

Research on the Impact of Economic Policy Uncertainty on Investor Sentiment and Stock Prices

Shujie Li

School of Economics and Management, Nanjing University of Science and Technology, Nanjing, China

18652966859@163.com

Abstract. This paper focuses on the time-varying relationship between economic policy uncertainty and investor sentiment and stock prices. Firstly, this paper summarizes the research status of the three variables, so as to conduct in-depth research on the basis of the existing research results. This paper selects China's data from 2010-2022 and estimates the TVP-SV-VAR model, finding that economic policy uncertainty not only inhibits investment, but also has a positive impact on investor sentiment and stock prices in some periods.

Keywords: Economic policy uncertainty, Stock price, TVP-SV-VAR model.

1. Introduction

China's stock market is greatly affected by the policy, and the uncertainty of economic policy will affect the stock price to a large extent. Because China's industrial structure is in the period of transformation and upgrading, it is facing great economic downward pressure, and the economic policy is changeable, and the instability of economic policy is also an important factor affecting investor sentiment. When the economic policy changes frequently, it will increase the difficulty for investors to predict the stock market. Thus, stock prices will be affected. Therefore, the research on the relationship among economic policy, investor sentiment and stock price has certain reference significance for formulating reasonable economic policy and making correct investment decision.

Economic Policy Uncertainty (EPU), that is, the unpredictable part of economic policy changes, has brought great troubles to people's investment decisions. In recent years, the uncertainty facing the world has become increasingly prominent. In order to maintain economic and financial stability, more and more studies have begun to pay attention to the negative impact of EPU on asset prices. Numerous studies have shown that EPUs reduce stock prices and returns. Kang and Ratti used the VAR model and found that a rise in EPU led to a fall in US share prices. Based on the DCC-GARCH model, Antonakakis et al. found that there was a correlation between the return rate, volatility and EPU of American stocks over time, and pointed out that the rise of EPU would reduce the return rate of stock prices. Chang et al. took OECD countries as samples and found that policy uncertainty would lead to stock price declines in some countries. Brogaard and Detzel conducted an empirical study on the data of 21 countries and found that EPU has a negative impact on global stock prices.

Existing studies have generally pointed out the adverse effects of EPU, but EPU itself is not a purely negative concept, and its increase does not mean that economic policy will change adversely. Most of the existing empirical studies have not found the positive impact of uncertainty on stock prices. This paper believes that there are two main reasons: First, the research objects of the existing literatures are mostly Western countries. These countries have slower growth rates and do not have the economic environment in which uncertainty can play a positive role. Second, most of the existing studies use fixed parameter models, which can only get the average value of the effects and fail to capture a small number of positive effects. In order to avoid these problems, this paper constructs a time-varying parameter vector autoregressive (TVP-SV-VAR) model using the relevant data of China from 2010 to 2022 to obtain the time-varying impact of EPU on stock prices, and finds the positive impact of EPU.

2. Theoretical analysis and Hypothesis

The relationship between economic policy uncertainty and stock price has not yet formed a relatively perfect and mature theoretical system. By combing the existing research results, it can be concluded that in the short term, economic policy uncertainty is negatively correlated with stock prices, and investor sentiment plays an important role. Typically, EPUs have a negative impact on investor sentiment. When investor sentiment is depressed, a rise in EPU can significantly depress stock prices. However, in many cases, the impact of EPU on investor sentiment is non-linear. When investor sentiment is still maintained at a high level, the inhibitory effect of EPU on stock prices will be significantly reduced or even disappear. This suggests that the EPU's impact on stock prices is closely related to investor sentiment. When EPU significantly reduces investor sentiment, EPU will have a negative impact on stock prices. When the EPU fails to lower investor sentiment, the negative impact of the EPU on stock prices is usually not significant. It can be seen that when EPU has a positive impact on investor sentiment, it will also promote the rise of stock prices. Therefore, EPU does not only have a negative impact on investor sentiment, but can also improve investor sentiment and promote stock prices in some cases.

