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Forecasting Chinese Stock Market Volatility Using the Range and Climate Policy Uncertainty

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Abstract

Within the conditional autoregressive range (CARR) framework, this paper introduces climate policy uncertainty (CPU) as a low-frequency macroeconomic variable and develops a CARR-MIDAS-CPU model for modeling and forecasting Chinese stock market volatility. Using data on the SSE 50 Index, the empirical results show that CPU has a significant effect on long-run stock market volatility. In terms of in-sample fitting performance, range-based CARR models consistently outperform their return-based GARCH counterparts, corroborating the informational value of intraday extreme price data in volatility modeling. We further conduct an out-of-sample forecasting comparison between the CARR-MIDAS-CPU model and a set of competing benchmark specifications, adopting two robust loss functions as the core evaluation criteria. Forecasting results demonstrate that the integration of climate policy uncertainty (CPU) delivers incremental predictive power for Chinese stock market volatility, and the CARR-MIDAS-CPU model achieves the highest predictive accuracy among all specifications under examination. Overall, the proposed model effectively exploits range-based volatility information and climate policy uncertainty to enhance forecasting performance, and offers a practical econometric tool to support risk management for both policymakers and market investors.

Keywords

Volatility Forecasting; Range; Climate Policy Uncertainty; Mixed-Frequency Sampling.

1. Introduction

Volatility modeling and prediction represent a foundational research pillar in financial econometrics, as accurate volatility estimates serve as critical inputs for derivatives valuation, asset allocation strategies, and risk management frameworks. For China's domestic stock market, the evolution of volatility follows a far more intricate trajectory, marked by well-documented stylized facts such as pronounced volatility clustering, long-run memory effects, and asymmetric reactions to macroeconomic shocks. Since the extraordinary market turmoil of 2015, China's capital market has stepped up its two-way opening-up agenda and market-oriented reform progress, which has in turn diversified the set of factors shaping market volatility dynamics. Under such market and institutional circumstances, accurately characterizing and forecasting stock market volatility in China carries substantial practical significance.

The seminal work of Bollerslev (1986), which introduced the generalized autoregressive conditional heteroskedasticity (GARCH) model, has laid the primary groundwork for traditional volatility modeling[1]. This model uses squared daily returns to estimate conditional variance. It is simple in structure and captures volatility clustering effectively, which explains its wide use in empirical research[2,3]. However, GARCH-type models have two major shortcomings. First, squared returns depend only on the closing price and completely

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ignore the extreme-value information contained in the intraday high and low prices. During periods of sharp market swings, volatility estimates based on returns often underestimate true volatility, leading to inefficient use of information[4]. Second, the standard GARCH model is a single-component model. It assumes a constant unconditional mean of volatility, making it difficult to capture long-run trend components driven by changes in the macroeconomic environment and preventing the direct incorporation of low-frequency macro variables[5].

To address these limitations, the literature has developed along two directions. One is to incorporate intraday extreme-value information. Parkinson (1980) showed that the range computed from the daily high and low prices is an efficient estimator of volatility, with much higher information efficiency than squared returns[4]. Alizadeh et al. (2002) and Brandt and Jones (2006) provided subsequent evidence that the range measure is insensitive to market microstructure noise[6,7]. Chou (2005), within a multiplicative error model framework, proposed the conditional autoregressive range (CARR) model, which characterizes the dynamics of the range in a manner similar to GARCH[8]. There is subsequent evidence that the CARR framework, which relies on the range, delivers more accurate volatility forecasts than the return-based GARCH approach (Chou, 2005; Wu et al., 2021)[8,9]. The other direction is the introduction of mixed-frequency data sampling (MIDAS). Engle et al. (2013) proposed the GARCH-MIDAS model, which decomposes conditional volatility into a high-frequency short-run component and a low-frequency long-run component[5]. The latter is linked to monthly or quarterly macroeconomic variables through MIDAS regression, thereby capturing long-run drivers of volatility effectively. Subsequently, a large number of studies have adopted the GARCH-MIDAS framework to explore the influence of economic policy uncertainty (EPU) on stock market and exchange rate volatility[10-13].

