Exploring The Main Factors Influencing Stock Price Volatility in China Based on The GARCH-MIDAS Model

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Abstract

This article comprehensively explores factors that affect stock price fluctuations from three perspectives: geopolitical events, economic indicators, and financial factors. In order to analyze these influences, we used data from July 1997 to February 2023 and employed the GARCH-MIDAS model with the Shanghai Composite Index variable for empirical analysis. The main findings of this study are summarized as follows. Firstly, the Chinese Investors' Confidence Index, Consumer confidence index, Entrepreneur Confidence Index, Housing starts, Default Spread, and Industrial Added Value positively impact long-term stock market volatility. This effect gradually strengthens over time. Other variables hurt the long-term volatility of the stock market. Secondly, Default Spread has the highest predictive power, followed by USDX and Retail of Consumer Goods. Thirdly, the impact of geopolitical events, economic indicators, and financial factors on stock market fluctuations varies significantly.

Keywords: Shanghai Composite Index, GARCH-MIDAS Model, Volatility Forecasting, Global Economic Uncertainty Index, Macroeconomic Variable

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การวิจัยปัจจัยที่มีอิทธิพลหลักของความผันผวนต่อราคาหุ้นจีนจากแบบจำลอง GARCH-MIDAS

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บทคัดย่อ

บทความนี้ สำรวจปัจจัยที่มีผลต่อความผันผวนของราคาหุ้นอย่างครอบคลุม 4 ด้าน ได้แก่ ปัจจัยเศรษฐกิจมหภาค เหตุการณ์ทางภูมิรัฐศาสตร์ ตัวชี้วัดทางเศรษฐกิจ และปัจจัยทางการเงิน ในการวิเคราะห์ผลกระทบครั้งนี้ ฉันได้ใช้ข้อมูล จากเดือน กรกฎาคม ปี 1997 ถึง เดือน กุมภาพันธ์ ปี 2023 โดยใช้แบบจำลอง GARCH-MIDAS และตัวแปรดัชนี เซี่ยงไฮ้คอมโพสิตเพื่อการวิเคราะห์ เชิงประจักษ์ ผลการวิจัยชิ้นนี้สรุปสาระสำคัญได้ดังนี้ ก่อนแรกคือ ดัชนีความเชื่อมั่น นักลงทุนจีน ดัชนีความเชื่อมั่นผู้บริโภค ดัชนีความเชื่อมั่นผู้ประกอบการอัตราการเปิดบ้าน ค่าสเปรดผิดนัดชำระหนี้ และมูลค่าที่เพิ่มขึ้นในภาคอุตสาหกรรม ส่งผลดีต่อความผันผวนของตลาดหุ้นในระยะยาว ผลกระทบนี้ค่อย ๆ เพิ่มขึ้น ตามกาลเวลา ตัวแปรอื่น ๆ ส่งผลลบต่อความผันผวนของตลาดหุ้นในระยะยาว ข้อ 2 คือ ความสามารถในการคาดการณ์ค่าสเปรดผิดนัดชำระหนี้สูงสุด รองลงมาคือ USDX และการค้าปลีกสินค้าอุปโภคบริโภค ข้อ 3 คือ ตัวแปรทางเหตุการณ์ทางภูมิรัฐศาสตร์ ตัวชี้วัดทางเศรษฐกิจ ปัจจัยทางการเงินมีผลกระทบที่แตกต่างกันอย่างมากต่อความผันผวนของตลาดหุ้น

คำสำคัญ : ดัชนีเซี่ยงไฮ้คอมโพสิต แบบจำลอง GARCH-MIDAS การคาดการณ์ความผันผวน ดัชนีความไม่แน่นอนของเศรษฐกิจโลก ตัวแปรทางเศรษฐกิจมหภาค

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Introduction

The arbitrage pricing theory can explain the theoretical relationship between stock prices and macroeconomic factors (Ross, 1973). This theory suggests that macroeconomic variables related to stock prices influence risk premiums, ultimately determining stock price volatility. When stock price volatility increases, it can lead to more significant variability in a firm's cash flows, reduced reliability, and difficulty creating investment strategies based on the risk-return relationship. As volatility expands, it may cause financial markets to become unstable, potentially spilling over into the real economy and impacting the overall economy negatively (Bakkar, Nilavongse, Saha, 2021; Jung, 2021). Therefore, it is crucial to identify the factors that impact stock price volatility and predict its fluctuations to ensure stability for firms, investors, and the broader national economy. And the stock market is an important part of China's economy. For the national economy, its change is the “barometer” that reflects the macro trend; For individual and institutional investors, the stock market, as an important part of asset allocation, has a considerable impact on investment decisions. The study of the interaction between the stock market and macroeconomic factors, geopolitical events, economic indicators and financial factors can help to regulate the stock market and understand how they affect economic growth.

Previous studies have examined the effects of short-term variables such as daily interest rates and exchange rates on stock market volatility (Desai et al., 2002; Agrawal, Srivastav, Srivastava, 2010; Chang, 2012; Mollick and Assefa, 2013; Yoon, Ohk, 2014; Sutrisno, 2020). Other studies have analyzed monthly stock market volatility using significant macroeconomic variables such as industrial production indices, oil prices, and unemployment rates (Chen, Roll, Ross, 1986; Schwert, 1989; Fama, French, 1989; Khalid, Khan, 2017). However, transforming high-frequency data (daily data) into low-frequency data (monthly or quarterly data) can potentially result in the loss of unique information contained in high-frequency data. Engle, Ghysels, and Sohn (2013) developed the GARCH-MIDAS model, which allows for mixed-frequency estimation using MIDAS filtering even when data has different frequencies. This way enables efficient parameter estimation without losing information. The GARCH-MIDAS model expresses total volatility as the product of low-frequency long-term volatility (persistent component) and high-frequency short-term volatility (transitory component), offering the advantage of capturing the multiplier effect and low-frequency information effect in volatility estimation (Engle, Ghysels, Sohn, 2013). Therefore, this study aims to use the GARCH-MIDAS model to examine the effects of domestic macroeconomic variables on stock market volatility.

Accurately modeling and forecasting stock market volatility plays a crucial role in financial market regulation, portfolio decision-making, financial risk management, credit derivative pricing, and various other areas. Traditionally, the research has focused on modeling and empirical research of volatility primarily based on GARCH models and their extensions. However, GARCH-type models can only model data at the same frequency, which is a primary reason they fall short in capturing long-term financial market volatility.

In response to this limitation, Engle, R. F. et al. (2013) introduced the GARCH-MIDAS model to explore the relationship between stock markets and macroeconomic activities. Subsequently, Zheng Tingguo, and Shang Yuhuang. (2014) developed the GARCH-MIDAS model based on macroeconomic fundamentals to estimate and forecast volatility in the Chinese stock market, revealing a significant positive impact of macroeconomic fluctuations on Chinese stock market volatility. Lei Li-Kun et al. (2018) utilizing the GARCH-MIDAS model, empirically found that Baker's Economic Policy Uncertainty (EPU) Index could effectively explain the long-term component of stock market volatility in China and significantly improve the accuracy of predicting the volatility of the Shanghai Composite Index.

