Resources Policy 72 (2021) 102110

Contents lists available at ScienceDirect

Resources Policy

journal homepage: http://www.elsevier.com/locate/resourpol

On the connection between oil and global foreign exchange markets: The role of economic policy uncertainty

Ismail O. Fasanya [a,*], Oluwasegun B. Adekoya [c], Abiodun M. Adetokunbo [b]

[a] School of Economics and Finance, University of the Witwatersrand, Johannesburg, South Africa
[b] Department of Economics, Augustine University, Epe, Lagos, Nigeria
[c] Department of Economics, Federal University of Agriculture, Abeokuta, Ogun State, Nigeria

A R T I C L E I N F O

Keywords:
Economic policy uncertainty
Oil-exchange rates nexus
Nonparametric quantile causality
Volatility spillover

A B S T R A C T

This paper examines the effect of U.S. economic policy uncertainty on the connectedness across oil and the most globally traded currency pairs. First, we examine volatility spillover among oil and the exchange rates, and find strong connection between crude oil and currency markets with oil being net receivers of shocks. Second, BDS test shows that nonlinearity is very important when examining the role of EPU in affecting the interactions between oil and exchange rate markets. Third, the nonparametric quantiles-based causality test shows that the spillover for each asset is driven by economic policy uncertainty around the lower and median quantiles. This finally suggests that the role of the U.S. economic policy in influencing global financial cycle which consequently leads to capital flows and movements in the prices of assets across financial markets cannot be overemphasized. Relevant policy implications can be drawn from these findings.

1. Introduction

As the global economy stands at present, the crude oil and foreign exchange markets rank high in the general categories of commodity and financial markets respectively. The importance of these markets is strictly connected to their facilitation of global economic activities. For instance, crude oil is adjudged not only as constituting the largest share of global energy use (Atems et al., 2015), but also the most globally traded commodity (Demirer et al., 2020). On the other hand, due to the increasing level of globalization, international dependency and variation in countries' currencies, the foreign exchange market is highly indispensable in aiding economic activities at the global scale. Meanwhile, foreign transactions involving crude oil is denominated in the world's most prominent currency, U.S. dollar, (see Jain and Biswal, 2016). This implies that domestic currencies of countries must be converted to the U.S. dollar to trade in the global crude oil market. This serves as the first basis upon which both markets are linked.

The literature has thus established various mechanisms through which the crude oil and foreign exchange markets are connected. The terms of trade channel due to Amano and Van Norden (1998a,b) comes from the perspective of relative price changes. Increase in oil price raises the aggregate price level of an energy-dependent economy and consequently its output price, relative to another economy whose tradable sector is not energy intensive. This leads to the currency appreciation of the energy-dependent economy (see Buetzer et al., 2016; Chen and Chen, 2007). Krugman (1983) introduces the wealth effect mechanism by arguing from the standpoint of oil-exporting countries. As oil price rises, current account balance of these countries also improves in local currency terms following an increase in oil revenue. The end result is an expectation of the appreciation of their currencies, while those of the oil dependent countries depreciate (see Bechmann and Czudaj, 2013). Beckmann et al. (2020) further argues that this scenario also has the tendency to cause short-run appreciation of the U.S. dollar if the huge revenues of the oil exporters are reinvested in assets that are priced in the U.S. dollar. However, the wealth effect is generally effective in the short-run (see Beckmann et al., 2020). The medium-run and long-run implication of the scenario is termed the portfolio effect, and it relates particularly to the U.S. dollar in terms of the currencies of oil-exporting countries. Considering first a case where the U.S. is a net oil exporter, trade effects will either depreciate the U.S. dollar against the currencies of the oil-exporters if the demand for oil by the U.S. dominates, or appreciate it if the demand for U.S. commodities dominates (Beckmann et al., 2020). The other aspect of the portfolio channel is in terms of the desire of the oil exporting countries for medium- or

* Corresponding author.
E-mail addresses: ismail.fasanya@wits.ac.za (I.O. Fasanya), adekoyaob@gmail.com (O.B. Adekoya), abiodun.adetokunbo@gmail.com (A.M. Adetokunbo).

https://doi.org/10.1016/j.resourpol.2021.102110
Received 6 August 2020; Received in revised form 13 February 2021; Accepted 8 April 2021
Available online 23 April 2021
0301-4207/

long-term financial assets denominated in the U.S. dollar. This leads to the demand for U.S. dollar thus causing it to appreciate (Buetzer et al., 2016; Coudert et al., 2008).

The literature also notes that there is a possibility for exchange rate to affect oil price. This theoretical proposition is led by the currency-pricing basis of oil price which is the U.S. dollar. Assuming that oil is homogenous and internationally traded, the denomination channel holds that the depreciation of the U.S. dollar causes a fall in domestic currency-based oil price for the foreign countries. Oil demand by these countries then fall, and the eventual outcome is a reduction in the U.S. dollar-based currency (see Bloomberg and Harris, 1995; Akram, 2009). The last theoretical proposition between the two markets discloses that oil and foreign exchange markets are linked through common indicators including gross domestic products (GDP), stock prices, interest rates, etc. These factors jointly affect the two markets thereby linking them.

So far, the literature is fraught with empirical studies that examine the link between the two markets with varying findings resulting. The first class of studies examines causal relationship either in a unidirectional or bidirectional framework (see Beckmann and Czudaj, 2013; Benassy-Quere et al., 2007; Coudert et al., 2008, Chen and Chen, 2007, etc.), while another focuses on the impact of shocks especially from oil price (see Buetzer et al., 2016; Huang and Guo, 2007; Basher et al., 2012). Due to various economic crisis and policy interventions, the relationship between oil price and exchange rate has also been found to be nonlinear and time-varying (see Akram, 2004; Zhang, 2013; Basher et al., 2016, Fan and Xu, 2011; Zhang et al., 2008; etc.).

In line with the objective of our study, we also observe that the literature on dynamic spillover among the crude oil and various foreign exchange markets is growing recently (see Malik and Umar, 2019; Albulescu et al., 2019; Tiwari and Albulescu, 2016; Jain and Biswal, 2016). However, what is yet to be explored is how the spillover among them is driven by notable exogenous factors, especially economic or financial markets uncertainty. The earliest theoretical foundation for this consideration is rooted in the works of Pastor and Veronesi (2012) and Gomes et al. (2012), followed by the subsequent studies of Arouri et al. (2016), Liu et al. (2017), etc. They note that returns and volatility connectedness in financial markets can be influenced by uncertainty through its impacts on the supply of labour, personal consumption and investment decisions. From another perspective, policy-induced uncertainty has diverse impacts on corporate entities, investors and consumers as it can dissuade corporations from involving in new investment projects and induce conservative spending behaviour of consumers (see Converse, 2017; Handley and Limao, 2015). Similarly, higher economic policy uncertainty causes lenders to be conservative in their lending habits which then causes interest rates to rise. It is thus not out of scope to assert that the wide effect of economic policy uncertainty on the economy can directly creep into financial and oil markets (see Albulescu et al., 2019).

However, empirical studies have largely linked policy uncertainty with financial and oil markets in different scenes, with majority focusing on stock markets. Even the recent studies (see, for, instance, Badshah et al., 2018; Fang et al., 2018) are limited in scope as they only link policy uncertainty with stock and oil markets. It thus still remains a debatable issue on how economic policy uncertainty drives the volatility spillovers across the foreign exchange and oil markets. The only known work till date that mirrors ours is Albulescu et al. (2019) which connects the spillover between oil and commodity currency markets with the U.S. economic policy uncertainty. However, our present study differs from theirs in three distinct ways. First, we determine how the spillovers among the most traded foreign exchanges and oil market are connected to policy-based uncertainty, rather than commodity currency and the U. S. economic policy-based uncertainty. We opine that, following the degree of integration among the countries whose foreign exchange markets are being studies, the exchange rates would be more sensitive to uncertainty in economic policy since they are the most traded.

Secondly, we use a quantile-based causality test of Jeong et al. (2012) to examine how the uncertainty connects the spillovers in the crude oil and foreign exchange markets. Financial and high frequency series are mostly known to exhibit heavy tails, excess kurtosis and non-normality. These are often as a result of inherent nonlinearity, structural breaks and regime changes. In the presence of these, linear frameworks become inappropriate. This therefore motivates our choice of the nonlinear test. This approach has two noble merits as highlighted in Balcilar et al. (2015). The first advantage is that it produces reliable results in the presence of functional misspecification errors and dependence of series, such as is common to financial series. Its other benefit is the dual causality testing. Apart from testing for causality in conditional mean, it additionally provides results for causality in conditional variance of series due to the non-normal distribution property of most financial series. Obviously, the nonlinear causality tests explored in Albulescu et al. (2019) cannot capture the nonlinear-causality in conditional-variance. Also, the study was unable to reveal the level at which causality holds unlike the quantiles-based approach used in this study. Meanwhile, the validity of the quantiles-based causality test is first established by applying another test, namely BDS test developed by Brock et al. (1996) to check for the evidence of nonlinearity in the series. This is perhaps another contribution of this study rather than a mere speculation approach employed in most past studies.

