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Time-varying effects of economic policy uncertainty on commodity prices in China: an empirical analysis based on the TVP-SVAR-SV model

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Abstract: *Based on data from March 2008 to June 2020, we use the TVP-SVAR-SV model to study the time-varying impact of economic policy uncertainty on Chinese commodity prices and analyze the effect of economic policy uncertainty on Chinese commodity prices in different periods. The results show that: Firstly, economic policy uncertainty has a significant time-varying impact effect on Chinese commodity prices, and the short-term effect is larger than the long-term effect. Secondly, economic policy uncertainty positively affects Chinese commodity prices during the Chinese stock market crash in June 2015; economic policy uncertainty negatively affects Chinese commodity prices during the global financial crisis in December 2008 and the COVID-19 outbreak in December 2019, and the negative effect is greater during the global financial crisis in December 2008.*

Keywords: *Economic policy uncertainty; Chinese commodity prices; TVP-SVAR-SV*

1. Introduction

As one of the basic materials for industry, commodities play a crucial role in a country's economic activities. As a major importer of commodities, changes in commodity prices inevitably have an important impact on China's real economy and financial markets. Since entering the 21st century, the occurrence of economic policy uncertainty events such as the global financial crisis and the US-China trade friction have severely impacted the commodity market, triggering increased commodity price movements. In particular, the global economic catastrophe caused by the COVID-19 outbreak in late 2019 triggered a sharp climb in economic policy uncertainty, further impacting commodity prices[1]. The IMF's commodity price index shows that at one point in the early stages of the COVID-19 outbreak, China's commodity prices fell to their lowest level in nearly four years; in the post-COVID-19 outbreak phase, commodity prices generally rose, with major commodity prices significantly above their pre-outbreak levels. As China is a major commodity-demanding country, increased commodity price movements triggered by economic policy uncertainty will inevitably pose challenges to the sustained growth of the Chinese real economy and the stable development of financial markets.

However, economic policy uncertainty triggered by the COVID-19 pandemic continues, but the existing literature examining the impact of economic policy uncertainty on commodity prices in China is scarce. Therefore, we use a TVP-SVAR-SV model to empirically study the time-varying impact of economic policy uncertainty on Chinese commodity prices, enriching the literature in this area. We make the following contributions: we select Chinese commodity prices as our study object and use a TVP-SVAR-SV model with time-varying parameters to empirically investigate the time-varying impact of economic policy uncertainty on Chinese commodity prices. On the one hand, we analyze the short-, medium- and long-term impact relationships between economic policy uncertainty and Chinese commodity prices. On the other hand, we compare and analyze the effect of economic policy uncertainty on Chinese commodity prices in different periods.

The remainder of this paper is organized as follows. Section 2 presents a review of the relevant literature. Section 3 presents the methodology and data used in this paper. Section 4 is an empirical analysis of the impact of economic policy uncertainty on commodity prices in China. Section 5 provides the conclusions of the study.

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2. Literature Review

After the outbreak of the financial crisis in 2008, the economic policy uncertainty brought about by the financial crisis has severely impacted the commodity market, triggering extensive attention from scholars on the topic of the relationship between economic policy uncertainty and commodity prices. Based on this, this paper presents a review of the relevant literature.

1). The impact of economic policy uncertainty on commodity prices. As an important driver of real economic activity, economic policy uncertainty can have an impact on the production plans or investment decisions of firms and investors, triggering changes in commodity demand and investment, which in turn affect commodity prices [2]. For example, Qin et al. (2020) examined the impact of economic policy uncertainty on the international oil market in the time and frequency domains based on wavelet analysis tools and found that economic policy uncertainty has both positive and negative effects on oil prices[3]. Frimpong et al. (2021) found that global economic policy uncertainty significantly affects the dependence of agricultural prices[4]. Bakas and Triantafyllou (2018) use a VAR model empirically based on data from January 1985 to December 2016 and find that positive shocks to economic uncertainty lead to increased movements in commodity prices[5].

