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Research article

The heterogeneous linkage of economic policy uncertainty and oil return risks

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Abstract: The recent financial crisis and its aftermath boost the research of economic policy uncertainty and its relevant topics. In this paper, we forecast the oil return risks based on the CAViaR method and further depict the dynamic and heterogeneous features during the crisis (or non-crisis) period, as well as in different markets via DCC-GARCH models. The empirical results show the linkage of economic policy uncertainty and oil return risks, indicating an increasing trend and stronger relationship with major events. Further study shows the heterogeneous feature existing during crisis or non-crisis period, and there is heterogeneity in values and variations of their linkage in different markets. Therefore, policymakers should intervene timely in the crude oil market, release good news, and stabilize oil prices during the crisis period. During the non-crisis period, however, investors need to rationally analyze the price trend of the oil market, thereby preventing possible risks in the market.

Keywords: heterogeneity; linkage; economic policy uncertainty; oil return risks; CAViaR

JEL code: C51, E65, G14, G18

1. Introduction

Research on the oil price is always hot, and the importance of exploring oil return risks has been widely proven. The recent financial crisis and its aftermath boost research on economic policy uncertainty and its relevant topics to a new height (Aloui, 2016; Antonakakis, 2014; Balcilar, 2017; Kang, 2015; Yin, 2016; You, 2017). There are great impacts of both economic policy uncertainty and oil price shocks on the stock return, corporate debt, and initial public offering (IPO) activities (Çolak, 2017; Kang, 2017; Li et al., 2018; Waisman, 2015). The linkage of economic policy uncertainty and oil return risks has a direct impact on the economic situation and firm-level performance, and the effect of their linkage worth further deep studying.

It is well known that crude oil is one of the most important energy sources for world development and an investment product with significant financial characteristics. A higher oil price has a negative effect on aggregate demand, as it redistributes income between net oil importing and exporting countries (Cunado, 2015; Ftiti, 2014). The contemporaneous negative effect of return risks suggests speculation in the oil market (Gong, 2017; Juvenal, 2015). Investors from different markets could react differently due to the diversification of information. Unsurprisingly, many researchers have implemented various models to forecast crude oil price and its determinants (Baumeister, 2015; 2016; Li, 2015; Naser, 2016; Wang, 2016; Zhang, et al., 2015). For example, Wang (2016) established a new neural network architecture which combines the Multilayer perception and the Elman recurrent neural network with a stochastic time effective function. Furthermore, they tested the predictive effects on four different crude oil series. Besides, researchers have explored the oil price shock on economic and financial markets. Cunado (2015) analyzed the macroeconomic impact of oil shocks in four of the top oil-consuming Asian economies and found the economic activity and prices respond very differently to oil price shocks depending on their types. Moreover, the literature has explained the effect of oil price on stock return and exchange rate (Caporale, 2015; Mensi, 2017; Narayan, 2015; Phan, 2015; Sim, 2015; Wen, 2018).

Recently, a new concept referred to economic policy uncertainty has been paid great attention to by many scholars. Handley (2017) examined the impact of policy uncertainty on trade, prices, and real income through firm entry investments in general equilibrium and found that reduced policy uncertainty lowered US prices and increased its consumers' income by the equivalent of a 13-percentage-point permanent tariff decrease. In addition, as a macroeconomic influence factor, EPU also impacts other economic activities, such as unemployment and monetary policy (Aastveit, 2017; Caggiano, 2017). Baker et al. (2016) developed a new index of economic policy uncertainty (EPU) based on newspapers coverage frequency and found that policy uncertainty is associated with greater stock price volatility and reduced investment and employment. In terms of financial market, scholars focus on examining the link between EPU and stock price and risk, credit default swap, volatility forecasting, gold and exchange rate (Alexopoulos, 2015; Aye, 2015; Balcilar, 2016; Berger, 2016; Bernal, 2016; Bordo, 2016a; Brogaard, 2015; Gao, 2016; Li, 2017; Liu, et al., 2017, Tsai, 2017; Wisniewski, 2015).

Understanding the oil return risks and furthermore exploring its linkage with policy uncertainty are crucial to academia, policymakers, and oil market investors. The linkage between economic policy uncertainty and oil return risks could be significantly heterogeneous during distinct periods, as well as in different markets (Aastveit, 2015; Jia, 2015; Zhang, 2015). First and foremost, the elasticity of oil supply could be lower because oil producers prefer to delay changing their production until more information on demand shock are available (Kellogg, 2014). Second, heterogeneous beliefs concerning uncertainty in the future economy would lead to price drifts and irrational volatility, even booms or busts (Singleton, 2013). Third, oil futures markets may respond quickly to economic uncertainty and then transfer information to oil spot markets (Baumeister, 2013).

The main objective of this paper is to explore the heterogeneous linkage of EPU and oil return risks, and in doing so, we provide two contributions. First, we explore the dynamic linkage between EPU and oil return risks. Researchers like Bekiros (2015) analyzed the importance of EPU in predicting within-sample oil price, and the same results can be seen in Antonakakis (2014); Reboredo (2016) explored the quantile effect of EPU on commodity future price. However, there is limited literature to study the time-varying linkage of EPU and oil return risks. Therefore, we analyze the linkage based on the DCC-GARCH-type model. Second, we demonstrate heterogeneity in their linkage in different periods and countries. Recent studies investigated the heterogeneity in oil price movement in different periods. Zhang (2015) found that the typical price regimes of Brent and WTI are the "sharply upward" and "relatively stable" regimes respectively after the financial crisis. Different movement regimes in recent years are mainly attributed to their different market fundamental situations and the dynamics in crude oil markets. Jia (2015) provided a novel perspective on multivariate dynamic correlations for studying the oil market by using an optimal wavelet analysis on the basis of grey correlation. These results allow us to estimate the heterogeneous linkage of EPU and oil return risks in different periods and countries.

The remainder of this paper is organized as follows. Section 2 briefly introduces the methodology in this paper. Section 3 describes the data and preliminary tests. Section 4 presents the empirical results in full-sample and sub-sample. Some conclusions can be seen in Section 6.

2. Methodology

As mentioned above, our analyzing of the heterogeneous feature of the linkage of economic policy uncertainty and oil return risks is based on the DCC-GARCH model of Engle (2002). In this section, we first briefly describe the CAViaR of Engle and Managanelli (2004) in forecasting the oil return risk. We then introduce the DCC-GARCH model proposed by Engle (2002) for exploring the connectedness between economic policy uncertainty and oil return risk.

2.1. CAViaR

Value-at-Risk (VAR) could be regarded as an effective tool to calculate the oil return risk. The VaR reflects the maximum amount of loss exposed in oil during a specific period. It also is defined as the left $\theta - quantile$ of the different condition distribution. Let $\{R_t\}_{t=1}^{T}$ be the log-returns of oil and T is the length of the return. It can be calculated as Equation 1.

$$R_t = \ln y_t - \ln y_{t-1}. \tag{1}$$

where y_t and y_{t-1} stand for the oil spot price at time t and $t-1$.

