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Economic Policy Uncertainty and Volatility Forecasting in China's Stock Market

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Abstract

This paper develops the GARCH-MIDAS-RV-EPU model, which integrates high-frequency realized volatility, low-frequency macro indicators and the exogenous Chinese Economic Policy Uncertainty (EPU) index to predict China's stock market volatility. Using 5-minute high-frequency data of the Shanghai Composite Index (SSEC) and the Shenzhen Component Index (SZSEC), we find that the proposed model outperforms alternative specifications in return fitting and volatility description. With robust loss functions as evaluation criteria, we compare the out-of-sample volatility forecasting performance of all models. The empirical results show that incorporating high-frequency, low-frequency and EPU information significantly boosts volatility predictability, and our model exhibits the strongest forecasting power among all competing specifications.

Keywords

Volatility Forecasting; Realized Volatility; Economic Policy Uncertainty; Mixed-Frequency Data Sampling.

1. Introduction

China's A-share stock market acts as a core platform for channeling funds to the real economy and facilitating direct financing. As a pivotal metric for gauging market risk, stock volatility plays an indispensable role in asset allocation, risk management and derivatives pricing. In recent years, China has witnessed frequent adjustments to fiscal, monetary, trade and industrial regulatory policies, resulting in persistent economic policy uncertainty that continuously disturbs A-share markets. Synchronous surges in the Economic Policy Uncertainty (EPU) index and stock volatility were observed during major turbulent episodes, including the 2008 global financial crisis, the violent stock market swings in 2015, and the COVID-19 outbreak in 2020. Against this backdrop, identifying how economic policy uncertainty drives volatility in the Shanghai and Shenzhen stock markets and developing volatility forecasting models with superior predictive power carries profound theoretical and practical implications for investors' risk hedging and regulators' efforts to stabilize capital markets.

Extensive literature has devoted itself to modeling stock market volatility. Engle (1982)[1] pioneered the ARCH model, which first captures the volatility clustering property of financial returns. Building on this foundation, Bollerslev (1986)[2] proposed the GARCH specification to substantially ease the complexity of parameter estimation. Later, Nelson (1991)[3] constructed the EGARCH model to characterize the asymmetric leverage effect embedded in stock volatility. Domestic scholars Pi (2003)[4] and Li et al. (2003)[5] verified using the Shanghai Composite Index that China's A-shares exhibit prominent volatility clustering and heteroskedasticity, and GARCH-type models can adequately reproduce fundamental volatility patterns of domestic equities. Nevertheless, conventional GARCH and EGARCH frameworks only accommodate single-frequency datasets. While stock returns are sampled at daily high frequency, macro policy indicators are mostly released monthly at low frequencies. Forcing daily stock data to

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match monthly frequency eliminates substantial intraday trading information and introduces biases in volatility estimation (Ghysels et al., 2007)[6].

To address the challenge of simultaneous modeling across mixed-frequency data, Engle et al. (2013)[7] integrated MIDAS (Mixed Data Sampling) techniques into the GARCH framework and developed the GARCH-MIDAS model. This model decomposes conditional variance into two multiplicative components: a short-run high-frequency volatility component and a long-run macroeconomic volatility component, allowing daily returns and monthly macro indicators to be jointly modeled without artificial frequency compression. Zheng and Shang (2014)[8] were the first to apply the GARCH-MIDAS framework to China's stock market, proving that macroeconomic fundamentals exert material long-run impacts on equity volatility and laying groundwork for subsequent mixed-frequency research on policy uncertainty. Lei et al. (2018)[9] and Xia & Wen (2018)[10] further incorporated the EPU index into GARCH-MIDAS specifications and confirmed EPU as a core macro driver of long-term A-share volatility. However, existing studies merely insert monthly EPU values into the long-run component while ignoring rich volatility information embedded in intraday high-frequency realized volatility (RV).

Economic policy uncertainty cannot be directly quantified. To resolve this issue, Baker et al. (2016)[11] constructed global EPU indices via news textual retrieval. The China EPU index compiled based on the South China Morning Post reliably quantifies uncertainty stemming from domestic policy revisions and serves as a valid proxy variable for quantitative analysis. From a data perspective, realized volatility (RV) computed from 5-minute intraday prices encapsulates complete intraday price movement information and outperforms daily returns in capturing short-term market shocks. Most mainstream domestic GARCH-MIDAS-EPU models construct their short-run components solely from daily returns, discarding abundant micro transaction data and yielding clear deficiencies in model fitting and out-of-sample forecasting performance.

A review of extant literature reveals two prominent research gaps. First, prevailing domestic GARCH-MIDAS-EPU models adopt monthly EPU alone without incorporating intraday realized volatility (RV), making them unable to simultaneously incorporate intraday short-term volatility signals and long-run policy shocks. Second, traditional single-frequency GARCH variants and baseline GARCH-MIDAS models struggle to integrate high- and low-frequency data concurrently, leading to elevated out-of-sample forecast errors. Li (2020)[12] documented that embedding policy indicators within mixed-frequency structures improves volatility prediction using overseas market data; this logic extends to China's A-shares, yet mixed-frequency specifications that jointly incorporate both RV and EPU remain underdeveloped.

