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Economic Policy Uncertainty, Investor Sentiment, and Stock Market Volatility in China: A Study based on the TVP-VAR-SV Model

Zhang Yun[a†], LOW Soo-Wah[b], Mohammad Enamul HOQUE[c], Mohd Azlan SHAH ZAIDI[d]

[a]*Graduate School of Business, Universiti Kebangsaan Malaysia (The National University of Malaysia), Selangor, Malaysia; School of Accounting, Shanxi Vocational University of Engineering Science and Technology, Shanxi Province, China*
[b]*Graduate School of Business, Universiti Kebangsaan Malaysia (The National University of Malaysia), Selangor, Malaysia*
[c]*BRAC Business School, BRAC University, Dhaka, Bangladesh*
[d]*Faculty of Economics and Management, Universiti Kebangsaan Malaysia (The National University of Malaysia), Selangor, Malaysia*

A B S T R A C T

Purpose: To effectively explain irrational fluctuations in the stock market, assist investors in managing risks more efficiently, and enhance the ability to identify potential risks.
Design/methodology/approach: This paper explores the effects of global and Chinese economic policy uncertainty (EPU) and investor sentiment (IS) on China's stock market using a Time-Varying Parameter Vector Autoregression model with stochastic volatility (TVP-VAR-SV) from 2003 to 2023.
Findings: The results reveal that China's stock market exhibits asymmetric, time-varying volatility, characterised by alternating positive and negative shifts, with a gradual decline in overall fluctuations. Due to differences in firm size, industry structure, and regional characteristics, the Shanghai market is more sensitive to IS, while the Shenzhen market responds more to Chinese and global EPU. IS has the most substantial short-term impact, whereas Chinese EPU, though less pronounced than global EPU, shows more persistent effects. IS and global EPU exert immediate positive influences on the stock market, while Chinese EPU is associated with an immediate adverse effect.
Research limitations/implications: This study's limitations lie in the need to employ more advanced approaches to measure IS from a broader perspective and integrate connectedness methodologies further to investigate the inter-sectoral spillover effects within China's market.
Originality/value: Incorporating EPU and IS provides a more comprehensive explanation of the price formation mechanism and helps uncover the underlying sources of market irrationality.

Keywords: Economic policy uncertainty, Investor sentiment, Chinese stock market volatility, TVP-VAR-SV model

I. Introduction

Acting as a key gauge of economic conditions, the stock market significantly affects the sustainability and resilience of a country's economic development (Lu et al., 2022). That said, analysing the causes of stock market volatility (SMV) is a crucial area of

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† Corresponding author: Zhang Yun
E-mail: p127731@siswa.ukm.edu.my

financial research. Earlier studies primarily examined the impact of macroeconomic factors, such as the GDP growth rate, inflation rate, and interest rate. Subsequent research gradually expanded to include policy-related factors, with particular emphasis on how economic policies affect the behaviour of the stock market (Keddad, 2024). Compared with economic policies, the uncertainty arising from the government's implementation of economic policy is more elusive. Post-2008, the global economy faced a prolonged period of restructuring and transformation, heightening the impact of EPU and attracting widespread academic attention (Ma et al., 2020). The literature recognises that EPU is a source of external risk to which the stock market reacts negatively (Shao et al., 2022). Considerable empirical literature supports that high EPU increases SMV (Goodell et al., 2019). However, recent studies have reported contrary findings (Wu et al., 2024). These conflicting outcomes have led some researchers to attribute the discrepancies to structural changes in the economic environment, which can affect parameter estimates through their impact on the stock market (Chen & Chen, 2022). Others have explored alternative explanations for these discrepancies, considering factors such as investor behaviour (Liu & Ma, 2024).

From a theoretical perspective, real options theory suggests that, under heightened uncertainty, firms may delay investment due to irreversibility and the option value of waiting, thereby eroding intrinsic value—a fundamental driving force behind stock price volatility (Dreyer & Schulz, 2022). Noise trading theory further highlights that elevated EPU generates noise that disrupts consensus formation, causing prices to deviate from fundamentals. Under such conditions, irrational and herding-driven behaviours induce investors to disregard private information and follow prevailing market views, leading to collective trading patterns that amplify fluctuations (Wu, 2022). These perspectives suggest that EPU and IS are crucial in driving SMV, yet their intertwined mechanisms remain insufficiently explored.

The Chinese market offers a distinctive context for examining the interplay among EPU, IS, and SMV. First, China's transition from a centrally planned to a market-oriented economy has been accompanied by frequent policy reforms, generating substantial uncertainty (Wang et al., 2023). Stock market reactions underscore this dynamic (Men et al., 2007); for example, following the release of Swap Facilities and Stock Buyback policies in 2024, the Shanghai Composite Index rose 21.89% and the Shenzhen Component Index 36.27% within two weeks[1)]. Second, the dominance of retail investors amplifies the role of sentiment (Leippold et al., 2022). As of August 2023, retailers accounted for 99.77% of all investors—over 220 million individuals versus about 515,200 institutions—and contributed more than 90% of trading volume, intensifying mispricing relative to fundamentals (Sun et al., 2021).