Based on the above analysis, this paper proposes the following hypothesis:

EPU has not only a negative impact on investor sentiment and stock price, but also a positive impact.

3. Study design and data explanation

3.1. Model design

At present, most of the existing studies use the fixed parameter model to obtain the impact of EPU on stock price. However, the fixed parameter model can only obtain the average value of the influence in the study period, and can not reflect the different influences in different periods. In order to investigate whether EPU can promote stock price increase in certain periods, this paper adopts a time-varying parameter autoregressive (TVP-SV-VAR) model to obtain the time-varying effects of EPU on stock price. The TVP-SV-VAR model is an extension of the SVAR model, and its biggest improvement is to allow the coefficient and variation-covariance to change over time to capture the nonlinear structural changes between the variables. A basic SVAR model structure is as follows:

$$Ay_t = F_1y_{t-1} + F_2y_{t-2} + \dots + F_sy_{t-s} + \mu_t, t = s + 1, \dots, n \quad (1)$$

Where y_t is the $k \times 1$ dimensional observable variable, A, F_1, F_2, \dots, F_s are $k \times k$ maintenance matrix, s is the lag period, μ_t is $k \times 1$ dimensional structural impact. Supposing that $\mu_t \sim N(0, \psi\psi)$:

$$\psi = \begin{bmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sigma_k \end{bmatrix}$$

At the same time, it is assumed that structural impact A is the lower triangular matrix:

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \dots & a_{k,k-1} & 1 \end{bmatrix}$$

Then, formula (1) can be simplified into the following form:

$$y_t = B_1y_{t-1} + B_2y_{t-2} + \dots + B_sy_{t-s} + A^{-1}\psi\varepsilon_t \quad (2)$$

Where ε_t is the residual term, and $\varepsilon_t \sim N(0, I_k)$, I_k is the identity matrix; $B_i = A^{-1}F_i$, which means that the elements of the matrix are stacked in rows and converted into β form, β is a vector of order $k^2 \times 1$. At the same time, $X_t = I_k \otimes (y_{t-1}, \dots, y_{t-s})$ is defined as the Kronecker product. Thus, formula (2) can be expressed as:

$$y_t = X_t\beta + A^{-1}\psi\varepsilon_t \tag{3}$$

In this case, all parameters in equation (3) are not time-varying. If the parameters can change with time, it is a TVP-VAR model. Therefore, the TVP-VAR model with random volatility can be expressed as:

$$y_t = X_t\beta_t + A^{-1}\psi_t\varepsilon_t \tag{4}$$

Where β_t , A_t and ψ_t are both time-varying matrices, $\varepsilon_t \sim N(0, I_k)$. α_t is the lower triangular stacked vector element in A_t , $h_t = (h_{1t}, \dots, h_{kt})$ and, $h_{jt} = \log\sigma_{jt, j=1, \dots, k, t=s+1, \dots, n}$.

$$\begin{bmatrix} \varepsilon_t \\ \mu_{\beta t} \\ \mu_{\alpha t} \\ \mu_{h t} \end{bmatrix} \sim N \left[0, \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \psi_{\beta} & 0 & 0 \\ 0 & 0 & \psi_{\alpha} & 0 \\ 0 & 0 & 0 & \psi_h \end{bmatrix} \right] \tag{5}$$

Among them, $\beta_{s+1} \sim N(\mu_{\beta 0}, \psi_{\beta 0})$, $\alpha_{s+1} \sim N(\mu_{\alpha 0}, \psi_{\alpha 0})$, $h_{s+1} \sim N(\mu_{h 0}, \psi_{h 0})$.

3.2. Variables and data sources of the TVP-SV-VAR model

The nonlinear estimation method of time-varying parameter model is computationally intensive and is not suitable for containing too many variables. The TVP-SV-VAR model in the existing literature usually contains only three to four variables. Therefore, the monthly data of economic policy uncertainty (EPU), consumer price index (CPI), stock price (SP) and investor sentiment (CICSI) are selected for empirical research.

