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# Research on the Impact of Economic Policy Uncertainty and Investor Sentiment on the Growth Enterprise Market Return in China—An Empirical Study Based on TVP-SV-VAR Model

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**Abstract:** This study employs the economic policy uncertainty index to gauge the level of economic policy uncertainty in China. Utilizing textual data from the growth enterprise market internet community, we construct the growth enterprise market investor sentiment index by applying the deep learning ERNIE (Enhanced Representation through Knowledge Integration) model, thereby capturing investors' sentiment within the growth enterprise market. The dynamic interplay between economic policy uncertainty, investor sentiment, and returns of the growth enterprise market is scrutinized via the TVP-SV-VAR (time-varying parameter stochastic volatility vector auto-regression) model, and the asymmetric response of different industries' stock returns within the growth enterprise market to economic policy uncertainty and investor sentiment shock. The findings of this research are that economic policy uncertainty exerts a negative influence on both investor sentiment and returns of the growth enterprise market. While it may trigger a temporary decline in stock prices, the empirical evidence suggests that the impact is of short duration. The influence of investor sentiment on the growth enterprise market returns is characterized by a reversal effect, suggesting that improved sentiment may initially boost stock prices but could lead to a subsequent decline over the long term. The relationship between economic policy uncertainty, investor sentiment, and returns of the growth enterprise market is time-variant, with heightened sensitivity observed during bull markets. Lastly, the effects of economic policy uncertainty and investor sentiment on the returns of different industries within the growth enterprise market are found to be asymmetric. These conclusions contribute to the existing body of literature on the Chinese capital market, offering a deeper understanding of the complex dynamics and the factors influencing market behavior.

**Keywords:** economic policy uncertainty; investor sentiment; growth enterprises market; TVP-SV-VAR model

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## 1. Introduction

The purpose of this study is to explore the dynamic changes in the impact of fluctuations in economic policy uncertainty (henceforth EPU) and investor sentiment (henceforth IS) on the returns of the Growth Enterprise Market (henceforth GEM) in China.

It is widely acknowledged that economic globalization has intensified the connections between nations, with economic policies implemented by countries capable of fostering social and economic stability and driving the prosperity of the stock market. Conversely, these policies may also lead to a stock market crash or even trigger a global financial crisis, as evidenced by events such as the 2007 U.S. subprime mortgage crisis, the 2015 Chinese stock market crash, the 2018 Sino–U.S. trade frictions, and the 2020 outbreak of COVID-19, all of which have had significant impacts on the Chinese stock market. On this foundation, a series of policy changes have led to varying market expectations among investors, resulting in different investment decisions. The fluctuation of IS can influence the pricing and returns of stocks (Baker and Wurgler 2006, 2007), indicating that an increase in EPU may lead to stock market instability. This instability can cause investors to have biased expectations regarding future returns and risks, thereby affecting the stock market's stability. Moreover, trade disputes between countries can rapidly spread risk throughout the market, making it extremely unstable; these factors are ultimately reflected in the stock returns of listed companies.

The GEM in China has attracted the sustained attention of many investors since its official establishment on 30 October 2009, and has now become an essential part of China's capital market. The GEM specifically assists technology-oriented, innovative startups, and small- and medium-sized enterprises that temporarily cannot meet China's main board stock market's listing requirements, helping them develop, provide services, and attract capital. It shares similarities with the National Association of Securities Dealers Automated Quotations (NASDAQ) in the U.S. and plays an increasingly important role in China's capital market. As of 30 June 2024, the GEM in China had 1348 companies listed for trading, accounting for 25.04% of the total listed companies in China. The total market value was approximately 8711.168 billion yuan, and the circulating market value was about 6678.554 billion yuan. The daily trading volume was around 130 billion yuan. The listed companies in GEM are mainly private enterprises, with a particularly evident trend of cluster development in key areas such as advanced manufacturing, digital economy, and green low-carbon. The performance of listed companies in these industries in GEM reflects the support and encouragement of China's capital market for high-tech and innovative enterprises. Individual investors constitute a large proportion of this market. In the Chinese stock market, individual investors are characterized by their susceptibility to the influence of internet information, which makes them prone to following market trends and engaging in speculative buying and selling behaviors. In the study by Bollen et al. (2011), IS, derived from community postings on Twitter, was found to significantly impact the returns of the U.S. stock market. Given this, GEM investors are likely to be influenced by sentiment. Therefore, in the face of government economic policy changes, the dynamic impact of IS tendencies embedded in internet community postings on the returns of the GEM is a question that merits thorough exploration.

In the context of changing economic policies, what kind of impact will the emotions contained in internet community posts have? Will emotional tendencies affect stock market returns? This paper choses the GEM Index returns as the object and crawled the daily posts of GEM from Guba forum (https://guba.eastmoney.com/list,zssz399006.html, accessed on 20 February 2024) by Python 3.10, the biggest stock forum in China, from 1 January 2016 to 31 December 2023, obtaining a total of 760 thousand posts. Combined with Enhanced Representation through Knowledge Integration (henceforth ERNIE) model, the sentiment classification of the posts was performed, the sentiment value of each post was calculated, and the IS index of GEM was constructed in this paper. In combination with the EPU index (Huang and Luk 2020), the time-varying impact of EPU and IS on the stock return of GEM was explored in this paper.

The distinctions between this study and existing research are in the following aspects. First, this study focuses on the GEM in China, where there is a scarcity of attention to the GEM in similar studies. Second, this paper constructs an index of market sentiment for the GEM based on internet community postings. Third, this study utilizes monthly data, whereas most researchers in similar studies tend to use quarterly or annual data (Qi et al. 2022; Hu et al. 2023; Liu et al. 2023). Fourth, this study incorporates EPU, IS derived from internet community postings, and GEM stock returns into a single model for analysis using the time-varying parameter stochastic volatility vector auto-regressive model (henceforth TVP-SV-VAR model) to characterize the impacts. Fifth, this study further analyzes the time-varying relationships of stock returns in different industries within the GEM affected by EPU and IS.

This study deepens our understanding of the impact of EPU and IS on GEM in China and provides empirical evidence for policymakers and market participants. As financial markets evolve and change, in-depth research on these factors will have enduring significance and practical application value. Through impulse response analysis, this paper reveals the reaction of monthly stock returns on the GEM and the monthly stock returns of different industries within the GEM to shock in EPU and IS, providing a new perspective for understanding the dynamics of the GEM. The structure of this study is as follows: Section 2 provides a literature review. Section 3 outlines our methodology. Section 4 describes the data. Section 5 presents the results of the empirical analysis. Finally, in Section 6, we summarize the research findings.

## 2. Literature Review

### *2.1. Economic Policy Uncertainty and Stock Market Returns*

The impact of EPU on stock market returns has been a focal point of financial research, with a plethora of studies examining the intricate relationship between these two variables. The IMF's 2012 World Economic Outlook report underscored EPU as a pivotal impediment to global economic recovery (International Monetary Fund 2012), a notion that has since corroborated by empirical research.

The EPU index, as developed by Baker et al. (2016), has emerged as a crucial tool in quantifying and analyzing the impact of policy uncertainty on financial markets. It has been extensively applied in studies that delineate the nexus between EPU and stock returns. Brogaard and Detzel (2015) identified a robust negative correlation between the frequency of economic policy adjustments and stock market returns, suggesting that increased policy volatility is detrimental to market performance. This finding is further supported by Arouri et al. (2016), who observed that heightened EPU exerts a pronounced and enduring depressive effect on actual stock returns, particularly during episodes of extreme market volatility. Batabyal and Killins (2021) expanded this discourse by revealing that investors tend to adopt a "risk offset" strategy in response to increased EPU, driven by the heightened perception of investment risk due to frequent policy shifts, which can precipitate a decline in asset prices. The predictive power of the EPU index in forecasting stock returns has been affirmed by Bekiros et al. (2016), who demonstrated that its inclusion significantly enhances the predictability of market outcomes. Phan et al. (2018) further nuanced this predictive capability by utilizing positive and negative EPU shock to predict stock excess returns, revealing evidence of asymmetric predictability. Antonakakis et al. (2017) contributed to the literature by establishing that EPU and its subcomponents possess substantial predictive power over U.S. stock returns and volatility, with only a few exceptions. Das et al. (2019) extended this analysis to the international sphere, examining the impact of global EPU, geopolitical risk, and financial stress on emerging equity markets and highlighting the significant influence of EPU. Guo et al. (2018) provided a comparative perspective by observing that an increase in EPU is associated with a reduction in stock market returns across various countries, including France and the United Kingdom. However, Li et al. (2016) presented contrasting findings, employing rolling window causality analysis to investigate the relationship between EPU and stock market returns in China and India and uncovering a weak correlation. This literature synthesis illustrates the multifaceted nature of the relationship between EPU and stock market returns, emphasizing the need for a nuanced understanding of how policy uncertainty can shape investment behavior and market dynamics. The varying findings across different contexts underscore the complexity of this relationship and the importance of considering EPU in economic and investment analyses.