Accordingly, fluctuations in China's stock market are driven by two significant factors: EPU and IS. Neglecting either factor would result in biased research outcomes. Therefore, the significance of examining EPU, IS, and SMV lies in revealing the driving mechanisms of multiple mixed factors from an academic perspective, while in practice, it provides valuable implications for policy-making, investment decisions, and market stability. This study applies a TVP-VAR-SV model, whose capacity to account for time-varying parameters and stochastic volatility enables the examination of the evolving effects of global EPU (GEPU), Chinese EPU (CEPU), and investor sentiment (IS) on two representative indices of China's stock market, namely the Shanghai Component Index (SCI) and Shenzhen Component Index (SZCI). Empirical evidence shows that the influence of IS on China's major stock indices is more immediate but fades over time. In contrast, the effects of CEPU demonstrate greater persistence throughout the observed period. Although GEPU exerts a more substantial effect than CEPU, particularly following the Sino-U.S. trade conflict in 2018, its influence is relatively short-lived but intensifies sharply during heightened uncertainty. The

1) The data is obtained from Investing.com (https://www.investing.com).

analysis reveals that IS disproportionately and substantially affects the Shanghai stock exchange (SSE) compared to the Shenzhen stock exchange (SZSE). This result is because the SSE is dominated by large-cap stocks (with a total share capital exceeding 50 billion), which risk-averse investors favour. Risk-averse investors are highly sensitive to uncertainty and potential losses in investment; therefore, their sentiment may fluctuate significantly. Similarly, the impacts of CEPU and GEPU are more pronounced in SZSE. This result is because, unlike SSE, the SZSE features more small- and medium-cap stocks[2)] and private enterprises, which generally have lower risk tolerance and are more vulnerable to uncertainty. Additionally, industry characteristics and geographical factors may contribute to the SZSE's heightened sensitivity to CEPU and GEPU. The SZCI is an index of 500 constituent stocks of technology-based, innovative, and emerging enterprises, which are more reliant on policy support and, thus, more susceptible to policy uncertainty than stocks of mature enterprises. Moreover, as one of China's earliest special economic zones, Shenzhen has over 40 years of experience with economic liberalisation. This long history of openness has made it particularly attuned to the international environment and highly responsive to changes in GEPU.

The study makes several notable contributions. To begin with, although the impacts of EPU and IS on SMV have been widely investigated in isolation, few have integrated these three factors into a comprehensive analysis. Integrating these three sheds light on the mechanisms through which policy uncertainty and changes in IS contribute to risks associated with the stock market, offering practical guidance for market practitioners and regulators. Second, by examining the SSE and SZSE, we found that the impacts of IS, CEPU, and GEPU vary across the two stock markets. Finally, a key contribution of this study lies in its differentiation between GEPU and CEPU and the examination of their respective effects on SMV, which may assist investors and policymakers in responding to global and domestic policy uncertainty.

The rest of the paper is structured as follows: Section 2 reviews the relevant literature. Sections 3, 4 and 5 describe the dataset, the methodology, empirical results and analysis, respectively. Section 6 discusses robustness tests. Finally, section 7 concludes the study.

II. Literature Review

A. EPU and SMV

Since John Kenneth Galbraith published The Age of Uncertainty in 1977, numerous high-profile events have underscored uncertainty's crucial role in influencing the financial industry. The effects of EPU have reached unprecedented significance, making EPU a prominent area of research. Early research on uncertainty typically relied on leadership transitions and significant events as measurement methods (Hensel & Ziemba, 2019). However, employing dummy variables to capture uncertainty is inappropriate when dealing with continuous data. As a result, the EPU index proposed by Baker et al. (2016) has been broadly regarded as a credible and standard proxy for measuring fundamental uncertainty arising from economic policies (Chen & Chen, 2022). The empirical literature reveals diverse conclusions regarding the influence of EPU on the stock market. While earlier research tends to find that EPU negatively affects stock returns or prices, it concurrently identifies a positive relationship with SMV (Shen et al., 2021). However, as external economic conditions have become more complex, subsequent studies have reached different empirical conclusions. In response to these contradictory findings, some studies argued that the link between EPU and stock returns is inherently asymmetric rather than consistent over time (Chen & Chen, 2022).

Davis (2016) proposes the GEPU index. Models

2) Mid-cap stocks have a total share capital between 10 and 50 billion, whereas small-cap stocks have less than 10 billion.

incorporating GEPU provide improved prediction of SMV (Wu et al., 2021). Changes in GEPU can forecast the corresponding changes in the Chinese EPU index. Liu et al. (2023) find that both GEPU and CEPU significantly and negatively shape the lasting dynamics of volatility in China's equity market in the tourism sector. Their results further indicate that the influence of GEPU on SMV in the tourism sector is more transient than that of CEPU.

