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Economic Policy Uncertainty and Gold Futures Volatility: A GARCH-MIDAS Approach

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Abstract

Gold, as a special precious metal, has long been regarded by investors as an effective hedging tool with "safe haven" characteristics. This paper embeds global economic policy uncertainty (EPU) into the GARCH-MIDAS framework to examine the impact and predictive contribution of EPU on the volatility of U.S. gold futures. The out-of-sample predictive accuracy of different models is statistically tested using loss functions, model confidence sets (MCS), and out-of-sample R^2. Empirical results show that EPU has a significant negative impact on the volatility of the gold futures market; compared with competing models, the GARCH-MIDAS-EPU model incorporating EPU exhibits consistently significant superiority in predictive accuracy.

Keywords

Gold Futures, Economic Policy Uncertainty, GARCH-MIDAS Model, Volatility Prediction, Out-of-Sample Testing

1. Introduction

The gold futures market serves as an indispensable platform for risk management and price discovery in modern financial systems. Its price evolution not only reflects the fundamental supply-demand dynamics of global precious metals but also embodies deeper information regarding macroeconomic fluctuations, inflation expectations, and geopolitical shocks. Recently, gold prices have surged to unprecedented levels, breaching the $4500 per ounce threshold at one point and reaching historical closing highs. As a complex asset encompassing commodity, monetary, and investment attributes, the trading behavior and price dynamics of gold futures exert significant influence on central bank reserve asset management, financial institution portfolio allocation, and cost hedging strategies for real economy enterprises.

Volatility, as a quantitative measure of return uncertainty, serves as a critical input for derivative pricing, portfolio optimization, and value-at-risk (VaR) calculation. Gold futures volatility, serving as a proxy for market uncertainty and risk sentiment, possesses guiding significance for asset allocation and VaR measurement. Accurate forecasting of gold futures volatility not only advances the development of GARCH-family econometric models but also helps decipher macro-financial shock transmission mechanisms in price formation, thereby providing crucial evidence for academic research and practical decision-making. Consequently, in-depth analysis of the generation mechanism and driving factors underlying gold futures volatility holds both profound theoretical value and practical implications for the efficacy of related financial decision-making.

In the field of volatility modeling, early studies predominantly adopted GARCH-class models to capture and characterize the conditional heteroskedasticity features of gold futures markets (Dyhrberg, 2016; Li et al., 2020). However, traditional GARCH-type models fail to effectively incorporate low-frequency macroeconomic variables into high-frequency financial data, limiting their applicability in macro-micro linkage analysis. To address this limitation, Engle, Ghysels, and Sohn (2013) proposed the GARCH-MIDAS model, which decomposes volatility into short-term and long-term components, thereby establishing a framework for modeling the impact of exogenous economic variables on the long-term volatility component. This model, which integrates daily volatility with monthly macroeconomic information, has been widely applied in the field of stock market volatility research. For instance, Fang et al. (2018) introduced global stock market implied volatility as a long-term component variable, revealing that it accounts for 35% of the long-term conditional variance in COMEX gold futures—a substantial improvement over conventional GARCH and rolling-window MIDAS specifications. In a pioneering study, Conrad and Kleen (2020) verified that incorporating low-frequency variables, such as interest rates and inflation, significantly enhances out-of-sample forecasting accuracy. To capture structural breaks, Ma et al. (2021) further advanced this line of research by embedding Markov regime-switching dynamics into the GARCH-MIDAS framework. Their findings reveal a striking asymmetry: during high-volatility regimes, gold's long-term volatility exhibits 2.3 times greater sensitivity to fluctuations in the U.S. dollar index compared to low-volatility regimes, accompanied by a reduction in out-of-sample prediction errors of approximately 12%.