To fill these research voids, this paper selects the Shanghai Composite Index and Shenzhen Component Index as research subjects. We compute daily realized volatility (RV) using 5-minute high-frequency data spanning 2005 to 2023, and combine this series with monthly China EPU data to construct the GARCH-MIDAS-RV-EPU mixed-frequency volatility model. The short-run component of this model is captured via intraday RV to reflect transient market fluctuations, whereas the long-run component jointly accounts for realized volatility and economic policy uncertainty, thereby fully synthesizing high-frequency trading information and low-frequency policy signals. Empirical procedures commence with stationarity, normality and ARCH effect tests for all variables. Within-sample fitting performance is compared across competing models via log-likelihood, AIC and BIC criteria, while two robust loss functions (MSE and QLIKE) are adopted to quantify out-of-sample forecasting accuracy. Empirical results demonstrate that the proposed GARCH-MIDAS-RV-EPU model achieves superior in-sample fit and out-of-sample predictive capacity, furnishing a quantitative tool for A-share risk measurement and policy shock evaluation.

The remainder of the paper is organized as follows. Section 2 introduces the theoretical framework of volatility models, including the baseline GARCH, asymmetric EGARCH and standard GARCH-MIDAS specifications, and elaborates the construction, logarithmic likelihood

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estimation and loss function evaluation criteria of our newly proposed GARCH-MIDAS-RV-EPU model. Section 3 describes the data sources, variable definitions and a series of preliminary diagnostic tests such as descriptive statistics, ADF unit root test, normality test, ARCH effect test and Ljung-Box autocorrelation test for SSEC, SZSEC and China's EPU index. Section 4 reports the in-sample maximum likelihood estimation results of all competing models, compares their fitting performance via log-likelihood, AIC and BIC indicators, and further presents out-of-sample volatility forecasting results based on expanding rolling windows, together with corresponding loss function comparisons. Finally, Section 5 concludes the whole paper.

2. Model and Evaluation

2.1. Model Specification

2.1.1. GARCH Model

Bollerslev (1986)[2] proposed the generalized autoregressive conditional heteroskedasticity (GARCH) model. The model assumes that the conditional heteroskedasticity of financial asset returns is driven by two factors: the past mean of the error term and the past variance of the error term. Compared with the autoregressive conditional model (AR) proposed by Engle (1982)[1], the GARCH model avoids an excessive number of parameters and is more flexible. We adopt the GARCH(1,1) specification, let the asset log return be defined as $r_t = \log(P_t) - \log(P_{t-1})$, where P_t denotes the closing price on day t. The return and volatility equations are given in Equations (1) and (2).

$$r_t = \mu + a_t \quad a_t = \delta_t \varepsilon_t \quad \varepsilon_t \sim N(0,1) \tag{1}$$

$$\delta_t^2 = \omega + \alpha a_{t-1}^2 + \beta \delta_{t-1}^2 \tag{2}$$

where $\omega, \alpha, \beta > 0$; r_t denotes the asset return at time t; μ is the mean return, usually assumed to be zero; δ_t^2 is the conditional variance of asset returns at time t; and a_t is the innovation term.

2.1.2. EGARCH Model

To capture asymmetry between positive and negative shocks, that is, the asymmetric effect of positive and negative asset returns (the leverage effect), the EGARCH model, whose conditional variance can be written as Equation (3).

$$\log \delta_t^2 = \omega + \beta \log \delta_{t-1}^2 + \alpha(|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|) + \gamma \varepsilon_{t-1} \tag{3}$$

If $\gamma \neq 0$, there is volatility asymmetry; when $\gamma < 0$, negative shocks generate larger volatility than positive shocks of the same magnitude.

2.1.3. GARCH-MIDAS Model

When matching macroeconomic information with stock market volatility, existing approaches often reduce the frequency of stock market data and use monthly or quarterly observations to build the model because macroeconomic information is low-frequency and delayed. However, converting daily stock data into monthly or quarterly data discards useful high-frequency information, may bias parameter estimation and volatility forecasting, and cannot fully assess the overall impact of macroeconomic information on stock market volatility. Ghysels et al.[6]

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first introduced the mixed data sampling (MIDAS) framework to improve estimation across different sampling frequencies. Engle et al.[1] then incorporated MIDAS into the GARCH framework, evaluated the impact of macroeconomic conditions on stock market volatility, improved estimation efficiency, and separated the effects of economic uncertainty on different volatility components.

