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Cryptocurrency uncertainty and volatility forecasting of precious metal futures markets

Yu Wei [a], Yizhi Wang [b,*], Brian M. Lucey [c,d,e,f], Samuel A. Vigne [g]

[a] School of Finance, Yunnan University of Finance and Economics, Kunming, China
[b] Cardiff Business School, Cardiff University, Aberconway Building, Cardiff CF10 3EU, United Kingdom
[c] Trinity Business School, Trinity College Dublin, Dublin 2, Ireland
[d] Institute of Business Research, University of Economics Ho Chi Minh City, 59C Nguyen Dinh Chieu ,Ward 6, District 3, Ho Chi Minh City, Viet Nam
[e] Institute for Industrial Economics, Jiangxi University of Economics and Finance, 169, East Shuanggang Road, Xialuo, Changbei District, 330013 Nanchang, Jiangxi, China
[f] University of Abu Dhabi, Zayed City, Abu Dhabi, United Arab Emirates
[g] LUISS Business School, LUISS University, Rome, Italy

A R T I C L E   I N F O

A B S T R A C T

Several common properties shared by cryptocurrencies and precious metals, such as safe haven, hedge and diversification for risk assets, have been widely discussed since Bitcoin was created in 2008. However, no studies have explored whether cryptocurrency market uncertainties can help to explain and forecast volatilities in precious metal markets. By using the GARCH-MIDAS model incorporating cryptocurrency policy and price uncertainty, as well as several other commonly used uncertainty measures, this paper compares the in-sample impacts and out-of-sample predictive abilities of these uncertainties on volatility forecasts of COMEX gold and silver futures markets. The in-sample results demonstrate the significant impacts of cryptocurrency uncertainty on the volatilities of precious metal futures markets, and the out-of-sample evidence further confirms the superior predictive power of cryptocurrency uncertainty on volatility forecasting of the precious metal market. Our conclusions are robust through various model evaluation approaches based not only on predicting errors but also on forecasting directions across different forecasting time horizons.

1. Introduction

Finance literature has provided somewhat mixed evidence about the relationships between uncertainty measures and gold market (Bilgin et al., 2018; Chiang, 2021; Chiang, 2022), to name but a few. Cryptocurrencies have become a significant asset class in recent years (Urquhart, 2016; Urquhart, 2017; Marobhe, 2021; Letho et al., 2022; Wang et al., 2022), and there is rising interest focusing on linkages between the cryptocurrency and precious metal markets [Klein et al., 2018; Bianchi et al., 2022]. There is some evidence that from a financial markets perspective, precious metals and cryptocurrencies share several common characteristics, such as safe haven, hedge and diversification for risk assets (Corbet et al., 2020). In particular, the hedging capability of precious metal is often compared to Bitcoin [Dyhrberg, 2016; Wu et al., 2019].

Recently, Lucey et al. (2022) developed the cryptocurrency uncertainty indices (UCRY Policy and UCRY Price), which can capture policy uncertainty and price uncertainty in the cryptocurrency market beyond price volatility. Faced with high cryptocurrency

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uncertainty recently, investors and researchers have begun to investigate the properties of precious metals to counter cryptocurrency uncertainty shocks (Hassan et al., 2021; Elsayed et al., 2022). Hassan et al. (2021) examine the time-varying inter-connections between precious metals and cryptocurrency indices using a DCC-GJR-GARCH model. Their research findings show that gold has a stable and reliable safe-haven property against cryptocurrency uncertainty. Similarly, Elsayed et al. (2022) investigate the dynamic connectedness of return- and volatility spillovers among cryptocurrency (CRIX), cryptocurrency uncertainty indices, CBOE S&P 500 Volatility Index (CBOE VIX), Global Economic Policy Uncertainty index (GEPU) and gold. The empirical results from this paper suggest that the cryptocurrency uncertainty policy index is the main transmitter of the return spillover to gold. Elsayed et al. (2022) discusses information spillover among the gold market and uncertainty measures.

However, these related researches have two major problems. On the one hand, most extant papers on the interactions between cryptocurrency and precious metal markets only use the same frequency data to conduct their empirical examinations (Hassan et al., 2021; Elsayed et al., 2022; Bianchi et al., 2022). For example, the spillover analysis massively used in recent studies can only adopt the same frequency data, e.g., daily return or volatility series, to measure the connectedness effects. Furthermore, this method can only show the direction and intensity of the spillovers but cannot provide evidence of whether these spillover effects are statistically significant. Moreover, as we know, many uncertainty measurements, such as Economic Policy Uncertainty (EPU) of Baker et al. (2016), Geopolitical Risk index (GPR) of Caldara and Iacoviello (2022), and the recently launched cryptocurrency uncertainty of Lucey et al. (2022), are only recorded in monthly or weekly frequency, which have been proved to be very informative in explaining or predicting the fluctuations of both cryptocurrency and precious metal markets in many recent studies (Wu et al., 2019; Hassan et al., 2021; Lucey et al., 2022; Dinh et al., 2022). Thus, ignoring these *low-frequency* (monthly or weekly) uncertainty measures in investigating cryptocurrency and precious metal markets will lose lots of useful information and may lead to unreliable conclusions.

On the other hand, most current studies focus only on the one-way influence of precious metals on cryptocurrencies, and ignore the possible reverse influence between them. For instance, Hassan et al. (2021) believe gold can provide a hedge against the cryptocurrency uncertainty indices, but they fail to discuss whether cryptocurrency uncertainty can help to explain and forecast the volatility of the gold market. Moreover, the existing literature about the uncertainty measures and gold markets which apply a mixed data sampling model either do not consider the linkages between the newly developed cryptocurrency uncertainty indices and gold market, or neglects the impacts of the uncertainty of the gold market itself [CBOE Gold ETF Volatility Index (CBOE GVZCLS)] on the volatility of gold market. To be more specific, the existing literature fails to show whether low-frequency uncertainty measures (especially the newly developed cryptocurrency uncertainty) can help to depict and forecast the volatilities of precious metal markets. The dependency between low-frequency cryptocurrency uncertainty and volatilities in precious metal markets, however, can provide new perspectives for policymakers and investors to inform regulatory and risk management strategies in both cryptocurrency and precious metal markets.

Motivated by the research gaps mentioned above, this paper contributes the extant literature in two major ways: firstly, to deal with the mixed frequency data dilemma, this paper extends the GARCH-MIDAS model of Engle et al. (2013) by incorporating various uncertainty indices to identify the impacts of the uncertainty indices [UCRY Policy, UCRY Price, GEPU, Geopolitical Risk index (GPR), Nominal Broad U.S. Dollar (USD index) Index, CBOE VIX, and CBOE GVZCLS] on the volatility of precious metal markets (COMEX gold and silver futures). Secondly, this paper is the first to quantify both the in-sample impacts and the out-of-sample predictive abilities of various uncertainty indices on the volatilities of precious metal markets. Moreover, to compare the predictive powers of different uncertainty indices, various model evaluation approaches, such as the DM test of Diebold and Mariano (2002), the out-of-sample R^2 test by Rapach et al. (2010), Model Confidence Set (MCS) test of Hansen et al. (2011), and the Direction-of-Change (DoC) rate test by Degiannakis and Filis (2017), are adopted to assess not only the forecasting errors, but also the accuracy in forecasting directions across different forecasting horizons.

In summary, our main findings can be concluded as follows. First, we find that different uncertainty indices can indicate the different long-term components of volatility in precious metal markets. These long-term components show distinct trends over time. Second, the in-sample results demonstrate the significant impacts of cryptocurrency uncertainty on the volatilities of precious metal markets, and the out-of-sample evidence further confirms the superior volatility predictive power of cryptocurrency uncertainty over other uncertainty indices. The empirical findings from this paper highlight the importance of cryptocurrency uncertainty and can provide new insights for investors, policymakers and academics into the investment and hedging strategies related to precious metal markets across different periods.

The remainder of the paper is organised as follows: Section 2 details the specification of the methodology. Section 3 presents a description of the data. Section 4 discusses the empirical results. Section 5 provides concluding remarks.

2. Methodology

2.1. GARCH-MIDAS-X model

In this paper, we utilise the GARCH-MIDAS model of Engle et al. (2013) to handle the problem in different data frequencies of daily precious metal returns and monthly uncertainty indices. Furthermore, we extend it to a GARCH-MIDAS-X one by incorporating an additional exogenous low-frequency impactor in the simple GARCH-MIDAS model, which allows us to quantify the impacts of various uncertainties on the volatility of precious metal futures. This GARCH-MIDAS-X model can decompose total conditional volatility of asset returns into short-term and long-term components, where the short-term volatility is driven by a simple GARCH

(1,1) process and the long-term one is determined by a MIDAS regression of low-frequency exogenous impactor. A standard GARCH-MIDAS model can be defined as Eq. (1):

$$r_{i,t} - \omega = \sqrt{g_{i,t}\tau_t} \times z_{i,t}, \ \forall i = 1, \ldots, N_t, \tag{1}$$

where, $r_{i,t}$ is the asset returns on day i of month t. ω is the unconditional mean of the return, and N_t is the number of trading days in month t. $g_{i,t}$ and τ_t are the short-term and long-term components of the conditional volatility, respectively. The short-term volatility can be expressed as Eq. (2):

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

and the logarithm form of long-term component τ_t is given by Eq. (3):

$$log(\tau_t) = m + \theta_{RV} \sum_{k=1}^{K} \varphi_k(w_{RV}) RV_{t-k} + \theta_X \sum_{k=1}^{K} \varphi_k(w_X) X_{t-k}, \tag{3}$$

where, K is the number of lags for smoothing the long-term volatility; $RV_{t-k} = \sum_{i=1}^{N_t} r_{i,t-k}^2$ is the realised volatility in month $t-k$. In discussing the in-sample impacts and out-of-sample predictive abilities of uncertainty indices on the precious metal future market volatility, we should eliminate the possible effects of other factors. In order to address this potential issue, we consider adding the Realised Volatility (RV) with a lag period in our forecasting models when we detect the predictive power of the uncertainty indices. This method is the same as adding a lag of the dependent variable Y when we do a forecasting test. And the lag of Y can include the impact of other factors on Y. This is a standard method to eliminate the potential effects of other factors when we process a forecasting test on our model. As noted early in the works of Schwert (1989), Paye (2012), because lagged volatility captures a rich set of information regarding current economic conditions, successful forecasting variables must capture additional relevant information. Thus, in this paper, we incorporate lagged realised volatility of precious metal futures in the GARCH-MIDAS model along with those uncertainty indices. X_{t-k} is the uncertainty measure we considered in this paper and $\varphi_k(w)$ is the weighting function set by a Beta polynomial as Eq. (4):

$$\varphi_k(w) = \frac{(1 - k/K)^{w-1}}{\sum_{j=1}^{K} (1 - j/K)^{w-1}}, \tag{4}$$

where, Eq. (4) is used to describe the declining effect of the uncertainty index on the long-term volatility over time. Therefore, in the following in-sample analysis, we focus on the four major model parameters (i.e., α, β, θ_{RV} and θ_X) to identify the effects of different uncertainty indices on the volatility of precious metal futures.

