive fluctuations in GEPU and the US long-term bond yields by estimating the quantile cointegration model and the IRFs of the censored variable approach of [Kilian and Vigfusson \(2011\)](#).

Accordingly, I contribute to the existing literature by addressing the issue of the 10-year long-term government bond yields of the USA, which are also an indicator of macroeconomic expectations about the US economy and can be recognized as the major source of the variations in oil prices. By using the quantitative techniques mentioned above, this study also enhances the approach by considering the role of GEPU, which is an indicator of the uncertainty about the course of the economy. The hypothesis of this study is to test whether GEPU ($gepu_t$) and long-term bond yields of the USA ($byie_t$) have different effects on oil prices ($opri_t$). For this purpose, the 10-year government bond yields of the USA and the global price of WTI crude are extracted from the database of the Federal Reserve Bank of St. Louis, while GEPU is derived based on [Baker et al. \(2016\)](#) [2]. All the series are in logarithms and seasonally adjusted with plausible techniques, while the online available Matlab code of [Troster et al. \(2018\)](#) and RATS 9.2 code for the estimation of [Kilian and Vigfusson \(2011\)](#) are used.

2. Literature review

The macroeconomic developments in oil after the GFC revealed that variations in bond markets may create significant changes in the dynamics of oil markets, while indicators related to bond markets can also be under the influence of monetary policy decisions. Accordingly, studies in the literature have incorporated empirical models to analyze the

effects of bond yields on oil prices. For instance, [Tule *et al.* \(2017\)](#) assumed that there might be strong interactions between the two indicators and estimated the vector autoregressive moving average asymmetric generalized autoregressive conditional heteroscedasticity (VARMA-AGARCH) model with daily data. More specifically, the authors focused on the relationship between Nigerian sovereign bonds, Brent oil and West Texas Intermediate (WTI) oil, respectively, and found that significant cross-market volatility transmission exists between oil and sovereign bond markets with ample sensitivity to structural breaks.

Considering the fact that bond market investors have shifted to shorter investment horizons, and thus an oil price shock may affect a country's ability to access international markets for funding, [Morrison \(2019\)](#) used a structural VAR (SVAR) model to assess the effects of global aggregate growth, change in the global oil supply, change in real oil prices and change in real total bond returns. It was revealed that oil prices have a statistically significant impact on portfolio total sovereign bond returns for oil exporters and importers. By using a multifactor linear model, [Demirer *et al.* \(2020\)](#) also investigated the impacts of the oil demand and supply shocks on sovereign bond markets for a large number of advanced and emerging economies and confirmed that the effect on sovereign bonds is driven by demand-related shocks. Furthermore, [Bouri *et al.* \(2020\)](#) examined the relationship between sovereign risk and oil prices (volatility) through a quantile-based analysis and found that shocks in oil prices and oil volatility had an impact on the sovereign risk of MENA, while the relevant predictability is asymmetric across quantiles and time varying. Most recently, [Balcilar *et al.* \(2020\)](#) enhanced the approach of [Bouri *et al.* \(2020\)](#) by using a higher-order nonparametric causality-in-quantiles framework. The results of [Balcilar *et al.* \(2020\)](#) indicated that oil uncertainty had a stronger effect on the shortest and longest maturities (two and five years).

The previously mentioned studies generally evaluated the effects of oil prices on the bond market, whereas [Nazlioglu *et al.* \(2020\)](#) assumed that the bond market dynamics could also have an impact on oil prices. By using a Fourier-based analysis, [Nazlioglu *et al.* \(2020\)](#) found that the feedback from bonds to oil prices is weak and detectable only for China and the US. In this regard, [Kang *et al.*'s \(2014\)](#) study differed from other studies in the literature, as the authors focused on the impacts of global supply-side shocks and oil market-specific demand shocks on the aggregate US bond index real returns. For this purpose, they used a SVAR model that also included a global indicator (the real aggregate demand shocks), and they showed that a positive oil market-specific demand shock causes decreases in real bond returns. A similar approach was developed by [Ratti and Vespignani \(2016\)](#), who included global industrial production, prices, the central bank policy interest rate and monetary aggregate in the analysis. Those variables are also related to the monetary policy framework, and it was revealed that positive innovation in the global oil price relates to global interest rate tightening with the help of the global factor-augmented error correction model. Therefore, it has become important to examine the asymmetric effects of the US 10-year government bond yields, which are a barometer for the macroeconomic and financial situation on the global scale, on oil prices.

On the other hand, the relevant interest rate is closely related to global economic expectations and uncertainties, and, at this point, it has been accepted by many studies in the scientific literature that EPU has a direct effect on oil prices. In this context, it has been acknowledged that the study conducted by [Kang and Ratti \(2013\)](#) is a pioneer in the scientific literature. By using a SVAR model, they assessed the impact of oil supply-side shocks, real aggregate demand shocks and oil market-specific demand shocks on the EPU of the USA. Accordingly, [Kang and Ratti \(2013\)](#) showed that the oil market-specific demand shocks had a considerable impact on the EPU of the USA, whereas the reactions of the EPU

of the USA to innovations in global oil production and in the world demand are not statistically significant. Antonakakis *et al.* (2014) showed that the total spillovers of oil prices to the EPU of a sample of both net oil-exporting and net oil-importing countries reached high levels in the GFC period. Moreover, Kang *et al.* (2019) indicated that the US EPU responds asymmetrically to increases and decreases in the real oil price through SVAR modeling.