The remainder of the paper is given the following structure. Next section outlays a brief review of the related literature. Methodological approaches adopted in this study is elaborated in Section 3 with a description of data. In Section 4, we offer a detailed discussion on the empirical analysis and the last section offers conclusion of our study.

2. Brief review of literature

The literature is replete with studies on the links among oil, foreign exchange markets and economic policy uncertainty, each producing unique results following their employment of variety of techniques for different economies. Essentially, oil-exchange rates connectedness could predict as well as respond to other economic and financial series (Xu et al., 2019; Dai et al., 2020).

Earlier, we have highlighted the various mechanisms through which oil and foreign exchange markets are connected. Based on these established mechanisms, the relationship between both markets has been examined in different forms. There is a strand of the literature that believes that the connection between the markets is dependent, among other factors, on the nature of oil price shocks and underlying nature of the economy under consideration. For instance, one of the standing empirical discoveries is that demand- and risk-driven oil price shocks significantly contribute to variation in exchange rates (Malik and Umar, 2019; Xu et al., 2019), while impacts from oil supply-side shocks are insignificant (see Xu et al., 2019). This partly contrasts the findings of Jiang et al. (2020) which disclose that oil supply and oil specific demand shocks have negative and asymmetric effects on exchange rate, and that developed currencies exhibit significant Granger-causality relationship coming from oil shocks. Huang et al. (2020) also observe that unexpected oil price shocks could have greater influence on currency markets over time. However, Wen and Wang (2020) prove that oil exports and foreign exchange regimes are the important factors that determine the volatility transmission across foreign exchange markets. On the other hand, the conditions of currency and oil markets explain the responses of exchange rates to oil price shocks (Youssef and Mokni, 2020).

Another strand of the literature seems to be concerned with the time-varying and nonlinear properties of the oil-foreign exchange markets nexus. Beckmann et al. (2020) confirm the links between oil prices and exchange rates to be time-varying and volatile. In support of nonlinear causality, Tiwari et al. (2019) show that the nature and direction of the causality differs from one country to another among the BRICS economies. Corroborating the nonlinear evidence, Mensi et al. (2017) reveal the presence of asymmetric systemic risks from oil to currencies, and at the same time, from currencies to oil. Using time-varying tri-variate vine-copula quantile regression model, Dai et al. (2020) prove that the US foreign exchange market connects oil and gold market in the short-run time scales, caused probably due to the fact that the two commodities are largely denominated in the U.S. dollar. Although, Chkir et al. (2020) find oil to be a weak hedge against exchange rates, Ahmad et al. (2020) discovers that oil and currency markets shocks have immediate reverse transmission mechanism. The latter further supports the asymmetric impact of currency price appreciation, or otherwise, on the oil market.

More recently, empirical focus has been driven to the spillover relationship between the oil and foreign exchange markets, either exclusively or in addition to other international financial markets. Albulescu et al. (2019) examine the time- and frequency-domain spillover between oil and commodity currencies, and how the connectedness is driven by economic policy uncertainty. They report that the financial markets are strongly connected with oil averagely being a net transmitter of shocks to the currencies across all the frequency cycles. More particularly, the currencies of New Zealand and Australia are the most sensitive to shocks in the oil shocks, explained by their use in carry trade strategies globally. This is in line with the findings of Singh et al. (2018) that the general currency market is a net receiver of shocks from the oil market. Furthermore, Malik and Umar (2019) provide evidence to support the intensified degree of connectedness between oil price shocks and exchange rate since the outbreak of financial crisis. The very recent study of Adekoya and Oliyide (2020) also discover that the oil and U.S. currency markets, in addition to other financial markets, are strongly connected during the COVID-19 pandemic period.

Meanwhile, since the construction of the economic policy uncertainty index by Baker et al. (2016), there has been tremendous influx of studies on the impact of economic policy uncertainty on various economic and financial indicators. On the role of economic policy uncertainty on foreign exchange rate market, Kido (2016) establishes the spillover effect of the U. S. economic policy uncertainty on real effective exchange rates. Accounting for nonlinearity and structural breaks, Al-Yahyaee et al. (2020) also confirms economic policy uncertainty and currency markets are nonlinearly related, as also consistent with the discovery of Chen et al. (2020).

Some studies take another dimension to examine the response of exchange rate to economic policy uncertainty. For instance, economic policy uncertainty intensifies exchange rate volatility as disclosed by Krol (2014), Bartsch (2019) and Zhou et al. (2020), and improves the forecasting power of macroeconomic models of exchange rates in different horizons (Abid, 2020). Beckmann and Czudaj (2017) find that exchange rate expectations are affected by uncertainty regarding future position of economic policy. Though, Huynh et al. (2020) examined and found strong volatility connectedness between foreign exchange rates and policy uncertainty, this study does not examine the role of policy uncertainty on the connectedness of oil and exchange rates markets, which is the objective of this study.

Turning to the link between economic policy uncertainty and the crude oil market, Hailemariam et al. (2019) reveals nonlinear and time-varying relationship. In support of this, Yang (2019) establishes connectedness and causal relationship between economic policy uncertainty and oil price shocks. They additionally confirm that crude oil prices receive information from economic policy uncertainty. Fang et al. (2018) also reveal the role of economic policy uncertainty in the correlation between oil and stock markets.

So far, it can be seen that there is a substantial number of studies on the oil-exchange rate nexus, as well as the role of economic policy uncertainty. However, there are still some crucial gaps yet to be addressed by the previous studies. First, most studies on the oil-exchange rate nexus are in the form of causal impact, with less investigation on their dynamic connectedness. Second, the role of economic policy uncertainty on oil market and foreign exchange rate markets has only been considered independently. The determinants of the connectedness between both markets are yet to be significantly explored. Studies that attempt to address this deficiency include Xu et al. (2019) and Dai et al. (2020) which respectively consider business cycle and gold as factors that connect both the oil and foreign exchange markets. This study addresses these concerns by: (i) looking into the dynamic connectedness between oil and globally traded exchange rates; (ii) determining the role of the U.S. economic policy uncertainty following the impact of the country in inducing global credits and capital flows. For now, only the study of Albulescu et al. (2019) resembles ours, but we consider globally traded exchange rates rather than commodity currencies used by them. Furthermore, our methodological choice is superior as it accounts for causality in both conditional mean and conditional variance.

3. Methodology and data

3.1. The Diebold – Yilmaz spillover approach

This study uses the Diebold and Yilmaz (DY, 2012) framework to examine the connection between oil and foreign exchange rate markets. The DY framework for the spillover analysis is grounded on the forecast error variance decomposition from the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), hereafter KPPS, which produces variance decompositions which are invariant to the ordering. In setting up the spillover indexes, a covariance stationary VAR (ρ) is considered.[1]

$$r_t = \Phi r_{t-1} + \varepsilon_t,\ \varepsilon_t \sim \sim \left(0, \sum\right) \tag{1}$$

where $r_t = (r_{1t,}r_{2t,\ldots\ldots,}r_{Nt})$ is an $N \times 1$ vector of volatility series, Φ is an $N \times N$ matrix of parameters, ε_t is a vector of independently and identically distributed disturbances and $\sum$ is the variance matrix for the error vector ε . The moving average representation can be written as:

$$r_t = \sum\nolimits_{i=0}^{\infty} A_i \varepsilon_{t-1} \tag{2}$$

where A_i is assumed to obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$. A_0 is an identity matrix with an $N \times N$ dimension and $A_i = 0$ for $i < 0$. Equation (2) forms the basis for the derivation of variance decompositions required to determine the spillover indexes. The spillover involves an own and cross variances share, where the former is defined as the fractions of the H-step-ahead error variances in forecasting r_i that are due to shocks to r_i , for $i = 1, 2 \ldots N$ and the latter is the fractions of the H-step ahead error variances in forecasting r_i that are due to shocks to r_j, for $i,j = 1, 2, \ldots, N$ for such that $i \neq j$.

Based on the generalized VAR framework of KPPS, H -step-ahead forecast error variance decompositions denoted by θ_{ij}^g is written as:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum\limits_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum\limits_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)} \tag{3}$$

Where σ_{jj} is the standard deviation of ε for the *jth* equation and e_i is the selection vector, with one as the *ith* element and zeros otherwise. Since the sum of the contributions to the variance of the forecast error is not equal to one – that is $\sum_{j=i}^{N} \theta_{ij}^g(H) \neq 1$; DY (2012) normalized each entry of the variance decomposition matrix by the row sum in order to use the full information of the matrix. The normalized KPPS H -step-ahead forecast error variance decompositions represented by $\widetilde{\theta}_{ij}^g(H)$ is expressed as:

[1] See Diebold and Yilmaz (2012) paper for a detailed exposition of the methodology.

$$\widetilde{\theta}^{g}_{ij}(H) = \frac{\theta^{g}_{ij}(H)}{\sum_{j=1}^{N}\theta^{g}_{ij}(N)} \tag{4}$$

where $\sum_{j=1}^{N}\widetilde{\theta}^{g}_{ij}(H) = 1$ and $\sum_{1,j=1}^{N}\widetilde{\theta}^{g}_{ij}(H) = N$ by construction.