### *2.2. Investor Sentiment and Stock Market Returns*

The relationship between IS and stock market returns has long been a central topic in financial research. Since De Long et al. (1990) introduced the DSSW model, the academic community has begun to focus on the impact of noise traders on the market, suggesting that investors' optimism or pessimism may lead to market bubbles or undervaluation of asset prices. Lee et al. (1991) demonstrated that IS affects securities returns and provided a theoretical basis for subsequent research. Baker and Wurgler (2006) further explored the influence of IS on securities with high arbitrage difficulty through the BW model in 2006, implying that a surge in market sentiment could foretell a decline in future returns. They believe that IS is a belief about future cash flows and investment risks, but this belief sometimes needs to be based on facts (Baker and Wurgler 2007).

With the rise of textual data research, Antweiler and Frank (2004) utilized Yahoo social media data and found a significant positive correlation between sentiment on stock message boards and stock returns. Bollen et al. (2011) analyzed Twitter data, discovering significant relationships between text-based IS and stock returns. The emergence of internet platforms has led to an increasing focus by stock market investors on information from social platforms such as Weibo, Twitter, and various stock forums (Kim and Kim 2014; Da et al. 2015; Renault 2017; Tsukioka et al. 2018; Behrendt and Schmidt 2018; Affuso and Lahtinen 2019; Zhao 2019, 2020; Chen and Chen 2022). In addition, researchers have found that major social events may also affect stock market returns by influencing IS, such as Edmans et al. (2007) exploring the negative impact of sports game losses, especially football game losses, on IS and stock market returns. Abudy et al. (2022) found that the Eurovision Song Contest impacts IS, and this emotional change can temporarily increase stock market returns. Subsequently, Abudy et al. (2023) found that an increase in national pride can have a positive impact on market sentiment and can have a positive effect on stock market returns in a short period. This provides rich real-time data for research and accelerates and broadens the dissemination of IS. Numerous researchers have started to utilize social information from internet platforms to study the impact of IS on stock market returns. These studies indicate that IS has become an essential factor affecting stock market returns, and its role in market dynamics has received extensive empirical support and academic recognition.

### *2.3. Economic Policy Uncertainty, Investor Sentiment and Stock Market*

The interplay between EPU, IS, and stock market performance is complex and has profound implications for market stability and investment decision-making. Pastor and Veronesi (2012) highlighted that investor confidence is eroded during periods of economic policy instability. Subsequently, Zhang (2019) further confirmed that an increase in EPU leads to a negative sentiment among investors, which in turn affects the efficiency of investment decision-making. Ftiti and Hadhri (2019) supported this view by finding that EPU has a significant negative impact on IS, and this sentiment fluctuation significantly affects stock market performance. Yao and Li (2020) expanded on this concept by considering IS as a critical index connecting EPU and stock market dynamics, emphasizing the interrelated nature of these variables. Nartea et al. (2020) also confirmed this finding, providing evidence that during periods of low IS, the negative impact of EPU on stock returns is more pronounced. Furthermore, Zhu et al. (2022) explored the impact of IS, EPU, and crude oil prices on emerging and developed stock markets, discovering that these impacts exhibit different dynamics depending on the time and market conditions. Wu (2022) found that the increase in economic policy uncertainty in the Chinese stock market will stimulate IS and reduce stock price synchronicity through IS. Idnani et al. (2023) investigated the impact of changes in India's EPU on IS. They found that changes in India's EPU have a positive effect on IS, but a negative effect on stock returns. Their study suggests that investors should not rush to make decisions in the face of uncertain events that may adversely affect stock prices. Zhou et al. (2023) found that an increase in EPU enhances the contagion effect of IS across different stocks and has a systematic positive impact on the cross-section of daily stock returns. In summary, these studies reveal the intricate relationship between EPU and IS and how this relationship affects stock market performance. These findings provide significant guidance for investors in formulating investment strategies in the face of market uncertainty.

Furthermore, according to the literature, the dynamic impact of EPU and IS on the returns of GEM in China has not yet been thoroughly explored. There is also a lack of research that combines IS based on information from internet community posts with EPU for the study of the GEM in China. Therefore, this paper employs a time-varying parameter vector auto-regressive model to conduct the abovementioned research.

## 3. Methodology

This section introduces the semantic analysis model ERNIE, which is based on deep learning, for constructing IS index. Additionally, we present the TVP-SV-VAR model for empirical analysis.

### 3.1. ERNIE Model Specification

The ERNIE model is a pre-trained language model that improves the masking strategy in the Bidirectional Encoder Representations from Transformers (BERT) pre-trained language model proposed by Google in 2018 (Devlin 2018). The ERNIE model utilizes huge Chinese datasets for training and referencing large-scale knowledge graph datasets (Sun et al. 2019), enabling the ERNIE model to better represent implicit relationships in Chinese text and enhance its semantic representation capabilities. It is also suitable for various natural language processing tasks, such as text classification, question-answering systems, information extraction, and machine translation. This study uses ERNIE for the sentiment classification of text.

Let $T$ be a set of textual data. The ERNIE model vectorizes the text data set $T$, standardizing the content of sentiment-classified texts $t_b$ to a fixed length $L_{\max}$, and converts each text $t_b$ in $T$ into its character form to obtain the character sequence $T'$, as depicted in Equation (1) below:

$$\boldsymbol{T}'=\{\boldsymbol{t}_1',\boldsymbol{t}_2',\cdots,\boldsymbol{t}_c',\boldsymbol{t}_{len(T')}'\} \tag{1}$$

where $t_c{}'$ denotes the character sequence of the $c$-th text, $c \in [1, len(T)], d \in [1, len(L_{max})]$, and $W_d$ denotes the $d$-th character in each text, as depicted in Equation (2) below:

$$\boldsymbol{t}_c'=\{\boldsymbol{W_1},\boldsymbol{W_2},\cdots,\boldsymbol{W_d},\cdots,\boldsymbol{W_{L_{max}}}\} \tag{2}$$

Each character $t_c{}'$ is individually fed into ERNIE's word-embedding layer, position-embedding layer, and dialogue-embedding layer, yielding three vectors, $V_1$, $V_2$, and $V_3$. The sum of these three vectors is then input into ERNIE's bidirectional-transformer layer, resulting in a sequence of character vectors $S_i$, as depicted in Equation (3) below:

$$\boldsymbol{S_i}=\{\boldsymbol{V(W_1)},\boldsymbol{V(W_2)},\cdots,\boldsymbol{V(W_e)},\cdots,\boldsymbol{V}(\boldsymbol{W_{L_{max}}})\} \tag{3}$$

where $V(W_e)$ denotes the character vector of the $e$-th character.

The final output is a sequence of word vectors $S$, each composed of $S_i$ elements of length $len(T)$, where $S_i$ denotes the output vector of the $i$-th character, as depicted in Equation (4) below:

$$S = \left\{S_1, S_2, \cdots, S_i, \cdots, S_{len(T')}\right\} \tag{4}$$

We use a well-trained ERNIE model to predict the sentiment tendency of all posts, and, on this basis, we constructed an IS index according to Antweiler and Frank (2004) and Li et al. (2020), as depicted in Equation (5) below:

$$IS = \frac{pos_t - neg_t}{pos_t + neu_t + neg_t} \times ln(1 + (pos_t + neu_t + neg_t)) \tag{5}$$

where $pos_t$ denotes the number of monthly posts representing positive emotions in one month, $neg_t$ denotes the number of monthly posts representing negative emotions in one month, and $neu_t$ denotes the number of monthly posts representing neutral emotions in one month.

### *3.2. TVP-SV-VAR Model Specification*

The TVP-SV-VAR model is based on the Vector Autoregressive (henceforth VAR) model and the Structural Vector Autoregressive (henceforth SVAR) model. Considering the impact of drift coefficients and random fluctuations in the production process of economic data, the TVP-SV-VAR model follows the idea of Bayesian estimation compared to the VAR model and the SVAR model. It assumes that all parameters in the model follow a first-order random walk process and that the allowed variance is random, which can better capture dynamic changes that are difficult to observe with traditional measurement methods and describe the potential asymptotic process of economic structure. This part introduces the structures of the TVP-SV-VAR model. Building upon the seminal work of Primiceri (2005) and further refined by Nakajima et al. (2011), the TVP-SV-VAR model addresses the limitations of the conventional VAR by accounting for the continuity and cumulative gradient characteristics of variables.