Focusing on the role of the time-varying impacts, Degiannakis *et al.* (2018) suggested that the SVAR and the time-varying VAR (TVP-VAR) models could be suitable for examining the relationship between economic and financial uncertainty and oil prices. Similarly to Kang *et al.* (2014), they diversified the effects of the supply side, aggregate demand and oil-specific demand shocks and indicated that the uncertainty responses to the three oil price shocks are heterogeneous over time. Kang *et al.* (2017) examined the relationships between oil price shocks and policy uncertainty and assumed that there may be considerable interactions between non-US oil production, US oil production, the global real economic activity index of Kilian (2009) and the real price of oil in terms of the SVAR model. Accordingly, it was found that positive shocks in oil prices increase the EPU in the US, whereas EPU shocks do not have a statistically significant effect on oil prices. In contrast to Kang *et al.* (2017), Yang (2019) stressed that the EPU of the USA has a crucial impact on the variations in crude oil prices, regardless of the time scale. However, Hailemariam *et al.* (2019) focused directly on the relationship between oil prices and EPU by excluding the effect of oil supply-side shocks. Moreover, they assumed that the relationship between oil prices and EPU may vary over time. Using monthly data from G7 countries over the period 1997:01–2018:06, they found that the estimated time-varying coefficient function of the oil price is negative in years in which increases in oil prices are driven by a surge in the global aggregate demand.

Based on studies emphasizing the importance of the interplay between the bond market and the oil market, this study examines the impact of the 10-year government bond yields of the US, which reflects the macroeconomic and financial course of the US economy, on oil prices (indicating the oil-specific demand). In addition, the study deals with GEPU and analyzes its long-term relationships with oil prices. In this study, the long-term government bond yields of the US, which reflect the expectations regarding the macroeconomic and financial situation of the US economy, and GEPU are not evaluated in the variable vector of the VAR type of models. However, the effects of the two factors on the oil price are examined separately. In other words, the role of GEPU, which is also an important determinant of long-term bond yields, is handled separately and the study is conducted by examining its direct impact on oil prices.

Throughout the scientific literature, it has been acknowledged that the role of asymmetry has gained ground in the relationship between macroeconomic and financial variables using advanced time-series models. However, unlike other studies, the main motivation of this study is to deal with the possible role of asymmetry in the relationship between long-term bond yields of the USA, GEPU on oil-specific demand. More specifically, this study assumes that the effects of long-term bond yields and GEPU on oil prices can be asymmetrical, parallel to Bouri *et al.* (2020) and Tule *et al.* (2017), whereas it evaluates this issue by focusing on the long run via Granger causality analysis and the quantile cointegration model. More specifically, unlike Bouri *et al.* (2020) and Degiannakis *et al.* (2018), who used time-varying impacts, this study assumes that the cointegration relationship between the variables changes over the distribution and exposes the role of all the quantiles of the distribution, following Troster *et al.* (2018). Here, I should also bear in mind that, although the indicators related to oil can be classified as oil supply shocks and oil-specific demand

shocks, in line with [Degiannakis et al. \(2018\)](#), [Kang and Ratti \(2013\)](#), [Kang et al. \(2017\)](#) and [Morrison \(2019\)](#), it can be difficult to identify the effects of GEPU on each variable theoretically. Instead, this study departs from the assumption that the impacts of GEPU on oil prices are indispensable, parallel to [Ratti and Vespignani \(2016\)](#). More specifically, the asymmetric effects of GEPU and long-term bond yields of the USA are examined through the quantile Granger causality test and the quantile cointegration model. The empirical models used in the study have monthly data covering the 1997:01 to 2019:07 period. It should also be noted that no theoretical framework exists indicating that there is a decisive role of monetary policy regimes in terms of the effects of long-term bond yields and EPU or GEPU on oil prices.

3. Methodology of analysis

This study is based on quantile cointegration analysis, and herein the stationary properties of the variables planned to be included in the model should be determined by relevant unit root tests. Thus, I use quantile autoregression unit root tests to determine the stationarity of each series at each quantile of the conditional distribution considering the conditional mean. Accordingly, the past information set is written as $I_t^Y := (Y_{t-1}, \dots, Y_{t-s})' \in \mathbb{R}^S$, assuming that Y_t is a strictly stationary time-series process. Additionally, $F_Y(\cdot | I_t^Y)$ refers to the conditional distribution function of Y_t given I_t^Y , and thus the quantile linear regression model in (1) is used to perform the quantile autoregressive unit root test.

$$Q_T^Y(Y_t | I_t^Y) = \mu_1(\tau) + \mu_2(\tau)t + \alpha(\tau)Y_{t-1} + \sum_{j=1}^p \alpha_j(\tau)\Delta Y_{t-j} + F_u^{-1}(\tau) \quad (1)$$

In [equation \(1\)](#), $Q_T^Y(\cdot | I_t^Y)$ denotes the τ -quantile of $F_Y(\cdot | I_t^Y)$, while $\mu_1(\tau)$ and t are the drift and linear trend terms, respectively. $\alpha(\tau)$ refers to the persistence parameter, and $F_u^{-1}(\tau)$ expresses the inverse conditional distribution of the errors for each quantile $\tau \in \mathcal{T} \subset [0, 1]$, \mathcal{T} being a compact set. In addition to the analysis carried out in line with [equation \(1\)](#), the quantile cointegration test proposed by [Xiao \(2009\)](#) can be used to consider the long-run relationship among model variables. The relevant test implies that the cointegrating vector changes over the distribution, while the quantile cointegration model also incorporates the systematic influences of conditioning variables on the location, scale and shape of the conditional distribution of the response variable. More specifically, the model of [Engle and Granger \(1987\)](#) with a vector of constants, namely, $\beta(\tau)$, constitutes a base to the quantile cointegration model. In this respect, the model can be specified as $Y_t = \alpha + \beta'Z_t + \sum_{j=-K}^K \Delta Z_{t-j}' \Pi_j + u_t$, and whereupon the equation including a quadratic term of the regressor in the quantile cointegration below is written as:

$$Q_T^Y(Y_t | I_t^Y, I_t^Z) = \alpha(\tau) + \beta(\tau)'Z_t + \gamma(\tau)'Z_t^2 + \sum_{j=-K}^K \Delta Z_{t-j}' \Pi_j + \sum_{j=-K}^K \Delta Z_{t-j}^2 \Gamma_j F_u^{-1}(\tau) \quad (2)$$