Given these preliminaries, the total spillover index is written as:

$$S^{g}(H) = \frac{\sum^{N}\widetilde{\theta}^{g}_{ij}(H)\begin{matrix} i,j=1 \\ i\neq j\end{matrix}}{\sum_{1,j=1}^{N}\widetilde{\theta}^{g}_{ij}(H)} \times 100 = \frac{\sum^{N}\widetilde{\theta}^{g}_{ij}(H)\begin{matrix} i,j=1 \\ i\neq j\end{matrix}}{N} \times 100 \tag{5}$$

All the parameters in equation (5) have been previously defined. Essentially, equation (5) measures the contribution of spillovers of volatility shocks across the assets under consideration. In our case, the total spillover index captures the contribution of spillovers of volatility shocks across the six (6) currency pairs and oil price to the total forecast error variance.

Also, it is possible to assess quantitatively the direction of spillovers across the entire markets using the DY (2012) approach. These directional spillovers are classified into two namely '*Directional Spillover To' and 'Directional Spillover From'*. The former measures the directional spillovers whether volatility transmitted by market *i* to all other markets *j* while the latter relates to volatility received by market *i* from all other markets *j*. The index for the computation of '*Directional Spillover To*' denoted by $S^{g}_{.i}$ is given as:

$$S^{g}_{.i}(H) = \frac{\sum\limits_{\substack{i,j=1 \\ i\neq j}}^{N}\widetilde{\theta}^{g}_{ij}(H)}{\sum\limits_{i,j=1}^{N}\widetilde{\theta}^{g}_{ji}(H)} \times 100 = \frac{\sum\limits_{\substack{i,j=1 \\ i\neq j}}^{N}\widetilde{\theta}^{g}_{ij}(H)}{N} \times 100 \tag{6}$$

Also, the '*Directional Spillover From*' denoted as $S^{g}_{i.}$ is measured using the index given below:

$$S^{g}_{i.}(H) = \frac{\sum\limits_{\substack{i,j=1 \\ i\neq j}}^{N}\widetilde{\theta}^{g}_{ij}(H)}{\sum\limits_{i,j=1}^{N}\widetilde{\theta}^{g}_{ij}(H)} \times 100 = \frac{\sum\limits_{\substack{i,j=1 \\ i\neq j}}^{N}\widetilde{\theta}^{g}_{ij}(H)}{N} \times 100 \tag{7}$$

Equally, the Net Spillovers can be obtained using the index expressed below:

$$S^{g}_{i}(H) = S^{g}_{.i}(H) - S^{g}_{i.}(H). \tag{8}$$

Equation (8) gives the difference between the gross volatility shocks transmitted to and received from all other markers. In other words, information about each market's contribution to the volatility of other markers can be obtained through the net spillovers.

To examine the net pairwise volatility spillover between markets *i* and *j*, we compute the difference between the gross volatility shocks transmitted from market *i* to market *j* and those transmitted from *j* to *i*:

$$S^{g}_{ij}(H) = \left[\frac{\widetilde{\theta}^{g}_{ji}(H)}{\sum\limits_{i,k=1}^{N}\widetilde{\theta}^{g}_{ik}(H)} - \frac{\widetilde{\theta}^{g}_{ij}(H)}{\sum\limits_{j,k=1}^{N}\widetilde{\theta}^{g}_{jk}(H)}\right].100 = \left[\frac{\widetilde{\theta}^{g}_{ji}(H) - \widetilde{\theta}^{g}_{ij}(H)}{N}\right].100 \tag{9}$$

In the analysis of this paper, the second order 7-variable VARs with 10-step-ahead forecasts was considered.

3.2. Nonlinear causality test

The study adopts the Balcilar et al. (2018) methodology which is crucial for the detection of nonlinear causality via a hybrid approach with a foundation from the frameworks of Nishiayama et al. (2011) and Jeong et al. (2012). As noted by Jeong et al. (2012), the variable x_t (EPU) does not cause y_t (market spillovers) in the $\sigma - quantile$ with respect to the lag-vector of $\{y_{t-1}, \ldots, y_{t-q}, x_{t-1}, x_{t-q}\}$ if

$$Q_{\sigma}(y_t|y_{t-1}, \ldots, y_{t-q}, x_{t-1}, \ldots, x_{t-q}) = Q_{\sigma}(y_t|y_{t-1}, \ldots, y_{t-q}) \tag{10}$$

While x_t causes y_t in the σth quantile with respect to $\{y_{t-1}, \ldots, y_{t-q}, x_{t-1}, x_{t-q}\}$ if

$$Q_{\sigma}(y_t|y_{t-1}, \ldots, y_{t-q}, x_{t-1}, x_{t-q}) \neq Q_{\sigma}(y_t|y_{t-1}, \ldots, y_{t-q}) \tag{11}$$

Definitively, $Q_{\sigma}(y_t|\cdot) = \sigma th$ quantile of y_t depending on t *and* $0 < \sigma < 1$. We denote $V_{t-1} \equiv (y_{t-1}, \ldots, y_{t-q})$, $U_{t-1} \equiv (x_{t-1}, \ldots, x_{t-q})$, and $W_t = (U_t, V_t)$; and $F_{y_t|W_{t-1}}(y_t|W_{t-1})$ and $F_{y_t|V_{t-1}}(y_t|V_{t-1})$ represents the conditional distribution of y_t given W_{t-1} *and* V_{t-1}, *respectively*. Also, $F_{y_t|V_{t-1}}(y_t|V_{t-1})$ is assumed to be absolutely continuous in y_t for almost all W_{t-1}. If we proceed by denoting $Q_{\sigma}(W_{t-1}) \equiv Q_{\sigma}(y_t|W_{t-1})$ and $Q_{\sigma}(V_{t-1}) \equiv Q_{\sigma}(y_t|V_{t-1})$, then we have $F_{y_t|W_{t-1}}\{Q_{\sigma}(y_t|W_{t-1})\} = \sigma$ with a probability of one. In essence, the hypothesis to be tested based on the specified definitions in equations (10) and (11) are

$$H_0 = P\{F_{y_t|W_{t-1}}\{Q_{\sigma}(y_t|W_{t-1})\} = \sigma\} = 1, \tag{12}$$

$$H_1 = P\{F_{y_t|W_{t-1}}\{Q_{\sigma}(y_t|W_{t-1})\} = \sigma\} < 1, \tag{13}$$

Furthermore, Jeong et al. (2012) utilize the distance measure $J = \{\tau_t E(\tau_t|W_{t-1})f_W(W_{t-1})\}$, where τ_t and $f_z(W_{t-1})$ are the regression error and marginal density function of Z_{t-1}, respectively. The regression error emanates through its basis in the null hypothesis as specified in equation (12), which can only be true if and only if $E[1\{y_t \leq Q_{\sigma}(V_{t-1})|W_{t-1}\} = \sigma$ or, equivalently, $1\{y_t \leq Q_{\sigma}(V_{t-1})\} = \sigma + \tau_t$, where $1\{\cdot\}$ is the indicator function. Thus, Jeong et al. (2012) specify the distance measure, $G \geq 0$, as follows:

$$G = E\left[\{F_{y_t|W_{t-1}}\{Q_{\sigma}(y_t|W_{t-1})\} - \sigma\}^2 f_W(W_{t-1})\right] \tag{14}$$

It is pertinent to note that, we will have a situation where $G = 0$ if and only if the null in equation (12) is true, while we will have $G > 0$ under the alternative hypothesis in equation (13). Also, Jeong et al. (2012) introduced a feasible kernel-based test statistic for J which has the following form:

$$\widehat{G}_T = \frac{1}{T(T-1)s^{2q}}\sum_{t=q+1}^{T}\sum_{r=q+1,r\neq t}^{T}K\left(\frac{W_{t-1} - Z_{s-1}}{s}\right)\widehat{\tau}_t\widehat{\tau}_s, \tag{15}$$

Where $K(\cdot)$ denotes the kernel function with bandwith s. T, q, $\widehat{\tau}_t$ is the sample size, lag-order and estimate of the regression error, respectively. The estimate of the regression error is computed as thus:

$$\widehat{\tau}_t = 1\left\{y_t \leq \widehat{Q_{\sigma}}(Y_{t-1})\right\} - \sigma \tag{16}$$

Also, we further use the nonparametric kernel method to estimate the σth conditional quantile of y_t given V_{t-1} as $\widehat{Q}_{\sigma}(V_{t-1}) = \widehat{F}^{-1}_{y_t|V_{t-1}}(\sigma|V_{t-1})$, where the Nadarya-Watson Kernel estimator is specified as follows

$$\widehat{F}_{y_t|V_{t-1}}(y_t|V_{t-1}) = \frac{\sum_{r=q+1,r\neq t}^{T}N\left(\frac{V_{t-1}-V_{r-1}}{s}\right)1\left(y_r \leq y_t\right)}{\sum_{r=q+1,r\neq t}^{T}N\left(\frac{V_{t-1}-V_{r-1}}{s}\right)} \tag{17}$$

Where $N(\cdot)$ is the kernel function and s is the bandwidth.