In recent years, a new research topic has emerged around the effects of climate policy uncertainty (CPU) on financial markets. As global climate governance has accelerated, countries have introduced major climate policies on carbon reduction and energy transition. Yet policy uncertainty remains. Through its effects on investors' expectations of future cash flows in carbon-intensive sectors, changes in risk premia, and reallocation of capital, such uncertainty ultimately transmits to asset price volatility[14,15]. Using text analysis, Gavriilidis (2021) built a monthly index of climate policy uncertainty and demonstrated that CPU significantly predicts energy stock returns[16]. Subsequent studies by Ren et al. (2022) and Xu et al. (2023) show that CPU also exacerbates tail risk in stock markets[17,18]. For the Chinese stock market, under the guidance of the dual-carbon goals, frequent policy announcements and continuous policy adjustments have become an important systematic factor. However, most of the existing literature focuses on the macroeconomic effects of EPU, and there is still little in-depth discussion of how CPU affects Chinese stock market volatility, especially its long-run component.

Building on the classic CARR model and borrowing the modeling logic of GARCH-MIDAS, this paper introduces the climate policy uncertainty index as a low-frequency driver and develops a CARR-MIDAS-CPU model for modeling and forecasting Chinese stock market volatility. The empirical sample consists of daily trading data for the SSE 50 Index from January 2015 to December 2025, including open, high, low, and close prices, together with the monthly CPU index. Our empirical analysis consists of two stages. In the first stage, we apply maximum likelihood estimation to assess the impact of CPU on the long-run volatility of the stock market. In the second stage, we adopt a rolling-window procedure and employ two robust loss functions-mean squared error (MSE) and quasi-likelihood (QLIKE)-to evaluate the out-of-sample forecasting performance of the CARR-MIDAS-CPU model against competing benchmarks, including GARCH, GARCH-MIDAS-CPU, and CARR.

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2. Model Construction and Estimation

Traditional volatility estimators are usually constructed only from daily returns, that is, price changes based on closing prices. This approach often ignores intraday price variation and therefore weakens estimation accuracy to some extent. To remedy this limitation, Parkinson (1980) proposed using the difference between the intraday high and low prices as a proxy for volatility, so as to more fully reflect the true variation of market prices[4]. Following this idea, this paper uses the intraday range as the volatility measure for the sample considered here. The proxy is defined as

$$R_{i,t}=\frac{\log(H_{i,t})-\log(L_{i,t})}{\sqrt{4\log(2)}} \tag{1}$$

Where $H_{i,t}$ and $L_{i,t}$ denote the high and low prices on the i-th trading day of month t. Existing studies show that the intraday range is an efficient and robust volatility estimator and retains favorable statistical properties even in the presence of microstructure noise[6].

2.1. CARR Model

The CARR model, originally developed by Chou (2005) to capture the dynamics of the intraday range[8], is specified as follows:

$$R_i=\lambda_i\varepsilon_i\,,\varepsilon_i\,|\,F_{i-1}\sim\exp(1) \tag{2}$$

$$\lambda_i=\omega+\alpha R_{i-1}+\beta\lambda_{i-1} \tag{3}$$

Where λ_i is the conditional mean of the price range, ε_i is an error term following an exponential distribution with unit mean, and F_{i-1} denotes the information set available up to day i-1. The parameters ω, α, and β are non-negative and measure the persistence of the conditional range. To ensure stationarity of the conditional range process, the model assumes $\alpha+\beta<1$. Hence, the unconditional mean of the range is $\omega/(1-\alpha-\beta)$.

2.2. CARR-MIDAS-CPU Model

Following the logic of the GARCH-MIDAS model proposed by Engle et al. (2013)[5], we extend the CARR framework to accommodate exogenous determinants such as climate policy uncertainty. This extension is motivated by the fact that the standard CARR model fixes the long-run trend of the intraday range at a constant, thereby overlooking potentially important drivers of volatility dynamics. The resulting CARR-MIDAS-CPU model is specified as follows:

$$R_{i,t}=\lambda_{i,t}\varepsilon_{i,t}\,,\quad R_{i,t}=\lambda_{i,t}\varepsilon_{i,t} \tag{4}$$

$$\lambda_{i,t}=\tau_i g_{i,t} \tag{5}$$

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

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$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \varphi_k(\gamma) \log(CPU_{t-k}) \tag{7}$$