Yu, H. et al. (2018) investigated the influence of the Global Economic Policy Uncertainty (GEPU) Index on Chinese stock market volatility, and their empirical research indicated a significant positive impact of the GEPU Index on the volatility of the Chinese stock market, reflecting China's gradual integration into the global economy. Wei, Y. et al. (2018) using the GARCH-MIDAS model, separately studied the impact of hot money on the overall Chinese stock market and on various industry-specific stock markets in China, finding that hot money had a significant positive effect on the long-term volatility of the Chinese stock market.

Shi Qiang et al. (2019) employed a multifactor GARCH-MIDAS model to investigate the relationship between China's macroeconomy and stock market volatility. The results showed that industrial value-added and total retail sales of consumer goods had a positive impact on the long-term stock market volatility, and this influence exhibited a growing trend. Zhong Lixin et al. (2020) utilizing the GARCH-MIDAS model, studied the impact of policy intensity on the long-term component of stock market volatility, and their empirical research revealed that incorporating policy variables into the model effectively improved prediction accuracy.

This study examines the impact of global economic uncertainty and sentiment indices on stock price volatility. Since the 2008 global financial crisis, factors such as deepening economic interdependence among countries, improved access to information through advances in communication technology, and the COVID-19 pandemic-induced global economic contraction have all significantly affected stock price volatility (Mazur, Dang, Vega, 2021). Thus, while past research has mainly focused on shocks in the real market as a significant factor influencing stock price volatility, it is now emphasized that various indicators such as global uncertainty and sentiment indices should be considered essential due to the transmission effect of information caused by the increasing globalization. Therefore, it is essential to consider various factors that can affect stock price volatility. While there are various global economic indicators available, the economic policy uncertainty (EPU) index developed by Baker, Bloom, and Davis (2016) and the macro uncertainty index developed by Jurado, Ludvigson & Ng (2015) is representative indices indicating the level of global economic uncertainty (Chuliá, Guillén & Uribe, 2017). The expansion of uncertainty, indicating a global economic downturn, leads to a delay in investment and consumption decisions of companies and households, resulting in an increase in firms' marginal costs, which can negatively affect financial markets (Bernanke, 1983; Elder & Serletis, 2010). Since changes in sentiment also include information about current and future conditions for investors and companies, they can directly affect financial markets (Barksy & Sims, 2012; Chun, 2021). Therefore, it is crucial to understand stock price volatility to consider information variables such as economic indicators, financial factors, and geopolitical events. Hence, this study aims to estimate stock price volatility while considering economic indicators, financial factors, and geopolitical events using a mixed-frequency estimation capable GARCH-MIDAS model.

Accordingly, investors or even the government must adjust their investment and expenditures decisions to better understand short-term and long-term influencing factors of stock price fluctuations. This study investigates how the long-term trend and short-term components of stock price volatility react to various influencing factors and further explores the contribution of different factors to stock price volatility.

Theoretical background and literature review

This chapter examines previous research on stock price volatility and macroeconomic variables. Chen, Roll, and Ross (1986) and Schwert (1989) are representative studies that consider macroeconomic factors in estimating stock price volatility. Chen, Roll, and Ross (1986) analyzed the impact of macroeconomic factors such as the industrial production index, money supply, inflation, exchange rates, and short- and long-term interest rates on US stock returns using the arbitrage pricing model. Schwert (1989) studied the relationship between US stock price volatility and real and nominal macroeconomic variables such as economic activity, financial leverage, and stock trading volume. Both studies found statistically significant relationships between macroeconomic variables and stock price volatility and returns, suggesting that macroeconomic variables are essential information variables for predicting and explaining stock returns and volatility.

Agrawal, Srivastav, and Srivastava (2010) analyzed the relationship between Indian stock market volatility and exchange rates using the Granger causality test. Theoretically, an increase in exchange rates leads to a reduction in stock investments and a shift towards investment in US dollars, thereby increasing stock market volatility. However, the empirical analysis did not support this. Both Agrawal et al. (2010) and Sutrisno (2020) analyzed the Indian and Indonesian stock markets, respectively, and found that exchange rates had a negative relationship with stock market volatility. They argued that exchange rates were a significant factor in explaining stock market volatility. Mollick and Assefa (2013) analyzed the relationship between US stock returns and oil prices, interest rates, gold prices, and exchange rates. Theoretically, an increase in interest rates negatively impacts firms' ability to raise capital, leading to decreased stock prices (Schwert, 1989; Kam & Shin, 2017; Koh, 2019). However, contrary to previous studies, Mollick and Assefa (2013) argued that an increase in interest rates could positively impact stock returns and volatility due to expectations of economic growth. Additionally, they demonstrated through empirical analysis that stock returns and volatility could react differently to news shocks of an interest rate increase depending on the economic situation (recession or expansion).

Recent studies have argued that models for estimating and predicting stock price volatility should include not only macroeconomic variables but also global economic conditions and investor sentiment indices due to globalization and the development of information and communication technologies (Kejlberg, 2018; Audrino, Sigrist, Ballinari, 2020; Liu, Zhang, 2015; Su, Fang, Yin, 2018). Liu and Zhang (2015) used the Economic Policy Uncertainty Index (EPU) to predict the volatility of the S&P 500. Their analysis found that increasing levels of EPU increased stock price volatility, and they claimed that using the EPU index to predict stock price volatility is more efficient than using macroeconomic variables. Su, Fang, and Yin (2018) used the US EPU index, which represents global economic uncertainty, to analyze the spillover effects on the stock markets of six advanced economies (Germany, France, the UK, Japan, Italy, and Canada) and three emerging markets (China, India, Russia). Their findings showed that the spillover effect of the EPU index on the stock markets of advanced economies was strong, while it was weak in emerging markets. Therefore, the studies by Su, Fang and Yin (2018) and Belcaid and Ghini (2019) demonstrated a new pathway through which the globalization of the economy and uncertainty in one country can affect the economy of another country by using the EPU index. Drechsler (2013) also emphasized that uncertainty is an important factor in determining the prices of financial assets in the US and can affect investor consumption and portfolio decisions, thereby causing changes in asset prices.

Upon reviewing prior research, it has been found that most studies analyzing the relationship between stock market volatility and macroeconomic variables focus on the impact of macroeconomic variables on the stock market. However, there is a significant lack of research considering global economic uncertainty and psychological variables. Nevertheless, as the development of information and communication technology and the integration of the global economy continue, the phenomenon of events in one country spreading to other countries is expanding. Therefore, it is necessary to comprehensively analyze the impact of global economic conditions and psychological indicators on stock market volatility, in addition to macroeconomic variables. In this study, we aim to analyze how these information variables affect stock market volatility using domestic macroeconomic variables, global economic uncertainty indices, and psychological indices applied in previous studies. However, there is a limitation in utilizing various variables with different frequencies in one model since they do not have the same frequency. To include different variables with different frequencies in the empirical analysis model, adjustments must be made to match the frequency of the considered variables (e.g., from monthly to daily or from daily to monthly). However, such frequency adjustments may potentially damage the unique information of the original data (Engle, Ghysels, Sohn, 2013). Therefore, this study utilizes the GARCH-MIDAS model that uses the MIDAS filter, which matches variables with different frequencies, to analyze the impact of multiple information variables with different frequencies on stock market volatility.