2). Time-varying parametric models. The existing literature studying the impact of economic policy uncertainty shocks on commodity markets mainly uses linear models such as VAR and assumes that the relationship between economic policy uncertainty and commodity prices does not change over time. However, the current international economic situation is complex and traditional fixed coefficient models cannot capture the time-varying impact of economic policy uncertainty shocks on commodity prices. Currently, many scholars use time-varying parametric vector autoregressive models to study the time-varying effects among variables[6][7]. For example, Chen et al. (2020) uses a TVP-SVAR-SV model to study the time-varying effects of oil shocks on inflation in China [8]. These applications provide useful references for the research in this paper. To fully understand the dynamic characteristics of commodity markets, it is important to use a framework that does not limit the effects of variables to one or a few possible states, but rather is flexible enough to capture potential time-variation. Therefore, we use a TVP-SVAR-SV model with time-varying parameters to empirically study the time-varying effects of economic policy uncertainty on commodity prices.

In summary, existing studies on the impact of economic policy uncertainty on commodity prices mainly focus on the global commodity level, and there is a lack of research on the relationship between economic policy uncertainty and commodity prices in China. Most of the existing literature selects linear models such as VAR to empirically study the impact of economic policy uncertainty on commodity prices, but linear models have static analysis and parameter invariance drawbacks that make it difficult to capture the time-varying effects between variables. Therefore, we use the TVP-SVAR-SV model to study the time-varying impact of economic policy uncertainty on commodity prices in China.

3. Methodologies and Data Description

3.1. Methodologies

The time-varying parametric vector autoregressive model (TVP-SVAR-SV) with stochastic volatility can be constructed on the basis of the SVAR model.

Firstly, we construct the SVAR model containing six variables, as detailed in equation (1).

$$Ay_t = \beta_0 + \sum_{i=1}^{n} \beta_i y_{t-i} + \varepsilon_t \tag{1}$$

In equation (1), $y_t = (EPU_t, VAL_t, CPI_t, IR_t, FIN_t, CCPI_t)'$, EPU denotes economic policy uncertainty, VAL denotes China's industrial value added, CPI denotes China's inflation rate, IR denotes interest rate, FIN denotes China's degree of commodity financialization, CCPI denotes China's commodity price, β_0 and β_i are 6×6 the coefficient matrices, ε_t representing the structural shock vector. Assuming matrix A is invertible, substituting matrix A^{-1} into equation (1) yields a simplified form of the SVAR model:

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$$y_t = A^{-1}\beta_0 + A^{-1}\sum_{i=1}^{n}\beta_i y_{t-i} + A^{-1}\varepsilon_t = \phi_0 + \sum_{i=1}^{n}\phi_i y_{t-i} + e_t \tag{2}$$

Where e_t is the perturbation term and $e_t = A^{-1}\varepsilon_t$. Here restrictions are A^{-1} imposed to better identify the SVAR model. First, economic policy uncertainty, as a primitive shock, is not affected by other factors. Second, according to real-cycle theory, long-run supply shocks are only affected by themselves. Then, according to the monocentric view, in the long run money supply is only affected by demand shocks and supply shocks, and thus inflation is only affected by demand shocks and supply shocks. Finally, interest rates are financialization of commodity prices and the increase in financialization will have an impact on commodity prices. Based on the above analysis, the error in simplified form is e_t expressed as equation (3).

$$e_t = A^{-1}\varepsilon_t \tag{3}$$

Secondly, we construct a TVP-SVAR-SV model by setting time parameters in the SVAR model, which can capture the time-varying effects of world pandemic uncertainty on commodity prices at various stages. According to Primiceri (2005) and Nakajima (2011)[9][10], equation (1) can be written in the form of equation (4).

$$A^{-1} \tag{4}$$

In Eq. (4), β is $36i \times 1$ dimensional vector, $X_t = I_k \otimes (y'_{t-1}, \cdots, y'_{t-i})$, Σ is a 6×6 dimensional diagonal matrix, and the diagonal is $[\sigma_1, \sigma_2, \cdots \sigma_6]$. Adding the time factor to Eq. (4) yields the TVP-SVAR-SV model as

$$y_t = X_t \beta_t + A_t^{-1}\Sigma_t \varepsilon_t \tag{5}$$

According to Primiceri (2005) [9], $h_t = (h_{1t}, h_{2t}, h_{3t}, h_{4t}, h_{5t}, h_{6t})'$, where $h_{jt} = \log \sigma_{jt}^2$, $j = 1, \ldots 6$, $t = s+1, \ldots n$. And we assume that the parameters follow the following random wandering process:

$$\beta_{t+1} = \beta_t + u_{\beta t}, \alpha_{t+1} = \alpha_t + u_{\alpha t}, h_{t+1} = h_t + u_{ht} \tag{6}$$

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{\alpha t} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_\alpha & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right) \tag{7}$$

where $\beta_{s+1} \sim N(u_{\beta_0}, \sum_{\beta_0}), \alpha_{s+1} \sim N(u_{\alpha_0}, \sum_{\alpha_0}), h_{s+1} \sim N(u_{h_0}, \sum_{h_0})$, Σ_β , Σ_α , and Σ_h are diagonal matrices.