Here, the conditional range is multiplicatively decomposed into a short-run component $g_{i,t}$ and a long-run component $\tau_{i,t}$. The following constraints are imposed on several parameters: $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$, which ensure the non-negativity and stationarity of the short-run component. Under the stationarity condition, the unconditional mean of $g_{i,t}$ satisfies $E[g_{i,t}] = 1$. This paper assumes that $\varphi_k(\gamma)$ is a Beta weight function satisfying $\sum_{k=1}^{K} \varphi_k(\gamma_1) = 1$, with the specification given by:

$$\varphi_k(\gamma) = \frac{(1 - k / K)^{\gamma - 1}}{\sum_{j=1}^{K} (1 - j / K)^{\gamma - 1}} \tag{8}$$

where K denotes the maximum MIDAS lag order. For computational simplicity, this paper sets K=24.

2.3. Maximum Likelihood Estimation

The parameters of the CARR-MIDAS-CPU model can be conveniently estimated via maximum likelihood, owing to its well-defined structure. The associated log-likelihood is expressed as:

$$\ell(R;\Theta) = -\sum_{t=1}^{T} \sum_{i=1}^{N_t} [\log(\lambda_{i,t}) + \frac{R_{i,t}}{\lambda_{i,t}}] \tag{9}$$

Where $\Theta = \{m, \alpha, \beta, \theta, \gamma\}$ is the parameter vector to be estimated. Maximizing the log-likelihood function yields the maximum likelihood estimate (MLE) of the CARR-MIDAS model parameters Θ:

$$\hat{\Theta} = \arg\max_{\Theta} \log L(\Theta) \tag{10}$$

Where constraints $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$ are imposed during the estimation process.

2.4. Robust Loss Functions

This paper evaluates the forecasting accuracy of the CARR-MIDAS-CPU model using loss functions. Because the true volatility is unobservable, a proxy is required for evaluation. We use the intraday range to proxy true volatility and evaluate forecasting accuracy using two loss functions that are robust to proxy noise, namely MSE and QLIKE, as suggested by Patton (2011). The formal definitions of these loss functions are given below:

$$\text{MSE：} L(\lambda_{i+1,t}, \lambda_{i+1,t|i}) = (\lambda_{i+1,t} - \lambda_{i+1,t|i})^2 \tag{11}$$

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$$\text{QLIKE:}\quad L(\lambda_{i+1,t},\lambda_{i+1,t|i}) = \log(\lambda_{i+1,t|i}) + \frac{\lambda_{i+1,t}}{\lambda_{i+1,t|i}} \tag{12}$$

Where $\lambda_{i+1,t}$ denotes the true volatility, and $\lambda_{i+1,t|i}$ denotes the volatility forecast. A smaller loss value indicates higher forecasting accuracy.

3. Variable Selection and Empirical Analysis

3.1. Variable Selection

This paper empirically examines, within the CARR-MIDAS-CPU framework, the role of climate policy uncertainty in forecasting Chinese stock market volatility. The sample consists of the SSE 50 Index daily open, high, low, and close prices from January 5, 2015 to December 31, 2025, covering 2,674 trading days.

The macroeconomic factor considered in relation to stock market volatility is climate policy uncertainty (CPU). The paper uses the CPU index as a proxy variable. Following Gavriilidis et al. (2021), the index is constructed from news reports to measure the degree of uncertainty associated with climate policy, regulation, and government action. The CPU index is also based on text analysis. The logic behind the index construction is that, when the direction of climate policy and its potential consequences become less clear, reports in mainstream news media that mention climate, policy, and uncertainty tend to become more frequent. A higher CPU index therefore indicates greater climate policy uncertainty in that month.

3.2. Data Analysis

The range series shows clear volatility clustering. In crisis periods around 2020, the range rises rapidly to a high level and then gradually declines, displaying the typical alternation between high-volatility and low-volatility regimes. By contrast, the daily return series fluctuates much less than the range series and contains more noise, which further suggests that the range is a more robust and efficient volatility proxy, see Figure 1.