The standard structural VAR model is depicted in Equation (5) below:

$$Ay_t = F_1 y_{t-1} + \cdots + F_p y_{t-p} + \mu_t, t = p+1, \cdots, n \tag{6}$$

where $t$ denotes time, $p$ denotes lag periods, $A$, $F_1, \ldots, F_P$ denotes the $k \times k$ matrix of coefficients, $y_t$ denotes the $k \times 1$ vector of endogenous variables, and $\mu_t$ denotes the $k \times 1$ structural shock vectors.

Here, specify the simultaneous relations of the structural shock by recursive identification, assuming that $A$ is lower-triangular matrix,

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

Under the reversible condition of $A$, Equation (6) could be rewritten as the following reduced form structural VAR model, as depicted in Equation (7) below:

$$y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + A^{-1}\Sigma\varepsilon_t, \varepsilon_t \sim N(0, I_k) \tag{7}$$

$\sum$ is a diagonal matrix, $\mu_t \sim N(0, \sum\sum)$, $\varepsilon_t \sim N(0, I_k)$, where $B_i = A^{-1}F_i, i = 1, \cdots, p$, and

$$\sum = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{bmatrix}$$

The $\sigma_i (i = 1, \cdots, k)$ is the standard deviation of structural shock vectors, stacking elements in the row of matrix $B_i$ to form a $k^2 p \times 1$ column vector of $\beta$, and defining $X_t = I_k \otimes \left(y'_{t-1}, \cdots, y'_{t-p}\right)$, $\otimes$ denotes the Kronecker product. The model can be written as depicted in Equation (8) below:

$$y_t = X_t \beta + A^{-1} \sum \varepsilon_t \tag{8}$$

Parameters in Equation (8) are time-invariant. When the non-time-varying parameters in Equation (8) are extended to time-varying parameters, an improved TVP-SV-VAR model can be obtained. The equation is depicted in Equation (9) below:

$$y_t = X_t \beta_t + A_t^{-1} \sum_t \varepsilon_t, t = p+1, \cdots, n \tag{9}$$

where the coefficients $\beta_t$ and the parameters $A_t$ and $\sum_t$ are time-varying. Following the work of Primiceri (2005) and Nakajima et al. (2011), let $a_t = (a_{21}, a_{31}, a_{32}, \cdots, a_{k,k-1})'$ denote the stacked vector of the lower triangular in $A_t$ and $h_t = (h_{1t}, \cdots, h_{kt})'$ with $h_{jt} = \log \sigma_{jt}^2, j = 1, \cdots, k, t = p+1, \cdots, n$. It is assumed that the parameters in Equation (8) follow the following random walk process depicted below:

$$\beta_{t+1} = \beta_t + \mu_{\beta t}, a_{t+1} = a_t + \mu_{at}, h_{t+1} = h_t + \mu_{ht}$$

$$\begin{pmatrix} \varepsilon_t \\ \mu_{\beta t} \\ \mu_{at} \\ \mu_{ht} \end{pmatrix} \sim N\left(0, \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & \sum_\beta & 0 & 0 \\ 0 & 0 & \sum_a & 0 \\ 0 & 0 & 0 & \sum_h \end{bmatrix}\right)$$

for $t = p+1, \cdots, n$, where $\beta_{p+1} \sim N\left(\mu_{\beta_0}, \sum_{\beta_0}\right), a_{p+1} \sim N(\mu_{a_0}, \sum_{a_0}), h_{p+1} \sim N(\mu_{h_0}, \sum_{h_0})$. Parameters $\beta_t$, $a_t$, and $h_t$ are assumed to be uncorrelated under the shock to the innovations of the time-varying parameters. To navigate the computational challenges posed by stochastic volatility in the likelihood function, in this study, specific steps which refer to Nakajima et al. (2011) employ the Markov Chain Monte Carlo (henceforth MCMC) algorithm, a Bayesian approach that facilitates the estimation of model parameters. The parameters are estimated with greater accuracy and reliability by harnessing the posterior distributions generated through the MCMC process.

## 4. Data

This article uses monthly data from January 2016 to December 2023. Using monthly data can better integrate with the monthly EPU index. The monthly data provide a more refined observation window, which is conducive to capturing short-term fluctuations, thereby more precisely measuring its dynamic impact on stock market returns (PH and Rishad 2020; Wang et al. 2021).

The GEM in China was established in 2009 and was not mature prior to the stock market crash in 2015. To accelerate the process of deflating bubbles and deleveraging, China began implementing a series of economic policy measures, such as index circuit breakers, starting in 2016. Subsequent significant events, such as the Sino–U.S. trade frictions and the outbreak of COVID-19, have had a profound impact on the stable development of China's stock market. Hence, the data started in January 2016.

The EPU index utilized in this paper is derived from the research findings of Huang and Luk (2020), who expanded upon the work of Baker et al. (2016). Huang and Luk (2020) selected ten authoritative Chinese newspapers, namely *Beijing Youth Daily*, *Guangzhou Daily*, *Jiefang Daily*, *People's Daily Overseas Edition*, *Shanghai Morning Post*, *Southern Metropolis Daily*, *The Beijing News*, *Today Evening Post*, *Wen Hui Daily*, and *Yangcheng Evening News.* They quantified the presence of policy uncertainty-related vocabulary in these newspapers, calculated the proportion of articles that contained such vocabulary among all articles published in a given month, and standardized this measure to construct the EPU index for China. The index formulated by Huang and Luk (2020) is considered more comprehensive than the one by Baker et al. (2016), as it covers a broader spectrum of newspaper sources and is thus better equipped to reflect the actual fluctuations in China's EPU.

The monthly IS index in this study was constructed by calculating the sentiment value of each post in GEM forum in Guba.com.cn (Gui et al. 2022). Guba.com.cn is the most active stock community on the internet in China, and it effectively records the information investors post. Python 3.10 was utilized to crawl posts related to the GEM in China from the Guba forum (https://guba.eastmoney.com/list,zssz399006.html, accessed on 20 February 2024) from January 2016 to December 2023. Each post obtained includes the posting URL, poster, title, number of comments, reads, and posting time. Invalid and duplicate posts in the text, including blank posts, advertisements, external links, and messy symbols, were deleted using Excel 2021. Finally, 760 thousand valid posts were obtained. After employing sentiment analysis using the ERNIE model, the posts were categorized monthly into positive sentiment, negative sentiment, and neutral sentiment.

The returns of the GEM are represented by the monthly returns of the GEM Composite Index. The monthly stock returns of the industry within GEM are indicated by the average monthly return of all companies' stocks within that industry.

The nonlinear estimation techniques for time-varying parameter models are computationally demanding and thus ill-suited for models encompassing a multitude of variables; the number of individual variable parameters should not exceed 100 at the same time (Nakajima et al. 2011; Baumeister and Kilian 2014). In the extant literature, the TVP-SV-VAR models conventionally incorporate a modest number of variables, ranging from three to four (Chen and Chen 2022; Qi et al. 2022; Qiao et al. 2022; Hu et al. 2023).

All variables used in this paper are presented in Table 1. This study focuses on the GEM in China, with data sourced from the China Stock Market & Accounting Research (CSMAR) database (https://data.csmar.com/, accessed on 5 March 2024), and the Economic Policy Uncertainty database (https://economicpolicyuncertaintyinchina.weebly.com/, accessed on 6 March 2024). Figures 1–3 show the monthly trend of EPU, IS, and CI Return of GEM from January 2016 to December 2023, respectively. Ultimately, we obtained 96 valid sample data points for each variable. Table 2 presents the results of the descriptive statistical analysis.

