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Energy Market Uncertainties and Gold Return Volatility: A GARCH-MIDAS Approach

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Abstract

In this study, we use the GARCH–MIDAS model to evaluate how predictable oil and energy market uncertainties are in relation to gold return volatility. We examine daily gold returns and monthly energy uncertainty measurements such as Oil Market Uncertainty (OMU) and Oil Price Uncertainty (OPU), as well as measurements of energy market uncertainties such as the Global Equally-Weighted Energy Uncertainty Index (GEUI-EQ), GDP-Weighted Global Energy Uncertainty Index (GEUI-GDP), and country-specific energy uncertainty indexes for twenty-eight countries. We calculate the total connectedness index (TCI) for the country-specific indexes as a measure of the composite energy uncertainty index. We find that higher uncertainties in the oil and energy markets lead to increased gold volatilities, suggesting that gold can serve as a reliable hedge against oil and energy market uncertainties. Enhanced trading in the gold market raises its volatility as oil and energy market uncertainties increase. Our analysis, both within the sample and out-of-sample, supports this conclusion, and our findings remain valid even when alternative measures of oil and energy market uncertainties are considered. We provide valuable insights into the practical implications of our findings for both practitioners and policymakers.

Keywords: Energy Market Uncertainties; Gold Return Volatility; GARCH-MIDAS; Forecast Evaluation

JEL Codes: C53, N50, Q43

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1. Introduction

Oil and gold are considered key global commodities as their demand transcends a single country, and therefore, any shock associated with them can have far-reaching effects. Historically, gold has been seen as a safe-haven asset during market downturns, offering stability to investors when traditional assets like stocks and bonds become too risky. Since the 2008 global financial crisis (GFC), there has been increased interest in precious metals among investors as they are viewed as a safe haven for investment opportunities (Mokni et al., 2020). On the other hand, oil is a fundamental commodity for the functioning of the global economy and is susceptible to factors related to both demand (such as a slowdown in the global economy due to the actions of fiscal and monetary authorities) and supply (such as geopolitical tensions). Nonetheless, shifts in currency values and the attitude of investors toward safe-haven investments affect gold prices (Li and Umair, 2023a).

Theoretically, the crude oil and gold markets are related as they substantially impact global macroeconomic fundamentals, which in turn affects the economies of different nations (Salisu et al., 2021a). For instance, gold is a desirable investment because of its inflation-hedging properties (Shafiee and Topal, 2010; Jain and Ghosh, 2013; Batten et al., 2014; Bildirici and Turkmen, 2015; Jin et al., 2019; Salisu et al., 2019). Oil price shocks frequently lead to inflation (Hooker, 2002; Zhang and Wei, 2010; Aguilera and Radetzki, 2017), it then implies that gold has a role to play when there is an oil price shock given its inflation hedging potential. Consequently, the relationship between gold and oil prices can be explained indirectly by the gold's hedging or safe haven role against inflation, a property that has already been established in the literature. In addition, rising oil costs may hurt asset values and economic expansion, leading investors to shift their investments to other portfolios like gold (Baur and McDermott, 2010; Reboredo, 2010). Moreover, investors may decide to boost their gold holdings as a safe haven if the exchange rate weakens relative to other major foreign currencies, which may be due to an oil price shock[1].

[1] The literature has established a strong connection between oil price and exchange rate behaviour (e.g., Atems et al., 2015; Buetzer et al., 2016; Salisu et al., 2021b). This understanding, however, is not without its nuances, as the outcome may vary depending on the nature of the oil shock.

In our study examining the connection between oil and gold, we make two significant contributions. Firstly, we utilize a GARCH-MIDAS model, i.e., the generalized autoregressive conditional heteroskedasticity (GARCH) variant of the mixed data sampling (MIDAS), to investigate whether monthly oil market uncertainties (OMU) can predict daily gold return volatility. Unlike previous studies such as Salisu and Adediran (2020), Salisu et al. (2021a), Li and Umair (2023b), and Salisu et al. (2023), which assume uniform frequency in their analyses, we incorporate the variables at their "natural frequencies" to prevent any loss of information due to aggregation. This approach allows for a more precise capture of the relationship between oil volatility/risk/shock and gold.