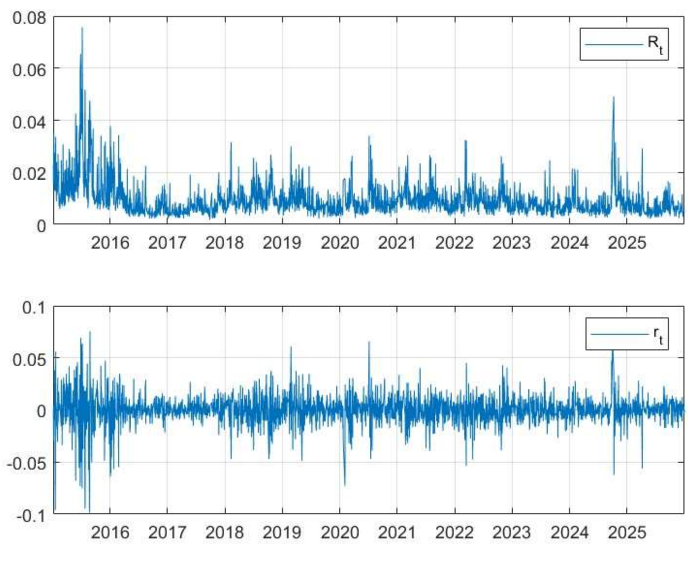

Figure 1. Time-series plots of SSE 50 daily returns and intraday range

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The CPU index reaches pronounced peaks around 2015 and 2025, corresponding respectively to the intensification of international policy contestation after the Paris Agreement and to the period in which new policies related to China's dual-carbon targets were issued intensively. Around 2020 the index is relatively stable, but it still exhibits an overall upward trend in fluctuations, see Figure 2.

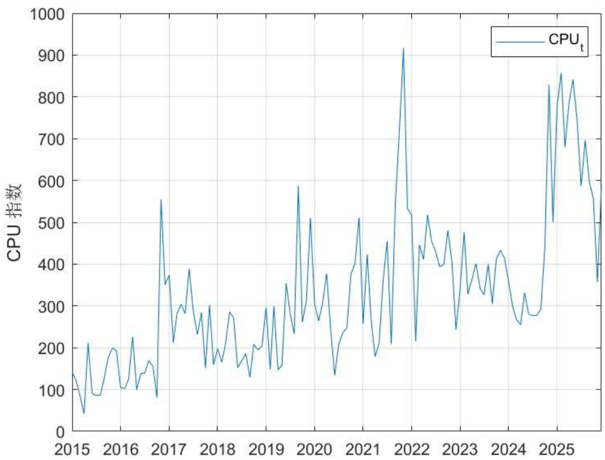

Figure 2. Time series of the CPU index

This slow decay pattern indicates strong long-memory and persistent dependence in the volatility series. A single-component CARR model alone cannot fully capture its dynamic evolution. We therefore adopt a MIDAS structure to capture the impact of low-frequency macro variables on long-run volatility, as shown in Figure 3.

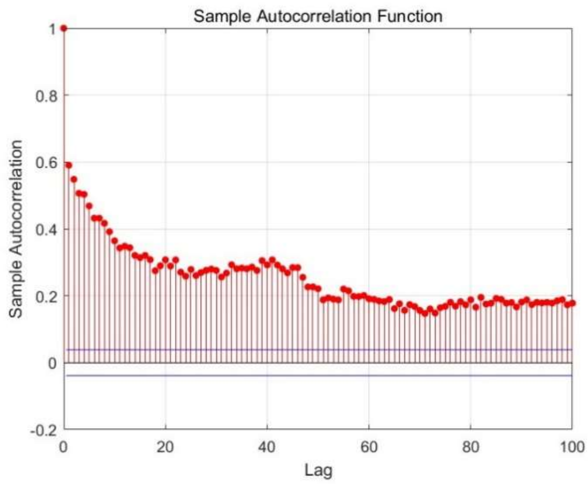

Figure 3. Autocorrelation function (ACF) of the SSE 50 intraday range

Table 1 reports the descriptive statistics of the intraday range, daily logarithmic returns of the SSE 50 Index, and the Climate Policy Uncertainty (CPU) index. For mean values, the average daily return of the SSE 50 Index stays near zero. The mean of the intraday range is 0.0093. This figure shows that intraday price swings are much larger than overnight return changes, and confirms the price range as a more effective volatility proxy. The CPU index has a mean of 330.74 and a relatively large standard deviation. This means climate policy uncertainty varies considerably during the sample period.