Nevertheless, these studies have predominantly concentrated on macroeconomic indicators and market sentiment drivers, overlooking the pervasive influence of economic policy on futures markets. In recent years, with the escalation of global economic policy uncertainty (EPU), the safe-haven attributes and volatility dynamics of financial markets have attracted increasing scholarly attention. The EPU index, constructed by Baker, Bloom, and Davis (2016), has been extensively utilized to quantify the impact of policy uncertainty on financial markets. Numerous studies suggest that rising EPU tends to exacerbate price volatility in equity and bond markets (Balcilar et al., 2016). Antonakakis et al. (2019) employed TVP-VAR to demonstrate that EPU exhibits significant predictive power for U.S. equity returns and volatility, with its impact on volatility markedly intensified during the subprime crisis. Kannadhasan and Das (2020) found that a 1% increase in global EPU corresponds to a 0.28% decline in average returns for emerging equity markets, with more pronounced declines in financially open economies. Huang and Liu (2022) distinguished between positive and negative EPU shocks, verifying asymmetric effects whereby only negative shocks possess significant predictive power for cross-sectional equity returns. More recently, Ghani and Ghani (2024) employed GARCH-MIDAS to compare the spillover effects of U.S., U.K., and Chinese EPU on Pakistani market volatility, with results indicating that U.S. EPU coefficients significantly exceed those of China and the U.K., highlighting the central role of U.S. dollar hegemony zone policy uncertainty in global risk pricing.

Despite the substantial methodological and empirical advances in existing literature, few studies have considered incorporating economic policy uncertainty (EPU) into the volatility decomposition of gold futures. To address this gap, this paper systematically investigates the long-term impact of global EPU on gold futures market volatility within the GARCH-MIDAS framework. This study offers several key contributions. First, it employs the longest sample period to date, enabling a more comprehensive assessment of the evolving relationship between EPU and gold futures volatility over time. Second, it conducts a broad set of robustness checks, including the R^2 and Doc test, to validate the reliability of out-of-sample volatility forecasts. Third, it elucidates the underlying mechanisms through which EPU influences gold futures markets, providing novel insights for both policymakers and investors. Collectively, these efforts furnish new empirical evidence and theoretical support for risk management and policy expectation guidance in gold markets.

2. Model Specification

2.1. GARCH-MIDAS

Generally, let $r_{i,t}$ denote the daily log return series for day i in month t. The structure of GARCH-MIDAS model is specified as follows:

$$r_{i,t} - E_{i-1,t}\left(r_{i,t}\right) = \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \forall i = 1, 2, \cdots, N_t \quad (2.1)$$

$$\varepsilon_{i,t} \mid \psi_{i-1,t} \sim N\left(0,1\right) \quad (2.2)$$

$$\sigma_{it}^2 = \tau_t g_{i,t} \quad (2.3)$$

where N_t represents the total number of trading days in month t, $E_{i-1,t}$ denotes the conditional expectation up to day $i-1$, $\psi_{i-1,t}$ is the information set from day 1 to day $i-1$ in month t, $\sigma_{i,t}^2$ is the conditional variance, and $\varepsilon_{i,t}$ follows a standard normal distribution. In practice, $E_{i-1,t}\left[r_{i,t}\right] = \mu$ is typically assumed, allowing Equation (2.1) to be expressed as:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \forall i = 1, 2, \cdots, N_t \tag{2.4}$$

evidently Equation (2.3) decomposes volatility into two components: the short-term component $g_{i,t}$, which captures high-frequency volatility dynamics; and the long-term component τ_t, which captures low-frequency movements. The former is primarily driven by return fluctuations and evolves according to return variations, following a GARCH(1, 1) process:

$$g_{i,t} = \omega + \alpha \frac{\left(r_{i,t} - \mu\right)^2}{g_t} + \beta g_{i-1,t} \tag{2.5}$$

subject to the non-negativity and stationarity constraints $\alpha > 0$, $\beta > 0$, $\alpha + \beta < 1$, where ω is the intercept term. Furthermore, the long-run trend τ_t is influenced by realized volatility (RV), with the specific functional form:

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k\left(\omega_1, \omega_2\right) RV_{t-k} \tag{2.6}$$

where m is a constant term, K denotes the maximum lag order for low-frequency variables (set to $K = 24$ in this study), and RV_t represents the realized volatility for month t, calculated as the sum of squared daily returns:

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{2.7}$$

where $\varphi_k\left(\omega_1, \omega_2\right)$ represents the weighting function for lagged variables. This study employs the Beta function as the weighting scheme, which offers greater flexibility and is commonly used in models with lag structures:

$$\varphi_k\left(\omega_1, \omega_2\right) = \frac{\left(k/(K+1)\right)^{\omega_1 - 1} \cdot \left(1 - k/(K+1)\right)^{\omega_2 - 1}}{\sum_{j=1}^{K} \left(j/(K+1)\right)^{\omega_1 - 1} \cdot \left(1 - j/(K+1)\right)^{\omega_2 - 1}} \tag{2.8}$$

typically, $\omega_1 = 1$ is fixed, as the weights on lagged variables exhibit decay characteristics, with the parameter ω_2 determining the decay speed of low-frequency data's influence on high-frequency data. Thus, the Beta weighting function simplifies to:

$$\varphi_k\left(\omega_2\right) = \frac{\left(1 - k/K\right)^{\omega_2 - 1}}{\sum_{j=1}^{K} \left(1 - j/K\right)^{\omega_2 - 1}} \tag{2.9}$$

2.2. GARCH-MIDAS-EPU

Modeling and forecasting volatility in commodity futures markets constitutes a critical issue in risk management, price discovery, asset allocation, derivative pricing, and policy formulation. Engle et al. (2013) proposed the GARCH-MIDAS model, incorporating macroeconomic variables based on MIDAS regression, substituting realized volatility in the long-term variance equation with macroeconomic predictors. This approach effectively extracts predictive information embedded in macroeconomic data. Let $r_{i,t}$ denote the daily log return series of gold futures prices for day i in month t. The return and volatility structure of the

GARCH-MIDAS-EPU model is specified as:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \forall i = 1,\cdots,N_t \tag{2.10}$$

$$\varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N(0,1) \tag{2.11}$$

$$\sigma_{i,t}^2 = \tau_t g_{i,t} \tag{2.12}$$

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{2.13}$$

$$\tau_t = m + \theta\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)X_{t-k} \tag{2.14}$$

$$\varphi_k(\omega_1,\omega_2) = \frac{\left(k/(K+1)\right)^{\omega_1-1}\cdot\left(1-k/(K+1)\right)^{\omega_2-1}}{\sum_{j=1}^{K}\left(j/(K+1)\right)^{\omega_1-1}\cdot\left(1-j/(K+1)\right)^{\omega_2-1}} \tag{2.15}$$

where the conditional variance is composed of the product of the short-term $g_{i,t}$ component and the long-term component τ_t. The former is driven by the joint dynamics of realized volatility and lagged EPU, with X_{t-k} representing the EPU index at lag k. This specification facilitates the examination of the relationship between EPU and gold1 futures markets. Other variables are defined consistently with the GARCH-MIDAS model.

To investigate the impact effect of economic policy uncertainty on gold futures market volatility, this study embeds the EPU index as an exogenous explanatory variable into the long-term volatility component equation within the GARCH-MIDAS framework, constructing the extended GARCH-MIDAS-EPU model. This specification retains the model's advantages in capturing long-term volatility memory and handling mixed-frequency data, while explicitly incorporating the EPU variable, thereby directly integrating policy uncertainty shocks into long-term volatility expectations. This enables the testing of two core hypotheses: whether "rising policy uncertainty significantly amplifies long-term volatility in gold futures" and whether "this effect exhibits lag structure heterogeneity". Compared with traditional GARCH models, GARCH-MIDAS-EPU can utilize mixed-frequency information from daily returns and monthly EPU without requiring data sampling frequency reduction, avoiding information loss and model misspecification. Meanwhile, the Beta weighting smoothing constraint ensures continuity and interpretability in long-term volatility estimation.