3.2.1 Economic policy uncertainty measurement indicators

Before Baker et al. (2012) released the economic policy uncertainty index, no scholars accurately measured the economic risks brought by policy uncertainty. After Baker et al. published the economic policy uncertainty index, domestic and foreign scholars used the index to do a lot of research. The Economic policy Uncertainty Index (EPU) constructed by Baker et al. has good continuity and time-variability, and can measure the short and medium term changes of economic policy uncertainty more accurately. Therefore, this paper intends to use the economic policy Uncertainty Index (EPU) compiled by Baker et al. as a proxy variable. China's Economic policy Uncertainty Index is based on South China Morning Post, an English newspaper based in Hong Kong, to measure the frequency of articles related to economic policy uncertainty through text search, and then obtain it through standard normalization processing. South China Morning Post is the English newspaper with the largest circulation and the most influential influence in Hong Kong, and its tracking reports on China's economy are very timely and close. Using it as a news report retrieval platform can ensure the comprehensiveness of the search scope and the accuracy of the search content to a large extent. Economic policy uncertainty index from the official web site (<http://www.policyuncertainty.com>), as the monthly data, during the samples for between January 2010 and March 2022.

3.2.2. Consumer Price Index indicators

Since the CSMAR and the International Bureau of Statistics could not find monthly data, this paper chose to use the consumer consumption index instead of GDP to represent the economic situation. The monthly data comes from the CSMAR database. The sample period was January 2010 to March 2022.

3.2.3. Indicators of investor sentiment

The index of investor sentiment in this paper adopts CICSI, the comprehensive sentiment index of Chinese stock market investors constructed by Yi Zhigao (2009). CICSI integrates the main variables that reflect the change of investor sentiment in domestic stock market, including closed-end fund discount (DCEF), turnover (TURN), number of initial public offerings (IPON) and first-day return

(IPOR), Consumer Confidence Index (CCI) and New Investor openings (NIA), and principal component analysis was used to determine the coefficients of each variable.

$$CICSI_t = 0.23DCEF_t + 0.244TURN_{t-1} + 0.257IPON_t + 0.322IPOR_t + 0.268CCI_t + 0.405NIA_{t-1} \quad (6)$$

The data is from the CSMAR database and is monthly data, and the sample period is from January 2010 to March 2022.

3.2.4. Stock price indicators

Since the CSI 300 Index was released late and the sample period was too short, the Shanghai Composite Index, the most widely used, the earliest and the most important price index, was selected to measure the changes and fluctuations of China's stock market prices. Data from the CSMAR database. Monthly closing prices are selected for the sample period from January 2010 to March 2022.

All the above data are treated with natural logarithms to eliminate dimensional effects. Based on the requirements of data stationarity, all the above data are transformed by first-order difference.

3.3. Stationarity test and hysteresis order selection

The ADF unit root test was carried out on all the processed variable data. In the test type (c, t, k), c means that the test contains a constant term, t means that the test contains a trend term, and k represents the optimal lag order. The optimal lag order is determined by the Akaike Information Criterion (AIC). The test results are shown in Table 1. According to the test results, the null hypothesis of the existence of unit root is rejected at the significance level of 1% for all variables after first-order difference, indicating that all variables are stationary. In order to estimate the TVP-SV-VAR model, it is also necessary to determine the lag order of endogenous variables according to the information law. Figure 1 shows the results of lag order selection in the regression model in this paper. In accordance with AIC and HQ information criteria, second-order lag is selected in this paper.