Similarly, there are many papers on the Chinese stock market. Due to the long time difference between opening and closing, the impact of Chinese stock market on European and American stock markets is mainly manifested as the impact of the closing of the former on the opening of the latter; The international influence of China's stock market has obviously changed in stages (Jiang Yu, 2019). Peng K S. (2021) finds that the fluctuation of international crude oil price has a significant lag effect on China's stock market, and the lag effect period is different for different sectors. Niu Tianjiao and Wang Lu. (2020) concluded that compared with normal fluctuations, the correlation between macroeconomic factors and China's stock market is more significant in extreme circumstances. Economic participants can make timely adjustments based on the links between the macro economy and the Chinese stock market. Wang Juan, and Li Rui. (2019) emphasized that there are three significant volatility states in Shanghai and Shenzhen stock markets, the probability of consolidation is the largest and the average duration is the longest. The return fluctuation has obvious time-varying memory and asymmetric effect.

Data and methodology

Data

Since the global market integration and the increased contagion and spillover effects across countries after the financial crisis, traditional paths that affect the stock market have been changing (Srivastava, Bhatia, Gupta, 2015; Inaba, 2020). In this study, we focus on the period from July 1997 to February 2023, which includes the post-financial crisis era, to analyze the impact of low-frequency information variables on stock price volatility. The daily closing prices of the Shanghai Composite Index were used for the stock market data, which were transformed into logarithmic returns for time series stability. We utilize three financial indicators: Housing starts, Default Spread and the US dollar index.

Three geopolitical events: Geopolitical Risk index, Geopolitical Threat and Geopolitical Action. Seven economic indicators: Global Economic Policy Uncertainty Index, Chinese Investors' Confidence Index, Consumer Confidence Index, Entrepreneur Confidence Index, Industrial added value, retail sales of consumer goods, and money supply.

Geopolitical risk

To assess geopolitical risk, we rely on the Geopolitical Risk (GPR) index developed by Caldara and Iacoviello (Caldara & Iacoviello, 2022), which includes two sub-indices known as Geopolitical Threat (GPT) and Geopolitical Action (GPA). The GPR index is calculated using a specific methodology that counts the number of monthly articles related to geopolitical risk in 11 major international newspapers through text search. The resulting count is then divided by the total number of published articles for that month to compute the GPR index, which is normalized to 100 from 2000 to 2009. The text search analyzes articles based on six categories of terms: the first category encompasses terms that explicitly mention geopolitical risks and tensions. In contrast, the second category focuses on nuclear tensions. The third and fourth categories centre around the threat of war and terrorism, respectively. Categories five and six aim to capture adverse geopolitical events covered by the media that can potentially exacerbate geopolitical risks, such as the outbreak of war or acts of terrorism.

Caldara and Iacoviello (2022) have developed two sub-indices to disentangle the influence of geopolitical threats from that of direct geopolitical events. The Geopolitical Threat (GPT) Index comprises words from categories 1 to 4 directly referring to risk threats. At the same time, the Geopolitical Action (GPA) Index includes words from categories 5 and 6, which are associated with negative event vocabulary. These indices are independent yet interconnected, with GPA shocks representing unfavourable geopolitical events that could increase geopolitical threats and GPT shocks capturing those threats that are not directly linked to geopolitical actions, such as tensions building up before or after wars or terrorist attacks. As a result, the GPT index starts to rise before major geopolitical events and may remain elevated afterwards. In short, this study utilizes the GPR index to analyze the overall impact of geopolitical risks on crude oil price fluctuations while using the GPT and GPA sub-indices to identify specific factors influencing geopolitical risks. Monthly data are available at https://www.matteoiacoviello.com/gpr.htm as of February 2023.

Macroeconomics factors: economic policy uncertainty EPU, US dollar index

The Economic Policy Uncertainty (EPU) index used in this study was developed by a team led by Scott Baker from Northwestern University, Nick Bloom from Stanford University, and Steven Davis from the Booth School of Business at the University of Chicago. The team began constructing the index in 2011 to quantify the uncertainty surrounding economic policies across significant economies worldwide, including the United States, Japan, France, Russia, China, and India.

Since its proposal, the index has garnered extensive attention and recognition from the academic community and is widely used by scholars in relevant research (Antonakakis et al., 2014; Feng et al., 2020; Ozcelebi, 2021). The EPU index is generally low when uncertainty factors are minor. However, significant economic, political, and military events such as war, leadership elections, and financial crises can cause an increase in uncertainty factors and lead to a rise in the EPU index. Major political and economic events or high policy uncertainty often impact economic activities, leading to uncertain oil prices. Monthly EPU data is tracked from July 1997 to December 2023 and is available on the website: https://www.policyuncertainty.com (Baker et al., 2016).

The price of oil on the international market is based on the US dollar, which means that any changes in the exchange rate of the US dollar can directly impact the price of oil. The petrodollar repatriation mechanism strengthens this link between oil and the US dollar. Additionally, many commodities worldwide are priced in US dollars, and numerous international organizations use the US dollar as their settlement currency. Therefore, any fluctuations in the exchange rate of the US dollar can impact the price of oil beyond the usual supply and demand factors. To represent the US dollar exchange rate level, we rely on the daily closing price of the US Dollar Index (USDX), which we obtained from the WIND database from July 1997 to February 2023. The variables used in this study are summarized in Table 1.

Table 1: Variable name and its abbreviation

Perspectives	Variable name	Abbreviation	Range
Geopolitical Events	Shanghai Composite Index	SSE	1997.07-2023.02
	Geopolitical Risk index	GPR	1997.07-2023.02
	Geopolitical Threat	GPT	1997.07-2023.02
	Geopolitical Action	GPA	1997.07-2023.02
Financial Factors	US dollar Index	USDX	2006.01-2023.02
	Housing Starts	HS	1997.07-2023.01
	Default Spread	DS	1997.07-2023.02
Economic Indicators	Global Economic Policy Uncertainty Index	EPU	1997.07-2022.12
	Chinese Investors' Confidence Index	CICI	2008.04-2023.02
	Consumer Confidence Index	COCI	1997.07-2023.01
	Entrepreneur Confidence Index	ENCI	2014.10-2023.02
	Industrial Added Value	IP	1997.07-2023.02
	Retail of Consumer Goods	SALES	1997.07-2023.02
	Money Supply	M2	1997.07-2023.02

Notes: we use daily frequency data.

Basic statistics of the analyzed data are summarized in Table 2. In terms of volatility, the standard deviation of M2 was approximately 772604.7, higher than that of other variables. DS is 0.4, the lowest standard deviation among the variables. The results of the Jarque-Bera test reject the null hypothesis at a significance level of 1%, indicating that the probability distribution of timing does not follow a normal distribution. This result suggests that the distributions of other variables and the stock price index differ from the normal distribution.