3. Data

The U.S. gold futures data used in this study are primarily sourced from the COMEX gold futures contracts traded on the Chicago Mercantile Exchange Group (CME Group). The sample period spans from January 2, 1997, to August 19, 2025, with a total of 7251 observations. Data are obtained from Investing.com (https://cn.investing.com/). The sample for EPU index spans from January 1997 to August 2025, comprising 343 monthly observations, sourced from the Economic Policy Uncertainty official website (https://www.policyuncertainty.com). In this study, gold futures closing prices are transformed into return series via log-differencing. To avoid scaling issues, the returns are multiplied by 100, calculated as follows:

$$r_t = 100 * \log\left(\frac{P_t}{P_{t-1}}\right) \quad (3.1)$$

where r_t denotes the return, P_t represents the closing price of gold futures on day t, and P_{t-1} represents the closing price on day $t-1$.

Our adoption of the global EPU index for U.S. gold futures is grounded in two fundamental mechanisms. First, the cross-border policy transmission channel operates through integrated financial markets, whereby policy uncertainty shocks propagate rapidly across economies via capital flows, investor risk appetite, and flight-to-safety behavior, rendering domestic gold markets susceptible to global policy perturbations. Second, the global gold-price formation mechanism is predominantly denominated in U.S. dollars and shaped by international macroeconomic conditions, implying that the long-run volatility component of U.S. gold futures is inherently tethered to global rather than idiosyncratic policy uncertainty dynamics.

Table 1 presents the descriptive statistics for gold returns and EPU. The mean return is 0.0363, close to zero, while the standard deviation of 0.0149 substantially exceeds the mean. The kurtosis of return is 5.9127, exceeding the normal distribution value of 3, and the skewness is slightly negative (−0.0212), indicating leptokurtic and left-skewed characteristics. The Jarque-Bera statistics reject the null hypothesis of normality at the 1% significance level, suggesting fat-tail properties in the return series. Furthermore, the Ljung-Box test also rejects the null hypothesis, suggesting strong serial correlation in the sample. As shown in Table 1, the EPU index exhibits substantial variation between its maximum and minimum values. To ensure data comparability, this study standardizes the raw EPU data using the Z-score method:

$$X_{EPU} = \frac{X-\mu}{\sigma} \quad (3.2)$$

where μ and σ denote the mean and standard deviation of the EPU variable, respectively, and X_{EPU} represents the normalized value.

Table 1. Descriptive statistics.

	Mean	Std. Dev	Min	Max	Skewness	Kurtosis	JB statistic	Q(10)	Q(20)
r_t	0.0363	1.0695	−9.3400	9.2300	−0.0212	5.9127	10562.9663***	21.1304**	40.1341***
EPU	146.1901	83.1128	47.8580	628.4796	1.7233	4.5872	470.4993***	1686.5348***	2693.8570***

Note: Lag orders for respective tests are indicated in parentheses. *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

4. Empirical Analysis

4.1. In-Sample Estimation Results

This subsection presents parameter estimation results for the GARCH-MIDAS models. In the GARCH-MIDAS-EPU model, the lag order for exogenous variables is set to $K = 24$, implying that the impact of EPU on gold futures market volatility extends over a 24-month horizon. The estimation results are reported in Table 2, where α 、 β are the GARCH process parameters; θ captures EPU's impact on the long-term component of gold futures volatility; and ω denotes the estimated parameter of the Beta weighting function associated with the EPU.

Table 2. The parameter estimation results.