Table 1. ADF unit root test for all variable data

Variables	Inspection type (c, t, k)	t	1% Critical value	5% Critical value	conclusion
lnepu	(c, t, 1)	-15.772***	-4.023	-3.441	Yes
lnspi	(c, t, 11)	-5.68***	-4.028	-3.444	Yes
lnccsi	(c, t, 3)	-9.627***	-4.024	-3.442	Yes
lnsp	(c, t, 4)	-9.412***	-4.025	-3.442	Yes

VAR Lag Order Selection Criteria
 Endogenous variables: DLNCICSI DLNCPI DLNEPU DLNSP
 Exogenous variables: C
 Date: 05/23/22 Time: 21:12
 Sample: 1 147
 Included observations: 138

Lag	LogL	LR	FPE	AIC	SC	HQ
0	785.7471	NA	1.41e-10	-11.32967	-11.24482*	-11.29519
1	809.0847	44.98408	1.27e-10	-11.43601	-11.01177	-11.26361
2	847.1171	71.10402*	9.23e-11*	-11.75532*	-10.99169	-11.44500*
3	854.9572	14.20308	1.04e-10	-11.63706	-10.53404	-11.18882
4	864.0259	15.90298	1.15e-10	-11.53661	-10.09419	-10.95045
5	874.9450	18.51511	1.25e-10	-11.46297	-9.681165	-10.73889
6	886.2498	18.51359	1.34e-10	-11.39492	-9.273726	-10.53292
7	891.3359	8.034571	1.59e-10	-11.23675	-8.776162	-10.23683
8	896.8873	8.447833	1.87e-10	-11.08532	-8.285342	-9.947480

Figure 1. Results of lag order selection

3.4. MCMC test

The TVP-SV-VAR model contains many parameters and introduces nonlinear factors of random fluctuations in the model, so it is very difficult to estimate the parameter process by using the traditional likelihood function method. Therefore, this paper refers to the Markov chain Monte Carlo

simulation (MCMC) proposed by Nakajima (2011) to achieve parameter estimation. The iteration times of MCMC algorithm was set to 10000 times, and valid samples were obtained by MATLAB 2018. Table 2 lists the parameter estimation results of the TVP-VAR model, including posterior mean, posterior standard deviation, 95% confidence interval, Geweke probability and invalid factor. From the convergence point of view, the Geweke value of each parameter does not exceed the critical value of 1.96 of 5%, which indicates that the null hypothesis converging to the posterior distribution cannot be rejected. In addition, the invalid factor of each parameter is far less than the sampling number of 10000 times. The above results show that the MCMC algorithm is effective and can be used for posterior inference.

Table 2. MCMC simulation estimation results

Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef.
sb1	0.0023	0.0003	0.0018	0.0028	0.961	7.73
sb2	0.0023	0.0003	0.0018	0.0029	0.101	7.28
sa1	0.0036	0.0006	0.0026	0.0051	0.232	15.08
sa2	0.0054	0.0015	0.0033	0.0089	0.305	36.19
sh1	0.0058	0.0019	0.0034	0.0108	0.630	47.97
sh2	0.0054	0.0015	0.0033	0.0091	0.001	59.64

TVP-VAR model (Lag = 2)

Iteration: 10000

Then, the parameter simulation path figure 1 is observed. The first row of the figure is the autocorrelation chart. It can be seen from the chart that the autocorrelation coefficient has a diving trend, rapidly decreases, and finally approaches 0, which proves that the samples have no great correlation. The second row is the sample path. It can be seen from the figure that the sample path fluctuates around the mean value and is generally stable. The third row is the post-density diagram, from which it can be seen that there are fluctuation clustering of parameters, indicating that the posterior distribution density function presents a normal distribution. Combined with Figure 1 and Table 3, the sample data obtained by the model through MCMC sampling are effective and independent of each other, and the model has a high degree of fitting. The simulation path diagram of MCMC parameters is shown in Figure 2.