In terms of [equation \(2\)](#), the stability of the cointegrating coefficients can be tested in line with [Xiao \(2009\)](#). The relevant test has a test statistic that proposes a supremum norm of the absolute value of the difference $\hat{V}_n(\tau) = \hat{\beta}(\tau) - \hat{\beta}$ under the null hypothesis that

$H_0: \beta(\tau) = \beta$ over all quantiles τ . Thus, I can use the test statistic $\sup_{\tau} |\hat{V}_n(\tau)|$ over all quantiles of the distribution. This framework also allows the incorporation of the Granger-causality approach, which can be adopted in mean and in quantiles. In this context, it is accepted that a series Z_t acts to Granger-cause another series Y_t , when past Z_t helps to forecast future Y_t . At this point, an explanatory vector can be expressed as $I_t \equiv (I_t^Y, I_t^Z)' \in \mathbb{R}^d$, where I_t^Y and I_t^Z refer to the past information sets of Y_t and Z_t , respectively. According, the null hypothesis of Granger-noncausality from Z_t to Y_t can be denoted as this:

$$H_0^{Z \rightarrow Y} : F_Y(y | I_t^Y, I_t^Z) = F_Y(y | I_t^Y), \text{ for all } y \in \mathbb{R} \quad (3)$$

where $F_Y(\cdot | I_t^Y, I_t^Z)$ is the conditional distribution function of Y_t given (I_t^Y, I_t^Z) . In terms of (3), the Granger-noncausality in conditional quantiles is tested to identify the pattern of causality and to meet a sufficient condition for testing the null hypothesis. Assuming that $Q_{\tau}^{Y,Z}(\cdot | I_t^Y, I_t^Z)$ refers to the τ -quantile of $F_Y(\cdot | I_t^Y, I_t^Z)$, equation (3) can be rewritten as in equation (4).

$$H_0^{QC:Z \rightarrow Y} : Q_{\tau}^{Y,Z}(Y_t | I_t^Y, I_t^Z) = Q_{\tau}^Y(Y_t | I_t^Y), \text{ for all } \tau \in \mathbb{R} \quad (4)$$

Accordingly, the test statistic S_T [3] can be derived from equations (3)-(4), and I used three quantile auto-regressive (QAR) models m (s0), for all $\tau \in \mathcal{T} \subset [0,1]$. The three QAR models are given in equation (5)-(7) below:

$$QAR(1) : m^1(I_t^Y, \theta(\tau)) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \sigma_t \Phi_u^{-1}(\tau) \quad (5)$$

$$QAR(2) : m^2(I_t^Y, \theta(\tau)) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \sigma_t \Phi_u^{-1}(\tau) \quad (6)$$

$$QAR(3) : m^3(I_t^Y, \theta(\tau)) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \mu_4(\tau)Y_{t-3} + \sigma_t \Phi_u^{-1}(\tau) \quad (7)$$

where the parameters $\theta(\tau) = (\mu_1(\tau), \mu_2(\tau), \mu_3(\tau), \mu_4(\tau), \sigma_t)'$ are estimated with maximum likelihood in an equally spaced grid of quantiles. Thus, $\Phi_u^{-1}(\cdot)$ is the inverse of a standard normal distribution function, while the estimation of the quantile autoregressive models in equation (7) indicates the sign of the causal relationship among the variables. Furthermore, the final specification of the QAR(3) model with the lagged values of the other variable can be expressed as below:

$$Q_{\tau}^Y(Y_t | I_t^Y, I_t^Z) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \mu_4(\tau)Y_{t-3} + \beta(\tau)Z_{t-1} + \sigma_t \Phi_u^{-1}(\tau) \quad (8)$$

As for the empirical exercise, I also incorporate the Kilian and Vigfusson (2011) approach, departing from the linear and symmetric and asymmetric data-generating processes. To verify the results of the quantile-based analysis, I consider the asymmetric impacts of GEP

and the US long-term bond yields on oil prices via a nonlinear VAR model. Accordingly, the asymmetric VAR model is estimated in terms of the equations below:

$$x_t = b_{10} + \sum_{i=1}^p b_{11,i}x_{t-i} + \sum_{i=1}^p b_{12,i}y_{t-i} + \varepsilon_{1,t} \quad (9)$$

$$y_t = b_{20} + \sum_{i=1}^r b_{21,i}x_{t-i} + \sum_{i=1}^r b_{22,i}y_{t-i} + \sum_{i=1}^r g_{21,i}x_{t-i}^+ + \varepsilon_{1,t} \quad (10)$$

Equation (9) refers to a linear VAR model showing the effects of x_t on y_t , while equation (10) deals with the effects of both x_t and x_t^+ on y_t [4]. Within this framework, the dynamic responses of y_t to positive and negative changes in x_t can be estimated, and moreover equations (11) and (12) specify a set of equations incorporating both censored variables and the nonlinear VAR model:

$$s_t = b_{10} + \sum_{k=1}^p b_{11,k}s_{t-k} + \sum_{k=1}^p b_{12,k}\lambda_{t-k} + \varepsilon_{1,t} \quad (11)$$

$$\lambda_t = b_{20} + \sum_{k=1}^p b_{21,k}s_{t-k} + \sum_{k=1}^p b_{22,k}\lambda_{t-k} + \sum_{k=1}^p g_{21,k}s_{t-k}^+ + \varepsilon_{2,t} \quad (12)$$

where p corresponds to the lag order of the VAR model and s_t denotes the variable whose possible asymmetric impacts is investigated. The equations above also have λ_t vector of variables that can be under the influence of s_t . Equation (11) refers to a linear symmetric model with s_t , while equation (12) has both s_t and a censored variable of s_t^+ . The s_t^+ represents the positive changes, and it can be accepted that $s_t^+ = \begin{cases} s_t & s_t > 0 \\ 0 & s_t \leq 0 \end{cases}$. Thus, b_{10} and b_{20} in (9) and (10) are the vector of intercept and dummy variables, respectively. The b_{12} and b_{22} vectors include the coefficients of the changes in s_t , while g_{21} denotes the vector of the coefficient of the censored variable. Finally, $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are the residual vectors of (11) and (12).