Parameter	Model 1	Model 2	Model 3
μ	0.1903*	0.0136**	0.1496***
m	0.1630***	−0.4175**	−0.0166***
θ	-	0.0884***	−0.0225***
ω	-	6.9261***	1.6776***
α	0.0397***	0.06198***	0.0976***
β	0.9472***	0.8684***	0.8784***
AIC	2.9253	2.6729	**2.3954**
BIC	2.9305	2.6819	**2.4045**

Note: Model 1 represents the GARCH model, Model 2 represents the GARCH-MIDAS model, and Model 3 represents the GARCH-MIDAS-EPU model. *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

Table 2 reveals that parameter estimates for all three forecasting models are statistically significant. Notably, the GARCH parameters in both GARCH-MIDAS and GARCH-MIDAS-EPU models indicate strong volatility clustering in short-term volatility of gold futures. The sum $\alpha + \beta$ is less than but close to unity, suggesting high persistence in gold futures price volatility that gradually decays over time. Furthermore, the positive and significant θ in the GARCH-MIDAS model shows that an increase in current-period realized volatility not only affects short-term volatility but also significantly raises the long-term volatility component in the subsequent period. In contrast, the negative θ in the GARCH-MIDAS-EPU model reveals a negative relationship between EPU and gold market volatility, implying that elevated economic policy uncertainty is associated with reduced long-term volatility components in the gold futures market. A plausible explanation is that faced with policy uncertainty, investors may become more cautious and conservative, preferring to holding assets rather than trade frequently. The corresponding decline in market trading activity naturally leads to lower volatility. Finally, $\omega > 1$ in both GARCH-MIDAS and GARCH-MIDAS-EPU models indicates that the Beta weighting coefficients for the lagged terms exhibit a gradually decreasing trend as the lag order increases.

Table 2 reports the Akaike information criterion (AIC) and Bayesian information criterion (BIC) values for the three models. Both criteria indicate a substantial improvement in fit for the MIDAS-inclusive models over the benchmark GARCH model. Moreover, the GARCH-MIDAS-EPU model achieves a better in-sample fit than traditional GARCH-MIDAS model, suggesting that incorporating EPU yields greater optimization benefits.

4.2. Out-of-Sample Forecasting Results

To evaluate the predictive accuracy gains from incorporating exogenous variables, this study conducts out-of-sample forecasting analysis using a fixed-size rolling window approach with a one-step-ahead ($h=1$) daily forecast horizon. The full sample is divided into in-sample and out-of-sample portions, with the first 70% of observations serving as the initial estimation window and the remaining 30% reserved for forecasting evaluation. At each step, the estimation window rolls forward by one day, discarding the oldest observation and adding the newest to maintain a constant window length. Realized volatility (RV), computed as the sum of squared daily returns within each month, serves as the proxy for true volatility in loss functions and R^2 calculations. For temporal alignment, monthly EPU observations are treated as step functions held constant throughout the respective month, ensuring synchronization with daily volatility forecasts. Thus, out-of-sample forecasting is rendered feasible.

The model confidence set (MCS) test, proposed by Hansen et al. (2011), is a popular quantitative method for evaluating the relative forecasting performance of competing models in financial applications. The MCS test operates as follows: First, an initial model set is established, and loss function values are computed for each model. Next, relative loss function values are computed for randomly selected model pairs, and a new set is defined accordingly. Finally, significance tests are performed for arbitrary model pairs under the null hypothesis H_0 that the competing models have identical forecasting ability, utilizing the equivalence test δ_M. Meanwhile, the elimination criterion e_M is employed to exclude models that reject the null hypothesis.

We utilize commonly used loss functions to conduct MCS test. Both T_R and T_{SQ} statistics are evaluated at the 90% confidence level to determine the set of surviving models—that is, a model is considered to have superior predictive ability if its corresponding p-value exceeds 0.1. Moreover, higher p-values indicate greater forecasting accuracy for gold volatility, with a p-value of 1 representing the highest possible predictive performance. The results reported in **Table 3** demonstrate that the GARCH-MIDAS-EPU model consistently outperforms its counterparts across all five loss functions, exhibiting stronger forecasting ability in gold futures volatility. However, neither the benchmark GARCH model nor the standard GARCH-MIDAS model demonstrates satisfactory forecasting performance in the MCS test.

