Hindawi
Complexity
Volume 2022, Article ID 6944318, 22 pages
https://doi.org/10.1155/2022/6944318

Research Article

Economic Policy Uncertainty Shocks and Chinese Stock Market Volatility: An Empirical Analysis with SVAR

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Received 20 April 2022; Accepted 12 August 2022; Published 10 October 2022

Academic Editor: Wei Zhang

This paper proposes a framework for examining the interaction between stock market volatilities and economic uncertainty shocks, aiming to understand better the influence of economic uncertainty shocks on the Chinese stock market. The major empirical results include the followings. First, the economic policy uncertainty shocks push the Chinese stock volatility up, increasing the market risk. A 1-standard-deviation shock of economic policy uncertainty will enhance the stock volatility of the two composite indices by approximately 7% in 12 months. Second, the stock volatility reacted more intensely to fiscal and monetary economic policy uncertainty shocks, with a 1-standard-deviation shock that can enhance the stock volatility of the two composite indices by more than 10% in 12 months. Third, different stock indices exhibit different patterns of cumulative impulse responses, and the reaction of the volatility of the SSE real estate index to economic policy uncertainty shocks is more significantly intense than other indices. Besides, we have proved the robustness of empirical results by reestimating the models with a lag order of 2. Overall, our research results can provide policy and managerial insights for the sustainable development of the Chinese stock market and beyond.

1. Introduction

The Chinese stock market has been undertaking substantial development during the last 30 years and has become one of the largest stock markets in the world. According to the World Bank, the market capitalization is 6.3 trillion at the end of 2018, accounting for about 8.5% of the global market capitalization. Along with the vast increase in the market scale, the Chinese stock market also undertakes continuous development toward openness. For example, in June 2018, China A-shares were incorporated into the MSCI Emerging Markets Index and the Global Benchmark Index. As a result, the Chinese stock market has become a vital investment channel for international investors.

As an emerging economy, China has been in the progress of economic system reforming for decades with the implementation of various economic policies. Consequently, the real economy and the stock market are subject to policy uncertainty shocks [1]. Economic policy uncertainty (EPU) refers to the uncertainty faced by economic entities because they cannot accurately predict whether, when, and how the government will change the current economic policies. It is the external condition of the operation of various markets, and its influence on the economy is very far reaching. However, the Chinese stock market is young, the system is not perfect, and the irrational characteristics of Chinese Stockholders are apparent. Therefore, the volatility of the stock market is abnormal, which brings not only vast losses and risks to the investors but also poses enormous challenges to the development of China's stock market and the sustainability of the economy. How China's increasingly internationalized stock market reacts to economic policy uncertainty (EPU) shocks is an exciting question for academia and practitioners. It is of great significance to the healthy development of China's stock market and increases the sustainability of economic growth. This paper aims to answer this question with a newly proposed framework for examining the interaction between stock market volatilities and economic uncertainty shocks.

The contributions of this paper to the literature are as follows. First, since China has been undergoing various economic policy reforms, the stock market is likely to be impacted by economic uncertainty shocks. This paper proposes an innovative framework based on the structural vector autoregression to examine the reaction of stock market volatilities to economic uncertainty shocks. Especially, this paper tries to address the following questions: whether economic uncertainty can increase the volatility of the Chinese stock market, and hence, increase the market risk; what proportion of stock volatilities can be explained by economic uncertainty shocks; and what the stock volatility would be like if there were no economic uncertainty shocks.

Second, choosing an appropriate index as the proxy for Chinese economic uncertainty is essential for empirical analysis. Most literature about Chinese economic uncertainty uses the Chinese EPU index proposed by Baker et al. [2]. However, this index only contains the Hong Kong-based English newspaper, which may not fully reflect the uncertain information about China. Recently, Huang and Luk [1] proposed a new China EPU index based on 10 mainland Chinese newspapers, which is more robust and targeted. This paper takes the newly proposed index as the proxy for the Chinese economic uncertainty to obtain more reliable empirical results.

Third, taking the different characteristics of the stock market sectors into consideration, we not only examine the effects of Chinese EPU shocks on the volatility changes of the two most important stock indices, Shanghai stock exchange (SSE) composite index and Shenzhen stock exchange (SZSE) composite index, but also on various sectoral stock indices in SSE, including commercial index, industrial index, real estate index, and utilities index, aiming at detecting any heterogeneities in the interactions.

Besides, this paper also analyses the reaction of Chinese stock volatilities to some other EPU indices for different policy categories. Such fiscal EPU index and monetary EPU indexes further test whether there are heterogeneities in which stock volatility reacts to different types of EPU shocks.

The rest of the paper proceeds as follows. Section 2 is the review of relevant literature. Section 3 describes the methodology and introduces the empirical model in detail. Section 4 shows the sample data and the primary analysis. Section 5 presents the main empirical results, and Section 6 presents our conclusions.

2. Literature Review

This paper is mainly related to three strands of literature. The first strand of literature is on measuring economic uncertainty. For example, Bloom [3] and Basu and Bundick [4] take observable economic indicators, such as VXO and VIX, as the proxy for economic uncertainty. Jurado et al. [5] define and measure economic uncertainty as the volatility of the unforecastable component of a large group of important economic (macroeconomic and financial) indicators. Finally, Baker et al. [2] developed a new index of economic policy uncertainty for major economies based on newspaper coverage frequency. And their EPU index has been widely used ever since (see, for example, [6–11]).

As the second-largest economy, China has been undergoing economic system reforms for decades, accompanied by significant economic uncertainties. Therefore, how to measure the influence of Chinese economic uncertainty properly has become an exciting topic for econometricians. In the existing literature, Baker et al. [2] construct EPU indices for many economies, including China. However, the text search does not include newspapers published in mainland China when creating the Chinese EPU index. Instead, only the information from a Hong Kong-based English newspaper, the South China Morning Post, is used. Since the Hong Kong-based newspaper is likely to choose to report news that has more relevance to the Hong Kong economy, it may not fully reflect the level of economic policy uncertainty in China. Following the work of Baker et al. [2], Huang and Luk [1] constructed a China EPU index based on 10 mainland Chinese newspapers to measure China's economic uncertainties correctly with a robust index not suffering from the media basis. In this paper, we follow Huang and Luk [1] to establish a proxy for Chinese economic uncertainty.

The second strand of literature is mainly about the impacts of economic uncertainties on the real economy and financial markets [12, 13]. Theoretical work on this topic dates back to Bernanke [14], who points out that high uncertainty gives firms an incentive to delay investment and to hire when investment projects are costly to undo or workers are expensive to hire and fire. Of course, once uncertainty recedes, firms increase hiring and investment to meet pent-up demand. Other reasons for the depressive effect of uncertainty include precautionary spending cutbacks by households, upward pressure on the cost of finance [15, 16], managerial risk aversion [17], and interactions between nominal rigidities and search frictions [18, 19]. Baker et al. [2] find that positive shocks to their policy uncertainty index are associated with significant decreases in industrial production, employment, GDP, and real investment.

Some of the literature points out that economic uncertainty significantly affects the financial market, particularly the stock and commodity futures markets [18]. For example, Pástor and Veronesi [15] propose a general equilibrium model and analyze the effects of changes in government policy on stock prices. On average, stock prices should fall at the announcement of a policy change. In addition, policy changes should increase volatilities and correlations among stocks [19]. Brogaard and Detzel [20] found that economic policy uncertainty in the United States positively forecasts log excess market returns. An increase of 1 standard deviation in EPU is associated with a 1.5% increase in the predicted 3-month abnormal returns (6.1% annualized). Bali et al. [21] investigate the role of economic uncertainty in the cross-sectional pricing of individual stocks and equity portfolios. They estimate stock exposure to an economic uncertainty index and that stocks in the lowest uncertainty beta decile generate 6% more annualized risk-adjusted return than stocks in the highest uncertainty beta decile. Some other studies analyze the relationship between economic uncertainty and the commodity market. For example, Van Robays [22] points out that macroeconomic uncertainty is an essential driving factor in oil price movements, and higher macroeconomic uncertainty causes higher oil price volatility. Bakas and Triantafyllou [23] examine the impact of U.S. uncertainty shocks on the volatility of commodity prices. Their findings indicate that a positive shock in unobservable uncertainty leads to a persistent increase in the volatility of the broad commodity market index and individual commodity prices. The impact is more potent in energy commodities than in agricultural and metals markets.

The existing literature provides the theoretical foundation for our research. However, most of the studies are focused on developed economies. The third strand of literature is specifically about the effects caused by economic uncertainties in China. For example, using the smooth transition vector autoregressive model, Fontaine et al. [24] investigated the possible spillovers from a shock to Chinese economic policy uncertainty to developed (the United States, the Euro Area, Japan, and South Korea) and emerging economies (Brazil and Russia). They find essential asymmetries in the responses to Chinese uncertainty shocks of macro-variables, especially for the United States, the Euro Area, and South Korea. These countries show merely any response to the identified shock during booms. However, when ongoing downturns, their economies suffer from a fall in industrial production, inflation, and exports, together with an increase in unemployment. Based on GARCH-MIDAS models, Li et al. [25] investigate the relationship between EPU indices (Chinese economic policy uncertainty and global economic policy uncertainty) and Chinese stock market volatility. Their empirical results show that the Chinese economic policy uncertainty and the global EPU index are beneficial for predicting stock volatility.

Although the economic uncertainty of China has rich research outcomes, there are still some significant concerns from scholars, investors, and regulators that require further exploration. To name a few questions, can economic uncertainty increase the volatility of the Chinese stock market or increase the market risk? What proportion of stock volatilities can be explained by economic uncertainty shocks? What would the stock volatility be like without economic uncertainty shocks? Our paper will address these questions.

3. The Theoretical Analysis and Empirical Methodology

The economic uncertainty will affect Chinese stock volatility. The reason is as follows.

Firstly, economic uncertainty will wrist the information from the capital market, which will mislead the estimation of risk of investors in the stock market [26]. It can intensify investor sentiment, thus leading to rampant speculation and arbitrage in the capital market, crowding out value investment. As a result, money moves in and out of the stock market more frequently, making it volatile [27]. Second, economic uncertainty increases the interactivity of different financial markets, thus increasing the risk of cross-market contagion [28]. Therefore, the risk in the foreign exchange, bond, or credit markets can be transferred to the stock market, resulting in more violent stock market volatility. Finally, economic uncertainty affects market pricing efficiency [29], affecting investors' macroeconomic expectations and confidence in the stock market. Therefore, higher systemic risk in the stock market is triggered. Based on the above analysis, the economic policy uncertainty shocks push the Chinese stock volatility up, increasing the market risk.

This paper examines the impacts of Chinese economic uncertainty shocks on the dynamics of Chinese stock volatilities. Inspired by previous studies, such as Baker et al. [2] and Huang and Luk [1], we fit vector autoregressive models to the multivariate time series consisting of economic policy uncertainty, volatilities of Chinese stock markets, and monetary policy (unlike Baker et al. [2], who take federal funds rate as controlling variables, this paper takes the M2 growth rate). The main reason is that different from many other countries, the central bank, People's Bank of China (PBoC), uses a combination of both "price" (controls on interest rates) and "quantity" (controls on credit supply) instruments in monetary policy implementation, and the unique feature of monetary policy in China is to use M2 growth as the intermediate target. [30] Therefore, we use the M2 growth rate as the proxy for Chinese monetary policy, and industrial production index.