B. IS and SMV

Behavioural finance suggests market participants' emotions can drive SMV (Xie et al., 2023). Market participants adjust their expectations about stock performance, although they frequently disagree on this issue. Such disagreement among competing participants creates a divergence between actual prices and intrinsic values (Lee, 2023). Changes in sentiment often drive SMV, sometimes resulting in extreme market movements (Li et al., 2018). IS reflects investors' psychological attitudes and emotional responses to the market or individual stocks, encompassing greed, fear, optimism, pessimism, and other sentiments. Many studies have analysed from the perspective of optimism and pessimism, finding that both surges in market sentiment and sharp declines can give rise to speculative bubbles and abrupt market collapses, which can heavily influence investor behaviour (Huerta & Perez-Liston, 2011; Sun et al., 2021). Specifically, IS tends to be overly optimistic during market peaks, leading to excessive price increases and bubbles. Conversely, IS is often overly pessimistic during downturns, which can result in excessive price declines and undervaluation. Therefore, there exists a clear positive correlation between IS and stock prices.

The complex influence of IS on SMV can be examined from the following perspectives: First, the dominance of IS is more evident in the short run, but over time, company fundamentals increasingly determine SMV (Wang et al., 2021). Second, the impact of IS tends to fluctuate rather than follow a consistent positive or negative direction. In other words, IS may reverse depending on market conditions (Fang et al., 2021). Third, information heterogeneity contributes to divergent findings on the relationship between IS and SMV. Some studies document a leverage effect, where negative news disproportionately amplifies volatility, while others identify a reverse leverage effect (Bhowmik & Wang, 2020). Fourth, distinctions in sentiment—positive vs. negative, market-wide vs. individual, and institutional vs. retail—generate heterogeneous impacts on volatility (Sun et al., 2021; Yang & Hu, 2021). Finally, the influence of IS further varies across market regimes, including bull and bear markets, sensitivity phases, and specific time periods (Han & Shi, 2022; Hsu & Tang, 2022).

C. EPU, IS and SMV

Building upon existing theoretical and empirical research, the EPU and IS significantly influence SMV. Several scholars have explored their interconnections. Zhou and Jia (2019) examined the transmission mechanism of EPU on SMV in China and found that IS mediates this relationship, with its effects varying across different periods. Xiao et al. (2024) further categorised different types of EPU and volatility, revealing that various forms of EPU positively impact both "good" and "bad" volatility, while IS can mitigate these effects to some extent. However, these studies primarily rely on traditional regression models, which have limited capacity to account for structural breaks and non-stationary economic conditions, thereby failing to capture the dynamic interactions among variables and their time-varying characteristics. These outcomes contribute meaningful insights that enhance the depth of this study, guiding the adoption of methodologies incorporating time-varying effects to explore further the dynamic relationship among EPU, IS and SMV in China.

D. Research Model Selection

Volatility is an inherent feature of stock markets, shaped by cross-sectional and temporal heterogeneity. Cross-sectional differences stem from industry- and firm-specific reactions to shocks and the asymmetric responses of emerging and developed economies. Temporal dynamics are reflected in volatility clustering, memory effects, and shifts in market structure. Together, macroeconomic conditions, market characteristics, firm-level factors, and behavioural elements—such as policy changes, asymmetric volatility, financial indicators, and IS—jointly account for these variations (Bhowmik & Wang, 2020; Dhingra et al., 2023; Gupta & Mishra, 2024).

The complexity of volatility has driven the development of increasingly flexible models. The GARCH family, while extensively refined, faces limitations in balancing parsimony and flexibility (Bhowmik & Wang, 2020). Alternative approaches also offer distinct strengths: ARDL captures both short- and long-term macroeconomic effects (Darsono et al., 2022), MIDAS integrates high- and low-frequency data (Wu et al., 2021), and VECM accounts for long-run equilibrium with short-run dynamics (Widjaja & Rokhim, 2020). However, these models remain constrained in addressing nonlinearities, abrupt shocks, and structural changes. To overcome such limitations, recent studies increasingly adopt the TVP-VAR-SV framework (Qiao et al., 2022; Yang et al., 2024; Yao et al., 2025).

III. Dataset Description

Monthly data covering the period from February 2003 to August 2023 were used to explore the evolving relationship between GEPU, CEPU, IS, and SMV in China, as shown in Table 1 (The IS data are available from February 2003 onwards). We used the GEPU index of Davis (2016) to measure GEPU. Davis et al. (2019) compiled the CEPU Index to quantify policy uncertainty in China. The IS indicator is measured using the China Investor Composite Sentiment Index (CISCI) (Yi & Mao, 2009). SMV is calculated based on China's two most representative stock indices, SCI and SZCI, serving as proxies for aggregate market performance across SSE and SZSE.