To assess the forecasting accuracy of each model, this study also adopts the R^2 statistic proposed by Campbell and Thompson (2008). This metric has been widely adopted in evaluating out-of-sample forecasting performance. The R^2 statistic is defined as:

$$R^2 = 1 - \frac{\sum_{m=N+1}^{N+M} \left(\sigma_m^2 - \hat{\sigma}_m^2 \right)^2}{\sum_{m=N+1}^{N+M} \left(\sigma_m^2 - \hat{\sigma}_{o,m}^2 \right)^2} = 1 - \frac{MSPE_{model}}{MSPE_{bench}} \tag{4.1}$$

where $MSPE_{model}$ and $MSPE_{bench}$ denote the mean squared prediction errors for the forecasting model and benchmark model, respectively; and σ_m^2, $\hat{\sigma}_m^2$, $\hat{\sigma}_{o,m}^2$ denote the true volatility, volatility forecast from the forecasting model, and volatility forecast from the benchmark model, respectively. A positive R^2 indicates that the forecasting model outperforms the benchmark in terms of out-of-sample predictive accuracy, whereas a negative R^2 suggests the opposite, with larger values reflecting greater improvement in predictive power. Additionally, the CW test is employed to assess the statistical significance of the out-of-sample forecasting results.

Table 3. The MCS test results.

	QLIKE		MSE		MAE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
Model 1	0	0	0.0124	0.0124	0	0	0	0	0	0
Model 2	0	0	0.0124	0.0124	0	0	0	0	0	0
Model 3	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

Table 4 reports that for both the GARCH-MIDAS and GARCH-MIDAS-EPU models, the out-of-sample test *p*-values reject the null hypothesis at the 1% confidence level. Moreover, both Model 1 and Model 2 yield positive out-of-sample R^2 values, implying superior predictive performance relative to the benchmark GARCH model. These findings demonstrate that forecasting models incorporating realized volatility achieve more precise forecasting accuracy. Notably, the inclusion of global economic policy uncertainty significantly enhances the accuracy of gold futures volatility forecasts, underscoring the value of policy-related information in improving out-of-sample predictions.

Table 4. The results of R^2 test.

	R^2 (%)	MSPE adjusted	*p*-values
Model 1	-	-	-
Model 2	0.9728	2.0692	0
Model 3	**19.1796**	**4.9560**	**0**

4.3. Robustness Analysis

Leitch and Tanner (1991) introduced the direction-of-change (Doc) to evaluate forecasting model performance in predicting directional changes (i.e., increase or decrease) of target variables, offering a useful perspective on market timing. Consequently, this study further employs Doc test to assess the precision of each forecasting model in predicting directional changes in gold futures volatility. The Doc statistic is computed as follows:

$$\text{Doc} = \frac{1}{T}\sum_{1}^{T} d_t \tag{4.2}$$

where T represents the number of out-of-sample forecasts, and d_t denotes the directional indicator for the forecasting model, defined as:

$$d_t = \begin{cases} 1, & \text{if } \sigma_i^2 > \sigma_{i-1}^2 \text{ and } \hat{\sigma}_i^2 > \hat{\sigma}_{i-1}^2 \\ 1, & \text{if } \sigma_i^2 < \sigma_{i-1}^2 \text{ and } \hat{\sigma}_i^2 < \hat{\sigma}_{i-1}^2 \\ 0, & \text{otherwise} \end{cases} \tag{4.3}$$

where σ_i^2 and σ_{i-1}^2 represent actual volatility at periods i and $i-1$, respectively, $\hat{\sigma}_i^2$ and $\hat{\sigma}_{i-1}^2$ denote corresponding volatility forecasts. To assess the statistical significance of the Doc statistics, this study employs the non-parametric method proposed by Pesaran and Timmermann (2009), with the null hypothesis $H_0 : \text{Doc} \le 0.5$ against the alternative and alternative hypothesis $H_1 : \text{Doc} > 0.5$. Rejection of the null hypothesis indicates that the model's Doc value exceeds 0.5, implying superior performance in predicting directional changes in gold futures volatility.