4. Analysis results

In determining the most appropriate form of the empirical model to be used in my study, the statistical summary of the model variables should be exposed, and unit root properties of model variables should be specified. Table 1 shows that all variables are stationary at first-difference, while it can be accepted that the normality tests of Jarque and Bera (1980) mean that the null hypothesis of normality can be rejected for each of the series at the 5% significance level, in line with Nusair and Olson (2019). This suggests that the employment of a nonlinear model can be robust to non-normal skewness in the estimation.

I also used the BDS test of Brock *et al.* (1996) to the residuals of regression models in Table 2 to verify whether the relationship between variables is nonlinear. It was indicated that the linearity conditions of alternative models are not met and the relationship between model variables contain nonlinearities. Accordingly, the Johansen cointegration analysis was not performed and quantile analysis was incorporated to take advantage of showing the reactions of oil prices to the changes in the GEPU and the long-term government bond yields of the USA corresponding to different quantiles.

Table 1.
Summary statistics
and traditional unit
root analysis results

Variables	Mean	Median	Maximum	Minimum	SD	Skewness	Kurtosis	Jarque-Bera	ADF test	PP test
$bnye_t$	4.54	4.63	5.22	3.70	0.39	-0.27	1.94	16.15 (0.00)	-1.85 [3]	-1.64 [2]
$\Delta bnye_t$	-0.004	-0.007	0.19	-0.37	0.06	-0.58	7.54	247.02 (0.00)	-8.54 [2]	-13.05 [3]
$gephu_t$	4.67	4.64	5.74	3.93	0.4	0.42	2.58	10 (0.01)	-2.16 [3]	-3.05 [9]
$\Delta gephu_t$	0.004	-0.003	0.76	-0.55	0.18	0.57	4.83	52.785 (0.00)	-8.18 [7]	-24.73 [29]
$opri_t$	4.23	4.33	5.26	2.78	0.59	-0.46	2.26	15.66 (0.00)	-1.87 [1]	-1.64 [2]
$\Delta opri_t$	0.003	0.016	0.21	-0.33	0.08	-0.70	4.22	39.18 (0.00)	-12.50	-12.4 [5]

Notes: The number of lags in the augmented Dickey-Fuller (ADF) test (in brackets) is imposed by the Akaike information criterion (AIC), while the bandwidth for the Phillips-Perron (PP) test is suggested automatically by the Newey-West bandwidth (in brackets), using the Bartlett kernel spectral estimation method. The 1%, 5% and 10% critical values for the ADF and PP tests with an intercept term are -3.47, -2.88 and -2.58, respectively. p-values of the Jarque-Bera are in parentheses

In this context, a quantile unit root test was used in addition to the traditional unit root tests [5]. The quantile unit root test considered the null hypothesis that $H_0: a(\tau) = 1$ within equation (1) for the grid of 19 quantiles to $\mathcal{T} = [0.05; 0.95]$, and thus Table 3 indicates the persistence estimates, t -Statistics of the null hypothesis, and the critical values of the test [6]. More specifically, $byie_t$ and $opri_t$ are non-stationary at the 5% significance level for all the quantiles of the conditional distribution parallel to the results of the unit root tests involving structural breaks (Lumsdaine–Papell test). However, $gepu_t$ is found as nonstationary at the median and lowest quantiles of the distribution, and the null hypothesis of the unit root for the relevant variable can be rejected at the median and higher quantiles of the conditional distribution at the 5% significance level.

According to the results of the quantile unit root test shown in Table 3, the variables were generally assumed to be nonstationary, and thus the quantile cointegration relationship between the variables was examined (Table 4). In this context, the quantile cointegration test was incorporated to specify whether the cointegration relationship between the variables changes over the distribution. Although the $gepu_t$ is stationary at the 5% level for all quantiles higher than $\tau = 0.4$, I used an equally spaced grid of all the quantiles to $\mathcal{T} = [0.05; 0.40]$ to perform the quantile cointegration analysis between $gepu_t$ and $byie_t$ and

Regression model	2	3	4	5	6
$opri_t = f(\text{cons}, gepu_t)$	0.00	0.00	0.00	0.00	0.00
$\Delta opri_t = f(\text{cons}, \Delta gepu_t)$	0.00	0.00	0.00	0.00	0.00
$opri_t = f(\text{cons}, byie_t)$	0.00	0.00	0.00	0.00	0.00
$\Delta opri_t = f(\text{cons}, \Delta byie_t)$	0.00	0.00	0.00	0.00	0.00

Table 2. BDS test results

Notes: The distance value of the test is 0.7. For the details of the BDS test, please see Brock *et al.* (1996)