Note: we use daily frequeney data

Table 2: Descriptive statistics of variables

	Mean	Max	Min	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	Obs.
SSE	0.0073	4.0828	-4,0199	0.6592	-0.3523	8.1548	7007.25***	6213
GPR	101.2307	512.5297	42.6891	51.0899	4.2565	29.3329	198270.3***	6213
GPT	101.2325	413.2928	41.6393	44.4527	3.1009	17.7150	66011.42***	6213
GPA	102.6278	854.0750	28.4546	82.0968	5.5101	45.3539	495823.6***	6213
EPU	137.3457	430.2744	48.8751	73.1706	1.2575	4.1046	1942.05***	6177
CICI	55.7922	71.2000	36.3000	6.9798	-0.1717	3.0184	17.1291***	3476
COCI	109.3624	127.0000	85.5000	7.8152	0.1779	3.6739	149.8382***	6193
ENCI	54.2959	60.2000	31.3000	3.6862	-2.6046	16.1524	17018.75***	2041
USDX	103.4067	127.4084	86.3178	11.1981	0.1433	1.5666	370.7410***	4164
HS	1327.0000	2273.0000	478.0000	434.3112	-0.1974	2.1718	217.2402***	6193
DS	1.0001	3.3800	0.5500	0.4000	3.0929	16.0398	53923.90***	6213
IP	10.6111	52.3400	-25.8700	5.9911	0.1719	12.0929	21434.44***	6213
SALES	15140.63	41268.90	2115.0000	12272.88	0.6221	1.9427	643.8787***	5797
M2	908824.4	2755200	83460.0000	772604.7	0.7029	2.2142	671.4085***	6213

Notes: ***denotes rejection of null hypothesis at the 1%significance levels.

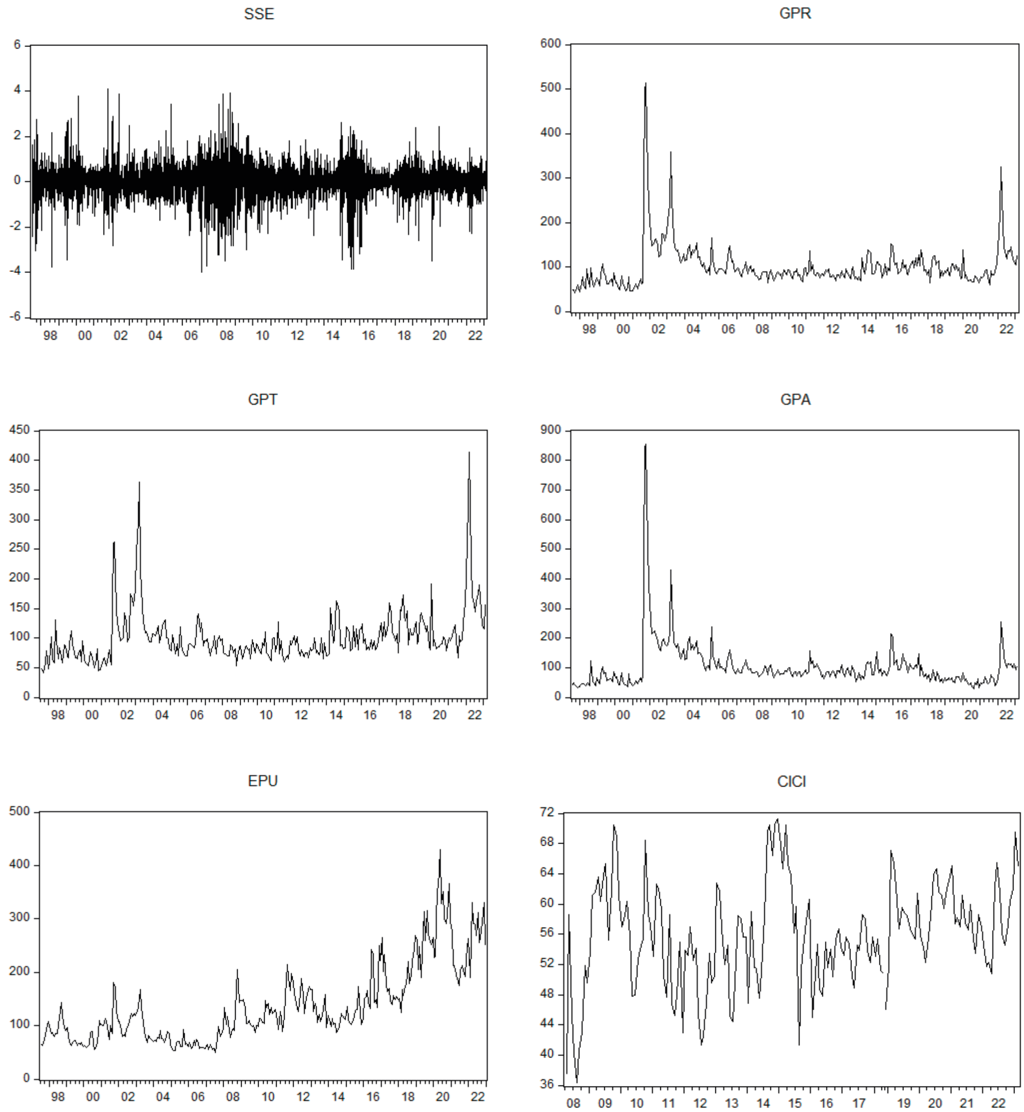
Before the empirical test, in order to ensure the accuracy of the results, the stationarity of the data should be tested first. The result is shown in Table 3. Through ADF test, PP test, KPSS test and ZA test, and it turns out that SSE, COCI, USDX, HS, SALES and M2 is stable at 1% significance level, indicating that the series is a stationary time series. The GPR, GPT, GPA, EPU, CICI, ENCI, DS and IP have a unit root and be stable after first difference.

Table 3: Descriptive statistics of variables

Variables	ADF	PP	KPSS	ZA
SSE	-77.27***	-77.26***	0.04	-77.63***
GPR	-6.33***	-6.58***	0.26***	-6.71***
GPT	-6.52***	-6.80***	0.36***	-6.89***
GPA	-6.29***	-6.54***	0.24***	-6.90***
EPU	-5.41***	-5.54***	0.99***	-6.55***
CICI	-5.85***	-6.06***	0.10	-5.95***
COCI	-78.67***	-78.67***	0.55***	-3.62
ENCI	-5.76***	-6.14***	0.25***	-6.07***
USDX	-64.53***	-64.53***	0.85***	-2.48
HS	-78.67***	-78.67***	1.41***	-3.40
DS	-4.12***	-78.79***	0.49***	-4.55**
IP	-6.78***	-9.49***	0.94***	-9.02***
SALES	-76.58***	-76.82***	2.08***	-4.43*
M2	-80.81***	-89.37***	2.35***	-1.07

Notes: *denotes rejection of null hypothesis at the 10%significance levels, **denotes rejection of null hypothesis at the 5%significance levels, ***denotes rejection of null hypothesis at the 1%significance levels.

