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Fluctuation in the global oil market, stock market volatility, and economic policy uncertainty: A study of the US and China

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ABSTRACT

This paper investigates the relationships between the global oil market, stock markets, and economic policy, focusing on China and the US. We use a time-varying parameter stochastic volatility vector autoregression model to examine the transmission mechanisms between fluctuation in the global oil price, the volatility of the Chinese and US stock markets, and economic policy uncertainty in China and the US from 2003 to 2020. We observe significant correlations between the volatility of the two countries' stock markets and fluctuation in the global oil price. Compared with the Chinese stock market, the US stock market has a greater impact on the global oil market. We also find that an increase in economic policy uncertainty in the two countries exacerbates fluctuation in the global oil price, particularly during times of crisis. In turn, greater fluctuation in the global oil price increases stock market volatility and economic policy uncertainty in both countries.

1. Introduction

The dominant role of crude oil in the energy market is well documented (Alvarez-Ramirez et al., 2003; Yu et al., 2008), especially in relation to institutional risks and uncertainties and the shift towards economic deglobalization (Schell, 2020; Wei, 2019). In recent decades, increasing uncertainties globally have triggered negative expectations in the global capital and oil markets (Albulescu, 2020a & 2020b; Donadelli et al., 2017). Specifically, both the 1997 Asian financial crisis and the 2007 subprime mortgage crisis in the US, which evolved into the 2007–2008 global financial crisis, led to a sharp drop in global stock and oil prices. Similarly, following the outbreak of the COVID-19 pandemic in 2020, the breakdown of negotiations between Russia and the Organization of the Petroleum Exporting Countries (OPEC) led to a continuous decrease in the price of oil and a meltdown in the US stock market.

Against this backdrop, several scholars attempt to provide a coherent understanding of the relationships between stock and oil markets in various countries and their correlations with the macroeconomic environment (Fang et al., 2018; Kang & Ratti 2013; You et al., 2017). However, their findings remain inconclusive (Kilian & Park, 2009).

Most studies of the transmission mechanisms between the global oil market and national stock markets and national economic policy focus on either the correlation between the price of oil and stock returns, or the effects of national uncertainties on stock markets and the global oil market. They tend to argue that both economic policy uncertainty and oil price fluctuation increase stock market volatility (Brogaard & Detzel, 2015; Cifarelli & Paladino, 2010; Pástor & Veronesi, 2012; Sadorsky, 1999). Oil price fluctuation exerts inflationary pressure and changes expectations of oil output, thereby increasing economic policy uncertainty (Bastianin et al., 2016; Kormilitsina, 2011). Changes to economic policy may bring systemic risks, which increase stock market volatility due to changes in capital market expectations (Pástor & Veronesi, 2013). However, very few studies coherently examine the dynamic correlations among stock prices, the price of oil, and economic policy uncertainty. It is thus necessary to explore these correlations, particularly in the contexts of the US and China, as the world's two largest economies.

Transmission mechanisms also exist between countries' stock markets. Zhang, Chen et al. (2021), Zhang, Gao et al. (2021) find a dynamic increasing spillover effect between the volatility of the US stock market and the risk of a crash in China's stock market. They also suggest that a higher risk of stock market crash

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in China leads to lower stock market volatility in the US, due to investor hedging. However, though the risk of a stock market crash reflects stock market volatility to a certain extent, it primarily captures the ratio of fluctuation when stock prices fall to fluctuation when stock prices rise. The volatility of stock prices may be underestimated in times of economic prosperity and overestimated during economic recessions. Therefore, it is necessary to investigate stock market volatility without distinguishing between rising and falling stock prices; instead, we should more broadly examine the general dynamic spillover effects of stock markets.

The US and China are the world's most influential advanced and emerging economies, respectively. To explore the correlations among fluctuation in the global oil price and stock market volatility and economic policy uncertainty in these two countries, we use a time-varying parameter stochastic volatility autoregression (TVP–SV–VAR) model. Our findings show that stock market volatility in the US, compared with that in China, has a greater positive impact on fluctuation in the global oil price. The findings also show that the impact of global oil price fluctuation on the two stock markets was significantly greater in 2020, due to the shock of the COVID-19 pandemic, than in 2008, during the global financial crisis.

This study makes several contributions to the literature on international capital markets and international energy economics. The research context integrates the world's two most influential emerging and advanced economies, the US and China. The findings suggest that these economies' capital markets are closely linked, and that economic policy uncertainty in one country affects the both the stock markets of the two countries, albeit to different extents. Our study also provides evidence that the global oil price plays a crucial role in the relationship between these two capital markets and mutually affects the two countries' economic policies.

The rest of the paper is organised as follows. The next section reviews the relevant literature. This is followed by an outline of the data source and methodology. We then present the results and discuss our findings. The final section concludes the study and discusses its implications.

2. Literature review

Many studies examine the relationship between economic policy uncertainty and stock price volatility, and most agree that economic policy uncertainty leads to risk premiums in stocks (Brogaard & Detzel, 2015; Campbell & Shiller, 1988; Hoque & Zaidi, 2019; Pástor & Veronesi, 2012; Pástor & Veronesi, 2013; Sum, 2012). Brogaard & Detzel (2015) find that an increase in the uncertainty of economic policy leads to a decrease in stock market returns but an increase in stock volatility. Another study shows that government policy adjustments have a negative impact on stock prices (Pástor & Veronesi 2012). Specifically, the announcement of a policy adjustment leads to a significant drop in stock prices. The extent of government policy uncertainty is thus significantly related to the volatility of stock prices. Pástor & Veronesi (2013) use a general equilibrium model to measure government policy changes and find that political uncertainties lead to risk premiums, which may be higher when the economy is weaker. Campbell & Shiller (1988) find that changes brought by economic uncertainties affect not only firms' cash flow and dividend payment methods but also the expected returns of stocks, ultimately increasing the volatility of the stock market.

Crude oil is an essential commodity in the global economy. A change in the price of oil directly affects the prices of other commodities (Barsky & Kilian, 2004) and may increase uncertainties relating to crude oil production and consumption. This in turn may affect investment behaviors and the entire global economy (Pindyck, 2004). Although understanding of the crude oil market is deepening, it is still difficult to predict fluctuations in the price of oil (Smith, 2009). Morana (2001) uses generalised autoregressive conditional heteroscedasticity (GARCH) characteristics to explain and predict the short-term global oil price via the bootstrap method. Baumeister & Kilian (2016) find that oil price fluctuations are associated with external political events (such as conflict between OPEC members or oil wars). Demand for oil is the major determinant of global oil price fluctuation (Barsky & Kilian, 2001; Barsky & Kilian, 2004; Kilian & Murphy, 2012; Kilian & Park, 2009). Oil supply is also an important factor (Baumeister & Hamilton, 2019; Lynch, 2002). Due to its effectiveness in predicting oil price fluctuations, VAR is one of the most influential analytical approaches in this area (Baumeister & Kilian, 2012; Baumeister & Peersman, 2013; Caldara et al., 2019; Lee & Ni, 2002; Sadorsky, 1999). General equilibrium models are widely used to examine the impact of oil price fluctuations on international trade (Bodenstein et al., 2011; Leduc & Sill, 2004).