By extension, Balcilar et al. (2018) extends the framework of Jeong et al. (2012) by developing a test for the second moment. Thus, they adopt the nonparametric Granger-quantile-causality approach by Nishiyama et al. (2011). To illustrate the causality in higher order moment, we assume

$$y_t = h(V_{t-1}) + \vartheta(U_{t-1})\tau_t, \tag{18}$$

Where τ_t is the white noise process and $h(\cdot)$ and $\vartheta(\cdot)$ equals the unknown functions that satisfy pertinent conditions for stationarity. Although, this specification allows no granger-type causality testing from U_{t-1} *to* y_t, however, it could detect the "predictive power" from U_{t-1} *to* y_t^2 when $\vartheta(\cdot)$ is a general nonlinear function. Thus, the study re-formulate equation (18) to account for the null and alternative hypothesis for causality in variance in equations (19) and (20), respectively.

$$H_0 = P\left\{F_{y_t^2|W_{t-1}}\{Q_\sigma(y_t|W_{t-1})\} = \sigma\right\} = 1, \tag{19}$$

$$H_1 = P\left\{F_{y_t^2|W_{t-1}}\{Q_\sigma(y_t|W_{t-1})\} = \sigma\right\} < 1, \tag{20}$$

This study obtains the feasible test statistic for the testing of the null hypothesis in equation (19), and then replace y_t in equation (15) – (17) with y_t^2 (that is, volatility). With the inclusion of Jeong et al. (2012) approach, the study overcomes the issue that causality in mean implies causality in variance. Specifically, the study interprets the causality in higher-order moments through the use of the following model:

$$y_t = h(U_{t-1}, V_{t-1}) + \tau_t, \tag{21}$$

Thus, we specify the higher order quantile causality as

$$H_0 = P\left\{F_{y_t^k|W_{t-1}}\{Q_\sigma(y_t|W_{t-1})\} = \sigma\right\} = 1, \quad for\ k = 1, 2, \ldots, k, \tag{22}$$

$$H_1 = P\left\{F_{y_t^k|W_{t-1}}\{Q_\sigma(y_t|W_{t-1})\} = \sigma\right\} < 1, \quad for\ k = 1, 2, \ldots, k. \tag{23}$$

Overall, we test that x_t granger causes y_t in σth quantile up to the K-th moment through the use of equation (22) to construct the test statistic of equation (15) for each k. Although, Nishiyama et al. (2011) note that it is not easy to combine different statistics for each $k = 1, 2, \ldots, k$ into one statistic for the joint null in equation (22) which is mutually correlated. However, to circumvent this issue, we adopt a sequential-testing method as described by Nishiyama et al. (2011) with some modifications. To begin with, we test for the nonparametric granger causality in mean (k = 1). Failure to reject the null of k = 1 does not translate into non causality in variance, thus, we construct the tests for k = 2. Finally, we test for the existence of causality-in-mean and variance successively. We determine the lag order using SIC. The bandwidth is selected through the use of least squares cross-validation method. For $K(\cdot)$ and $L(\cdot)$, we utilize the Gaussian kernels.

3.3. Data description

This paper utilizes daily data of oil price, six (6) currency pairs and Economic Policy Uncertainty (EPU) index of the US covering the period between 1/4/2000 and 6/25/2020. The start and end dates are governed based on data availability of US EPU index. The currency pairs considered for the analysis are The Australian Dollar and US Dollar (AUD/USD) (nicknamed 'aussie'), The British Pound and US Dollar (GBP/USD) (nicknamed 'cable'), The Euro and US Dollar (EUR/USD) (nicknamed 'euro'), The US Dollar and Canadian Dollar (USD/CAD) (nicknamed 'loonie'), The US Dollar and Japanese Yen (USD/JPY) (nicknamed 'gropher'), and The US Dollar and Swiss Franc (USD/CHF) (nicknamed 'swissie'). These currency pairs, along with their various combinations (such as EUR/JPY, GBP/JPY and EUR/GBP) have continued to drive all speculative trading in global FX.[2]These currency pairs are the most traded currency pairs in the world that account for more than 95% of all speculative trading in global Foreign exchange (Salisu et al., 2018). The currency pairs data are freely downloadable from the database of Forex Forum Global View (www.global-view.com/forex-trading-tools/forexhistory/). As for oil price, we use the daily price of Brent Crude as it serves as a benchmark price for purchases of oil worldwide, and is used to price two thirds of the world's internationally traded crude oil supplies. The data is derived from the FRED database of the Federal Reserve Bank of St. Louis source from the DataStream database of Thomson Reuters. For the proxy of the EPU, we select the US EPU index constructed by Baker et al. (2016), which are available for download from Baker's personal website, http://www.policyuncertainty.com.

For the basic conditions of stationarity of the variables required for our nonlinear causality to hold, we decided to work with logarithmic returns series of both oil price and the currency pairs (daily natural logarithmic change expressed in percentages) since both series returns were non-stationary following the standard unit root tests.[3] As for the EPU, we work with the logarithmic levels of EPU index which was later found to be stationary following the standard unit root tests.[4]

4. Empirical results

4.1. Preliminary analyses results

It is often a standard practice in most empirical studies that the prerequisite knowledge about the statistical properties of the underlying series be first provided. We keep this norm by revealing brief statistical information about the series. The descriptive statistics reported in Table 1 shows that oil price and all the major exchange rates considered except USD/CHF, GBP/USD and USD/CAD observe positive returns on average over the period under consideration, indicating a likely evidence of positive gains by investors. However, the negative returns recorded by the three highlighted exchange rates do not indicate losses at all times. In fact, among the exchange rates, USD/CHF and GBP/USD whose average returns are negative give the highest positive returns (9.1950% and 8.7246% respectively). In terms of their volatilities, we observe that with the standard deviation value of oil price which is 2.1811, it is more than twice as volatile as the most volatile exchange rate (AUD/USD) whose standard deviation statistic is 0.7893. USD/CAD exhibits the least degree of variability. It is not surprising how that the Jarque-Bera test rejects the null hypothesis of normal distribution for all the series following from the reports of both the skewness and kurtosis statistics. While the skewness values hover between positive and negative for all the returns series, their kurtosis estimates are exceedingly larger than the standard threshold. This suggests the presence of extreme fluctuations in these financial and commodity markets. Interestingly, Albulescu et al. (2019) find evidence largely similar to this study for their commodity currencies and WTI oil price.

Certain implications could be drawn from this brief descriptive analysis. Firstly, the non-normality of the series gives a relative indication of heavy right or left tail and excess kurtosis. This could further suggest the presence of nonlinearity and/or structural shifts along the time paths of the series such that the use of linear or constant parameter models would bring about spurious results (see Adekoya and Oliyide, 2020b; Adekoya et al., 2020). This gives a concrete justification for our choice of quantiles-based causality test. Secondly, the evidence of heavy tails as well as high volatility passes motivates the necessity to examine the relationship in both the conditional-mean and conditional-variance (see Balcilar et al., 2015).

4.2. Spillover results

Since the objective of this study is to examine how economic policy

[2] This statement is ascribed to Boris Schlossberg at: http://www.investopedia.com/articles/forex/06/sevenfxfaqs.asp.

[3] The full details of the preliminary analysis are available on request from the authors.

[4] These results contradict the theoretical argument of measures of uncertainty which are meant to be stationary. However, the statistical results presented here deviate from this which may be as a result of the sample frame used in this study. The full preliminary results are available on request from the authors.

Table 1
Descriptive statistics of returns series.