Consider the following model:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \cdots + \beta_k y_{t-k} + u_t, \quad t = 1, \ldots, T, \tag{1}$$

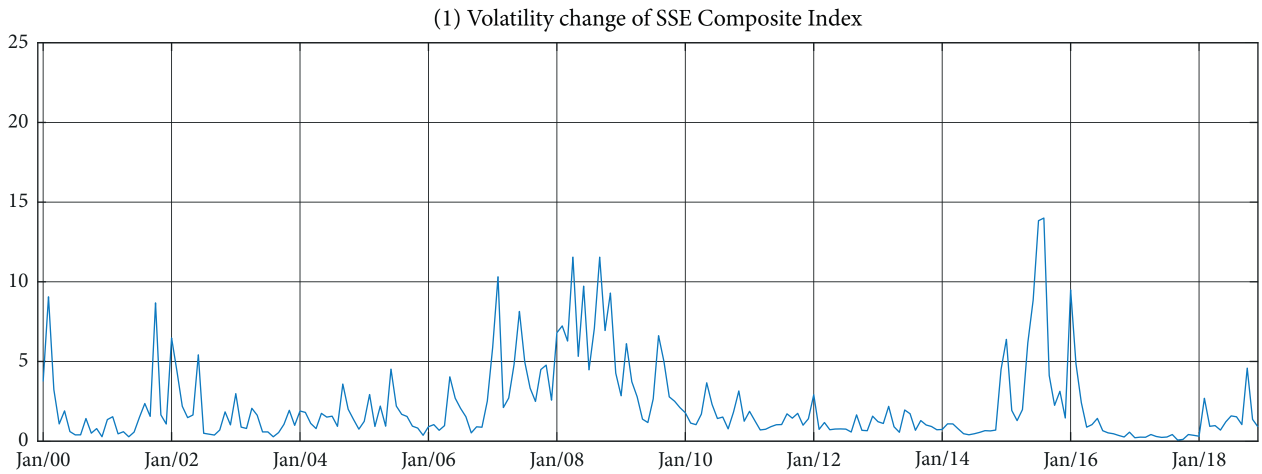
where y_t denotes the vector of four endogenous variables, β_i denotes the $n \times 1$ vectors of time-varying coefficients with $n = 4$. Following the literature, we take $k = 3$ as the lag order. u_t denotes the heteroskedastic shocks with the variance-covariance matrix Ω.

Structural shocks are routinely used for separating the effects of economically unrelated influences in VAR models. Restrictions are needed for the identification of the structural shocks from reduced form models. In this paper, we take the recursive restrictions following the literature [2]. More specifically, consider the Cholesky decomposition of Ω such that $\Omega = A\Sigma\Sigma' A'$ with the lower triangular matrix

$$A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n1} & \cdots & \alpha_{nn-1} & 1 \end{bmatrix}, \tag{2}$$

and the diagonal matrix

$$\Sigma = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_n \end{bmatrix}. \tag{3}$$



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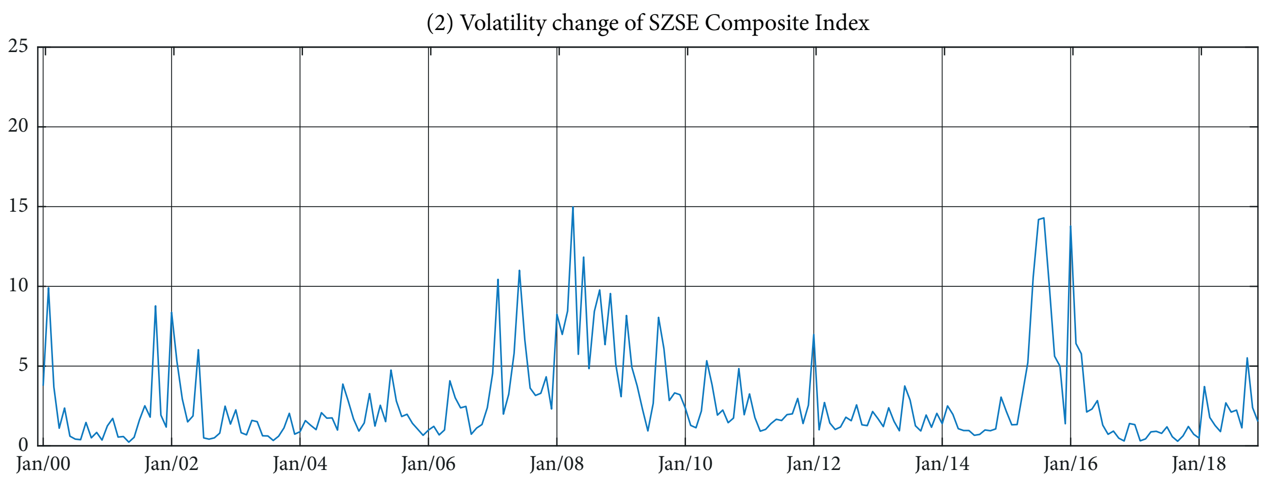

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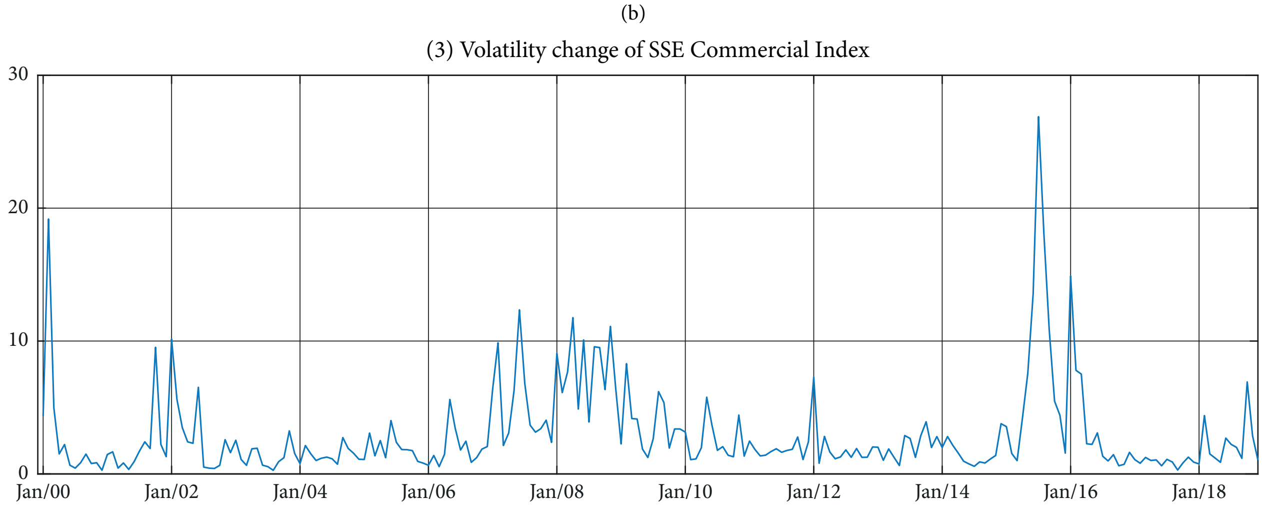

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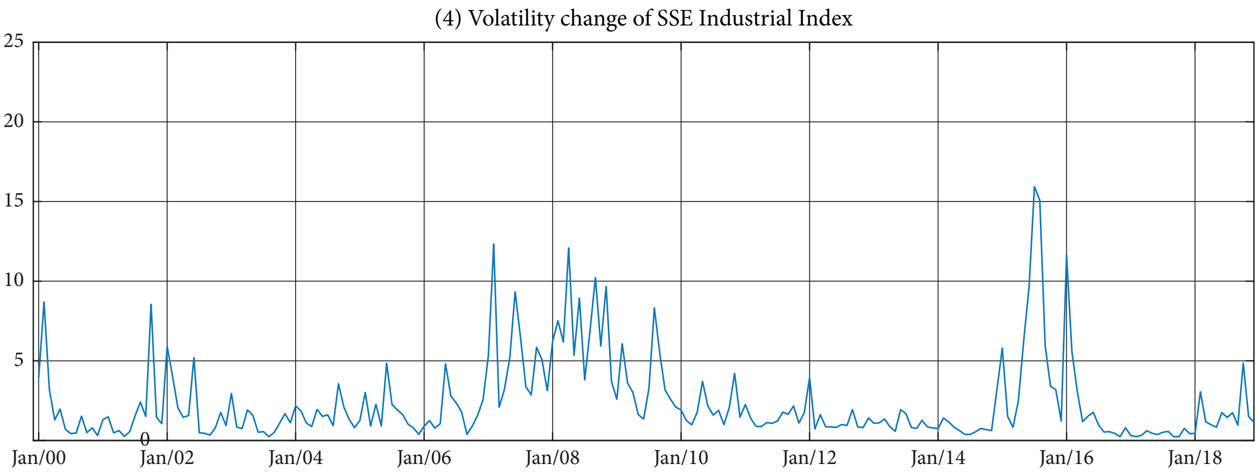

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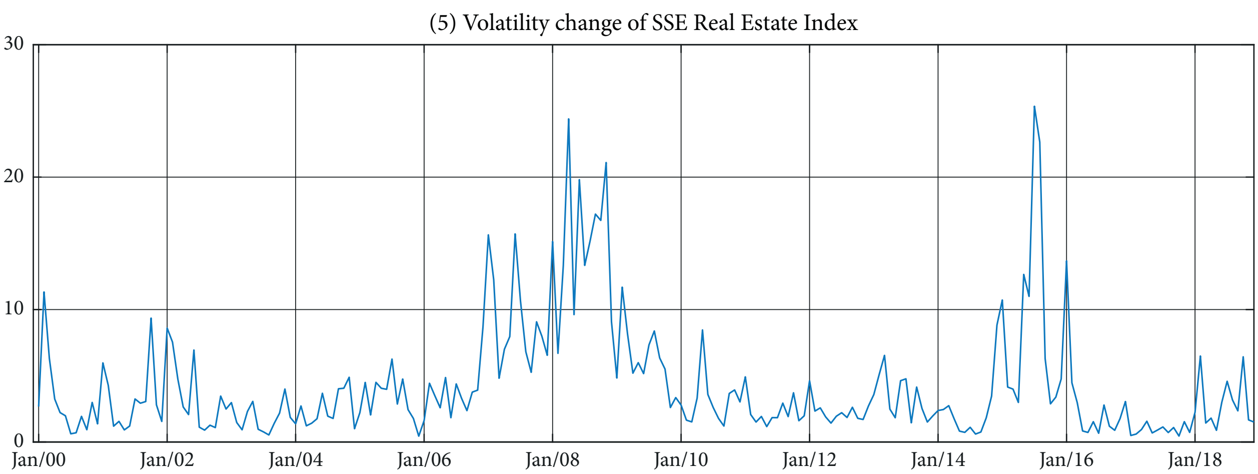

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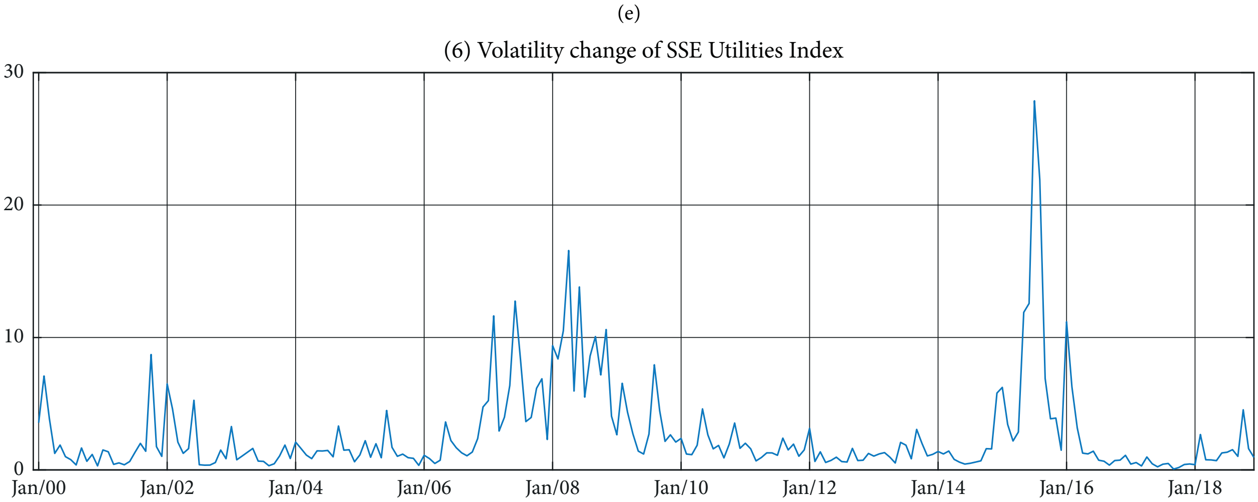

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Figure 1: Monthly volatilities of six Chinese stock indices.

