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How does the economic policy uncertainty factor in the dynamics of oil price uncertainty?

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Abstract

This paper investigates the endogenous relationship between economic policy uncertainty (EPU) and oil price uncertainty within a framework of a supply-demand shock identification model. Our empirical strategy relies on a structural vector autoregressive approach. Our major findings reveal a significant increase in oil price uncertainty from a positive EPU shock. We also demonstrate that a negative oil supply shock contributes to raising oil price uncertainty, whereas a positive demand shock causes oil price uncertainty to decline.

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1. Introduction

The global economic engine is sputtering as it struggles to move forward under the heavy burden of a war in Ukraine, mass supply chain disruptions, questions about energy and food security, the consequences of the COVID-19 pandemic and the highest inflation in 40 years. In this atmosphere of high uncertainty, the oil market has undergone major distortions that require policymakers to react, involving changes in government policy direction. Since Baker et al. (2016) developed an index of economic policy uncertainty (EPU), bulk of empirical studies investigate the interrelations between the EPU, macroeconomic aggregates, financial and commodity markets. Indeed, the EPU refers to risk of changes in existing policies that define parameters of the decision making process of economic agents such as consumers, investors, firms and banks. Thus, high policy uncertainty affects the economy and delays agents' decisions on spending, investment or employment. In the crude oil market, this situation may operate through demand and supply channels and lasts until uncertainty, per se, is completely eliminated.

Commodity markets are closely linked to financial markets that fluctuate with policy challenges and investors' behaviors. Most of the literature has widely explored the exogenous effect of the EPU on stock market returns (Pástor and Veronesi, 2013). Some of them highlight the negative effect of the EPU on stock market returns which contributes to increase the stock market volatility (Arouri et al., 2016; Liu et al., 2017). Other findings indicate the existence of a linear and non-linear causal relationship between the EPU, oil and currency markets after the gold financial crisis (Albulescu et al., 2019). At the world level, Antonakakis et al. (2014) highlight that the EPU affects the global oil price through spillover effect across countries, including the United States (US) and China. Likewise, Yin and Han (2014) and Ahmed and Sarkodie (2021) emphasize the time-varying relationship between the EPU and commodity markets to predict volatility in commodity returns. Reciprocally, the literature also provides insights on the role of commodity prices in predicting the pattern of the EPU (Wang et al., 2015). For instance, Lin and Bai (2021) reveal that oil prices and EPU nexus matter for both oil-exporting and importing countries. Their results report that oil price shocks have a larger effect on the oil-exporters' EPU index than on that of oil-importers. In contrast, the causal link between the EPU and commodity prices is not always proven. Thus, some find a non significant effect of the EPU on most commodity markets returns (Andreasson et al., 2016; Reboredo and Uddin, 2016). In the same vein, Li et al. (2016) evoke no evidence of a significant relationship with stock returns in China and India markets.

This paper considers a bi-causal relationship between EPU and oil price uncertainty, amid supply and demand factors, using a structural vector autoregressive (SVAR) model. However, a great interest is given to the impact of the EPU on oil price uncertainty. Examining uncertainty dynamics in the global crude oil market is empirically challenging because it requires the quantification of an unobservable concept. Scholars interested in assessing oil price uncertainty have historically relied on proxies, such as generalised autoregressive conditional heteroscedasticity (GARCH) or stochastic volatility (Elder and Serletis, 2010; Jo, 2014). However, these popular approaches do not accurately address the fact that what matters for economic decision-making is not whether particular economic variables have become more or less dispersed, but whether an overall economy has become more or less predictable (Diebold and Kilian, 2001; Jurado et al., 2015). As a result, uncertainty should not be defined in terms of volatility, but instead in terms of predictability. For this purpose, following Jurado et al. (2015), we develop a time-varying predictability-based oil price uncertainty measure. Thereby, this paper contributes to the literature insofar as we endogenously investigate the role of the EPU in the dynamics of oil price uncertainty. In other words, the novelty lies in exploring a new insight for identifying shocks in the crude oil market through reasoning in terms of uncertainty, while considering the EPU as a key factor, among others.

