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Research on the Predictive Impact of Global Energy Instability on Chinese Stock Price Volatility of Different Sectors

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Abstract. In recent years, the global energy supply and demand contradiction has worsened sharply, the international energy price fluctuates frequently, and the global energy instability has become more and more serious under the influence of geopolitical conflicts, climate change, exchange rate fluctuations and other factors. Since energy is an asset with both commodity and financial attributes, rising uncertainty is bound to have an impact on financial markets. Therefore, it is of great significance to explore how global energy instability affects our stock market for the steady development of our financial market and the strategic layout of maintaining financial stability. The subject of this paper is the impact of global energy instability on the prediction of Chinese industrial stock price volatility. In this paper, we choose EUI (energy uncertainty index) which are constructed by Tam Hoang-nhat Dang et al., and 10 Shanghai Stock Exchange Index. Based on autoregressive (AR) model, a volatility forecasting model is established to explore EUI's ability to predict stock volatility both in-sample and out-of-sample. The results show that, firstly, when the prediction horizon is small, the prediction effect of EUI is not significant. And the longer the prediction horizon is, the more significant the prediction effect of EUI on volatility is. Secondly, global energy instability has a negative effect on the volatility of energy, health and utility sectors when the forecast horizon is large. Finally, in out-of-sample predictions one month in advance, EUI has a remarkable ability to predict fluctuations in information technology sector and communication services sector. The conclusion of this paper provides a new way to measure and forecast the fluctuation of stock price from the perspective of the sector.

Keywords: Energy uncertainty; Stock market volatility; Forecast.

1. Introduction

Energy is closely linked to the nation's economy and the lives of its people; it is a matter of paramount national importance that cannot be overlooked. The CPC Central Committee, with Comrade Xi Jinping at its core, has attached great importance to energy issues. Since the 18th National Congress of the Communist Party of China, General Secretary Xi Jinping has repeatedly issued important instructions on energy issues and put forward the new energy security strategy of "four revolutions and one cooperation." In the report to the 20th National Congress, he further emphasized the importance of "stability" that the underlying philosophy must remain stable, the process must proceed steadily, the resource base must remain secure, and the operational outcomes must be stable.

However, in the strategic assessments issued by the State Council in recent years, "uncertainty" has been mentioned repeatedly; national development has entered a period characterized by an increasing number of uncertain and unpredictable factors. Due to factors such as the COVID-19 pandemic, global primary energy consumption has fallen sharply, and major global energy companies have suffered substantial losses; oil companies have cut capital expenditures and implemented large-scale layoffs, while institutional investors have also begun to withdraw. By 2020, global energy investment and energy output had declined by 20% and 4%, respectively. Since 2021, as the economy has gradually recovered, energy demand has seen a certain degree of boost; however, the recovery of energy supply capacity has been subject to a time lag, causing the supply–demand gap to continue widening, and some regions have already experienced energy crises.

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Subsequently, the economic recovery drove oil prices upward, while the outbreak of the Russia–Ukraine conflict further intensified abnormal volatility in the energy market. As crude oil prices surged to $120 per barrel, European TTF natural gas futures prices reached record levels; diesel and gasoline prices even broke the usual pattern of moving in tandem. Typically, one gallon of diesel costs only $0.06 more than gasoline; however, in April 2022, the price difference between diesel and gasoline reached $2. As of the end of 2022, WTI closed at $80.51 per barrel, up 6.71% for the year.

Sudden geopolitical events, exemplified by the Ukraine crisis, have posed severe challenges to the energy security of countries around the world. In 2021, the European Union's demand for natural gas exceeded 80%, of which approximately 40% came from Russia; Russia's total volume of natural gas transported to Europe via pipelines was about 144 billion cubic meters. In February 2022, the Ukraine crisis broke out, prompting Russia to demand that certain countries pay for natural gas in rubles; in September, the Nord Stream pipelines were shut down following explosions and have not yet been restored, cutting off Russia's natural gas supplies to Europe. Prices for natural gas and other commodities surged sharply, further exacerbating inflation.

At present, tensions between oil-producing countries and developed economies are deepening; the conflict is gradually shifting from a singular geopolitical contest to a multifaceted contest among competing energy powers. Consequently, the global energy security landscape has become more complex, and global energy instability has become increasingly pronounced. Energy issues have been politicized, instrumentalized, and weaponized; bloc-based opposition has intensified; and uncertain events—such as economic and trade sanctions, energy supply disruptions, and damage to critical infrastructure—occur with increasing frequency [1]. Under the combined influence of multiple factors, including geopolitical conflicts, climate change, and exchange-rate fluctuations, the imbalance between global energy supply and demand has deteriorated sharply, and international energy prices have fluctuated violently. Energy issues have thus become one of the most significant and urgent challenges facing the development efforts of nations worldwide.

With the continuous development of financial products such as crude oil options and futures, the financial attributes of international energy have become increasingly prominent. Additionally, as China's dependence on foreign crude oil continues to rise, the Chinese stock market will also continue to be affected by fluctuations in international energy prices. Changes in international energy prices not only directly impact listed companies in energy-intensive industries but also transmit through investors' psychological and behavioral responses to the broader stock market and sector-specific stock markets.

2. Literature Review

2.1. Research on Global Energy Instability

The IEA (International Energy Agency), in its “World Energy Outlook 2022,” stated that the world is currently facing an unprecedentedly complex energy crisis that has had a profound impact on global markets, policy, and the economy. After the outbreak of the Russia–Ukraine war, Europe was the first to show signs of energy instability, triggering panic. With the frequent occurrence of “black swan” and “gray rhino” events, the world is in the greatest period of turbulence in a century, and the international energy market has become a key area of competition among various forces. It can be predicted that the occurrence of similar uncertainty events will become the norm in the future.