2.2. Model evaluation methods

For the reason that different evaluation methods can test distinct predictive powers of the forecasting models, we employ four different model evaluation methods to assess the predictive abilities of various uncertainty indices from multi-dimension criteria.

2.2.1. Diebold and Mariano test

In model evaluation literature, the DM test proposed by Diebold and Mariano (2002) is a very popular and basic one, which compares the forecasting accuracy of two models by using the statistics as Eq. (5):

$$DM_i = \frac{\frac{1}{H} \sum_{t=1}^{H} (Loss_{t,i} - Loss_{t,benchmark})}{\sqrt{Var(Loss_{t,i} - Loss_{t,benchmark})}}, \tag{5}$$

where i denotes the ith GARCH-MIDAS-X model incorporating different uncertainty indices, and H is the length of forecasting sample. $Loss_{t,i}$ and $Loss_{t,benchmark}$ are the forecasting errors of model i and benchmark model at time t, respectively. Following commonly used loss functions, we use squared error (i.e., $[\sigma_t^2 - \hat{\sigma}_t^2]^2$) and absolute error (i.e., $|\sigma_t^2 - \hat{\sigma}_t^2|$) as measures of forecasting error in the DM test, where $\hat{\sigma}_t^2$ is the volatility forecasts obtained by a specific model and σ_t^2 is the true volatility of the asset returns. The null hypothesis of a DM test is that there is no difference in predictive accuracy of model i and the benchmark one. Thus, a negative DM statistic indicates higher predictive accuracy of model i than that of the benchmark model. In the following evaluations, we choose GARCH-MIDAS-VIX as the benchmark for the tight connections between VIX and gold markets proved.

2.2.2. Out-of-sample R^2 test

To assess the predictive ability of one model compared to a benchmark one, the out-of-sample R^2 test proposed by Rapach et al. (2010) is also massively adopted in many recent literature (Walther et al., 2019; Zhang et al., 2019; Li et al., 2020; Li et al., 2021; Liang et al., 2020; Wei et al., 2020). The out-of-sample R^2 (R_{OOS}^2) is calculated as the percentage reduction in mean squared error (MSE) of forecasting model i relative to that of a benchmark Eq. (6):

$$R_{OOS}^2 = 1 - \frac{\sum_{t=1}^{H} (\sigma_t^2 - \hat{\sigma}_{t,i}^2)^2}{\sum_{t=1}^{H} (\sigma_t^2 - \hat{\sigma}_{t,benchmark}^2)^2}, \tag{6}$$

where σ_t^2, $\hat{\sigma}_t^2$, and $\hat{\sigma}_{t,benchmark}^2$ are the true volatility, forecasted volatility by model i and forecasted volatility of the benchmark model, respectively. Clearly, a positive R_{OOS}^2 of model i indicates that this model can outperform the benchmark model with smaller MSE. The statistical significance of the R_{OOS}^2 test is obtained by the method of Clark and West (2007) with the null hypothesis that the MSE of the benchmark model is less than or equal to that of the forecasting model i. Therefore, if the R_{OOS}^2 of one model i is positive with significant rejection, it means that this model has significant smaller MSE than that of the benchmark one.

2.2.3. Model confidence set (MCS) test

Although the DM and out-of-sample R^2 (R_{OOS}^2) tests introduced above are wildly used in recent researches, they can only compare the predictive performance between two competing models, i.e., an interested model and a benchmark one. Therefore, to get a whole picture on the forecasting accuracy across all the interested models (e.g., the GARCH-MIDAS-X models incorporating various uncertainty indices considered in this paper), we turn to adopt the Model Confidence Set (MCS) test proposed by Hansen et al. (2011).

This MCS test is based on some traditional model evaluation approaches, such as the DM test of Diebold and Mariano (2002), reality check of White (2000), and superior predictive ability (SPA) test by Hansen (2005). However, it has several clear advantages over others. For example, firstly, the MCS test does not need a specific benchmark, while other methods, such as DM test and reality check, have to choose one. This can be highly subjective and tends to cause non-robust test results. Secondly, the p-values of MCS test are obtained by a bootstrap method, which can greatly reduce the influence of outliers in the forecasts. Lastly, the MCS test allows to select more than one *best* model, offering policy makers and investors more options in their decision making. The MCS process is handled as follows.

Suppose that we want to compare the forecasting performances of k models in a model set, $M_0 = \{m_1, m_2, \ldots, m_k\}$. These models are evaluated on a forecasting sample of length H and a loss function (or a criterion). In practice, we can use different loss functions for some particular evaluation purposes. Following the suggestions of Hansen (2005), Hansen et al. (2011), we choose six loss functions as:

$$QLIKE = \frac{1}{H}\sum_{t=1}^{H}(ln(\hat{\sigma}_t^2) + \sigma_t^2/\hat{\sigma}_t^2), \tag{7}$$

$$MSE = \frac{1}{H}\sum_{t=1}^{H}(\sigma_t^2 - \hat{\sigma}_t^2)^2, \tag{8}$$

$$MAE = \frac{1}{H}\sum_{t=1}^{H}|\sigma_t^2 - \hat{\sigma}_t^2|, \tag{9}$$

$$HMSE = \frac{1}{H}\sum_{t=1}^{H}(1 - \sigma_t^2/\hat{\sigma}_t^2)^2, \tag{10}$$

$$HMAE = \frac{1}{H}\sum_{t=1}^{H}|1 - \sigma_t^2/\hat{\sigma}_t^2|, \tag{11}$$

$$R^2LOG = \frac{1}{H}\sum_{t=1}^{H}[ln(\sigma_t^2/\hat{\sigma}_t^2)]^2 \tag{12}$$

where QLIKE indicates the loss implied by a Gaussian likelihood. MSE and MAE are two commonly used criteria of mean square error and mean absolute error, respectively. Moreover, HMSE and HMAE are the MSE and MAE adjusted for heteroskedasticity, and R^2LOG is similar to the R^2 of the Mincer–Zarnowitz regressions. These loss functions can serve for different practical uses. For example, in the case of value-at-risk applications, investors are more interested in the accurate forecasts of large volatilities rather than small volatilities. Thus, MSE is more suitable than MAE for risk management applications.

The MCS test is a series of significance tests in a set of forecasting models M_0, and the models with poor predictive power in the set M_0 are removed. Therefore, the null hypothesis of MCS test is that two models in M_0 have the same predictive power as Eq. (13):

$$H_{0,M} : E(d_{\ell,uv,t}) = 0 \; for \; all \; u, v \in M \subset M_0, \tag{13}$$

where $d_{\ell,uv,t} \equiv L_{u,t}^{\ell} - L_{v,t}^{\ell}$, and $L_{u,t}^{\ell}$ and $L_{v,t}^{\ell}$ are the results of loss function ℓ defined in Eq. (7) to Eq. (12) for models u and v at time t, respectively. $E(d_{\ell,uv,t})$ is the mathematical expectation of $d_{uv,t}$. Then, the MCS process utilises an equivalence test (δ_M) and an elimination rule (e_M) to continuously test the models in the model set M_0 until no model is removed from the set. Following (Hansen, 2005; Hansen et al., 2011), we set the significance level of the MCS test to be 0.1. This means that, if the p-value of one forecasting model in the MCS test is larger than 0.1, it is a *surviving* model in M_0. A larger p-value indicates a higher prediction accuracy of the corresponding model. In particular, a p-value equal to 1 suggests that the corresponding model has the best forecasting performance.

The above three tests are usually employed to assess the forecasting errors of different models. However, besides forecasting error, investors may also be very interested in the accuracy in the forecasting direction for better designing their trading strategy. Thus, besides MCS test, we further employ the Direction-of-Change (DoC) rate test utilised in Degiannakis and Filis (2017) to compare

the accuracy in the forecasting direction of various GARCH-MIDAS-X models. The DoC calculates the proportion of forecasts that correctly predict the direction of volatility movements. That is Eq. (14):

$$DoC = \frac{1}{H} \sum_{t=1}^{H} D_t,$$

(14)

where H is the number of return forecasts, and

$$D_t = \begin{cases} 1, if\ \sigma_t^2 > \sigma_{t-1}^2\ and\ \hat{\sigma}_t^2 > \sigma_{t-1}^2, \\ 1, if\ \sigma_t^2 < \sigma_{t-1}^2\ and\ \hat{\sigma}_t^2 < \sigma_{t-1}^2, \\ 0, otherwise. \end{cases}$$

(15)

Then, a nonparametric test proposed by Pesaran and Timmermann (1992) is employed to test the null hypothesis that the DoC rate of an interested model is not larger than that of the benchmark.

3. Data

Based on the research question, this study explores whether cryptocurrency uncertainty can forecast volatility in precious metal futures markets. Firstly, this study considers selecting the Top 2 precious metal assets with the highest trading volume to represent the precious metal market. Therefore, gold and silver these two assets are utilised. Based on the existing, we further decide to use COMEX Gold Futures (Bailey, 1987) and COMEX Silver (Chng, 2009) as an indicator to represent the gold and silver markets, separately. Secondly, we innovatively employ the newly issued cryptocurrency policy uncertainty index (UCRY Policy) and cryptocurrency price uncertainty index (UCRY Price) (Lucey et al., 2022) to serve as proxies for the cryptocurrency uncertainty.