3.2. Data Description

Our dataset includes the China Commodity Price Index (CCPI), the Economic Policy Uncertainty Index (EPU), China Industrial Value Added (VAL), China Consumer Price Index (CPI), Interest Rate (IR) and the Financialization of China Commodities Index (FIN) from March 2008 to June 2020.

China Commodity Price Index (CCPI). In order to reflect the changes of Chinese commodity prices, we choose the CCPI data provided by the China Flush database, which is measured by the Ministry of Science and Technology of China and covers nine categories of commodities such as minerals, steel, energy and non-ferrous metals, which can reflect Chinese commodity prices well.

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Economic policy uncertainty index (EPU). To accurately measure Chinese economic policy uncertainty, we select monthly data from the Chinese Economic Policy Uncertainty Index jointly published by Baker et al[11], where robustness tests are conducted using the Chinese Economic Policy Uncertainty Index developed by Huang and Luk (2020)[12].

China's industrial value added (VAL): changes in demand due to economic growth are an important factor affecting commodity prices, we choose China's industrial value added (VAL) to react to changes in demand due to China's economic growth, data from the WIEGO statistical database and calculated by the author himself.

China Consumer Price Index (CPI): we select the China Consumer Price Index (CPI) provided by the WIEGO statistical database as a proxy variable for inflation in China.

Interest rate (IR): after the global financial crisis in 2008, monetary policy has gradually become an important factor influencing commodity prices[13], and we choose the seven-day weighted average interbank interest rate in China provided by the WIEGO statistical database as a proxy variable for China's monetary policy.

Financialization degree index (FIN) of Chinese commodities: we use the DCC-GARCH model to obtain the dynamic correlation coefficients between the Chinese commodity futures price index and the Chinese SSE Composite Index to measure the financialization degree of Chinese commodities based on Liu et al. (2020)[14], with data from the Flush database. In addition, we convert all data into monthly data to ensure the uniformity of data frequency.

3.3. Unit root test

The data used in this paper are time series data, and the smoothness of the data is a prerequisite for the accuracy of the regression results. We use the ADF test to test the smoothness of the time series data.

Table 1: Unit root ADF test results.

	Variable	ADF	1%	5%	Conclusion
Original Level	EPU	-0.05872	-3.47582	-2.88140	Unstable
	CCPI	-2.50584	-3.47582	-2.88140	Unstable
	VAL	-1.001	-3.47647	-2.88168	Unstable
	CPI	-3.38125	-3.47518	-2.88112	Stable
	IR	-3.450503	-3.47518	-2.88112	Stable
	FIN	-2.148963	-3.47582	-2.88140	Unstable
First-order Difference	epu	-16.44067	-3.47582	-2.88140	Stable
	ccpi	-6.097840	-3.47582	-2.88140	Stable
	val	-13.36830	-3.47647	-2.88168	Stable
	cpi	-6.408732	-3.47518	-2.88112	Stable
	ir	-10.58034	-3.47518	-2.88112	Stable
	fin	-11.27455	-3.47582	-2.88140	Stable

As can be seen from Table 1, only the CPI and IR variables are stationary at the 1% level of significance, but the first-order differences of all subsequent variables are stationary at the 1% level of significance. Therefore, in this paper, the TVP-SVAR-SV model is constructed using first-order difference series.

3.4 Determination of the order of the lag period

The construction of TVP-SVAR-SV model needs to determine the optimal lag order, and the results of the optimal lag order of the model are shown in Table 2. According to the principle of LR, AIC, SC, HQ minimum, the optimal lag order is chosen as 2 in this paper.