SMV is defined as the standard deviation of the logarithmic return, calculated using daily closing prices of the two indices, as shown in (1). Table 2 presents the descriptive statistics. All the raw data were processed to ensure data stationarity.

$$SMV = \sqrt{\sum_{i=1}^{n}\left(r_i - \bar{r}\right)^2/(n-1)} \tag{1}$$

Figures 1-5 illustrate the stochastic volatilities of CISCI, CEPU, GEPU, SCI, and SZCI, with posterior means and one-standard-deviation bands. Figures 4 and 5 reveal pronounced fluctuations across several periods, notably in 2005 (stamp duty reduction, pilot equity split reform), 2007-2010 (equity reform

Table 1. Variable description & data source

Variable	Variable Description	Data Source
CEPU	From Davis et al. (2019). It is calculated based on two newspapers in mainland China.	https://www.policyuncertainty.com/china_epu.html
	From Huang and Luk (2020). It uses a broad set of mainland Chinese newspapers.	https://economicpolicyuncertaintyinchina.weebly.com/
GEPU	From Davis (2016). It is derived by averaging national EPU indices of 21 countries, weighted according to their GDP.	https://www.policyuncertainty.com/china_epu.html
IS	From Yi and Mao (2009). Measures the aggregate IS in China based on CICSI. From Wei et al. (2014). Measures the aggregate IS in China based on the IS Index (ISI).	CSMAR Database
SMV	The standard deviation of the log-transformed daily closing returns for the SCI and the SZCI.	CSMAR Database

Table 2. Descriptive statistics

Variables	Mean	Median	S.D.	Min	Max	Skewness	Kurtosis
CEPU-S	161.82	121.01	120.77	23.72	661.83	1.40	4.75
CEPU-H	130.05	132.07	37.85	39.53	238.32	0.14	3.05
GEPU	157.22	132.85	81.04	55.13	437.08	0.89	3.05
IS-CICSI	-8.06	0.16	1.17	-2.49	3.59	-0.12	2.87
IS-ISI	0.005	-0.12	1.50	-2.49	6.16	1.10	4.95
SSE	0.013	0.011	0.007	0.003	0.039	1.487	5.043
SZSE	0.018	0.014	0.007	0.005	0.041	1.380	4.621

Note: CEPU-S as defined in Davis et al. (2019)and CEPU-H as defined in Huang and Luk (2020). IS-CICSI as defined in Yi and Mao (2009), and IS-ISI as defined in Wei et al. (2014).