Energy prices, supply, and demand fluctuate frequently, and energy instability continues to rise. From a risk perspective, energy prices are affected by various factors such as the global macroeconomic situation, geopolitics, investor sentiment, and the climate environment, and in turn generate risk spillovers to these factors. The rise in energy instability has a huge impact on the global economy, changing many macroeconomic parameters, from inflation to consumption, from national income to the unemployment rate. Domestic and foreign scholars’ research on the impact of energy market fluctuations on the stock market is mainly based on the effect of oil price fluctuations on the

macroeconomy, forming the shock path of "oil price shock—economic output—stock market." Large fluctuations in oil prices often lead to turbulence in global stock markets and even cause systemic financial risks [2]. The rise in oil prices also reduces industrial output, and when facing specific demand shocks, the degree to which oil prices suppress the industrial sector is much higher than that of supply and demand shocks [3]. Although China's strong GDP and the adoption of delayed adjustment measures have weakened the negative effect of oil price fluctuations on China's macroeconomy to a certain extent, the negative effect of oil price shocks still exists after one year [4]. In environmental terms, risk events in domestic and foreign oil markets have a positive spillover effect on China's carbon market, and the risk spillover effect of foreign oil markets is greater [5].

Energy, as an asset with both commodity and financial attributes, will inevitably affect the real economy and financial markets when its instability rises, bringing greater market volatility to investors and decision-makers [6]. Therefore, how to measure energy instability is particularly important. Tam Hoang-Nhat Dang et al. [7] constructed the Energy-related Uncertainty Index (EUI) using text analysis of the country monthly reports of the Economist Intelligence Unit (EIU) for 28 developed and developing countries.

2.2. Research on the Predictability of Stock Market Volatility

The world is currently experiencing great changes unseen in a century. Facing various uncertainties, how to accurately predict the volatility of stock prices has become an urgent need for effective risk management and rational decision-making. Zhang Chi et al. [8] found short-term and long-term correlations among the recurrence intervals of fluctuations using the recurrence interval analysis method. When the stock market exhibits repeated fluctuations, how to predict them effectively becomes a noteworthy issue.

2.2.1. Internal Factors of Stock Volatility Predictability

As research has deepened, scholars have gradually discovered more volatility predictors. Gong Xu et al. [9], based on the HAR-family models with leverage effects and structural breaks, studied the strong predictive power of continuous volatility, downside volatility, upside volatility, realized volatility, leverage effects, and structural breaks for stock market fluctuations. Qu Hui and Shen Wei [10] introduced the HAR model into realized volatility and pointed out that the introduction of the nonlinearity of investor attention contributes significantly to volatility forecasting. However, the greatest advantage of the HAR-type models lies in effectively capturing heterogeneity, while they cannot well capture the long-memory characteristics that are very important in financial markets [11]. Zhu Qifeng and Wu Hengyu [12], based on the dynamic model averaging method and combined with heterogeneous market theory while considering the volume–price relationship of the market, established the DMA-LHAR-RV-T model, and through empirical research found that the volatility of the heterogeneous structure, positive and negative returns, and turnover rate all have significant impacts on future volatility.

2.2.2. External Uncertainty Factors of Stock Volatility Predictability

Economic, political, and environmental factors are closely linked and interact with each other. Research has found that economic policy uncertainty is affected by climate policy uncertainty, and the dynamic spillover pattern between the two changes over time in response to different economic events and financial crises [13]. Climate policy uncertainty is also a main reason for risk spillovers among energy markets [14], mainly manifesting as high-frequency spillovers, with time-varying characteristics and susceptibility to extreme sudden events [15]. The Economic Policy Uncertainty index (EPU) has an information spillover effect on crude oil price fluctuations and can predict its future volatility [16]. In recent years, the rise in uncertainty has prompted extensive research on the impact of uncertainty on stock market volatility.

In recent years, the world economy has faced a high degree of uncertainty. Qi Yue and Liao Kezhi [17], using the ICSS method, sorted out and classified the abrupt change points of China's stock

market volatility, and concluded that economic policy factors are an important cause of the abrupt change points. Economic policy can directly affect the stock market through the expectations and behaviors of market participants and can also indirectly affect the stock market through consumption and investment. Factors such as financial crises, international trade frictions, the pandemic, and geopolitics have posed severe challenges to the economic development of various countries, and many scholars have begun to study the impact of economic policy uncertainty on stock market volatility.

So, how should we measure the uncertainty of economic policy? Baker et al. [18] developed the Economic Policy Uncertainty index (EPU) for major global economies, Zhang Yifeng et al. [19] proposed a new herd-effect measurement index, and Huang et al. [20] used information from multiple local newspapers to construct China's Economic Policy Uncertainty index. Chen et al. [21] constructed an index based on news and concluded that China's economic policy uncertainty has a significant negative impact on the overall future returns of China's stock market. Yang Jianlei et al. [22], based on this, conducted text big-data analysis of China's newspaper news and constructed a news index (CEMV) that can better measure China's stock market volatility.

In addition, considering the difference in frequency between predictors and economic policy uncertainty data, the GARCH-MIDAS model can connect multi-frequency data and simultaneously capture volatility characteristics. Based on this model, Lei Likun et al. [23] argued that the EPU index has a strong explanatory power for the long-term volatility of the stock market and can significantly improve its predictive power for the volatility of the Shanghai Composite Index; Xia Ting and Wen Yuechun [24] focused on China's economic policy uncertainty (CEPU) and found that this factor has no obvious effect on China's A-share market, but has a significant effect on the long-term trend of the B-share market.

With the frequent occurrence of climate change and climate disasters, countries have introduced policies to address climate change to mitigate its impact on society and the economy. However, destructive disasters caused by the novel coronavirus, the US withdrawal from the Paris Agreement, the Russia–Ukraine conflict, and other events have greatly damaged the obligations of countries in addressing climate change and caused some changes in the implementation of climate policy [25], leading to a surge in climate policy uncertainty. This constantly changing climate policy uncertainty may affect the fluctuation of financial markets and asset prices [26,27], for example, exacerbating the price fluctuation of cryptocurrencies [28], adversely affecting the volatility of sovereign bonds [29], and having a favorable effect on green energy stocks [30].

Tedeschi [31], to approximate the inherent nonlinearity in the data, used a Bayesian time-varying parameter vector autoregression (TVP-VAR) model to depict the changes in European financial markets under climate policy uncertainty. As the world's second-largest stock market, China's stock market has also been confirmed to be widely affected by weather factors. Chen et al. [32], under the realized GARCH-MIDAS framework, verified that climate policy uncertainty has a significant spillover effect on the volatility of China's stock market. From a sector perspective, the climate policy uncertainty index has a greater impact on the energy, materials, industrials, discretionary consumer, health care, and utilities sectors [33]. From a temporal perspective, the impact of climate policy uncertainty on the stock market is positive in the short term, but in the long run it reduces future volatility and may lead to a decline in stock returns [34]. Specifically, low climate policy uncertainty has little impact on stock market returns, but higher climate policy uncertainty may prompt enterprises to delay investment, thereby bringing adverse effects to the financial market [35].