Exchange rates and oil price	Mean	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque-Bera
EUR/USD	0.0017	3.6763	−2.8181	0.6005	0.0321	4.8744	**783.1127**
USD/JPY	0.0010	3.8320	−4.5829	0.6168	−0.1989	6.8387	**3315.7605**
USD/CHF	−0.0094	9.1950	−15.7117	0.6791	−1.9438	64.5226	**846007.90**
GBP/USD	−0.0053	8.7246	−8.3235	0.6018	−0.5536	25.7768	**115766.36**
USD/CAD	−0.0011	3.2737	−4.3346	0.5438	0.1031	6.5802	**2862.9915**
AUD/USD	0.0007	5.6326	−10.0619	0.7893	−0.7951	14.2468	**28722.872**
Oil price	0.0090	32.3825	−40.7835	2.1811	−2.0643	68.5346	**959919.51**

EUR/USD, USD/JPY, USD/CHF, GBP/USD, USD/CAD, and AUD/USD respectively represent euro to U.S. dollar, U.S. dollar to Japanese Yen, U.S. dollar to Swiss Franc, Pounds to U.S. dollar, U.S. dollar to Canadian dollar and Australian dollar to U.S. dollar. The bolded values of the Jarque-Bera statistic indicate the rejection of the null hypothesis of normal distribution of series.

uncertainty (EPU) drives the connectedness among oil and financial markets, it is expedient to first reveal the dynamic volatility spillover among the markets. The summarized spillover results are shown in Table 2. Uniquely, the table shows the contribution to the variance forecast errors of a particular asset to and from other assets. Then, the net spillover is computed by the difference between the total contributions given by an asset and the total it gives, with a positive value implying that the asset in question is a net transmitter, rather than a net receiver. In other words, if the net spillover value is positive, then the asset transmits more shocks or information to other assets than it receives from them. We observe from Table 2 that the highest receiver of shocks from all the remaining assets combined is USD/CAD with a value of 36.10, followed by AUD/USD whose value is 27.20. Although the shocks received by the oil market from all the major currencies appear small (2.70), but it is still fair compared to USD/CHF that is not responsive to shocks from even its co-currencies. Interestingly, USD/CAD and AUD/USD are still among the highest transmitters of shocks, in addition to EUR/USD and USD/CHF. We could link the likely reason for the high spillovers of USD/CAD and AUD/CAD to the significant role of Canada and Australia in the global supply of the most globally traded commodity, i.e. crude oil. The high degree of integration of the G-7 countries is another factor that drives high transmission of shocks among them.

Furthermore, it is seen that among the currency pairs, EUR/USD and USD/CAD receive more shocks than they give, thus leading to their negative net spillover values of −5.10 and −17.30 respectively. Oil is also a net receiver of shocks (−1.5) being inconsistent with Albulescu et al. (2019) and Sing et al. (2018). The reason is obviously due to differences in the currency pairs considered. However, oil seems to connect stronger with USD/CAD and AUD/USD (see Appendix Table A) than other currency pairs, again confirming the role of Canada and Australia in the global oil market, and reflecting the U.S. dollar as the major currency for pricing crude oil. Thus, this is probably the reason oil is a net receiver of shocks in line with the theoretical proposition (exchange rate channel) that discloses the possibility of oil price to be driven by exchange rates (see Akram, 2009).

Concluding this section on volatility spillovers in the financial and oil markets, it is evident that there is established transmission of shocks. Although the degree and direction of shocks transmission vary, just like oil seems to be closely knitted to USD/CAD and AUD/USD, and USD/CHF being a weak receiver of shocks, the overall performance still suggests significant connectedness among the markets. Also, three factors seem to be obvious for the transmission of shocks in the markets. The first is the degree of integration among the G-7 countries whose exchange rates are the most traded and being considered in this study. The integration results in high transmission of shocks among them. The second factor is the role of Canada and Australia in the global supply of crude oil. This, coupled with the fact that oil is denominated in the U.S. dollar, leads the strong volatility spillover connection between oil and each of USD/CAD and AUD/USD. Thirdly, the Australian dollar, as revealed by Albulescu et al. (2019) is often associated with high rates of interest compared to other currencies, thus making it to enjoy wide use as an investment currency when making trade strategies. In other words, investors would shun currencies with lower interest rates in favour of the ones with high interest rates. Again, U.S. and Canada are closely related in terms of economic cooperation and trade agreements, and the former is one of the largest importers of the crude oil of the latter. Therefore, the combination of all these factors may be responsible for the connectedness between the currency and oil markets.

Linking these spillover transmissions to uncertainty in economic policy, the U.S. is an indispensable factor driving the global financial cycle through her various monetary policies pronounced by the Federal Reserves. Thus, the connectedness across the markets may be driven by policy uncertainty having first affected global liquidity and investors' decisions. This implies that uncertainty in economic policy that drives fluctuations in exchange rate and/or oil price may induce volatility shocks to the other markets. The possibility of economic policy uncertainty to affect the volatility spillover between the currency and oil markets is therefore the main thrust of this paper and focused on in the next section.

Table 2
Spillover results.

Exchange rates and oil price	Total contribution				Net spillover (b-a)
	From others (a)	To others (b)	To self (c)	Including own (b + c)	
EUR/USD	26.80	21.70	73.40	95.10	−5.10
USD/JPY	24.40	31.10	75.70	106.80	6.70
USD/CHF	0.00	0.10	100.00	100.10	0.10
GBP/USD	6.90	8.60	93.10	101.70	1.70
USD/CAD	36.10	18.80	63.80	82.60	−17.30
AUD/USD	27.20	43.60	72.80	116.2	16.40
Oil price	2.70	0.20	97.30	97.50	−1.5

EUR/USD, USD/JPY, USD/CHF, GBP/USD, USD/CAD, and AUD/USD respectively represent euro to U.S. dollar, U.S. dollar to Japanese Yen, U.S. dollar to Swiss Franc, Pounds to U.S. dollar, U.S. dollar to Canadian dollar and Australian dollar to U.S. dollar.

4.3. Causality test results

Following the observed evidence of volatility transmissions between the foreign exchange and oil markets, we proceed to the examination of the causal effect of economic policy uncertainty on the established connectedness in the markets. Doing this requires that we test the null hypothesis that economic policy uncertainty does not cause the total spillover and the net spillover for each currency pair and oil price under consideration. We initially examine the causal effect from the perspective of linear relationship with the results reported in Table 3. It is observed that the effect of economic policy uncertainty is found to be insignificant in most cases. The three exemptions are the total spillover, net spillovers for USD/JPY and oil price, which are all significant at 10%.

However, we perceive that this weak performance of the policy-

Table 3
Linear causality test results.

Null hypothesis	F-statistics	Prob. value
EPU does not Granger-cause Total spillover	2.6845*	0.0684
EPU does not Granger-cause Net spillover for EUR/USD	0.2946	0.7448
EPU does not Granger-cause Net spillover for USD/JPY	2.3748*	0.0932
EPU does not Granger-cause Net spillover for USD/CHF	0.7831	0.4571
EPU does not Granger-cause Net spillover for GBP/USD	0.5747	0.5629
EPU does not Granger-cause Net spillover for USD/CAD	0.4299	0.6506
EPU does not Granger-cause Net spillover for AUD/USD	0.7337	0.4802
EPU does not Granger-cause Net spillover for oil	2.4386*	0.0874

* denotes significance at 10% critical level.

based uncertainty in affecting the connectedness in the markets is due to likely presence of nonlinearity in the series. At the most basic level, the presence of heavy tails, excess kurtosis and non-normality are pointers to the possibility of nonlinear nature of the series. However, we conduct a more formal test (BDS test)[5] developed by Brock et al. (1996) to establish the presence of nonlinearity in the series. The BDS test results (see Table 4) show strong evidence of nonlinear relationship between economic policy uncertainty and all the spillover series as the null hypothesis of serial dependence is resoundingly rejected across all dimensions. An implication of these results is that there is more to what the linear Granger-causality test reveals, it likely could have suffered from the problem of misspecification.

Having detected strong evidence of nonlinear relationship in the relationship between economic policy uncertainty and the connectedness among the assets, we turn to the results of the quantiles-based causality test. In order not to miss out from any important information, the quantiles-based causality analysis is conducted in both the conditional-mean and conditional-variance. It is also important to point out that although some studies favour graphical presentation of the results (see, for instance, Balcilar, et al., 2018; Balcilar et al., 2015), this study considers the tabular presentation in order to reveal the depth of the nonlinear relationship at all the conventional significance levels, i.e. 1%, 5% and 10%. The limitation of the graphical presentation is that, significance line is drawn for only 5% significance level, thus making significance at 10% to be missed. Notwithstanding, we still present the quantiles-based graphical results in Appendix Figs. 1 and 2. In sharp contrast to the results of the linear causality test, Tables 5 and 6 which reports the nonlinear results for the conditional-mean and conditional-variance show strong evidence of the rejection of the null hypothesis of no Granger-causality. The causal evidence is mostly significant at the lower quantiles, with some reaching the median region. However, the causality becomes weak at the extreme quantiles, suggesting that the effect of economic policy on the connectedness among the markets is sensitive to the degree of the performance of the foreign exchange and oil markets. When the markets are performing at their peak, economic policy seems to be weak in affecting their interactions.

Table 4
BDS test of independence results.