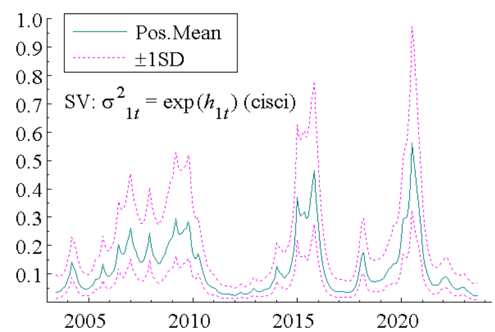

Figure 1. Stochastic volatility of IS

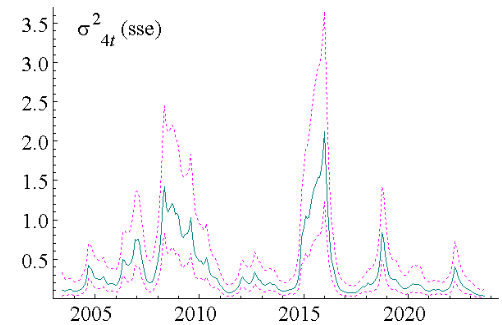

Figure 4. Stochastic volatility of SCI

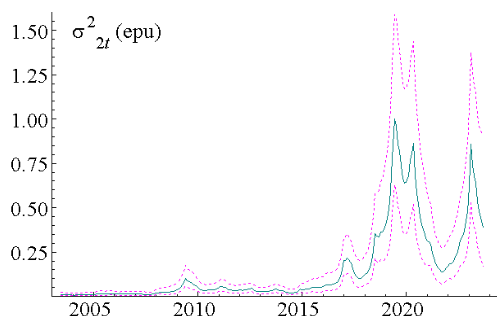

Figure 2. Stochastic volatility of CEPU

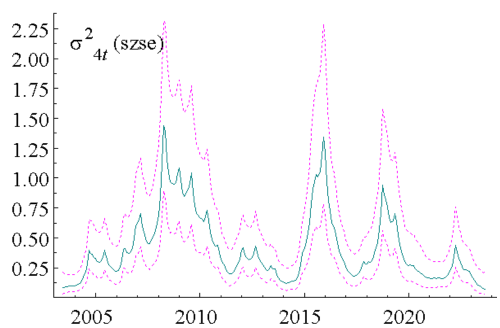

Figure 5. Stochastic volatility of SZCI

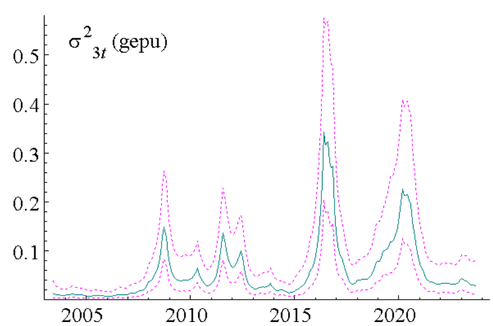

Figure 3. Stochastic volatility of GEPU

completion, U.S. mortgage crisis), 2015-2016 (China's stock market crash, Brexit, U.S. presidential election), 2019-2020 (COVID-19), and 2022-2023 (Russia-Ukraine war). Similar volatility spikes appear in Figures 1-3, suggesting that IS, CEPU, and GEPU may have influenced the SSE and SZSE. Moreover, SZSE volatility consistently exceeds the SSE's, reflecting its inclusion of ChiNext and SME Board stocks, whose lower listing thresholds make them more sensitive to market shocks.

Based on Figures 4 and 5, the evolution of China's stock market can be divided into three phases. The first phase, prior to 2008, was marked by frequent but moderate fluctuations, reflecting the transition from exploratory development to regulatory adjustment. During this period, policy interventions—including strengthening oversight and the split-share structure reform—induced recurrent but relatively small shocks. The global financial crisis and subsequent domestic policy responses shaped the second phase (2008-2016). The government introduced a RMB 4 trillion stimulus package, promoted multi-tiered capital markets (Xie Dejun, 2023), and advanced market internationalisation. Although volatility remained broadly stable, the lingering impact of the crisis and the 2015 crash generated pronounced turbulence. The third phase, beginning in 2016, witnessed a gradual market recovery under stricter supervision by the CSRC. Despite policy adjustments (e.g., capacity reduction, housing destocking, and the liberalisation of insurance capital inflows) and external shocks (e.g., Brexit, the U.S. election, COVID-19, U.S.-China trade frictions, and the Russia-Ukraine conflict), volatility largely subsided, with instability confined to short-term episodes. Overall, China's stock market remains highly sensitive to policy shifts and increasingly exposed to global events, underscoring the dual influence of domestic regulation and international integration on market volatility.

Given potential structural shifts in the external environment, this study applies the Bai and Perron (2003) multiple structural break test. Table 3 shows two breaks for the SSE and SZSE (2009 and 2016), aligning with earlier market phases. These shifts suggest abrupt changes in variable relationships that fixed-parameter models cannot capture, thus justifying the use of time-varying parameter models.

Stationarity, a prerequisite for time series modelling, is assessed using the Augmented Dickey-Fuller (ADF) Test. Results (Table 4) show that CISCI is non-stationary, while CEPI, GEPU, SSE, and SZSE are stationary; first-order differencing renders all series

Table 3. Bai and Perron test outcomes

	Break Test	F-statistic	Scaled F-statistic	Critical Value	Break Dates
SSE	0 vs. 1	18.66100	74.64402	16.19	200903 201604
	1 vs. 2	16.81195	67.24782	18.11	
	2 vs. 3	4.241298	16.96519	18.93	
SZSE	0 vs. 1	12.99779	51.99114	16.19	200903 201606
	1 vs. 2	10.99798	43.99190	18.11	
	2 vs. 3	4.286304	17.14522	18.93	

Table 4. ADF unit root test outcomes

	Variable	ADF Value	5% Critical Level	P-Value	Conclusion
Level	CEPU-S	-5.356554	-3.428198	0.0001	Stable
	GEPU	-5.825937	-3.428123	0.0000	Stable
	IS-CICSI	-3.020034	-3.428273	0.1289	Unstable
	SSE	-6.995734	-3.428123	0.0000	Stable
	SZSE	-7.341516	-3.428123	0.0000	Stable
First Difference	CEPU-S	-13.70584	-3.428349	0.0000	Stable
	GEPU	-12.48194	-3.428349	0.0000	Stable
	IS-CICSI	-15.91451	-3.428273	0.0000	Stable
	SSE	-13.28177	-3.428426	0.0000	Stable
	SZSE	-12.45524	-3.428426	0.0000	Stable

Table 5. Johansen cointegration test outcomes

	Hypothesised No. of CE(s)	Eigenvalue	Trace Statistic	5% Critical Value	Prob. Critical Value
SSE	None	0.144912	81.51213	47.85613	0.0000
	At Most 1	0.103124	43.15726	29.79707	0.0008
	At Most 2	0.057153	16.49192	15.49471	0.0353
	At Most 3	0.008427	2.073437	3.841465	0.1499
SZSE	None	0.145667	82.70777	47.85613	0.0000
	At Most 1	0.105670	44.13640	29.79707	0.0006
	At Most 2	0.057879	16.77469	15.49471	0.0319
	At Most 3	0.008808	2.167455	3.841465	0.1410

stationary. The Johansen cointegration test (Table 5) further confirms long-run equilibrium relationships among the original series, mitigating the risk of spurious regression and validating subsequent estimations.