Our empirical analysis demonstrates that a positive shock in EPU significantly increases oil price uncertainty; thus, uncertainty regarding policymakers' actions favours a self-perpetuating oil price uncertainty. The uncertainty of governments' economic decisions leads economic agents to engage in speculative and precautionary activities which drive oil price instability. Likewise, a negative shock to oil supply favours a significant rise in oil price uncertainty. This result is supported by the finding of Kang et al. (2017) indicating that oil supply disruptions in the US are associated with increases in EPU, which results in an oil price-induced rise in overall Consumer Price Index (CPI). Conversely, a positive aggregate demand shock has a shrinking effect on oil price uncertainty, likely due to a more optimistic perception of the macroeconomic environment.

The remainder of the paper is organised as follows. Section 2 presents the methodology. Sections 3 and 4 report data and results discussion, respectively. Finally, section 5 concludes the paper.

2. Methodology

This section is subdivided into two parts, namely the construction of oil price uncertainty, then the presentation of the SVAR model.

2.1. Measuring oil price uncertainty

The construction of oil price uncertainty is developed from monthly inflation-adjusted oil price obtained as the nominal price over the US CPI (also called real oil price), and references the predictability-based approach of Jurado et al. (2015). The computation process engages three steps:

(i) A fixed rolling window estimation of a seasonal autoregressive integrated moving average (SARIMA) model on the oil price. Let's consider op_t denoting the time series of the real oil price. To help tackle non-stationary issue of the real oil price, we introduce an integration operator Δ^d where d is the order of differencing used. The general form of a SARIMA $(p, d, q)(P, D, Q)$ model is given as follows:

$$\Phi(L)^p \phi(L^s)^P \Delta^d \Delta_s^D op_t = \Theta(L)^q \theta(L^s)^Q \Delta^d \Delta_s^D \epsilon_t \tag{1}$$

D takes on the similar meaning to d, but instead applies to seasonal lags of order s. Therefore, Δ_s^D is the differencing operator for seasonal lags in the times series of the oil price. $\Phi(L)^p$ and $\Theta(L)^q$ represent the including-constants lag polynomials of the non-seasonal AR and MA part of the model, respectively. By analogy, $\phi(L^s)^P$ and $\theta(L^s)^Q$ correspond to including-constants lag polynomials of the AR and MA seasonal part of the model.[1]

(ii) The previous step allows, for each rolling window estimation, to extract a one-step ahead out-of-sample forecast $E(op_{t+1}|I_t)$ defined as the expectation of the oil price with respect to the information available at time t. Also, the associated forecast error w_{t+1} is given by:

$$w_{t+1} = op_{t+1} - E(op_{t+1}|I_t) \tag{2}$$

[1]The model determines the optimal order of the SARIMA model (according to Akaike (1974) and Schwarz (1978) information criteria) to perform valuable forecasts. In our case, we choose a SARIMA (2,1,2) with a common seasonal autoregressive and moving average component of order 12.

(iii) The estimation of the stochastic volatility of the series of the one-step ahead forecast error. The estimation of the moving average stochastic volatility model references the works of Chan and Jeliazkov (2009) and Chan and Hsiao (2013). Commodity prices generally exhibit clustering phenomena amid volatility, which justifies this particular modelling. The series of the one-step ahead forecast error w_t is defined by the following equation:

$$w_t = \mu + v_t \tag{3}$$

where μ represents the mean of the forecast error and v_t is the vector of errors that are serially dependent and assumed to follow a MA(q) process of the form:

$$v_t = \varepsilon_t + \psi_1 \varepsilon_{t-1} + ... + \psi_q \varepsilon_{t-q} \tag{4}$$