The price of crude oil also significantly influences stock markets (Sadorsky, 1999). Cifarelli & Paladino (2010) find that fluctuation in the global oil price is negatively related to stock prices. Another study argues that fluctuation in the crude oil price is driven by supply and demand in the global market and thus influences the long-term returns of stocks in the US stock market (Kilian & Park 2009). Zhang (2017) acknowledges that large oil shocks have a significant impact on stock prices. Cifarelli & Paladino (2010) argue that speculation plays an important role in the global crude oil market. Due to the negative impact of oil price fluctuation on economic growth and inflation, active speculation in commodity markets also increases the volatility of stock prices. Sadorsky (1999) reports that the price of oil and its fluctuations affect the actual return rates of stocks and, compared with interest rate, can better explain actual stock returns.

As crude oil is an essential global commodity, fluctuations in its price bring great uncertainties to the macro-economic environment and economic policy. Barsky & Kilian (2004) find that the price of crude oil has a significant impact on exchange rates, inflation, and interest rates. Focusing on the US, Bjørnland et al. (2018) analyse the effects of oil price fluctuation on macroeconomic stability and find that oil price shocks are a regular source of economic fluctuation. Simultaneously, oil plays an important role in stabilising the US economy (Nakov & Pescatori, 2010). During the 2007–2008 financial crisis, international oil price shocks led to inflationary pressure and an output decline in oil-importing countries (Bastianin et al., 2016). This forced governments to make a trade-off between stabilising inflation and reducing the output gap, resulting in greater policy uncertainty (Kormilitsina, 2011).

Most studies on the global crude oil price and its fluctuation focus on developed economies. However, with growing energy demand from emerging economies, interactions between the economic and financial markets of emerging and developed economies are increasing. This leads researchers to highlight the dynamic correlations among the global crude oil price and stock markets and economic policy uncertainty in emerging and developed economies, calling for a shift in focus from pair-wise to simultaneous correlation to capture the dynamic reality of these relationships. Research should also address systemic risk over time, as investors' expectations, policy preferences, and financial market risk contagion are constantly changing. Filling these gaps in the literature, this paper uses a TVP–SV–VAR model to examine the correlations among fluctuation in the global oil price, stock market volatility, and economic policy uncertainty, focusing on China and the US.

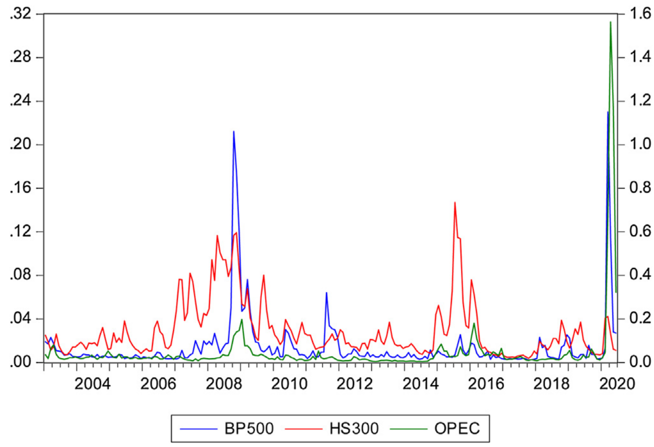

Fig. 1. Volatility of S&P 500, CSI 300, and OPEC crude oil price.

3. Method

3.1. Data specifications

The sampling time frame is from January 2003 to June 2020, and thus includes the impact of the global financial crisis and the outbreak of COVID-19. The five main variables are stock market volatility in China, stock market volatility in the US, economic policy uncertainty in the US, economic policy uncertainty in China, and OPEC crude oil price fluctuation. Economic policy uncertainty in China and the US is captured by the economic policy uncertainty index (EPU) constructed by Baker et al. (2016). The monthly volatility of the S&P 500 Index is used to represent the volatility of the US stock market. The monthly volatility of the CSI 300 Index is used to represent the volatility of the Chinese stock market. The closing prices of the S&P 500 Index and the CSI 300 Index are from the Wind database. The crude oil price data come from OPEC's official website. Following Mala & Reddy (2007), a GARCH (1,1) model is used to measure stock market volatility. This model captures the aggregation distribution of volatility as well as its unconditional heavy-tailed return distribution. The GARCH (1,1) model is as follows:

$$y_t = x_t^{\prime}\beta + \varepsilon_t \tag{1}$$

The above is the conditional mean equation, where x_t is a vector of exogenous variables. The conditional variance σ_t^2 can be expressed as

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \gamma_1\sigma_{t-1}^2 \tag{2}$$

where α_0 is a constant term, $\alpha_1\varepsilon_{t-1}^2$ is an ARCH term, and $\gamma_1\sigma_{t-1}^2$ is a GARCH term. The generation process of the disturbance term ε_t in GARCH (1,1) is

$$\varepsilon_t = \upsilon_t\sqrt{\alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \gamma_1\sigma_{t-1}^2} \tag{3}$$

By calculating the logarithmic return rates of the S&P 500 Index, CSI 300 Index, and OPEC crude oil price index, we obtain the conditional variance of the above GARCH (1,1) model. We then multiply this variance by 100 and calculate the monthly average to obtain the percentage monthly volatility.

Fig. 1 shows the percentage monthly volatility of the S&P 500, the CSI 300, and the OPEC crude oil price. The blue line represents the volatility of the S&P 500. The red line represents the volatility of the CSI 300. The green line represents the volatility of the OPEC crude oil price. The left-hand coordinates measure the volatility of the S&P 500 and CSI 300. The right-hand coordinate measures the volatility of the OPEC crude oil price. The figure implies that due to the impact of the global financial crisis, the US stock market, the Chinese stock market, and the price of crude oil were particularly volatile in 2008. It also shows that the subsequent sovereign debt crisis in Europe impacted the US stock market. The significant volatility of China's stock market in 2015 also affected the US stock market and the global oil price in that year. In 2020, with the meltdown of US stocks, the volatility of the oil market reached a peak exceeding that in 2008, during the global financial crisis. Further, the demand for crude oil in the global market decreased greatly during the COVID-19 pandemic.

3.2. Unit root tests

As a non-stationary series may lead to pseudo-regression, we perform a unit root test of each time variable before conducting the empirical analysis. Table 1 presents the test results for the stability of the variables, which are processed in logarithmic form. The table shows that the volatility of the US stock market, the volatility of the Chinese stock market, the EPU of the US, the EPU of China, and OPEC crude oil price fluctuation are all stable variables.

3.3. Model specification

Many studies use VAR to analyse the volatility effects of stock markets and energy markets (Chiu et al., 2018; Kang et al., 2021; Stoupos & Kiohos, 2021; Yu et al., 2020). However, the traditional VAR model does not take into account differences in the stochastic volatility of variables in different periods. For example, during the 2007–2008 financial crisis, the stochastic volatility of stocks may have been significantly higher than during stable periods. Additionally, the traditional VAR model does not take into account the characteristics of parameters that change dynamically. To deal with these problems, most recent studies adopt TVP–SV models (Anand & Paul, 2021; Ding et al., 2021; Jebabli et al., 2014; Toparlı et al., 2019; Zhang, Chen et al., 2021; Zhang, Gao et al., 2021). To capture dynamic changes in the two focal economies and the global economy during 2003–2020, we use a TVP–SV–VAR model to examine the correlations among Chinese stock market volatility, US stock market volatility, the EPU of the US, the EPU of China, and fluctuation in the OPEC crude oil price. To justify our choice of model, we first implement the traditional VAR model and then compare its results with those of our TVP–SV–VAR model.