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For distributional properties, the return series is negatively skewed. The range series and CPU index, by contrast, both show positive skewness. All three series have kurtosis values above 3. Specifically, the range series has a kurtosis of 19.40, and the return series has a kurtosis of 10.45. Both series present clear leptokurtic and heavy-tailed features. All Jarque–Bera statistics exceed their corresponding critical values, and thus strongly reject the normality hypothesis for every series.

In addition, Ljung–Box Q statistics at lag 20 show significant serial dependence across all three variables. The Q(20) statistics for returns, price ranges and the CPU index are 96.21, 8647.83 and 346.71 respectively, and all reach high statistical significance. These results indicate that all three series have strong autocorrelation and long-memory traits. Notably, the range series has the strongest persistence. This finding provides empirical support for adding a MIDAS structure to the CARR framework, to capture the long-run component of volatility movements.

Table 1. Descriptive statistics for the SSE 50 intraday range, daily returns, and CPU

	Daily return	Intraday range	CPU
Mean	0.0001	0.0093	330.7435
Min	-0.0985	0.0018	42.5871
Max	0.0755	0.0757	916.2815
Std	0.0135	0.0064	184.8374
Skewness	-0.5892	3.1655	1.0595
Kurtosis	10.4455	19.4009	3.8600
Jarque-Bera	6328.7187	34435.7328	28.7628
Q(20)	96.2146	8647.8261	346.7137

Note: Q(20) is the 20-lag Ljung-Box statistic.

3.3. Benchmark Models

In addition, we include the GARCH model and the GARCH-MIDAS-CPU model as competing benchmarks.

The GARCH model, proposed by Bollerslev, has attracted wide attention in the financial econometrics literature and remains one of the most widely used volatility models in the field. The model assumes that asset returns follow the process below:

$$r = \sigma_i \varepsilon_i , \quad \varepsilon_i \mid F_{i-1} \sim i.i.d.N(0,1) \tag{13}$$

$$\sigma_i^2 = \omega + \alpha r_{i-1}^2 + \beta \sigma_{i-1}^2 \tag{14}$$

Where r_i is the (log) return of the asset on day i and σ_i is the conditional volatility of returns.

Extending the standard GARCH-MIDAS model by introducing CPU into the long-run volatility component yields the GARCH-MIDAS-CPU model:

$$r_{i,t} = \sigma_{i,t} \varepsilon_{i,t} , \quad \varepsilon_{i,t} \mid F_{i-1,t} \sim i.i.d.N(0,1) \tag{15}$$

$$\sigma_{i,t}^2 = \tau_t g_{i,t} \tag{16}$$

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$$g_{i,t} = (1-\alpha-\beta) + \alpha \frac{r_{i-1,t}^2}{\tau_t} + \beta g_{i-1,t} \tag{17}$$

$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \varphi_k(\gamma) \log(CPU_{t-k}) \tag{18}$$

where the long-run component τ_t is linked to the monthly CPU index through a MIDAS weighting scheme.

4. Empirical Results

4.1. Parameter Estimation Results

Maximum likelihood estimation yields the parameter estimates of the CARR-MIDAS-CPU model and the three benchmark models, as reported in Table 2.

Table 2. Parameter estimates

	GARCH	GARCH-MIDAS-CPU	CARR	CARR-MIDAS-CPU
$m(\omega)$	0.0000 (0.0000)	-6.8511 (0.2871)	0.0003 (0.0000)	-4.0721 (0.2874)
α	0.0764 (0.0130)	0.0812 (0.0088)	0.1790 (0.0302)	0.1766 (0.0318)
β	0.9126 (0.0130)	0.9074 (0.0095)	0.7910 (0.0302)	0.7915 (0.0439)
θ		-0.2878 (0.0907)		-0.1122 (0.0540)
γ		9.9998 (0.4108)		9.9988 (0.2409)
Log-lik	8128.3343	8139.8603	10029.4404	10030.4419

First, in terms of volatility persistence, the persistence coefficient in the return-based GARCH model and the range-based CARR model is very close to 1, indicating that both the SSE 50 returns and the intraday range exhibit strong volatility persistence. After introducing the MIDAS structure, the persistence coefficient of the short-run component in the GARCH-MIDAS-CPU model and the corresponding coefficient in the CARR-MIDAS-CPU model decline slightly relative to the original models, suggesting that CPU, as the only low-frequency variable, absorbs part of the long-run trend.