τ	$byie_t$			$gepu_t$			$opri_t$		
	$\hat{\alpha}$	t -statistic	Critical values	$\hat{\alpha}$	t -statistic	Critical values	$\hat{\alpha}$	t -statistic	Critical values
0.05	0.822	0.022	-3.033	0.640	-2.791	-3.056	0.882	-2.670	-3.389
0.10	0.890	-0.398	-3.153	0.661	-2.368	-3.160	0.890	-2.531	-3.213
0.15	0.921	-0.254	-3.083	0.693	-1.481	-3.001	0.921	-3.549	-3.286
0.20	0.930	-1.042	-3.093	0.701	-0.489	-2.954	0.930	-2.794	-3.361
0.25	0.950	-0.885	-3.103	0.741	-0.679	-3.020	0.950	-2.238	-3.277
0.30	0.967	-1.243	-3.083	0.741	0.167	-2.962	0.967	-1.736	-3.303
0.35	0.961	-1.865	-3.202	0.749	1.009	-2.918	0.961	-2.143	-3.071
0.40	0.973	-1.687	-3.172	0.736	0.343	-2.791	0.973	-1.730	-2.975
0.45	0.987	-2.166	-3.185	0.780	-5.333	-2.310	0.987	-0.873	-3.024
0.50	0.989	-2.630	-3.137	0.788	-8.804	-2.398	0.989	-0.804	-3.094
0.55	0.991	-2.825	-3.155	0.859	-7.336	-2.557	0.991	-0.701	-3.021
0.60	0.997	-2.675	-3.171	0.890	-8.358	-2.700	0.997	-0.194	-2.938
0.65	0.994	-2.562	-3.244	0.898	-6.978	-2.715	0.994	-0.416	-2.893
0.70	1.007	-2.566	-3.286	0.929	-6.952	-2.788	1.007	0.497	-2.794
0.75	1.018	-2.245	-3.324	0.975	-6.676	-2.899	1.018	1.130	-2.807
0.80	1.060	-1.609	-3.227	0.959	-6.473	-2.882	1.059	3.235	-2.771
0.85	1.048	-1.480	-2.984	1.013	-6.028	-2.866	1.048	2.491	-2.824
0.90	1.081	-1.832	-3.087	1.094	-5.616	-2.879	1.081	4.099	-2.663
0.95	1.084	-2.607	-2.434	1.105	-3.493	-2.986	1.084	3.171	-2.310

Table 3. Quantile autoregression unit root analysis

Notes: Italic values indicate the relevant series is stationary the 5% significance level

$gepu_t$ and $opri_t$. The quantile cointegrating model depends on equation (2), while I used two lags and two leads of $(\Delta Z_t, \Delta Z_t^2)$ in the quantile cointegrating model, following Troster *et al.* (2018). As indicated in Table 4, I found evidence for a nonlinear cointegration relationship between the quantiles of $byie_t$, $gepu_t$, and $opri_t$ even at the 5% significance level.

Thus, I incorporated the quantile cointegration model to expose the relationships between $gepu_t$ and $opri_t$, $gepu_t$ and $byie_t$, and $opri_t$ and $byie_t$. The long-term nonlinear cointegrating relationships between the variables indicated in Table 5 are represented by the cointegration coefficients $\beta(\tau)$ and $\gamma(\tau)$ of the model specified in (2). Considering the long-term relationships between $gepu_t$ and $opri_t$, it is seen that both estimated coefficients have negative values. More specifically, when a significance level of 5% is considered, the $\beta(\tau)$ and $\gamma(\tau)$ coefficients may be considered statistically significant below $\tau = 0.40$. The quantile cointegration model also showed that there may be a relationship between the

Model	Coefficient	$sup_{\tau} \hat{V}_n(\tau) $	CV1	CV5	CV10
$gepu_t$ vs $opri_t$	β	927.143	262.865	170.215	138.681
	γ	93.708	19.775	12.253	8.736
$gepu_t$ vs $byie_t$	β	467.134	593.811	375.184	305.857
	γ	57.989	80.776	45.147	35.127
$opri_t$ vs $byie_t$	β	855.634	994.613	723.272	566.001
	γ	101.064	121.285	78.399	57.187

Table 4.
Quantile
cointegration test

Notes: CV1, CV5 and CV10 denote the critical values of statistical significance at 1, 5 and 10%, respectively. We used 1,000 Monte Carlo simulations to obtain the critical values. An equally spaced grid of 19 quantiles is also used

τ	$gepu_t$ vs $opri_t$		$gepu_t$ vs $byie_t$		$opri_t$ vs $byie_t$	
	$\beta(\tau)$	$\gamma(\tau)$	$\beta(\tau)$	$\gamma(\tau)$	$\beta(\tau)$	$\gamma(\tau)$
0.05	-5.460***	0.492***	-2.823**	0.298*	-2.406***	0.293***
0.10	-5.327***	0.413***	-2.101*	0.208	-2.716***	0.338***
0.15	-5.042***	0.408***	-1.805**	0.163	-2.598***	0.329***
0.20	-4.750**	0.376**	-1.488	0.121	-2.938***	0.351***
0.25	-4.424**	0.262**	-0.982	0.060	-2.453***	0.299***
0.30	-3.515*	0.136*	-0.715	0.032	-1.156	0.157*
0.35	-3.171*	0.114*	-0.906	0.055	-0.915	0.127
0.40	-3.065*	0.091*	-0.686	0.029	-0.809	0.118
0.45	-	-	-	-	-0.585	0.092
0.50	-	-	-	-	-0.245	0.050
0.55	-	-	-	-	-0.401	-0.029
0.60	-	-	-	-	-0.888	-0.084
0.65	-	-	-	-	-0.867	-0.083
0.70	-	-	-	-	-1.188	-0.125
0.75	-	-	-	-	-1.487	-0.160
0.80	-	-	-	-	-3.032**	0.327**
0.85	-	-	-	-	-3.109**	0.335**
0.90	-	-	-	-	-3.598	0.405**
0.95	-	-	-	-	-4.971***	0.601***

Table 5.
Quantile
cointegration model

Note: ***, ** and * refer to rejection of the null hypothesis at the 1, 5 and 10% significance level, respectively

10 year government bond yields of the USA and oil prices in the low and high quantiles. Thus, it is suggested that changes in GEPU and the long-term bond yields of the USA may have a significant impact on the global economic activity, which in turn can be determinative of the dynamics of oil prices. However, the long-term relationship between the GEPU and the 10-year government bond yields of the USA may be less effective because the estimated coefficients of the relevant model are negative and statistically significant for the quantiles below $\tau = 0.25$.