Secondly, our research includes in-sample and out-of-sample forecast analyses to provide a comprehensive understanding of the relationship between oil and gold. This allows us to determine if the connection between oil and gold extends beyond the in-sample period, providing a more thorough and balanced representation of the relationship. In addition, the out-of-sample forecast evaluation, which has not been considered in the related studies, provides a more reliable framework for evaluating the potential predictive value of oil for gold volatility forecasts. This is especially important from both policy and investment perspectives as it helps in projecting how much of the future oil market risk can be hedged with gold holdings.

Finally, we also utilize alternative measures of oil market uncertainties as well as broad-based energy market uncertainties. For instance, we use the oil market uncertainty measures including the Abiad and Qureshi (2023)-constructed Oil Price Uncertainty (OPU), and Oil Market Uncertainty (OMU), as well as energy market uncertainties such as the equally-weighted global energy uncertainty index (GEUI-EQ), GDP-weighted global Energy Uncertainty Indexes (GEUI-GDP), as well as country-specific energy uncertainty indexes for twenty-eight different nations. Also, rather than consider separately the country-specific EUIs, employ the Diebold and Yilmaz (2009, 2012, 2014) connectedness [further refined by Antonakakis et al., (2020)) to generate the total connectedness index (TCI), which is also considered as an alternative measure of uncertainty.

In summary, the findings show that higher oil and energy market uncertainties drive higher gold volatility, suggesting that gold can be a good hedge against these uncertainties. Improved trading in the gold market raises its volatility as oil and energy market uncertainties increase. The rest of the paper is organized as follows: Section 2 describes the data and methodology used in the study. Section 3 discusses the empirical results, and section 4 concludes the study.

2. Data and Methodology

We employ daily PM gold prices in United States (US) dollars, obtained from the Bloomberg terminal, and monthly uncertainty measures: the oil price uncertainty (OPU) constructed by Abiad and Qureshi (2023); oil market uncertainty (OMU) of Nguyen et al. (2022), and; Dang et al.'s (2023) various energy market related uncertainties namely, the equally-weighted global energy uncertainty index (GEUI-EQ), the GDP-weighted global energy uncertainty index (GEUI-GDP), and country-specific energy uncertainty indexes for twenty-eight countries.[2] In terms of the latter, rather than considering separately/individually the country-specific EUIs, we employ the Diebold and Yilmaz (2009, 2012, 2014) connectedness to generate the total connectedness index (TCI), which is also considered an alternative measure of uncertainty.[3] In this regard, the TCI is obtained from a time-varying parameter vector autoregressive (TVP-VAR) model framework, which provides a more representative stance of connectedness, capturing all possible short-term dynamics in a flexible and robust manner, as it relies on a full-fledged time-varying method rather than the window-length-sensitive rolling approach (Antonakakis et al., 2020). The start- and end dates vary across the considered variables, with the earliest start date being (3rd) January 1969 (as determined by gold prices and OPU) and the latest end date being (31st) October 2022 (based on the availability of the various EUIs). However, for the purpose of comparison, we summarize the data on a unified start date (January 1996) and end date (December 2019) for all the variables. The

[2] Australia, Belgium, Brazil, Canada, Chile, China, Colombia, Croatia, Denmark, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, Netherlands, New Zealand, Pakistan, Russia, Singapore, South Korea, Spain, Sweden, the United Kingdom (UK), the US, and Vietnam.