**Table 1.** Variables design and specification.

| Variables | Variable Abbreviation | Variable Description | Data Source |
|---|---|---|---|
| Economic Policy Uncertainty | EPU | China economic policy uncertainty index | Data are sourced from https://economicpolicyuncertaintyinchina.weebly.com/, accessed on 6 March 2024 |
| Investor Sentiment | IS | The monthly IS index was constructed by calculating the sentiment value of each post in GEM forum in Guba.com.cn | Posts are sourced from https://guba.eastmoney.com/list,zssz399006.html, accessed on 20 February 2024 |
| Growth Enterprise Market (GEM) Return | CI Return | Composite Index return of GEM | Data are sourced from China Stock Market & Accounting Research Database (CSMAR) https://data.csmar.com/, accessed on 5 March 2024 |
| Manufacturing Industry Sector Stock Price Return | MS Return | Average monthly stock returns by industry sector of GEM | |
| Information Transmission, Software and Information Technology Services Industry Sector Stock Price Return | ITS Return | | |
| Scientific Research and Technical Services Industry Sector Stock Price Return | SRS Return | | |
| Forestry, Animal Husbandry, and Fishery Industry Sector Stock Price Return | FAS Return | | |

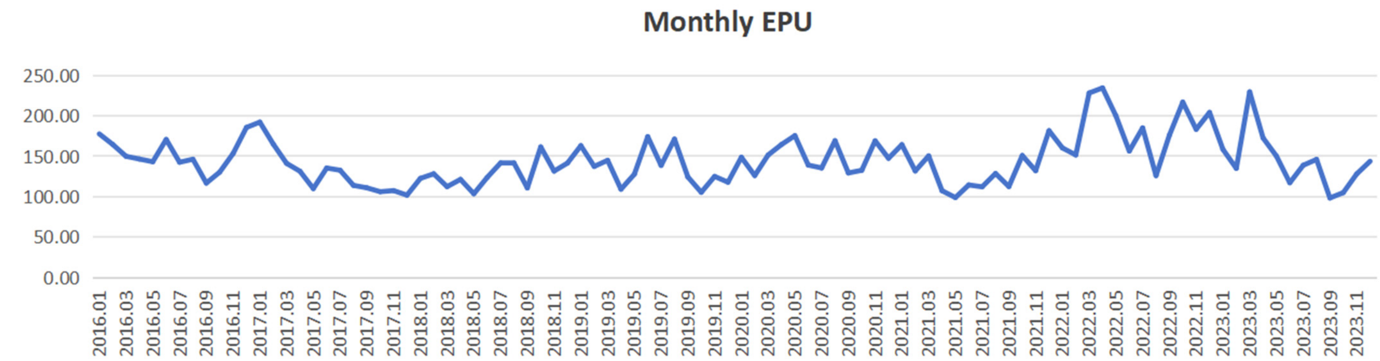



**Figure 1.** China's EPU from January 2016 to December 2023.

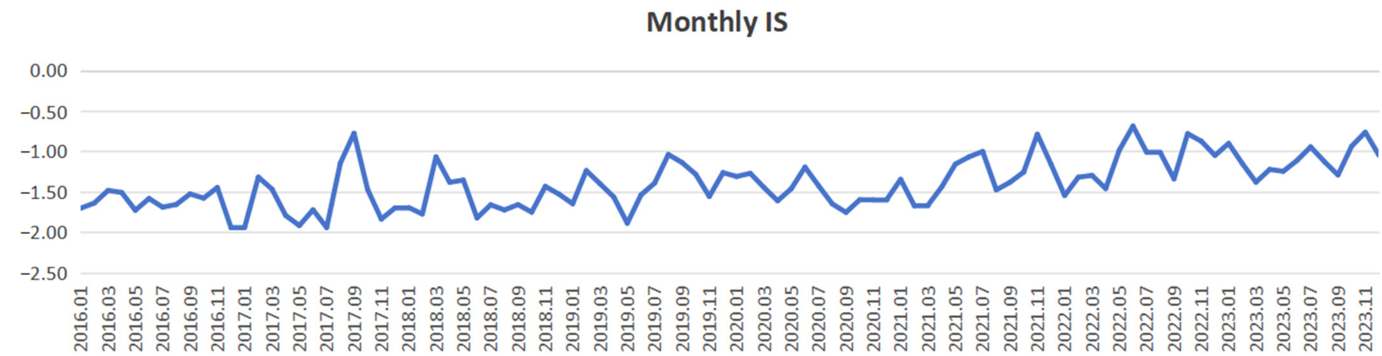



**Figure 2.** IS of GEM from January 2016 to December 2023.

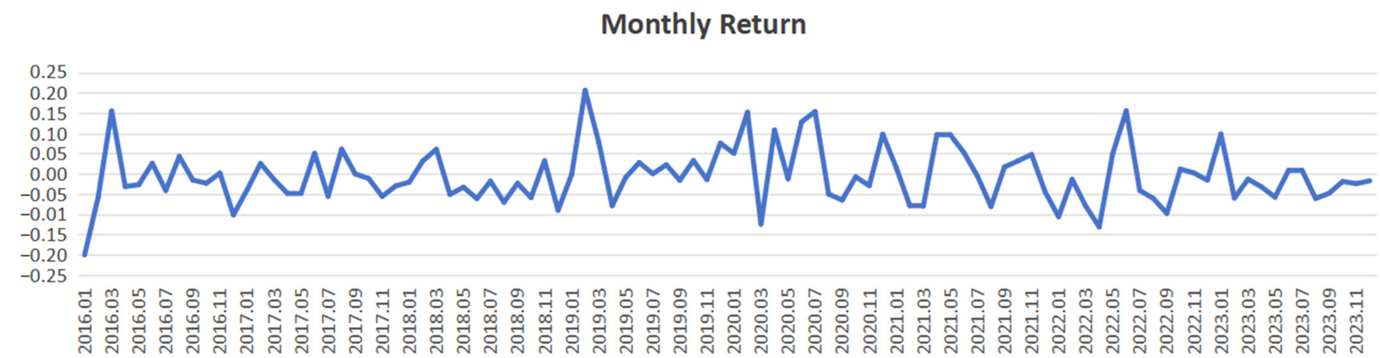



**Figure 3.** CI Return from January 2016 to December 2023.

**Table 2.** Descriptive Statistics.

| Variables | Mean | S.D. | Min | Max | Num. |
|---|---|---|---|---|---|
| EPU | 144.54 | 30.07 | 98.36 | 234.52 | 96 |
| IS | −1.39 | 0.31 | −1.94 | −0.68 | 96 |
| CI Return | −0.39 | 6.94 | −19.95 | 20.79 | 96 |

## 5. Empirical Results and Discussion

### *5.1. Stationarity Test*

Non-stationary time series data can lead to "pseudo regression" issues, invalidating an analysis's results. To address this, we apply the Augmented Dickey–Fuller (ADF) unit root test to assess the stationarity of each variable at its original level before proceeding with parameter estimation. The outcomes of the ADF test, as presented in Table 3, suggest that the series is stationary.

**Table 3.** ADF unit root test results.

| Variables | ADF Value | 5% Critical Level | $p$-Value | Conclusion |
|---|---|---|---|---|
| EPU | −13.78181 | −2.892536 | 0.0001 | Stable |
| IS | −4.810739 | −2.893956 | 0.0001 | Stable |
| CI Return | −9.560846 | −2.892200 | 0.0000 | Stable |

### 5.2. Parameter Estimation

In this section, we run the TVP-SV-VAR model by Matlab R2022b. According to the Akaike Information Criterion (AIC), the optimal lag period is four; the main empirical results are obtained using four lags. Utilizing the MCMC algorithm, a total of 10,000 iterations were performed, with the first 1000 iterations being discarded as a "burn-in" phase to ensure the convergence of the Markov chain. Subsequently, sampling from the converged posterior distribution was conducted to obtain the estimated means of various parameters. To validate the effectiveness of the MCMC algorithm, the Geweke and the efficiency factor test were employed for assessment. Table 4 gives the estimates for posterior means, standard deviations, the 95% credible intervals, Geweke values, and inefficiency factors. Based on the Geweke values (less than 1.96), the null hypothesis of convergence to the posterior distribution is not rejected for the parameters at the 5% significance level. The invalid factor values are less than 100, which indicates an efficient sampling for the parameters in the TVP-SV-VAR model.

**Table 4.** Selected parameters estimation results in the TVP-SV-VAR model.

| Parameter | Mean | Stdev | 95%U | 95%L | Geweke | Invalid Factor |
|---|---|---|---|---|---|---|
| $(\sum_\beta)_1$ | 0.0023 | 0.0003 | 0.0018 | 0.0028 | 0.993 | 3.62 |
| $(\sum_\beta)_2$ | 0.0020 | 0.0002 | 0.0016 | 0.0023 | 0.000 | 6.01 |
| $(\sum_a)_1$ | 0.0054 | 0.0016 | 0.0033 | 0.0094 | 0.405 | 26.91 |
| $(\sum_a)_2$ | 0.0055 | 0.0017 | 0.0034 | 0.0095 | 0.131 | 18.38 |
| $(\sum_h)_1$ | 0.0061 | 0.0066 | 0.0034 | 0.0105 | 0.176 | 54.34 |
| $(\sum_h)_2$ | 0.0057 | 0.0019 | 0.0034 | 0.0108 | 0.127 | 38.63 |

Figure 4 shows the parameter auto-correlation (graphs in the first row), the sample path (graphs in the second row), and the posterior densities (graphs in the third row). The graphs in the first row show that the parameters show that the sample coefficient decreases rapidly with each simulation and finally converges to zero. This means that most of the samples do not have auto-correlation. The graphs in the second row indicate that the sampled data are stable and fluctuate around the sample mean, showing apparent fluctuation clustering phenomena. The stability indicates that the number of uncorrelated samples obtained using the MCMC algorithm is sufficient and effective. The images in the third row show that the parameter's distribution converges to the posterior distribution. Therefore, the sampling is convergent. These results further indicate that the samples drawn by the MCMC method are valid.