Then, we have $y_t = \beta_0 + \beta_1 y_{t-1} + \cdots + \beta_k y_{t-k} + A\Sigma\varepsilon_t$, where ε_t denotes the structural shocks with $V(\varepsilon) = I_n$.

For the structural VAR model, the orthogonalized impulse responses can be obtained based on the Wold moving average representation of the model and the contemporaneous relation matrix A. The forecast error variance decomposition can then be calculated based on the orthogonalized impulse responses so as to analyze the contribution of one variable to the h-step forecast error variance of another variable.

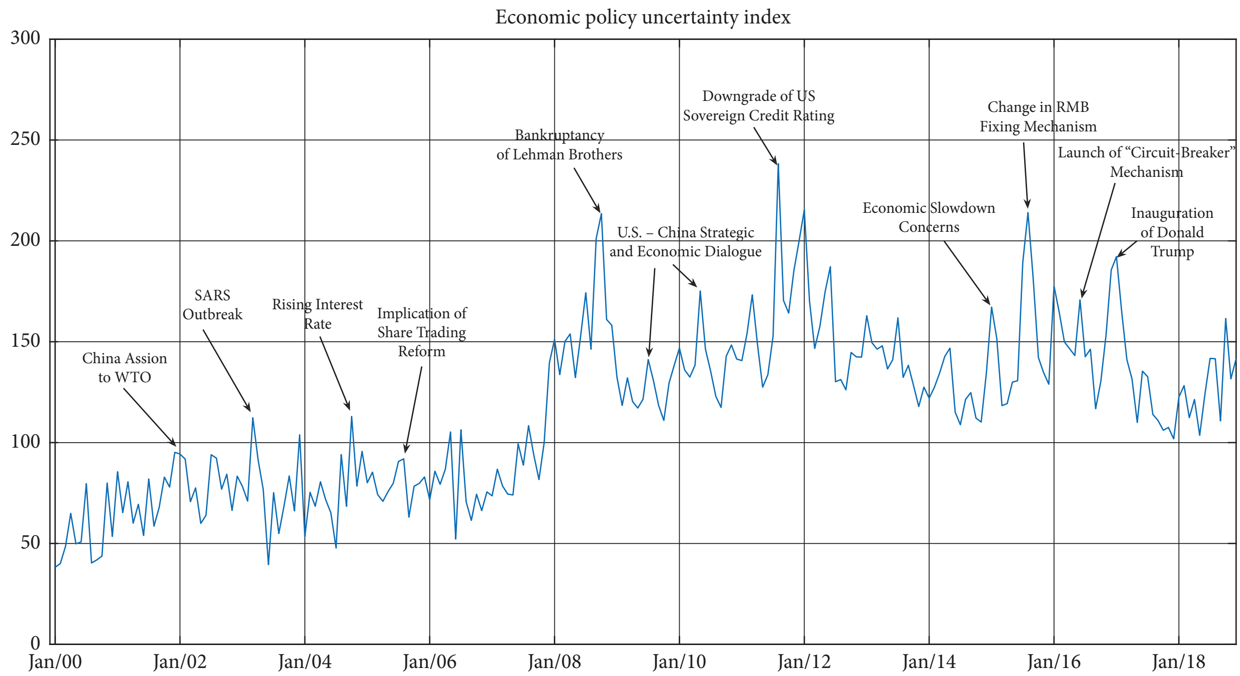


Figure 2: EPU index of China. Notes: the index is available at https://economicpolicyuncertaintyinchina.weebly.com.

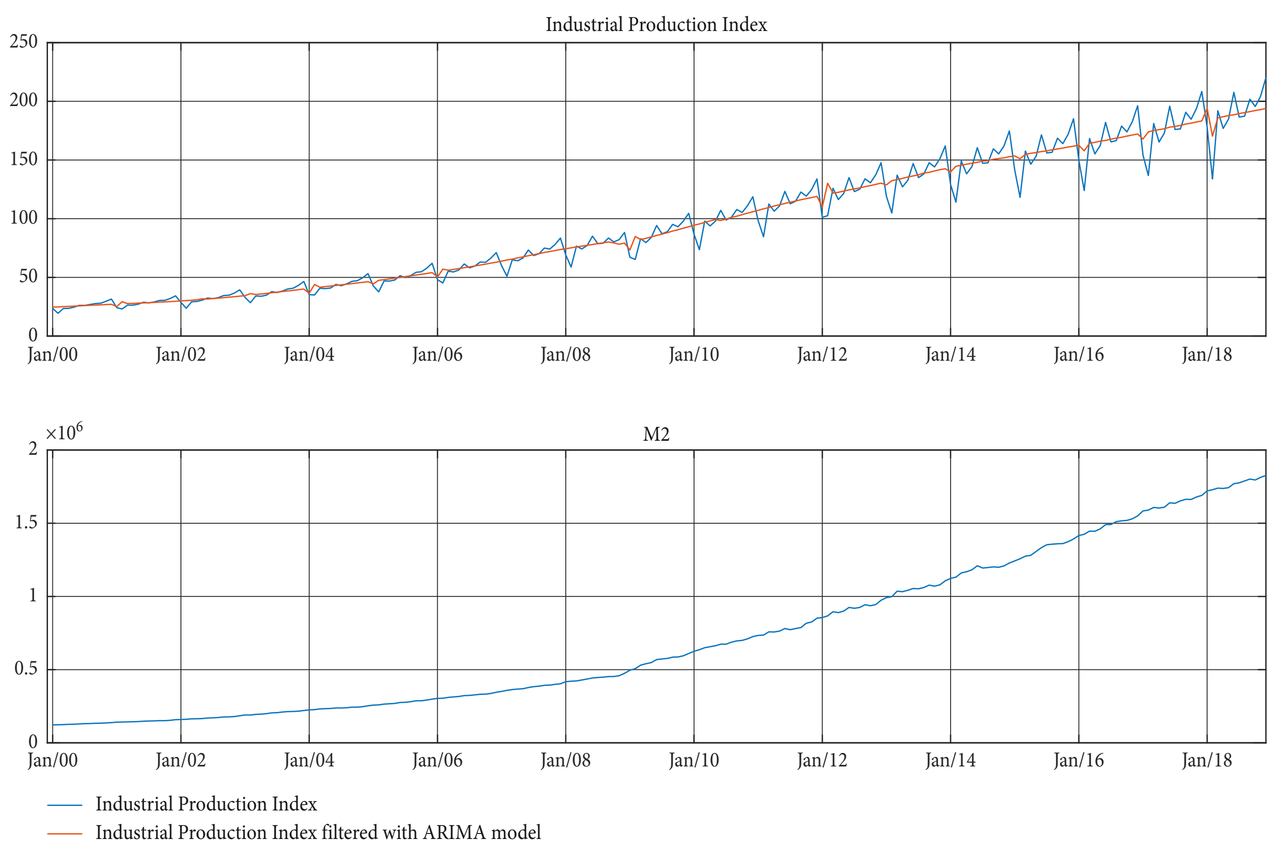
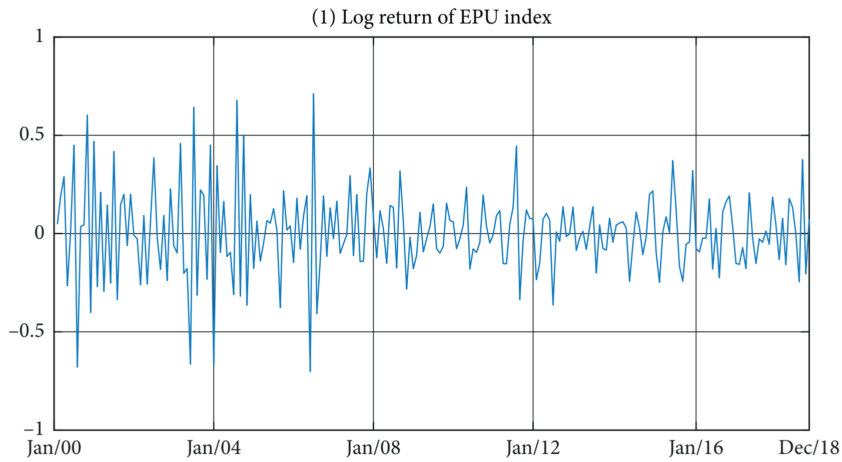


Figure 3: Industrial production index and M2.

4. Data and Preliminary Analysis

This paper examines the impacts of Chinese economic uncertainty shocks on the dynamics of Chinese stock volatility after controlling for economic activities and monetary policy. For analyzing the change in volatilities of the Chinese stock market, we collect daily price indices for the two most important stock market composite indices and



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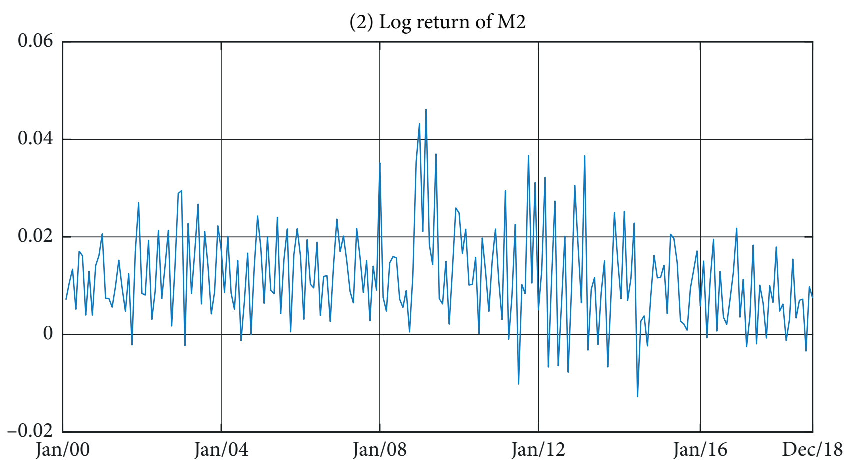

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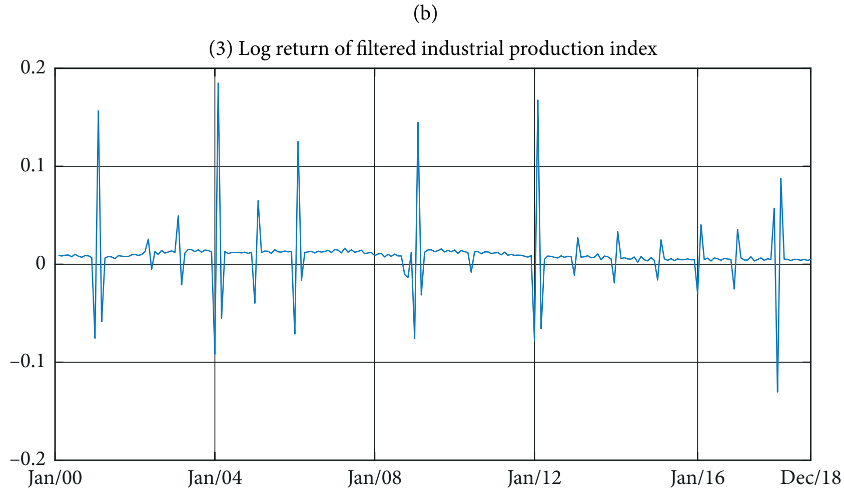