According to the existing literature, we further include serial widely used uncertainty or volatilities indices as comparable variables. The reasons why we chose these comparable variables are presented as follows. Firstly, many existing studies have thoroughly discussed the effects of the equity market on the precious metal market (Baur and McDermott, 2010). Therefore, we select the world's premier barometer of the equity market, Chicago Board Options Exchange's CBOE Volatility Index (CBOE VIX), to quantify the uncertainty of equity market (Whaley, 2009). Secondly, the volatility of the precious metal market is often discussed with the variations in the foreign exchange market (Ghonghadze and Lux, 2016), then we include the U.S. Dollar Index (USD Index) to represent the foreign exchange market. Thirdly, CBOE Gold ETF Volatility Index (CBOE GVZCLS) estimates the expected 30-day volatility of returns on the SPDR Gold Shares. Similar to CBOE VIX for the stock market, CBOE GVZCLS quantifies the implied volatility for the gold market and indicates people's expectations on the gold price (Wei et al., 2020). Therefore, we use the CBOE GVZCLS as a volatility forecasting factor to compare with other possible impactors. In the end, considering UCRY indices can capture policy uncertainty and price uncertainty in the cryptocurrency markets, we further employ the global economic policy uncertainty index (GEPU) and geopolitical risk index (GPR) as comparable indicators.

The time span of this study ranges from 02/Jan/2014 to 13/May/2022. The reasons for selecting this sample period are as follows. Firstly, the data of all the selected variables, including the UCRY indices, are available from this date. Secondly, this time interval comprises the bull and turbulent periods in the cryptocurrency market. In the end, this sample period includes the 2018 financial crisis, recent pandemics, and the Russia–Ukraine war, among others. These special events mentioned above could significantly influence the uncertainty indices and the precious metal market. The data relating to UCRY indices are collected from their official website.[1] In addition, we obtain the GEPU and GPR from Economic Policy Uncertainty[2] and the other variables are all downloaded from Thomson Reuters.

In the empirical analysis, the daily gold and silver prices are converted to logarithm returns and monthly uncertainty indices are used in their levels. Fig. 1 shows the time evolutions of daily COMEX gold and silver prices, and other six uncertainty indices.[3] It shows that the gold/silver prices remain relatively stable from January 2014 to January 2019/January 2020. While since then, they have maintained a rapid upward trend. Then, the monthly CBOE S&P 500 Volatility Index, CBOE Gold ETF Volatility Index, GEPU, and USD index show a significant increase after the outbreak of the COVID-19 pandemic. The Geopolitical Risk index and UCRY Policy experience a sharp increase at the end of 2021, especially after the explosion of the war in Ukraine in February 2022. Finally, after a fairly long period of flatness since January 2014, UCRY Policy index experiences a sharp rise at the end of 2020. These findings reveal that different uncertainty indices are sensitive to different information sources, which may explain the price fluctuations in precious metal markets from multiple perspectives. The descriptive statistics are reported in Table 1.

Table 1 shows that, firstly, in terms of daily precious metal returns, we find that COMEX gold futures return has larger mean but smaller standard deviation than those of silver futures, implying that COMEX gold futures is a safer but more profitable asset than silver futures. Then, both gold and silver returns present left skewed and leptokurtic distributions. The Jarque–Bera statistics further confirm the rejection of normal distribution for these gold and silver returns. Moreover, the Ljung–Box Q tests suggest no significant autocorrelation in the daily gold and silver returns. Secondly, regarding to monthly uncertainty indices, we find that all their means are positive, indicating the increasing uncertainties in stock market, economic policy, geopolitical risk, USD exchange rate, and cryptocurrency markets during the data sample. The Jarque–Bera statistics also demonstrate that all this uncertainty indices are not

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[1] https://sites.google.com/view/cryptocurrency-indices/home?authuser=0
[2] https://www.policyuncertainty.com/index.html
[3] Due to UCRY Policy and UCRY Price having very similar trends, we only display UCRY Policy here.
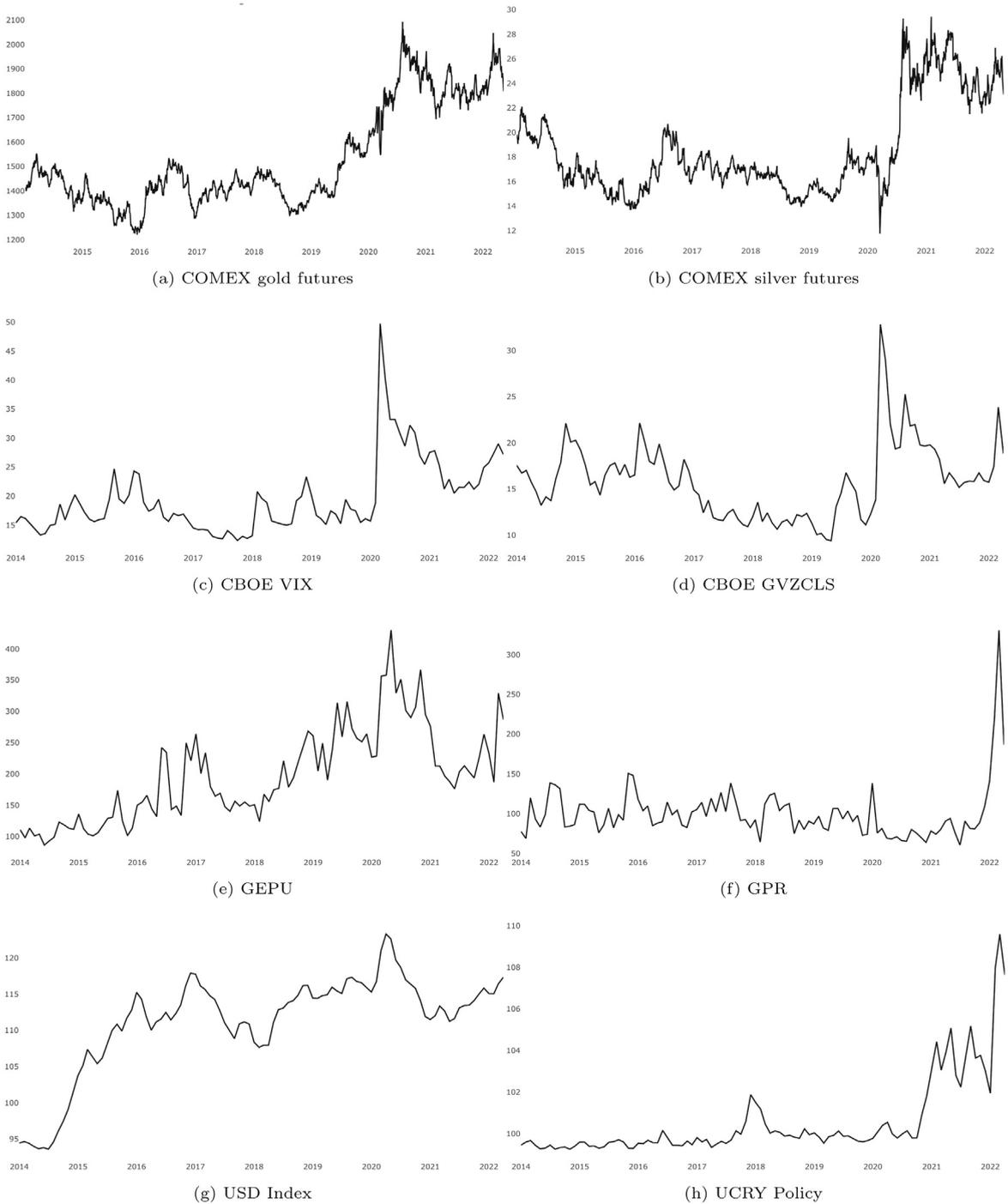
Fig. 1. Daily gold and silver futures prices and various monthly uncertainty indices.
Notes: The graphs displayed above are the time series plots of the COMEX Gold Futures, COMEX Silver Futures, CBOE VIX, CBOE GVZCLS, GEPU, GPR, USD index and UCRY Policy. The COMEX Gold Futures and COMEX Silver Futures are in the high-frequency daily data, and the uncertainty indices, including CBOE VIX, CBOE GVZCLS, GEPU, GPR, USD index and UCRY Policy are all in the low-frequency monthly data. The sample is from 02/Jan/2014 to 13/May/2022.

normally distributed, and the Ljung–Box Q tests show that they are auto-correlated up to 10 lags. Finally and most importantly, the Phillips–Perron unit root tests suggest that all the time series are stationary, and therefore can be modelled directly without further transformation.

Table 1

Descriptive statistics.

	COMEX gold	COMEX silver	CBOE VIX	CBOE GVZCL	GEPU	GPR	USD Index	UCRY Policy	UCRY Price
Obs.	2098	2098	100	100	100	100	100	100	100
Mean	0.0215	0.0076	1.7654	1.5924	1.9741	1.0033	1.1123	4.3746	4.3756
Maximum	6.2546	7.9464	5.7740	3.2850	4.3016	3.3078	1.2330	5.3929	5.3902
Minimum	−5.8363	−16.2790	1.0130	0.9390	0.8631	0.6068	0.9360	3.9703	3.9712
Median	0.0319	0.0254	1.5700	1.5755	1.8721	0.9252	1.1296	4.0176	4.0168
Std. Dev	0.9057	1.6788	0.6880	0.4074	0.7523	0.3440	0.0681	0.4880	0.4880
Skewness	−0.0285	−0.6512	2.6177	1.1121	0.6518	3.6438	−1.3097	0.6217	0.6194
Kurtosis	7.0302	11.7669	13.9895	5.4381	2.8434	22.8072	4.1946	1.5119	1.5136
J.-B.	1420.1167***	6866.9199***	617.4047***	45.3819***	7.1823**	1855.9803***	34.5353***	15.6676***	15.6008***
Q(5)	5.4274	8.6328	105.1256***	145.8673***	268.9158***	48.6619***	344.6507***	51.284***	50.757***
Q(10)	9.6227	15.1205	132.3274***	200.7231***	417.6058***	49.0409***	460.6627***	112.4792***	111.3165***
P–P	−45.7591***	−46.0576***	−4.0191***	−3.531***	−2.8231*	−4.21***	−2.3916	−16.7438***	−16.7365***

Notes: This table reports the descriptive statistics for daily precious metal futures returns and seven uncertainty indices. For the sake of comparability of different uncertainty indices, we perform a 10-fold reduction for CBOE VIX and CBOE GVZCL, and a 100-fold reduction for the other five indices. Q(n) is the Ljung–Box Q statistics with lag length of n. P–P is the Phillips–Perron unit root statistics. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$, respectively.