Table 2: Number of optimal model lags

Lag	LogL	LR	AIC	SC	HQ
0	1095.760	NA	-15.13556	-15.01182*	-15.08528
1	1159.385	121.0636	-15.51923	-14.65304	-15.16726
2	1230.420	129.2444*	-16.00583*	-14.39718	-15.35217*
3	1249.451	33.04035	-15.77016	-13.41905	-14.8148

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4. Empirical analysis

4.1. Estimation of selected parameters

Based on Nakajima's (2011) settings, we set the initial values $u_{\alpha_0} = u_{\beta_0} = u_{h_0} = 0$, $\Sigma_{\alpha_0} = \Sigma_{\beta_0} = \Sigma_{h_0} = 10 \times I$, $(\Sigma_\beta)_i^{-2} \sim Gamma(20, 10^{-4})$, $(\Sigma_\alpha)_i^{-2} \sim Gamma(4, 10^{-4})$, $(\Sigma_h)_i^{-2} \sim Gamma(4, 10^{-4})$ and empirically ran the TVP-SVAR-SV model using Oxmetrics6 software[10]. The MCMC sample size was set to 10,000 while searing 1000 times as a way to obtain robust model estimates.

Table 3: Results of parameter estimation for MCMC simulation method

Parameters	Mean	St. dev.	95% interval	Geweke	Inef.
sb1	0.0225	0.0025	[0.0182,0.0280]	0.958	9.22
sb2	0.0229	0.0027	[0.0185,0.0285]	0.884	7.48
sa1	0.0288	0.0034	[0.0228,0.0362]	0.917	6.26
sa2	0.0240	0.0025	[0.0195,0.0292]	0.303	20.01
sh1	0.3146	0.0803	[0.1779,0.4957]	0.117	40.84
sh2	0.6103	0.1073	[0.4348,0.8487]	0.338	54.00

Notes: Mean denotes posterior means; St. dev. denotes standard deviations; and Inef. denotes the inefficiency factor.

As shown in Table 3, the Geweke values of each parameter are less than 1.96, indicating that the original hypothesis that the results obey the posterior distribution cannot be rejected at the 5% confidence level. And the maximum value of the null factor does not exceed 54, indicating that at least 185 (10,000/54) uncorrelated samples are generated during the 10,000 iterations, which indicates that the samples generated during the iterations are valid.

The sample autocorrelation plot, sample path and posterior density plot of the parameters are given in Figure 1. The results show that the MCMC sampling is valid and the model is well estimated.

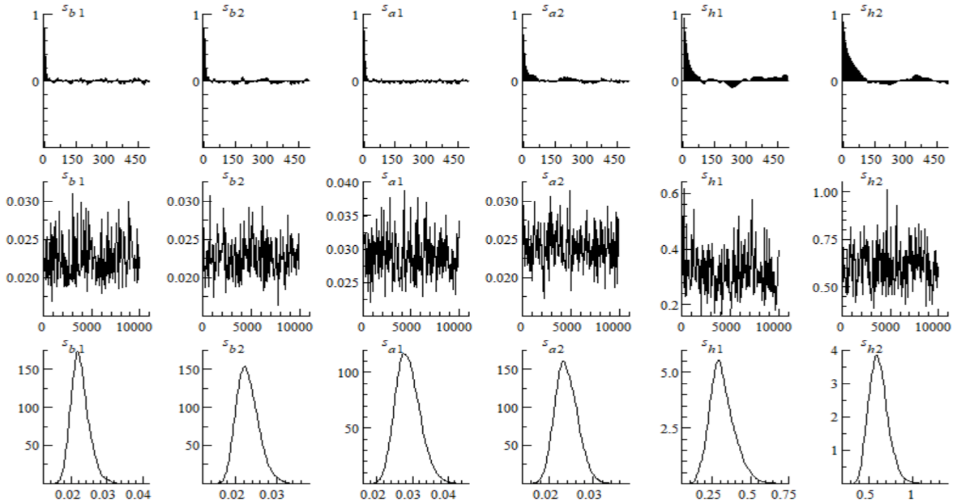

Figure 1: Sample autocorrelation plot, sample path and posterior density plot

4.2. The time-varying effects of EPU on China's commodity prices

To investigate the time-varying impact of economic policy uncertainty on Chinese commodity prices, we use a TVP-SVAR-SV model with equal-interval time-varying impulse responses with lags of 4, 8 and 12 periods to describe the impact of economic policy uncertainty on Chinese commodity prices in the short, medium and long run.