Drawing on Engle et al.[1], this paper extends the GARCH-MIDAS framework by including an exogenous variable to analyze the effect of economic policy uncertainty on stock market volatility. The return and volatility specifications are given in Equations (4) and (5).

$$r_{it} = u_t + \sqrt{\tau_t g_{it}}\varepsilon_t, \varepsilon_t \mid \Phi_{i-1,t} \sim N(0,1) \tag{4}$$

$$\delta_{it}^{\ 2} = \tau_t g_{i,t} \tag{5}$$

where $\Phi_{i-1,t}$ denotes the information set available on the (i-1)th day of month t. Volatility $\delta_{it}^{\ 2}$ is decomposed into a long-term trend τ_t and a short-term component, $g_{i,t}$ and the short-term component follows a GARCH(1,1) process as shown in Equation (6).

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t}-u)^2}{\tau_t} + \beta g_{i-1,t} \tag{6}$$

where α >0, β >0, $\alpha+\beta$ <1. The long-term trend is affected by realized volatility (RV) and the economic policy uncertainty indicator X; τ_t specific form is given in Equations (7) and (8).

$$\tau_t = m + \theta_1\sum_{k=1}^{K}\phi_{1k}(\omega_{11},\omega_{12})RV_{t-k} + \theta_2\sum_{k=1}^{K}\phi_{2k}(\omega_{21},\omega_{22})X_{t-k} \tag{7}$$

$$RV_t = \sum_{i=1}^{Nt} r_{it}^2 \tag{8}$$

where K is the maximum lag length of the low-frequency variable, and the coefficients θ_1, θ_2 represent the long-run effects of RV and X on volatility. $\phi_{1k}(\omega_1,\omega_2)$ is the Beta-type lag-weight function, as shown in Equation (9).

$$\phi_k(\omega_1,\omega_2) = \frac{(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K}(j/K)^{\omega_1-1}(1-j/K)^{\omega_2-1}} \tag{9}$$

To ensure that the lag weights decay over time, with observations closer to the current period exerting larger influence, $\omega_{11}=\omega_{12}=1$ is typically fixed, and the coefficients ω_{21} , ω_{22} determine the decay rate of the low-frequency effects on the high-frequency series. The Beta weighting function then simplifies to Equation (10).

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$$\phi_k(\omega_2) = \frac{(1-k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K}(1-j/K)^{\omega_2 - 1}} \tag{10}$$

Because this paper uses daily stock returns and monthly economic uncertainty data, we set the maximum lag length in the weighting function to K = 12 for computational convenience. $\phi_{1k}(\omega_1,\omega_2) \geq 0$ is the weighting function and satisfies $\sum_{k=1}^{K}\phi_k(\omega_1,\omega_2) = 1$.

Based on the return distribution and model specification, the required parameters are estimated by maximum likelihood, and the log-likelihood function is given in Equation (11).

$$\mathrm{LLF} = -\frac{1}{2}\sum_{t=1}^{T}\left[\log g_t(\Phi)\tau_t(\Phi) + \frac{(r_t-\mu)^2}{g_t(\Phi)\tau_t(\Phi)}\right] \tag{11}$$

2.2. Evaluating Volatility Forecasting Performance

This paper evaluates the volatility forecasting accuracy of the GARCH-MIDAS-(RV+EPU) model using loss functions. Specifically, we use two commonly employed loss functions in the literature to measure volatility forecasting errors: mean squared error (MSE) and quasi-likelihood loss (QLIKE). It is worth noting that both MSE and QLIKE are robust loss functions and can deliver consistent evaluations of volatility forecasts even when the volatility proxy is imperfect and contaminated by noise (Patton, 2011). The two loss functions are defined in Equations (12) and (13).

$$MSE: L_t(\delta_t^2, \hat{\delta}_t^2) = (\delta_t^2 - \hat{\delta}_t^2)^2 \tag{12}$$

$$QLIKE: L_t(\delta_t^2, \hat{\delta}_t^2) = \frac{\delta_t^2}{\hat{\delta}_t^2} + \log(\hat{\delta}_t^2) \tag{13}$$

where the δ_t^2 denotes the true volatility and the $\hat{\delta}_t^2$ denotes the forecast volatility.

3. Variable Selection and Data Analysis

3.1. Variable Selection

This paper empirically examines the roles of high-frequency information, economic policy uncertainty, and long memory in volatility forecasting for the Chinese stock market within the GARCH-MIDAS framework. The empirical sample consists of 5-minute high-frequency data for the Shanghai Composite Index (SSEC) and the Shenzhen Component Index (SZSEC). The sampling period runs from 4 January 2005 to 30 November 2023 and contains 4,595 trading days. The data are obtained from the Wind database. Daily log returns are computed from daily closing prices. Daily RV is computed from 5-minute intraday prices and is used as the realized measure in the model.

The macroeconomic factor affecting stock market volatility is economic policy uncertainty. In this paper, the economic policy uncertainty (EPU) index is used as a proxy variable. Following the method of Baker et al.[11], the Stanford University and the University of Chicago jointly

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release the EPU index to measure economic policy uncertainty in a country or region. The index is constructed using text analysis and covers three dimensions. Its underlying logic is that economic policy uncertainty is positively related to the frequency of news articles discussing the economy, policy, and uncertainty; when uncertainty is greater, related news coverage becomes more frequent. A higher EPU index indicates higher economic policy uncertainty in the corresponding month. For China, the EPU index is built using the South China Morning Post, an English-language newspaper with the largest circulation and strongest influence in Hong Kong, as the search platform. Articles related to economic policy uncertainty are identified using a content-filtering procedure, and the resulting monthly index is obtained after aggregation and standardization.