Because the considerable long-term effect was not detected between $gepu_t$ and $byie_t$ according to the quantile cointegration model, Granger-causality analysis was conducted only on the responses of $\Delta opri_t$. As shown in Table 6, I found that GEPU acts to Granger-cause changes in oil prices at the 1% significance level, considering the extreme tails of the conditional distribution such as $\tau = \{0.05, 0.10, 0.15\}$ or $\tau = \{0.85, 0.90, 0.95\}$. Following to the empirical framework of Troster *et al.* (2018), this finding suggests that large negative or positive fluctuations in GEPU may lead to extreme changes in oil prices because changes in the relevant index also incorporate the impacts of foreign trade polices of major economies that can be assessed in terms of the so-called “trade wars.” In other words, the impact of GEPU on the international trade volume is noteworthy, and thus it is possible to infer that the EPU of each country may eventually affect oil prices, especially over their contribution to changes in the volume of world trade. This finding is parallel to those of Antonakakis *et al.* (2014), Degiannakis *et al.* (2018), Hailemariam *et al.* (2019), Kang and Ratti (2013), Kang *et al.* (2019) and Yang (2019), which revealed the strong relationships between EPU and oil-specific demand, and it underlines that the incorporation of global indicators, in accordance with Kang *et al.* (2014) and Ratti and Vespignani (2016), is supported.

	$\Delta gepu_t$ to $\Delta opri_t$			$\Delta byie_t$ to $\Delta opri_t$		
	$I_t^{\Delta opri} = 1$	$I_t^{\Delta opri} = 2$	$I_t^{\Delta opri} = 3$	$I_t^{\Delta opri} = 1$	$I_t^{\Delta opri} = 2$	$I_t^{\Delta opri} = 3$
[0.05; 0.95]	0.117	0.099	0.013	0.149	0.149	0.162
0.05	<i>0.027</i>	<i>0.045</i>	0.058	0.748	0.698	0.838
0.10	<i>0.019</i>	0.059	0.083	0.586	0.770	0.721
0.15	0.067	<i>0.028</i>	<i>0.036</i>	0.923	0.626	0.703
0.20	0.698	0.149	0.536	0.937	0.360	0.604
0.25	0.212	0.284	0.432	0.140	0.428	0.432
0.30	0.595	0.635	0.586	0.761	0.775	0.815
0.35	0.185	0.374	0.360	0.374	0.374	0.360
0.40	0.095	0.050	0.135	0.095	0.050	0.135
0.45	0.045	0.104	<i>0.040</i>	0.045	0.104	0.050
0.50	0.203	0.072	0.059	0.203	0.072	0.059
0.55	0.239	<i>0.045</i>	<i>0.005</i>	0.221	0.059	0.005
0.60	0.117	0.180	0.239	0.117	0.180	0.248
0.65	0.500	0.459	0.586	0.500	0.459	0.608
0.70	0.432	0.689	0.486	0.432	0.707	0.491
0.75	0.545	0.725	0.644	0.545	0.833	0.640
0.80	0.062	0.073	<i>0.049</i>	0.250	0.372	0.259
0.85	0.085	<i>0.048</i>	<i>0.042</i>	0.157	0.292	0.132
0.90	<i>0.036</i>	<i>0.046</i>	<i>0.028</i>	<i>0.036</i>	<i>0.046</i>	<i>0.028</i>
0.95	<i>0.009</i>	<i>0.005</i>	<i>0.036</i>	<i>0.009</i>	<i>0.005</i>	<i>0.020</i>

Table 6. Granger-causality to oil prices (*p*-values)

Notes: This table shows the subsampling *p*-values of the test. Italic *p*-values refer to the rejection of the null hypothesis at the 5% significance level denotes the first difference of the series

On the other hand, it is indicated that large negative variations in the 10-year government bond yields of the USA do not Granger-cause variations in oil prices, whereas only large positive fluctuations in the long-term government bond yields of the US lead to changes in oil prices. These results are partly in line with those of Balcillar *et al.* (2020), Bouri *et al.* (2020), Demierer *et al.* (2020), Kang *et al.* (2014), Morrison (2019), Nazlioglu *et al.* (2020) and Tule *et al.* (2017), which indicated a considerable relationship between bond yields and oil prices. In this respect, it can be stressed that significant deterioration in the expectations of economic agents and investors in terms of the course of the US economy can lead to a decrease in the demand for the long-term government bonds of the USA, which in turn triggers a fall in oil prices. It can also be suggested that these developments in the bond market may cause negative effects on other financial markets and on the performance of the world economy. In other words, large increases in 10-year government bond yields are also perceived as serious changes in liquidity conditions in the US economy and in the FED's monetary policy and, when the transmission of the US interest rates on financial markets is taken into consideration, it can significantly affect oil prices through the commodity market. Because the aforementioned effect may vary in the case of increases and decreases in bond yields, it should be noted that the role of asymmetric effects can be indispensable.

The causality analysis shows the relationships between the variables, while the investigation of the direction of the relationship between the variables in different quantiles can allow us to make robust economic interpretations. In this respect, I used the QAR(3) model with the lagged values of the other variable as specified in equation (8) to expose the sign of the Granger-causality between the variables, following Troster *et al.* (2018). Table 7 indicates the coefficients showing the effect of GEPU on oil prices for all quantiles; more specifically, it was stressed that both large negative and positive variations in GEPU may influence oil prices in terms of the estimated coefficients β (τ) of the relevant quantile regression model. Additionally, the QAR models' results show that the high rate of increase/decrease in GEPU will slow down/speed up global economic activity, which will deteriorate/improve the expectations of economic agents and thus

τ	$\Delta gepu_t$ to $\Delta opri_t$	$\Delta byie_t$ to $\Delta opri_t$
0.05	0.074	-0.036
0.10	0.050	-0.049
0.15	0.038	-0.052
0.20	0.019	-0.069
0.25	0.018	-0.096
0.30	0.032	-0.095
0.35	0.029	-0.081
0.40	0.042	-0.051
0.45	-0.037	-0.071
0.50	-0.040	-0.043
0.55	-0.046	-0.038
0.60	-0.045	-0.019
0.65	-0.016	-0.016
0.70	-0.013	-0.002
0.75	-0.019	-0.007
0.80	-0.032	-0.030
0.85	-0.074	-0.041
0.90	-0.058	-0.121
0.95	-0.036	-0.111