4. Empirical results

4.1. In-sample estimation results

In this sub-section, we first quantify the overall impacts of the seven monthly uncertainty indices on the volatility (especially the long-term volatility) of daily COMEX gold and silver returns. The estimation results of GARCH-MIDAS-X model fitting daily COMEX gold and silver returns incorporating various uncertainty indices are presented in Fig. 2, Tables 2 and 3.

For simplicity, Fig. 2 shows estimated total and long-term volatility of daily COMEX gold futures returns by various monthly uncertainty indices. We find that different uncertainty indices can depict the different long-term components of volatility in gold prices, and these long-term components show distinct trends over time. Among them, the long-term volatilities estimated by GARCH-MIDAS incorporating CBOE VIX and GVZCLS indices seem to be very close to total volatility, indicating the information contained in these two uncertainty indices has similar impacts on the total and long-term components of COMEX gold volatilities. Furthermore, we find that the other four uncertainty indices, i.e., GEPU, GPR, USD index and UCRY Policy, have comparable but subtle impacts on the long-term volatility of COMEX gold futures. When we analyse Fig. 2(f), we can see the highest total volatility time corresponds to some flash events related to the cryptocurrency market. For example, during the 2020 Crypto Black Thursday, more than $200 billion erases from the entire crypto market in a day. This finding implies that the precious metal market volatility is driven more by specific, behavioural financial uncertainties such as price bubbles, media coverage and herding. That is, the precious metal market is more likely to turn to a high-volatility regime when the cryptocurrency market stays in a high fluctuation condition, intrinsically consistent with the cyclical behaviour of the precious metal market volatility (Elsayed et al., 2022) and cryptocurrency market uncertainty (Lucey et al., 2022). These outcomes highlight that cryptocurrency uncertainty can lead to precious metal market volatility with regard to the gold markets, and these statistical results also suggest that various uncertainties may capture different aspects of long-term price fluctuations in the precious metal market. Therefore, Fig. 2 may offer policymakers and investors in gold markets a distinct perspective to design their regulatory and risk management strategies.

The in-sample estimation results for GARCH-MIDAS-X model incorporating different uncertainty indices for COMEX gold and silver futures are listed in Tables 2 and 3, respectively. First, in general, most estimated parameters in these two tables are significant, suggesting the overall good fitness of GARCH-MIDAS model in capturing the short-term and long-term volatility of these two precious metal futures markets. Second, the β parameters quantifying GARCH effect in short-term volatility are all significantly positive, ranging from about 0.82 to 0.98, indicating strong short-term volatility persistence in precious metal markets, and this persistence patterns in gold market are stronger than those in silver market. Third, most of the θ_{RV} coefficients are significantly negative, implying that higher historical realised volatility will lead to lower long-term volatility in precious metal markets. This is also commonly observed as the mean-reversion effect in asset volatility (Engle et al., 2013; Bai et al., 2021). More importantly, we are interested in the impacts of various uncertainties on the long-term volatility of precious metal markets, especially the effect of monthly cryptocurrency uncertainty determinants on the long-term volatility of precious metal futures. The estimation results of θ_X coefficients are displayed in Tables 2 and 3. In Table 2, we find that five uncertainty indices (i.e., CBOE VIX, CBOE GVZCLS, GEPU, UCRY Policy uncertainty, and UCRY Price uncertainty) have significantly positive impacts on the long-term volatility of COMEX gold futures market, while the other two (GPR and USD index) have no such significant effects. In terms of silver futures in Table 3, there are some differences from those in Table 2. For example, although CBOE VIX and GVZCLS still have significant positive effects on the long-term volatility of silver futures, the UCRY Policy and UCRY Price uncertainties turn to have significant negative impacts on the silver market. The statistically significant values of the θ_X in UCRY Policy and UCRY Price point out that a high cryptocurrency policy uncertainty and price uncertainty causes significant divergence in the expectations of the precious metal future investors. This result is qualitatively consistent with the finding in Shang et al. (2022) about the interconnection between gold price volatility and cryptocurrency uncertainty. The authors show that UCRY Policy does have good predictive power in forecasting weekly gold returns. Moreover, GEPU, GPR and USD index cannot have significant effects on the long-term volatility of silver futures.
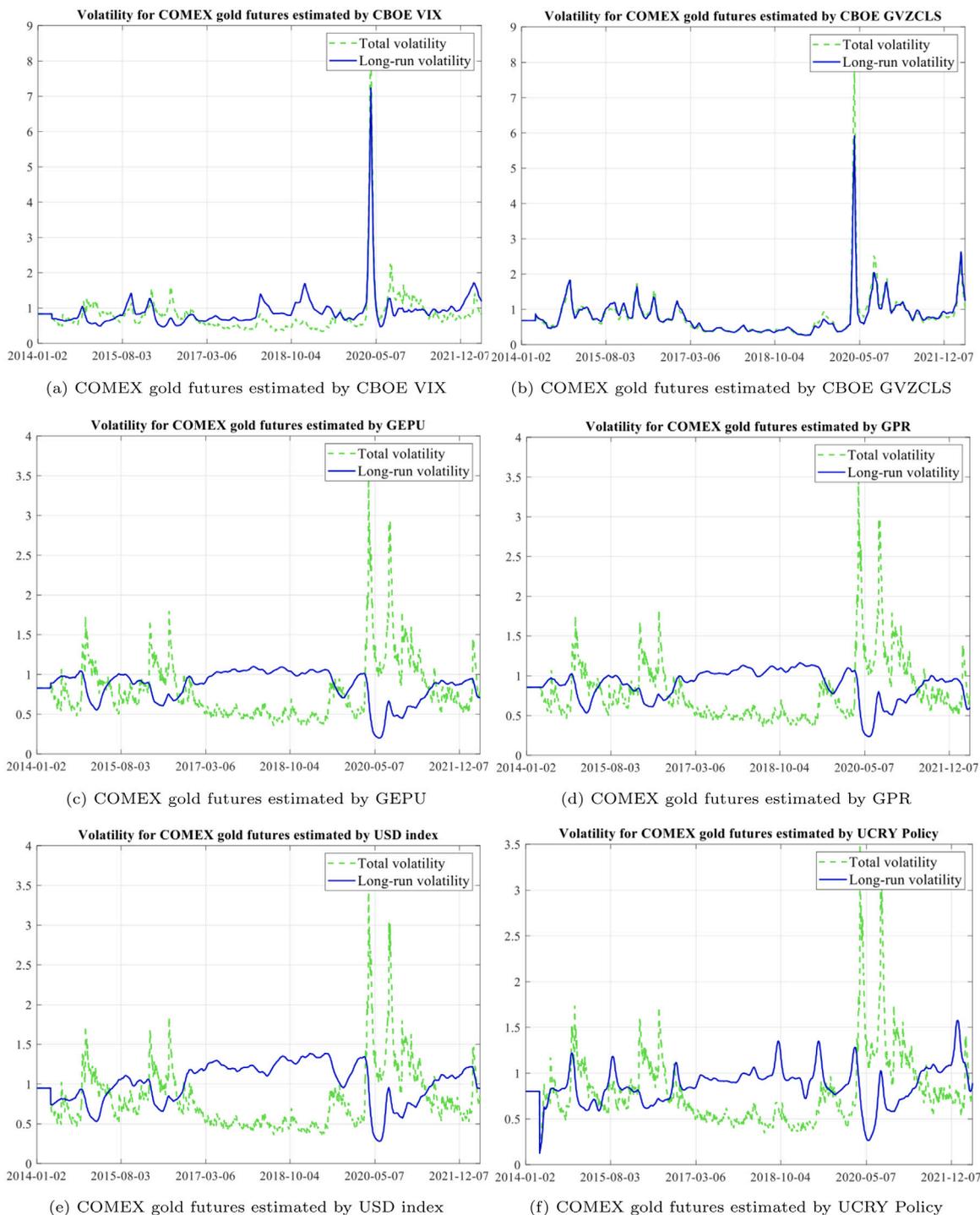
Fig. 2. Estimated total and long-term volatilities of COMEX gold futures by various monthly uncertainty indices.
Notes: This plot shows the estimated total daily volatility and long-term volatility of GARCH-MIDAS. The green dashed line indicates the COMEX Gold Futures total daily volatility, and the blue line means the COMEX Gold Futures long-term volatility determined by CBOE VIX, CBOE GVZCLS, GEPU, GPR, USD index and UCRY Policy, these uncertainty indices. The COMEX Gold Futures is in the high-frequency daily data, and the uncertainty indices are all in the low-frequency monthly data. The sample is from 02/Jan/2014 to 13/May/2022. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2

The estimation results of various GARCH-MIDAS-X models for COMEX gold futures returns.