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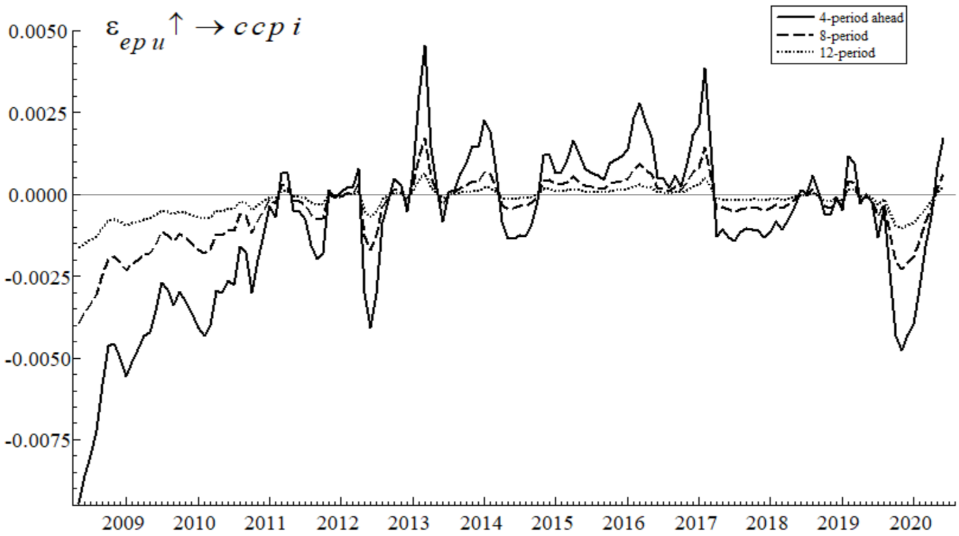

Figure 2: Time-varying effects of EPU on China's commodity prices.

Note: Solid lines represent short-term effects, dashed lines represent medium-term effects, and dotted lines represent long-term effects.

Figure 2 shows that the short-run impact of economic policy uncertainty on China's commodity prices is larger than the medium- and long-term impact. Specifically, given a positive shock to the unit of economic policy uncertainty, the impulse response volatility range of Chinese commodity prices with a lag of 4 periods is [-0.0095, 0.005]; the impulse response volatility range of Chinese commodity prices with a lag of 8 periods is [-0.004, 0.001]; and the impulse response volatility range of Chinese commodity prices with a lag of 12 periods is [- 0.0015, -0.0005]. The reason for this is that commodity prices are dominated by financial attributes in the short run, and rising economic policy uncertainty exacerbates commodity price volatility in the short run through the risk premium channel and the financial speculation channel.

The overall trend of the impulse response results in Figure 2 shows that the impact of economic policy uncertainty on Chinese commodity prices has time-varying characteristics. 2008-3013, economic policy uncertainty has a negative relationship with Chinese commodity prices; 2014-2017, the negative impact of economic policy uncertainty on Chinese commodity prices turns positive; 2017-2020 In 2017-2020, economic policy uncertainty shows more negative correlation with Chinese commodity prices, and the negative impact is the largest at the end of 2019, which is due to the outbreak of COVID-19 epidemic at the end of 2019 severely impacting China's real economy and financial markets, and the massive shutdown of production leading to China's economic recession and sharp decline in commodity demand, which in turn aggravates the decline of commodity prices.

4.3. Analysis and Results of Impulse Response at Different Time Points

To study the impact of WPU on Chinese commodity prices in different periods, we choose three key time points for our study, namely December 2008, June 2015 and December 2019. First, the global financial crisis erupted in December 2008 and quickly spread to China, leading to a recession in the Chinese real economy and triggering a decline in Chinese commodity demand, reflecting the commodity attributes of commodities. Second, the Chinese stock market experienced a sharp rise and a sharp fall in June 2015, and the rise and fall of the Chinese stock market triggered a different proportion of investors in the Chinese commodity futures market, leading to a change in the degree of financialization of Chinese commodities, reflecting the financial attributes of commodities. Third, the outbreak of the COVID-19 epidemic in December 2019 and the massive shutdown led to a recession and rising unemployment in China, increasing the uncertainty faced by China's real economy and financial markets.