Spillovers	2	3	4	5	6
Total spillover	0.0175***	0.0316***	0.0385***	0.0395***	0.0373***
Net spillover for EUR/USD	0.0178***	0.0339***	0.0417***	0.0436***	0.0425***
Net spillover for USD/JPY	0.0201***	0.0354***	0.0424***	0.0447***	0.0437***
Net spillover for USD/CHF	0.0180***	0.0339***	0.0412***	0.0430***	0.0421***
Net spillover for GBP/USD	0.0161***	0.0298***	0.0383***	0.0403***	0.0386***
Net spillover for USD/CAD	0.0163***	0.0309***	0.0399***	0.0431***	0.0431***
Net spillover for AUD/USD	0.0150***	0.0298***	0.0362***	0.0380***	0.0368***
Net spillover for oil	0.0229***	0.0410***	0.0501***	0.0530***	0.0512***

The reported values are the BDS statistics. *** indicates significance at 1% critical level.

In summary, our results reveal three facts: (i) there is strong connectedness between the foreign exchange and oil markets; (ii) the connectedness among these markets are primarily driven by economic policy uncertainty, although the causal effect seems to be stronger around the lower and middle quantiles in most cases; (iii) nonlinearity is a very crucial factor to be put into consideration when examining the role of economic policy uncertainty in affecting the interactions between foreign exchange and oil markets. In these scenarios, our results confirm those of Albulescu et al. (2019) who reveal that commodity currencies and oil market are dynamically connected, and policy-induced uncertainty is significant in driving this interaction. Fortunately, their nonlinear causality techniques are different from the one explored in this study, but yet, the results do not differ. This indicates that the impact of economic policy uncertainty on the interactions among financial and commodity markets is stable and strong. On the other hand, although their study is mainly on the impact of economic policy uncertainty on stock returns, Balcilar et al. (2015) use similar technique as this study (quantiles-based causality test) to prove that the jettisoning nonlinearity in the predictability of financial variables (and their connectedness) with economic policy uncertainty may lead to unreliable results.

5. Conclusion

Following the recent development and computation of the index of economic policy uncertainty by Baker et al. (2016), an ongoing move in the literature relates to how international markets are connected by this new measure of uncertainty. The validity of this recent empirical drive also has to do with the high degree of integration being observed in these markets, thus leaving a puzzle as to what could be the likely cause. Could uncertainty induced by economic policy be responsible? In sharp contrast to most past empirical studies that merely examined the impact of economic policy uncertainty on the performance of financial markets in terms of their volatility and returns (see for instance Liu et al., 2017; Kang et al., 2017; You et al., 2017; Arouri et al., 2016; etc.), this study focus on how the U.S. economic policy uncertainty affect connectedness among oil and the globally most traded currency pairs. The significant role of the U.S. in driving global financial cycle through capital flows and movements in the prices of assets across financial and commodity markets make us consider the uncertainty resulting from her economic policy. Thus, our analyses are in two folds, with the first being the evaluation of volatility spillover among the considered assets (oil and the exchange rates). The second entails the assessment of the effect of the economic policy uncertainty on the total spillover and the net spillover series of each asset through the use of the quantiles-based causality test which handles inherent nonlinearity, structural breaks and regime changes in the series.

Expectedly, our findings show that there is a significant

[5] The BDS test is carried out on the residuals of each spillover series (overall and net) in the VAR(1) model that includes the EPU. In other words, the EPU index and each of the spillover series are captured in a VAR(1) model, after which the residuals of the latter are generated. Then, the BDS test is conducted on the generated residuals (see Balcilar et al., 2015 for a similar approach).

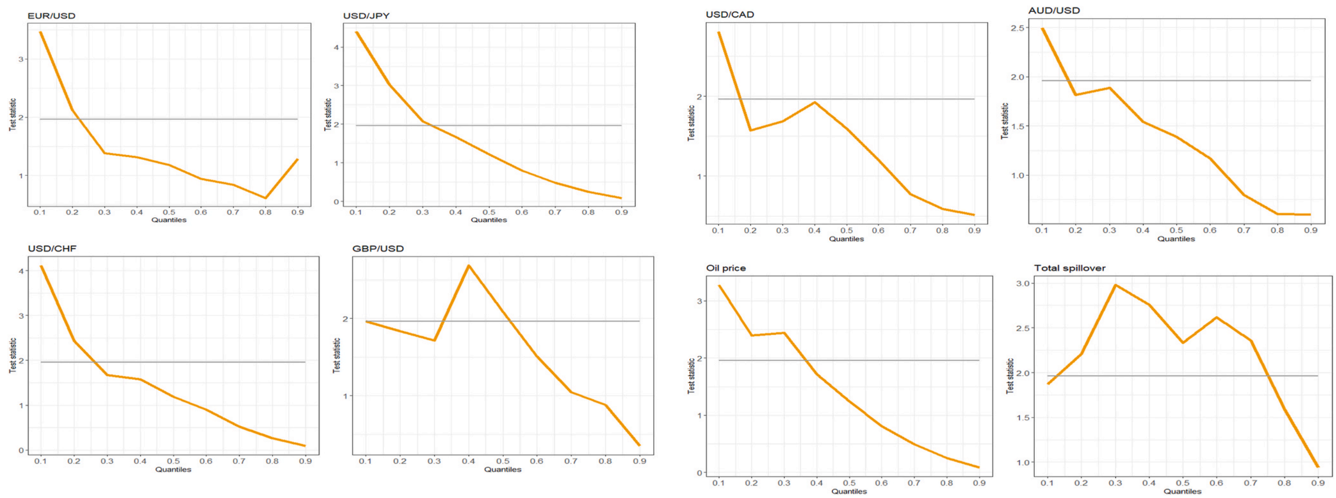

Fig. 1. Non-linear causality in mean for net spillovers.

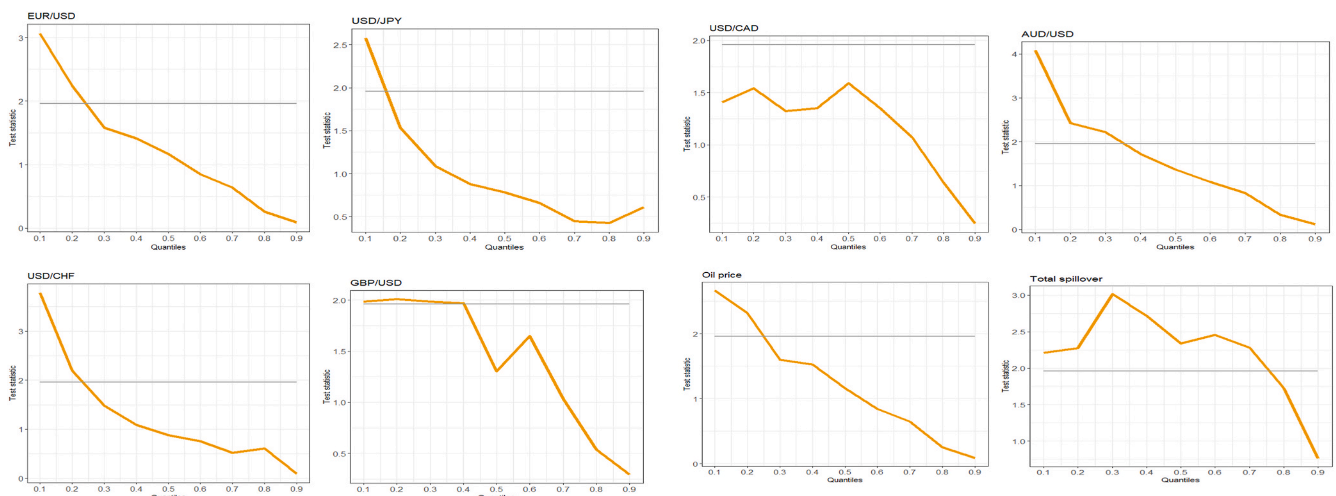

Fig. 2. Non-linear causality in variance for net spillover.

Table 5
Quantile-based (nonlinear) causality test in conditional mean results.

Quantiles	Null hypothesis: EPU does not cause:							
	Total	EUR/USD	USD/JPY	USD/CHF	GBP/USD	USD/CAD	AUD/USD	Oil price
0.1	1.8713*	3.4716***	3.3027***	4.1172***	1.9591*	2.8091***	2.4981**	3.2796***
0.2	2.2077**	2.1173**	1.9816**	2.4350**	1.8330*	1.5729	1.8146*	2.3962**
0.3	2.9792***	1.3841	1.4443	1.6680*	1.7159*	1.6879*	1.8874*	2.4423**
0.4	2.7578***	1.3174	1.0954	1.5759	2.6863***	1.9240*	1.5424	1.7186*
0.5	2.3346**	1.1762	0.8866	1.1897*	2.0811**	1.5953	1.3895	1.2431
0.6	2.6183***	0.9419	0.8596	0.9007	1.5072	1.2036	1.1705	0.8128
0.7	2.3584**	0.8411	0.7844	0.5211	1.0445	0.7767	0.7980	0.4905
0.8	1.5891	0.6106	0.6518	0.2680	0.8768	0.5916	0.6029	0.2516
0.9	0.9391	1.2883	1.3101	0.0914	0.3480	0.5132	0.5977	0.0853

Values reported are t-statistics. ***, ** and * respectively denote significance at 1%, 5% and 10% critical levels.

connectedness among the assets, with EUR/USD, USD/CAD and oil being net receivers of shocks, and others net transmitters. With this, we are well positioned to conduct the causality test. However, we first conduct the linear Granger-causality test with the results revealing weak evidence of causal effect of economic policy uncertainty on the volatility connectedness measures. This we believe is as a result of the nonlinearity features of the series, which is further confirmed by the BDS test. The quantile-based nonlinear results show that, for both conditional mean and conditional variance, the economic policy uncertainty significantly affects the net spillover of each asset, mostly at the lower and middle quantiles. In essence, we find, in line with the global financial cycle channel, that risk transmissions across the oil and most globally traded currency pairs are driven by uncertainty induced by the U.S. economic policy.