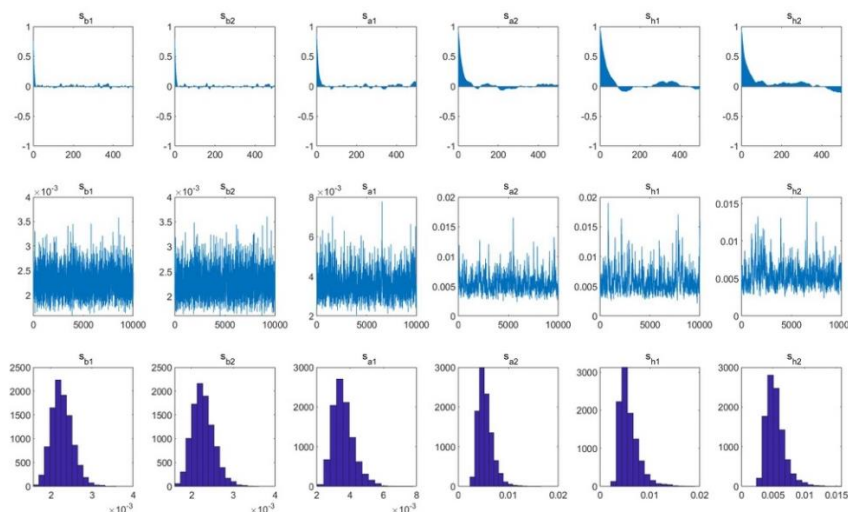


Figure 2. MCMC parameter simulation path diagram

4. Time-varying impulse response analysis

The biggest advantage of the TVP-SV-VAR model is that it can use variable parameters to calculate the impulse response graph of each variable at all time points in different lag periods to study the time-varying characteristics of the relationship between variables, and further analyze

whether there are structural mutations in the relationship between variables under different economic states. Therefore, in order to fully understand the impact of EPU on investor sentiment and stock price, this paper will make use of impulse response charts on the whole sample interval and impulse response charts representing different time points to analyze the results.

4.1. Analysis of time-varying characteristics of impulse response at different lag periods

The time-varying impulse response function can well analyze the time-varying characteristics of impulse response at different time points in the whole sample period. Generally speaking, the cycle of policy changes is relatively long, and the phenomenon of "abrupt changes" rarely appears. People have a certain time to react and cope with EPU, and the impact of EPU is usually relatively sustained. Therefore, this paper presents dynamic impulse response charts constructed for the lead time of 2 months, 5 months and 10 months, corresponding to the short, medium and long term dynamic impulse response, respectively, in order to observe the impact of EPU on investor sentiment and stock price after 2, 5 and 10 months.

As can be seen from Figure 3, EPU can not only have a negative impact on investor sentiment and stock price, but also a positive impact. The response of investor sentiment and stock price to economic policy uncertainty has different effects in different lag periods. In the short term, the response has been positive, indicating that EPU's impact on investor sentiment is mainly promoting. In the medium term, the EPU's response to investor sentiment was negative before 2013, quickly turned positive after 40 months, and then, despite fluctuations, the overall response was positive. In the long run, the EPU's response to investor sentiment has turned from positive to negative since the 60th month, that is, 2015, and has remained negative. This shows that after 2015, EPU can promote investor sentiment in the short term and inhibit it in the long term.

Looking at the impulse response of EPU to stock price, generally speaking, the impact of EPU on stock price and investor sentiment in the short term shows a consistent trend, both of which are positive. It shows that EPU has a short-term promotion effect on stock prices in China at any time. In the medium term, positive and negative transitions occur at 20 months, 80 months and 130 months respectively. Corresponding to 2012, 2017 and 2021, the overall response fluctuated greatly. This indicates that the medium-term effect of EPU on stock prices is unstable throughout the period. In the long run, the EPU's impulse response to stock prices has been negative until it approaches zero around 130 months. It shows that EPU has a significant short-term effect on stock prices and a short duration. From 2012 to 2014, the impact of economic policy uncertainty on stock prices intensified significantly, and the absolute value of the impact reached the largest, with both positive and negative effects. This is because after China's economy entered a new stage, the government developed innovative ways to grasp the macro economy and formulated "micro-stimulus" policies, which promoted the stock market. At the same time, the real estate bubble, overcapacity and other problems in the economic development, the regulation and control policies on these problems have a negative inhibitory effect on the stock market.