3.2. Data Analysis

Table 1 reports the descriptive statistics of daily log returns, RV, and the Chinese EPU index for SSEC and SZSEC. As shown in Table 1, the mean returns of both indices are positive but statistically insignificant. Their skewness is negative and kurtosis exceeds 3, indicating negatively skewed, leptokurtic, and heavy-tailed return distributions. The Jarque-Bera statistics strongly reject the hypothesis of normality for both return series. By contrast, the RV series of both indices display positive skewness and kurtosis far above 3, again implying a positively skewed, leptokurtic distribution, and the Jarque-Bera statistics also reject normality. Comparing RV and log-RV, the latter has skewness closer to zero and kurtosis closer to 3; accordingly, log-RV is closer to normality than RV, and its Jarque-Bera statistic is markedly smaller. The ARCH effect test shows pronounced volatility clustering in the return, RV, and log-RV series. The Ljung-Box Q statistics indicate that the volatility of SSEC and SZSEC exhibits clear autocorrelation. In addition, the ADF test strongly rejects the null hypothesis of a unit root, implying that all variables are stationary time series. These results justify further econometric modeling.

Table 1. Descriptive statistics for daily log returns, RV, and EPU for SSEC and SZSEC

	SSEC			SZSEC			CHINA
	Return	RV	Log-RV	Return	RV	Log-RV	EPU
Mean	0.0002	0.0002	-9.4243	0.0003	0.0002	-9.0295	317.2469
Minimum	-0.0926	0.0000	-12.0260	-0.0975	0.0000	-11.8412	26.1441
Maximum	0.0903	0.0039	-5.5450	0.0916	0.0053	-5.2414	970.8299
Standard deviation	0.0152	0.0003	1.0324	0.0177	0.0003	0.9618	264.6274
Skewness	-0.5839	6.1197	0.5792	-0.5002	5.8443	0.3970	0.8770
Kurtosis	8.1487	60.8560	3.0806	6.2978	58.5862	3.1073	2.4636
ADF	-38.1865***	-17.7063***	-12.9676***	-38.0383***	-19.1851***	-13.324***	-3.2448*
J-B	5335.3665	669406.3222	258.1314	2272.8104	617462.2122	122.8742	31.8225
ARCH	491.3467	1079.8168	3410.6402	464.4207	1007.7159	3275.3626	175.5433
Q(20)	69.9725	18437.5353	44121.1871	49.7334	15400.8097	39728.4484	2447.7996

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. ADF denotes the augmented Dickey-Fuller unit-root test statistic; J-B denotes the Jarque-Bera normality test; ARCH is the lag-10 statistic after de-meaning; Q(20) is the 20-lag Ljung-Box Q statistic.

Figure 1 illustrates the daily returns of SSEC and SZSEC. The two indices show episodes of higher volatility during 2007-2009, 2015-2016, and 2020.Figure 2 illustrates the square root of RV for the two indices. Similar to returns, RV also shows substantial volatility during 2007-2009, 2015-2016, and 2020, with pronounced time-varying behavior.

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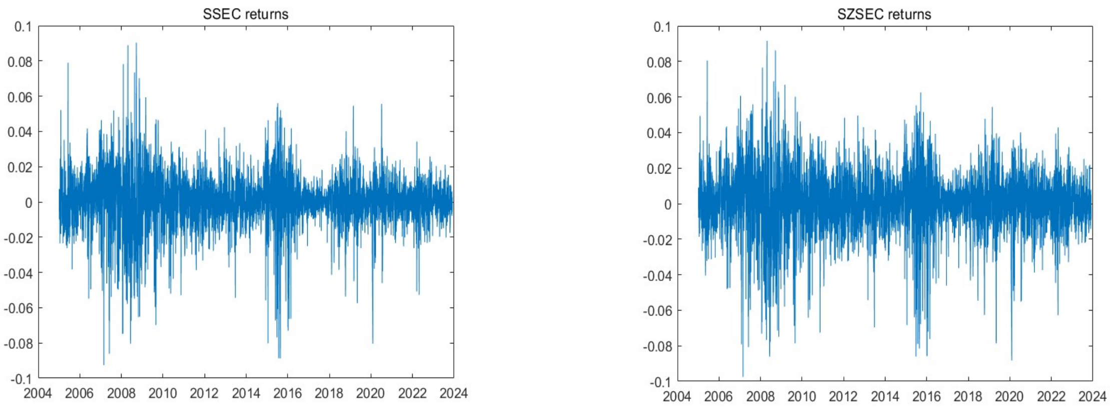