3.3.1. VAR model

The VAR model is as follows:

$$y_t = c + B_1y_{t-1} + \cdots + B_sy_{t-s} + e_t,\ e_t \sim N\left(0, \Omega\right),\ t = s+1, \cdots, n \tag{4}$$

where y_t is a k*1 vector of observable variables, $B_1, \cdots, B_s$ is a k*k parameter matrix, and Ω is a k*k positive definite covariance matrix. To accommodate possible simultaneous effects among the variables, we use a structural VAR model for the analysis. Table 2 presents the lag order selection statistics for various information criteria. As the results for lag order 1 and lag order 2 are similar, the lag order of the model is set to 1 according to HQIC (Hannan and Quinn information criterion) and SBIC (Schwarz's Bayesian information criterion).

Fig. 2 presents the impulse response results for the five-variable VAR. The shaded area represents the confidence interval of plus or minus one standard deviation. As seen in the first row of the figure, given one positive standard deviation innovation on the volatility of the U.S. stock market, the volatility of China's stock market, the volatility of crude oil price, the uncertainty of U.S. economic policy and the uncertainty of China's economic policy show positive responses. This signifies that the US stock market has a wide range of risk contagion, with spillover effects on China's stock market and the price of crude oil. Meanwhile, an increase in US stock market

Table 1
Unit root test results.

Variable	Lag	DF-GLS tau test statistic	1 %	Conclusion
σ_{bp}	3	−3.841	−3.480	stable
σ_{hs}	2	−3.676	−3.480	stable
epu_{usa}	1	−3.559	−3.480	stable
epu_{chn}	1	−4.424	−3.480	stable
σ_{oil}	1	−3.583	−3.480	stable

Table 2
Information criteria.

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	−916.488				0.005285	8.946	8.979	9.027
1	−388.218	1056.5	25	0	0.00004	4.060	4.256*	4.545*
2	−347.028	82.379	25	0	0.000034*	3.903*	4.263	4.792
3	−324.795	44.466	25	0.01	0.000035	3.930	4.453	5.222
4	−302.696	44.198*	25	0.01	0.000036	3.958	4.644	5.654

Note: *p<0.05.

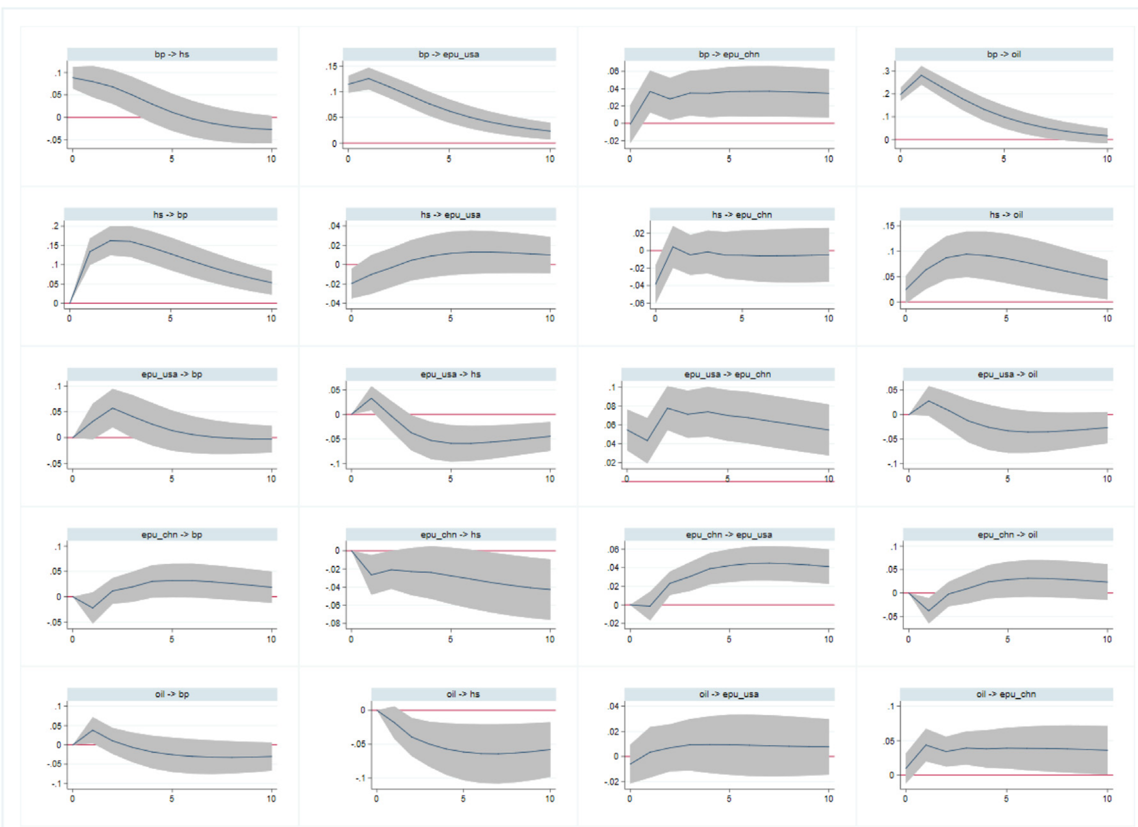

Fig. 2. Five-variable VAR.

volatility leads to a rapid increase in the EPU of the US, but its effect on the EPU of China is one of hysteresis. The table also shows that given one positive standard deviation innovation on the volatility of China's stock market, the volatility of the U.S. stock market also has a positive response, which indicates that there is a spillover effect between the US and Chinese stock markets. Additionally, the Chinese stock market has a spillover effect on the global crude oil price. The results shows that the response of the volatility of US stock market to one standard deviation EPU of US innovation is positive; The response of EPU of China to one standard deviation EPU of US innovation is also positive; The response of the EPU of US to one standard deviation the EPU of China innovation is also positive. Given one standard deviation innovation in crude oil price volatility, the responses of US stock market volatility and the EPU of China are positive, while the response of Chinese stock market volatility is negative. The EPU of the US is not significantly affected.

The results of the VAR model indicate that although traditional VAR is widely used for stock market volatility and oil price fluctuation, it is not flexible enough to accommodate potential structural instability in the time series, which is particularly relevant when examining EPU and the impulse responses of crude oil price volatility to the other variables. In addition, the traditional VAR model fails to capture the interactions between the variables at specific time points (especially in 2008, during the global financial crisis; and in 2020, during the meltdown of US stocks). In light of this, we

Table 3
Marginal likelihood for various time-varying VARs.