[3] The total connectedness index (TCI); derived from a TVP-VAR framework (see Antonakakis et al., (2020), for detail description and merits), which is an extension of Diebold and Yılmaz (2009, 2012 and 2014) connectedness approach; measures the overall spillover effects or connectedness among the energy markets of the countries in the study. It consolidates the connectedness measures from all pairwise interactions of the country-specific EUIs into a single value, reflecting how shocks or movements in one country's energy market (represented by EUI) affect the energy markets of other countries. A high TCI indicates a high degree of connectedness, suggesting that a shock to the energy market of one the countries in the system is more likely to have significant spillover effects on the energy markets of the other countries. Conversely, a low TCI indicates a more segmented system with shocks being more contained within individual country energy markets. The TCI is valuable for risk management, portfolio diversification, and understanding systemic risk among the countries in this study. This informs the adoption of the TCI as a measure of uncertainty in the study.

summary statistics for gold returns and oil price uncertainty, which are the longest daily and monthly series, respectively, are presented in Table A1 in the appendix.

Abiad and Qureshi (2023) constructed their OPU index based on frequency counts of newspaper articles, whereby they use the collection of English-language articles with at least 100 words that have been published in 50 different newspapers worldwide and are stored in the Factiva database. These authors count the number of articles that contain the following words: “oil”, “petrol”, “petroleum”, “gas” or “gasoline” within two words of “pric*”, and in which “pric*” appears within two words of “uncert*”, “volatil*”, “fluct*”, “erratic”, “unstable”, “unsteady”, “chang*”, “unpredict*”, “vary*”, “swing*” or “move*”. The number of articles in the same newspaper and month is used to scale these raw OPU figures. The scaled frequency counts of each newspaper are then standardized to have a unit standard deviation over the duration of the data coverage. Lastly, Abiad and Qureshi (2023) normalize the average OPU index value to a mean of 100 across the sample size by taking the monthly average over the resultant newspaper-level series.[4]

Nguyen et al. (2022) proposed a novel construction of the oil price uncertainty index that is unconditional on a model.[5] The authors develop a measure of oil price uncertainty as the one-period-ahead forecast error variance of a forecasting regression with stochastic volatility (SV) in the residual terms. The novelty of this approach is in its flexibility, given that it includes a large number of additional information that is important in explaining fluctuations in oil prices namely, exchange rate, oil production, global economic conditions, and co-movement in the fuel market. In this sense, the index is able to capture uncertainty in oil price rather than volatility as measured by both GARCH and SV models. Thus, this feature of the uncertainty metric informs our preference for oil price uncertainty, which Nguyen et al. (2022) calls oil market uncertainty, i.e., OMU.

Dang et al. (2023) construct monthly EUI indexes in three steps.[6] Firstly, they construct an economic uncertainty index for each country by counting the number of terms such as “uncertain”,

[4] The data is available for download from: https://policyuncertainty.com/oil_uncertainty.html.
[5] The data can be accessed from: https://sites.google.com/site/nguyenhoaibao/datasets/oil-market-uncertainty.
[6] The data can be downloaded from: https://policyuncertainty.com/energy_uncertainty.html.

"uncertainty", and "uncertainties" that occur in monthly report of the Economist Intelligence Unit (EIU) for various countries. They then find its ratio with respect to total word counts in the entire report and normalize each resulting country-level index to a mean of 100 over time. As for second stage, they employ the same step as in the previous approach to construct country-level energy-related index using similar source. Specifically, energy-related keywords in Table 1 of their paper are used. In the final step, they derive country-level EUI values at monthly frequency as the simple mean of the economic uncertainty and energy-related indexes. Dang et al. (2023) also compute two Global EUI series as the equal-weighted and GDP-weighted means of the country-specific EUI series.

Table 1 summarizes the data characteristics with measures of location, variability, and distribution shape, presents statistics showing the conditional heteroscedasticity, and the first and higher order serial correlation statuses for the daily gold price returns and the monthly uncertainty measures (OPU, OMU, GEUI_EQ, GEUI_GDP and TCI). Gold return series is positive on average, having negative skewness and excess kurtosis. All the uncertainty measures exhibit positive skewness and leptokurtic (except OMU and TCI) characteristics. The oil price uncertainty and total connectedness index appear to be the most and least volatile uncertainty measures, respectively, viewing from the perspective of the coefficient of variation. All the series exhibit evidence of conditional heteroscedasticity (except OPU and TCI), first-order (except TCI) and higher-order (except OPU and TCI) serial correlations and persistence (the predictor variables only). All the data features associated with gold returns (except the positive skewness) and oil price uncertainty (except conditional heteroscedasticity) in the shorter (reduced) sample are also observed when the longer (expanded) sample period was considered (see results in Table A1 in the appendix). These observed salient features, cum the mixed frequency nature of our data, are most effectively addressed within a GARCH-MIDAS framework, which we will discuss in the subsequent section.