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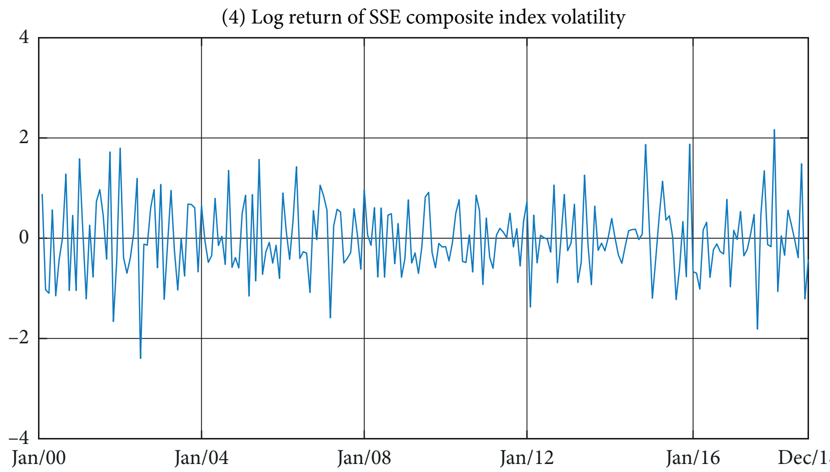

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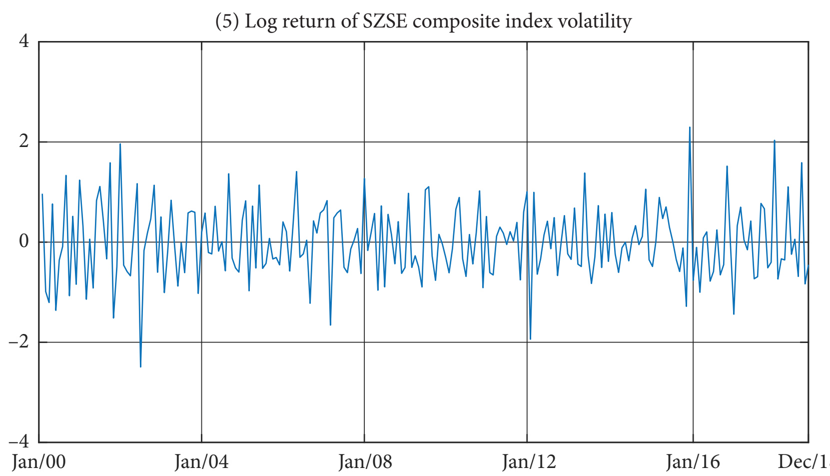

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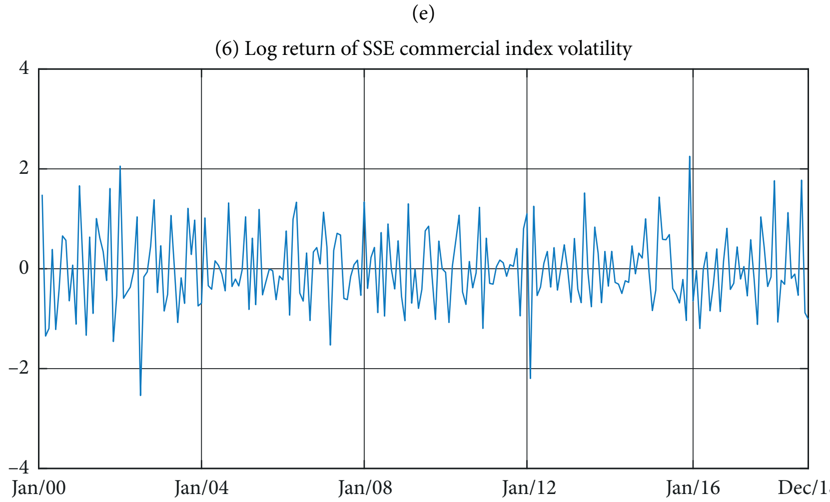

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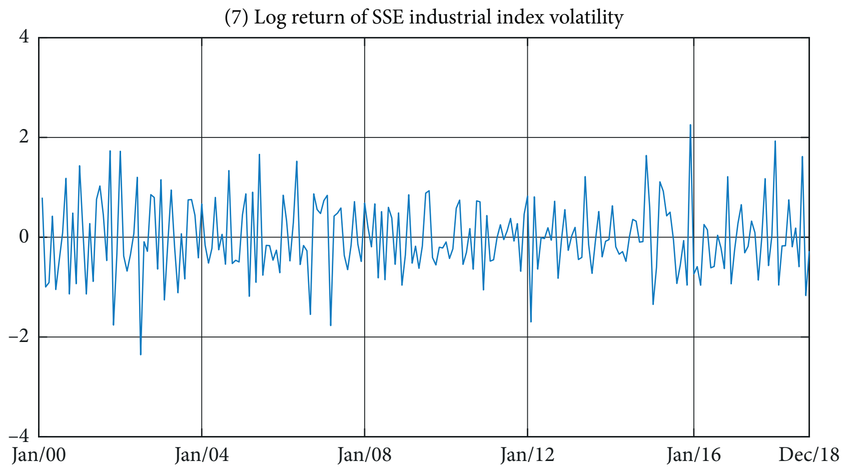

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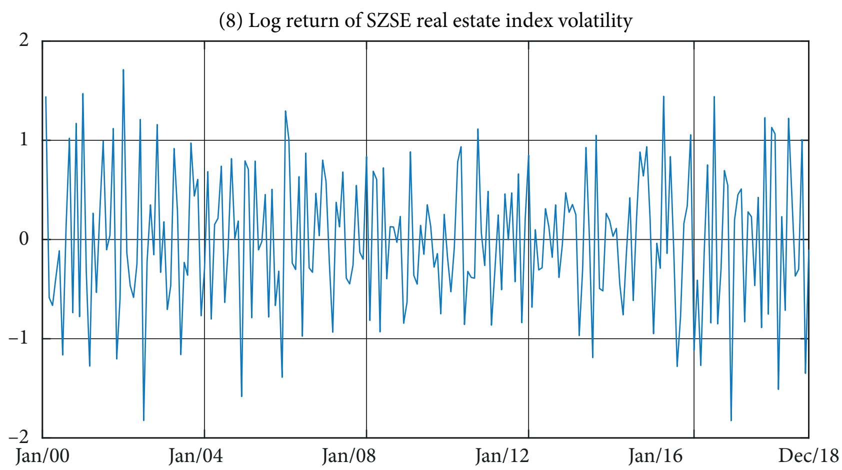

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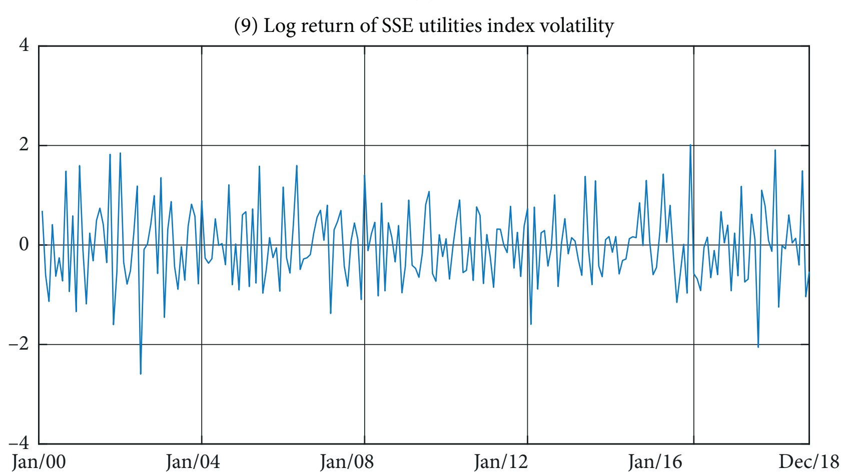

(i)

Figure 4: Log returns of all the samples.

four sectoral indices, including the Shanghai Stock Exchange (SSE) composite index, the Shenzhen Stock Exchange (SZSE) composite index, the commercial index in SSE, the industrial index in SSE, the real estate index in SSE, and the utility index in SSE. The sampling period is from January 2000 to December 2018. We obtained the data from the Wind database.

Similar to previous studies such as Bakas and Triantafyllou [23] and Wang et al. [31], we take the realized variance as the proxy for the monthly volatility of the daily

Table 1: Descriptive statistics of sample data.

	Mean	Std	*LQ* (1)	*LQ* (5)	*PP*	*ADF*
EPU	0.006	0.218	52.152***	68.569***	−26.518***	−13.130***
M2	0.012	0.010	0.314***	72.450***	−6.928***	−2.424***
Industrial production index	0.009	0.031	87.469***	93.660***	−25.149***	−7.659***
SSE composite index	−0.006	0.737	17.543***	24.685***	−20.873***	−12.076***
SZSE composite index	−0.004	0.737	20.181***	28.564***	−21.720***	−12.747***
SSE commercial index	−0.006	0.769	22.495***	32.131***	−22.190***	−12.035***
SSE industrial index	−0.005	0.741	19.812***	26.841***	−21.423***	−12.342***
SSE real estate index	−0.003	0.698	17.614***	30.795***	−21.029***	−11.621***
SSE utilities index	−0.006	0.759	26.662***	30.448***	−22.677***	−12.141***

Note. *LQ* (*i*) is the ljung and box statistics of the return series of the *i*th order. *ADF* and *PP* are the statistics of the augmented Dickey–Fuller and Phillips–Perron unit root tests, respectively, based on the lowest AIC value. *J-B* is the Jarque–Bera statistic, which confirms the nonnormality of all of the sample returns. (***, **, *) denote the significance level of 1%, 5%, and 10%, respectively.

stock returns. Denoting the nearby stock price at time t as S_t, the realized variance from time *1* to time T can be computed as follows:

$$\mathrm{RV}_{t,T} = \frac{1}{T}\sum_{i=1}^{T}\left(r_{t+i} - \overline{r_{t+i}}\right)^2, \tag{4}$$

where $r_{t+i} = 100\times \ln(S_{t+i}/S_{t+i-1})$ and $\overline{r_{t+i}} = 100\times \ln(S_{t+i}/S_{t+i-1})$ are the one period return and the average return for T periods, respectively. Figure 1 shows the estimated monthly volatilities for all six Chinese stock indices.

Choosing a proper index as the proxy for Chinese economic uncertainty is a critical part of our research. Most of the literature on Chinese economic uncertainty take the index of Baker et al. [2]. However, the Chinese EPU index is constructed only based on the Hong Kong-based English newspaper, which may not fully reflect the uncertain information about China. To reflect China's economic uncertainty more accurately, Huang and Luk [1] construct a new China EPU index using 10 mainland Chinese newspapers, which is proved to be more robust and targeted. (The index is available at https://economicpolicyuncertaintyinchina.weebly.com) This paper takes the economic policy uncertainty index following Huang and Luk [1]. Figure 2 shows the EPU index.

As for the controlling variables, we selected the monetary policy and the industrial production index according to Baker et al. [2]. Since the M2 growth is the only intermediate target of PBoC for maintaining the growth of GDP in China, it is chosen as our proxy for monetary policy [30]. The industrial production index is calculated based on the base index of industrial production from the Wind database. As the industrial production index also shows a significant seasonal trend, on the reference of Baumeister and Peersman [32], we take *ARIMA* models to filter the seasonal trend in our analysis. Figure 3 shows the time series of the macroeconomics variables, that is, the industrial production index.