Accordingly, these findings present opportunities for viable policy implications for both investors/portfolio managers and policy

Table 6
Quantile-based (nonlinear) causality test in conditional variance results.

Quantiles	Null hypothesis: EPU does not cause:							
	Total	EUR/USD	USD/JPY	USD/CHF	GBP/USD	USD/CAD	AUD/USD	Oil price
0.1	2.2116**	3.0664***	3.2834***	3.7829***	1.9864**	1.4104	4.0854***	2.6653***
0.2	2.2734**	2.2400**	1.8956*	2.1963**	2.0097**	1.5439	2.4269**	2.3182**
0.3	3.0161***	1.5827	1.2734	1.4817	1.9856**	1.3255	2.2216**	1.5990
0.4	2.7178***	1.4089	1.1985	1.0882	1.9685**	1.3535	1.7237*	1.5225
0.5	2.3363**	1.1685	1.0712	0.8783	1.3048	1.5892	1.3629	1.1580
0.6	2.4536**	0.8464	0.7565	0.7530	1.6493*	1.3517	1.0819	0.8430
0.7	2.2824**	0.6371	0.5647	0.5211	1.0311	1.0717	0.8292	0.6450
0.8	1.7253*	0.2608	0.2769	0.6064	0.5358	0.6386	0.3382	0.2516
0.9	0.7604	0.0892	0.0950	0.0914	0.2933	0.2459	0.1168	0.0853

Values reported are t-statistics. ***, ** and * respectively denote significance at 1%, 5% and 10% critical levels.

implications. For the former, the weak connectedness of oil price and the USD/CHF and GBP/USD exchange rates with other assets in the system suggest that these assets can assets can serve as safe haven during periods of extreme market stress. This is particularly stronger for the USD/CHF which receives no shocks from other assets. Turning to the latter, policy makers need to introduce policies that safeguard the risks exposures of both the crude oil and foreign exchange markets. This is because, for the crude oil market, risks exposure could result into significant fluctuations in oil price which would eventually affect both the oil exporters and oil importers adversely, depending on the direction of the movement in the oil price. On the other hand, with the currency pairs being the most globally traded, their undue exposure to risks can lead to significant fluctuations and consequently impose harmful effects for multinational corporations, investors and macroeconomic performance. Investments in foreign assets denominated in these currencies can result into significant losses for investors and the multinational firms, while policy makers can find it difficult to implement appropriate macroeconomic policies required to optimally manage the economy's finances to enhance economic growth and development and other macroeconomic objectives. Finally, policy makers must closely monitor movement in the uncertainty of the U.S. economic policies as it is a major driver of the connectedness between the crude oil and exchange rates.

Author statement

The authors of this article certify that we have seen and approved the final version of the manuscript being submitted. It is our original work, hasn't received prior publication and isn't under consideration for publication elsewhere. There are no conflicts of interests among the authors.

Appendix

Table A1
Full spillover results

Exchange rates and oil price		From							Total spillover from others	Net spillover
		Exchange rates						Oil price		
		EUR/USD	USD/JPY	USD/CHF	GBP/USD	USD/CAD	AUD/USD			
To	EUR/USD	73.40	6.20	0.10	4.30	7.80	8.40	0.00	26.80	−5.10
	USD/JPY	6.70	75.70	0.00	2.60	2.10	13.00	0.00	24.40	6.70
	USD/CHF	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.10
	GBP/USD	1.90	2.60	0.00	93.10	1.30	1.10	0.00	6.90	1.70
	USD/CAD	7.30	6.80	0.00	0.90	63.80	21.00	0.10	36.10	−17.30
	AUD/USD	5.80	13.10	0.00	0.80	7.40	72.80	0.10	27.20	16.40
	Oil price	0.00	2.40	0.00	0.00	0.20	0.10	97.30	2.70	−1.5
Total spillover to others		21.70	31.10	0.10	8.60	18.80	43.60	0.20	124.10	

References

Adekoya, O.B., Oliyide, J.A., 2020. How COVID-19 drives connectedness among commodity and financial markets: evidence from TVP-VAR and causality-in-quantiles techniques. Resour. Pol. https://doi.org/10.1016/j.resourpol.2020.101898.

Adekoya, O.B., Oliyide, J.A., Oduyemi, G.O., 2020. How COVID-19 upturns the hedging potentials of gold against oil and stock markets risk: nonlinear evidence through threshold regression and Markov regime switching models. Resour. Pol. https://doi.org/10.1016/j.resourpol.2020.101926.

Abid, A., 2020. Economic policy uncertainty and exchange rates in emerging markets: short and long run evidence. Finance Res. Lett. 37.

Ahmad, W., Prakash, R., Uddin, G.S., Chahal, R.J.K., Rahman, M.L., Dutta, A., 2020. On the intraday dynamics of oil price and exchange rate: what can we learn from China and India? Energy Econ. 91.

Akram, Q.F., 2004. Oil prices and exchange rates. Norwegian evidence. Econ. J. 7, 476–505.

Akram, Q.F., 2009. Commodity prices, interest rates and the dollar. Energy Econ. 31, 838–851.

Albulescu, C.T., Demirer, R., Raheem, I.D., Tiwari, A.K., 2019. Does the U.S. economic policy uncertainty connect financial markets? Evidence from oil and commodity currencies. Energy Econ. 83, 375–388.

Al-Yahyaee, K.H., Shahzad, S.J.H., Mensi, W., 2020. Tail dependence structures between economic policy uncertainty and foreign exchange markets: nonparametric quantiles methods. International Economics 161 (c), 66–82.

Amano, R., Van Norden, S., 1998a. Exchange rates and oil prices. Rev. Int. Econ. 6, 683–694.

Amano, R., Van Norden, S., 1998b. Oil prices and the rise and fall of the US real exchange rate. J. Int. Money Finance 17, 299–316.

Arouri, M., Estay, C., Rault, C., Roubaud, D., 2016. Economic policy uncertainty and stock markets: long-run evidence from the U.S. Financ. Res. Lett. 18, 136–141.

Atems, B., Kapper, D., Lam, E., 2015. Do exchange rates respond asymmetrically to Shocks in the Crude oil market? Energy Econ. 49 (c), 227–238.

Badshah, I., Demirer, R., Suleman, T., 2018. The effect of economic policy uncertainty on stock-commodity correlations and its implications on optimal hedging. Work. Pap. https://doi.org/10.2139/ssrn.3240962. Available at: SSRN 3240962.

Baker, S., Bloom, N., Davis, S., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131, 1593–1636.

Balcilar, M., Gupta, R., Kyei, C., 2015. South African Stock Returns Predictability Using Domestic and Global Economic Policy Uncertainty: Evidence from a Nonparametric Causality-In-Quantiles Approach. University of Pretoria Department of Economics Working Paper Series. Working Paper: 2015-70.

Balcilar, M., Gupta, R., Pierdzioch, C., Wohar, M.E., 2018. Terror attacks and stock market fluctuations: evidence based on a nonparametric causality-in-quantiles test for the G7 countries. Eur. J. Finance 24 (4), 333–346.

Bartsch, Z., 2019. Economic policy uncertainty and dollar-pound exchange rate return volatility. J. Int. Money Finance 98.

Basher, S.A., Haug, A.A., Sadorsky, P., 2012. Oil prices, exchange rates and emerging stock markets. Energy Econ. 34, 227–*240*.

Basher, S.A., Haug, A.A., Sadorsky, P., 2016. The impact of oil shocks on exchange rates: a Markov-switching approach. Energy Econ. 54, 11–23.

Beckmann, J., Czudaj, R., 2017. Exchange rate expectations and economic policy uncertainty. Eur. J. Polit. Econ. 47 (c), 148–162.

Beckmann, J., Czudaj, R., 2013. Oil prices and effective dollar exchange rates. Int. Rev. Econ. Finance 27, 621–636.

Beckmann, J., Czudaj, R.L., Arora, V., 2020. The relationship between oil prices and exchange rates: revisiting theory and evidence. Energy Econ. https://doi.org/10.1016/j.eneco.2020.104772.