Table 7.
Quantile regression
estimated coefficients

Note: This table indicates the estimated coefficients of the quantile autoregressive model in (8)

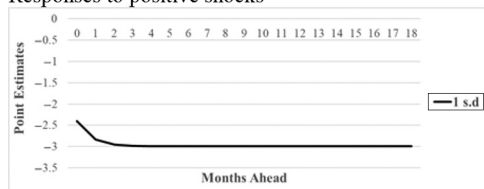
negatively/positively affect oil prices. More specifically, quantile analysis suggests that the impacts of the GEPU on oil price can be symmetrical. In this respect, it should also be borne in mind that the assumption that international trade policy remains constant can contribute to global economic stability, which in turn can promote foreign trade flows and increase the demand for oil.

The QAR models also revealed that positive variations in the 10-year government bond yields of the USA may influence oil prices in the opposite direction. According to the QAR model, negative variations in the relevant bond yields may also lead to an increase in oil prices. When quantile regression results are considered together with quantile Granger causality results, it can be suggested that, although the increase in the interest of the US long-term treasury bills and thus the decrease in the 10-year government bond yields can be attributable to the positive expectations about the US economy, it can be argued that this may arise from international investors seeking safe-haven assets. As investors' demand for safe-haven assets shows uncertainties and negative expectations regarding the course of the world economy, it can be asserted that the positive effects of the improvement in borrowing conditions in the USA on the oil demand can be decreased. Nevertheless, it can be put forward that asymmetric effects found by the quantile analysis should also be assessed by using the nonlinear VAR model considering future periods.

At this point, I used the nonparametric test of [Diks and Panchenko \(2006\)](#) to verify that the VAR framework can be suitable to investigate the asymmetric relationship between variables. In this vein, the relevant test was applied on the residuals obtained from a VAR specification to find whether there is nonlinear causality from GEPU to oil prices and long-term bond yields of the USA to oil prices. The nonlinear causality test of [Diks and Panchenko \(2006\)](#) [7] indicated a causality relationship between GEPU and oil prices and the long-term government bond yields of the USA and oil prices at least at the 10% significance level. Thus, VAR-type models would be useful for evaluating the asymmetric effect between $\Delta gepu_t$ and $\Delta opri_t$ and $\Delta byie_t$ and $\Delta opri_t$. To reveal the asymmetric relationship between the variables, the IRFs were estimated based on the nonlinear VAR model, [8] and the asymmetric relationships were evaluated over the direction and magnitude of the coefficients [9].

Within the framework of the nonlinear VAR model, an impulse response analysis was performed, and it was indicated that oil prices will decrease in the following periods as a result of 1-standard-deviation positive shocks in the $\Delta gepu_t$ ([Figure 2](#)). More specifically, the impulse response analysis suggested that oil prices will decline as a result of a decreasing demand for oil. Hence, it can be argued that the increases in GEPU will disrupt the foresight capabilities of economic agents, adversely affect macroeconomic expectations, and thus decrease global real economic activity. The effects of 1-standard-deviation negative shocks in the $\Delta gepu_t$ (decrease in GEPU) on oil prices were also examined with the IRFs; in this

Responses to positive shocks



Responses to negative shocks

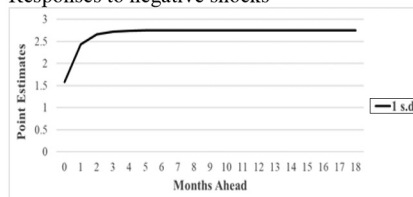


Figure 2. Responses of oil prices to positive and negative shocks in the GEPU

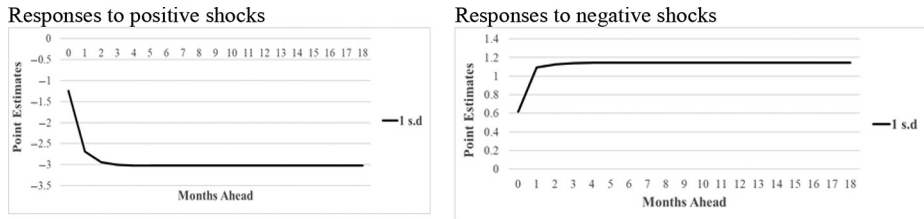
Source: Author's calculations

respect, it was found that Δopr_t will take positive values as a result of the relevant shock. The results of the IRFs are also in line with the quantile regression and the quantile Granger causality results; thus, it can be put forward that a decline in GEPU will accelerate global real economic activity and increase the demand for oil. My findings also implied that exchange rates and capital regimes that may limit international trade volume will negatively affect oil-exporting economies. Furthermore, IRFs exposed that foreign trade policy measures in the context of trade wars will affect the current balances of oil-exporting countries negatively and the current balances of oil-importing countries positively.

In this context, it has been acknowledged that the quantitative easing and macroprudential policies implemented by major central banks after the GFC and the borrowing conditions of the US economy became important drivers of the global real economic activity. Thus, it can be assumed that the impact of long-term bond yields of the USA on other macroeconomic and financial variables has increased. In this context of the nonlinear VAR model, the impacts of positive and negative shocks in the 10-year government bond yields of the USA on oil prices are assessed with the IRFs, as shown in Figure 3. Accordingly, I find that one-standard-deviation positive shocks in the $\Delta byie_t$, which correspond to the deterioration of the borrowing conditions in the USA, will lead to a fall in Δopr_t owing to the deterioration of the global real economic activity. This result suggests that these developments, which could also reflect a contractionary monetary policy in the USA, will be followed by the central banks of other countries, while the assumption that capital flows are significantly dependent on interest rate differences between countries is also supported. On the other hand, despite revealing that Δopr_t will rise as a result of one-standard-deviation negative shocks (an improvement in borrowing conditions) in the $\Delta byie_t$, this result is not confirmed by the quantile Granger causality results.