2.3. Research on the Impact of Energy Instability on Stock Market Volatility

With the continuous enrichment of energy derivatives and the deepening of energy financialization, many scholars have begun to study the correlation between energy markets and financial markets [36]. Research shows that crude oil prices have a one-way guiding effect on both the Shanghai and Shenzhen stock indices and returns [37]. During the outbreak of the novel coronavirus pandemic,

China's stock market was continuously subject to risk spillover shocks from the international crude oil market [38]. Based on the CC-MSV model, Zhu Huiming et al. [39] established a Bayesian dynamic correlation Wishart volatility model and found a strong correlation between the stock market and the crude oil market during financial crises, with difficulty in distinguishing positive and negative. From the perspective of extreme contagion behind the higher-order moments of return covariation, international crude oil prices have a significant impact on global stock markets, especially emerging stock markets [40]. Guo Na and Zhang Jun [41], using a time-varying regression analysis method, studied the volatility spillover relationship between China's three major energy markets (coal, oil, and natural gas) and China's A-share market, showing significant time-varying characteristics.

2.4. Literature Review Summary

Existing studies have explored many external factors to explain the future volatility of the stock market, such as crude oil prices, coal prices, and natural gas prices, but few have examined the predictive impact on stock volatility from the perspective of energy instability. Although a few studies have explored the impact of uncertainty indices such as economic policy uncertainty and climate policy uncertainty on stock price volatility, energy instability is significantly different from these uncertainty indices. For example, in terms of construction method, the energy instability index is not measured by the weighted average of multiple energy prices, but uses a text-search method; in terms of text source, the energy instability index does not use newspaper news, but is based on the country monthly reports of the Economist Intelligence Unit, making it comparable across different countries; from the perspective of correlation, energy instability, like other indices, focuses on the energy market, while other uncertainty indicators pay more attention to other aspects of the economy such as industrial production. In addition, some studies have discussed the linkage between crude oil markets and stock markets, but few have explained their impact on the securities market from the perspective of energy instability, especially from the sector perspective.

In summary, to explore the impact of energy instability on stock market volatility, this paper, based on the Energy Uncertainty Index (EUI) proposed by Tam Hoang-Nhat Dang et al. [7], and drawing on Lv and Li [33] to study China's stock market volatility from the sector perspective, conducts research around "the impact of global energy instability on the volatility of China's sector stock prices." From a theoretical perspective, compared with existing results, this paper studies the impact of energy instability on stock market volatility from the perspective of different sectors, attempts to understand market risk from a new angle, and provides new evidence for the existing literature on the predictability of stock price volatility. From a practical perspective, this paper provides some references for China to build an effective energy-related risk prevention mechanism and a theoretical basis for the scientific decision-making of investors in China's securities market.

3. Model Design for the Predictive Impact of Global Energy Instability on Stock Price Volatility

3.1. Variable Design and Data Processing

We use the Energy Uncertainty Index (EUI) proposed by Tam Hoang-Nhat Dang et al. [7] to measure global energy instability. This index uses text analysis of the country monthly reports of the Economist Intelligence Unit to construct the EUI, measuring the energy-market-related uncertainty of 28 developed and developing countries from 1996 to 2022. In addition, during the global financial crisis, the European debt crisis, the COVID-19 pandemic, and the Russian invasion of Ukraine, the EUI and other uncertainty measures surged. Further analysis confirmed that an increase in the EUI tends to hinder economic activity and output, not only at the national level but also at the industry level.

Compared with macro-level research based on market indicators, this study starts from sector data to better reflect the heterogeneity among different sectors and combines the different sensitivities of different sectors to oil prices, so as to better reveal the transmission path and impact mechanism of

energy instability shocks. We select ten representative Shanghai Stock Exchange series indices: the SSE Energy Index (Ener.), the SSE Materials Index (Mate.), the SSE Industrials Index (Indu.), the SSE Consumer Discretionary Index (DCons.), the SSE Consumer Staples Index (SCons.), the SSE Health Care Index (Heal.), the SSE Financials & Real Estate Index (Fina.), the SSE Information Technology Index (Info.), the SSE Communication Services Index (Comm.), and the SSE Utilities Index (Util.).

$$RV_t = \sum_{i=1}^{M_t} r_{t,i}^2 \tag{1}$$

According to the realized volatility formula (1), we square and sum the daily closing indices to obtain the monthly realized volatility. Among them, RV_t denotes the realized volatility of the t-th month, $r_{t,i}$ is the return on the i-th trading day of the t-th month, and M_t is the number of trading days in the t-th month. Table 1 presents the variable names of the realized volatilities for each sector index.

Table 1. Variable names of realized volatility for each sector index

Variable	Name
RVEner	Realized volatility of energy sector
RVMate	Realized volatility of materials sector
RVIndu	Realized volatility of industrials sector
RVDcons	Realized volatility of consumer discretionary sector
RVScons	Realized volatility of consumer staples sector
RVHeal	Realized volatility of health care sector
RVFina	Realized volatility of financials & real estate sector
RVInfo	Realized volatility of information technology sector
RVComm	Realized volatility of communication services sector
RVUtil	Realized volatility of utilities sector

To reduce the estimation error in the regression model, in the empirical analysis we refer to the data processing methods of Gong [42] and Wu Xinyu [43] et al., taking the logarithm of the realized volatility of the ten SSE sector indices and the global energy uncertainty index to obtain ln RV and ln EUI.