GARCH-MIDAS-X	ω	α	β	m	θ_{RV}	θ_X	w_{RV}	w_X	BIC
CBOE VIX	0.0051	0.0239***	0.9722***	−0.8340***	−0.0265***	0.6493***	1.0010***	49.9960	5203.79
	(0.0179)	(0.0035)	(0.0040)	(0.1693)	(0.0038)	(0.0871)	(0.1169)	(84.3560)	
CBOE GVZCLS	0.0151	0.0087***	0.9805***	−3.1186***	−0.0379***	2.1751***	2.4754***	49.9970	5146.44
	(0.0172)	(0.0048)	(0.0118)	(0.2284)	(0.0076)	(0.2150)	(0.3862)	(66.0450)	
GEPU	0.0040	0.0352***	0.9618***	−0.1777	−0.0297***	0.3864***	1.0013***	50.0000	5235.14
	(0.0178)	(0.0042)	(0.0044)	(0.2464)	(0.0048)	(0.1132)	(0.1090)	(169.9800)	
GPR	0.0036	0.0374***	0.9571***	0.4420*	−0.0245***	−0.1420	1.0015***	6.5721	5241.30
	(0.0184)	(0.0042)	(0.0047)	(0.2441)	(0.0044)	(0.1977)	(0.1341)	(19.4150)	
USD index	0.0040	0.0374***	0.9590***	−1.6320	−0.0262***	1.9045	1.0014***	49.9980	5195.77
	(0.0180)	(0.0041)	(0.0046)	(1.2971)	(0.0045)	(1.3151)	(0.1245)	(1164.0000)	
UCRY Policy	0.0037	0.0352***	0.9586***	−6.0406***	−0.0156***	1.4121***	1.0010***	1.0605***	5234.92
	(0.0181)	(0.0043)	(0.0050)	(1.8078)	(0.0057)	(0.4014)	(0.2178)	(0.1543)	
UCRY Price	0.0037	0.0352***	0.9586***	−6.0832***	−0.0155***	1.4215***	1.0011***	1.0653***	5234.76
	(0.0181)	(0.0043)	(0.0050)	(1.8047)	(0.0057)	(0.4006)	(0.2195)	(0.1562)	

Notes: This table reports the estimation results of GARCH-MIDAS-X models incorporating various uncertainty indices. θ_{RV} and θ_X indicate the impacts of lagged RV and different uncertainty indices on the long-term volatility of COMEX gold futures returns, respectively. BIC is the Bayesian info criterion of the estimation. The bracketed numbers are the standard errors of the estimations. *p < 0.1; **p < 0.05; ***p < 0.01, respectively.

Table 3

The estimation results of various GARCH-MIDAS-X models for COMEX silver futures returns.

GARCH-MIDAS-X	ω	α	β	m	θ_{RV}	θ_X	w_{RV}	w_X	BIC
CBOE VIX	0.0302	0.0340***	0.9597***	0.2589	−0.0059***	0.5334***	1.0010***	49.9990	7498.3
	(0.0307)	(0.0033)	(0.0040)	(0.1851)	(0.0009)	(0.0899)	(0.1002)	(88.1120)	
CBOE GVZCLS	0.0251	0.0454***	0.9170***	−1.6356***	−0.0059***	1.7803***	6.5471***	49.9970	7465.62
	(0.0305)	(0.0076)	(0.0144)	(0.2350)	(0.0015)	(0.1711)	(1.3606)	(61.8320)	
GEPU	0.0274	0.0740***	0.8413***	0.4469***	0.0056***	0.0488	1.2136***	49.4400	7536.42
	(0.0321)	(0.0085)	(0.0245)	(0.1108)	(0.0008)	(0.0597)	(0.3239)	(1044.1000)	
GPR	0.0272	0.0760***	0.8367***	0.6640***	−0.0058***	−0.1285	1.2239***	6.5264	7536.23
	(0.0323)	(0.0084)	(0.0246)	(0.1799)	(0.0007)	(0.1626)	(0.3159)	(27.6940)	
USD index	0.0245	0.0787***	0.8277***	1.2453**	0.0062***	−0.6631	1.2266***	1.1232	7536.05
	(0.0321)	(0.0089)	(0.0255)	(0.5484)	(0.0007)	(0.5011)	(0.2911)	(8.1990)	
UCRY Policy	0.0810***	0.0771***	0.9229***	4.0156	−0.0020*	−4.5222***	12.2670	1.0776***	8479.37
	(0.0302)	(0.0063)	(0.0059)	(14713.00)	(0.0011)	(0.4909)	(14.2550)	(0.0651)	
UCRY Price	0.0850***	0.0755***	0.9245***	−2.0827	−0.0022**	−3.3603***	12.2110	1.4980***	8464.25
	(0.0311)	(0.0064)	(0.0061)	(3.7620)	(0.0011)	(0.5007)	(12.2160)	(0.1481)	

Notes: This table reports the estimation results of GARCH-MIDAS-X models incorporating various uncertainty indices. θ_{RV} and θ_X indicate the impacts of lagged RV and different uncertainty indices on the long-term volatility of COMEX silver futures returns, respectively. BIC is the Bayesian info criterion of the estimation. The bracketed numbers are the standard errors of the estimations. *p < 0.1; **p < 0.05; ***p < 0.01, respectively.

The plausible explanations for the reported values can be concluded as follows. These findings remind us that despite many common attributes, gold and silver markets still have several different fundamentals. For instance, there is a difference between gold and silver in terms of value preservation. Gold has always been a reserve tool for global central banks, especially in recent years with the growing call for de-dollarisation. Therefore, central banks have increased their gold reserves, becoming an important source of growth in global gold consumption. While after World War II, silver's monetary properties gradually faded to zero, and its financial roles may have been transformed mainly into an investment tool. The market volume of silver is much smaller than gold, and once the fundamental changes, the volatility of silver prices can be much higher than that of gold, fuelled by a large amount of speculative capital. Therefore, it is not difficult to understand that various uncertainty indices may have distinct impacts on the gold and silver markets.

In summary, we find that, besides GEPU, CBOE VIX and CBOE GVZCLS, which have been proven massively in literature to have direct or indirect impacts on precious metal markets, uncertainty information from the cryptocurrency market can additionally help us to depict the volatility (especially the long-term volatility) in gold and silver markets, and more considerable uncertainty in cryptocurrency market usually leads to more significant/more minor long-term fluctuations in gold/silver prices. This fact offers us a new perspective to understand the long-term drivers of precious metal market volatility and validates the protracted and deep interdependence between precious metal and cryptocurrency markets.

4.2. Out-of-sample volatility forecasting results

In the sub-section of Section 4.1, we have proved the significant in-sample impacts of UCRY indices, and several other commonly used uncertainty indices on the volatilities of COMEX gold and silver futures. However, compared to in-sample performance, policymakers and investors may be more interested in the out-of-sample predictive abilities of the cryptocurrency uncertainty indices in forecasting the volatilities of precious metal markets. Financial market participants would be more concerned about the model's capability to improve future performance than its ability to explore past paradigms. Thus, in this sub-section, we first conduct the

Table 4

DM tests for various GARCH-MIDAS-X models in forecasting volatilities of COMEX gold futures returns.

GARCH-MIDAS-X	OOS = 630 days		OOS = 840 days		OOS = 1050 days		OOS = 1260 days	
	MSE statistics	MAE statistics	MSE statistics	MAE statistics	MSE statistics	MAE statistics	MSE statistics	MAE statistics
CBOE GVZCLS	−5.9229***	−6.7849***	−5.7172***	−6.6350***	−4.3577***	−5.8139***	−4.3293***	−5.6394***
GEPU	−4.3906***	−4.8222***	−5.2888***	−6.6018***	−4.3619***	−6.1926***	−4.3496***	−6.2765***
GPR	−5.9376***	−6.8517***	−5.1911***	−5.2980***	−4.3648***	−6.0127***	−4.3574***	−5.9340***
USD index	−5.7369***	−6.9497***	−5.3550***	−5.8384***	−4.3510***	−5.7148***	−4.3563***	−6.0149***
UCRY Policy	−5.8953***	−6.7030***	−4.7832***	−4.6981***	−4.3194***	−5.3669***	−4.2229***	−4.9282***
UCRY Price	−5.8950***	−6.7011***	−5.5326***	−5.6140***	−4.3192***	−5.3656***	−4.2248***	−4.9380***

Note: This table presents the MSE and MAE statistics of DM tests, with the null hypothesis that there is no difference in predictive accuracy of model i and the benchmark one. Thus, a negative DM statistic indicates higher predictive accuracy of model i than that of the benchmark model. The benchmark model is set to be GARCH-MIDAS-VIX model. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$, respectively.

Table 5

DM tests for various GARCH-MIDAS-X models in forecasting volatilities of COMEX silver futures returns.

GARCH-MIDAS-X	OOS = 630 days		OOS = 840 days		OOS = 1050 days		OOS = 1260 days	
	MSE statistics	MAE statistics	MSE statistics	MAE statistics	MSE statistics	MAE statistics	MSE statistics	MAE statistics
CBOE GVZCLS	−5.5620***	−5.4930***	2.1746**	4.4402***	−5.9308***	−5.4379***	2.9527***	2.0555**
GEPU	9.7125***	11.7707***	8.5498***	9.4566***	−7.9042***	−9.7308***	−1.9015**	−3.6031***
GPR	−1.8640**	0.9034	−8.6627***	−10.7938***	−7.9071***	−9.7842***	6.3888***	6.9525***
USD index	−5.8823***	−5.6005***	−8.6240***	−10.7171***	−7.8358***	−9.5996***	2.8831***	1.6726**
UCRY Policy	−8.4718***	−10.5196***	−8.3112***	−9.8284***	−7.8933***	−9.6406***	4.1941***	3.7808***
UCRY Price	−8.4669***	−10.4960***	−8.3080***	−9.8222***	−7.8922***	−9.6379***	4.2101***	3.8095***

Notes: This table presents the MSE and MAE statistics of DM tests, with the null hypothesis that there is no difference in predictive accuracy of model i and the benchmark one. Thus, a negative DM statistic indicates higher predictive accuracy of model i than that of the benchmark model. The benchmark model is set to be GARCH-MIDAS-VIX model. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$, respectively.

one-day-ahead volatility forecasting of COMEX gold and silver futures by using various GARCH-MIDAS-X models, and then assess these out-of-sample forecasts by different model evaluation approaches. Moreover, because there are no widely accepted rules for choosing the out-of-sample lengths, we choose 30%, 40%, 50%, and 60% of the total sample size, i.e., the last 630, 840, 1050, and 1260 days of the data sample as the out-of-sample (OOS) forecasting horizons. All the following model evaluation results are then based on the four out-of-sample forecasting horizons.