Figure 1 shows the trend of Shanghai Composite Index, Geopolitical Risk index, Geopolitical Threat, Geopolitical Action, Global Economic Policy, Uncertainty Index, Chinese Investors' Confidence Index, Consumer confidence index, Entrepreneur Confidence Index, US dollar Index, Housing starts, Default Spread, Industrial Added Value, Retail of Consumer Goods and Money Supplied. As can be seen from the figure 1, Sales, EPU and M2 increase year by year. Housing starts fell sharply during the 2008 economic crisis. Instead, the Default Spread rose sharply in 2008. On the contrary, the Default Spread rose sharply in 2008. All the other variables are going up and down.



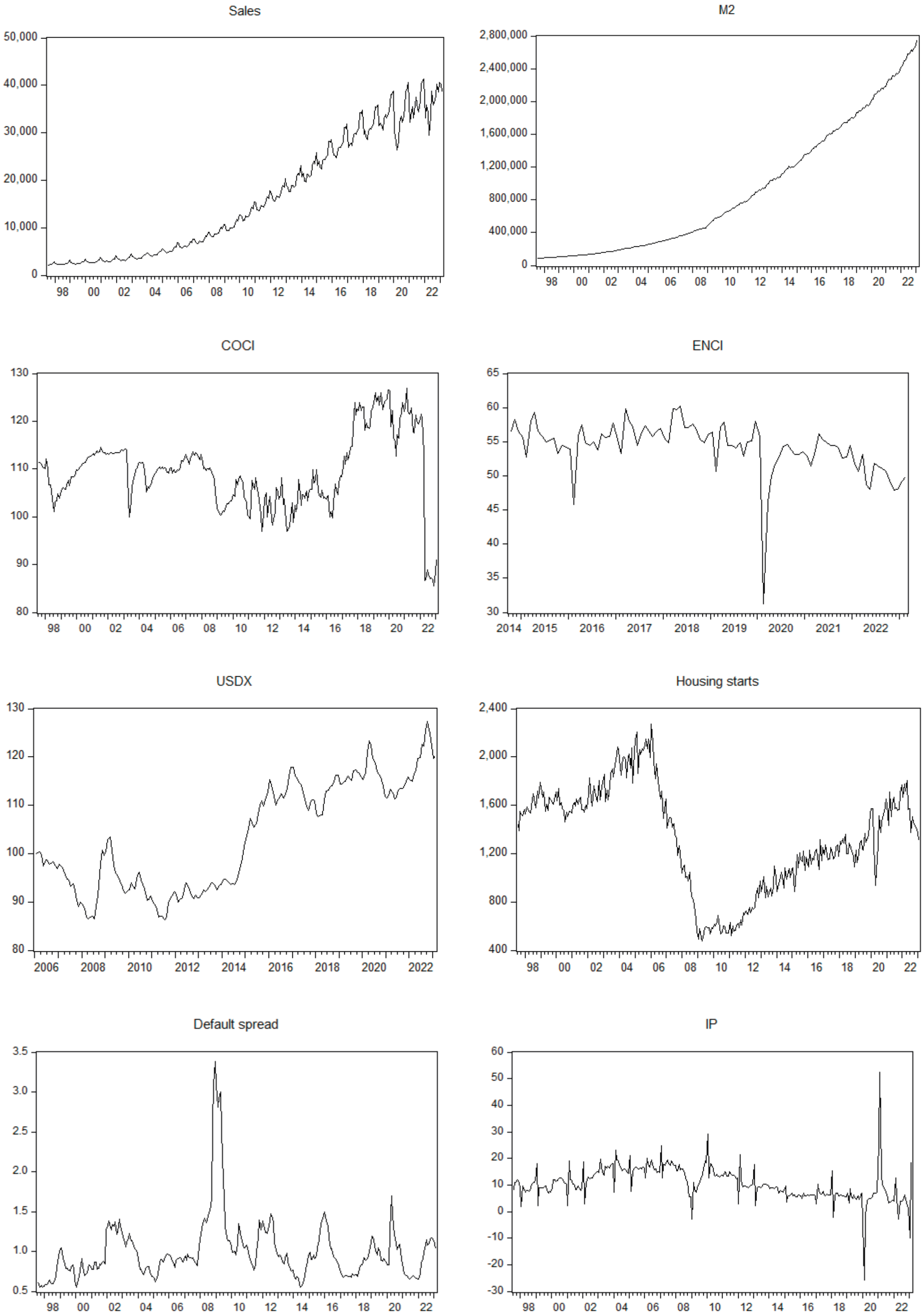


Figure 1: Dynamics of change rate of variables

Analysis method

In this study, we used the GARCH-MIDAS (Generalized Autoregressive Heteroskedastic-Mixed Data Sampling) model to analyze the impact of economic indicators, financial factors, and geopolitical events on the volatility of the Chinese stock market. The GARCH-MIDAS model has the advantage of including variables with different frequencies, such as daily and monthly data, to minimize information loss and processing.

Engle and Rangel (2008) and Engle, Ghysels, and Sohn (2013) proposed using spline functions and the MIDAS filtering method to estimate low-frequency volatility. In this study, we applied Engle, Ghysels, and Sohn's GARCH-MIDAS method so that we will provide a detailed explanation of the GARCH-MIDAS model. The GARCH-MIDAS model decomposes volatility into frequency-specific components based on the duration of news shocks. Specifically, it decomposes volatility into low-frequency (trend factor) and high-frequency (transitory factor) components based on their persistence, where the former shows long-term movements and the latter reflects short-term fluctuations.

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}\ \forall i = 1,2,\ldots,N_t \tag{1}$$

Here, t represents the month as a low-frequency variable, and i represents the i-th day of that month as a high-frequency variable. This means that while the conditional volatility of returns is represented by the low-frequency variable $\boldsymbol{\tau_t}$ reflecting long-term movements, the total volatility reflecting short-term movements can be expressed as $\boldsymbol{\tau_t} \times \boldsymbol{g_{i,t}}$, where $\boldsymbol{g_{i,t}}$ represents the high-frequency short-term volatility. Assuming that the error follows a GARCH (1,1) process, high-frequency short-term volatility ($\boldsymbol{g_{i,t}}$) can be expressed as follows.

$$g_{i,t} = \left(1 - \alpha - \frac{\gamma}{2} - \beta\right) + \left(\alpha + \gamma I_{i-1,t}\right)\frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{2}$$

Where,

$$I_{i-1,t} = \begin{cases} 0\ r_{i-1,t} - \mu \geq 0 \\ 1\ r_{i-1,t} - \mu < 0 \end{cases} \tag{3}$$

A MIDAS filtering is used with weighting functions to match the low-frequency variable $\boldsymbol{\tau_t}$ with high-frequency variables using economic indicators $\mathbf{X_t}$ as information variables with lagged variables. In this study, the low-frequency variable is based on monthly data, while the high-frequency variable is based on daily data. Therefore, it is assumed that one month has 22 days to match the monthly data with daily data. The expression for MIDAS filtering can be represented as follows.