Model	Lag	Log marginal likelihood	Standard error
TVP–SV–VAR	1	−525.5975	(0.2420)
	2	−612.8491	(0.5695)
	3	−707.3113	(0.8763)
TVP–VAR	1	−671.1575	(0.1926)
	2	−773.3267	(0.3540)
	3	−886.5795	(0.5368)
SV–VAR	1	−556.0254	(0.0459)
	2	−617.9507	(0.0575)
	3	−693.2644	(0.0629)
VAR	1	−651.5922	(0.0178)
	2	−711.8138	(0.0156)
	3	−787.3327	(0.0508)

Note: Numerical standard errors in parentheses.

use a TVP–VAR model to examine the correlations among the five variables.

3.3.2. TVP–SV–VAR

The TVP–SV–VAR model is as follows:

$$y_t = c_t + B_{1t}y_{t-1} + \cdots + B_{st}y_{t-s} + e_t,\ e_t \sim N\left(0, \Omega_t\right),\ t = s+1, \cdots, n \quad (5)$$

where y_t is a k*1 vector of observable variables, $B_{1t}, \cdots, B_{st}$ is a k*k time-varying coefficient matrix, and Ω_t is a k*k time-varying covariance matrix. Recursive identification is assumed by decomposing $\Omega_t = A_t^{-1}\sum_t\sum_t A_t^{-1'}$, where A_t is the lower triangular matrix with diagonal elements equal to 1 and $\sum_t = diag(\sigma_{1t}, \cdots, \sigma_{kt})$. β_t is the stacked row vector of $B_{1t}, \cdots, B_{st}$; $a_t = (a_{1t}, \cdots, a_{qt})'$ is the stacked row vector of any lower triangular element of A_t ; and $h_t = (h_{1t}, \cdots, h_{kt})'$, where $h_t = \log\sigma_{it}^2$. The time-varying parameters follow the stochastic walking process:

$$\begin{matrix} \beta_{t+1} = \beta_t + u_{\beta t}, \\ a_{t+1} = a_t + u_{at}, \\ h_{t+1} = h_t + u_{ht}, \end{matrix} \quad \begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & O & O & O \\ O & \sum_\beta & O & O \\ O & O & \sum_a & O \\ O & O & O & \sum_h \end{pmatrix}\right), \quad (6)$$

$t = s+1, \cdots, n$, and $e_t = A_t^{-1}\sum_t \varepsilon_t$, where $\sum_a$ and $\sum_h$ are diagonal, $\beta_{t+1} \sim N\left(u_{\beta 0}, \sum_{\beta 0}\right)$, $a_{t+1} \sim N\left(u_{a0}, \sum_{a0}\right)$ and $h_{t+1} \sim N\left(u_{h0}, \sum_{h0}\right)$. The prior distribution is set as:

$$\left(\sum_\beta\right)_i^{-2} \sim Gamma(20, 0.01),\ \left(\sum_a\right)_i^{-2} \sim Gamma(2, 0.01),$$
$$\left(\sum_h\right)_i^{-2} \sim Gamma(2, 0.01) \quad (7)$$

There are five main variables in our study. Following Chan & Eisenstat (2018), we calculate marginal likelihood estimates to help us select a model and its lag order. Four models are tested: TVP–SV–VAR, TVP–VAR, SV–VAR, and traditional VAR. Table 3 shows the logarithmic marginal likelihood values obtained for each of the models for lag orders of 1, 2, and 3. Table 3 shows that the logarithmic marginal likelihood obtained for all four models is higher with a lag order of 1 than with a lag order of 2 or 3. As the estimated value of the logarithmic marginal likelihood is largest for the TVP–SV–VAR model, this model is chosen for our analysis, with the lag order set to 1.

3.3.3. Parameter estimation and model diagnosis

To verify our hypotheses, the sequence of variables in the empirical model is set as the volatility of the Chinese stock market, the volatility of the US stock market, the EPU of the US, the EPU of China, and the volatility of the OPEC crude oil price. The TVP–SV–VAR model is estimated using OxMetric 6 software. We use a five-variable TVP–SV–VAR model. The effective sample size, obtained using the Markov chain Monte Carlo (MCMC) algorithm, is 10,000. The lag order of the model is 2. Fig. 3 shows the autocorrelation function, sample value path, and density function of the posterior distribution. After deleting 1000 samples from the pre-trigger period, the autocorrelation coefficient steadily decreases while the sample selection path remains stable. The parameter estimation results are shown in Table 4. The Geweke diagnostic value is less than 1.96, indicating that the Markov chain converges to the posterior distribution at a significance level of 5 %; the effect of the influencing factor is very small, indicating that the MCMC algorithm is an effective approach to estimation (Nakajima et al. 2011).

4. Results and discussion

4.1. Time-varying parameter analysis of TVP–SV–VAR model

Fig. 4 shows the stochastic volatility of the five variables: Chinese stock market volatility, US stock market volatility, OPEC crude oil price volatility, the EPU of the US, and the EPU of China. As seen in the upper left corner of Fig. 2, the global financial crisis triggered by the US subprime mortgage crisis led to stochastic volatility in the US stock market, which reached a peak and then stabilised due to to the implementation of an expansionary policy by the US Federal Reserve. The sovereign debt crisis in Europe also led to an increase in the volatility of the US stock market in 2011. The results also suggest that the volatility of the US stock market increased significantly in 2018, probably due to the reduction of quantitative easing by the US Federal Reserve. In addition, in the COVID-19 pandemic period, the US stock market triggered circuit breakers four times. These financial crises also affected the Chinese stock market. As shown in Fig. 1, the 2020 US stock meltdown was transmitted to the Chinese stock market, significantly increasing its volatility.

The EPUs of the two countries are also found to be closely related to their capital markets. The increasing fluctuation in the US stock market due to the financial crisis increased the EPU of the US after 2008. The increased volatility of the US stock market in 2018 led to another increase in the US's EPU. In 2020, the significant volatility of the US stock market during the COVID-19 pandemic led to an increase in the US's EPU. The EPU of China also increased significantly in response to the European debt crisis, when the Chinese government implemented a proactive fiscal policy.

Stock market volatility was also transmitted to the global oil market during the sample period. We find positive correlations between fluctuation in the OPEC crude oil price and the volatility of the two stock markets in 2008, 2018, and 2020.

In general, incorporating time-varying volatility is found to improve the VAR estimation and help identify structural shocks with appropriate variances. For the data analysed here, the estimation of the constant parameter time-invariant VAR model leads to deviation in the perturbed covariance matrix and the autoregressive coefficient due to the non-standard dynamics of the parameters.