$$\theta_t = \mu_\theta + \phi_\theta(\theta_{t-1} - \mu_\theta) + \varsigma_t \tag{5}$$

where $\varepsilon_t \sim N(0, e^{\theta_t})$ and $\varsigma_t \sim N(0, \sigma_\theta^2)$ are independent of each other. The variable θ_t is the log-volatility of ε_t and is assumed to follow an AR (1) process, μ_θ is the level of the log-variance and $\mid \phi_\theta \mid < 1$ represents the persistence of the log-variance. Note that this variance is not allowed to vary unrestrictedly with time. The feature of this model fundamentally differs from GARCH-type models where the time-varying volatility is assumed to follow a deterministic, rather than stochastic, evolution. The stochastic volatility model is thus conveniently expressed in hierarchical form and is center-parameterised. According to Chan and Hsiao (2013), under the assumption of moving average extension, the conditional variance of the series w_t is given by:

$$V(w_t|\mu, \psi, \theta) = e^{\theta_t} + \psi_1^2 e^{\theta_{t-1}} + ... + \psi_q^2 e^{\theta_{t-q}} \tag{6}$$

Equations (4) and (5) capture the moving average and the log-volatility, respectively. Equation (6) that derives from the latter provides the estimation of the stochastic volatility process so that the series of the one-period ahead oil price uncertainty (opu_t) satisfies the condition $opu_t = V(w_t|\mu, \psi, \theta)$.[2]

This predictability-based uncertainty measure in the oil price derives from the seminal work of Jurado et al. (2015) who set the path to the empirical literature on the distinction between modeling volatility and uncertainty for macroeconomic and financial variables. Likewise, Joëts et al. (2018) underscore that volatility and uncertainty in oil price are not alike. Unlike major volatility measures which rely on a backward-looking approach, uncertainty relies on a forward-looking approach that includes agents' anticipation through forecasting based on financial and economic events Joëts et al. (2017). In the same vein, Cadoret et al. (2022) investigating mechanisms of price uncertainty diffusion across groups of commodity markets (agriculture, energy, industry and precious metals), emphasize that while periods of significant uncertainty amplify volatility, periods of high volatility are not necessarily accompanied by heightened uncertainty.

2.2. Structural VAR model

We estimate a four-factors SVAR model where Y_t is the vector of endogenous variables given by the expression: $Y_t = (\Delta oil\_sup, agg\_dem, epu, opu)$.[3] The terms in parentheses represent the logarithm of oil supply, the aggregate demand, the logarithm of EPU and oil price uncertainty,

[2] Relying on this methodology, we also computed at 3 and 12 months horizon oil price uncertainty. Additional details are available upon request.

[3] Unit root tests are performed to transform variables accordingly.

respectively. The operator Δ indicates the first order difference.[4] The specification of the SVAR is defined as follows:

$$\Gamma Y_t = B(L)Y_t + \varepsilon_t \tag{7}$$

where Γ is the matrix of contemporaneous interconnections among variables. $B(L)$ is the lag polynomial of endogenous variables. The reduced form of the structural representation is given by:

$$Y_t = B^*(L)Y_t + u_t \tag{8}$$

where $B^*(L) = \Gamma^{-1}B(L)$. The relationship between the reduced form errors, u_t, and structural innovations, ε_t, is: $u_t = \Gamma^{-1}\varepsilon_t$. Following Kilian (2009), we obtain structural innovations by imposing short-run exclusive restrictions on the lower triangular matrix Γ^{-1} as follows:

$$\begin{bmatrix} u_t^{\Delta oil\_sup} \\ u_t^{agg\_dem} \\ u_t^{epu} \\ u_t^{opu} \end{bmatrix} = \begin{bmatrix} \gamma_{11} & 0 & 0 & 0 \\ \gamma_{21} & \gamma_{22} & 0 & 0 \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & 0 \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{oil\_sup\_shock} \\ \varepsilon_t^{agg\_dem\_shock} \\ \varepsilon_t^{epu\_shock} \\ \varepsilon_t^{opu\_shock} \end{bmatrix} \tag{9}$$