Table 1: Summary Statistics

Statistics	Gold Returns	Global Energy Uncertainty Index (Equally-Weighted)	Global Energy Uncertainty Index (GDP-Weighted)	Oil Market Uncertainty Index	Oil Price Uncertainty	Total Connectedness Index
	Daily			***Monthly***		
Mean	0.02	22.54	19.74	0.76	108.96	69.74
Standard Deviation	1.03	7.37	9.30	0.14	77.08	2.42
Coef. of Variation	5150.00	32.70	47.11	18.42	70.74	3.47
Skewness	-0.14	0.44	0.13	0.22	1.37	0.15
Kurtosis	9.26	4.56	3.14	2.74	5.02	1.54
Observations	6019	288	288	288	288	288
Conditional Heteroscedasticity Test						
$ARCH(5)$	74.68***	9.10***	1.82	22.13***	0.88	0.13
$ARCH(10)$	44.98***	8.62***	1.87**	10.71***	0.52	0.85
$ARCH(20)$	28.39***	5.67***	1.13	5.32***	0.98	0.46
Serial Correlation Test						
$Q(5)$	6.41	27.15***	9.93*	206.69***	15.25***	4.32
$Q(10)$	11.92	36.87***	21.14**	217.41***	17.04*	13.41
$Q(20)$	30.64*	73.81***	40.17***	237.76***	29.32*	18.81
$Q^2(5)$	538.20***	56.26***	9.25*	105.94***	4.89	0.99
$Q^2(10)$	874.93***	132.24***	17.88*	108.27***	6.09	9.31
$Q^2(20)$	1486.80***	181.96***	23.05	114.60***	22.43	10.26
Persistence	-	0.73***	0.77***	1.00***	0.69***	0.99***

Note: $ARCH(\#)$, $Q(\#)$ and $Q^2(\#)$ are formal tests for the presence of ARCH effects, first and higher-order serial correlation, respectively, at the specified lags. ***, **, and* denote the formal tests' statistical significance at 1%, 5%, and 10% levels of significance, respectively. The statistical significance of these tests indicates evidence of the presence of conditional heteroscedasticity and serial correlation.

Given the evidenced conditional heteroscedasticity and mixed frequency characteristics of our data, we employ the GARCH-MIDAS model framework introduced by Engle et al. (2013) study, comprising two main parts: the unconditional mean part and the conditional variance part, which is multiplicatively decomposed into high- and low-frequency components. Equations (1) to (5) define the GARCH-MIDAS model specification.

$$r_{i,t} = \mu + \sqrt{h_{i,t} \times \tau_t} \times \varepsilon_{i,t}, \qquad \forall\ i = 1,2,\ldots,N_t \tag{1}$$

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

$$\tau_i^{(rw)} = m_i^{(rw)} + \theta_i^{(rw)} \sum_{k=1}^{K} \phi_k(\omega) X_{i-k}^{(rw)} \tag{3}$$

$$\phi_k(w) = \frac{\left[1 - k/(K+1)\right]^{w-1}}{\sum_{j=1}^{K}\left[1 - j/(K+1)\right]^{w-1}} \tag{4}$$