4.2. Time-varying impulse response analysis of TVP–SV–VAR model

Fig. 5 shows the time-varying characteristics of the correlations among the volatility of the US stock market, the volatility of the Chinese stock market, the EPU of the US, the EPU of China, and OPEC crude oil price fluctuation over the same period. The first row of Fig. 5 shows that the volatility of the US stock market exerted a significant and increasing positive impact on the volatility of the Chinese stock market and the volatility of the global crude oil price

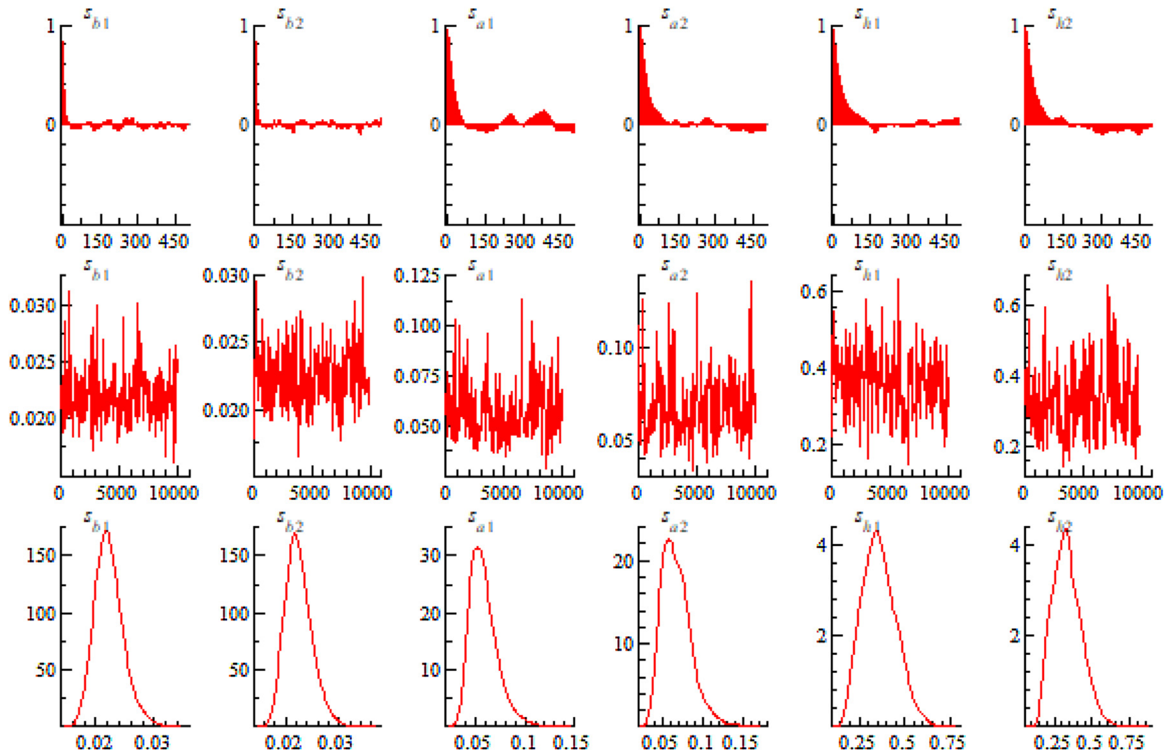

Fig. 3. Parameter estimation results of TVP–SV–VAR model.

Table 4
Parameter estimation results for TVP-VAR.

Parameter	Mean	Stdev	95 % confidence interval	Geweke	Inef.
sb1	0.0223	0.0024	[0.0180, 0.0279]	0.936	8.56
sb2	0.0225	0.0025	[0.0183, 0.0280]	0.695	8.56
sa1	0.058	0.0139	[0.0377, 0.0918]	0.976	37.06
sa2	0.067	0.0185	[0.0394, 0.1109]	0.617	58.52
sh1	0.3612	0.0919	[0.2043, 0.5547]	0.015	63.26
sh2	0.335	0.0955	[0.1789, 0.5399]	0.837	65.14

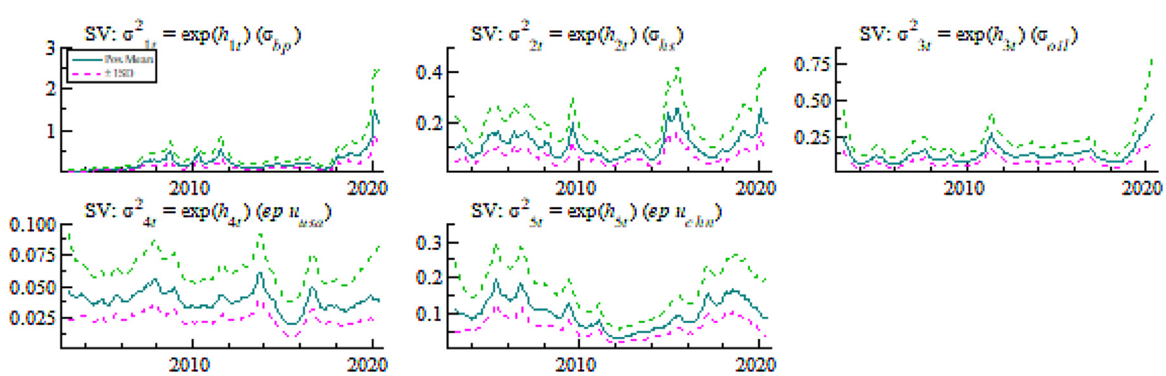

Fig. 4. Time-varying characteristics of stochastic volatility.

during the sample period. This signifies that systemic risks in the US stock market spread to the Chinese stock market and the global crude oil market quickly. The increase in the volatility of the US stock market had a positive impact on the EPUs of the two countries during the same period, especially the EPU of the US during the global financial crisis and the COVID-19 pandemic. The results also reveal a positive correlation between the volatility of the US stock market and crude oil price volatility. This relationship was particularly strong during the global financial crisis, consistent with the findings of Liu et al. (2020). Further, volatility in the Chinese stock market is found to exert a positive impact on fluctuation in the price of crude oil, although this impact was insignificant during the global financial crisis. During the sample period, fluctuation in the price of oil only exerted a significant positive effect on the EPUs of the two countries in March 2020, due to the huge crude oil shock caused by the outbreak of the pandemic. Finally, the EPUs of the US and China are found to be increasingly positively correlated, which signifies that the two countries' economic policies are becoming more interconnected.