Following the definition, the subject of VaR can be described as Equation 2.

$$\Pr[R_t < Risk_t \left| \Omega_{t-1} \right.] = \theta. \tag{2}$$

where $Risk_t$ stands for the oil return risk at time t, and Ω_{t-1} is the information set available at time $t-1$.

A main reason for using the conditional autoregressive quantile specification (CAViaR) to forecast the oil return risk is that there are cluster and time-varying features in oil return series. In the existing literature, there are many studies focus on the application and some alternative risk measures based on GARCH-type models (Bernardi, 2016; Ferraty, 2016; Gkillas, 2018; Li et al., 2018; Qureshi, 2016). But these approaches often assume that the distribution of oil return is invariable across time. In general, there are speculation and significant intra-cluster in global oil markets, which make oil return risks more dynamic (Dai, 2016; Gong, 2017;

Juvenal, 2015; Zhang, 2015). Therefore, we use the CAViaR, proposed by Engle and Manganelli (2004), to calculate the oil return risk in this paper.

The CAViaR can be generally written as Equation 3.

$$Risk_t(\boldsymbol{\beta}) = \beta_0 + \sum_{i=1}^{q} \beta_i Risk_{t-i}(\boldsymbol{\beta}) + \sum_{j=1}^{r} \beta_j l(R_{t-j}). \tag{3}$$

where $p = q + r + 1$ is the dimension of β, and l is a function of lagged value of oil return. The autoregressive term is $\beta_i Risk_{t-i}(\boldsymbol{\beta})$, where $i = 1, 2, \ldots q$, ensuring the oil return risk changes smoothly over time. Specially, β_2 depicts the cluster feature of oil return risks. The role of $l(R_{t-j})$ is to link $Risk_t(\boldsymbol{\beta})$ to oil return that belongs to Ω_{t-1}.

Engle and Manganelli (2004) developed four CAViaR models. These could be described as Equations 4–7.

Symmetric absolute value:

$$Risk_t(\boldsymbol{\beta}) = \beta_1 + \beta_2 Risk_{t-1}(\boldsymbol{\beta}) + \beta_3 \left|R_{t-1}\right|. \tag{4}$$

Asymmetric slope:

$$Risk_t(\boldsymbol{\beta}) = \beta_1 + \beta_2 Risk_{t-1}(\boldsymbol{\beta}) + \beta_4 (R_{t-1})^+ + \beta_3 (R_{t-1})^-. \tag{5}$$

Indirect GARCH (1,1):

$$Rsik_t(\boldsymbol{\beta}) = (\beta_1 + \beta_2 Risk_{t-1}^2(\boldsymbol{\beta}) + \beta_3 R_{t-1}^2)^{1/2}. \tag{6}$$

Adaptive:

$$Risk_t(\beta_1) = Risk_{t-1}(\beta_1) + \beta_1 \left\{[1 + \exp(G[R_{t-1} - Risk_{t-1}(\beta_1)])]^{-1} - \theta\right\}. \tag{7}$$

where $(R_{t-1})^+ = \max(R_{t-1}, 0)$, $(R_{t-1})^- = -\min(R_{t-1}, 0)$, and G is a positive finite number.

Furthermore, Engle and Manganelli (2004) proposed a new test for the evaluation of the alternative specification which has better power properties than other existing tests. It can be defined as Equation 8.

$$Hit_t(\boldsymbol{\beta}) \equiv I(R_t < Risk_t(\boldsymbol{\beta})) - \theta. \tag{8}$$

where function $Hit_t(\boldsymbol{\beta})$ follows an assumption that value $(1-\theta)$ every time oil return is less than the quantile and $-\theta$ otherwise. It is clear that the expectation of $Hit_t(\boldsymbol{\beta})$ is zero. What's more, conditional expectation of $Hit_t(\boldsymbol{\beta})$ given any information known at time $t-1$ must also be zero. Specially, $Hit_t(\boldsymbol{\beta})$ must be uncorrelated with its own lagged values and with $Risk_t(\boldsymbol{\beta})$. If $Hit_t(\boldsymbol{\beta})$ satisfies these features, then there will be no autocorrelation in the hits, no measurement error, and the correct fraction of exception. Furthermore, they extend two test statistics: The in-sample dynamic quantile test and the out-of-sample dynamic quantile test.

The generation shown in Equations 9 and 10.

$$DQ_{IS} \equiv \frac{Hit'(\hat{\boldsymbol{\beta}}) X(\hat{\boldsymbol{\beta}}) (\hat{M}_T \hat{M}'_T) - X'(\hat{\boldsymbol{\beta}}) Hit'(\hat{\boldsymbol{\beta}})}{\theta(1-\theta)} \overset{d}{\sim} \chi_q^2 \tag{9}$$

$$DQoos \equiv N_R^{-1} Hit'(\hat{\boldsymbol{\beta}}_{T_R}) X(\hat{\boldsymbol{\beta}}_{T_R})[X'(\hat{\boldsymbol{\beta}}_{T_R}) \cdot X(\hat{\boldsymbol{\beta}}_{T_R})]^{-1}$$

$$\times X'(\hat{\boldsymbol{\beta}}_{T_R}) Hit'(\hat{\boldsymbol{\beta}}_{T_R}) / \theta(1-\theta) \overset{d}{\sim} \chi_q^2, \text{ as } R \to \infty. \tag{10}$$

where

$$\hat{M}_T = X'(\hat{\boldsymbol{\beta}}) - \left\{ (2T \hat{c}_T)^{-1} \sum_{t=1}^{T} I(|R_t < Risk_t(\hat{\boldsymbol{\beta}})| < \hat{c}_T) X'(\hat{\boldsymbol{\beta}}) \nabla Risk_t(\hat{\boldsymbol{\beta}}) \right\}$$

$$\times \hat{D}_T^{-1} \nabla' Risk_t(\hat{\boldsymbol{\beta}}). \tag{11}$$

2.2. DCC-GARCH models

Engle (2002) developed the dynamic conditional correlation (DCC)-GARCH model, which offers flexibility to simultaneously model the multivariate conditional volatility of financial assets and their time-varying linkage. A major advantage of using this model is the detection of possible changes in conditional correlations over time, which allows us to detect dynamic linkage in response to economic policy uncertainty. Another advantage is that the DCC-GARCH model estimates linkage of the standardized residuals and thud accounts for the heteroscedasticity existing in EPU and oil return risk directly. Moreover, since the volatility of EPU or oil return risk is adjusted by the procedure, the time-varying DCC does not have any bias from volatility. Hence, the DCC-GARCH provides a superior measurement for linkage.