$$\varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N(0,1) \tag{5}$$

where $r_{i,t}$ is the i^{th} day of the month t gold price returns, with N_t indicating the number of days in month t; μ represents the unconditional mean of the gold price returns; $h_{i,t}$ represents the short-run that is assumed to follow a GARCH(1,1) process; τ_t represents the long-run components of the conditional variance $\left(\sqrt{h_{i,t} \times \tau_t}\right)$ part of Equation (1); α and β in Equation (2) are the ARCH and GARCH terms, respectively, with the following imposed constraints, $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$; in Equation (3) m represents the long-run constant, θ denotes the slope coefficient that indicates the predictability stance of the realized volatility (RV) or the incorporated exogenous variable (OPU, OMU, GEUI-EQ, GEUI-GDP and TCI) for gold price returns; $\phi_k(w)$ represents a flexible (Colacito et al., 2011) one parameter beta polynomial weighting scheme[7], where the following conditions, $\phi_k(w) \geq 0,\ k = 1,2,\ldots,K$ and $\sum_{k=1}^{K} \phi_k(w) = 1$, are imposed to ensure that the model identification condition is satisfied; while the constraint $(w > 1)$ is also imposed to ensures that immediate past observation lags are assigned larger weights than distant observation lags, X_{i-k} represents the exogenous predictor (OPU, OMU, GEUI-EQ, GEUI-GDP and TCI); and the superscript "*rw*" indicates the adoption of a rolling window framework for the estimation

[7] This is obtained from the two-parameter beta weighting scheme $\phi_k(w_1, w_2) = \left[k/(K+1)\right]^{w_1-1} \times \left[1-k/(K+1)\right]^{w_2-1} \Big/ \sum_{j=1}^{K}\left[j/(K+1)\right]^{w_1-1} \times \left[1-j/(K+1)\right]^{w_2-1}$ by constraining w_1 to 1 and setting $w = w_2$.

exercise; while $\varepsilon_{i,t} \mid \Phi_{i-1,t}$ denotes the information set that is available at the $(i-1)^{th}$ day of the month t, which is normally distributed.

Our predictive uncertainty-based GARCH-MIDAS models' out-of-sample forecast performances are pair-wisely compared with the conventional GARCH-MIDAS-RV (benchmark) model using the modified Diebold and Mariano test [*DM**] (Harvey et al., 1997), which is an extension of the conventional Diebold and Mariano [DM] (1995) test for paired non-nested model evaluations. The statistical formulations are delineated in Equations (6) and (7) below:

$$DM^{*} = \left(\sqrt{\frac{T+1-2h+T^{-1}h(h-1)}{T}}\right) DM \qquad (6)$$

$$DM = \frac{\bar{d}}{\sqrt{V(d)/T}} \sim N(0,1) \qquad (7)$$

where DM^{*} represents the modified DM statistic; T denotes the number of the out-of-sample periods of the forecast errors and h indicates the forecast horizon; $\bar{d} = 1/T\left[\sum_{t=1}^{T} d_t\right]$ is the average of the loss differential, $d_t \equiv g(\varepsilon_{it}) - g(\varepsilon_{jt})$; the loss functions of the forecast errors (ε_{it} and ε_{jt}) from the paired competing models are given by $g(\varepsilon_{it})$ and $g(\varepsilon_{jt})$, respectively; while $V(d_t)$ represents the unconditional variance of the loss differential d_t. The DM^{*} test null hypothesis asserts equality in the forecast accuracy of the paired non-nested contending models $(H_0 : d = 0)$ in contrast to a mutually exclusive alternative, $(H_1 : d \neq 0)$. Rejection of the null hypothesis would indicate that the forecast accuracies of the paired models differ markedly, whereas rejection would imply equality. The associated sign of the DM^{*} statistic determines the direction of preference: a negative value indicates superiority of our uncertainty-based GARCH-MIDAS model over the conventional GARCH-MIDAS-RV model; whereas a significant positive DM* value suggests the converse. Furthermore, we compare GARCH-MIDAS models incorporating variants of the global energy uncertainty indexes (GEUI-EQ, GEUI-GDP and TCI) with the GARCH-MIDAS models that incorporate each of the oil-based variants (OPU and OMU), using the latter of the pair as the benchmark model. We conduct the in-sample estimation using the full data set, while the forecast evaluation is conducted on a 75:25 data sample split that allows for the out-of-sample forecast assessment to be performed on the remaining 25%, over three different forecast horizons (20-, 60-, and 120-days ahead).