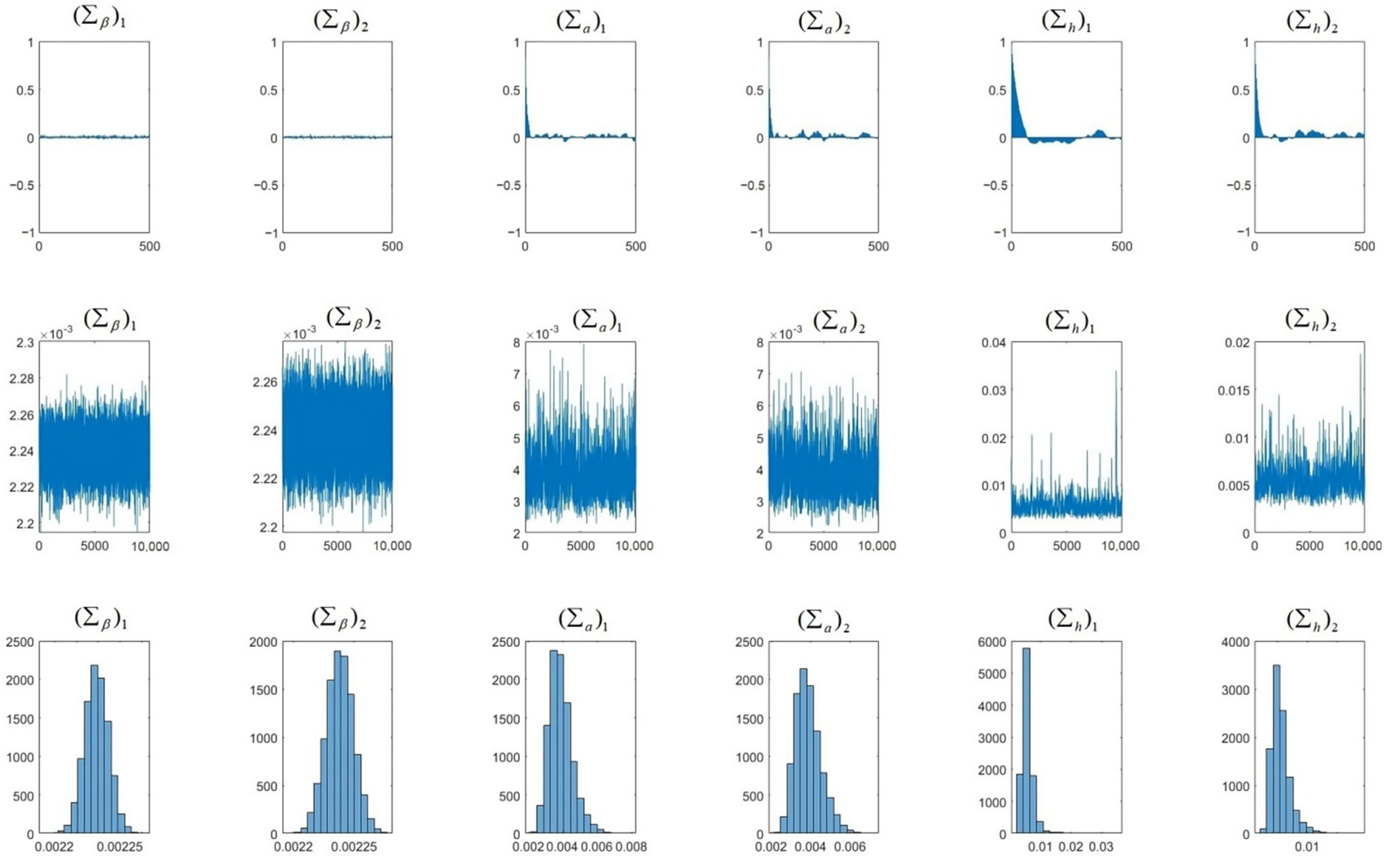



**Figure 4.** Distribution plot of selected parameters estimation results in the TVP-SV-VAR model. Sample auto-correlations (**first row**), sample paths (**second row**), and posterior densities (**third row**).

### *5.3. Time-Varying Impulse Responses*

The impulse responses, which quantify the influence of a one-standard-deviation shock on a variable's immediate and subsequent values, are computed at each date throughout the sample period, reflecting the coefficients' temporal variability (Nakajima et al. 2011). In this section, we analyze the impulse response of EPU, IS, and CI Return.

#### 5.3.1. Analysis of Time-Varying Characteristics

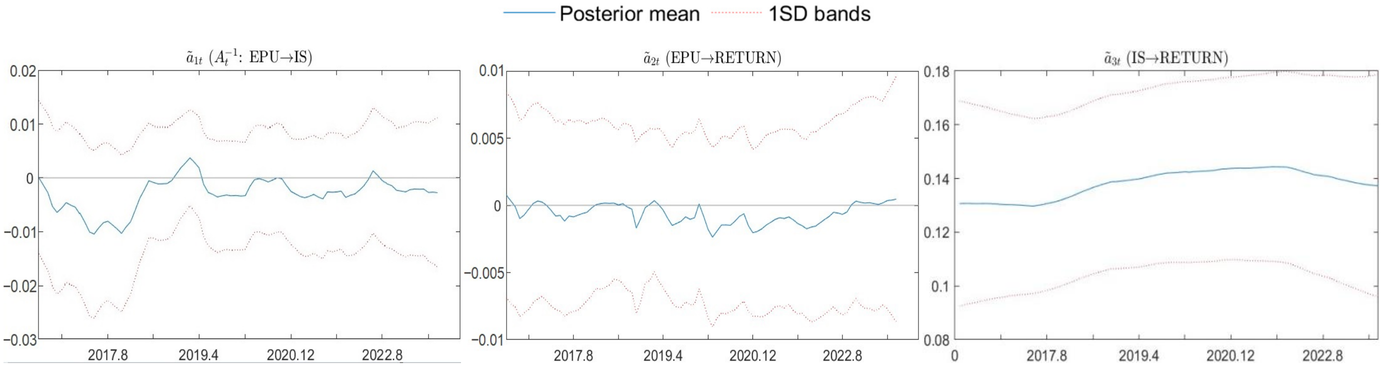
Figure 5 shows the time-varying characteristics of the contemporaneous impact of EPU to IS, EPU to CI Return, and IS to CI Return.

In Figure 5a, the contemporaneous impact of EPU on IS is positive in 2018 and part of 2022, and the rest of the time shows a time-varying fluctuation with a negative effect. In general, the impact of EPU on IS is mainly negative, but the degree of influence varies in different periods.

In Figure 5b, the contemporaneous impact of EPU on CI Return shows an up-and-down trend, with a mainly negative effect. This impact shows an apparent time-varying feature, which to a certain extent indicates that the level of EPU will have a negative effect on CI Return.

In Figure 5c, the impact of IS on CI Return first moves slightly downward, changes upward, and then decreases. In general, the IS contained in internet texts significantly positively impacts CI Return, but it behaves differently under different market conditions (Yin et al. 2022).

The findings on contemporaneous influence relationships indicate that these relationships are not static but exhibit discernible time-variant characteristics. These characteristics manifest not only in the magnitude, but also in the direction of the influence. Thus, utilizing time-varying parameter methods is imperative to uncover the dynamic nature of these influence relationships. An intriguing observation is that during periods of low EPU and high IS, the negative impact of EPU on GEM stock market returns is mitigated. These indicate that IS has a modulating effect in such scenarios.




(**a**) (**b**) (**c**)

**Figure 5.** Time-varying characteristics of the contemporaneous impacts. (**a**) Time-varying characteristics of the contemporaneous impact of EPU to IS, (**b**) Time-varying characteristics of the contemporaneous impact of EPU to CI Return, (**c**) Time-varying characteristics of the contemporaneous impact of IS to CI Return.