To ensure the stationariness of each variable, all the above sample data are converted to a logarithmic rate of return. Define p_t as the closing price on month t and the logarithmic rate of return r_t is computed as $r_t = \ln(P_t/P_{t-1})$. In summary, the multivariate time series fitted to the SVAR model consists of four variables: (1) log rate economic policy uncertainty; (2) six corresponding log returns of volatilities of Chinese stock markets; (3) growth rate of M2; and (4) log rate of the filtered industrial production index. The orders of the estimating models are set to be 3, which is consistent with Baumeister and Peersman [32]. Figure 4 exhibits log returns of each variable, and Table 1 shows the descriptive statistics.

Figures 1–4 and Table 1 can make several observations. First, as is evident from Figure 1, the monthly volatilities of the Chinese stock market fluctuated dramatically during the years from 2008 to 2009, when the global financial crisis took place. Another period when the volatilities fluctuated dramatically was from 2015 to 2016. An unsuccessful launch of the "circuit-breaker" mechanism in Chinese stock markets during that period possibly explains the increase in volatilities. Meanwhile, the changes in volatilities vary among different stock indices. For example, the real estate index in SSE presents higher volatility during the global financial crisis than other indices.

Second, the EPU index of Huang and Luk [1] reflects fundamental domestic policy changes in China, including the accession to WTO in 2001, a change in the fixing mechanism in August 2015, and an unsuccessful launch of the "circuit-breaker" mechanism in Chinese stock markets in January 2016. We can also find that the index appears to be an upward structural shift in EPU in China after 2008.

Third, as seen in Figures 3 and 4, the industrial production index and the monetary supply exhibit obvious growing tendencies. The industrial production index also shows a significant seasonal trend. Following Baumeister and Peersman [32], ARIMA models are used to filter the seasonal trend in our analysis. The M2 supply proliferates after January 2009. The reason is mainly that the Chinese central government stimulated economic growth by adopting a loose monetary policy in 2009.

Fourth, from Table 1, we find that the augmented Dickey–Fuller and Phillips–Perron unit root tests both support the rejection of the null hypothesis of a unit root at the 1% significance level, implying that all the return series are stationary.

5. Main Empirical Results

5.1. The Impact of Uncertainty Shocks on Stock Price Volatility. In this section, we report the cumulative impulse response of monthly Chinese stock volatility returns to shocks of the Chinese EPU in Figure 5 and the impulse response without cumulative in Figure 6.

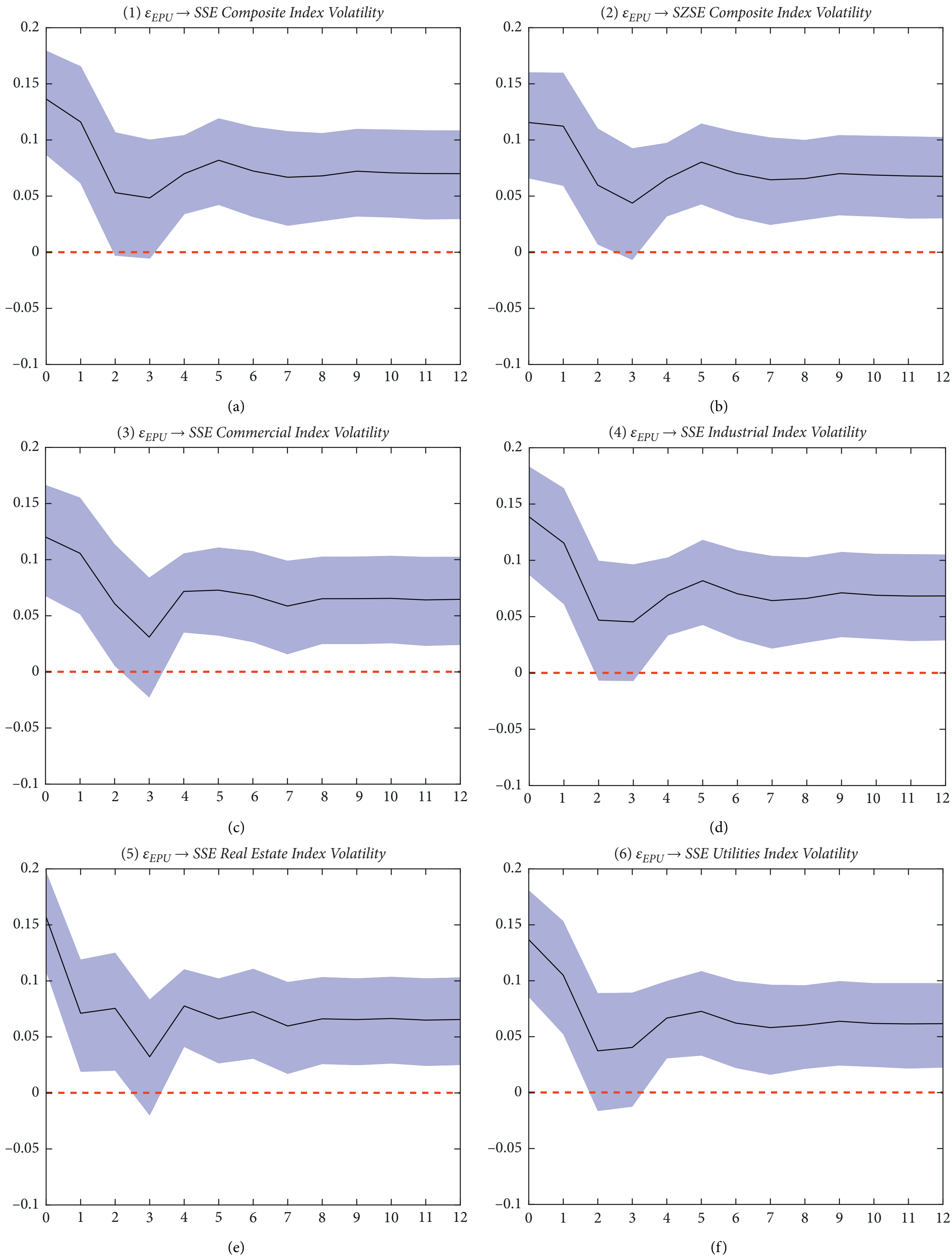

Figure 5: Cumulative impulse response of different stock volatility returns to EPU shocks. Note: the solid black lines denote the median impulse response, the shaded region represents 68% error bands, and each period is a month.

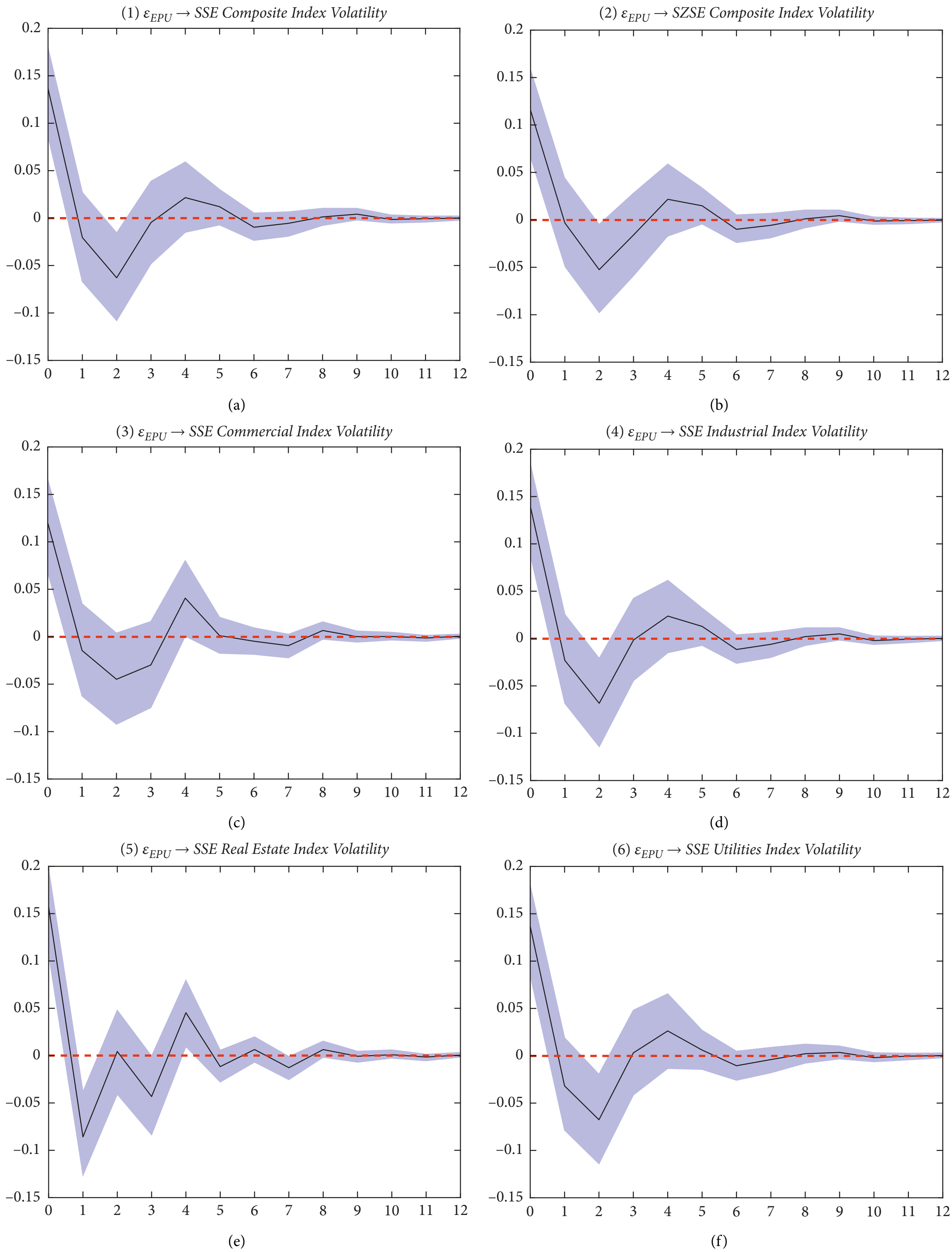

Figure 6: Impulse response of different stock market volatility to EPU shocks. Note: the solid black lines denote the median impulse response. The light-colored region denotes 68% error bands. Each period is a month.

Table 2: Forecast error variance decomposition of stock volatility return to EPU.

	1	2	3	4	5	6	7	8	9	10	11	12
SSE composite index	0.039	0.035	0.041	0.041	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042
SZSE composite index	0.029	0.025	0.029	0.029	0.030	0.030	0.030	0.031	0.031	0.031	0.031	0.031
SSE commercial index	0.029	0.025	0.028	0.029	0.032	0.032	0.032	0.032	0.032	0.032	0.032	0.032
SSE industrial index	0.040	0.035	0.043	0.043	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044
SSE real estate index	0.057	0.065	0.064	0.067	0.071	0.071	0.071	0.071	0.072	0.072	0.072	0.072
SSE utilities index	0.038	0.033	0.040	0.040	0.041	0.041	0.041	0.041	0.041	0.042	0.042	0.042

Note. This table displays the variance decomposition with respect to the shocks for horizons from 1 to 12.