The estimation of DCC-GARCH models comprises two steps: The first is the estimation of univariate GARCH, and the second is the estimation of conditional correlations that vary through time.

The multivariate DCC-GARCH model is defined as Equations 12 and 13.

$$X_t = \mu_t + H_t^{1/2} \varepsilon_t. \tag{12}$$

$$\begin{cases} H_t = D_t R_t D_t \\ R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \\ D = diag(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \ldots, \sqrt{h_{NN,t}}) \end{cases} \tag{13}$$

where $X_t = (X_{1t}, X_{2t})$ is the vector of EPU and oil return risk; H_t is the multivariate conditional variance; $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$ is the vector of the standardized residuals; R_t is a 2 × 2 symmetric dynamic correlations matrix, and D_t is the diagonal matrix of conditional standard deviation for EPU or oil return risk, obtained from estimating a univariate GARCH model[1].

[1] In this paper, we estimate GARCH, TGARCH, EGARCH based on different distribution. The GARCH-type specification can be seen at Appendix A.

The DCC specification could be defined as Equation 14.

$$
\begin{aligned}
Q_t &= (1-\psi-\zeta)\bar{Q} + \zeta Q_{t-1} + \psi \delta_{i,t-1}\delta_{j,t-1} \\
R_t &= Q_t^{*-1} Q_t Q_t^{*-1}
\end{aligned} \tag{14}
$$

where $Q_t = \{q_{ij,t}\}$ is a 2 × 2 time-varying covariance matrix of standardized residuals ($\delta_{i,t} = \varepsilon_{i,t} / \sqrt{h_{i,t}}$); $\bar{Q}$ is the unconditional correlation of δ_{it}, δ_{jt}, and ψ and ζ are nonnegative scalar parameters that satisfy $\psi + \zeta < 1$. $Q_t^* = \{q^*_{ii,t}\} = \sqrt{q_{ii,t}}$ is a diagonal matrix with square root of the i^{th} diagonal element of Q_t on its i^{th} diagonal position.

Therefore, for a pair of EPU (i) and oil return risk (j) their conditional linkage at time t could be defined as Equation 15.

$$
\rho_{ij,t} = \frac{(1-\psi-\zeta)\bar{q}_{ij} + \psi\delta_{i,t-1}\delta_{j,t-1} + \zeta q_{ij,t-1}}{\left[(1-\psi-\zeta)\bar{q}_{ii} + \psi\delta^2_{i,t-1} + \zeta q_{ii,t-1}\right]^{1/2}\left[(1-\psi-\zeta)\bar{q}_{jj} + \psi\delta^2_{j,t-1} + \zeta q_{jj,t-1}\right]^{1/2}}. \tag{15}
$$

Otherwise, the parameters are estimated using quasi-maximum likelihood method (QMLE) introduced by Bollerslev et al. (1988). Under the Gaussian assumption, the log-likelihood of the estimators could be defined as Equation 16.

$$
L(\lambda) = -\frac{1}{2}\sum_{t=1}^{T}\left[(n\log(2\pi) + \log|D_t|^2 + \varepsilon_t' D_t^{-1} D_t^{-1}\varepsilon_t) + (\log|R_t| + \delta_t' R_t^{-1}\delta_t - \delta_t'\delta_t)\right]. \tag{16}
$$

where $n = 2$; T is the number of observations, and λ is the vector of parameters to be estimated.

3. Data and preliminary analysis

3.1. Data

The data in this paper come from a variety of sources. Our objective is to explore the linkage existed between EPU and oil return risk. In this respect, we should first consider the evolution of oil return risk. Thus, we select the monthly closing spot price data for Brent, which represents the oil price expectation of the global oil trade. What's more, the Brent has become the virtual international oil benchmark, partly because of its location. The sample period ranges from May 1985 to December 2018 based on data availability. And data for the Brent oil spot price could be collected from the U.S. Energy Information Administration (https://www.eia.gov/). Furthermore, the oil price is expressed in log-returns.

Second, the EPU we consider is obtained from http://www.policyuncertainty.com/. Our period of analysis covers May 1985–December 2018 on a monthly frequency due to the availability of policy uncertainty index starting from May 1985. It is important to investigate whether heterogeneous linkage does in fact exist. Thus, we select the EPU indices for aggregate Europe (EEPU), the US (UEPU), and Global (GEPU). It is worth noting that the choice of EEPU is directed by the location of Brent oil. For exploring the heterogeneous linkage in different countries, our study could be limited to countries such as the US, which is the most important determinant of crude oil prices.

3.2. Preliminary analysis

For the estimation of the CAViaR, we used the first 340 to estimate parameters and the last 39 for out-of-sample tests. Especially, we forecast 1% and 5% 1-month oil return risks ($Risk$) for K = 4 and 6, and set G = 10, entered the definition of the adaptive model[2]. From the test in Equations 9 and 10, we can clearly notice that the asymmetric slope does a good job in describing the evolution of oil return risk. Thus the asymmetric slope results could be regarded as oil return risks. Above all, a detailed description of all variables is presented in Table 1.

As shown in Table 1, there are significant divergences on average and variation of all variables. First, we focus on the average. Table 1 shows that EEPU displays the highest mean (125.89), whereas the Risk is among the lowest average (0.123). Furthermore, we consider the variation in different variables. The measurement of the variation includes standard deviation (Std. D.), and range and coefficient of variation (Coef.var). The same results could be obtained by these two measurements. Taking Coef.var, which is meaningful for positive values, as an example, we note that the Risk has the least variation (0.33), while the EEPU has the most (0.48). What's more, the difference of variation facilitated the model fitting and made it possible to explore the heterogeneous linkage of economic policy uncertainty and oil return risks. Otherwise, it is interesting to note that the Jarque-Bera (J-B) test statistics for normality clearly confirms the rejection of the null hypothesis for all variables at a 5% level of significance. The results indicate that all variables are significantly different from the normal distribution, which provide further motivation to use GARCH-type models based on different distribution to take account into the heteroscedasticity existing in the EPU and oil return risks directly. Further, we examine the unit root and the existence of the ARCH effect. The result shows in Table 2.

Table 1. Statistics description of all variables.

	Total Number	Mean	Max.	Min.	Std. D.	Coef.var	J-B
Risk	379	0.123	0.31	0.03	0.04	0.33	239.83***
EEPU	379	125.89	433.28	33.79	61.35	0.48	289.37***
UEPU	379	112.08	283.67	44.78	41.77	0.37	133.52***
GEPU	264	112.71	304.33	50.31	46.98	0.41	111.00***

*Note: *, ** and *** indicate significance at 1%, 5%, and 0.1% level, respectively.