Figure 1. Stock Index Return Series

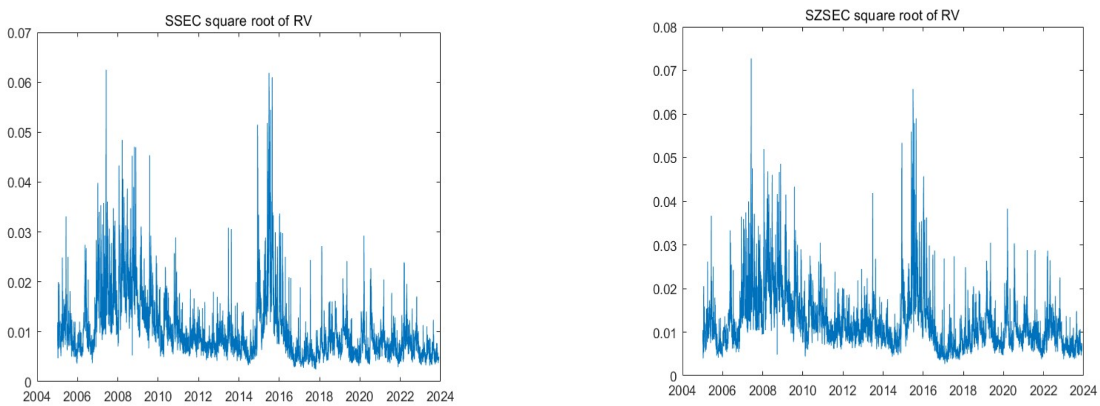

Figure 2. Square Root of Stock Index Realized Volatility

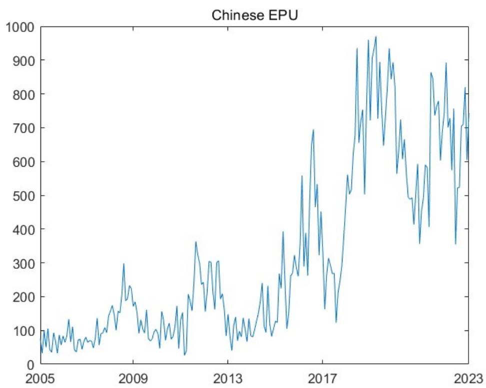

Figure 3. Chinese EPU Index

Figure 3 shows the evolution of China's EPU index. The index captures major economic crisis events reasonably well, including the global financial crisis (2007-2009), the European sovereign debt crisis (2011-2022), and concerns about China's economic slowdown (2015-2016). Moreover, the Chinese EPU index reached local peaks in 2008, 2012, 2016, and 2019.

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During the financial crisis, the government introduced a series of strong stimulus policies, led by the 4-trillion-yuan package, to revive the economy and mitigate the crisis. In 2011-2012, the negative side effects of the 2008 rescue program began to emerge, and as political transition got underway, the CEPU index rose again. From the second half of 2015 onward, sharp market turmoil driven in part by off-balance-sheet capital and pessimistic expectations that China would continue to grow by more than 7% pushed the EPU index higher again. In 2019, the outbreak of COVID-19 and the increasing downward pressure on China's economy in a weak global environment drove the EPU index to a peak of 970. Overall, the Chinese EPU index tracks the basic pattern of economic policy uncertainty in China fairly well.

4. Empirical Results

4.1. Parameter Estimation Results

To demonstrate the superiority of the proposed GARCH-MIDAS-(RV+EPU) model, we consider three competing models-GARCH, EGARCH, and GARCH-MIDAS-RV-and compare them empirically with the GARCH-MIDAS-(RV+EPU) model.

Table 2. Parameter estimates for the SSEC index

	GARCH	EGARCH	GARCH-MIDAS-RV	GARCH-MIDAS-(RV+EPU)
μ	0.0004	1.1955e-05	4.5887e-05	0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
ω	0.0000	-0.0396		
	(0.0000)	(0.0124)		
α	0.0539	0.1232	0.0586	0.0573
	(0.0040)	(0.0082)	(0.0052)	(0.0050)
β	0.9449	0.9945	0.9185	0.9178
	(0.0037)	0.0015)	(0.0076)	(0.0077)
γ		-0.0032		
		(0.0043)		
m			-4.2027	-2.7011
			(0.0436)	(0.0349)
θ			0.7429	
			(0.0122)	
θ_1				0.7330
				(0.0098)
θ_2				-0.3289
				(0.0117)
ζ			2.6308	
			(0.0351)	
ω_{11}				2.2945
				(0.0352)
ω_{21}				1.1189
				(0.0246)
LL	8394.7846	8397.8705	8394.5144	8399.0313
AIC	-16781.5692	-16785.7409	-16777.0288	-16782.0626
BIC	-16757.5437	-16755.7091	-16740.9906	-16734.0117

Note: LL is the log-likelihood; AIC and BIC are information criteria; robust standard errors are reported in parentheses.