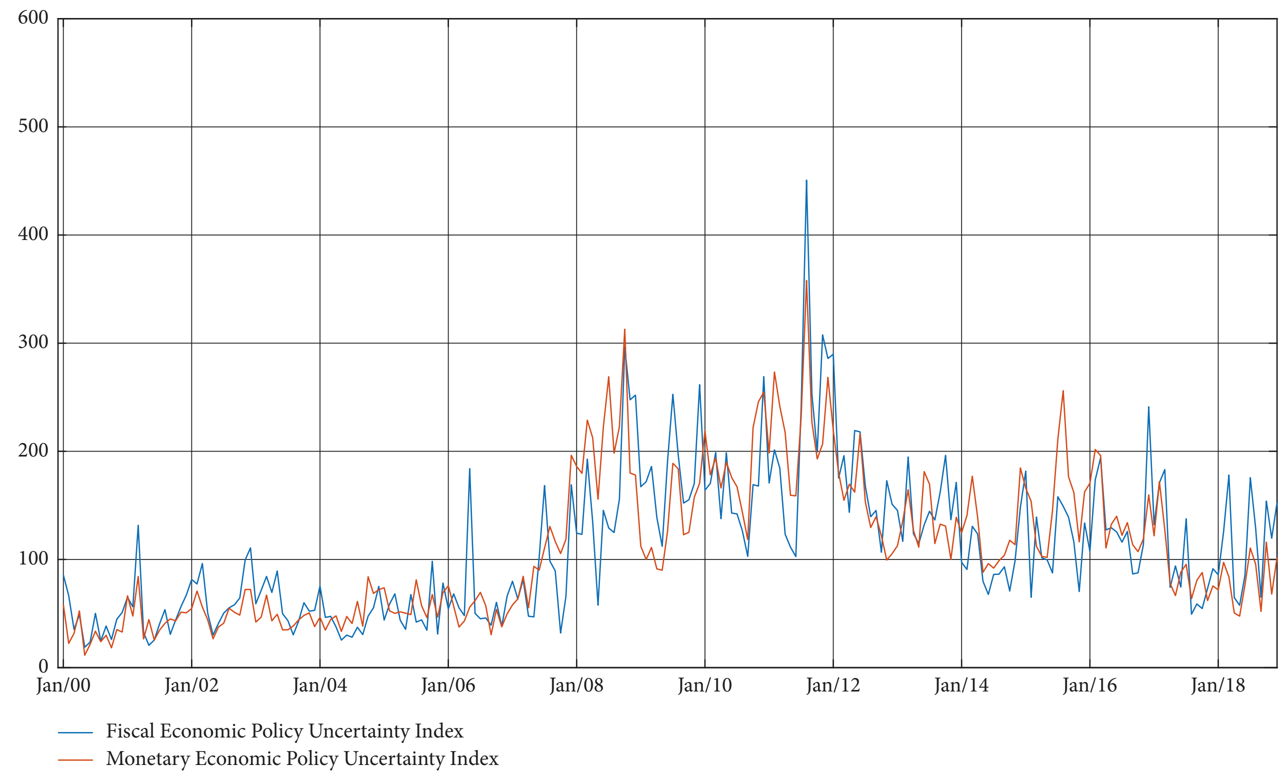

Figure 7: The two other EPU indices: The fiscal EPU index and monetary EPU index. Note: these two EPU indexes are also constructed by Huang and Luk [1].

There are a few findings. First, the EPU shocks significantly push the Chinese stock volatility up, implying that the EPU may serve as useful leading indicators for the stock volatility changes. For example, from Figure 5, the magnitude of the 12-month cumulative impulse response of volatility returns of SSE composite index volatility is about 7%. This result also implies that a standard deviation shock on EPU may enhance the stock volatility by approximately 7% in 12 months. Similar results can be obtained from the cumulative response of the SZSE composite index.

Second, the volatility of each stock index responds to economic uncertainty shocks most strongly in the contemporaneous period, then gradually declines and converges to a certain value. For example, as shown in Figure 5, the magnitude of cumulative impulse responses of the SSE composite index is the biggest in the contemporaneous period at about 13%, then gradually converges to 7%. The variation trends of other indices are similar to the SSE composite index.

Third, the impulse response of the SSE composite index and the SZSE composite index is significantly positive in the contemporaneous period, then turns negative in the second month, as shown in Figure 6. This overshoot arises possibly because the stock market has overreacted to economic uncertainties and shocks simultaneously, followed by adjustments in the following month, and the volatility tends to decrease to some extent. Besides, other stock indices also present an overshoot in the second month after a standard deviation shock, such as SSE industrial index, SSE real estate index, and SSE utilities index.

Fourth, some sectoral stock indices exhibit different patterns of cumulative impulse responses and impulse responses with the two main composite indices. For example, compared to other indices, the reaction of the volatility of

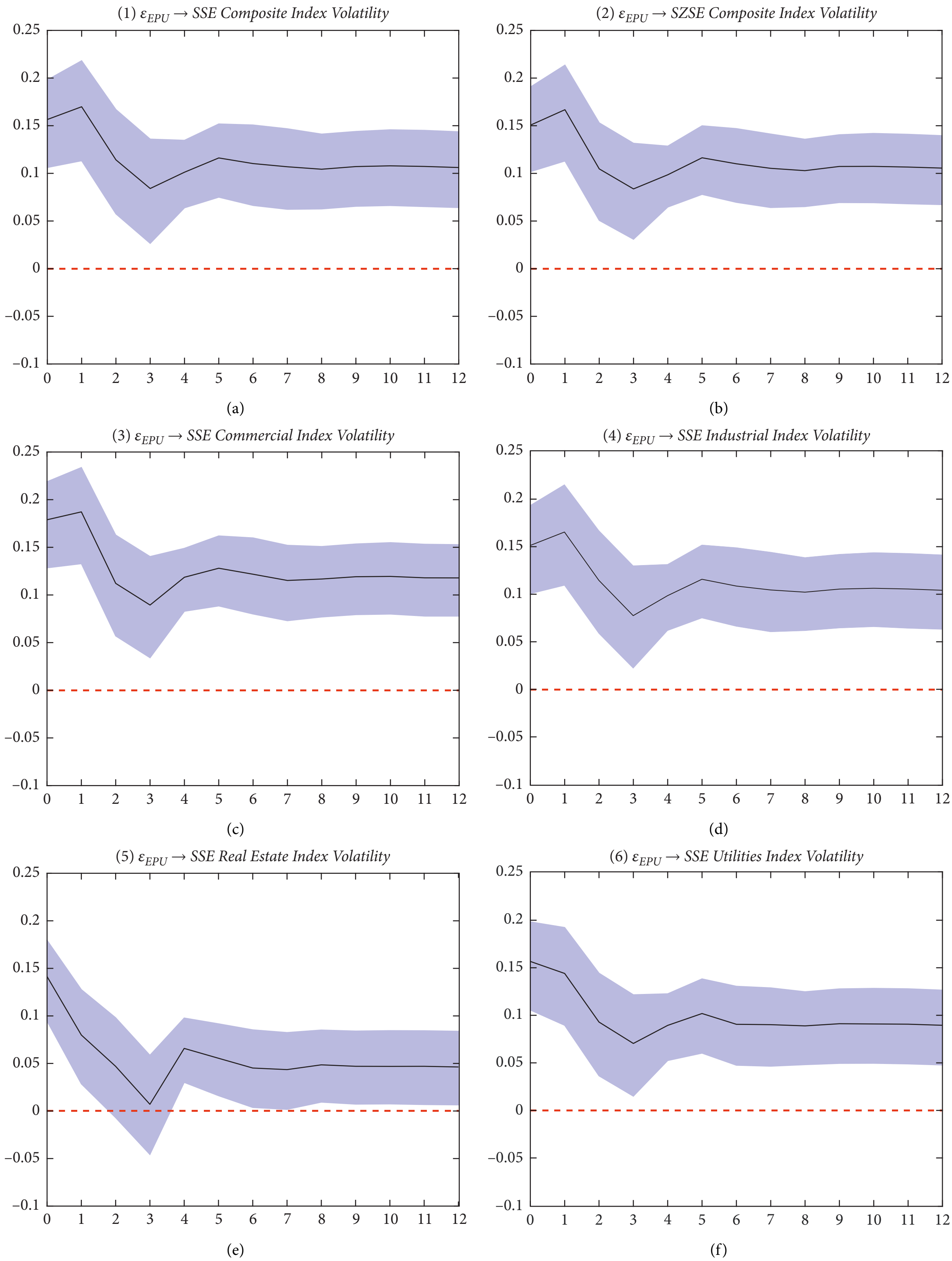

FIGURE 8: Cumulative impulse response of stock market volatility to fiscal EPU (FEPU) shocks. Note: the solid black lines denote the median impulse response. The light-colored region represents 68% of error bands. Each period is a month.

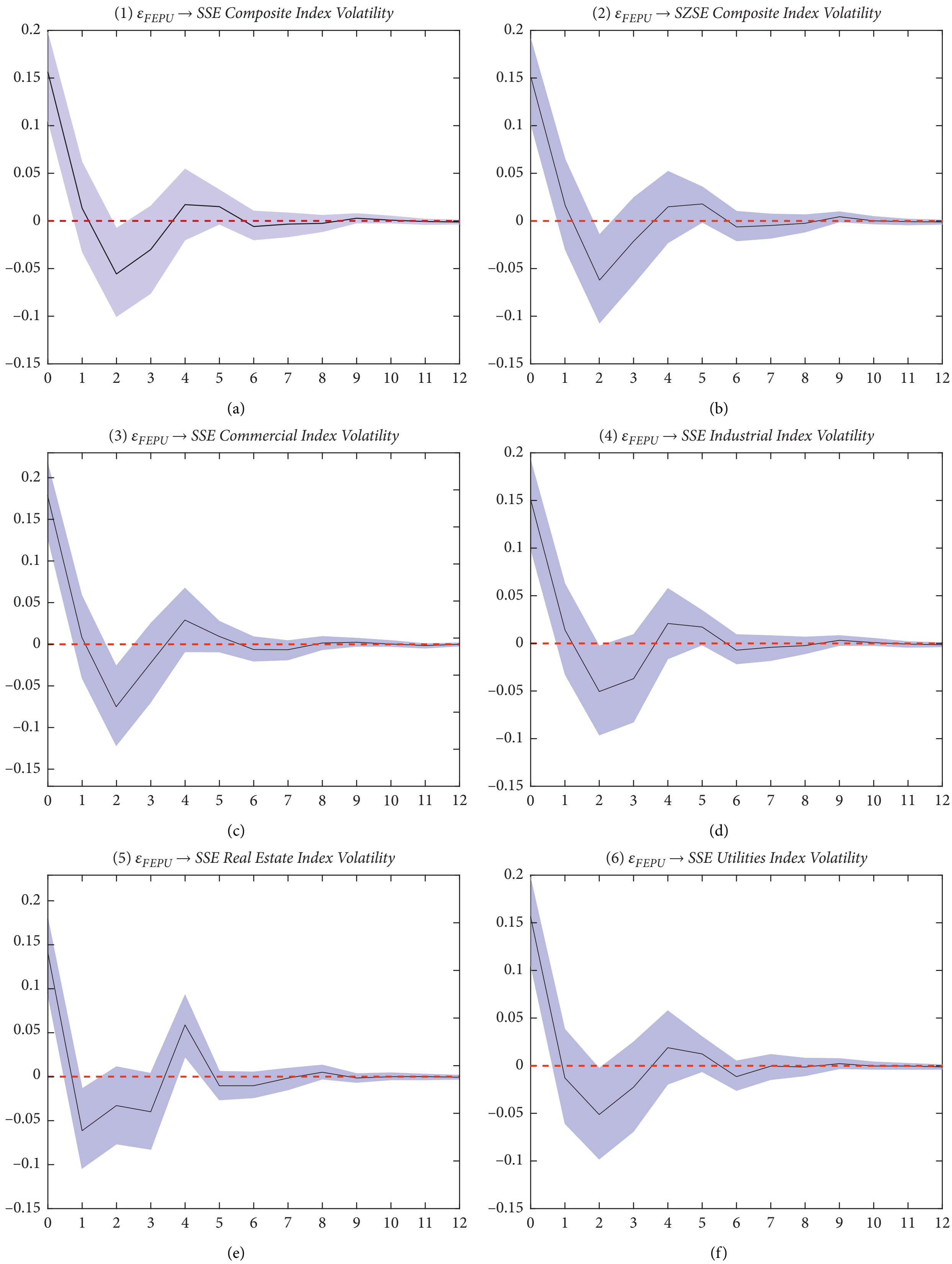

Figure 9: Impulse response of stock market volatility to fiscal EPU (FEPU) shocks. Notes: the solid black lines denote the median impulse response. The light-colored region represents 68% of error bands. Each period is a month.