3.2. Model Specification for the Predictive Impact of Global Energy Instability on Stock Price Volatility

We refer to the studies of Lv and Li [33] and Yu [44], and based on the dynamic dependence of the volatility series, establish a standard first-order autoregressive model, AR(1), as the benchmark model to study the predictive power of historical volatility information for future volatility. Among them, h denotes the forecast horizon, and ε is an independently and identically distributed error term.

$$\ln RV_{t+h} = \alpha + \beta \ln RV_t + \varepsilon_{t+h} \tag{2}$$

To explore the predictive power of global energy instability for the stock realized volatility, we introduce the variable EUI into the benchmark model to study the predictive impact of the EUI on future volatility.

$$\ln RV_{t+h} = \alpha + \beta \ln RV_t + \gamma \ln EUI_t + \varepsilon_{t+h} \tag{3}$$

3.3. Prediction Mechanism and Evaluation Mechanism

The out-of-sample prediction in this paper adopts a fixed-window prediction mechanism. The sliding window is mainly realized by adding one sample and discarding one sample on the time series each time. Specifically, the total sample size T is divided into a training data set with an initial sample length L, namely T_1, T_2, ..., T_L, and the remaining data serve as the out-of-sample test set with length T−L. During the sliding-window prediction process, the sample size of the training data remains unchanged; each time one is added in the time dimension, one is subtracted. That is: the first time, T_1, T_2, ..., T_L data are used to fit the model and make predictions; the second time, T_2, T_3, ..., T_{L+1} data are used to fit the model and make predictions; and so on, finally obtaining the data over the entire sample.

To test the predictive impact of the EUI on the sector realized volatility, the evaluation mechanism selects the following three evaluation indicators:

Mean Squared Prediction Error:

$$MSE = \frac{1}{N}\sum_{t=M+1}^{T}(RV_t - R\hat{V}_{t,F})^2 \tag{4}$$

Mean Squared Percentage Error:

$$MSPE = \frac{1}{N}\sum_{t=M+1}^{T}\left(\frac{RV_t - R\hat{V}_{t,F}}{RV_t}\right)^2 \times 100\% \tag{5}$$

The out-of-sample R^2 proposed by Campbell and Thompson [45]:

$$R^2_{oos} = 1 - \frac{\sum_{t=M+1}^{T}(RV_t - R\hat{V}_{t,F})^2}{\sum_{t=M+1}^{T}(RV_t - R\hat{V}_{t,B})^2} \tag{6}$$

Among them, T is the length of the entire sample,M is the length of the in-sample period, N is the sample length of the prediction interval, RV_t denotes the actual value, $R\hat{V}_{t,F}$ is the volatility prediction of the competing model, and $R\hat{V}_{t,B}$ is the volatility prediction of the benchmark model.

4. Empirical Analysis of the Predictive Impact of Global Energy Instability on Stock Price Volatility

4.1. Sample Selection and Data Sources

This study uses the daily data of the SSE series indices and the monthly data of the Energy Uncertainty Index (EUI) developed by Tam Hoang-Nhat Dang et al. [7] as the data sample. Among them, the SSE series indices extracted from the CSMAR database cover the period from January 9, 2009, to October 31, 2022 (excluding holidays, etc., totaling 3,355 trading days). The EUI sample covers January 2009 to October 2022, totaling 166 monthly data points, sourced from the official website of the Policy Uncertainty index (www.policyuncertainty.com).

4.2. Descriptive Statistics

Table 2 presents the descriptive statistics of the realized volatility of the ten sector indices and the global uncertainty index. According to the mean, the information technology sector has the largest mean, 0.0085, and the utilities sector has the smallest mean, 0.0045; according to the maximum,

minimum, and standard deviation, the communication services, materials, industrials, and information technology sectors have a large gap between the upper and lower limits of the stock market volatility level, while the staples consumer and financials & real estate sectors fluctuate less; the skewness is all greater than 0, indicating right skewness, meaning that there are more stock market volatility levels below the average and very high volatility is rare; the kurtosis is all greater than 3, showing a leptokurtic distribution, indicating that the distribution of stock market volatility is relatively concentrated; according to the Jarque-Bera test, it can be judged that all variables do not follow a normal distribution. The unit root test shows that all variables reject the null hypothesis of a unit root, indicating that the data are stationary.

Table 2. Descriptive statistics

Variable	Mean	Max	Min	Std	Skewness	Kurtosis	ADF stat	JB stat
RVEner	0.0070	0.0407	0.0005	0.0070	2.4520	10.0600	-6.6250	507.6000
RVMate	0.0069	0.0653	0.0009	0.0080	4.0390	24.2100	-6.4110	3541.0000
RVIndu	0.0054	0.0636	0.0004	0.0074	4.7700	31.4700	-5.8430	6198.0000
RVDcons	0.0056	0.0430	0.0004	0.0062	3.5360	18.5100	-6.3740	1998.0000
RVScons	0.0054	0.0395	0.0009	0.0052	3.2740	17.2800	-7.1340	1697.0000
RVHeal	0.0059	0.0479	0.0004	0.0059	3.7640	22.2500	-6.5350	2938.0000
RVFina	0.0052	0.0369	0.0005	0.0055	2.9330	13.7000	-6.6850	1023.0000
RVInfo	0.0085	0.0488	0.0006	0.0074	2.6500	11.9800	-6.3260	747.1000
RVComm	0.0075	0.0641	0.0011	0.0087	4.1910	24.1300	-5.6450	3553.0000
RVUtil	0.0045	0.0494	0.0003	0.0065	3.7600	20.4200	-6.0400	2476.0000
EUI	22.6500	50.6600	9.4660	8.2100	0.8050	3.2830	-5.2730	18.3900

4.3. In-Sample Analysis

Using the entire sample period from January 2009 to October 2022, based on ordinary least squares (OLS) estimation, we estimate the parameters of Equation (3) with forward horizons h = 1, 3, 6, 9, 12, 15. Tables 3 to 9 report the estimation results of the volatility model. When h = 1, h = 3, and h = 6, the global energy instability has little explanatory power for the stock volatility of various sectors in China. Facing shocks in the international energy market, China is a large energy-consuming country; based on its energy resource endowment, it pays more attention to the autonomy and controllability of energy rather than relying solely on the international market to ensure energy security. In addition, our country is also a large energy producer. The import channels for crude oil and natural gas have become diversified, and there is a large proportion of long-term contracts, so imports can basically remain stable; at the same time, the country is actively promoting the high-quality development of renewable energy, and the rapid growth of clean energy has also become an effective means of hedging and mitigating external shocks.