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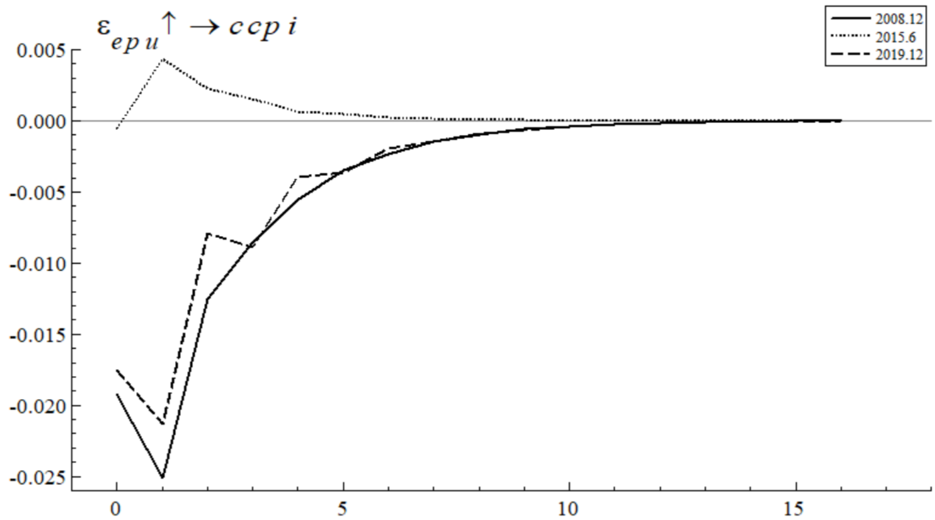

Figure 3: The effect of EPU on China's commodity prices at different points in time.

Note: Solid line represents December 2008, dashed line represents June 2015, and dotted line represents December 2019.

From the impulse response results in Figure 3, giving a positive shock to the unit of economic policy uncertainty, the impulse response results of Chinese commodity prices differ at the three points in time. (1) In terms of the impact effect, economic policy uncertainty in June 2015 positively affects Chinese commodity prices; economic policy uncertainty in December 2008 and December 2019 negatively affects Chinese commodity prices, and the negative impact of economic policy uncertainty in December 2008 on Chinese commodity prices is stronger than that in December 2019. (2) In terms of the speed of convergence of impulse results, the impulse response results of all three time points converge from lag 1, but the impulse response of June 2015 converges to zero at lag 6, and the impulse responses of December 2008 and December 2019 converge to zero at lag 11. This leads to the conclusion that economic policy uncertainty has different effects on Chinese commodity prices in different periods.

4.4. Robustness tests

To test the robustness of the above benchmark model results, we replace the variables in the above model. In the benchmark model, we choose the China EPU index measured by Baker et al. (2016) as a proxy variable for China's economic policy uncertainty. Further, we choose the Chinese EPU index by Huang and Luk (2020) as a proxy. The results show that economic policy uncertainty has a significant time-varying impact on Chinese commodity prices, with a stronger short-term impact than a medium- to long-term impact; the impact of economic policy uncertainty on Chinese commodity prices is differentiated across the three periods of December 2008, June 2015 and December 2019. This is broadly consistent with the results in Figures 2 and 3, indicating the robustness of the model results.

5. Conclusion

Based on data from March 2008 to June 2020, this paper uses the TVP-SVAR-SV model to study the time-varying effects of economic policy uncertainty on Chinese commodity prices, and selects three periods: the global financial crisis in December 2008, the stock market crisis in China in June 2015, and the COVID-19 epidemic crisis in December 2019, to compare and analyze the economic the effect of policy uncertainty on Chinese commodity prices. We find that, first, economic policy uncertainty has a significant time-varying impact effect on Chinese commodity prices, and the short-term effect is larger than the long-term effect. Second, economic policy uncertainty positively affects Chinese commodity prices during the June 2015 stock market crash in China; economic policy uncertainty negatively affects Chinese commodity prices during the December 2008 global financial crisis and the December 2019 COVID-19 outbreak, and the negative effect is greater during the December 2008 global financial crisis.

Based on the above findings, we propose the following policy recommendations: as a major commodity importer, economic policy uncertainty in China will lead to increased commodity price movements in China, and the impact of economic policy uncertainty on commodity prices is time-varying over time. As a major commodity importer, policymakers in emerging economies need to consider the

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impact of economic policy uncertainty on commodity markets and make the right policy decisions in the context of the macroeconomic environment of the times, so as to respond more effectively to commodity price shocks and stabilize commodity markets.

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