Second, the coefficient gauges how CPU affects the long-run volatility of the SSE 50 Index within the MIDAS framework's long-run component. The estimates show that in the GARCH-MIDAS-CPU model, with a standard error of 0.0907 and a t-statistic of approximately -3.17, which is significant at the 1% level. In the CARR-MIDAS-CPU model, , with a standard error of 0.0540 and a t-statistic of approximately -2.08, which is significant at the 5% level. In both models, θ is negative and statistically significant, implying that a rise in the CPU index corresponds to a reduction in the SSE 50's long-run volatility.

Finally, comparing the log-likelihood values shows that the CARR-type models fit the data much better than the GARCH-type models, which suggests that volatility models based on the range describe the dynamics of the SSE 50 Index more effectively than models based on returns. Adding the CPU variable improves fitting performance for models within the same category:

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the log-likelihood of GARCH-MIDAS-CPU rises by about 11.5 against the baseline model, while CARR-MIDAS-CPU sees an increase of around 1, which confirms that including CPU helps boost volatility forecasting outcomes. Among all examined models, CARR-MIDAS-CPU posts the highest log-likelihood value, meaning this model with the exogenous CPU input delivers the best in-sample fit and captures the SSE 50 Index's volatility dynamics more effectively.

4.2. Out-of-sample Forecasting Results

We proceed to evaluate the out-of-sample forecast accuracy of the CARR-MIDAS-CPU model for the SSE 50 Index in this section. The forecast evaluation is conducted using a rolling-window scheme. The full sample is divided into two subsamples: an initial in-sample estimation period from January 4, 2015 to December 31, 2022, and an out-of-sample forecasting period from January 1, 2023 to December 31, 2025.

Figure 4 reports the volatility forecasts for the SSE 50 Index generated by the GARCH model, the GARCH-MIDAS-CPU model, the CARR model, and the CARR-MIDAS-CPU model. As shown in the figure, all four models are able to forecast volatility in the Chinese stock market reasonably well and exhibit satisfactory predictive accuracy.