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Table 3. Parameter estimates for the SZSEC index

	GARCH	EGARCH	GARCH-MIDAS-RV	GARCH-MIDAS-(RV+EPU)
μ	0.0003	1.7805e-05	-0.0001	2.3136e-05
	0.0003	(0.0003)	(0.0003)	(0.0003)
ω	0.0000	-0.0651		
	(0.0000)	(0.0132)		
α	0.0506	0.1170	0.0551	0.0537
	(0.0042)	(0.0088)	(0.0051)	(0.0052)
β	0.9439	0.9913	0.9226	0.9241
	(0.0042)	(0.0016)	(0.0076)	(0.0073)
γ		-0.0092		
		(0.0048)		
m			-4.6936	-3.6146
			(0.0735)	(0.0697)
θ			0.6360	
			(0.0130)	
θ_1				0.6307
				(0.0145)
θ_2				-0.2330
				(0.0135)
ζ			1.9936	
			(0.0380)	
ω_{11}				1.5771
				(0.0307)
ω_{21}				1.0891
				(0.0399)
LL	7909.4647	7915.8076	7910.3771	7912.5586
AIC	-15810.9294	-15821.6151	-15808.7542	-15809.1172
BIC	-15786.9040	-15791.5833	-15772.7160	-15761.0663

Note: LL is the log-likelihood; AIC and BIC are information criteria; robust standard errors are reported in parentheses.

The parameter estimation results of the GARCH-MIDAS-(RV+EPU) model and three competing models obtained via the maximum likelihood estimation method are presented in Tables 2 and 3. According to the estimation outputs of the GARCH, EGARCH, GARCH-MIDAS-RV, and GARCH-MIDAS-(RV+EPU) models in the tables, the estimated values of the persistence coefficient of conditional variance $\alpha+\beta$ (for the GARCH, GARCH-MIDAS-RV and GARCH-MIDAS-(RV+EPU) models) and the coefficient β (for the GARCH-MIDAS-(RV+EPU) model) of the SSEC and SZSEC indices are close to unity. This indicates that both indices exhibit extremely strong volatility persistence. In the EGARCH model, the leverage coefficient $\gamma<0$, which implies that negative shocks generate larger volatility for the SSEC and SZSEC indices compared with positive shocks of identical magnitude.

For the two models embedded with the MIDAS structure, namely the GARCH-MIDAS-RV model and the GARCH-MIDAS-(RV+EPU) model, the conditional variance is multiplicatively decomposed into a long-run component τ_t and a short-run component $g_{i,t}$.Within the long-run component of both models, the estimated coefficients θ and θ_1 are significantly positive, which implies that realized volatility (RV) exerts a positive impact on long-term volatility: a rise in the

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RV level corresponds to an increase in expected long-run volatility. Furthermore, the estimated values of ζ and ω_{11} are greater than unity, demonstrating that the marginal effect of RV on long-run volatility diminishes as the lag length increases.

Comparing the log-likelihood (LL), AIC, and BIC values for SSEC and SZSEC, we find that both the EGARCH model and the GARCH-MIDAS-(RV+EPU) model achieve clearly higher LL values and lower AIC and BIC values. This suggests that accounting for leverage effects and introducing the exogenous EPU variable substantially improve the fit of the mixed-frequency volatility model.

Figure 4 and Figure 5 present the time series of the conditional variance and its long-run component for SSEC and SZSEC based on the GARCH-MIDAS-RV and GARCH-MIDAS-RV-EPU models, respectively. Both models show that the long-run component captures the long-term trend in conditional variance well.

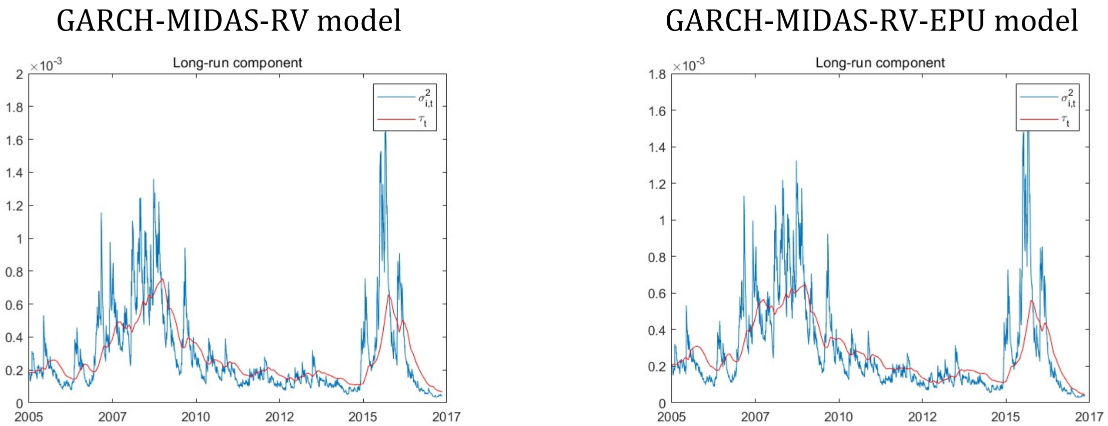

Figure 4. Time Series Plots of Conditional Variance and Its Long-Run Component for the SSEC Index