Table 3. Estimation results of the volatility model (h = 1)

	γCoef.	Std. Err.	t	p
Energy	-0.1548	0.1567	-0.9900	0.3250
Materials	-0.0950	0.1406	-0.6800	0.5000
Industrials	0.0667	0.1435	0.4600	0.6430
Cons. Disc.	0.0425	0.1404	0.3000	0.7630
Cons. Staples	-0.0152	0.1362	-0.1100	0.9110
Health Care	-0.0148	0.1341	-0.1100	0.9120
Fin. & RE	-0.0263	0.1440	-0.1800	0.8550
Info. Tech	0.1650	0.1296	1.2700	0.2050
Comm. Serv.	0.1470	0.1330	1.1000	0.2710
Utilities	-0.0309	0.1611	-0.1900	0.8480

Table 4. Estimation results of the volatility model (h = 3)

Sector	γCoef.	Std. Err.	t	p
Energy	-0.2377	0.1753	-1.3600	0.1770
Materials	-0.2629	0.1701	-1.5500	0.1240
Industrials	0.0490	0.1684	0.2900	0.7710
Cons. Disc.	-0.0373	0.1690	-0.2200	0.8260
Cons. Staples	-0.0803	0.1542	-0.5200	0.6030
Health Care	-0.1415	0.1626	-0.8700	0.3850
Fin. & RE	-0.1326	0.1721	-0.7700	0.4420
Info. Tech	0.0065	0.1500	0.0400	0.9660
Comm. Serv.	0.0914	0.1539	0.5900	0.5540
Utilities	-0.0947	0.1900	-0.5000	0.6190

Table 5. Estimation results of the volatility model (h = 6)

Sector	γCoef.	Std. Err.	t	p
Energy	-0.2702	0.1779	-1.5200	0.1310
Materials	-0.1020	0.1690	-0.6000	0.5470
Industrials	-0.0765	0.1663	-0.4600	0.6460
Cons. Disc.	-0.0677	0.1745	-0.3900	0.6990
Cons. Staples	-0.0255	0.1566	-0.1600	0.8710
Health Care	-0.1557	0.1723	-0.9000	0.3670
Fin. & RE	-0.0619	0.1726	-0.3600	0.7200
Info. Tech	0.0345	0.1550	0.2200	0.8240
Comm. Serv.	0.0776	0.1602	0.4800	0.6290
Utilities	-0.1554	0.1991	-0.7800	0.4360

Table 6. Estimation results of the volatility model (h = 9)

Sector	γCoef.	Std. Err.	t	p
Energy	-0.4284**	0.1891	-2.2700	0.0250
Materials	-0.1724	0.1751	-0.9800	0.3260
Industrials	-0.1128	0.1777	-0.6300	0.5270
Cons. Disc.	-0.2343	0.1870	-1.2500	0.2120
Cons. Staples	-0.1224	0.1620	-0.7600	0.4510
Health Care	-0.3616*	0.1837	-1.9700	0.0510
Fin. & RE	-0.2279	0.1859	-1.2300	0.2220
Info. Tech	-0.0273	0.1614	-0.1700	0.8660
Comm. Serv.	-0.0796	0.1652	-0.4800	0.6310
Utilities	-0.3755*	0.2146	-1.7500	0.0820

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels respectively.

When h = 9, global energy instability has a significant negative impact on the volatility of the energy, health care, and utilities sectors. Changes in the global energy market have a great impact on China's energy supply; at present, several leading enterprises in China have long supplied energy to the European market, and under the background of energy shortages and rising energy prices, the status of these enterprises has become more stable. The health care and utilities sectors are at the final demand end; the shock of global energy instability has a significant impact on their stock market volatility, indicating that the impact path of the two is through the aggregate supply channel rather than the aggregate demand channel. When h = 12, the negative effect of global energy instability on the energy sector weakens, while the negative impact on the health care and utilities sectors deepens. When h = 15, global energy instability not only has a significant negative impact on the energy, health care, and utilities sectors, but also exerts a negative effect on the materials, industrials, discretionary

consumer, and financials & real estate sectors. Among them, the utilities, energy, and financials & real estate sectors are the most affected. The mechanism of global energy instability on the financials & real estate sector is different from other sectors: although the financials & real estate sector is not directly involved in the production and consumption of energy, it can be connected to the international energy market through lending to enterprises with oil price risk exposure, holding the bonds of these companies, speculative trading, and asset allocation in response to energy price fluctuations.

Table 7. Estimation results of the volatility model (h = 12)

Sector	γCoef.	Std. Err.	t	p
Energy	-0.3799*	0.1959	-1.9400	0.0540
Materials	-0.1648	0.1754	-0.9400	0.3490
Industrials	-0.1551	0.1810	-0.8600	0.3930
Cons. Disc.	-0.2541	0.1889	-1.3500	0.1810
Cons. Staples	-0.0097	0.1612	-0.0600	0.9520
Health Care	-0.4250**	0.1816	-2.3400	0.0210
Fin. & RE	-0.1865	0.1887	-0.9900	0.3250
Info. Tech	-0.0297	0.1599	-0.1900	0.8530
Comm. Serv.	-0.0723	0.1651	-0.4400	0.6620
Utilities	-0.4708**	0.2216	-2.1200	0.0350

Table 8. Estimation results of the volatility model (h = 15)

Sector	γCoef.	Std. Err.	t	p
Energy	-0.5531***	0.1957	-2.8300	0.0050
Materials	-0.4472**	0.1728	-2.5900	0.0110
Industrials	-0.3481*	0.1824	-1.9100	0.0580
Cons. Disc.	-0.4470**	0.1878	-2.3800	0.0190
Cons. Staples	-0.0260	0.1584	-0.1600	0.8700
Health Care	-0.4611***	0.1765	-2.6100	0.0100
Fin. & RE	-0.5425***	0.1862	-2.9100	0.0040
Info. Tech	-0.0830	0.1592	-0.5200	0.6030
Comm. Serv.	-0.1698	0.1647	-1.0300	0.3040
Utilities	-0.6582***	0.2222	-2.9600	0.0040

4.4. Out-of-Sample Analysis

To study the out-of-sample prediction of global energy instability on China's stock market volatility, we use the rolling-window estimation method for out-of-sample prediction. In the time dimension, the estimation window is rolled forward by adding a new sample while reducing an initial sample each time, so as to ensure a fixed sample size for estimating the model parameters. The sample is divided into two parts: in-sample and out-of-sample. From January 2009 to December 2012, a total of 48 months, is the in-sample period, and from January 2013 to October 2022 is the out-of-sample period.