We clearly note that all variables are stationary and exhibit ARCH behavior. It could be seen from Table 2 that the ADF statistics on original series are −19.06, −4.33, −8.83, and −5.06 respectively. And all ADF statistics significantly refuse the null hypothesis at a 5% level. Similarly, the ARCH test confirms the rejection of the null hypothesis for all variables at a 5% level of significance. The results indicate that all variables exhibit the ARCH, underscoring that some stylized facts such as fat-tails, clustering volatility, and persistence characterizes the EPU and oil return risk. In addition, Table 3 reports the results of unconditional correlation levels between EPU and oil return risks, and Figure 1 plots the EEPU, the UEPU and the GEPU, and oil return risks, respectively.

[2] See Engle and Manganelli (2004). In principle, the parameter G itself could be estimated; however, this would go against the spirit of this model, which is simplicity. What's more, we test different value of G, like 5, 15, 20, and get a same result as G = 10. In addition, the estimation results of CAViaR could be seen in Appendix B.

Table 2. The results of unit root and ARCH test.

	ADF(0)	ARCH(1)	ARCH(5)	ARCH(10)
Risk	−19.06***	41.20***	43.52***	49.84***
EEPU	−4.33***	5.55**	30.26***	32.33***
UEPU	−8.83***	2.82*	7.07	9.51
GEPU	−5.06***	12.92***	36.79***	39.99***

*Note: The lag shows in parentheses. *, ** and *** indicate significance at 1%, 5%, and 0.1% level, respectively.

There are significant heterogeneous linkages of the EPU and oil return risks. From Table 3, we note that the unconditional correlations between the GEPU and the Risk are the highest and positive (0.889), followers between the UEPU and the Risk (0.879), whereas the correlation between the EEPU and the Risk has the least (0.859). This could be resulted from the notation and portion of the economy. The GEPU Index is a GDP-weighted average of national EPU indices for 20 countries[3]. It presents an aggregate of the global economy and depicts the global shock on oil return. The US has the sizable portion of the global economy.

Table 3. Historical unconditional correlations of all the variables.

	Risk	*EEPU*	*UEPU*	*GEPU*
Risk	1.000			
EEPU	0.859*** (27.202)	1.000		
UEPU	0.879*** (29.995)	0.984*** (89.153)	1.000	
GEPU	0.889*** (31.511)	0.954*** (51.344)	0.973*** (68.626)	1.000

*Note: Standard error shows in parentheses. *, ** and *** indicate significance at 1%, 5%, and 0.1% level, respectively.

There are dynamic and heterogeneous features in the linkage of the EPU and oil return risks. On the one hand, the dynamic feature is mainly caused by the phased of oil return risks and the EPU, that is, the magnitude of oil risk fluctuations and EPU fluctuations are significantly different at different stages. Specifically, at the beginning of the sample, the EEPU is less volatile, and so is the risk. At this time, the risk and uncertainty trends are basically the same. By 2001, Brent crude oil had achieved reforms, while the volatility of the EEPU has widened, and the magnitude of the oil return risk has also increased significantly. In the latter part of the sample, due to the impact of Brexit on the EEPU, the volatility of EEPU continued to expand, and the fluctuation of oil return risk at this time is smaller than that in 2001. This indicates that the linkage of the EPU and oil return risks is dynamic. On the other hand, the heterogeneous feature mainly results from the heterogeneity of EPU in different markets. Overall, the EEPU is on the rise, and the volatility is gradually expanding. However, there is no obvious trend in the UEPU and the GEPU, and it also has certain periodic characteristics. These heterogeneous features contribute to the heterogeneity of linkage between different markets. Above all, this provides motivation for us to explore the time-varying and heterogeneous features in the linkage of EPU and oil return risk.

[3] This could be found at *http://www.policyuncertainty.com/global_monthly.html.*

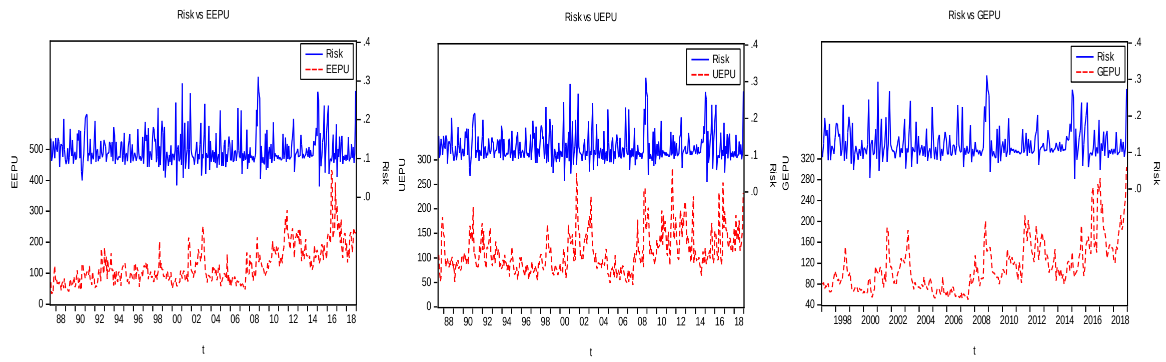

Figure 1. Time variation of all variables. The left and right y-axes denote EPU and oil return risk respectively.

4. Empirical results

This section reports and discusses the dynamic and heterogeneous linkage of EPU and oil return risk. To facilitate a comparison, we first report the results for the full sample. Further, we discuss the heterogeneous linkage during crisis and non-crisis periods in different markets.

4.1. Dynamic linkage for the full sample

The most adequately selected model is the one that reports the minimum value for the BIC and AIC information criteria. To select the best marginal model, we examine different GARCH (standard GARCH, TGARCH, and EGARCH) models based on Normal and student *t* distribution by considering a different combination of the parameters, BIC and AIC information criteria. Table 4 reports the estimation of DCC-GARCH models based on different distribution.

Panel A, B and C of Table 4 report the estimation results of different GARCH models. It can be seen AIC and BIC is the least and LogL is the highest in two marginal models with GARCH model based on student *t* distribution (GARCH-T). This indicates that the GARCH-T model has the best fitness. Therefore, we calculate the dynamic linkage with the DCC-GARCH-T model.

The estimation results are shown as Panel D of Table 4. It is worth noticing that the significance of parameters λ_1 and λ_2 indicates the appropriateness of the DCC-GARCH-T model in modeling the dynamic linkage of EPU and oil return risk. The λ_2 is significant and very close to one, revealing a higher persistence of volatility across the EPU and oil return risk. Moreover, the sum of λ_1 and λ_2 are <1, indicating that the estimated DCC parameters lie within the range of typical estimates from the GARCH-T model. Furthermore, we explore the relationship between the linkage and major events. Figure 2 reports this relationship.