Benassy-Quere, A., Mignon, V., Penot, A., 2007. China and the relationship between the oil price and the dollar. Energy Pol. 35, 5795–5805.

Bloomberg, S.B., Harris, E.S., 1995. The commodity-consumer price connection: fact or fable? Federal Reserve Board of New York. Economic Policy Review 21–38.

Brock, W., Dechert, D., Scheinkman, J., LeBaron, B., 1996. A test for independence based on the correlation dimension. Econom. Rev. 15, 197–235.

Buetzer, S., Habib, M.M., Stracca, L., 2016. Global exchange rate fluctuations: do oil shocks matter? IMF Econ. Rev. 64, 443–470.

Chen, L., Du, Z., Hu, Z., 2020. Impact of economic policy uncertainty on exchange rtae volatility of China. Finance Res. Lett. 32.

Chen, S.-S., Chen, H.-C., 2007. Oil price and real exchange rates. Energy Econ. 29, 390–404.

Chkir, I., Guesmi, K., Brayek, A.B., Naoui, K., 2020. Modelling the nonlinear relationship between oil prices, stock markets, and exchange rates in oil-exporting and oil-importing countries. Res. Int. Bus. Finance 54.

Converse, N., 2017. Uncertainty, capital flows, and maturity mismatch. J. Int. Money Finance 88, 260–275.

Coudert, V., Mignon, V., Penot, A., 2008. Oil price and the dollar. Energy Stud. Rev. 15, 45–58.

Dai, X., Wang, Q., Zha, D., Zhou, D., 2020. Multi-scale dependence structure and risk contagion between oil, gold, and US exchange rate: a wavelet-based vine-copula approach. Energy Econ. 88 (c).

Demirer, R., Ferrer, R., Shahzad, S.J.H., 2020. Oil price shocks, global financial markets and their connectedness. Energy Econ. 88.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28, 57–66.

Fan, Y., Xu, J.-H., 2011. What has driven prices since 2000? A structural change perspective. Energy Econ. 33, 1082–1094.

Fang, L., Chen, B., Yu, H., Xiong, C., 2018. The effect of economic policy uncertainty on the long-run correlation between crude oil and the U.S. stock markets. Finance Res. Lett. 24, 56–63.

Gomes, F.J., Kotlikoff, L.J., Viceira, L.M., 2012. The excess burden of government indecision. Tax Pol. Econ. 26, 125–164.

Hailemariam, A., Smyth, R., Zhang, X., 2019. Oil prices and economic policy uncertainty: evidence from a nonparametric pane; data model. Energy Econ. 83, 40–51.

Handley, K., Limao, N., 2015. Trade and investment under policy uncertainty: theory and firm evidence. Am. Econ. Pol. 7, 189–222.

Huang, S., An, H., Lucey, B., 2020. How do dynamic responses of exchange rates to oil price shocks co-move? From a time-varying perspective. Energy Econ. 86 (c).

Huang, Y., Guo, F., 2007. The role of oil price shocks on China's real exchange rate. China Econ. Rev. 18 (4), 403–416.

Huynh, T.L.D., Nasir, M.A., Nguyen, D.K., 2020. Spillovers and connectedness in foreign exchange markets: the role of policy uncertainty. The Quarterly Review of Economics and Finance. https://doi.org/10.1016/j.qref.2020.09.001.

Jain, A., Biswal, P.C., 2016. Dynamic linkages among oil price, gold price, exchange rate and stock market in India. Resour. Pol. 49, 179–185.

Jeong, K., Härdle, W.K., Song, S., 2012. A consistent nonparametric test for causality in quantile. Econ. Theor. 28, 861–887.

Jiang, Y., Feng, Q., Mo, B., Nie, H., 2020. Visiting the effects of oil price shocks on exchange rates: quantile-on-quantile and Causality-in-quantiles approaches. N. Am. J. Econ. Finance 52.

Kang, W., Perez de Gracia, F., Ratti, R.A., 2017. Oil price shocks, policy uncertainty, and stock returns of oil and gas corporations. J. Int. Money Finance 70, 344–359.

Kido, Y., 2016. On the link between the US economic policy uncertainty and exchange rates. Econ. Lett. 144, 49–52.

Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in non-linear multivariate models. J. Econom. 74, 119–147.

Krol, R., 2014. Economic policy uncertainty and exchange rate volatility. Int. Finance 17 (2), 241–256.

Krugman, P., 1983. Oil and the dollar. In: Jagdeeps, B., Buldfordh, P. (Eds.), Economic Interdependence and Flexible Exchange Rates. MIT Press, Cambridge, MA.

Liu, Z., Ye, Y., Ma, F., 2017. Can economic policy uncertainty help to forecast the volatility: a multifractal perspective. Physica A 482, 181–188.

Malik, F., Umar, Z., 2019. Dynamic connectedness of oil price shocks and exchange rates. Energy Econ. 84 (c).

Mensi, W., Hammoudeh, S., Shahzad, S.J.H., Al-Yahyaee, K.H., Shahbaz, M., 2017. Oil and foreign exchange market tail dependence and risk spillovers for MENA, emerging and developed countries: VMD decomposition based copulas. Energy Econ. 67, 476–495.

Nishiyama, Y., Hitomi, K., Kawasaki, Y., Jeong, K., 2011. A consistent nonparametric test for nonlinear causality - specification in time series regression. J. Econom. 165, 112–127.

Pastor, L., Veronesi, P., 2012. Uncertainty about government policy and stock prices. J. Finance 67, 1219–1264.

Pesaran, M.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ Lett 1998 58, 17–29.

Salisu, A.A., Oyewole, O.J., Fasanya, I.O., 2018. Modelling return and volatility spillovers in global foreign exchange markets. J. Inf. Optim. Sci. 39 (7), 1417–1448.

Singh, Vipul Kumar, Nishant, Shreyank, Kumar, Pawan, 2018. Dynamic and directional network connectedness of crude oil and currencies: evidence from implied volatility. Energy Econ., Elsevier 76 (C), 48–63.

Tiwari, A.K., Albulescu, C.T., 2016. Oil price and exchange rate in India: fresh evidence from continuous wavelet approach and asymmetric, multi-horizon Granger-causality tests. Appl. Energy 179, 272–283.

Tiwari, A.K., Trabelsi, N., Alqahtani, F., Bachmeier, L., 2019. Modelling systemic risk and dependence structure between the prices of crude oil and exchange rates in BRICS economies: evidence using quantile coherency and NGCoVaR approaches. Energy Econ. 81 (c), 1011–1028.

Wen, T., Wang, G.-J., 2020. Volatility connectedness in global foreign exchange markets. J. Multinatl. Financ. Manag. 54.

Xu, Y., Han, L., Wan, L., Yin, L., 2019. Dynamic link between oil prices and exchange rates: a nonlinear approach. Energy Econ. 84 (c).

You, W., Guo, Y., Zhu, H., Tang, Y., 2017. Oil price shocks, economic policy uncertainty and industry stock returns in China: asymmetric effects with quantile regression. Energy Econ 68 (2017), 1–18.

Yang, L., 2019. Connectedness of economic policy uncertainty and oil price shocks in a time domain perspective. Energy Econ. 80 (c), 219–233.

Youssef, M., Mokni, K., 2020. Modeling the relationship between oil and USD exchange rates: evidence from a regime-switching-quantile regression approach. J. Multinatl. Financ. Manag. 55 (c).

Zhang, Y., 2013. The link between the price of oil and the value of the US dollar. Int. J. Energy Econ. Pol. 3 (4), 341–351.

Zhang, Y.J., Fan, Y., Tsai, H.T., Wei, Y.M., 2008. Spillover effect of US dollar exchange rate on oil prices. J. Pol. Model. 30, 973–991.

Zhou, Z., Fu, Z., Jiang, Y., Zeng, X., Lin, L., 2020. Can economic policy uncertainty predict exchange rate volatility? New evidence from GARCH-MIDAS model. Finance Res. Lett. 34.

Further reading

Alam, M.S., Shahzad, S.J.H., Ferrer, R., 2019. Causal flows between oil and forex markets using high-frequency data: asymmetries from good and bad volatility. Energy Econ. https://doi.org/10.1016/j.eneco.2019.104513.

Baghestani, H., Chazi, A., Khallaf, A., 2019. A directional analysis of oil prices and real exchange rates in BRIC countries. Res. Int. Bus. Finance. https://doi.org/10.1016/j.ribaf.2019.06.013.

Bai, S., Koong, K.S., 2017. Oil prices, Stock returns and exchange rates: empirical evidence from China and the United States. N. Am. J. Econ. Finance. https://doi.org/10.1016/j.najef.2017.10.013.

Cifarelli, G., Paladino, G., 2010. Oil price dynamics and speculation: a multivariate financial approach. Energy Econ. 32, 363–372.