The Γ^{-1} matrix specification is subject to discussion regarding economic theory. Studies of Kilian (2009), and Kang et al. (2017) evoke assumptions on interdependencies among variables in the crude oil market, as highlighted by the stylised facts:

(i) An oil supply shock is an exogenous shift of oil production. Oil supply adjustment to oil price shocks only occurs in the long run due to OPEC's quotas, geopolitical events, or intensive capital requirements. Therefore, we assume that oil supply is not affected by other variables within 1 month.

(ii) An aggregate demand shock represents an unexpected change in the global real economic activity. The real economic activity reacts more contemporaneously to oil supply shock but with a lag to EPU and oil price shocks (Hamilton, 1983).

(iii) EPU shock indicates an unexpected shift in government policy direction. We posit that oil supply shock and aggregate demand shock instantaneously impact EPU; however, in reality, oil price uncertainty only affects EPU with a delay.

(iv) Finally, oil price uncertainty shock reflects an unpredictable shift in oil price. We assume that oil supply, aggregate demand and EPU have a contemporaneous impact on oil price uncertainty.

3. Data and preliminary analysis

We collect monthly nominal prices of crude oil from the World Bank.[5] Thereafter, nominal oil prices are deflated by the monthly US CPI to obtain real oil prices. Following Joëts et al. (2018), real oil prices are used to estimate oil price uncertainty (subsection 2.1). We retrieve monthly world crude oil production data from the US Energy Information Administration.[6] Aggregate demand is represented by Kilian's index.[7] We use the US-EPU index developed by Baker et al. (2016).[8] Our final sample across variables covers the period 1985:1-2020:3. In Appendix,

[4]The optimal lag length is set to 2, according to Schwarz (1978) and Hannan-Quinn (1979) information criteria.