IV. Empirical Method

Structural shifts in time series may distort causal inferences between variables (Li et al., 2015), prompting dynamic modelling approaches. To address this, Nakajima et al. (2011) proposed the TVP-VAR-SV model, which this study applies to examine the dynamic effects of CEPU, GEPU, IS, and SMV. Given China's evolving economic structure and policy shifts, the model's time-varying features make it a suitable and robust tool for empirical analysis.

$$y_t = X_t\beta_t + A_t^{-1}\phi_t\epsilon_t (t = s+1,\ s+2, \cdots, n) \qquad (2)$$

In (2), the parameters β_t, A_t^{-1}, and φ_t are time-varying. The variable y_t is a k×1-order vector composed of the variables under examination, where k represents the number of variables (in this case, k = 4). Let s denote the lag order, X_t the matrix of intercepts and lagged variables, and ε_t the vector of structural shocks or stochastic disturbances.

V. Results and Analysis

A. Parameter Setting and Estimation Results

A VAR model was constructed for CISCI, CEPU, GEPU, and SMV. The Akaike Information Criterion determined an optimal lag order of three to maintain parsimony within the TVP-VAR-SV framework. Estimation results are presented through three-dimensional visualisations to illustrate dynamic interactions more intuitively.

The parameters of the TVP-VAR-SV model are set as follows: $\mu\beta0 = \mu\alpha0 = \mu h0 = 0$, and $\sum\beta0 = \sum\alpha0 = \sum h0 = 10I$. The model's prior assumptions are defined as $(\sum\beta)$ - 2i ~ Gamma (40, 0.02), $(\sum\alpha)$ -2i ~ Gamma (40, 0.022), $(\sum h)$ - 2i ~ Gamma (40, 0.02). To obtain valid samples, the MCMC algorithm is run for 10,000 iterations. Based on the prior probability distribution, 10,000 samples are drawn. To mitigate the impact of initial values on the simulation estimation, the first 1,000 samples are discarded as a 'burn-in' period.

Table 6 reports the estimation outcomes of the model for key variables—IS, CEPU, GEPU, and SCI. All posterior mean values lie within their respective 95% credible intervals, while the Geweke statistics remain below the critical value of 1.96, indicating no firm evidence of non-convergence. These results imply that the chosen burn-in period is sufficient for achieving Markov chain stationarity. Furthermore, the inefficiency factors, which reflect the number of draws required to obtain effectively independent

Table 6. Parameter estimation outcomes

	Estimation Result					
Parameter	Mean	S.D.	95%L	95%U	Geweke	Inef.
sb1	0.0226	0.0026	0.0182	0.0283	0.052	9.02
sb2	0.0229	0.0027	0.0184	0.0289	0.144	19.04
sa1	0.0571	0.0137	0.0363	0.0899	0.016	47.42
sa2	0.0584	0.0145	0.0372	0.0928	0.589	38.71
sh1	0.4610	0.0925	0.2944	0.6518	0.239	40.38
sh2	0.3985	0.0877	0.2470	0.5893	0.716	48.58

Notes: The Geweke test's critical thresholds are 1.96 at the 5% significance level.

samples, suggest satisfactory sampling efficiency— the lower these values, the more efficient the MCMC process. All values in Table 6 are below 100, suggesting that the samples exhibit high validity for parameter estimation. The MCMC-generated samples are deemed adequate for reliable posterior inference within the TVP-VAR-SV framework.

Figure 6 presents the time-varying characteristics of parameters, including three components. The sample's autocorrelation coefficients, sample path, and posterior distribution are illustrated in the top, middle, and bottom rows, respectively. The autocorrelation coefficient graph demonstrates that the autocorrelation coefficients exhibit a rapid downward trend, ultimately reaching zero. The stability of the sample path suggests that most samples effectively generate unrelated observations, indicating the absence of autocorrelation. As illustrated in the sample path diagram, the data exhibits stable fluctuations around the sample mean, with a pronounced clustering of volatility and overall structural stability. This result indicates that the MCMC algorithm has produced sufficiently independent samples. Finally, the posterior distribution plot demonstrates that the sample has converged to the target posterior distribution, confirming overall convergence. Therefore, based on the characteristics of each time-varying parameter shown in Figure 6, the model's results are robust and reliable.