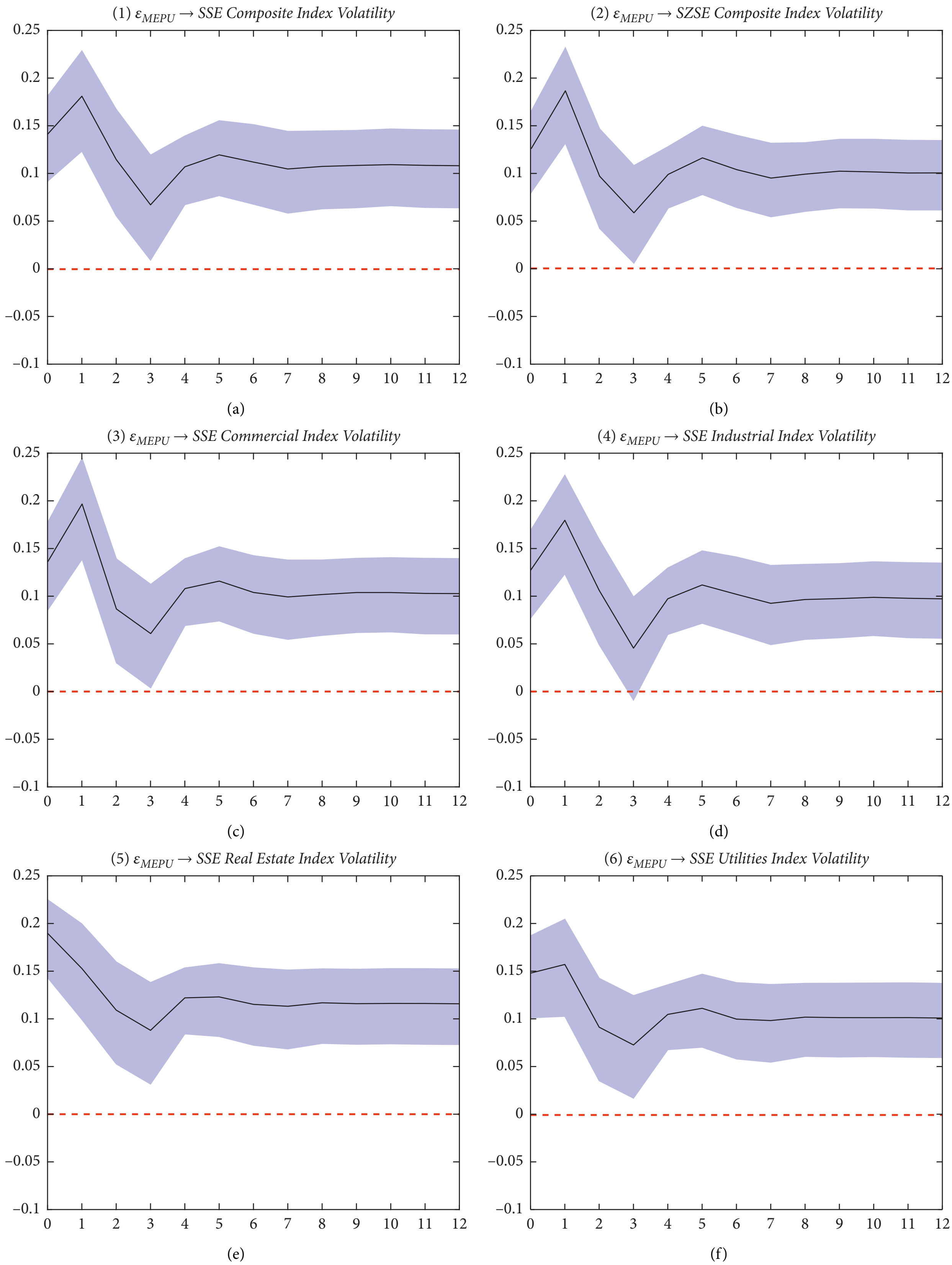

Figure 10: Cumulative impulse response of stock market volatility to monetary EPU (MEPU) shocks Notes: the solid black lines denote the median impulse response. The light-colored region represents 68% of error bands. Each period is a month.

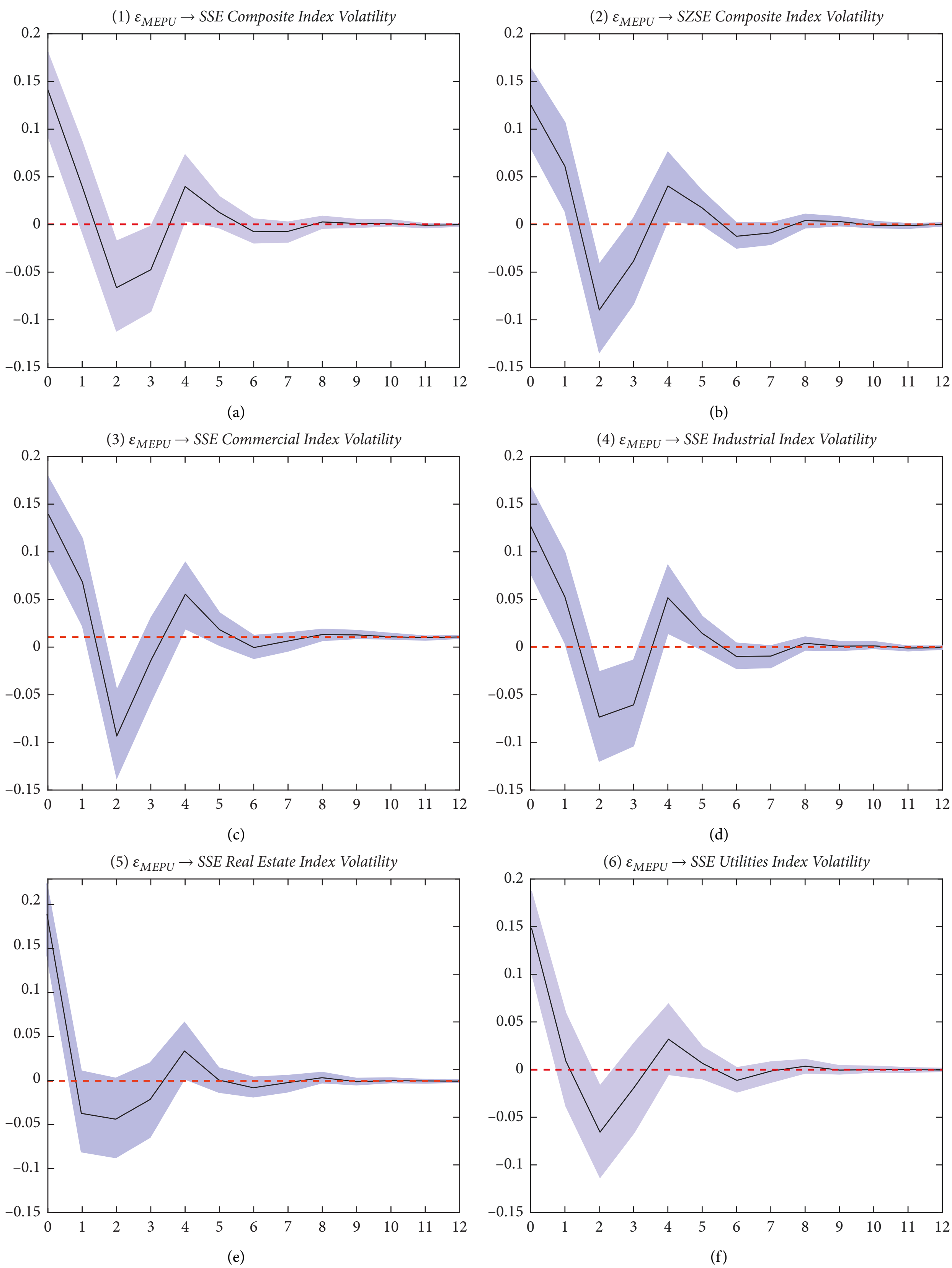

FIGURE 11: Cumulative impulse response of stock market volatility to monetary EPU (MEPU) shocks Notes: the solid black lines denote the median impulse response. The light-colored region represents 68% of error bands. Each period is a month.

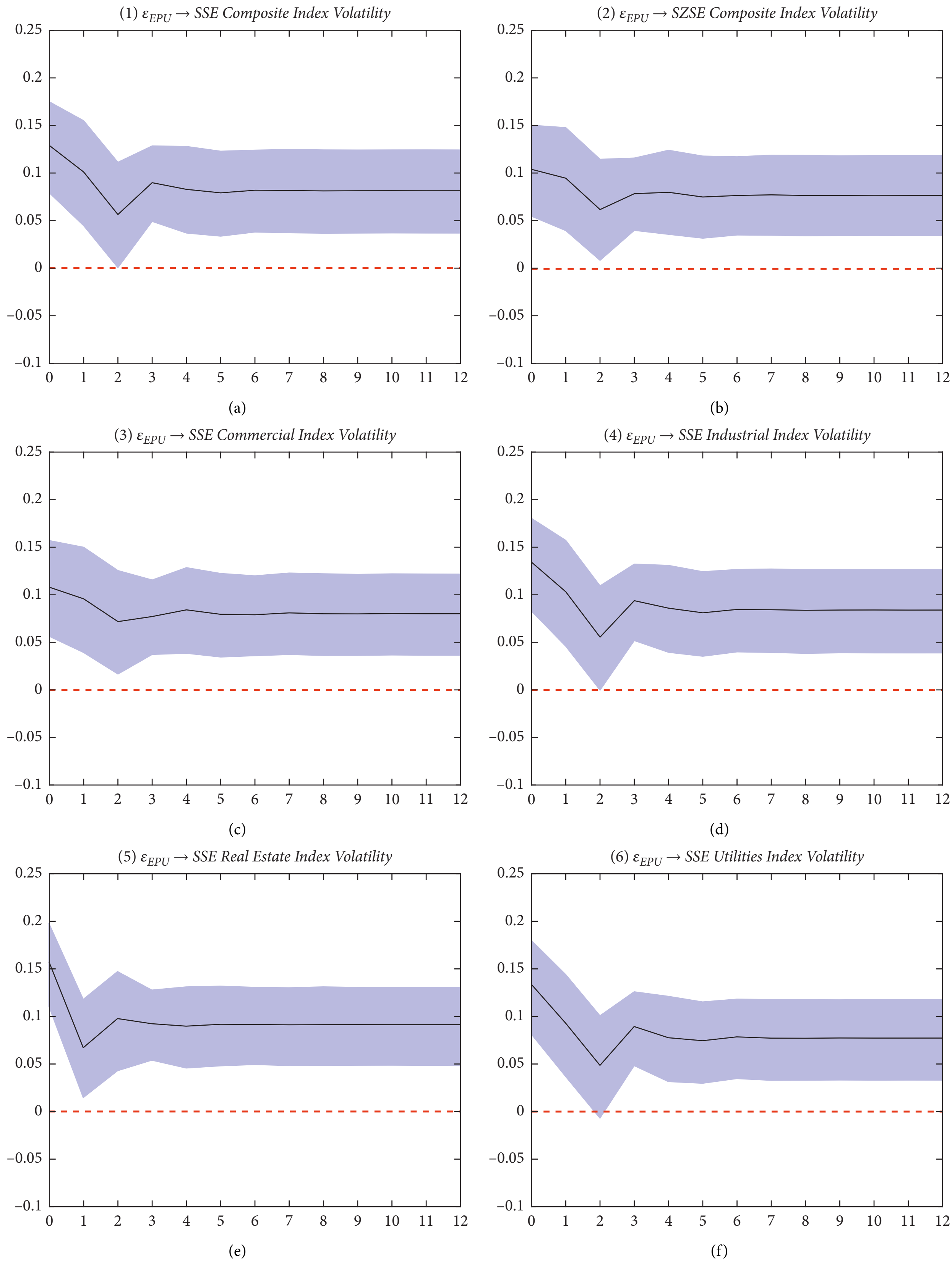

Figure 12: Cumulative impulse response of stock market volatility to EPU shocks. Notes: for robustness, we also estimate the SVAR models with lag order 2, inspired by the research of Huang and Luk [1]. The solid black lines represent the median impulse response. The light-colored region represents 68% of error bands. Each period is a month.