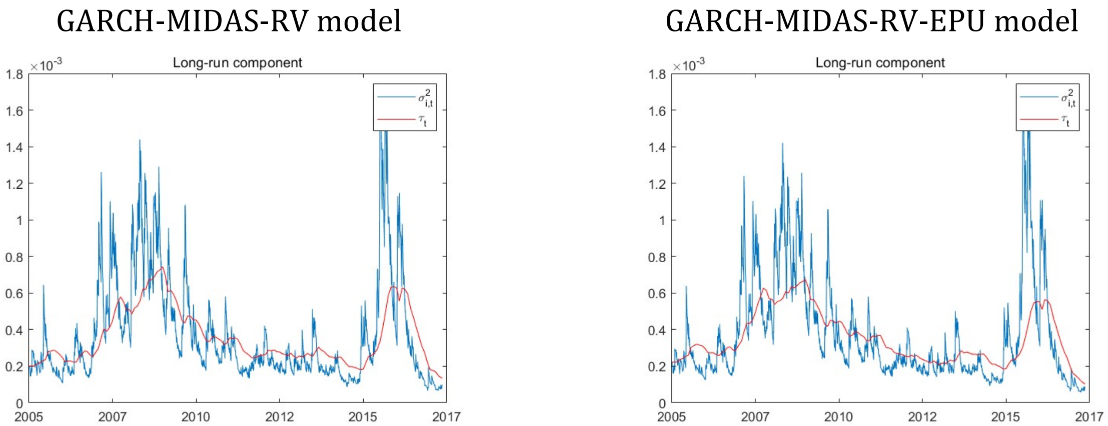

Figure 5. Time Series Plots of Conditional Variance and Its Long-Run Component for the SZSEC Index

4.2. Out-of-Sample Forecasting Performance

Compared with in-sample fit, out-of-sample forecasting performance is of greater importance for market participants. This paper uses an expanding-window scheme to forecast volatility and splits the full sample into two parts: an estimation sample and a forecasting sample. The estimation sample contains the first 3,000 trading days of returns and RV, and the forecasting sample contains the last 1,594 trading days, corresponding to a forecast window of 1,594 days.

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Figures 6 and 7 show the volatility forecasts for the two indices based on the GARCH, EGARCH, GARCH-MIDAS-RV, and GARCH-MIDAS-RV-EPU models. The four models all forecast Chinese stock market volatility reasonably well and exhibit good predictive accuracy.