[5]Commodity-prices-pink-sheets

[6]Energy-International-Association

[7]Kilian-global-real-economic-activity

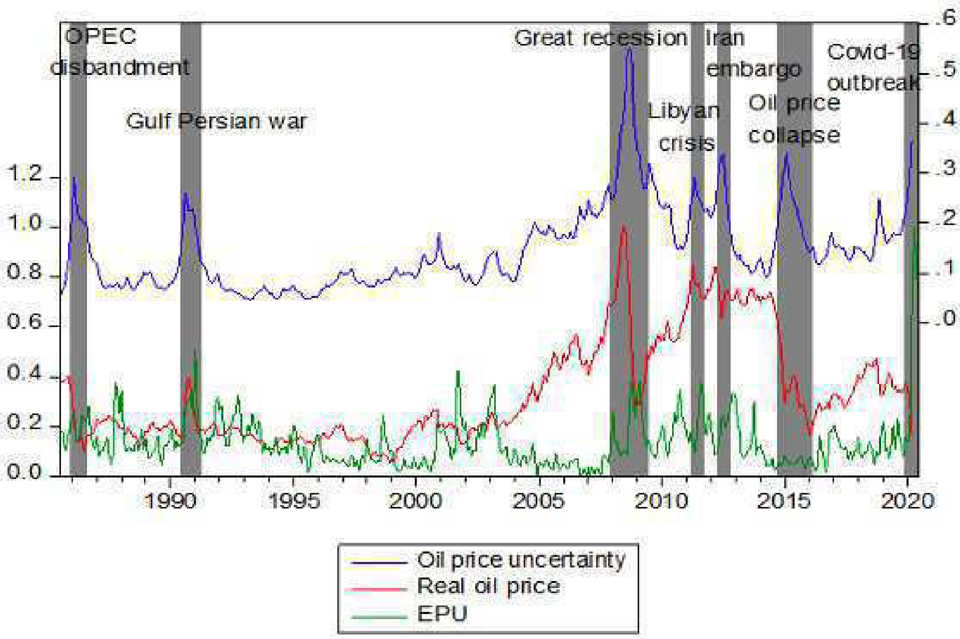
[8]US-EPU-index

we report on the one hand the descriptive statistics of the aggregate demand, the EPU, and the oil price uncertainty (Table A.1) and the linear correlation matrix among variables on the other hand (Table A.2). We observe that series are not normally distributed given the Jarque and Bera (1980) statistics. We reject the null hypothesis of normal distribution for all the variables suggesting are asymmetric and fat-tail distributed (non-zero skewness and positive excess kurtosis). According to unit root tests (Table A.3), the aggregate demand, the economic policy uncertainty and the oil price uncertainty are stationary in level and in first difference. Only the oil supply variable is non stationary in level and needs to be transformed in first difference to pass all unit root tests.[9]

4. Empirical results

Figure 1 illustrates the co-movements between oil price uncertainty, EPU and real oil price. Shaded areas refer to episodes of heightened oil price uncertainty consecutive to sudden booms or busts in real oil price due to unfavourable supply or demand conditions.

Figure 1 – **Oil price uncertainty, real oil price and economic policy uncertainty (EPU).**



Note: This figure depicts a 1-month oil price uncertainty measure (on the right axis) along with real oil price and EPU (on the left axis). The grey bands represent specific events affecting oil markets and global economic events. For scaling convenience, we apply min-max normalisation of the series.

Figure 2 presents the results of our four-factors SVAR model, showing impulse response functions (IRFs) for oil price uncertainty when simulating a positive one-standard deviation on both EPU and demand shock as well as a negative one-standard deviation on oil supply shock.[10]

First, a positive EPU shock has a positive effect on oil price uncertainty up to 8 months after the initial shock. Economic policy disturbances are characterised by deadlines for making economic policy decisions, that not only cause delays in spending and investment by individuals and businesses but also raise incentives for speculative actions. In this context, oil price dynamics

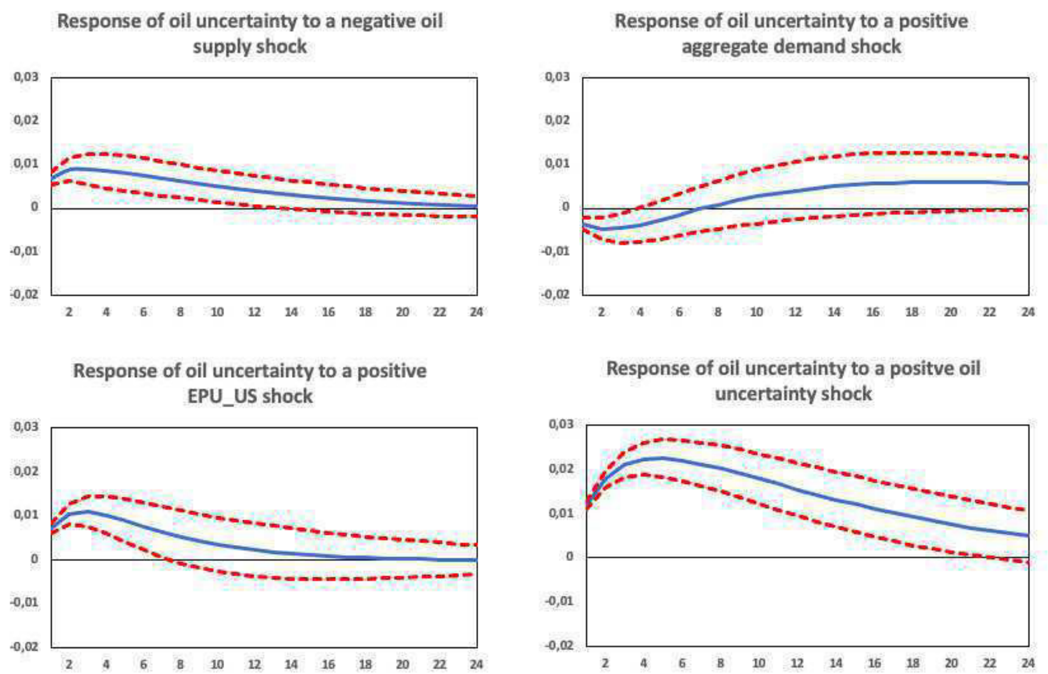
[9]The corresponding tables are available in Appendix.
[10]Noteworthy that results of the reverse impact of the oil price uncertainty on the economic policy uncertainty are available upon request.