### 5.3.2. Impulse Response Analysis at Different Lag Periods

As shown in Figure 6, the impulse response results formed by different lead times have different trends and directions. At the same time, there are short-term impacts on EPU, IS, and stock prices, but there are insufficient long-term impacts. A time series of equal-interval impulse responses was conducted with 1, 3, 6, and 12 lag periods to analyze the effect of current EPU and IS shock on CI Return after 1, 3, 6, and 12 months, and the effect of current EPU shock on IS after 1, 3, 6, and 12 months. Figure 6a–c shows that the shock exhibits a pattern of fluctuation, indicating that the impacts have a structural characteristic of time-varying.

In Figure 6a, the impulse response of IS to the shock of EPU has positive and negative differences at different lead times. The impulse response of 1 period and 3 periods in advance have similar trends, with positive and negative changes in different periods. The impulse response of the 6 periods in advance begins to weaken, and the impulse response of the 12 periods in advance is basically negative, with a weaker impact than before. When EPU fluctuates, IS will be low in the short term. However, as time goes by, IS will rebound. When facing EPU, investors of GEM will directly impact their investment decisions due to their aversion to future uncertainty. In the case of more severe information loss, investors will be more hesitant, hope to collect more information, and be more cautious in their investment decisions. Therefore, changes in EPU will have a negative impact on IS in the short term. IS will rebound once investors have more information and the degree of EPU decreases. At this time, EPU will have a positive impact on IS. The impulse responses of IS to EPU are different at different times. During 2016–2017, China’s economic policies mainly focused on structural reforms to address long-term accumulated structural problems, suppress stock market overheating, and prevent the risk of stock market collapse. During this period, a circuit breaker mechanism was implemented, but then it was suspended, significantly impacting stock market prices and negatively impacting IS. Specifically, the impulse response of IS to EPU is mainly negative, indicating that economic policy uncertainty has a restraining effect on investment activities. From 2017 to 2019, the impact of EPU on IS of the GEM gradually increased. Especially in the context of the Sino–U.S. trade friction, China adopted a series of monetary and fiscal policies to promote economic growth and stabilize employment by reducing taxes and expanding government spending, which increased investors’ confidence in the Chinese government and promoted the rise of IS, especially in 2018, with the stability of China’s financial deleveraging policy and the adjustment of refinancing policy. As a result, the impulse response of IS to EPU shock began to turn positive, reaching a high level by the end of the year, indicating that investor confidence has been strengthened to a certain extent. Then it reached a peak. In the following years, the sensitivity of IS to EPU gradually decreased. Since the 2020 COVID-19 pandemic, the negative impact of EPU on IS has gradually increased, the degree of EPU in China has become increasingly higher, and the IS of the GEM has also been increasingly affected by EPU. At the beginning of 2023, China fully implemented the stock issuance registration system. At the same time, the reserve requirement ratio of financial institutions will be lowered by 0.25 percentage points, releasing about 530 billion yuan of long-term funds and subsequent interest rate cuts. These policies will help improve the efficiency and vitality of the capital market and, in the short term, enhance IS. However, with the downgrading of consumption, the impulse response of IS to EPU gradually turned negative.

Figure 6b illustrates the impulse response of CI Return to EPU shock, exhibiting positive and negative deviations at various lead times. The impulse responses for 1 period and 3 periods ahead are characterized by similar trends, with pronounced oscillations across different intervals. The impulse response for the 6 periods ahead begins to attenuate, and, by the 12-period lead, it approaches negligible levels, signifying a minimal impact. Generally, an increase in the level of EPU is associated with a detrimental effect on the stock market, particularly in the short term, with this effect diminishing over time. Between 2016 and 2017, the negative influence of EPU on CI Return intensified. Under the economic policies facing structural reforms, this negative reaction is relatively weak compared to IS, indicating that the response of CI Return to adjusting or restrictive economic policies is sustained and negative in the period. From 2017 to 2019, this negative impact on CI Return progressively declined, reaching a peak during the bull market 2018. This indicates that the stability of China's financial deleveraging policy, the adjustment of its refinancing policy, and the accompanying positive IS have positively driven CI Return. The onset of the COVID-19 pandemic in 2020 led to a resurgence in the short-term impact of EPU on GEM stock market returns. This resurgence is related to the strict lockdown of COVID-19 and the reduction in social mobility, which has had a more significant impact on individual investors, making the impact of EPU on CI return rapidly decline. The COVID-19 blockade ended at the beginning of 2023. To promote market recovery as soon as possible, CI Return's impulse response to the EPU has an apparent short-term rebound under the stimulus of favorable policies such as interest rate reduction. Concurrently, IS also exerted a negative influence on CI Return. Upon comparing the short-term impulse responses of IS and CI Return returns to EPU, a high degree of alignment in the trends is observed. This convergence suggests that EPU can significantly influence CI Return by shaping IS in the short term. The temporal dynamics of these relationships underscore the intricate interplay between EPU and market responses, highlighting the need for a nuanced understanding of the underlying mechanisms.

In Figure 6c, the impulse response analysis reveals that CI Return exhibits a negative reaction to IS shock at one and three periods ahead, while the responses for six and twelve periods ahead approach negligible levels. This analysis suggests a short-term reversal effect of IS on CI Return. Specifically, IS positively influences CI Return within the first month, yet this effect inverts after the initial period, leading to a negative impact on CI Return after one month. A plausible interpretation of this phenomenon is that heightened IS may initially boost stock prices due to short-term emotional factors. However, as time progresses, the premium driven by these emotions is likely to dissipate, resulting in a decline in CI Return within the subsequent 1 to 3 periods. This pattern indicates a pronounced reversal effect. Furthermore, the influence of IS on CI Return is not static; it fluctuates over time, highlighting the time-varying nature of this relationship. These findings underscore the importance of considering the temporal dynamics of IS when analyzing its impact on stock market movements.

By analyzing the relationship between EPU, IS, and GEM stock market returns, we can find that the future reaction of IS on the internet to the GEM market will change with the change of economic policies, and their market expectations may be bullish or bearish. Investors adjust their investment strategies based on their expectations, impacting future GEM stock market returns. The uncertainty of economic policies may also affect the GEM stock market returns by influencing the sentiment of internet investors.

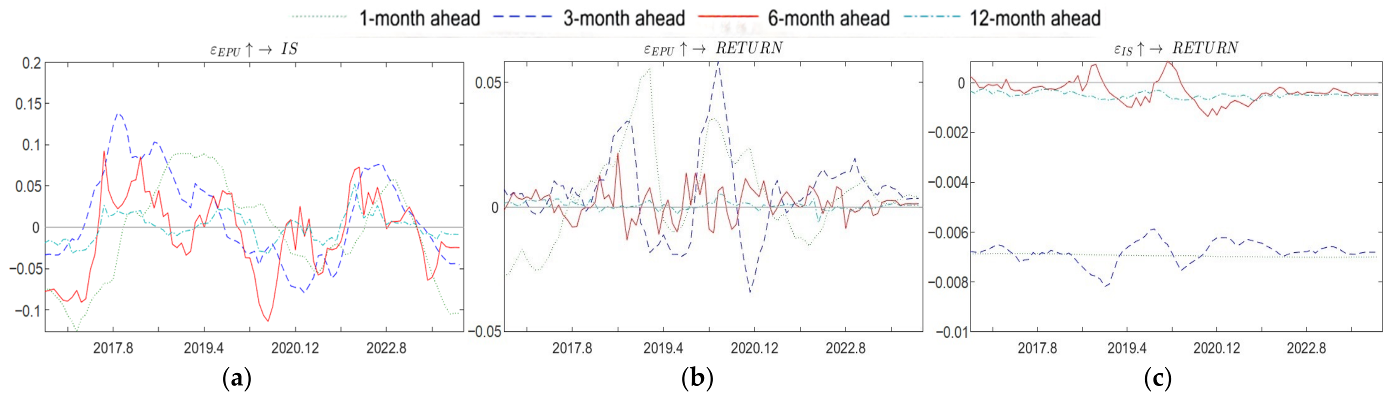



**Figure 6.** Time series of equal-interval impulse responses of IS to EPU shock, CI Return to EPU shock, and CI Return to IS shock after 1, 3, 6, and 12 months. (**a**) Impulse responses of CI Return to EPU shock, (**b**) Impulse responses of IS to EPU shock, (**c**) Impulse responses of CI Return to IS shock.

### 5.3.3. Impulse Response Analysis at Different Points

We further selected the following three key time points: the start of the Sino–U.S. trade friction in April 2018, the strict lockdown after the outbreak of COVID-19 in November 2020, and the end of China's COVID-19 lockdown in December 2022 to study the impulse responses at different time points.