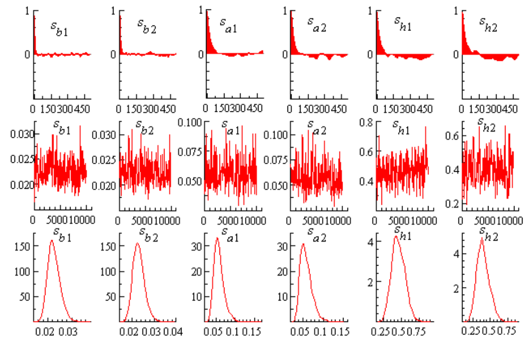

Figure 6. Time-varying parameter features

B. Analysis of Impulse Response

1. The Impact of IS on the Volatility of SSE and SZSE

Figures 7 and 8 reveal that the SSE and SZSE are subject to a short-term impact from IS during the sample period, with the impulse response function converging to zero from the sixth period. This conclusion is consistent with Wang et al. (2021), who demonstrated that, in emerging markets, IS tends to affect stock returns more in the short term. However, the relationship between IS and SMV exhibits clear time-varying characteristics in the short periods. As horizons change, the impact of IS on the market exhibits a pattern of positive and negative reversals. This result aligns with the conclusions drawn in Hu and Xia (2023), which suggest that IS has a cumulative effect, leading to substantial price corrections once it reaches a certain level. The impact of IS on SMV peaked between 2005 and

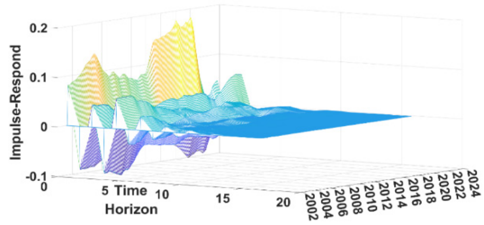

Figure 7. CISCI on SSE at equal time intervals

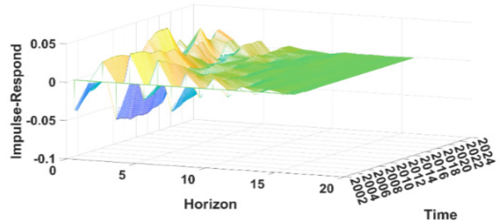

Figure 9. CEPU on SSE at equal time intervals

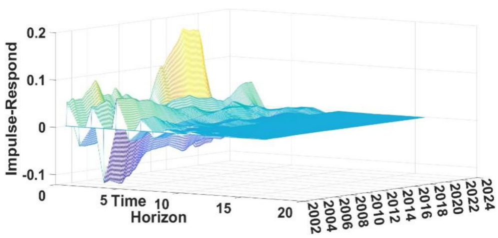

Figure 8. CISCI on SZSE at equal time intervals

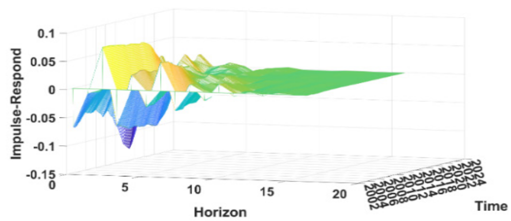

Figure 10. CEPU on SZSE at equal time intervals

2007 and again between 2015 and 2020. These two periods coincided with significant financial policy changes in China, optimising the market structure and significantly boosting investors' enthusiasm. Consequently, the impact of IS on SMV experienced a moderate increase. Moreover, as large-cap stocks were listed on the SSE, they attracted more risk-averse investors, who tend to be highly sensitive to uncertainty and prone to drastic emotional reactions (Keddad, 2024). Overall, market volatility in the SSE is significantly higher than in the SZSE. Between 2015 and 2020, the impact of IS on SMV reached an extreme level due to a series of major global events, which triggered sharp shifts in IS, transmission from high optimism to extreme pessimism before gradually stabilising, which increases market mispricing, intensifies speculative trading, and ultimately exacerbates volatility (Hiia et al., 2023).

2. The Impact of CEPU on the Volatility of SSE and SZSE

As illustrated in Figures 9 and 10, CEPU has a relatively limited long-term impact on the SMV of SSE and SZSE during the sample period. The impulse response function converges to zero from the 10th period onward. Compared to IS, the impact of CEPU lasts longer, considering that particular policy changes may take time to manifest in the market or be fully recognised by retailers, the effect is often delayed (Xiao et al., 2024). However, in the short term, SMV exhibits apparent time-varying effects in response to CEPU, with the degree of impact varying under different time constraints.

The SZSE demonstrates a greater impact amplitude than the SSE, indicating that the SZSE is more susceptible to CEPU. The SZCI includes a significant proportion of technology-based, innovative (such as science-technology, biopharmaceutical, and new energy enterprises, among others), small and medium-sized, and emerging enterprises. These enterprises depend highly on policies and are more sensitive to policy uncertainties than traditional, mature enterprises (Park & McQuaid, 2023). The impact of CEPU is relatively minor compared to that of IS. From a temporal perspective, the impact of CEPU on the market in 2019 was minimal compared with other periods, potentially because of the international financial turmoil and the COVID-19 outbreak. The rescue plan and policy measures introduced by the Chinese government to boost market confidence contributed to stabilising the stock market (Iglesias, 2022).