are predominantly governed by uncertainty. This finding aligns with empirical studies which highlight the exogenous positive effect of EPU on oil price volatility (Ahmed and Sarkodie, 2021).

Second, a negative oil supply shock, indicating an unexpected decrease in global oil supply, contributes to increasing oil price uncertainty at an upward point of 2 months following the initial shock. Afterwards, this positive effect is slightly reduced up to 12 months. The dynamics of oil price uncertainty in response to a negative oil supply shock highlights the role of expectations in the crude oil market. Indeed, investors appear to be more concerned by the uncertainty of future supply conditions than perceiving the exogenous drop in oil supply as a turmoil event (geopolitical tensions, trade wars, OPEC's monopoly power) that could affect the global value chain. In addition to the well-known effect of rising price resulting from the insufficient supply (Kilian, 2009), this implies that the uncertainty driven by agents acting in the oil market is strongly reflected in oil price.

Third, a positive aggregate demand shock leads to a significant decrease in oil price uncertainty up to 4 months following the initial shock, the impact being less persistent than that of oil supply shock. This could be interpreted as a near-term unexpected demand shock. One possible explanation is that if an aggregate demand shock occurs, sharp spikes in oil prices are more likely to generate volatility but not uncertainty because demand shocks are more predictable in the short-run; thus, the effect on oil price uncertainty is limited.

Figure 2 – **Responses of the oil price uncertainty.**



From the VAR estimates, we obtain the forecast error variance decomposition (FEVD) estimates of oil price uncertainty in Table I, which provides evidence that oil price uncertainty contributes about 60% of its own shocks at a three-month horizon. The highest contributions of EPU to oil price uncertainty shocks is about 20% at a three-month horizon on average.

Table I – **Forecast error variance decomposition of oil price uncertainty.**

FH	Oil supply	Aggregate demand	EPU	Oil uncertainty
1	17.80	5.01	20.13	57.06
2	16.04	4.44	20.17	59.35
3	14.15	3.90	19.13	62.82
4	13.01	3.33	17.76	65.90
5	12.29	2.80	16.40	68.51
6	11.77	2.37	15.18	70.68
7	11.36	2.05	14.11	72.48
8	11.02	1.84	13.20	73.94
9	10.73	1.75	12.43	75.09
10	10.46	1.77	11.78	75.99
11	10.23	1.88	11.24	76.65
12	10.01	2.08	10.78	77.13

Note: FH= Forecast horizon. Data are in percentage.

5. Conclusion

This study focuses on EPU and supply and demand factors as a driver of oil price uncertainty. Using VAR IRFs, we reveal that a positive EPU shock significantly contributes to magnifying oil price uncertainty; however, both negative supply and positive demand shocks are transmitted onto oil price uncertainty in opposite directions. A policy implication of this finding is that policymakers should be aware of the consequences of decisions regarding the crude oil market by promoting action to establish a multi-level oil reserves management system. In addition, investors' incentives for hedging strategies could mitigate the effects of EPU on the crude oil market. Finally, an in-depth investigation considering a potential non-linear pattern of the EPU and oil price uncertainty nexus to identify shocks, could also be great of interest.

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