Table 9 shows the out-of-sample prediction results of global energy instability on the realized volatility of stock market sectors, measured by two heteroscedasticity-adjusted loss functions, MSE and MSPE, to measure the difference between the competing model and the benchmark model. It is found that the R^2_oos statistic ranges from 1.3229% to −3.6004%. Except for the information technology and communication services sectors, all out-of-sample R^2_oos statistics are negative. The communication services sector has the largest R^2_oos statistic. The results show that the EUI has a significant predictive ability for the volatility of the information technology and communication services sectors.

Table 9. Out-of-sample prediction of the volatility model (h = 1)

Sector	MSE	MSPE	R^2oos (%)
Energy	0.6137	0.0203	-2.4370
Materials	0.4719	0.0167	-3.6004
Industrials	0.4806	0.0158	-1.3283
Cons. Disc.	0.4256	0.0142	-2.8019
Cons. Staples	0.4363	0.0141	-1.9631
Health Care	0.3899	0.0131	-3.0391
Fin. & RE	0.4993	0.0160	-1.5870
Info. Tech	0.3492	0.0137	0.9362
Comm. Serv.	0.4028	0.0159	1.3229
Utilities	0.6222	0.0167	-2.5210

4.5. Robustness Tests

4.5.1. Winsorization

Since global energy stability is highly susceptible to extreme events, geopolitical and other sudden events, and simple linear regression models have difficulty capturing such structural breaks, this section studies whether the above conclusions are robust through outlier treatment. Specifically, we winsorize all variable data at the upper and lower 1% to replace the original values, replacing values above the 99th percentile with the 99th percentile and values below the 1st percentile with the 1st percentile. The results are shown in Tables 10 to 15, and the in-sample conclusions still hold. When the forecast horizon h is less than 6 months, global energy instability has no obvious impact on the volatility of various sectors. When h = 9 and h = 12, global energy instability has a significant negative effect on the energy, health care, and utilities sectors. When h = 15, global energy instability has a significant negative impact on the energy, health care, materials, industrials, discretionary consumer, and financials & real estate sectors, among which the utilities, energy, and financials & real estate sectors are the most affected.

Table 10. Winsorized results (h = 1)

Sector	γCoef.	Std. Err.	t	p
Energy	-0.1607	0.1572	-1.0200	0.3080
Materials	-0.1078	0.1411	-0.7600	0.4460
Industrials	0.0642	0.1430	0.4500	0.6540
Cons. Disc.	0.0379	0.1416	0.2700	0.7890
Cons. Staples	-0.0247	0.1369	-0.1800	0.8570
Health Care	-0.0297	0.1348	-0.2200	0.8260
Fin. & RE	-0.0348	0.1448	-0.2400	0.8100
Info. Tech	0.1678	0.1297	1.2900	0.1980
Comm. Serv.	0.1551	0.1339	1.1600	0.2480
Utilities	-0.0406	0.1620	-0.2500	0.8030

Table 11. Winsorized results (h = 3)

Sector	γCoef.	Std. Err.	t	p
Energy	-0.2518	0.1759	-1.4300	0.1540
Materials	-0.2833	0.1698	-1.6700	0.0970
Industrials	0.0328	0.1673	0.2000	0.8450
Cons. Disc.	-0.0498	0.1704	-0.2900	0.7700
Cons. Staples	-0.1006	0.1541	-0.6500	0.5150
Health Care	-0.1616	0.1626	-0.9900	0.3220
Fin. & RE	-0.1406	0.1730	-0.8100	0.4170
Info. Tech	-0.0014	0.1501	-0.0100	0.9930
Comm. Serv.	0.0872	0.1550	0.5600	0.5750
Utilities	-0.1207	0.1900	-0.6400	0.5260

Table 12. Winsorized results (h = 6)

Sector	γCoef.	Std. Err.	t	p
Energy	-0.2909	0.1785	-1.6300	0.1050
Materials	-0.1387	0.1690	-0.8200	0.4130
Industrials	-0.0967	0.1651	-0.5900	0.5590
Cons. Disc.	-0.0875	0.1760	-0.5000	0.6200
Cons. Staples	-0.0556	0.1567	-0.3500	0.7230
Health Care	-0.1903	0.1724	-1.1000	0.2710
Fin. & RE	-0.0778	0.1735	-0.4500	0.6540
Info. Tech	0.0253	0.1547	0.1600	0.8700
Comm. Serv.	0.0679	0.1611	0.4200	0.6740
Utilities	-0.1884	0.1996	-0.9400	0.3470

Table 13. Winsorized results (h = 9)

Sector	γCoef.	Std. Err.	t	p
Energy	-0.4419**	0.1897	-2.3300	0.0210
Materials	-0.1734	0.1747	-0.9900	0.3230
Industrials	-0.1043	0.1759	-0.5900	0.5540
Cons. Disc.	-0.2432	0.1885	-1.2900	0.1990
Cons. Staples	-0.1220	0.1620	-0.7500	0.4520
Health Care	-0.3688**	0.1838	-2.0100	0.0470
Fin. & RE	-0.2347	0.1871	-1.2500	0.2120
Info. Tech	-0.0329	0.1609	-0.2000	0.8380
Comm. Serv.	-0.0843	0.1660	-0.5100	0.6120
Utilities	-0.3777*	0.2145	-1.7600	0.0800

Table 14. Winsorized results (h = 12)

Sector	γCoef.	Std. Err.	t	p
Energy	-0.3909**	0.1967	-1.9900	0.0490
Materials	-0.1709	0.1750	-0.9800	0.3300
Industrials	-0.1634	0.1792	-0.9100	0.3630
Cons. Disc.	-0.2628	0.1904	-1.3800	0.1700
Cons. Staples	-0.0138	0.1611	-0.0900	0.9320
Health Care	-0.4351**	0.1818	-2.3900	0.0180
Fin. & RE	-0.1919	0.1899	-1.0100	0.3140
Info. Tech	-0.0232	0.1594	-0.1500	0.8840
Comm. Serv.	-0.0706	0.1660	-0.4300	0.6710
Utilities	-0.4818**	0.2216	-2.1700	0.0310

Table 15. Winsorized results (h = 15)