Figure 2 illustrates the dynamic linkage of the EPU and oil return risks and reports the relationship between their linkage and major events. Overall, the linkage of EEPU and oil return risk is on the rise, and the volatility has gradually increased. Moreover, there are significant impact of crude oil market and external political environment on the linkage between EPU and oil return risk. It is interesting to notice that there is also strong relationship between linkage and major events. On the one hand, the main reason for the linkage is the supply of crude oil market. The Gulf War, the Iraq War, and the Venezuelan strike have affected the supply of oil, which in turn affected the linkage. What's more, the impact on oil price and linkage is different at different times. Specifically, oil price experienced a sharp increase induced by the Gulf War, and the impact on the fluctuation of linkage is not significant. However, the Iraq War and the strike of oil workers in Venezuela caused a sharp fluctuation in oil prices linkage of EEPU and oil return risk. This indicates a correlation with the different nature of war. The Gulf War is a short-running war initiated by means of United Nations resolutions. Its impact is only on the oil market, and its impact on the external environment and policies is not obvious. In contrast, the long duration of the Iraq war, coupled with the economic status of the United States in the global market, caused insufficient supply of oil, which in turn led to a sharp rise in oil prices, and then eventually led to linkage fluctuations.

Table 4. Estimation of DCC-GARCH models based on different distribution.

	Risk	EEPU	Risk	EEPU
Distribution	Normal		Student t	
Panel A: GARCH				
c	0.001***	360.93***	0.002***	274.22***
	(0.0003)	(130.18)	(0.0006)	(80.95)
α_1	0.295***	0.657***	0.792**	0.731***
	(0.1088)	(0.121)	(0.403)	(0.158)
β_1	0.151	0.275***	−0.080**	0.291***
	(0.199)	(0.103)	(0.037)	(0.093)
AIC	−3.549	10.459	−3.738	10.448
BIC	−3.507	10.501	−3.686	10.500
LogL	676.58	−1978.08	713.30	−1974.97
Panel B: TGARCH				
c	0.001***	441.94***	0.002***	339.81***
	(0.0002)	(139.20)	(0.0003)	(99.196)
α_1	0.558***	0.748***	0.340**	0.792***
	(0.189)	(0.137)	(0.138)	(0.199)
β_1	−0.073**	0.245**	−0.154	0.272***
	0.037	(0.097)	(0.104)	(0.105)
γ_1	−0.569***	−0.402**	−0.323**	−0.366
	(0.209)	(0.174)	(0.155)	(0.283)
AIC	−3.602	10.451	−3.695	10.445
BIC	−3.549	10.503	−3.633	10.507
LogL	687.54	−1975.56	706.18	−1973.33
Panel C: EGARCH				
c	−4.683***	1.404**	−6.508***	0.961**
	(1.484)	(0.681)	(0.917)	(0.437)
α_1	−0.024	0.722***	0.012	0.757***
	(0.169)	(0.100)	(0.231)	(0.143)
β_1	0.269	0.735***	−0.045	0.789***
	(0.228)	(0.089)	(0.144)	(0.062)
γ_1	0.426***	0.187**	0.693***	0.152
	(0.109)	(0.076)	(0.228)	(0.094)

Continued on next page

	Risk	EEPU	Risk	EEPU
Distribution	Normal	Student t		
AIC	−3.581	10.492	−3.721	10.485
BIC	−3.529	10.545	−3.659	10.548
LogL	683.54	−1983.38	711.16	−1980.94
Panel D:Estimates of DCC-GARCH				
λ_1				0.017
				(0.013)
λ_2				0.976***
				(0.022)
df				5.467***
(Degree of t-Distribution)				(0.771)
AIC				6.851
BIC				6.986
LogL				−1285.3

*Note: Standard error shows in parentheses. *, ** and *** indicate significance at 1%, 5%, and 0.1% level, respectively.

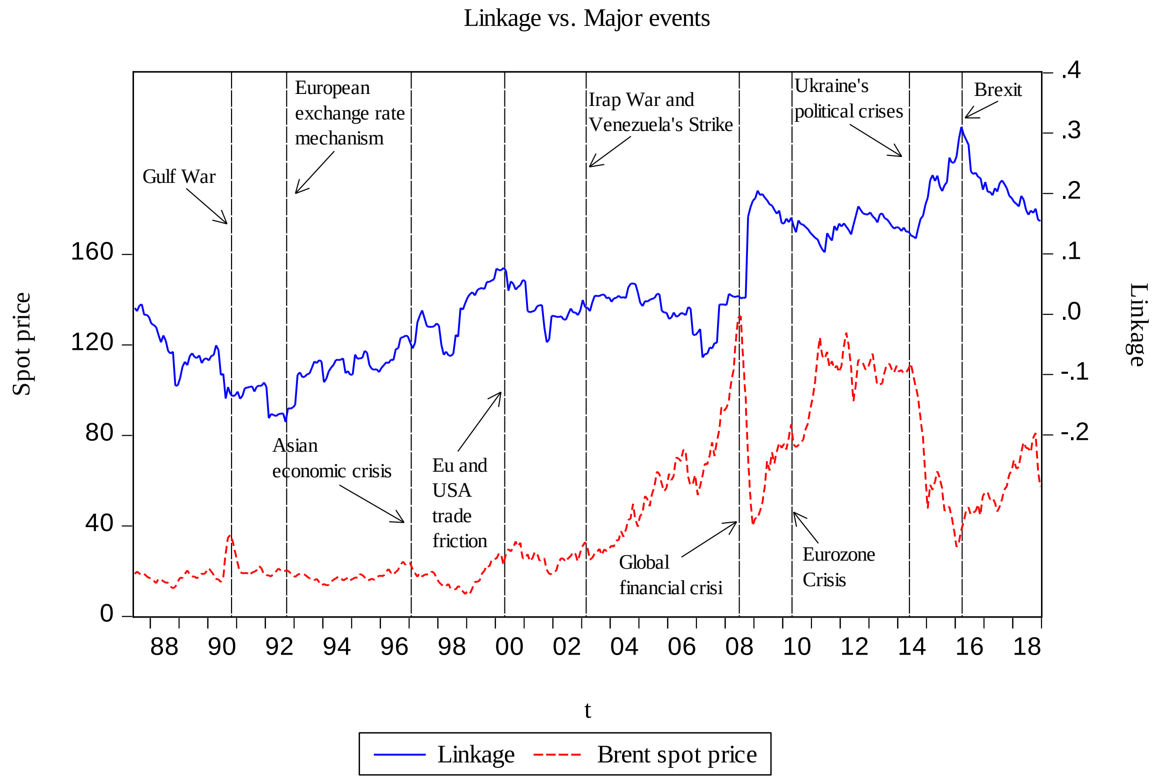

Figure 2. Relationships between dynamic linkage of the EEPU, oil return risks, and major events. The left and right y-axes denote the Brent spot price and the linkage respectively.