4.2.1. Results of Diebold and Mariano test

In this first round evaluation, we assess the forecasting performances of various models by using the DM test proposed by Diebold and Mariano (2002). DM test can evaluate the pairwise forecasting differences between each extension and the benchmark model. Tables 4 and 5 summarise the testing results for COMEX gold and silver futures, respectively. As discussed above, a negative DM statistic indicates higher predictive accuracy of model i over the benchmark model. Therefore, in terms of COMEX gold market, Table 4 shows that all the six GARCH-MIDAS-X models incorporating CBOE GVZCLS, GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty indices can significantly beat the benchmark model (i.e., GARCH-MIDAS-VIX) across all the four OOS forecasting horizons. This outcome demonstrates that CBOE GVZCLS, GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty indices have higher predictive abilities than that of the CBOE VIX. Moreover, the DM MSE and MAE statistics in Table 4 are very close within a specific forecasting time horizon, indicating the comparable predictive powers among the CBOE GVZCLS, GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty indices. However, the empirical results in Table 5, depicting the forecasting performances of silver futures, show a number of differences compared to Table 4. For example, the results for out-of-sample 630 days forecasts show that model with GEPU cannot beat the benchmark model for the significant positive MSE and MAE statistics. Regarding to the 840-day results, both models incorporating CBOE GVZCLS and GEPU are not superior to the benchmark model. Finally, the 1260-day outcome reveals that only GARCH-MIDAS-GEPU can outperform the benchmark. These results in Tables 4 and 5 imply that various uncertainty have distinct predictive powers on gold and silver markets, and it is worth noting that cryptocurrency uncertainty indices have a relatively good performance in precious metal market volatility forecasting. Additionally, these predictive powers may also switch at different market environments and forecasting horizons. All in all, CBOE GVZCLS, GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty have comparable predictive abilities and can outperform CBOE VIX in predicting the daily volatilities of COMEX gold futures, while they are not surely superior to VIX in forecasting the daily volatility of COMEX silver futures. Future scholars, investors and government decision-makers can value cryptocurrency uncertainty indices as useful proxies to achieve accurate forecasting in the cryptocurrency market volatility and then reduce potential financial risk from the unstable cryptocurrency market.

4.2.2. Results of out-of-sample R^2_{OOS} test

Then, we perform the out-of-sample R^2_{OOS} test of Clark and West (2007) to further assess the predictive powers of various uncertainty models. Tables 6 and 7 report the results of R^2_{OOS} test for COMEX gold and silver futures, respectively. In general, we find in Table 6 that all the out-of-sample R^2 are significantly positive, suggesting that GARCH-MIDAS models with CBOE GVZCLS,

Table 6

Out-of-sample R^2_{OOS} test for various GARCH-MIDAS-X models in forecasting volatilities of COMEX gold futures returns.

GARCH-MIDAS-X	OOS = 630 days		OOS = 840 days		OOS = 1050 days		OOS = 1260 days	
	R^2_{OOS}(%)	MSFE-adjusted	R^2_{OOS}(%)	MSFE-adjusted	R^2_{OOS}(%)	MSFE-adjusted	R^2_{OOS}(%)	MSFE-adjusted
CBOE GVZCLS	33.4023	5.9192***	17.0074	5.7096***	97.0575	4.3695***	94.5934	4.3659***
GEPU	31.9450	6.1214***	37.8915	5.9383***	97.1240	4.3897***	95.0420	4.4040***
GPR	29.9941	5.9474***	37.2462	5.9405***	97.2116	4.3795***	95.2338	4.3854***
USD index	37.7024	5.9012***	38.2994	5.9646***	96.9097	4.3647***	94.8048	4.3840***
UCRY Policy	31.9204	5.8586***	34.0141	5.7024***	96.2145	4.3521***	92.3140	4.3395***
UCRY Price	31.9153	5.8584***	38.5479	5.7910***	96.2113	4.3521***	92.3546	4.3398***

Notes: This table presents the out-of-sample forecasting performance based on the out-of-sample R^2 test of Clark and West (2007), with the null hypothesis that the benchmark model has obviously smaller or equal MSE compared to the interested model i. The benchmark model is set to be GARCH-MIDAS-VIX model. A positive value of out-of-sample R^2 implies that the forecasting model of interest has higher prediction accuracy than the benchmark model. *p < 0.1; **p < 0.05; ***p < 0.01, respectively.

Table 7

Out-of-sample R^2_{OOS} test for various GARCH-MIDAS-X models in forecasting volatilities of COMEX silver futures returns.

GARCH-MIDAS-X	OOS = 630 days		OOS = 840 days		OOS = 1050 days		OOS = 1260 days	
	R^2_{OOS}(%)	MSFE-adjusted	R^2_{OOS}(%)	MSFE-adjusted	R^2_{OOS}(%)	MSFE-adjusted	R^2_{OOS}(%)	MSFE-adjusted
CBOE GVZCLS	4.3791	5.6491***	−1.4065	−1.9803	19.4682	6.1294***	−2.7007	−2.6518
GEPU	−49.3908	−9.5714	−22.6054	−8.7691	66.5027	7.8603***	2.3511	2.3240**
GPR	1.7035	2.1965**	64.1562	8.6305***	73.7713	7.8335***	−10.2995	−6.2963
USD index	7.8314	5.9600***	58.2845	8.5873***	67.8488	7.7702***	−3.0321	−2.5239
UCRY Policy	60.7139	8.9253***	26.9195	8.2198***	63.8418	7.8412***	−7.4455	−3.9659
UCRY Price	60.7496	8.9262***	26.9251	8.2165***	63.8219	7.8400***	−7.4880	−3.9836

Notes: This table presents the out-of-sample forecasting performance based on the out-of-sample R^2 test of Clark and West (2007), with the null hypothesis that the benchmark model has obviously smaller or equal MSE compared to the interested model i. The benchmark model is set to be GARCH-MIDAS-VIX model. A positive value of out-of-sample R^2 implies that the forecasting model of interest has higher prediction accuracy than the benchmark model. *p < 0.1; **p < 0.05; ***p < 0.01, respectively.

GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty can beat the benchmark model (GARCH-MIDAS-VIX) across various forecasting horizons. Nevertheless, we still observe several differences in Table 7 for COMEX silver futures from the results in Table 6. For example, the 630-day R^2_{OOS} for GARCH-MIDAS-GEPU is about −49.4%; those values for GARCH-MIDAS-GVZCLS and GARCH-MIDAS-GEPU at 840-day evaluation are about −1.4% and −22.6%, respectively, indicating the poor predictive abilities of GVZCLS and GEPU at these two forecasting horizons. However, when considering the 1260-day results, GEPU turns to be the only one index can outperform VIX in R^2_{OOS} test.

In summary, the R^2_{OOS} evaluation results are highly consistent to those in DM tests. The six uncertainty indices, i.e., CBOE GVZCLS, GEPU, GPR, USD index, UCRY Policy, and UCRY Price uncertainty, are superior to VIX in forecasting daily volatility of COMEX gold futures. While the situations for COMEX silver futures are more complicated. CBOE GVZCLS and GEPU seem do not perform well in 630- and 840-day out-of-sample evaluations, but GEPU turns to be only one can beat VIX in 1260-day forecasting horizon. Comparing our forecasting results with the in-sample results of earlier studies, we cannot only confirm the findings of Elsayed et al. (2022) for the relationship between cryptocurrency and gold but also contribute to bringing valuable insights that cryptocurrency uncertainty indicators contain important information for the precious metal market volatility. However, we cannot support the existing literature that the GEPU is vital for the volatility of the precious metal market in the long run. The findings from Tables 6 and 7 imply that cryptocurrency uncertainty indices, two qualitative-based indices for the cryptocurrency policy and cryptocurrency price uncertainty area, are very robust predictors of the precious metal market's volatility over their time cross-section. Remarkably, UCRY Policy and UCRY Price are among the best predictors, showing that not only the price volatility of cryptocurrency (Klein et al., 2018; Hassan et al., 2021) but also cryptocurrency policy uncertainty and cryptocurrency price uncertainty are important in precious metal markets (Elsayed et al., 2022).

4.2.3. Results of Model Confidence Set (MCS) test

Third, both the DM and R^2_{OOS} tests can only compare the forecasting performances of two single models. To get an overall evaluation on a set of competing models, we further adopt the Model Confidence Set (MCS) test proposed by Hansen et al. (2011). By using bootstrap method to obtain the statistical significance of the test, and with more loss functions as criteria, the MCS approach offers us a robust evaluation on predictive ability of a set of different models.

Due to MCS test does not need a benchmark model, therefore Tables 8 and 9 report the p-values of MCS test for all the seven competing models. Those p-values larger than 0.1 are marked in bold, indicating the corresponding model can survive in a model confidence set, and this model has equal predictive accuracy to others in this model set. Additionally, a larger *p*-value indicates a higher predictive accuracy of the corresponding model, and the p-values equal to 1 are marked in bold and underlined, suggesting that the corresponding models have the best forecasting performance. The evaluation results in Table 8 indicate that under the loss functions of QLIKE and MSE, all GARCH-MIDAS-X models can survive in the MCS, implying that all the seven uncertainty indices can make accurate daily volatility forecasts for COMEX gold futures. However, under the criteria of MAE, HMSE, HMAE,

Table 8

Model confidence set (MCS) tests for various GARCH-MIDAS-X models in forecasting volatilities of COMEX gold futures returns.