Although this finding contradicts the quantile Granger causality analysis, the slope-based Mork test deriving from the nonlinear VAR model is also presented in Table 8 to verify the quantile-based analysis. Because the test confirms that the impact of $\Delta byie_t$ on Δopr_t is asymmetrical, parallel to the quantile-based analysis, it is not robust enough to

Figure 3. Responses of oil prices to positive and negative shocks in the 10-year government bond yields of the US



Source: Author's calculations

Table 8. Test of symmetry in GEPU (a) and in the 10-year government bond yields of the USA increases and decreases (b)

Variable	(a) Mork's test of symmetric slope coefficients	(b) <i>p</i> -value
Δopr_t	2.191	0.222
Δopr_t	5.864	0.015

make an interpretation only in terms of the IRFs of the nonlinear VAR model 10. On the other hand, I obtain test results confirming that there can be no asymmetric effects of $\Delta gepu_t$ on $\Delta opri_t$, in line with the quantile-based analysis.

5. Conclusion

Because the effects of the expansionary monetary and macroprudential policies implemented in the USA after the GFC have also been found to show significant reflections on commodity prices, this study analyzes the asymmetric effects of the 10-year government bond yields of the USA on oil prices. In this study, the asymmetric effects of GEPU, which have become more prominent in terms of recent global economic developments, are also evaluated with quantile causality analysis and a quantile cointegration model.

In this respect, the existence of long-term nonlinear relationships among the previously mentioned variables was determined by a nonlinear cointegration relationship, while the coefficients of the quantile cointegration model showed that the long-term relationship between the variables could be in the opposite direction. Long-term relationships between variables were also examined by Granger-causality analysis, and it was found that positive and negative variations in GEPU can have significant effects on oil prices. In other words, this finding suggested that changes in GEPU will affect global economic activity and have consequences for oil demand. In my study, it is suggested that the changes that may occur in oil prices are also related to the EPU of countries, while it was also revealed that GEPU have a direct effect on oil prices through commodity markets. The results of Granger-causality analysis were supported by the quantile regression model's coefficients and the nonlinear VAR model's IRFs, and it was suggested that positive/negative variations in GEPU will have opposite effects on oil prices. More specifically, it is exposed that increasing/decreasing economic policy uncertainty of a country, which is included in the calculation of GEPU, will negatively/positively affect macroeconomic and financial stability, decelerate/accelerate global economic activity and thus lead to a fall/rise in oil prices. Additionally, because the slope-based Mork test indicated that the relevant relationship can be symmetrical, this confirms other studies supporting international policy coordination to reduce GEPU. More precisely, it was indicated that global uncertainties like trade wars, which also lead to considerable changes in foreign trade policy framework, may change the pass-through of oil prices to inflation, particularly in oil-importing countries over different time horizons. Thus, I suggest that the monetary authorities of the oil-importing countries, aiming to maintain price stability, should determine the optimal theoretical and empirical framework dealing with the time-varying effects of uncertainty, which is also the scope of another study.

To ensure macroeconomic stability on a global scale, it is also important to examine the asymmetric transmission of the 10-year government bond yields of the USA, which reflect the expectations about the course of the USA and the global economy, to oil prices. In this context, the quantile cointegration model shows the existence of an inverse relationship between the long-term government bond yields of the USA and the oil prices, whereas the quantile Granger causality analysis suggests that increases in the 10-year government bond yields of the USA may have a reducing impact on oil prices. Additionally, the quantile Granger causality analysis and the Mork test results indicate that the impact of long-term government bond yields of the USA on oil prices is asymmetrical. More specifically, it is suggested that the positive effects of the improvement of borrowing conditions in the USA are balanced by investors' negative expectations about the course of the world economy and their search for safe-haven assets. In this respect, I suggest that optimal control theory can also be adapted to increase the effectiveness of monetary policy authorities in oil-importing

and oil-exporting countries taking into account the asymmetrical impacts of the long-term government bond yields of the USA on oil prices and thus inflation.

Notes

1. Each country-specific EPU index shows the relative frequency of own-country newspaper articles that include a trio of terms pertaining to the economy, policy and uncertainty. For instance, countries' EPU can eventually incorporate the likelihood of trade wars, which may significantly affect the dynamics of the oil market. It should also be noted that global economic policy uncertainty (GEPU), reflecting the GDP-weighted average of the national EPU of 21 countries, can be used as a decisive factor. Thus, the increase/decrease in the GEPU index indicates that the uncertainties rise/fall.
2. For details, please see www.policyuncertainty.com/global_monthly.html
3. For the derivation of the test statistic, please see [Xiao \(2009\)](#) and [Troster et al. \(2018\)](#).
4. The data-generation process of x_t can be assumed as both asymmetric and symmetric, as $x_t = \alpha_1 + \varepsilon_{1,t}$ in the framework of a regression model. The substitution of negative values of x_t with zero leads to the generation of a censored variable x_t^+ , which can be represented as $x_t^+ = \begin{cases} x_t^+ & x_t > 0 \\ 0 & x_t \leq 0 \end{cases}$.
5. The results of the unit root test and summary statistics are not given to save space; however, they can be provided upon request.
6. To avoid serial correlation of the residuals, 10 lags of the difference of the dependent variable are used.
7. The results of the relevant test are not presented to save space; however, they can be provided upon request.
8. For details of the derivation of the model, please see [Kilian and Vigfusson \(2011\)](#).
9. An important drawback of the nonlinear VAR framework of [Kilian and Vigfusson \(2011\)](#) is that it does not use confidence bands, which will determine the statistical significance of IRFs.

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