$$\tau_t^{(r\omega)} = m_t^{(r\omega)} + \theta_t^{(r\omega)} \sum_{k=1}^{K} \square\,(\omega_1, \omega_2) X_{t-k}^{(r\omega)} \tag{4}$$

In equation (3), $\mathbf{m^{(r\omega)}}$ and $\boldsymbol{\theta^{(r\omega)}}$ represent the intercept and slope of MIDAS filtering, respectively. The slope ($\boldsymbol{\theta^{(r\omega)}}$) of the low-frequency variable determines whether the long-term volatility increases or decreases. If the slope is positive (+), it means that the long-term volatility increases; if the slope is negative (-), it means that the long-term volatility decreases. Using the above equation, we can derive the low-frequency long-term volatility through the rolling-window technique and beta weighting function. The beta weighting function can be expressed as follows.

$$\varphi(\omega_1, \omega_2) = \frac{(^k/_K)^{\omega_1-1}(1-^k/_K)^{\omega_2-1}}{\sum_{i=1}^{K}(^i/_K)^{\omega_1-1}(1-^i/_K)^{\omega_2-1}} \tag{5}$$

When using MIDAS filtering to match low-frequency data with high-frequency data, a beta weighting function is used to reflect the movement of the high-frequency data and generate the low-frequency data. The resulting low-frequency data has the same frequency as the high-frequency data, allowing data with different frequencies to be included in the estimation when using MIDAS filtering. The distribution of the weighting function is determined by ω_1, ω_2 (the weighting parameter). To ensure that the lag term's weight is in the form of attenuation as well as the simplicity of the model, we referred to the research of Engle et al. (2013) to set the constraint weighting conditions for the weighted eqution ω_1=1, only allowing parameters ω_2 to determine the attenuation rate of low-frequency variables to long-term components.

Thus, the distribution takes on a monotonically increasing or decreasing form depending on the value of the weighting parameter. In the above model, we need to determine the value of K, which represents the lag of the low-frequency variable. In previous studies, the optimal weighting function has been observed when determining the lag to reflect low-frequency volatility, and a lag of 3-5 years (K=36-60) has been set. However, recent studies have set the lag to be shorter than 3-5 years (K=36-60), specifically two years (K=24), to reflect rapidly changing economic conditions (Yu, Fang, Sun, 2018; Su, Fang, Yin, 2018; Liu, Han, Yin, 2019). Therefore, in this study, we set K=24 accordingly and included information on economic indicators from the last two years to reflect volatility.

In addition, to evaluate the contribution of the low-frequency variable used in this study to stock volatility, we calculated the variance ratios proposed by Engle, Ghysels, and Sohn (2013). The variance ratios can be expressed as follows:

$$VR(X) = \frac{Var(\log(\tau_t)}{Var(\log(\eta_t)} = \frac{Var(\log(\tau_t)}{Var(\log(\tau_t \times g_{i,t}))} \quad (6)$$

The explanatory power of the low-frequency long-term factor in overall volatility is high if the calculated variance ratio is large.

Empirical results

Estimation and analysis on the single-factor model

In order to understand the behavior of stock market volatility, it is essential to consider various news factors, such as significant economic indicators. In particular, changes in economic indicators are more likely to vary with economic fluctuations rather than temporary phenomena, so it is necessary to consider long-term factors. We also need to consider geopolitical events, and financial factors, analyzing the volatility of stock prices.

Table 4 summarizes the results of constructing a GARCH-MIDAS model for each low-frequency variable (geopolitical events, economic indicators, and financial factors) to estimate the SSE's long- and short-term volatility.

The MIDAS polynomial is used to characterize the long-term fluctuations in crude oil prices. It involves using a Beta function, where the optimal estimation coefficient for weight attenuation of low-frequency variables is represented by ω. The coefficients θ reflect the impact of different factors on the long-term composition of crude oil price fluctuations, which is the main parameter focused on in these models.

Level effect of single-factor model

The estimation results of the single-factor level value mixed model are presented in Tables 4 and 5. The results indicate that the parameters of GJR-GARCH (α, β) in all other models are significant. Firstly, the parameter values of β are close to 1, suggesting that previous fluctuations influence short-term fluctuations in SSE and have strong memory and persistence. Additionally, all parameters γ are positive, which indicates an asymmetrical impact on short-term fluctuations in SSE. The impact of adverse shocks is more significant than that of positive impacts of the same degree; all parameters α are slightly greater than zero, indicating that the effect of positive shocks on short-term fluctuations in SSE is minimal. When the coefficient θ is positive and statistically significant, it suggests that an increase in the factor level will promote volatility in SSE. ω is weighting parameter. m is a constant term.

Based on the coefficient estimates of θ, it appears that only EPU, IP, Sales, and M2 significantly impact the volatility of the SSE. The other selected factors do not seem to have a significant effect. CICI, COCI, HS, DS, and IP coefficients are positive.

On the contrary, Geopolitical factors have a significant adverse effect, indicating that the decrease in geopolitical risks will intensify the long-term fluctuation of SSE, contradicting the discovery made by Mei et al. (2020). The θ coefficients of EPU, ENCI, USDX, Sales, and M2 are significantly negative for the other variables.

By comparing the absolute value of the coefficients, we can assess each factor’s varying degrees of influence on SSE fluctuations. For SSE, the order of the degree of influence is USDX, CICI, COCI, ENCI, GPT, and GPR. Regarding value significance, the level values of EPU and IP are significant at 5%, while the levels of Sales and M2 are significant at 10%.

Table 4: Estimation results of GARCH-MIDAS models

Panel A: geopolitical events							
	μ	α	β	γ	θ	ω	m
GPT	0.0049	0.0740 ***	0.9117 ***	0.0270*	-0.7254	2.3997	4.6232
GPR	0.0046	0.0751***	0.9092 ***	0.0294 *	-0.7259	1.0002	4.4696
GPA	0.0046	0.0728***	0.9125***	0.0276*	-0.3998	1.0007	3.0389
Panel B: economic indicators							
EPU	0.003082	0.073596***	0.910357***	0.02937*	-0.75416**	14.12984	4.5833756***
CICI	0.0067	0.0609 ***	0.9287 ***	0.0177	3.2432	10.0655	-12.8119
COCI	0.0050	0.0656 ***	0.9228 ****	0.0189	1.9156	57.3034	-8.8682
ENCI	0.0062	0.0840 ***	0.8649 ***	0.0652	-1.1353	4.7965 *	3.3159
IP	0.0043	0.0768 ***	0.9081 ***	0.0287*	0.0864 **	1.0316 ***	0.6361
Sales	0.0021	0.0701 ***	0.9167 ***	0.0241 *	-0.2364 *	1.0001	3.1904 ***
M2	0.0047	0.0728 ***	0.9121***	0.0276 *	-0.2390 *	1.0384	4.1272 ***
Panel C: financial factors							
USDX	0.0036	0.0653***	0.9235 ***	0.0169	-3.5403	60.0530	16.3845
Housing starts	0.0047	0.0649***	0.9235 ***	0.0192	0.0252	39.8612	-2.6268
Default Spread	0.00447	0.075604***	0.909641***	0.028078*	0.566063	4.507228*	1.5739862***

Notes: the ‘Level’ item represents the index series, and the ‘Returns’ item represents the rate of change (logarithmic returns of the index). * denotes rejection of null hypothesis at the 10% significance levels *** denotes rejection of null hypothesis at the 1% significance levels.