3. Empirical Findings

3.1 In-Sample Predictability

We present the in-sample predictability results (see Table 2) of the estimation of the GARCH-MIDAS models that incorporate realized volatility and the different variants of uncertainty (OPU, OMU, GEUI-EQ, GEUI-GDP, and TCI). We only report the slope coefficients associated with the aforementioned uncertainty measures that indicate the predictability stances. Given that the variables in our data set have different start and end dates, the in-sample estimation periods are determined by the dates for which the daily gold returns and each monthly uncertainty measure are available. Hence, the results in Table 2 are thus sub-sectioned. We also replicate the same for the case when the start and end dates have been unified based on the OPU and OMU (see results in Table 3).

Table 2 reports significantly positive coefficients for the realized volatility as well as the different uncertainty measures (OPU, OMU, GEUI-EQ, GEUI-GDP, and TCI). On the realized volatility, there are pieces of evidence of gains associated with gold-based investments when the gold market volatility heightens. This is evidenced regardless of the sample period considered. Similarly, the heightened oil and/or energy related uncertainties (OPU, OMU, GEUI-EQ, GEUI-GDP, and TCI) tend to also lead to increased gold market volatility. This is essentially an indication that gold is an appropriate hedge option whenever the oil and/or energy markets are in crisis. In other words, during episodes of high oil and energy market uncertainties, there appears to be improved trading in the gold market, raising its returns and, by extension, volatility. This aligns with several extant studies (Salisu and Adediran, 2020; Salisu et al., 2020, 2021a, 2023; Li and Umair, 2023b; among others) establishing the stance of a positive nexus between gold returns and external uncertainties. A similar feat is also observed in Table 3, which is a further confirmation of the robustness of the model to the sample periods and the choice of the uncertainty measure that is employed.

Table 2: In-Sample Predictability Results (Different Start and End Periods)

Predictor Variables	Coefficient Estimates
January 1969 – December 2019	
Realized Volatility	0.0517*** [0.0016]
Oil Price Uncertainty	0.2303*** [0.0160]
February 1975 – May 2020	
Realized Volatility	0.0438*** [0.0014]
Oil Market Uncertainty	0.1902*** [0.0269]
January 1996 – October 2022	
Realized Volatility	0.0339*** [0.0019]
Global Energy Uncertainty Index (Equally-Weighted)	0.4675*** [0.0408]
Global Energy Uncertainty Index (GDP-Weighted)	0.4886*** [0.0377]
Total Connectedness Index	0.4827*** [0.0378]

Note: The figures in each cell are the estimated coefficients and their associated standard error in square brackets, while *** denotes the estimated coefficient's statistical significance at the 1% level. The sampled interval varies based on the predictor variable's start and end dates.

Table 3: In-Sample Predictability Results (Unified Start and End Periods)

Predictor Variables	Coefficient Estimates	
	January 1996 – December 2019	***January 1996 – May 2020***
Realized Volatility	0.035551*** [0.0019295]	0.035053*** [0.0020722]
Oil Price Uncertainty	0.014825*** [0.0012198]	-
Oil Market Uncertainty	-	0.014624*** [0.0012534]
Global Energy Uncertainty Index (Equally-Weighted)	0.014730*** [0.0012420]	0.014639*** [0.0012555]
Global Energy Uncertainty Index (GDP-Weighted)	0.014751*** [0.0012395]	0.014660*** [0.0012531]
Total Connectedness Index	0.014732*** [0.0012401]	0.014641*** [0.0012537]

Note: The figures in each cell are the estimated coefficients and their associated standard error in square brackets, while *** denotes the estimated coefficient's statistical significance at the 1% level. The sampled interval varies based on the start and end dates of OPU (second column) and OMU (third column).