Figure 7a shows that the influence of EPU on IS varies across three distinct time points. Yet, after a lag of six months, the impulse response of IS to EPU shock attenuates and approaches zero. In April 2018, IS exhibited an adverse reaction to the shock of EPU, shifting to a positive response by the second-month lag, which gradually dissipated. This suggests that in the face of EPU during the Sino–U.S. trade friction, investors' negative sentiment intensified in the current period; subsequently, the Chinese government took measures including tax and fee reductions, support for small- and medium-sized enterprises, and promotion of industrial upgrading to stabilize the capital market and boost investor confidence. The IS recovers and ascends in the subsequent lag periods. A plausible rationale is that despite the volatility of China's economic policies, their primary objective was market stabilization, which paradoxically fostered investor confidence during the lag periods, aligning IS with the direction of EPU. During the periods of November 2020 and December 2022, the negative impulse response of IS to the shock of EPU was less pronounced than in April 2018. Post-November 2020, the impact of EPU on IS was predominantly negative, with the negative response intensifying after the second period, followed by minor fluctuations and a brief positive pulse at the sixth month, indicative of the substantial influence of the macro environment during the COVID-19 on IS. The possible explanation is related to investors' panic during the COVID-19 lockdown and the reduction in social mobility. By December 2022, an increase in EPU had a marginal adverse effect on IS, which later transformed into a positive effect enduring over a more extended period. Yet, the magnitude of the impact was subdued compared to April 2018, signifying a diminished influence of EPU on IS during bearish market conditions compared to bullish periods.

Figure 7b illustrates that the impact of EPU on CI Return at the three time points differs in magnitude but follows a similar overall trend. The CI Return is observed to have an initial negative response to the shock of EPU, which then transitions to a positive impulse response, peaking in the lag of the second month before trending to zero after the six-month lag. The impulse response indicates that EPU negatively affects the CI Return, contributing to a decline in stock prices. The magnitude of the impulse response in November 2020 surpasses that of the other two time points, suggesting a more pronounced adverse impact on CI Return during that period compared to April 2018 and December 2022. The EPU influences the future expectations of GEM investors; heightened expectations of future uncertainty led to an increased demand for risk premiums, resulting in a decrease in stock prices. Notably, during the COVID-19 lockdown, the impact of EPU on CI Return manifested as the most substantial negative effect in the lag period, mirroring its influence on IS.

Figure 7c demonstrates that the impulse response of CI Return to IS shock is consistent across the three time points. The IS elicits a positive response in CI Return in the current period, which then diminishes, transitioning to a minor negative response in the subsequent period and ultimately trending towards zero after a six-month lag. These responses suggest that improved IS can temporarily boost CI Return, yet a "reversal effect" occurs in the lag period. When investor optimism is high, they are prone to make optimistic judgments and overlook market risks, leading to active market participation and a tendency to chase rising stock prices. This surge in stock prices, driven by heightened IS, is expected to revert to rational levels over time, resulting in a decline.

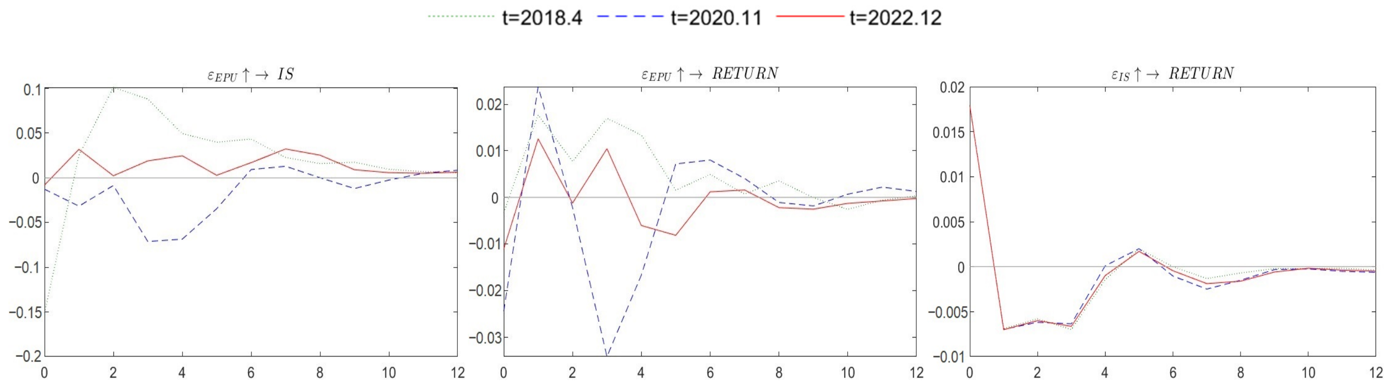



**Figure 7.** Time-point impulse responses of IS to EPU shock, CI Return to EPU shock, and CI Return to IS shock on April 2018, November 2020, and December 2022. (**a**) Time-point impulse responses of IS to EPU shock, (**b**) Time-point impulse responses of CI Return to EPU shock, (**c**) Time-point impulse responses of CI Return to IS shock.

5.3.4. Impulse Response Analysis at Different Points of Different Industries in GEM

To further analyze the asymmetric impact of EPU and IS on stock prices, this paper selects different industries of the GEM to explore the impact of EPU and IS on stock prices of different categories. Figure 8 shows the time-point impulse response of stock price returns in different industries to EPU shock and IS shock on April 2018, November 2020, and December 2022.

As can be seen from Figure 8, at three different time points, the impulse response of different industries' stock returns in GEM when EPU impacts them have similar trends. Still, the impulse response in April 2018 exceeds those at the other two time points. When stock returns are impacted by EPU, the current stock price falls, and the stock price decline caused by previous uncertainty will rise in the lag period. The EITS Return and SRS Return are most negatively impacted by EPU. The FAS Return and MS Return are less affected by EPU. Compared with the stocks' return in other sectors, SRS Return and MS Return have larger lag response values. When IS impacts stock prices, the impulse response of different industries' stock returns in GEM has different trends. When IS changes, ITS Return has the most significant increase in current stock prices, followed by MS Return and SRS Return. The high stock prices brought about by the previous IS will show different trends in the lag period. The "reversal effect" of SRS Return is the most obvious. The number of positive and negative reversals in the lag period is the largest. The second is ITS Return, which has had the most impact in the current period. The reversal of MS Return and FAS Return in the lag period will show different trends. This finding is similar to the research of (Al-Nasseri et al. 2021), which shows that the impact of IS on stock market returns is asymmetric under different market conditions.