Sector	γCoef.	Std. Err.	t	p
Energy	-0.5680***	0.1963	-2.8900	0.0040
Materials	-0.4498**	0.1726	-2.6100	0.0100
Industrials	-0.3506*	0.1805	-1.9400	0.0540
Cons. Disc.	-0.4562**	0.1893	-2.4100	0.0170
Cons. Staples	-0.0246	0.1582	-0.1600	0.8770
Health Care	-0.4640**	0.1769	-2.6200	0.0100
Fin. & RE	-0.5442***	0.1873	-2.9000	0.0040
Info. Tech	-0.0839	0.1586	-0.5300	0.5980
Comm. Serv.	-0.1782	0.1655	-1.0800	0.2840
Utilities	-0.6676***	0.2223	-3.0000	0.0030

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.5.2. Performance across Different Sample Periods

A large amount of research shows that the predictability of stocks changes over time, so this section studies the performance of the above conclusions in different periods. The outbreak of the COVID-19 pandemic has seriously affected the economy, politics, and social life of countries around the world in many aspects. The stock market was the first to be hit: on the first trading day after the 2020 Spring Festival, the domestic A-share market saw thousands of stocks hit the limit-down, and financial risks spread and infected each other worldwide. Referring to the definition of the COVID-19 pandemic by Lv and Li [33] and Chen Yun [46] et al., we divide the sample interval with January 2020 as the node. Tables 16 to 21 show the in-sample regression results of global energy instability on various sectors before and after the COVID-19 pandemic. It can be seen that in the short term, before the outbreak of COVID-19, global energy instability had no significant impact on all sectors; after the outbreak of COVID-19, it had a significant impact on a few specific sectors. As the forecast horizon increases, before the pandemic, global energy instability had a significant negative impact on the volatility of the energy and health care sectors; when the forecast horizon was 15 months, global energy instability had a significant negative effect on the volatility of the energy, health care, utilities, materials, industrials, discretionary consumer, and financials & real estate sectors, especially the utilities, energy, and financials & real estate sectors, and after the pandemic, the impact on the utilities sector remained significant.

Table 16. In-sample results before and after COVID-19 (h = 1)

Sector	Pre γCoef.	Pre Std.Err.	Pre t	Pre p	Post γCoef.	Post Std.Err.	Post t	Post p
Energy	-0.1592	0.1702	-0.9400	0.3510	-0.2230	0.3909	-0.5700	0.5730
Materials	-0.1106	0.1503	-0.7400	0.4630	-0.0487	0.3421	-0.1400	0.8880
Industrials	0.0533	0.1565	0.3400	0.7340	0.1713	0.3282	0.5200	0.6050
Cons.Disc.	-0.0231	0.1566	-0.1500	0.8830	0.5008	0.3023	1.6600	0.1080
Cons.Staples	-0.0642	0.1547	-0.4200	0.6790	0.1148	0.2678	0.4300	0.6710
Health Care	-0.0618	0.1547	-0.4000	0.6900	0.1315	0.2430	0.5400	0.5920
Fin. & RE	-0.0253	0.1585	-0.1600	0.8740	0.0914	0.3087	0.3000	0.7690
Info. Tech	0.0833	0.1475	0.5600	0.5730	0.9472***	0.2774	3.4100	0.0020
Comm.Serv.	0.0813	0.1477	0.5500	0.5830	0.9443**	0.3534	2.6700	0.0120
Utilities	0.0044	0.1689	0.0300	0.9790	-0.2198	0.4355	-0.5000	0.6180

Table 17. In-sample results before and after COVID-19 (h = 3)

Sector	Pre γCoef.	Pre Std.Err.	Pre t	Pre p	Post γCoef.	Post Std.Err.	Post t	Post p
Energy	-0.1616	0.1948	-0.8300	0.4080	-0.6596	0.4006	-1.6500	0.1110
Materials	-0.1854	0.1928	-0.9600	0.3380	-0.5805*	0.2911	-1.9900	0.0560
Industrials	0.1310	0.1892	0.6900	0.4900	-0.1841	0.2699	-0.6800	0.5010
Cons.Disc.	-0.0499	0.1947	-0.2600	0.7980	0.3098	0.2873	1.0800	0.2900
Cons.Staples	-0.0663	0.1772	-0.3700	0.7090	-0.2027	0.2411	-0.8400	0.4070
Health Care	-0.1851	0.1878	-0.9900	0.3260	0.0045	0.2304	0.0200	0.9850
Fin. & RE	-0.1644	0.1943	-0.8500	0.3990	0.2035	0.2477	0.8200	0.4180
Info. Tech	0.0119	0.1753	0.0700	0.9460	0.4646	0.2825	1.6400	0.1110
Comm.Serv.	0.1244	0.1743	0.7100	0.4770	0.4764	0.3484	1.3700	0.1820
Utilities	0.0323	0.2037	0.1600	0.8740	-0.6725	0.4680	-1.4400	0.1620

Table 18. In-sample results before and after COVID-19 (h = 6)

Sector	Pre γCoef.	Pre Std.Err.	Pre t	Pre p	Post γCoef.	Post Std.Err.	Post t	Post p
Energy	-0.1066	0.1990	-0.5400	0.5930	-1.1334***	0.3186	-3.5600	0.0020
Materials	-0.0616	0.1958	-0.3100	0.7540	-0.3076	0.3077	-1.0000	0.3270

Industrials	-0.0372	0.1959	-0.1900	0.8500	-0.2322	0.2677	-0.8700	0.3940
Cons.Disc.	-0.1339	0.2026	-0.6600	0.5100	0.3893	0.2923	1.3300	0.1950
Cons.Staples	-0.0736	0.1820	-0.4000	0.6870	0.0548	0.2687	0.2000	0.8400
Health Care	-0.2086	0.2030	-1.0300	0.3060	-0.0508	0.2557	-0.2000	0.8440
Fin. & RE	-0.0445	0.2021	-0.2200	0.8260	-0.0475	0.2826	-0.1700	0.8680
Info. Tech	0.1066	0.1805	0.5900	0.5560	0.0930	0.3018	0.3100	0.7600
Comm.Serv.	0.2263	0.1786	1.2700	0.2070	-0.1211	0.3577	-0.3400	0.7380
Utilities	-0.0403	0.2235	-0.1800	0.8570	-0.7442*	0.4074	-1.8300	0.0800

Table 19. In-sample results before and after COVID-19 (h = 9)