3.2 Out-of-Sample Forecast Evaluation

Having ascertained the in-sample predictability of oil and energy-based uncertainties for gold returns volatility in the in-sample period, we extend the evaluation to the out-of-sample period to assess the performances of our predictive uncertainty-based GARCH-MIDAS model in comparison with the realized volatility-based GARCH-MIDAS as the benchmark. In the same vein, we also consider the comparison of the global energy uncertainty-based GARCH-MIDAS models with the oil-based variants, using the latter of the pair as the benchmark model. Table 4 presents the results of the modified Diebold and Mariano test for the estimated models when we considered different start and end dates under three out-of-sample forecast horizons (20-, 60-, and 120-day ahead). Across the forecast horizons, the different uncertainty measures, and different sample periods, we find an overwhelming outperformance of our predictive uncertainty-based GARCH-MIDAS models over the GARCH-MIDAS-RV model, given the significantly negative DM*. This is prominently so, especially with respect to the OPU and OMU. The case of the energy uncertainty variants showed that there may not be a significant outperformance of our predictive GARCH-MIDAS model over the GARCH-MIDAS-RV model in the shorter forecast horizon ($h = 20$). However, at medium to longer out-of-sample forecast horizons, the precision of our predictive model improves. Again, there is evidence of the robustness of the out-of-sample forecast precision with respect to the choice of uncertainty measure and forecast horizons. This is also an indication that the predictability stance transcends the in-sample period and the specified forecast horizons.

As a further validation of the out-of-sample forecast performance stance, we consider the case where the periods are unified, to enable comparison of the different paired uncertainty measures. The result is presented in Table 5, where the upper panel reports the stance when our uncertainty-based GARCH-MIDAS model variants are compared with the GARCH-MIDAS-RV model, while the lower panel reports the stance of the comparison of our energy-based GARCH-MIDAS modes with GARCH-MIDAS-OPU (lower left) and GARCH-MIDAS-OMU (lower right). On the lower panel, the oil-based GARCH-MIDAS are the benchmark models. The stance of outperformance of our predictive uncertainty-based GARCH-MIDAS model over the GARCH-MIDAS-RV is upheld, irrespective of the uncertainty measure that was used. considered. However, on the paired comparison of the energy-based model and the oil-based model, there was an overwhelming outperformance of the latter over the former. This is indicative that the information provided by the oil-based uncertainty measures is sufficient for the prediction of the gold returns volatility, such that the information from the energy-based variants does not outperform the oil-based model. The results are again robust to the energy and oil uncertainties used.

Table 4: Diebold and Mariano Out-of-Sample Forecast Evaluation (Different Start and End Periods)

Predictor Variables	$h = 20$	$h = 60$	$h = 120$
January 1969 – December 2019			
Oil Price Uncertainty	-3.887***	-5.049***	-4.946***
February 1975 – May 2020			
Oil Market Uncertainty	-4.081***	-4.687***	-8.573***
January 1996 – October 2022			
Global Energy Uncertainty Index (Equally-Weighted)	0.465	-3.048***	-5.270***
Global Energy Uncertainty Index (GDP-Weighted)	-0.523	-4.491***	-6.693***
Total Connectedness Index	-0.377	-4.329***	-7.235***

Note: The figures in each cell are the Diebold and Mariano statistics and their associated levels of significance at 1% and 10%, respectively, denoted by while *** and *. The benchmark model is the conventional GARCH-MIDAS-RV model. The sampled interval varies based on the start and end dates of the predictor variable.

Table 5: Diebold and Mariano Out-of-Sample Forecast Evaluation (Unified Start and End Periods)

Predictor Variables	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$
	January 1996 – December 2019			*January 1996 – May 2020*		
	GARCH-MIDAS RV is the benchmark					
Oil Price Uncertainty	-3.543***	-6.614***	-8.755***	-	-	-
Oil Market Uncertainty	-	-	-	-3.951***	-4.733***	-1.651
Global Energy Uncertainty Index (Equally-Weighted)	-3.404***	-6.465***	-8.543***	-3.917***	-4.659***	-1.505
Global Energy Uncertainty Index (GDP-Weighted)	-3.399***	-6.46***	-8.534***	-3.912***	-4.637***	-1.439
Total Connectedness Index	**-3.400*****	**-6.461*****	**-8.532*****	**-3.911*****	**-4.637*****	**-1.438**
	GARCH-MIDAS-OPU is the benchmark			**GARCH-MIDAS-OMU is the benchmark**		
Global Energy Uncertainty Index (Equally-Weighted)	4.381***	7.026***	10.190***	5.300***	8.237***	11.098***
Global Energy Uncertainty Index (GDP-Weighted)	4.417***	7.276***	10.467***	5.219***	8.094***	11.788***
Total Connectedness Index	**4.398*****	**7.146*****	**10.400*****	**5.253*****	**8.192*****	**12.104*****