	QLIKE	MSE	MAE	HMSE	HMAE	R^2LOG
Panel A: OOS = 630 days						
CBOE VIX	**0.2950**	**0.3461**	**0.2518**	0.0000	0.0000	0.0000
CBOE GVZCLS	**0.2950**	**0.3461**	**0.2518**	0.0000	0.0000	0.0000
GEPU	**0.2950**	**0.3461**	**0.2518**	0.0000	0.0000	0.0000
GPR	**0.2950**	**0.3461**	**0.2518**	0.0000	0.0000	0.0000
USD index	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**	0.0000	0.0000	0.0000
UCRY Policy	**0.5199**	**0.3461**	**0.2518**	0.0000	0.0000	0.0000
UCRY Price	**0.2950**	**0.3461**	**0.2518**	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**
Panel B: OOS = 840 days						
CBOE VIX	**0.3097**	**0.4277**	0.0047	0.0000	0.0000	0.0000
CBOE GVZCLS	**0.5815**	**0.4277**	0.0047	0.0000	0.0000	0.0000
GEPU	**0.1994**	**0.6831**	**<u>1.0000</u>**	0.0000	0.0000	0.0000
GPR	**0.5815**	**0.4277**	0.0047	0.0000	0.0000	0.0000
USD index	**<u>1.0000</u>**	**0.8214**	0.0047	0.0000	0.0000	0.0000
UCRY Policy	**0.3097**	**0.4277**	0.0047	0.0000	0.0000	0.0000
UCRY Price	**0.7479**	**<u>1.0000</u>**	0.0047	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**
Panel C: OOS = 1050 days						
CBOE VIX	**0.2359**	**0.2268**	0.0104	0.0000	0.0000	0.0000
CBOE GVZCLS	**0.7893**	**0.2268**	0.0104	0.0000	0.0000	0.0000
GEPU	**0.4060**	**0.2268**	**<u>1.0000</u>**	0.0000	0.0000	0.0000
GPR	**<u>1.0000</u>**	**<u>1.0000</u>**	0.0104	0.0000	0.0000	0.0000
USD index	**0.7893**	**0.2268**	0.0104	0.0000	0.0000	0.0000
UCRY Policy	**0.4060**	**0.2268**	0.0104	0.0000	0.0000	0.0000
UCRY Price	**0.4060**	**0.2268**	0.0104	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**
Panel D: OOS = 1260 days						
CBOE VIX	**0.3145**	**0.2337**	0.0060	0.0000	0.0000	0.0000
CBOE GVZCLS	**0.9750**	**0.2337**	0.0060	0.0000	0.0000	0.0000
GEPU	**0.2543**	**0.2337**	**<u>1.0000</u>**	0.0000	0.0000	0.0000
GPR	**0.9913**	**<u>1.0000</u>**	0.0060	0.0000	0.0000	0.0000
USD index	**<u>1.0000</u>**	**0.2337**	0.0060	0.0000	0.0000	0.0000
UCRY Policy	**0.3145**	**0.2337**	0.0060	0.0000	0.0000	0.0000
UCRY Price	**0.3145**	**0.2337**	0.0060	**<u>1.0000</u>**	**<u>1.0000</u>**	**<u>1.0000</u>**

Notes: This table presents the p-values of MCS tests based on six loss functions, i.e. quasi-likelihood loss (QLIKE), mean square error (MSE), mean absolute error (MAE), heteroskedasticity-adjusted MSE and MAE (HMSE and HMAE), and R^2LOG similar to R^2 of the Mincer–Zarnowitz regressions. The p-values larger than 0.1 are marked in bold, indicating that the corresponding model can survive in the MCS. The p-values equal to 1.0000 are marked in bold and underlined, suggesting that the corresponding models have the best forecasting performance.

and R^2LOG, only one model can survive except for the case of 630-day out-of-sample assessment. To be more specific, in 630-day results, both UCRY Price and USD index achieve three p-values of 1.0000, suggesting their superior predictive performances over other uncertainty indices. To sum up the results over the cases of 840-, 1050- and 1260-day evaluations, GEPU gets three p-values of 1.0000, USD index obtains two p-values of 1.0000, and GPR has three p-values of 1.0000. The UCRY Price, however, achieves ten p-values of 1.0000. More notably, under the HMSE, HMAE and R^2LOG criteria, only UCRY Price model can survive in the MCS with p-values of 1.0000, suggesting its absolute advantage in forecasting the daily volatilities of COMEX gold futures over other uncertainty indices. The evaluation results in Table 9 for COMEX silver futures demonstrate similar findings to those in Table 9. It shows that UCRY Price model get 15 p-values of 1.0000 in total, and under the criteria of HMSE, HMAE, and R^2LOG, it is also the only model can survive in the MCS, furthering implying its outstanding predictive power in forecasting daily volatilities of COMEX silver futures.

In conclusion, the MCS results further support the previous findings from the DM test, and the meaningful primary point is that the cryptocurrency price uncertainty index is more helpful for predicting volatility in the precious metal market. Our results also reflect the existing research findings of Klein et al. (2018), Hassan et al. (2021), Elsayed et al. (2022), Shang et al. (2022). While the researchers find evidence of dependency between the cryptocurrency market and the precious metal market, we can summarise that cryptocurrency uncertainty indices do also have predictive information for the long-run volatility in the precious metal market. A plausible explanation of why the cryptocurrency price uncertainty index performs better is that UCRY Price tries to capture and reflect the price uncertainty in the cryptocurrency market. Therefore, it is more sensitive to price variation than other political-driven factors. In addition, with the development of cryptocurrency, blockchain and Web 3.0, cryptocurrency assets have gradually integrated into investors' portfolios, and these digital assets can already be included in the traditional asset classes. After a series of cryptocurrency collapse events, such as the Cryptocurrency Crash of 2018 (From January to February 2018, the price of Bitcoin fell 65%), the 2020 Crypto Black Thursday, the 2021 Crypto Bubble Burst (By the end of 2021, Bitcoin had fallen nearly 30% from its peak down to $47,686.81 and Ethereum had plummeted about 23% to $3,769.70), among others. With these flash events related to the cryptocurrency market and the volatility transmission in financial markets, investors cannot ignore cryptocurrency

Table 9
Model confidence set (MCS) tests for various GARCH-MIDAS-X models in forecasting volatilities of COMEX silver futures returns.

	QLIKE	MSE	MAE	HMSE	HMAE	R^2LOG
Panel A: OOS = 630 days						
CBOE VIX	0.0213	**0.1013**	0.0798	0.0000	0.0000	0.0000
CBOE GVZCLS	0.0213	**0.1013**	0.0798	0.0000	0.0000	0.0000
GEPU	0.0114	**0.1013**	0.0798	0.0000	0.0000	0.0000
GPR	0.0114	**0.1013**	0.0798	0.0000	0.0000	0.0000
USD index	0.0213	**0.1013**	0.0798	0.0000	0.0000	0.0000
UCRY Policy	**0.4173**	**0.1013**	**0.4480**	0.0000	0.0000	0.0000
UCRY Price	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Panel B: OOS = 840 days						
CBOE VIX	0.0307	**0.1328**	0.0923	0.0000	0.0000	0.0000
CBOE GVZCLS	0.0307	**0.1328**	0.0923	0.0000	0.0000	0.0000
GEPU	0.0307	**0.1176**	0.0920	0.0000	0.0000	0.0000
GPR	**1.0000**	**1.0000**	**1.0000**	0.0000	0.0000	0.0000
USD index	0.0307	**0.1328**	0.0923	0.0000	0.0000	0.0000
UCRY Policy	0.0307	**0.1328**	0.0923	0.0000	0.0000	0.0000
UCRY Price	0.0307	**0.1328**	0.0923	**1.0000**	**1.0000**	**1.0000**
Panel C: OOS = 1050 days						
CBOE VIX	**0.2359**	**0.2268**	0.0104	0.0000	0.0000	0.0000
CBOE GVZCLS	**0.7893**	**0.2268**	0.0104	0.0000	0.0000	0.0000
GEPU	**0.4060**	**0.2268**	**1.0000**	0.0000	0.0000	0.0000
GPR	**1.0000**	**1.0000**	0.0104	0.0000	0.0000	0.0000
USD index	**0.7893**	**0.2268**	0.0104	0.0000	0.0000	0.0000
UCRY Policy	**0.4060**	**0.2268**	0.0104	0.0000	0.0000	0.0000
UCRY Price	**0.4060**	**0.2268**	0.0104	**1.0000**	**1.0000**	**1.0000**
Panel D: OOS = 1260 days						
CBOE VIX	**0.2841**	**0.6729**	**0.4618**	0.0000	0.0000	0.0000
CBOE GVZCLS	0.0133	**0.1599**	**0.1257**	0.0000	0.0000	0.0000
GEPU	**1.0000**	**1.0000**	**1.0000**	0.0000	0.0000	0.0000
GPR	0.0133	**0.1599**	0.1004	0.0000	0.0000	0.0000
USD index	**0.2841**	**0.1599**	**0.1257**	0.0000	0.0000	0.0000
UCRY Policy	**0.2841**	**0.1599**	**0.1217**	0.0000	0.0000	0.0000
UCRY Price	0.0133	**0.1599**	0.1004	**1.0000**	**1.0000**	**1.0000**

Notes: This table presents the p-values of MCS tests based on six loss functions, i.e. quasi-likelihood loss (QLIKE), mean square error (MSE), mean absolute error (MAE), heteroskedasticity-adjusted MSE and MAE (HMSE and HMAE), and $R^2 LOG$ similar to R^2 of the Mincer–Zarnowitz regressions. The p-values larger than 0.1 are marked in bold, indicating that the corresponding model can survive in the MCS. The p-values equal to 1.0000 are marked in bold and underlined, suggesting that the corresponding models have the best forecasting performance.

uncertainty. To put the results of Tables 8 and 9 simply, these statistical results suggest that including cryptocurrency uncertainty is capable of generating higher forecast accuracy, and the UCRY indices can improve the predictive accuracy of the precious metal market. Additionally, these findings may provide clear signals to help market regulators and investors to make beneficial strategies.

4.2.4. Results of Direction-of-Change (DoC) rate test

Finally, besides evaluation of forecasting errors, we utilise the Direction-of-Change (DoC) rate test of Degiannakis and Filis (2017) to compare the accuracy in the forecasting direction by various GARCH-MIDAS-X models.

Tables 10 and 11 reveal that all the DoC rates estimated are significantly larger than 0.5 (from about 0.64 to 0.71), suggesting that all the uncertainty indices help to get better volatility forecasting direction in COMEX gold and silver futures. Moreover, the DoC rates calculated in a specific forecasting horizon are very close to each other, implying the comparable forecasting direction accuracy of various GARCH-MIDAS-X models. A point worth noting is that UCRY Price and UCRY Policy models get the largest DoC rates of about 0.71 and 0.69 in the cases of 1260-day evaluation for COMEX gold futures and 630-day assessment for silver futures, further suggesting that uncertainty information in cryptocurrency markets may provide us a new angle to understand the possible drivers of precious metal market volatility, and can really contribute to make better volatility forecasts in these markets.