3. Impact of GEPU on SMV in SSE and SZSE

Figures 11 and 12 reveal that the persistent effect of GEPU on the SMV of the SSE and SZSE over the sample period is relatively limited, with the impulse response function converging to zero from the sixth period. The impact of GEPU is shorter than that of CEPU, which is consistent with Liu et al. (2023). The immediate impact of GEPU on the market shows a significant positive shock, consistent with Yu et al. (2018), indicating the continuous alignment of the Chinese stock market with the global economic landscape. The impact amplitude for the SZSE is more pronounced than the SSE's, indicating that the SZSE is more susceptible to GEPU. In addition to the previously mentioned factors related to enterprises and industry types, location dynamics may also contribute to this difference. The SZSE is in the special economic zone in China, and it has become more closely aligned with the global economic landscape and increasingly responsive to shifts in international economic policies. By contrast, the SSE is in China's financial centre, and serves as a buffer that lessens the capital market's direct exposure to

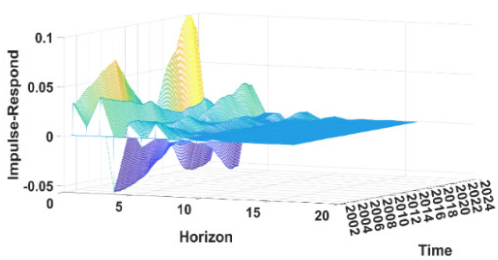

Figure 11. GEPU on SSE at equal time intervals

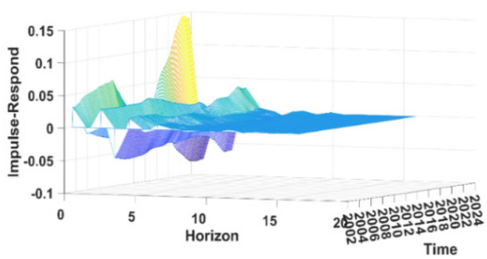

Figure 12. GEPU on SZSE at equal time intervals

GEPU. Located in a special economic zone, the SZSE is more integrated with global markets and responsive to international policy shifts, whereas the SSE, as China's financial centre, buffers direct exposure to GEPU. Overall, GEPU exerts a more decisive influence than CEPU, consistent with Isah et al. (2024). The impact of GEPU on China's market was weakest in 2016-2017, when domestic investors focused more on national economic development. By contrast, its influence intensified during 2008-2009 and after 2018, driven by heightened sensitivity to global shocks such as the financial crisis, Sino-US tensions, and COVID-19 (Wu et al., 2022).

VI. Robustness Test

In this study, we employ the index replacement and variable order adjustment methods following Hu et al. (2023) to assess the robustness of the model. First, following Huang and Luk (2020) and Wei et al. (2014), we replace the EPU indicators and IS indicators; the optimal lag order was altered from the third order to the second and fifth orders. Then we modify the variable order in the TVP-VAR-SV model (CEPU, GEPU, IS, and SMV) and observe that these adjustments result in minor changes in the magnitude and direction of the effects of the CEPU, GEPU, and IS on the SSE and SZSE. However, parameter estimation results confirm that the sample pairs in the model have high validity, aligning with previous studies that found the results robust. The effects of CEPU, GEPU and IS on the Shanghai and Shenzhen stock markets follow a time-varying fluctuation structure, with IS influencing the SSE more than the SZSE. In contrast, CEPU and GEPU have a greater impact on the SZSE than the SSE.

VII. Conclusion

The complexity of SMV arises from multiple interacting factors. Using a TVP-VAR-SV model, this study captures their time-varying interrelations and the linkage between China and the global economy. Results show that SMV evolves in a dynamic, asymmetric pattern, with fluctuations alternating around zero and converging within 6-10 periods. In the short term, IS exerts the strongest but transient effect, amplified under uncertainty and more pronounced for the SSE than the SZSE, contrary to expectations of large-cap stability. CEPU's influence is milder but more persistent, while GEPU generates stronger yet shorter-lived shocks, with its impact notably expanding during 2017-2018. Comparatively, IS has greater effects on the SSE, whereas the SZSE is more responsive to CEPU and GEPU.

This study provides insights for market participants and regulators to identify better and mitigate risks arising from policy shifts and IS. First, the government should monitor IS-induced SMV for at least six months and address reversal effects from sentiment accumulation, with particular attention to the SSE, where sensitivity to IS shocks is greater. Second, policymakers should adopt prudence in economic reforms while improving transparency and communication to stabilise expectations. Third, as GEPU is exogenous, strengthening investors' awareness of global economic conditions is essential for enhancing domestic risk management.

Several limitations remain. Future research could apply advanced methods, such as deep learning with social media and financial reports, to capture IS more effectively. Moreover, extending the analysis to sectoral spillovers via connectedness approaches would yield further insights for risk prevention.

Conflicts of Interest

No potential conflict of interest was reported by the authors.

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