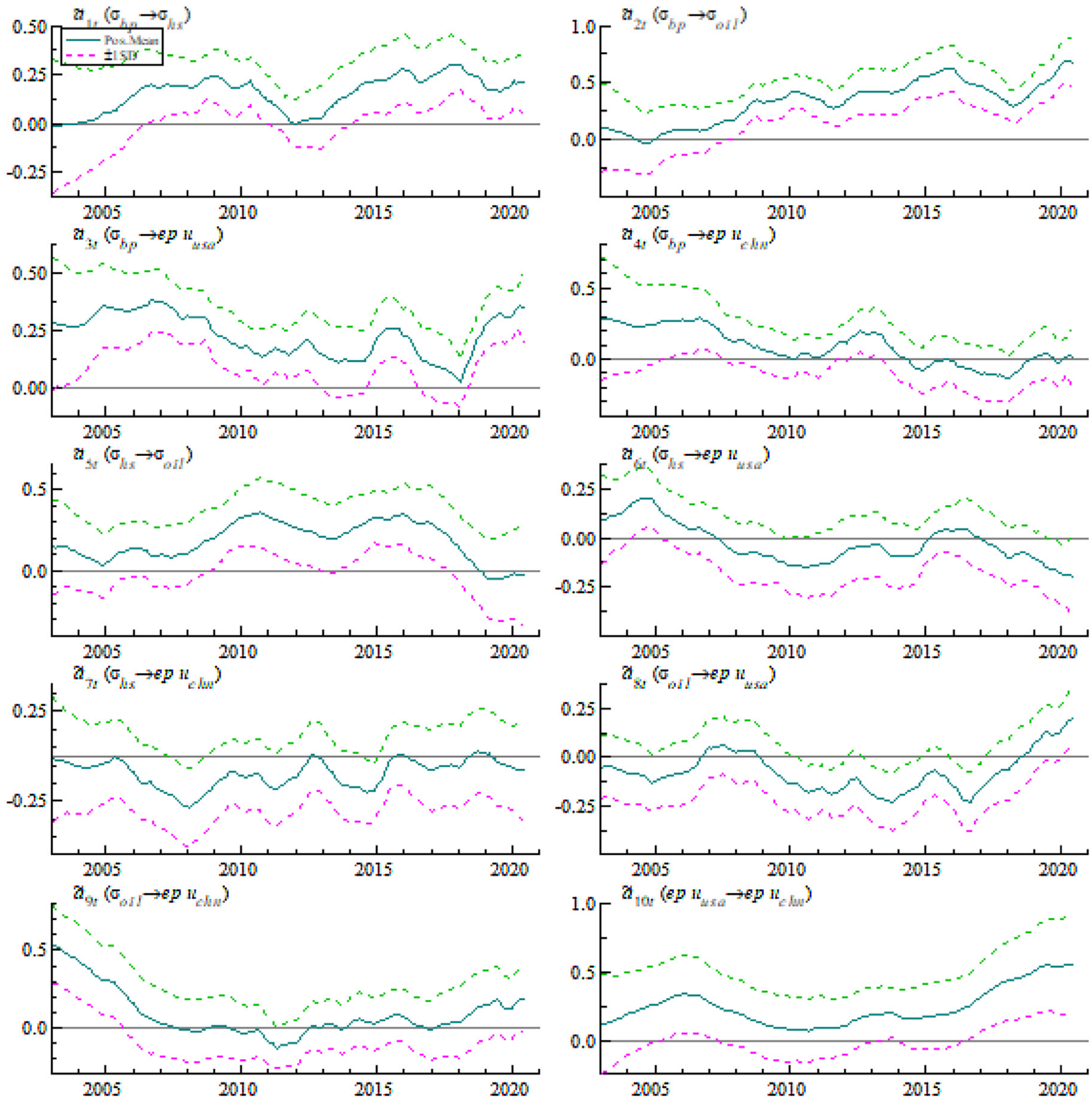

Fig. 5. Time-varying characteristics of contemporaneous relation.

Unlike the constant coefficient VAR model, the TVP–-SV–-VAR model can be used to investigate the impulse responses of various variables with different lead times. To capture the impact of systemic financial risk on risk contagion, economic policy uncertainty, and OPEC crude oil price fluctuation, we select the impulse response durations of 1 month, 3 months, and 6 months to represent short-term, medium-term, and long-term impacts, respectively.

The first row of Fig. 6 shows the impulse responses of other four variables to volatility of US stock market innovation. The volatility of Chinese stock market has a positive impulse response to that of the US stock market. Although this response gradually weakens after 2018, it can still be observed in the medium and long terms. Given one positive shock to the volatility of the US stock market, the impulse response of crude oil price volatility is positive in the short, medium, and long terms. It shows local peaks in 2008, during the global financial crisis, and 2020, during the circuit breaker period of the US stock market. Compared with its impulse response in the contemporaneous relation, the volatility of the US stock market has a longer lasting impact on crude oil price fluctuation, although this impact gradually weakens. Similarly, positive correlations are seen between the volatility of the US stock market and the EPU of the US during the focal three periods. However, the impact of US stock market volatility on the EPU of China is close to 0 for the period after 2008, suggesting that China's economic policy is not affected by US stock market volatility.

The second row of Fig. 6 shows the impulse responses of other four variables to Chinese stock market volatility innovation. The Chinese stock market's volatility exerts a positive impact on the US stock market's volatility in the short term. This impact strengthens in the medium term but weakens in the long term, particularly during the European debt crisis of 2011. However, the impact is still visible at the time points of 2008, during the global financial crisis, and 2015, during China's stock market disaster, which suggests that the Chinese stock market has a growing impact on the US stock market. It also indicates that there is a certain time lag in the risk contagion from the Chinese stock market to the US stock market. The volatility of the Chinese stock market has a positive impact on the volatility of the price of crude oil. The risk contagion of the Chinese stock market to the crude oil market also shows a certain time lag. However, the volatility of the Chinese stock market has only a small negative impact on the EPUs of both countries.

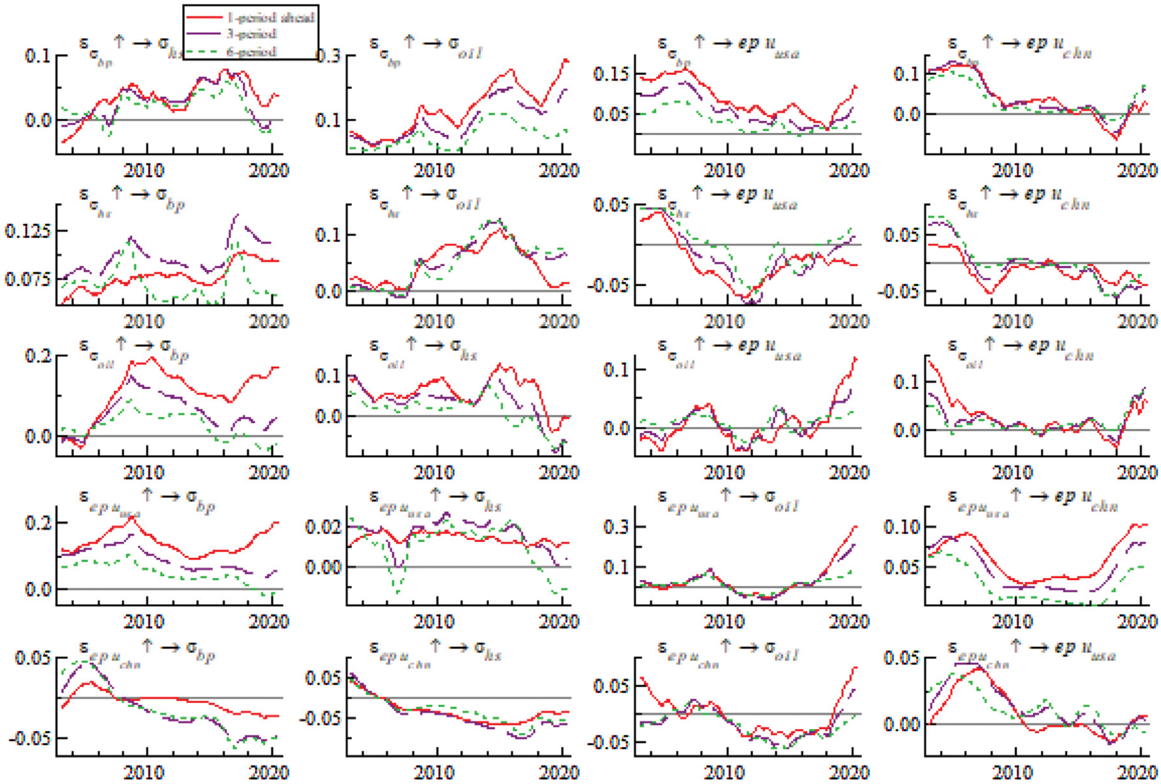

Fig. 6. Impulse responses for different time horizons.