Table 5 presents the variance ratios, log-likelihood, and AIC values for the overall volatility estimated using the GARCH-MIDAS model. The variance ratio represents the proportion of low-frequency long-term factors estimated as level variables for each information variable in the overall volatility. A higher variance ratio indicates that the low-frequency long-term information variables have greater explanatory power for stock market volatility.

In Panel A, the variance ratios of geopolitical events are presented, and among the geopolitical events, GPA (74.3%) is the highest, followed by GPR (71.87%) and GPT (65.17%). Panel B presents the variance ratio of economic indicators. COCI (101.9%) is the highest, followed by EPU (71.87%), CICI (49.81%), and ENCI (65.17%). This result means that COCI is the most persuasive. In Panel C, we find that USDX (167.88%), DS (176), Sales (153.83%), and M2 (144.76%) provide a good indication of the volatility of the stock market.

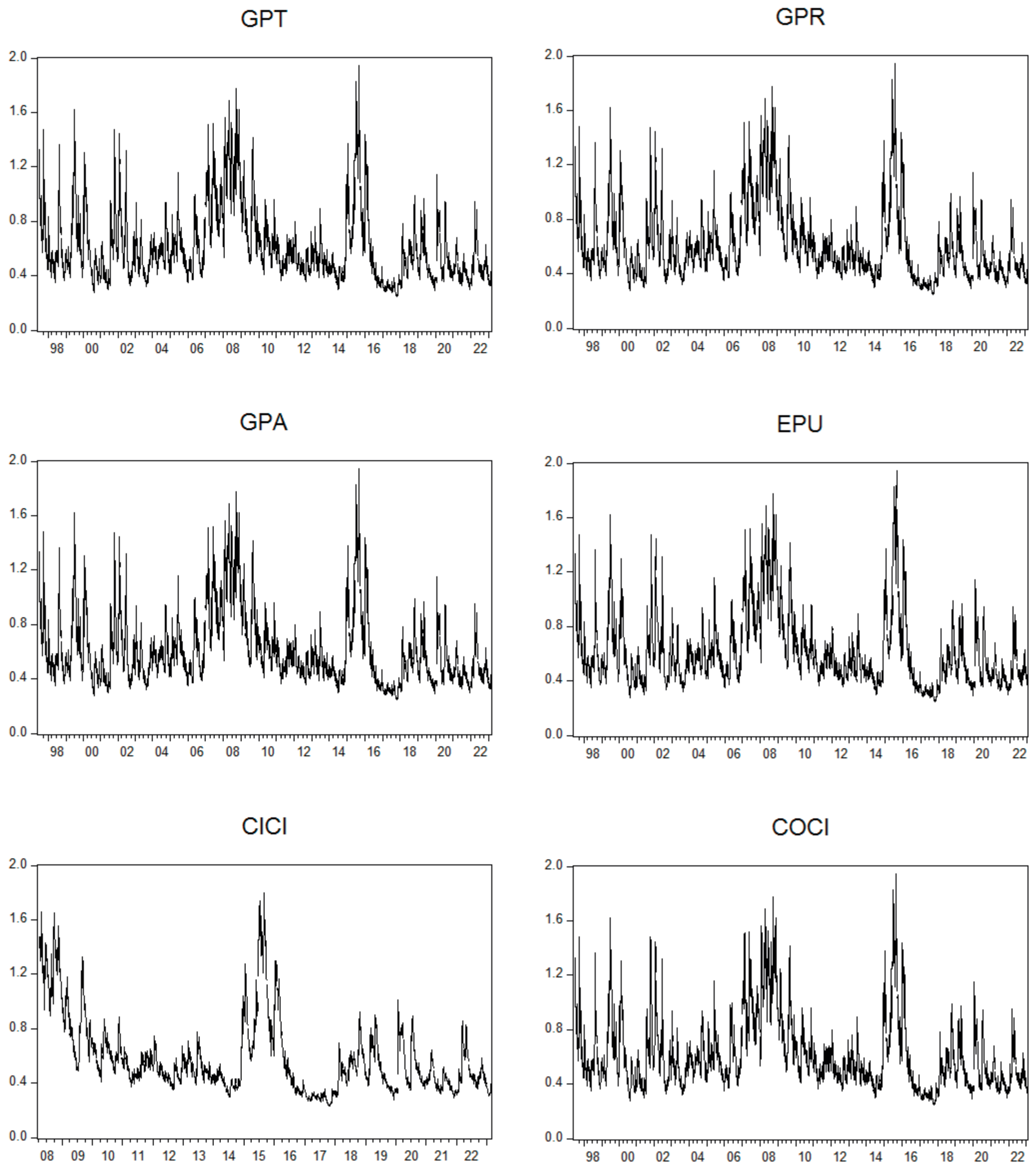
Table 5: Variance ratio, log-likelihood, and AIC of estimation results

	AIC	Variance ratio	Log-likelihood		AIC	Variance ratio	Log-likelihood
Panel A: geopolitical events				Panel B: economic indicators			
GPT	2.00	65.17	-6225.66	EPU	2.01	52.78	-6203.13
GPR	2.00	71.87	-6225.32	CICI	1.95	49.81	-3383.51
GPA	2.00	74.30	-6225.46	COCI	2.01	101.90	-6213.64
Panel C: financial factors				ENCI	1.82	36.06	-1852.43
USDX	2.05	167.88	-4276.12	IP	2.00	32.14	-6226.20
Housing starts	2.01	46.65	-6213.43	Sales	2.01	153.83	-5815.92
Default Spread	2.00	176.00	-6226.06	M2	2.00	144.76	-6226.11

As can be seen from these graphs, economic indicators, financial factors, and geopolitical events describe the trend of the overall volatility well. However, it can be seen that there are various phenomena according to the event information of each variable. Such a result implies that the stock market's volatility varies according to the characteristics of information variables of economic indicators, financial factors, and geopolitical events.

Based on the results, it can be concluded that geopolitical events, economic indicators, and financial factors affect stock price fluctuations through various channels, with USDX, Default Spread, Sales, and M2 having the highest descriptive values.

Upon closer examination, USDX, Default Spread, Sales, and M2's influence on stock price fluctuations appear consistent with findings from prior research (Fang, T., Lee, T. H., & Su, Z., 2020). As each geopolitical events, economic indicators, and financial factors have different information content. It is necessary to select economic indicators that reflect the current stock market well to speculate and predict stock price fluctuations. In other words, domestic macroeconomic conditions, geopolitical events, economic indicators, and financial factors must be considered to predict the stock market's volatility.