On the other hand, the external environment is also a main reason for the dynamic linkage. From the perspective of the location of Brent oil market, the linkage of EEPU and oil return risk experienced a sharp increase in European (EU) exchange rate mechanism reform and the Ukrainian's political crises. Similarly, the EU and the USA trade friction and the Brexit also have triggered sharp fluctuations of linkage of the

EEPU and oil return risks. In terms of another external environment, it could be seen that the linkage is mainly affected by financial or economic crisis, and furthermore it has a significant impact on the scope of the crisis. Specifically, the Asian economic crisis and the Eurozone crisis caused a small fluctuation in the linkage, whereas the global financial crisis made the linkage increased sharply. This indicates that there is heterogeneity in different crises.

4.2. Heterogeneous linkage during crisis and non-crisis periods

In this subsection, it is necessary to explore whether there is heterogeneity during crisis and non-crisis periods. Following Bordo (2016b), the sample could be divided into two groups according to crisis and non-crisis period. Concretely, the crisis period includes the Nordic Crisis (1991–1992), the Asian Crisis (1997–1998), the Global Crisis (2007–2009), and the Eurozone Crisis (2010–2014). The estimation results are shown in Table 5.

Table 5. Estimation of DCC-GARCH-T models.

Period	Crisis		Non-crisis	
	Risk	EEPU	Risk	EEPU
Panel A: GARCH-T				
c	0.002	537.533**	0.002***	226.18**
	(0.010)	(250.98)	(0.0009)	(93.95)
α_1	4.517	0.588**	0.208	0.766***
	(16.72)	(0.287)	(0.159)	(0.265)
β_1	−0.033	0.219	−0.361*	0.302**
	(0.054)	(0.237)	(0.210)	(0.145)
AIC	−3.804	10.497	−3.665	10.312
BIC	−3.701	10.601	−3.592	10.385
LogL	278.87	−750.81	435.701	−1206.62
Panel B: Estimates of DCC-GARCH				
λ_1		0.087		0.007
		(0.061)		(0.019)
λ_2		0.893***		0.947***
		(0.083)		(0.145)
df		4.332***		5.101***
(Degree of t-Distribution)		(0.829)		(0.797)
AIC		7.438		6.723
BIC		7.706		6.915
LogL		−552.54		−776.98

*Note: Standard error shows in parentheses. *, ** and *** indicate significance at 1%, 5%, and 0.1% level, respectively.

Panel A and B of Table 5 report the parameters estimation of GARCH-T and DCC respectively. Similarly, we focus on the parameters λ_1 and λ_2. The parameter λ_2 reveals a higher persistence of volatility across the EPU and oil return risk during crisis or non-crisis period, since it is significant and close to one. What's more, the value λ_2 in different distinct periods also shows that there is a stronger persistent feature during the non-crisis period. This indicates that the linkage during the non-crisis period is more stationary than their linkage during the crisis period. Moreover, the sum of λ_1 and λ_2 is less than 1, indicating that the estimated DCC parameters lie within the range of typical estimates from the GARCH-T model. Furthermore, we graph the heterogeneous feature during crisis and non-crisis periods in Figure 3.

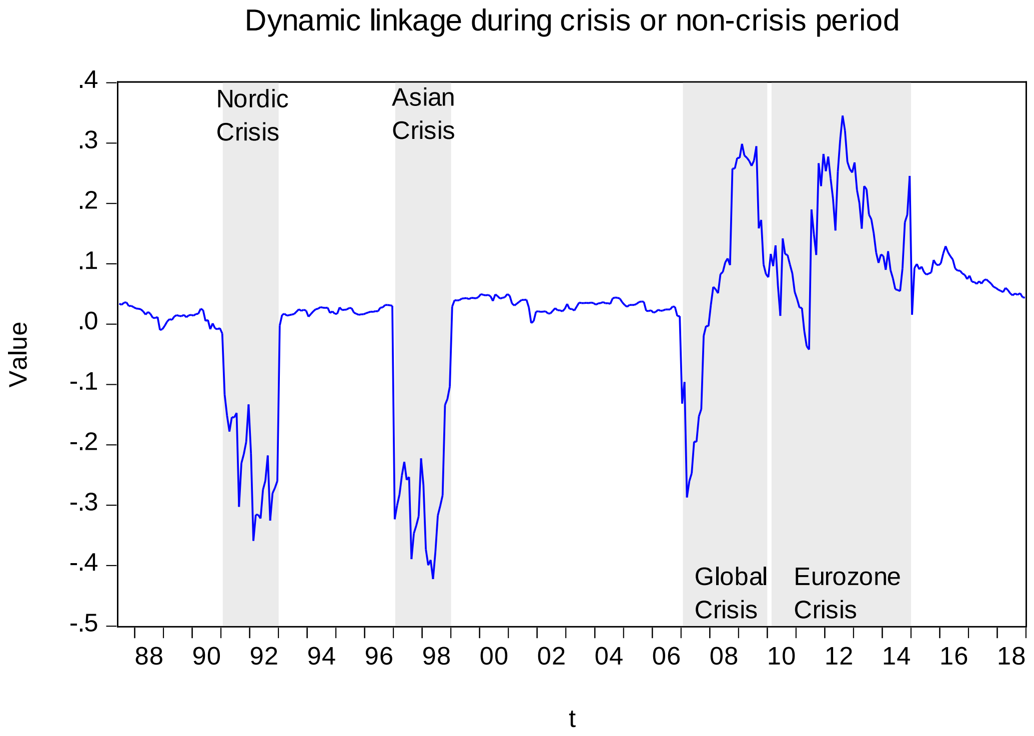

Figure 3. The linkage of the EEPU and oil return risks during crisis and non-crisis periods. The shadow part is about the crisis period, and the other is about the non-crisis period.

The heterogeneity exists during the crisis or non-crisis period. It could be seen from Figure 3 that the linkage of the EEPU and oil return risks (CE) fluctuated greatly during the crisis, while it is more stable and fluctuated around zero during the non-crisis period. This mainly results from the heterogeneity of oil price movement in different periods. During the crisis period, the crude oil market is less effective, and it also provides opportunities for risk spillover in different markets with the development of financial integration. In addition, it is easier to change the investors' expectation with the movement of the EPU because of the deterioration of the overall financial situation during the crisis period, which in turn impacts the crude oil prices. In contrast, the crude oil market is more efficient and can better regulate the spillover effects of other markets during the non-crisis period, so the CE is relatively stable at this time. What's more, this indicates that the EPU is one of the sources of oil return risk, and the impact of the EPU on oil return risk is not obvious during non-crisis periods. Therefore, policymakers need to timely intervene in the crude oil market, release good news, and stabilize oil prices. Otherwise, they also need to expand market transparency and reduce EPU, thereby reducing the oil return risk and stabilizing the oil market during the crisis period. During the non-crisis period, however, investors need to rationally analyze the price trend of the oil market, and avoid follow-up operations, thereby preventing possible risks in the market.