The third row of Fig. 6 presents the impulse responses of other four variables to crude oil price volatility innovation. It shows that the volatility of the price of crude oil has a significant positive impact on the volatility of the US stock market, which is consistent with the findings of Tang et al. (2021). This impact is particularly strong during periods of crisis, which is consistent with the results of Park & Ratti (2008). This finding also indicates a volatility spillover effect between the crude oil market and stock returns, which echoes the findings of Arouri et al. (2011). Given one positive standard deviation innovation to crude oil price volatility, the impulse response of Chinese stock market volatility is positive, especially after the global financial crisis, reflecting the increasing demand for crude oil in the Chinese market. Furthermore, the great turbulence in the price of oil during the COVID-19 pandemic increased the EPUs of both countries. The rising oil price may have led to an increase in oil-related costs. The greater the market distortion caused by monopolistic competition, the greater the impact of an oil price increase on the actual marginal costs for enterprises. This may decrease total output and real wages, requiring governments to adjust policies to stabilise prices (Natal, 2012). Therefore, fluctuation in the global oil price may affect national economic policy uncertainty (Antonakakis et al. 2014).

The fourth row in Fig. 6 presents the impulse responses of other four variables to EPU of US innovation. Given one positive standard deviation innovation to the EPU of the US, the impulse response of the volatility of the US stock market is also positive, especially during the global financial crisis and the 2020 meltdown of US stocks, signifying that the correlation between the EPU of the US and the volatility of the US stock market is stronger during times of crisis. Economic policy uncertainty increases the risk of collapse through managers' concealment of bad news and the heterogeneous beliefs of investors (Jin et al., 2019). The results reveal that the volatility of the Chinese stock market has a steady positive impulse response to the US's EPU innovation in the short term. This signifies that the volatility of the stock market is a crucial source of economic policy uncertainty (Liu & Zhang, 2015). In addition, the impact of the US's EPU on crude oil price volatility is observed to be positive for 2018, when the US Federal Reserve's balance sheet led to the meltdown of US stocks. Given one positive standard deviation innovation to the EPU of the US, the response of the EPU of China is positive, although the duration of this impact gradually decreases.

The fifth row in Fig. 6 presents the impulse responses of other four variables to EPU of US innovation. The results show that the impact of China's economic policy uncertainty on the stock market fluctuations of China and the United States is small or even negative, and the impact on the crude oil price fluctuations is similar, which shows that the transmission capacity of China's EPU is weak. Although US and Chinese stock market volatility and oil price fluctuation have positive spillover effects on the EPU of China, this effect is weakened over time.

This study further analyses the time-varying features of the observed impulse responses. With increased stock market volatility and changes in economic policies, fluctuation in the global crude oil price is strengthened. We select three representative time points from January 2003 to June 2020 to examine the impact of stock market volatility and economic policy uncertainty in the US and China on the crude oil market. The first time point is 2008, when the US subprime mortgage crisis triggered a global financial recession. The second time point is 2011, when Greece's default triggered the European sovereign debt crisis, which in turn had a significant impact on the US stock market. The third time point is 2020, when the outbreak of the COVID-19 pandemic led to four circuit breakers in the US stock market. Fig. 6 presents impulse response graphs for these three time points.

First, as shown in Fig. 7, the volatility of the US stock market has a positive impact on the volatility of the Chinese stock market for all three time points. The impact observed for 2008 (during the global financial crisis) is more significant than that observed for 2011 (dur-

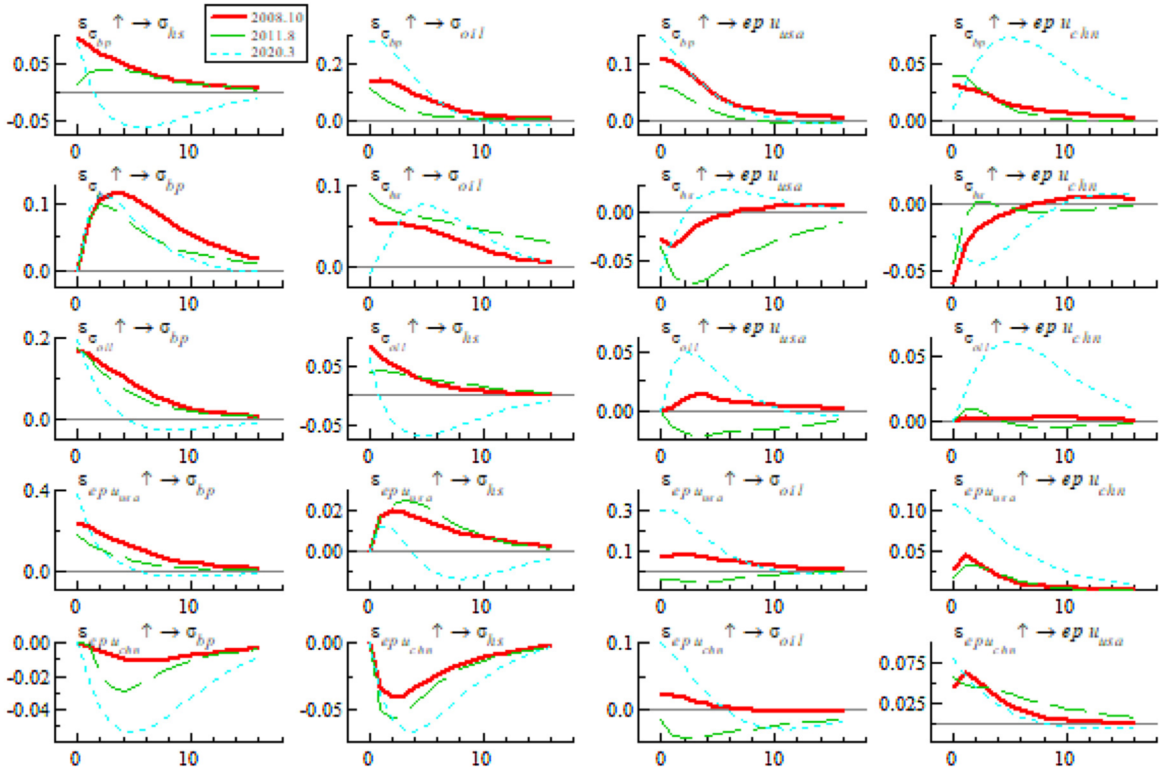

Fig. 7. Impulse response graphs for different time points.