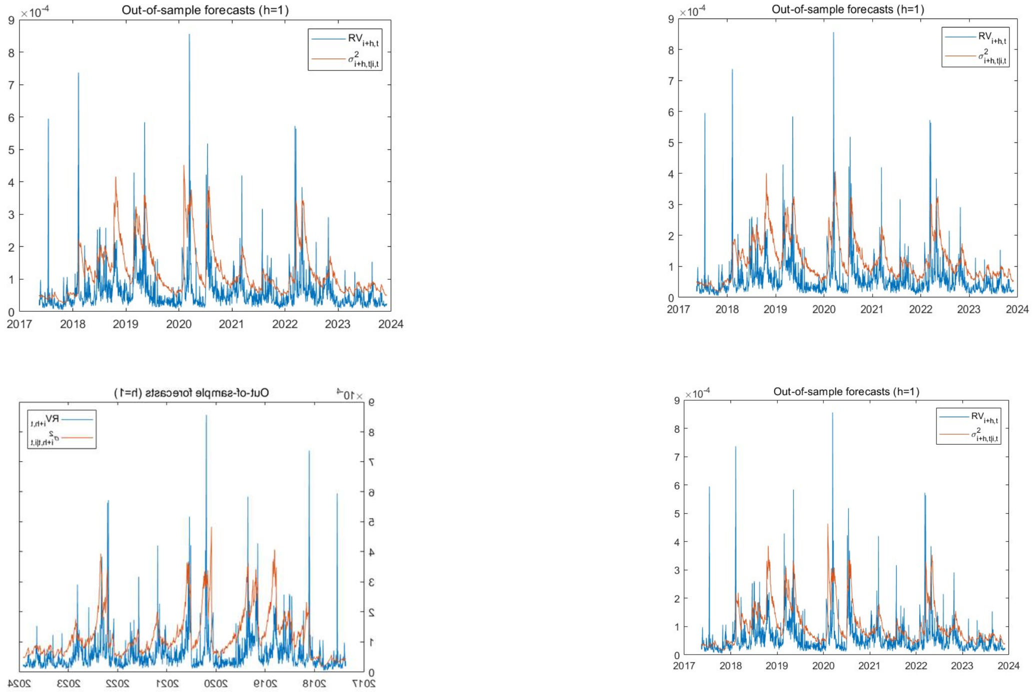

Figure 6. Out-of-Sample Forecasting Plot for the SSEC Index

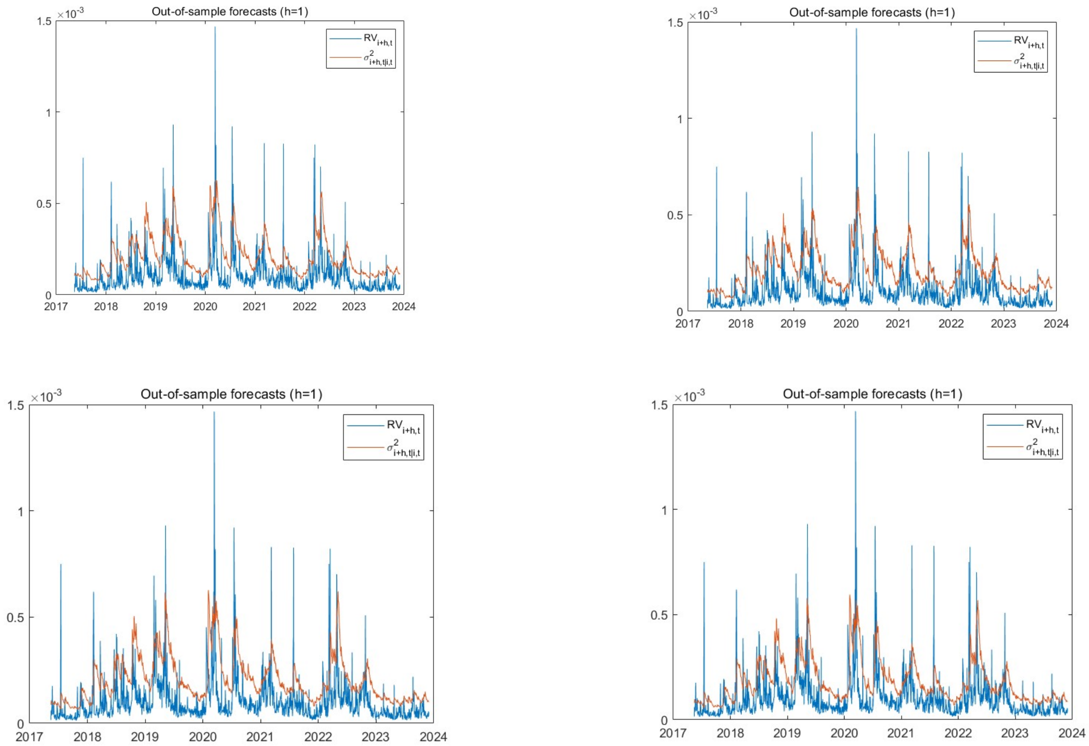

Figure 7. Out-of-Sample Forecasting Plot for the SZSEC Index

Table 4 reports the forecast evaluation results for SSEC and SZSEC using the two loss functions. The results show that introducing RV and the exogenous EPU variable into the GARCH-MIDAS

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framework significantly improves the forecasting performance relative to the GARCH, EGARCH, and GARCH-MIDAS-RV models. This indicates that economic policy uncertainty contains important information for volatility forecasting.

Table 4. Volatility forecast evaluation results

	SSEC		SZSEC	
	MSE	QLIKE	MSE	QLIKE
GARCH	9.7193e-09	3.7183e-01	2.2891e-08	3.8598e-01
EGARCH	8.8119e-09	3.7843e-01	2.3625e-08	4.0048e-01
GARCH-MIDAS-RV	9.2361e-09	3.6788e-01	2.1537e-08	3.7104e-01
GARCH-MIDAS-(RV+EPU)	6.9061e-09	2.9963e-01	1.6930e-08	3.1193e-01

Note: Bold numbers in the table indicate the lowest loss values. MSE is mean squared error, and QLIKE is quasi-likelihood loss.

5. Conclusion

This paper constructs a GARCH-MIDAS-RV-EPU model to model and forecast Chinese stock market volatility. Using 5-minute high-frequency data for SSEC and SZSEC, the empirical results show that the GARCH-MIDAS-RV-EPU model fits return data better than many competing models, including the GARCH, EGARCH, and GARCH-MIDAS-RV models, and provides a more accurate description of stock market volatility. Using robust loss functions as the evaluation criterion, we further compare the out-of-sample forecasting performance of the proposed model with that of other competing models. The results indicate that incorporating high-frequency information, low-frequency information, and EPU information is important for volatility forecasting; among the competing models, the GARCH-MIDAS-RV-EPU model achieves the best forecasting performance.

This study provides a useful methodological reference for modeling and forecasting Chinese stock market volatility and is relevant both for academic research and for practitioners. Several extensions are worth pursuing. For example, macroeconomic variables could be introduced into the current framework to examine the impact of macro information on volatility. In addition, the model could be extended by taking into account skewness, leptokurtosis, and time-varying higher moments in asset returns, and then applied to market risk measurement. Another important direction is the application of the model to option pricing.

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