In addition, there is also heterogeneity in different crisis periods. It is interesting to note that during the Nordic crisis and the Asian economic crisis, the CE is the most negative; while the CE experienced large fluctuations in the positive direction during the European debt crisis. Moreover, during the global financial crisis, the amplitude of CE is the largest. This shows that there are significant effects of location and the development of the financial market on the linkage. For one thing, the CE experienced the opposite direction during the Asian crisis and the Eurozone crisis. This mainly results from that the Asian crisis mainly occurs in Southeast Asian countries, and the exchanges between different financial markets are also less, thus the risk spillover between different markets is not obvious. For another, the heterogeneity of the Nordic crisis, the global crisis, and the Eurozone crisis are mainly caused by the development of financial integration. The manipulation of prices by speculators during the crisis has further reduced market efficiency. As policy interventions increase market efficiency and provide opportunities for speculators to obtain excess profits, policy uncertainty reduces the expected returns of speculators in the market and controls their manipulation of the market. Because the Nordic crisis occurred earlier, the degree of financial market integration is not high, and the scope also is small. While during the global financial crisis and the European debt crisis, the scope of its occurrence is large, and with the increase in the integration of financial markets, the risk spillover effects between different markets are obvious. Therefore, this indicates that the wider the scope of the crisis the greater the fluctuation amplitude of the CE, thereby the more severe the fluctuation.

4.3. Heterogeneous linkages in different markets

In this subsection, we attempt to explore the heterogeneous linkage in different markets. As shown in last subsection, during the global financial crisis, the CE has the most fluctuation and also could be regarded as achieving a cycle of fluctuations. Considering that the global financial crisis in 2008 was mainly caused by the US subprime crisis, we further explore the heterogeneous linkage of EEPU (CE), UEPU (CU) or GEPU (CG) and oil return risk during the sample period[4]. The estimation results are shown in Table 6.

The same results as in Table 5 are also obtained in Table 6. The parameter λ_2 reveals a higher persistence of volatility across the EPU and oil return risk in different markets since it is significant and close to one. What's more, the value λ_2 in global is also significant, whereas in the USA, it is not significant. Moreover, the sum of λ_1 and λ_2 is less than 1, indicating that the estimated DCC parameters lie within the range of typical estimates from the GARCH-T model. Furthermore, we graph the heterogeneity in different markets in Figure 4.

As shown in Figure 4, it is worth noting that there are heterogeneous features in the value and the variation of the linkage. Firstly, we focus on the value of linkage in different markets. The vertical line in Figure 4(b) could be regarded as segmentation, that is, the left of vertical line (end of 2008) shows that CU is larger than CE, and conversely, the CE is larger than the CU. In addition, it is worth noticing that between 1997 and 2008, the difference between CE, CU and CG is significantly reduced compared to other times. What's more, the difference is the highest in 2008, and by the end of 2018, the difference between the three gradually narrowed. This mainly results from the economic status. Prior to 1997, the US's dominance in the global economic environment made it gained a higher correlation with crude oil prices. Since the 20th century, the development of emerging countries has promoted the diversification of global economy, and the development of financial market integration has further reduced the differences among different markets. The global financial crisis caused by the US subprime crisis in 2008 expanded the differences of CE, CU

[4] The UEPU covers June 1985–December 2018 and the GEPU covers January 1997–December 2018 on a monthly frequency due to the availability of the policy uncertainty index.

and CG. Because of the development of emerging markets, the CU has reduced, whereas the CE exceeds the CU. With the outbreak of the Eurozone crisis, the CE shows a significant upward trend. The global economic environment has gradually warmed up in recent years, thus the differences of CE, CU and CG have also reduced.

Table 6. Estimation of DCC-GARCH-T models.

Area	USA		GLOBAL	
	Risk	UEPU	Risk	GEPU
Panel A: GARCH-T				
c	0.002***	482.33***	0.002	324.49***
	(0.0006)	(111.01)	(0.001)	(76.58)
α_1	0.792**	1.170***	1.313	1.138***
	(0.403)	(0.347)	(1.043)	(0.267)
β_1	−0.080**	0.056	−0.059**	−0.037
	(0.037)	(0.081)	(0.024)	(0.097)
AIC	−3.738	10.013	−3.617	9.991
BIC	−3.686	10.065	−3.549	10.058
LogL	713.29	−1892.54	482.40	−1313.81
Panel B: Estimates of DCC-GARCH				
λ_1		0.015		0.056
		(0.035)		(0.045)
λ_2		0.725		0.841***
		(0.809)		(0.146)
df		3.480***		4.592***
(Degree of t-Distribution)		(0.227)		(0.594)
AIC		6.327		6.577
BIC		6.462		6.753
LogL		−1186.04		−855.17

*Note: Standard error shows in parentheses. *, ** and *** indicate significance at 1%, 5%, and 0.1% level, respectively.

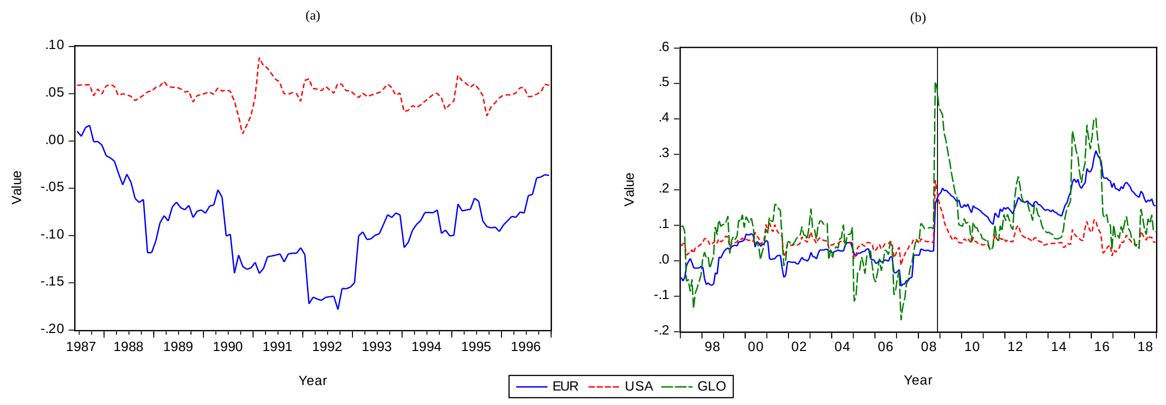

Figure 4. The linkage of EEPU and oil return risk during crisis and non-crisis periods. (a) reports CE vs CU during 1987–1997 and (b) reports CE, CU, and CG during 1997–2018. The vertical line is the dividing line between CE and CU size exchanges.