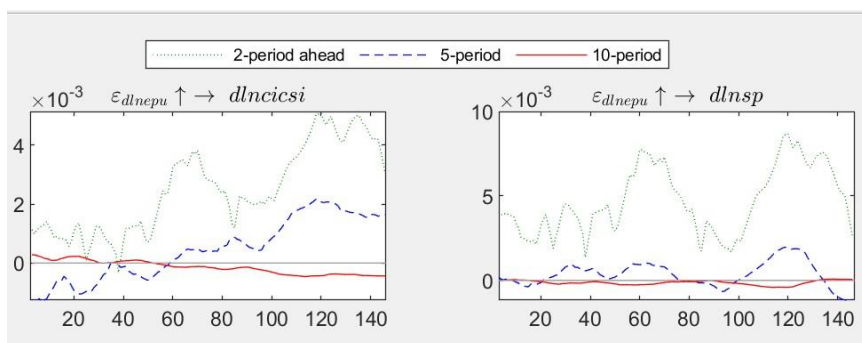


Figure 3. The effect of EPU on investor sentiment and stock price: different lag pulse responses

4.2. Analysis of time-varying characteristics of impulse response at specific time points

In order to further study the detailed characteristics of the impact of economic policy uncertainty on investor sentiment and stock price, this section will analyze the impulse response function of a special time point. The impulse response of time points constructed in August 2011, September 2014 and January 2020 were selected respectively to obtain the complete impact path of EPU at these time points. The result is shown in Figure 3.

As can be seen from Figure 4, in 2011, EPU had a negative impact on investor sentiment and stock price before the two periods, and turned positive and tended to zero after the two periods. In 2014, the EPU had a similar impact on investor sentiment and stock prices as it did in 2011, but with more volatility. In 2020, the EPU's impact on investor sentiment and stock prices will be even more variable. It is mainly reflected as negative first and then positive and then approaching zero. It can be found that the influence of EPU in the impulse response of the three time points basically conforms to the characteristics of its stage: in the early stage, the influence is mainly negative, in the middle stage, there is a certain positive and negative fluctuation, and the influence tends to disappear in the late stage. It can also be found that the influence of EPU fluctuates greatly before the second stage and becomes stable after the second stage. Therefore, the equal-interval pulse response with 2, 5, and 10 months as the lead period can well reflect the long-term rule of EPU influence, but because it does not include the immediate and first-phase influence with greater influence, it cannot well reflect the influence degree. Most of the existing studies used the fixed parameter model to obtain the average value of the influence. In the studies, the weak positive influence was covered by the strong negative influence, so it was not found.

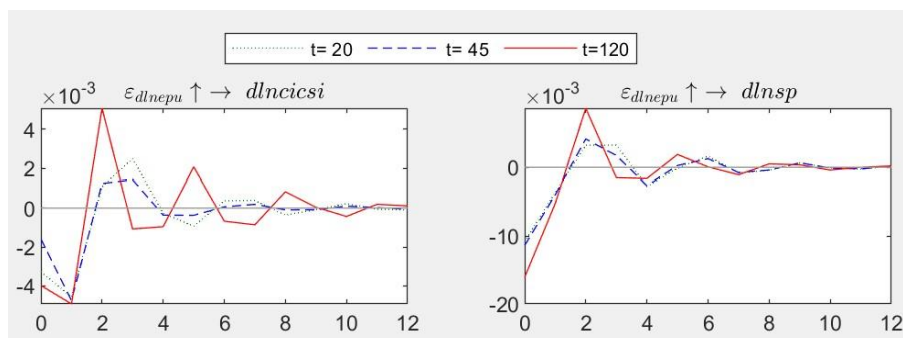


Figure 4. The effect of EPU on investor sentiment and stock price: time-point impulse response

Combined with CPI data, which represents China's economic development, we can also find that the positive impact of EPU is mainly concentrated in the economic upswing period. From 2010 to 2015, under the influence of the US financial crisis and the downward pressure of the domestic economy, China's CPI index changed greatly, and the influence of EPU also changed greatly, with positive and negative effects appearing alternately. In 2011 and 2012, under the influence of "stabilizing growth" and tightening policies, the EPU had a negative impact on investor sentiment and stock prices. It can be preliminarily judged that the impact of EPU on investor sentiment and stock prices is closely related to economic conditions. When the economy is good and GDP is growing rapidly, EPU will have a positive impact on investor sentiment and stock prices. When the economy is normal and GDP growth slows down, EPU will have a negative impact on investor sentiment and stock prices.