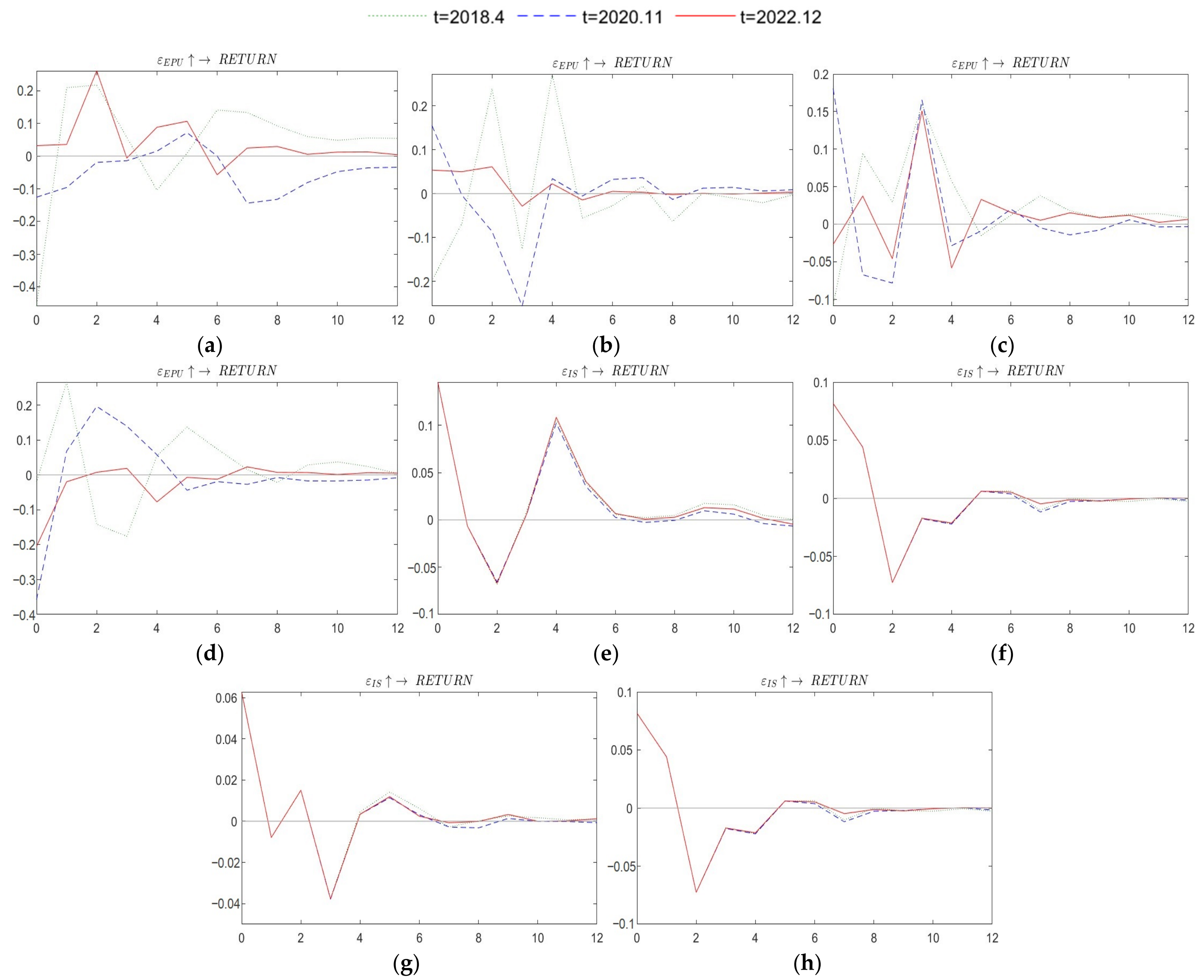



**Figure 8.** Time-point impulse responses of stock price returns in different industries to EPU shock and IS shock on April 2018, November 2020, and December 2022. (**a**) Time-point impulse responses of ITS Return to EPU shock, (**b**) Time-point impulse responses of FAS Return to EPU shock, (**c**) Time-point impulse responses of MS Return to EPU shock, (**d**) Time-point impulse responses of SRS Return to EPU shock, (**e**) Time-point impulse responses of ITS Return to IS shock, (**f**) Time-point impulse responses of FAS Return to IS shock, (**g**) Time-point impulse responses of MS Return to IS shock, (**h**) Time-point impulse responses of SRS Return to IS shock.

*5.4. Robustness Test*

The estimation results of the TVP-SV-VAR model may be influenced by the order of variables, as mentioned in the study by Nakajima et al. (2011). To further verify the robustness of the results, we adjusted the order of variables in the model. According to the analysis results in Figure 9, the impact of EPU and IS on GEM Return at different lags and different time points is consistent with the results of previous studies, indicating that our model estimation results are robust.

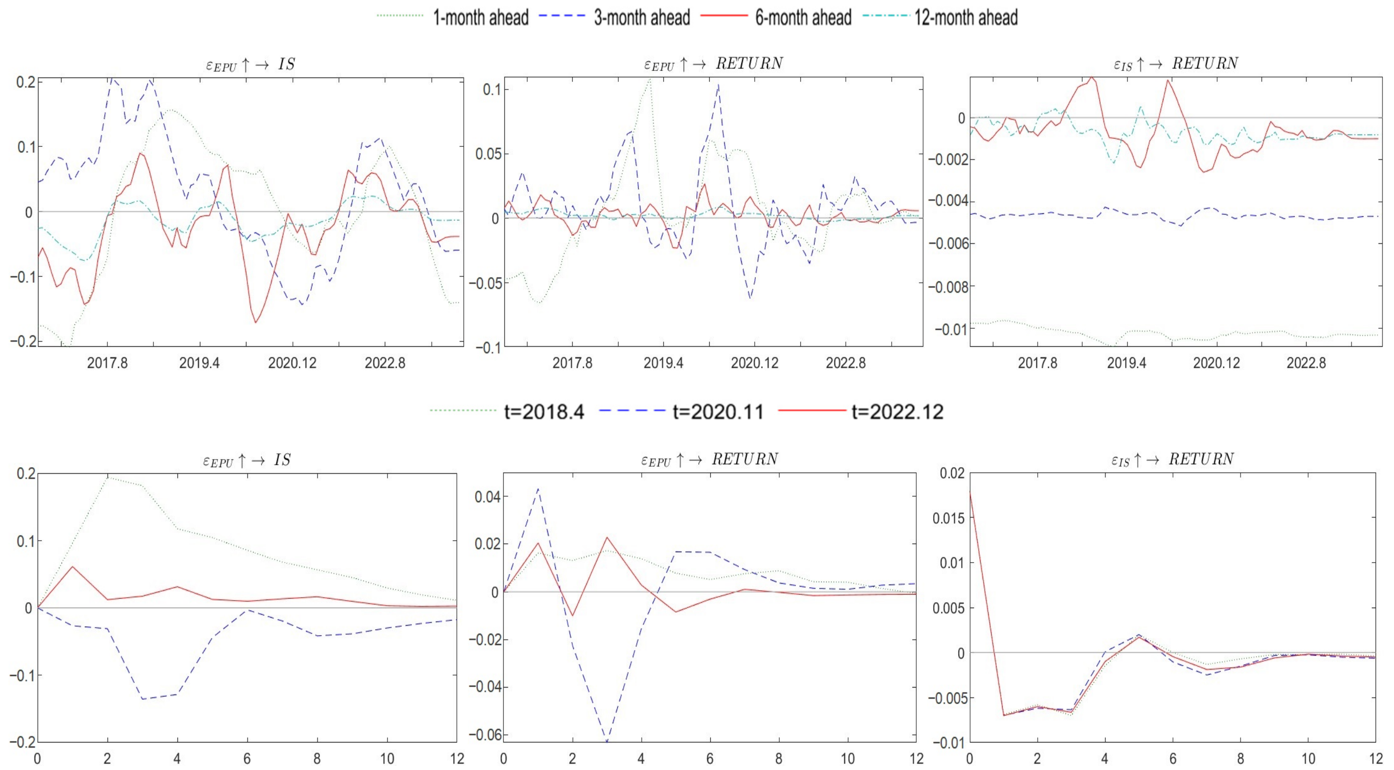



**Figure 9.** Impulse response after variable order changes.

## 6. Conclusions

In this study, we selected the EPU Index Huang and Luk (2020) as an indicator to measure China's EPU. This study used the posting text of the GEM internet community and constructed the GEM's IS index through the deep learning ERNIE model to characterize the IS of the GEM market. Through empirical analysis, this study used the TVP-SV-VAR model to analyze the dynamic relationship between EPU, IS, and GEM stock market returns and the asymmetric response of GEM stock returns in different industries to EPU and IS shock. The research concludes that firstly, EPU has a negative impact on the IS and returns of the GEM. However, empirical analysis shows that this impact will change according to the degree of economic policy regulation. When economic policies tend to control market overheating, the negative impact of EPU on the IS and returns of the GEM will continue. When economic policies tend to promote market development, the impact of EPU on the IS and returns of the GEM will turn positive during the lag period. Secondly, the impact of the IS on the GEM returns shows a reversal effect in both the short and long term. Improved IS may push up stock prices in the short term, but over time, the price premium caused by emotions may ultimately lead to a decline in stock prices. Thirdly, the dynamic relationship between EPU, IS, and GEM market returns exhibits time-varying characteristics across different market cycles. Especially during bull markets, the stock market is more sensitive to the impact of these factors. Fourth, the impact of EPU and IS on the returns of different GEM stocks is asymmetric.

The Growth Enterprise Market (GEM) holds a pivotal position within China's stock market, serving as a crucial source of financing for small- and medium-sized enterprises while actively contributing to the overall economic development. Therefore, based on the above findings, this study makes the following recommendations: First, policymakers should be urged to maintain flexibility in adjusting policies, harness the power of internet information for proactive risk management, and closely monitor stock market risks through platforms such as regulatory social media, positive guidance on possible negative internet emotions. Second, in the era of seamless information exchange facilitated by internet technology, investors are encouraged to bolster their information processing capabilities to effectively identify and harness the wealth of available data, continually adapt their investment strategies in response to economic policy uncertainty (EPU), shifts in internet information, and the evolving dynamics of the stock market. Third, for enterprises listed on the GEM, a keen focus on changes in corporate governance, reinforced communication with investors through social media, and timely dissemination of high-quality company information is emphasized to combat misinformation and uphold market stability.

The analysis of this research is limited to the EPU index (Huang and Luk 2020), IS based on the posts of the Guba forum, and the GEM composite index of China. Future analysis can focus on the impact of EPU and IS on the stock price volatility and stock price crash of the GEM, as well as international evidence or geographical differences. Secondly, all these empirical results show that there is a significant correlation between IS, the GEM composite index of China and the EPU index. Our findings may be influenced by other political, economic, and financial factors.

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