Further, it is interesting to notice that the variation exerts heterogeneity in different markets. As can be seen from Figure 4, the fluctuations of CU are the most gradual, and the most volatile is CG. While the CG is in line with the largest linkage, it has a magnifying effect on it. This indicates the impact of market perfection on the linkage. The higher the degree of the market perfection, the easier it is to timely regulate the situation that may occur in the market, further the spillover effect on other markets is more obvious. Before 2008, the spillover effect of the US market on other markets is more obvious, but due to its protection of the market, the degree of spillover is low. Since the outbreak of the global financial crisis, the timely monitoring of the US market has given it a certain degree of enhancement to the CU. Then, with the gradual adjustment of the market, the CU returns to the average level. In addition, before 2008, the CG is in line with the CU. However because the global market could also measure the total effect of other markets, it has a magnified effect on the linkage. After 2008, the CG remains basically in line with the CE. As the global economy picking up, the CG is in line with the CU.

5. Conclusions

There is significant impact of the linkage of economic policy uncertainty and oil return risk on economy and firm performance. In this paper, we forecast the oil return risk based on the CAViaR method and analyze the dynamic and heterogeneous features in the linkage of EPU and oil return risk. Furthermore, we depict the dynamic and heterogeneous features during the crisis (non-crisis) period or in different markets via DCC-GARCH models. Specific conclusions are as follows.

The linkage of policy uncertainty and oil return risk shows increased trend and stronger relationship with major events. The empirical results show that there are significant effects of crude oil markets and external political environment on the linkage between EPU and oil return risk. On the one hand, the main reason for the linkage is the supply of crude oil markets. On the other hand, the external environment, including the location of Brent oil market and other external environment, is also a main reason for the dynamic linkage.

The heterogeneity exists during the crisis or non-crisis period. Concretely, the linkage of EEPU and oil return risk (CE) fluctuates greatly during the crisis, while it is more stable and fluctuates around zero during the non-crisis period. In addition, there is also heterogeneity in different crisis periods. Above all, policymakers could better to timely intervene in the crude oil market, release good news, and stabilize oil prices during the crisis period. During the non-crisis period, however, investors need to rationally analyze the price trend of the oil market, thereby preventing possible risks in the market.

It is also worth noticing that there are heterogeneous features in value and variation of the linkage in different markets. For one thing, between 1997 and 2008, the differences between CE, CU and CG are significantly reduced compared to other times. What's more, the difference is the highest in 2008, and by the end of 2018, the difference between the three gradually narrowed. For another, the fluctuations of the CU are the most gradual, and the most volatile one is the CG. Thus, policymakers also should focus on the policy trend and further take account into the policy spillover effects in different countries.

Appendix A: The GARCH-type specification

The basic structure of the GARCH model can be written as (A1) and (A2).

$$X_t = \mu_t + H_t^{1/2}\varepsilon_t. \quad \text{(A1)}$$

$$H_t = c + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j H_{t-j}. \quad \text{(A2)}$$

where $X_t = (X_{1t}, X_{2t})$ is the vector of the EPU and oil return risks, H_t is the multivariate conditional variance; $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$ is the vector of the standardized residuals.

The mean equation of the TGARCH model and the EGARCH could be captured by (A1), but the conditional variance equation is given as (A3) and (A4) respectively.

$$H_t = c + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j H_{t-j} + \gamma \varepsilon_{t-1}^2 B. \quad \text{(A3)}$$

where B stands for an indicative function. B =1 when $\varepsilon_{t-1}^2 < 0$, and B =0 for otherwise.

$$\ln H_t = c + \sum_{j=1}^{q} \beta_j \ln H_{T-J} + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{H_{t-i}^{1/2}} - E\left(\frac{\varepsilon_{t-i}}{H_{t-i}^{1/2}}\right) \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{H_{t-i}^{1/2}}. \quad \text{(A4)}$$

where γ explains the leverage of the conditional variance. If the shock is negative, γ is negative. γ represents the asymmetric effect in the market. If γ is equal to zero, it indicates that the fluctuation effect in the market is symmetrical. However, if γ isn't equal to zero, the fluctuation effect is asymmetrical.

Appendix B: The estimation of CAViaR

As mentioned above, we use the first 340 to estimate the parameters and the last 39 for out-of-sample tests. Especially, we forecast 1% and 5% 1-month oil return risks ($Risk$) for K = 4 and 6, and set G = 10, entered the definition of the adaptive model. All of the results of parameters are reported in Table B1.

Table B1 shows the estimates and relevant statistics for the four CAViaR specifications. The first striking result is the coefficient of the autoregressive term (β_2), which is always very significant. This indicates that the phenomenon of clustering of volatility is also relevant in the tail. A second interesting point is the precision of all the specifications as measured by the percentage of in-sample hits. The results for the 5% show the symmetric absolute value and asymmetric slope and indirect GARCH models do a good job describing the evolution of the Bitcoin return risk. Finally, it is interesting to note the asymmetric slope model. We clearly notice that there are differences between the coefficients of the positive and negative parts of lagged returns, and these are always strongly significant. This indicates the performance of strong asymmetric effects on oil return risks. Thus the asymmetric slope results could be regarded as oil return risks.

Table B1. Estimates and relevant statistics for the four CAViaR specifications.

Panel a: 1% VaR				
	(a)	(b)	(c)	(d)
β_1	−0.001 (0.003)	0.116* (0.239)	−0.001*** (0.0005)	0.002 (0.021)
β_2	0.903*** (0.015)	0.416*** (1.201)	0.798*** (0.004)	
β_3	0.312*** (0.014)	−0.323 (0.461)	1.667*** (0.063)	
β_4		0.507 (0.325)		
Hit in-sample(%)	0.990	1.320	0.990	0.660
Hit out-of-sample(%)	5.236	1.316	0	0.000
DQ_{IS} (p)	0.975	0.982	0.985	0.199
DQ_{OOS} (p)	0.000	0.869	0.703	0.996
Panel b: 5% VaR				
	(a)	(b)	(c)	(d)
β_1	0.049 (0.192)	0.146*** (0.008)	0.020 (0.185)	2.070e−05 (0.012)
β_2	0.499 (1.617)	−0.331*** (0.014)	−0.304*** (0.029)	
β_3	0.328 (0.511)	−0.176*** (0.058)	0.911*** (0.131)	
β_4		0.736*** (0.023)		
Hit in-sample (%)	5.281	4.621	4.951	4.621
Hit out-of-sample(%)	7.895	7.895	7.895	6.579
DQ_{IS} (p)	0.689	0.767	0.999	0.048
DQ_{OOS} (p)	0.016	0.383	0.016	0.477

*Note: Standard errors shown in parentheses; *, ** and *** indicate significance at 1%, 5%, and 0.1% level, respectively. (a) Symmetric absolute value; (b) Asymmetric slope; (c) Indirect GARCH (1,1); (d) Adaptive.

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Conflict of interest

The authors declare no conflict of interest.

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