5. Research conclusions

Existing studies usually regard uncertainty as a negative factor for economic development, and believe that uncertainty will restrain investment and cause stock prices to decline. Based on the relevant data of China from 2010 to 2022, this paper finds that uncertainty not only inhibits investment, but also has a positive impact on investor sentiment and stock prices. Moreover, the

impact of economic policy uncertainty on investor sentiment and stock price changes is the strongest in the short term, and the effect decreases over time.

In addition, through the connection with the relevant economic data, this paper also obtained a preliminary conjecture: when the economic situation is good and GDP is growing rapidly, EPU will have a positive impact on investor sentiment and stock price; When the economy is normal and GDP growth slows down, EPU will have a negative impact on investor sentiment and stock prices. Of course, this conclusion still needs further analysis and research.

References

- [1] Kang W, Ratti, R. A. Oil shocks, policy uncertainty and stock market return [J]. *Journal of International Financial Markets, Institutions and Money*, 2013(26): 305–318.
- [2] Nikolaos Antonakakis, Ioannis Chatziantoniou, George Filis, Dynamic co-movements of stock market returns, implied volatility and policy uncertainty [J]. *Economics Letters*, 2013(1): 87-92.
- [3] Chang T, Wen-Yi Chen, Gupta R, et al. Are stock prices related to the political uncertainty index in OECD countries? Evidence from the bootstrap panel causality test [J]. *Economic Systems*, 2015(2): 288-300.
- [4] Brogaard J, Detzel A. The Asset-Pricing Implications of Government Economic Policy Uncertainty [J]. *Management Science*, 2015(1): 3-18.
- [5] Baker S R, Bloom N, Davis S J. Measuring economic policy uncertainty [J]. *Chicago Booth Research Paper*, 2013, 13(2): 1-29.
- [6] Nakajima J. Time-varying parameter VAR model with stochastic volatility: An overview of methodology and empirical applications [J]. *IMES Discussion Paper Series* 2011(9): 1-40.
- [7] Cepni Oguzhan, Gupta Rangan. Time-varying impact of monetary policy shocks on US stock returns: The role of investor sentiment [J]. *North American Journal of Economics and Finance*, 2021, 58.
- [8] Debata Byomakesh, Dash Saumya Ranjan, Mahakud Jitendra. Monetary policy and liquidity: Does investor sentiment matter? [J]. *IIMB Management Review*, 2021 (prepublish).
- [9] Junmao Chiu and Huimin Chung and Keng-Yu Ho. Fear Sentiment, Liquidity, and Trading Behavior: Evidence from the Index ETF Market [J]. *Review of Pacific Basin Financial Markets and Policies*, 2014, 17(3).
- [10] Ebenezer Asem et al. Liquidity, investor sentiment and price discount of SEOs in Australia [J]. *International Journal of Managerial Finance*, 2016, 12(1): 25-51.
- [11] Licheng Sun, Mohammad Najand, Jiancheng Shen. Stock return predictability and investor sentiment: A high-frequency perspective [J]. *Journal of Banking and Finance*, 2016, 73.
- [12] Davis S J, Liu D, Sheng X S. Economic policy uncertainty in China since 1949: The view from mainland newspapers [C]. *Fourth Annual IMF-Atlanta Fed Research Workshop on China's Economy Atlanta*, 2019.
- [13] Ouyang Z, Dou Z, Wei L, et al. Nonlinear spillover effect of US monetary policy uncertainty on China's systematic financial risks [J]. *Journal of Business Economics and Management*, 2022, 23(2): 364–381.