Table 5 presents Doc values and PT test results for each forecasting model. All models reject the null hypothesis at the 1% confidence level, with Doc values exceeding 0.5, indicating that each model is capable of predicting the directional changes in gold futures volatility with reasonable accuracy. The GARCH-MIDAS model achieves higher Doc than the benchmark model, suggesting that the inclusion of RV provides richer predictive information and enhances the volatility forecasting accuracy of gold futures. Moreover, the GARCH-MIDAS-EPU model yields the highest Doc value among three models, demonstrating that incorporating EPU index further improves predictive power and model generalization, leading to more reliable directional forecasts of gold futures volatility.

Table 5. The results of Doc test.

	Doc	PT statistic	*p*-values
Model 1	0.6837	20.1566	0
Model 2	0.6855	20.4148	0
Model 3	**0.7462**	**24.4115**	**0**

Rossi and Inoue (2012) note that different estimation windows may lead to substantial variations in out-of-sample forecasting results. Accordingly, we evaluate the stability of model forecasts by selecting an alternative estimation window comprising 80% of the full sample (January 1997 to April 2014) to re-estimate the models and forecast daily gold futures volatility.

The results reported in Table 6 and Table 7 indicate that the conclusions drawn under alternative forecasting windows remain consistent with those obtained from the baseline specification. Specifically, the GARCH-MIDAS-EPU model successfully passes the MCS test under all loss functions and consistently achieves the maximum *p*-values across evaluation windows. Furthermore, the out-of-sample R^2 results confirm that the GARCH-MIDAS-EPU model enhances forecasting accuracy to a greater extent than the other two competing models, underscoring the value of incorporating economic policy uncertainty in volatility prediction. In summary, these findings strongly suggest that this novel model offers the greatest advantage in forecasting the volatility of the U.S. gold futures market, and that its predictive superiority is robust to the choice of estimation window.

Table 6. The result of MCS test under alternative forecasting window.

	QLIKE		MSE		MAE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
Model 1	**1**	0.1467	0.0033	0.0058	0	0	0	0	0	0
Model 2	**1**	**1**	0.0033	0.0058	0	0	0	0	0	0
Model 3	**1**	0.1467	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

Table 7. The results of R^2 test under alternative forecasting window.

	R^2 (%)	MSPE adjusted	*p*-values
Model 1	-	-	-
Model 2	0.4439	1.5426	0
Model 3	**41.0908**	**6.6549**	**0**

5. Conclusion

Unlike conventional financial assets, gold—as a physical commodity with multiple attributes—has long been regarded as an effective hedge against economic and political shocks. Modeling and forecasting volatility has consistently been a central topic in finance, and accurately estimating fluctuations in gold futures volatility is therefore crucial for portfolio construction and risk management. Against this backdrop, this study employs the EPU index proposed by Baker et al. (2016) to investigate its impact on gold futures volatility. Given the mixed-frequency nature of the data—daily COMEX gold futures price and monthly EPU observations—the GARCH-MIDAS framework is adopted to avoid information loss due to frequency mismatch. The EPU index is incorporated into the model to examine its role in influencing and predicting volatility in the gold futures market.

The empirical results indicate that the EPU index exerts a significant negative impact on gold futures market volatility. Specifically, an increase in current-period EPU not only affects short-term volatility but also reduces the long-term volatility component in the subsequent period. Forecast evaluation tests indicate that, compared with the benchmark GARCH model, the GARCH-MIDAS model incorporating realized volatility yields more accurate out-of-sample forecasts. Moreover, further embedding the EPU index into the GARCH-MIDAS framework significantly enhances predictive performance, with the proposed GARCH-MIDAS-EPU model achieving the highest forecasting accuracy. These findings remain robust across a series of alternative specifications and estimation windows.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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