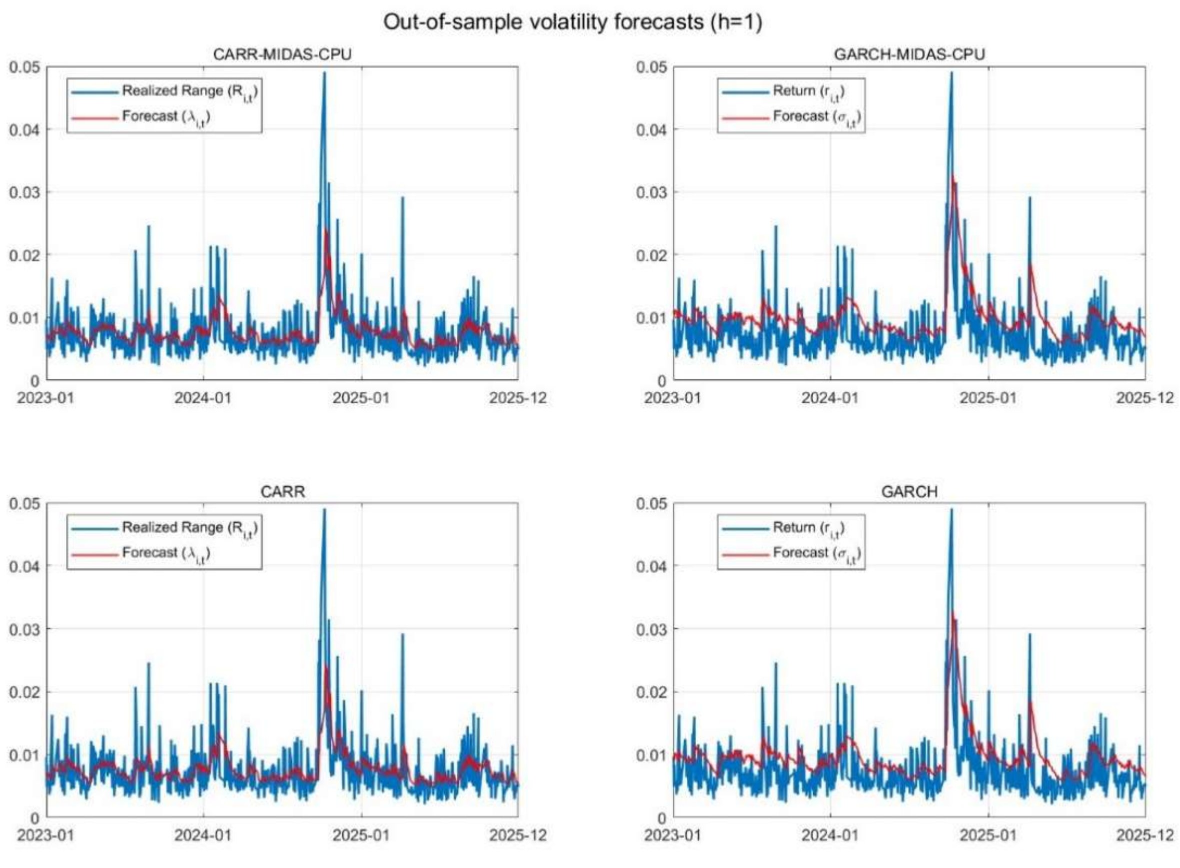

Figure 4. Out-of-sample forecast performance for the SSE 50 Index

Using MSE and QLIKE as evaluation criteria, we find that range-based CARR-type models deliver superior out-of-sample forecasting performance relative to return-based GARCH-type models. This confirms the informational advantage of intraday extreme values. Furthermore, the CARR-MIDAS-CPU model exhibits the lowest forecast errors among all competitors, highlighting the predictive value of climate policy uncertainty for volatility forecasting, see Table 3.

Table 3. Forecast evaluation results

Model	MSE	QLIKE
GARCH	2.1137e-05	1.1998e-01
GARCH-MIDAS-CPU	2.2483e-05	1.2543e-01
CARR	1.4019e-05	8.7188e-02
CARR-MIDAS-CPU	1.4011e-05	8.7035e-02

5. Conclusion

Accurate modeling and forecasting of volatility in China's stock market is of great importance to investors and risk managers, as it underpins core tasks such as portfolio allocation, derivative pricing and risk management. While existing research has made substantial progress in forecasting Chinese stock market volatility, studies exploring the impact of climate policy uncertainty within the range-based CARR-MIDAS framework are still relatively few. Against this background, this paper extends the baseline CARR-MIDAS model to the CARR-MIDAS-CPU specification. The proposed model draws on intraday extreme price data, and accounts for how climate policy uncertainty affects volatility in China's stock market.

In-sample estimation results show that the CPU index exerts a significant negative effect on the long-run volatility of the SSE 50 Index; that is, rising climate policy uncertainty tends to coincide with declining long-term stock market volatility. Specifically, the estimated coefficient θ of CPU is significant at the 1% level in the GARCH-MIDAS-CPU model, and significant at the 5% level in the CARR-MIDAS-CPU model. Out-of-sample results indicate that range-based CARR models outperform return-based GARCH models in predictive performance. Notably, the CARR-MIDAS-CPU model achieves the best overall performance, with both MSE and QLIKE loss values lower than all competing models. Overall, the study confirms that incorporating intraday range information and climate policy uncertainty is critical for effective modeling and forecasting of Chinese stock market volatility.

These findings carry practical relevance for both investors and policymakers. Investors can leverage the relationship between climate policy uncertainty and stock market volatility to identify risk sources more effectively, optimize portfolio structures, and make more well-founded investment decisions.

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