In a nutshell, the DoC rate test results can re-confirm the empirical findings mentioned above. And the statistical results also prove that the cryptocurrency policy uncertainty index and cryptocurrency price uncertainty index contain more useful information in determining the future volatility of the precious metal markets. These findings reveal that cryptocurrency indices may simultaneously change the expectations of cryptocurrency speculators and precious metal futures' investors and thus synthetically affect the volatility of precious metals' prices. It is also worth mentioning that Shang et al. (2022) have proven that the cryptocurrency policy uncertainty index has better predictive power than many commonly used gold predictors. As the global cryptocurrency market capitalisation is around $841.15B now, and also supported by the existing findings of the volatility spillover transmission mechanism between the cryptocurrency and precious metal markets (Klein et al., 2018; Hassan et al., 2021; Elsayed et al., 2022). Then we can infer that uncertainties from the cryptocurrency markets can have strong direct or indirect effects on precious metal futures' prices.

Table 10

Direction-of-Change tests for various GARCH-MIDAS-X models in forecasting volatilities of COMEX gold futures returns.

GARCH-MIDAS-X	OOS = 630 days		OOS = 840 days		OOS = 1050 days		OOS = 1260 days	
	DoC rate	PT statistic	DoC rate	PT statistic	DoC rate	PT statistic	DoC rate	PT statistic
CBOE VIX	0.6741	10.5249***	0.6865	12.4925***	0.6406	12.2181***	0.6608	14.3116***
CBOE GVZCLS	0.6741	10.4766***	0.6913	12.7648***	0.6988	14.4924***	0.7077	16.3851***
GEPU	0.6852	10.7202***	0.7044	12.9784***	0.7102	14.8979***	0.7085	16.2723***
GPR	0.6789	10.6291***	0.6865	12.5307***	0.6835	13.8082***	0.6839	15.2509***
USD index	0.6900	11.1848***	0.6937	12.8073***	0.6988	14.4924***	0.6823	15.2760***
UCRY Policy	0.6757	10.5431***	0.6794	12.2579***	0.6988	14.6220***	0.7101	16.5588***
UCRY Price	0.6757	10.5431***	0.6830	12.4744***	0.6988	14.6220***	0.7101	16.5588***

Notes: This table reports the Direction-of-Change (DoC) rates and the PT statistics of Pesaran and Timmermann (1992) test for various forecasting models. The greater a DoC rate is, the higher directional accuracy is obtained by the corresponding model. The null hypothesis of PT test is that the volatility forecasting model does not have directional accuracy. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$, respectively.

Table 11

Direction-of-Change tests for various GARCH-MIDAS-X models in forecasting volatilities of COMEX silver futures returns.

GARCH-MIDAS-X	OOS = 630 days		OOS = 840 days		OOS = 1050 days		OOS = 1260 days	
	DoC rate	PT statistic	DoC rate	PT statistic	DoC rate	PT statistic	DoC rate	PT statistic
CBOE VIX	0.6614	9.1046***	0.6806	11.4635***	0.6873	13.6722***	0.6894	15.0322***
CBOE GVZCLS	0.6630	9.1805***	0.6818	11.5591***	0.6883	13.6802***	0.6902	15.1102***
GEPU	0.6645	9.2947***	0.6853	11.7837***	0.6854	13.5143***	0.6878	14.9594***
GPR	0.6630	9.1805***	0.6841	11.6880***	0.6902	13.7906***	0.6894	15.0322***
USD index	0.6614	9.1046***	0.6830	11.6236***	0.6873	13.6563***	0.6894	15.0600***
UCRY Policy	0.6963	10.6364***	0.6818	11.5591***	0.6864	13.5387***	0.6847	14.7020***
UCRY Price	0.6979	10.7097***	0.6818	11.5591***	0.6864	13.5387***	0.6847	14.7020***

Notes: This table reports the Direction-of-Change (DoC) rates and the PT statistics of Pesaran and Timmermann (1992) test for various forecasting models. The greater a DoC rate is, the higher directional accuracy is obtained by the corresponding model. The null hypothesis of PT test is that the volatility forecasting model does not have directional accuracy. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$, respectively.

The empirical findings from the DoC rate test have significant financial implications. For example, integrating with the classic demand–supply fundamentals and speculation behaviours, market participants and regulators of cryptocurrencies and precious metals should also pay more attention to cryptocurrency uncertainty, especially policy and price uncertainty. Both the UCRY Policy and UCRY Price have been proven to significantly affect the precious metal market, implying that the financial activities in the cryptocurrency market, such as transactions, halving, speculations, and herding, among others, can shock the precious metal market. At the same time, adjusting cryptocurrency laws and regulations may also bring volatility to the precious metal market. Therefore, investors of the precious metal market also should watch the policy adjustment closely in the cryptocurrency market when analysing the precious metal market trend. In the end, as we have mentioned several times in this study, the high volatility periods of the precious metal market are closely linked to the cryptocurrency market collapses. Therefore, strict laws and regulations on the cryptocurrency market speculation transaction are necessary if policymakers aim to stabilise the precious metal market.

5. Conclusion

Although the tight connections between cryptocurrency and precious metal markets have been recognised for a long time, no studies focus on whether cryptocurrency market uncertainty can help to explain and forecast volatilities in precious metal markets. This study extends the existing literature in two major aspects: on the one hand, it is the first one to extend the simple GARCH-MIDAS model of Engle et al. (2013) by incorporating the newly developed cryptocurrency uncertainty indices (UCRY Policy and UCRY Price) of Lucey et al. (2022), and compare the in-sample impacts and out-of-sample predictive abilities of cryptocurrency uncertainty with many other commonly used uncertainty measures on the precious metal markets. On the other hand, the superior out-of-sample predictive power of cryptocurrency uncertainty are assessed by various model evaluation methods across different forecasting horizons, based not only on predicting errors but also on the accuracy of forecasting directions.

This study achieves several important empirical findings. For example, we find that various uncertainty measures may capture different types of long-term fluctuations in precious metal prices, and cryptocurrency uncertainty has significant but inverse in-sample impacts on the long-term volatility of COMEX gold and silver futures markets. Moreover, UCRY Policy and UCRY Price uncertainty can outperform several commonly used uncertainty indices (i.e., CBOE VIX, CBOE GVZCLS, GEPU, GPR, and USD index) in forecasting the daily volatility of precious metal markets. These findings are checked robustly by various evaluation methods and different forecasting horizons.

Our innovative study could provide several valuable implications for developing and improving the precious metal markets and cryptocurrency uncertainty measures. Our findings suggest that cryptocurrency uncertainty proxies are significant robust predictors for volatility forecasting in precious metal markets. Therefore, the empirical results from this study can first have essential implications for risk management. Referencing our empirical findings, investors and portfolio managers could make optimal and timely decisions based on forecasting the changes in precious metal prices by adjusting their long positions. This study not only can

deepen our understanding of precious metal volatility forecasting but also help to bring new sharp insights into a more accurate valuation for precious metal assets, which in turn could benefit the effectiveness of financial risk management strategies. Second, from a policy-making perspective, the empirical findings indicate that the shocks from the cryptocurrency uncertainties can exert significant effects on precious metal return dynamics. Moreover, cryptocurrency uncertainties have significant information contents that can signal impending turbulence in precious metal markets early. Therefore, cryptocurrency uncertainty indices can be used to trace unusual fluctuations in the precious metal markets in real-time by market regulators and also can raise an early warning call to policymakers to remind them to launch more effective stabilisation policies and prevent possible recessions.

The financial econometrics models in this study only focus on statistical evaluations. This work will be the direction of future research by further considering the tests related to economic values for volatility forecasting. Referring to the GARCH-MIDAS model, now we can only achieve the volatility forecasting in 1-day-ahead. Future research could extend our research by using the HAR-RV model to forecast the volatility in 5-day- or 20-day-ahead.

CRediT authorship contribution statement

Authors shared the first authorship and contributed equally to this work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix. Cryptocurrency uncertainty indices

Cryptocurrency uncertainty indices are qualitative-based indices developed by Lucey et al. (2022). The new family of cryptocurrency uncertainty indices includes the cryptocurrency policy uncertainty index (UCRY Policy) and cryptocurrency price uncertainty index (UCRY Price). These two newly issued indices can capture the level of uncertainty that investors experience regarding cryptocurrencies. The search strings for the UCRY Policy and UCRY Price in the LexisNexis News & Business database are:
• *("Uncertain" OR "Uncertainty") AND ("Bitcoin" OR "Ethereum" OR "Ripple" OR "Litecoin" OR "Tether" OR "Cryptocurrency" OR "Cryptocurrencies") AND ("Regulator" OR "Regulators" OR "Central bank" OR "Government")*
• *("Uncertain" OR "Uncertainty") AND ("Price") and ("Bitcoin" OR "Ethereum" OR "Ripple" OR "Litecoin" OR "Tether" OR "Cryptocurrency" OR "Cryptocurrencies").*

Supported by 726.9 million news articles, cryptocurrency uncertainty indices are standardised and normalised from large-scale text mining to reflect the mimetic and emergent nature of the uncertainty in cryptocurrency areas. Cryptocurrency uncertainty indices can capture sound movements and moments in the cryptocurrency space, such as Thursday, March 12th 2020, Crypto 'Black Thursday', 2021 China's Bitcoin mining ban, and 2022 'Crypto Winter', among others. The standardisation and normalisation processes of cryptocurrency uncertainty indices can be expressed as, in other words, UCRY indices can be denoted as Eq. (16):

$$UCRY_t = (\frac{N_t - \mu}{\sigma}) + 100,$$ (16)

where $UCRY_t$ is the value of the UCRY Policy or UCRY Price in the week t. N_t is the weekly observed value of news articles on the LexisNexis News & Business database concerning cryptocurrency policy or price uncertainty. If the search string related to UCRY Policy or UCRY Price appears in one article's title, keywords, main content, or the other parts, this article will be collected and recorded as one unit for N_t. μ is the mean value of the collected articles related to cryptocurrency policy or price uncertainty. σ is the standard deviation value of such. Adding an average value of 100 to eliminate the potential negative impacts caused by the overall volume of articles varies across publication sources and time.

Cryptocurrency uncertainty indices are available on 1st January 2021. Since then, many scholars have extended these indices into many research fields, especially in the applied finance and economics areas.

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