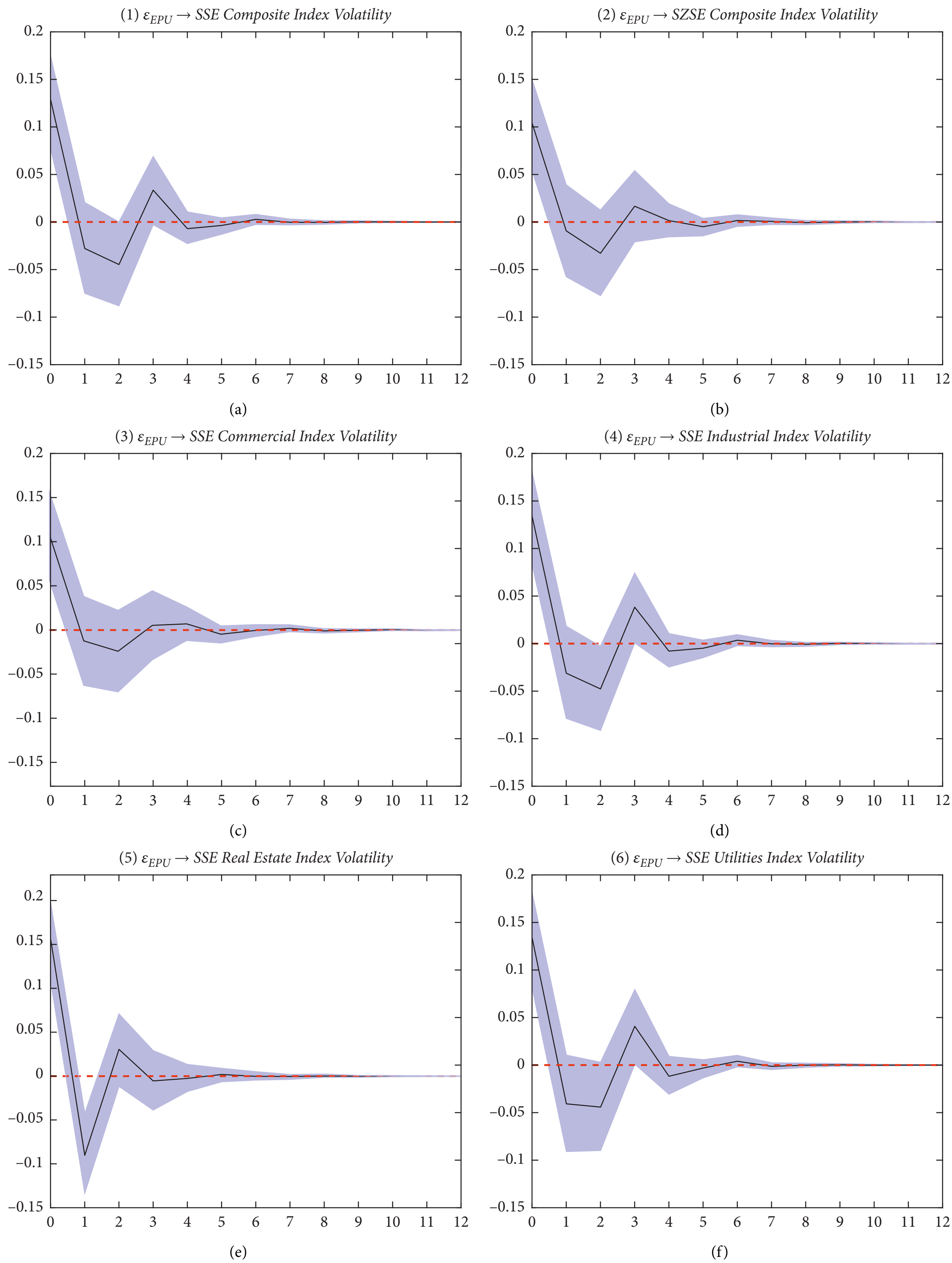

Figure 13: Impulse response of stock market volatility to EPU shocks. Notes: for robustness, we also estimate the SVAR models with lag order 2, inspired by the research of Huang and Luk [1]. The solid black lines represent the median impulse response. The light-colored region represents 68% of error bands. Each period is a month.

the SSE real estate index to EPU shocks is particularly intense. As from Figure 6, the EPU shocks induced more than 15% in a simultaneous period, and then induced overshoot with a decline of about 8%. The magnitude of fluctuation is significantly greater than other indices.

5.2. Forecast Error Variance Decomposition. Based on the variance decomposition methods, Table 2 reports the contribution of structural EPU shocks to stock volatility variation at different horizons.

We can get several inferences from Table 2. First, regarding the contribution to the variation in stock volatility, EPU shocks generally account for 3% to 4% of the variability in stock volatility of the two composite indices. As Table 2 shows, EPU shocks, on average, account for about 4% of the stock volatility of the SSE composite index and 3% of the variability in the SSE composite index.

Second, there is significant heterogeneity in monetary policy shocks' contributions to different stock sectors. For example, EPU shocks on average account for 7% of the variation in the SSE real estate index; in contrast, they on average account for 3% of the variation in the SSE commercial index.

5.3. Other Empirical Analysis. For comprehensiveness and robustness, we further research the reaction of Chinese stock volatility to EPU shocks. In Section 5.3.1, we analyze the reaction of Chinese stock volatilities to some other policy-specific EPU indices, such as the fiscal EPU index and monetary EPU index. In Section 5.3.2, we reestimate the results of Section 5.1 with a lag order of 2.

5.3.1. Fiscal EPU Index and Monetary EPU Index. In this section, we analyze Chinese stock volatilities' reaction to other policy-specific EPU indices, such as the fiscal EPU (FEPU) index and monetary EPU (MEPU) index. This part of the research will further explore whether there is a difference in stock volatility reactions to different types of EPU shocks. Figure 7 shows the FEPU index and MEPU index.

As above, the lag orders of the estimating models are set to be 3. Figures 8 and 9 present the cumulative impulse response and impulse response of the returns of monthly Chinese stock volatility to the shocks of FEPU. Figures 10 and 11 exhibit the cumulative impulse response and impulse response to MEPU shocks.

We can get several inferences from Figures 8–11. First, both the FEPU and monetary MEPU shocks significantly push the Chinese stock volatility up, and they have a more considerable impact on stock volatility than EPU. For example, from Figures 8 and 10, the magnitude of the cumulative impulse response of stock volatility to FEPU and MEPU shocks is more significant than that of EPU shocks. Specifically, the importance of the 12-month cumulative impulse response of volatility returns of the SSE composite index and SZSE composite index is more than 10%, compared with the magnitude of the 12-month cumulative response to EPU shocks is about 7%.

Second, FEPU and MEPU have a more sustained and intense impact on the SSE composite index and SZSE composite index stock volatility than EPU. As in Figures 8 and 10, different from the previous empirical results that the volatilities of the two indices show the strongest cumulative impulse response to EPU shocks in the simultaneous period, they show the strongest cumulative impulse response to FEPU and MEPU in the first month, then gradually decline and converge to a certain value. Specifically, in Figures 8 and 10, the magnitude of cumulative impulse responses of the SSE composite index is biggest in the first month at about 17%, then gradually converges to 10%. The results indicate that FEPU and MEPU have a more sustained and intense impact on stock volatility than EPU. The cumulative impulse responses of the SSE commercial index and the industrial index also present similarly varying trends.

Third, the impulse response of stock volatility of the SSE composite index and the SZSE composite index to MEPU and FEPU turned negative in the second month, as seen in Figures 9 and 11. Similar to the analysis in Section 5.1, this overshoot arises possibly because the stock market has overreacted to economic uncertainties and shocks in a simultaneous period followed by adjustment in the following months. Other sectoral stock indices also present the overshoot in the second month after a standard deviation shock.

Fourth, different stock indices exhibit different patterns of cumulative impulse responses. For example, compared to other indices, the reaction of the volatility of the SSE real estate index to EPU shocks is particularly intense. As from Figure 11, the MEPU shocks induced 17% more in the simultaneous period, and the magnitude is significantly greater than other indices.

5.3.2. Robustness with Different Orders. In Section 5.1, the lag orders of the estimating models are set to be 3, which is consistent with Baker et al. [2]. However, for robustness check, this section will reestimate the models with a lag order of 2 following Hang and Luk [1].

We get a similar conclusion from Figures 12 and 13 as in Section 5.1. The EPU shocks significantly pushed the Chinese stock volatility up. Moreover, the volatility of each stock index shows the most robust response to economic uncertainty in a simultaneous period, then gradually declines and stabilizes at a specific value. These conclusions support the main empirical results in Section 5.1.

6. Conclusions

The Chinese stock market developed substantially within 30 years and has become an important investment market for international investors to make asset allocations. However, as an emerging economy, China has been in the progress of economic system reform for decades. As a result, both the real economy and the stock market are subject to policy uncertainty shocks. Motivated by this, this paper provides a new framework for examining the dynamical reaction of the Chinese stock market volatility to the Chinese economic policy uncertainty shocks.

Our findings are broadly consistent with previous studies highlighting the adverse economic effects of economic uncertainty shocks on markets. This paper shows that the EPU shocks push the Chinese stock volatility up, increasing the market risk. One standard deviation of EPU shock will induce the stock volatility of the two composite indexes to increase by approximately 7% in 12 months. Moreover, the stock volatility reacted more intensely to the FEPU and MEPU shocks. A 1-standard-deviation shock of the MEPU and the FEPU will increase the stock volatility of the two composite indices by more than 10% in 12 months. Moreover, stock indices exhibit different patterns of cumulative impulse responses, and the reaction of the volatility of the SSE real estate index to EPU shocks is particularly intense.

Our paper has the following policy implications. Firstly, the central bank must always pay attention to the changes in the economic environment, enhance the transparency, continuity, and stability of macroeconomic policies, maintain the smooth operation of the macroeconomy, guide the healthy development of China's stock market, and reduce systemic risks. Secondly, uncertainty has a significant spillover impact on financial risk contagion. Therefore, financial regulators should strengthen the tracking of the level of economic policy uncertainty and effectively monitor systemic financial risks from the macroprudential perspective. Finally, we should improve the multitiered capital market system to improve the ability of the financial system to resolve shocks and reduce the possibility of market collapse caused by spillover effects caused by external shocks.

Admittedly, this study has some limitations. On the one hand, the research on the influence mechanism of economic policy uncertainty on stock market volatility is fascinating and meaningful. Still, due to the limitation of data, our paper fails to study further. On the other hand, the measurement of economic policy uncertainty is a complex problem. Although we have used scientific methods to measure it, there are still some shortcomings that we expect future scholars to improve.

Data Availability

The data used to support the findings of this study have been made available. The data used to support the findings of this study can be obtained from the Wind database.

Conflicts of Interest

The authors declare that the authors have no conflicts of interest or other interest that might be perceived to influence the results and/or discussion reported in this paper.

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