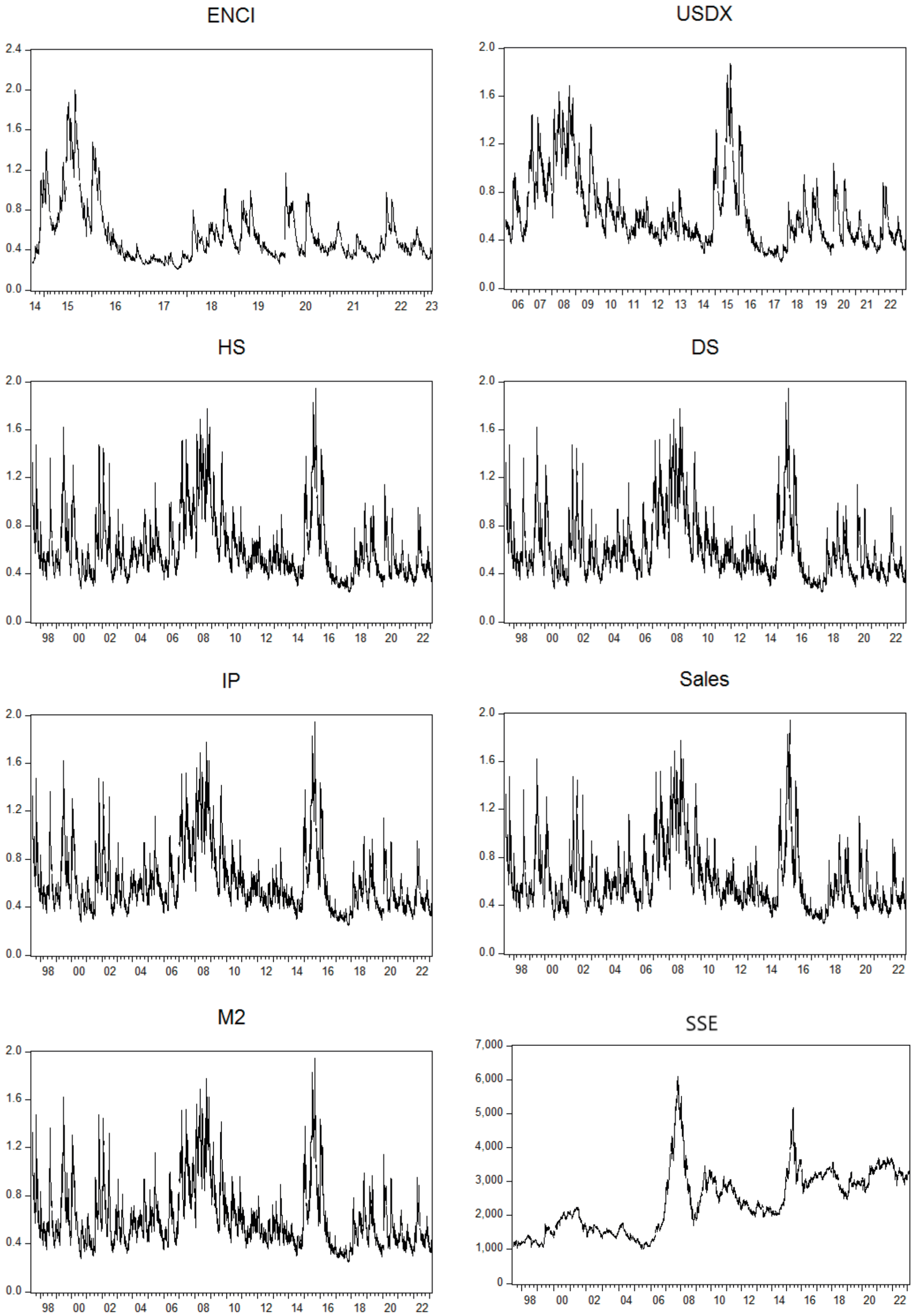


Figure 2: Conditional volatility estimated with geopolitical events, economic indicators, financial factors and SSE total volatility

Conclusions

Recent studies have focused on analyzing the impact of the real economy (macroeconomic variables) on the stock market's performance (Schwert, 1989; Huang, Kracaw, 1984; Kaul, 1987; Hamilton, J.D. Lin, 1996). However, recent research suggests that globalization and information and communication technology advancements are accelerating global economic integration. Therefore, in addition to economic indicators, financial factors and geopolitical events can also influence the stock market. This study employs the GARCH-MIDAS model to analyze the impact of economic indicators, financial factors, and geopolitical events on the volatility of the Chinese stock market. The main empirical results can be summarized as follows.

First, we will examine the impact of geopolitical events. Contrary to Mei et al.'s (2020) findings, a reduction in geopolitical risks is likely to increase the long-term volatility of SSE. In explaining stock market fluctuations, GPA has the highest predictive power, followed by GPR and GPT.

Second, our result is similar to the result of Kim Boo-kwon et al. (2021). Regarding the impact of economic indicators on SSE's overall volatility, EPU and ENCI have a significantly negative effect on SSE volatility, while CICI and COCI have a positive effect. Among them, COCI has the most substantial predictive power (101.9%) in explaining stock market fluctuations, followed by EPU (71.87%), ENCI (65.17%), and CICI (49.81%). IP, Sales, and M2 significantly impact SSE volatility. Specifically, IP has a positive effect, while Sales and M2 have a negative effect. Among them, Sales (153.83%) and M2 (144.76%) offer reasonable indications of stock market volatility.

Third, regarding the impact of financial factors on SSE's overall volatility, HS and DS have a positive effect, while USDX has a negative effect. USDX (167.88%) and DS (176%) provide good insights into stock market volatility. The result of Wang and Lv (2013) is also consistent with our result.

This study used geopolitical events, economic indicators, and financial factors to estimate and analyze the volatility of SSE. Using data with different frequencies, the GARCH-MIDAS model was applied to minimize information loss. The analysis results confirmed that information variables with different frequencies provide helpful information for explaining changes in the volatility of SSE. These findings suggest that the impact of geopolitical events, economic indicators, and financial factors on stock market volatility varies. Therefore, investors who want to manage stock investment risks and policymakers who want to maintain stock market stability must consider geopolitical events, economic indicators, and financial factors.

The significance of this study lies in its estimation of the impact of information variables on the volatility of SSE using geopolitical events, economic indicators, and financial factors that reflect current global economic conditions based on data with varying frequencies. However, since stock price volatility is influenced by various factors when combining two or more information variables, the resulting pattern will likely differ from the existing path. Furthermore, due to the significant influence of global economic conditions on the Chinese stock market, it is necessary to consider various factors such as BDI, stock prices of other countries, and comprehensive economic indices that accurately reflect global economic conditions, in addition to geopolitical events, economic indicators, and financial factors. In future research, we aim to incorporate a variety of indicators that reflect global economic conditions and analyze the impact of multiple information variables on stock price volatility using two variables GARCH-MIDAS analysis.

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