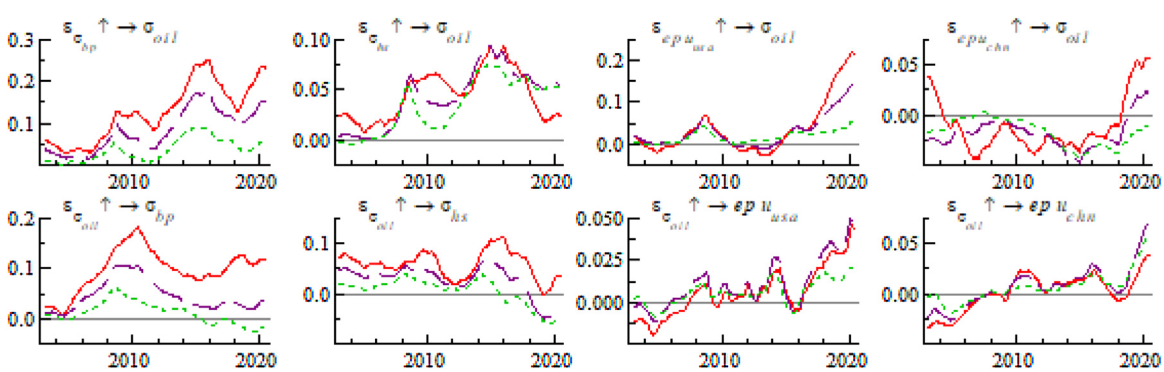

Fig. 8. Main impulse response results.

ing the European sovereign debt crisis). We find that the impact of US stock market volatility on Chinese stock market volatility in 2020 (during the COVID-19 pandemic) is similar in degree to that in 2008 but lasts for a shorter period. The relatively brief effect of the US's 2020 stock meltdown on China's capital market, although significant, may be attributable to China's extensive connections with other global markets. Given one positive standard deviation innovation to the volatility of the US stock market, the impulse response of crude oil price fluctuation is positive for all three time points. The 2020 value is almost twice as high as the 2008 and 2011 values. Given one positive standard deviation innovation to the volatility of the US stock market, the impulse response of the EPU of the US is also positive for all three time points (with a significant impact observed for 2008 and 2020), but it subsequently decreases to 0. This impact is found to be strongest at the 2020 time point. In general, we infer that systemic risks in the US stock market in these three periods had dynamic spillover effects on the Chinese stock market and the global crude oil market. These risks also increased economic policy uncertainty in China and the US.

Second, given one positive standard deviation innovation to the global crude oil price, the impulse response of the volatility of the US stock market is observed to be positive for all three time points. This suggests that fluctuation in the price of oil has a spillover effect on the volatility of the US stock market. For the 2020 time point, the strong fluctuation in the global crude oil price is positively related to the EPUs of both countries, although its relationships with their stock markets are insignificant.

Third, the impulse response of the volatility of the US stock market to the EPU of US innovation is positive for the time points 2008 and 2011 but insignificant for 2020. The impact is particularly prominent in 2008.

Fourth, the impulse response of the volatility of China's stock market to the EPU of the US innovation is also found to be positive at all three time points. At the 2008 and 2020 time points, the EPU of the US positively impacts fluctuation in the global crude oil price. For 2008 and 2011, we observe that the EPU of the US has a positive impact on the EPU of China. The value for 2020 is four times greater than those at the previous two time points. This impact lasts for a

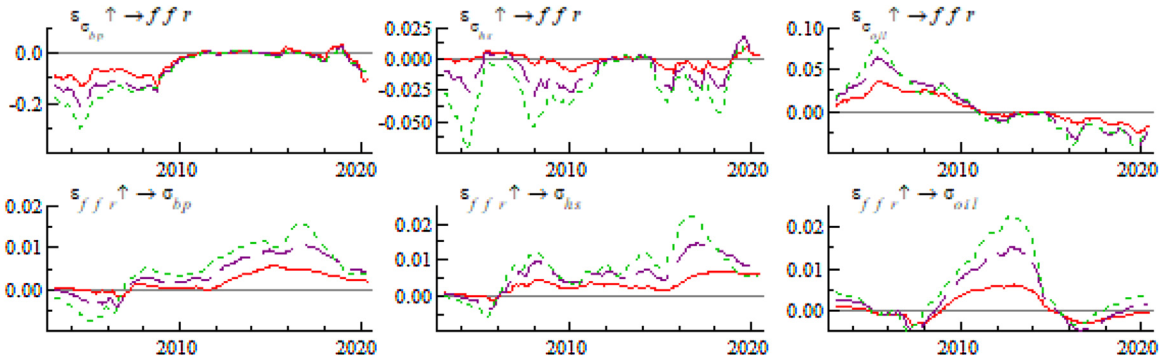

Fig. 9. The impact of monetary policy.

long time, which indicates that the EPU of China is closely related to US economic policy.

Finally, we observe that the EPU of China has a similarly positive impact on the EPU of the US at these three time points, which further verifies the strong correlation between the economic policies of these two economies during periods of crisis.

4.3. Robustness check and additional test

Monetary policy is closely related to stock prices and economic policy uncertainty (Gupta et al., 2019; Kishor & Marfatia, 2013; Marfatia, 2020). The index of economic policy uncertainty used here incorporates monetary policy uncertainty (Baker et al., 2016). However, due to the significant correlations between monetary policy and the stock market (Gupta et al., 2019; Kishor & Marfatia, 2013; Marfatia, 2020), we further add this variable to our measurements to test the robustness of our model. As the US's federal funds rate has an important influence on both the US economy and the economies of foreign countries, we put the effective interest rate of US federal funds into our model to control for this influence. Figs. 7 and 8 show impulse response graphs for the main variables with different lead times and impulse response graphs for three volatility and the effective interest rate of US federal funds, respectively. The impulse responses of the main variables are similar to those obtained using the original measurements, which indicates that controlling for US monetary policy does not change the main results of our analysis (Fig. 9).

5. Conclusion and implications

Using a TVP–SV–VAR model, this study explores the correlations among the volatility of the Chinese and US stock markets, economic policy uncertainty in China and the US, and fluctuation in the global oil price. Our findings indicate that the two countries' stock markets are closely related, especially during periods of crisis. Their mutual dynamic risk spillover effects are significant. Further, an increase in the volatility of the US stock market aggravates fluctuation in the global oil price. An increase in the volatility of the Chinese stock market also increases the volatility of the oil market though hysteresis. Compared with the EPU of China, that of the US has a stronger effect on the stock markets of both countries. Finally, fluctuation in oil price affects the stock markets of both countries. The effect is found to be more significant during periods of crisis, such as the global financial crisis and the COVID-19 pandemic.

The findings of this study offer practical implications for policymakers. First, it is important to manage capital market expectations. Fluctuation in the global oil price may trigger panic in capital markets and lead to short-term irrational speculation. Therefore, it is necessary to build investment environment detection and early-stage risk warning systems to ensure that individual investors are aware of the huge potential risks of volatility. Further, the monitoring of capital markets and their risk identification capabilities should be strengthened. In addition, the governments of developing economies should accelerate the development of clean energy for economic growth.

6. Limitations and future study

This study has several limitations that point to directions for future research. First, although China is the world's most influential emerging economy, due to its unique characteristics, such as a huge domestic market, a short history of capital market development, and strict government supervision, the study's conclusions may not be generalisable to other emerging economies. Therefore, future studies could extend our research to other emerging economies, such as India, Brazil, and Russia. Second, due to the short development history of China's capital market, long-term observation of the correlations among these markets and economic policy uncertainty is needed, especially because China is likely to play an increasing role in the global economy.

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Declaration of Competing Interest

None.

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