Sector	Pre γCoef.	Pre Std.Err.	Pre t	Pre p	Post γCoef.	Post Std.Err.	Post t	Post p
Energy	-0.4158**	0.2071	-2.0100	0.0470	-0.4158**	0.2071	-2.0100	0.0470
Materials	-0.2953	0.1981	-1.4900	0.1380	-0.2953	0.1981	-1.4900	0.1380
Industrials	-0.1653	0.2051	-0.8100	0.4220	-0.1653	0.2051	-0.8100	0.4220
Cons.Disc.	-0.3619*	0.2161	-1.6700	0.0970	-0.3619*	0.2161	-1.6700	0.0970
Cons.Staples	-0.2151	0.1830	-1.1700	0.2420	-0.2151	0.1830	-1.1700	0.2420
Health Care	-0.4287**	0.2115	-2.0300	0.0450	-0.4287**	0.2115	-2.0300	0.0450
Fin. & RE	-0.3040	0.2168	-1.4000	0.1630	-0.3040	0.2168	-1.4000	0.1630
Info. Tech	-0.0107	0.1876	-0.0600	0.9550	-0.0107	0.1876	-0.0600	0.9550
Comm.Serv.	-0.0440	0.1841	-0.2400	0.8120	-0.0440	0.1841	-0.2400	0.8120
Utilities	-0.2705	0.2366	-1.1400	0.2550	-0.2705	0.2366	-1.1400	0.2550

Table 20. In-sample results before and after COVID-19 (h = 12)

Sector	Pre γCoef.	Pre Std.Err.	Pre t	Pre p	Post γCoef.	Post Std.Err.	Post t	Post p
Energy	-0.3602*	0.2132	-1.6900	0.0930	-0.7076*	0.3413	-2.0700	0.0520
Materials	-0.3046	0.1957	-1.5600	0.1220	0.6463*	0.3267	1.9800	0.0630
Industrials	-0.1494	0.2080	-0.7200	0.4740	-0.1484	0.2823	-0.5300	0.6050
Cons.Disc.	-0.3524	0.2159	-1.6300	0.1050	0.1303	0.3203	0.4100	0.6890
Cons.Staples	-0.0598	0.1778	-0.3400	0.7370	0.2238	0.3117	0.7200	0.4810
Health Care	-0.5123**	0.2032	-2.5200	0.0130	-0.0338	0.2559	-0.1300	0.8960
Fin. & RE	-0.2263	0.2184	-1.0400	0.3020	0.0132	0.2430	0.0500	0.9570
Info. Tech	-0.0039	0.1835	-0.0200	0.9830	-0.4011	0.3209	-1.2500	0.2270
Comm.Serv.	-0.0168	0.1814	-0.0900	0.9260	-0.7298**	0.3057	-2.3900	0.0280
Utilities	-0.3521	0.2437	-1.4400	0.1510	-1.0386**	0.4613	-2.2500	0.0360

Table 21. In-sample results before and after COVID-19 (h = 15)

Sector	Pre γCoef.	Pre Std.Err.	Pre t	Pre p	Post γCoef.	Post Std.Err.	Post t	Post p
Energy	-0.6415***	0.2083	-3.0800	0.0030	-0.1868	0.3892	-0.4800	0.6380
Materials	-0.5803***	0.1915	-3.0300	0.0030	0.3894	0.3464	1.1200	0.2780
Industrials	-0.3654*	0.2074	-1.7600	0.0800	-0.2462	0.2955	-0.8300	0.4170
Cons.Disc.	-0.4880**	0.2123	-2.3000	0.0230	-0.2586	0.3457	-0.7500	0.4650
Cons.Staples	-0.0811	0.1742	-0.4700	0.6420	0.1499	0.3315	0.4500	0.6570
Health Care	-0.5856***	0.1936	-3.0200	0.0030	0.0226	0.3136	0.0700	0.9430
Fin. & RE	-0.6287***	0.2098	-3.0000	0.0030	0.0409	0.2940	0.1400	0.8910
Info. Tech	-0.0940	0.1788	-0.5300	0.6000	-0.2436	0.3656	-0.6700	0.5150
Comm.Serv.	-0.1621	0.1793	-0.9000	0.3680	0.0228	0.3777	0.0600	0.9530
Utilities	-0.6226**	0.2414	-2.5800	0.0110	-1.1119**	0.4769	-2.3300	0.0330

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels respectively.

5. Conclusion

This paper, based on the stock volatility of different sectors, explores whether the global energy uncertainty index EUI helps predict stock market volatility. Based on the autoregressive (AR) model, this paper constructs a volatility forecasting model and applies it to analyze the impact of energy instability on the volatility of China's sector stock prices. Based on monthly data from 2009 to 2022, this paper selects ten sector indices released by the Shanghai Stock Exchange as sector data and chooses the energy-related uncertainty index EUI, constructed based on text analysis, as a proxy variable for energy instability. Using the standard first-order autoregressive AR (1) model as the benchmark model, it represents the impact of realized volatility on China's stock price volatility. Second, based on the full sample, it analyzes the impact of energy instability on sector volatility and compares the results of different forecast horizons. Then, it divides the sample into in-sample and out-of-sample parts to test the predictability of energy instability for the volatility of different sectors. Finally, it conducts robustness tests on the conclusions of the in-sample analysis, passing the winsorization treatment and the test of different sample periods.

The research conclusions are as follows: First, in in-sample predictions, when the forecast horizon is short, the predictive effect is not significant, and the longer the forecast horizon, the more significant the EUI's predictive effect on volatility becomes. Second, when the forecast horizon is 9 and 12 months, global energy instability has a significant negative impact on the volatility of the energy, health care, and utilities sectors; when the forecast horizon is 15 months, global energy instability has a significant negative impact on the energy, health care, utilities, materials, industrials, discretionary consumer, and financials & real estate sectors, and the impact on the utilities, energy, and financials & real estate sectors is the most pronounced. Third, in the one-month-ahead out-of-sample prediction, the EUI has a significant predictive ability for the volatility of the information technology and communication services sectors.

This paper hopes that the above research will provide new perspectives and ideas for scholars to measure and predict stock price volatility, provide a reference for investors to allocate funds, and at the same time conform to the national energy security policy, providing more empirical evidence for China's stock market to cope with the risks brought by shocks from the international energy market, so as to promote the steady development of China's financial market. In addition, this paper has not yet compared with other energy-related indicators, and we look forward to scholars conducting more in-depth research in this direction.

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