Note: The figures in each cell are the Diebold and Mariano statistics and their associated significance levels at 1% and 10%, respectively, denoted by while *** and *. The benchmark model is the conventional GARCH-MIDAS-RV model. The sampled interval varies based on the start and end dates of the predictor variable.

4. Conclusion

This paper empirically evaluates the relationship between oil and energy-based uncertainties for gold return volatility using daily gold returns and monthly oil market uncertainty measures such as the Oil Price uncertainty (OPU) constructed by Abiad and Qureshi (2023), Oil Market Uncertainty (OMU), as well as energy market uncertainties such as equally-weighted global energy uncertainty index (GEUI-EQ), GDP-weighted global energy uncertainty index (GEUI-GDP) and country-specific energy uncertainty indexes for twenty-eight countries. Also, rather than considering the country-specific EUIs separately, we generate the total connectedness index (TCI), which is also considered an alternative measure of uncertainty. The TCI is obtained from a time-varying parameter vector autoregressive (TVP-VAR) model framework, which provides a more representative stance of connectedness, capturing all possible short-term dynamics in a more flexible and robust manner (Antonakakis et al., 2020). To observe salient features, cum the mixed frequency nature of our data; we employ the GARCH-MIDAS model framework introduced by Engle et al. (2013) study, comprising two main parts: the unconditional mean part and the conditional variance part, which is multiplicatively decomposed into high- and low-frequency components. We conduct both in-sample and out-of-sample forecast analyses, and for the latter, we compare the benchmark model for GARCH-MIDAS, which is the variant that involves the realized volatility as the exogenous factor with those of the oil and energy market uncertainties. We also compare GARCH-MIDAS models incorporating variants of the global energy uncertainty indexes (GEUI-EQ, GEUI-GDP and TCI) with the GARCH-MIDAS models incorporating each oil-based variant (OPU and OMU).

The findings indicate a positive connection between oil and energy market uncertainties and gold return volatility. Heightened oil and energy-related uncertainties (OPU, OMU, GEUI-EQ, GEUI-GDP, and TCI) are associated with increased volatility in the gold market due to increased trading, suggesting that gold can serve as a hedge option during oil and energy market crises. The out-of-sample forecast evaluation demonstrates the superior performance of our predictive uncertainty-based model, particularly with OPU and OMU. For energy uncertainty variants, our predictive model does not show significant outperformance. This suggests that the information from oil-based uncertainty measures is sufficient for predicting gold return volatility and that information from energy-based variants does not outperform the oil-based model, thus highlighting the dominant role of the oil market in shaping the behavior of the energy sector.

Accurate forecasting volatility of gold returns is of interest to investors for devising hedging strategies, as well as, in the pricing of related derivatives. This exercise, highlighting the role of oil market uncertainty in determining the future path of gold returns volatility should thus be of importance to investors. At the same time, gold returns volatility is also known to be a metric for global uncertainty (Salisu et al., 2022), and its forecasts would allow the design of appropriate monetary and fiscal policy responses in preventing recessionary outcomes.

In light of the importance of energy market movements, and particularly oil, as part of future research, it would be interesting to perform such an analysis on other commodities as well, for the sake of comparability with our findings associated with real gold returns volatility.

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Appendix

Table A1: Summary Statistics for the full data sample for gold returns and oil price uncertainty

Statistics	Gold Returns	Oil Price Uncertainty
Mean	0.03	89.09
Standard Deviation	1.22	111.63
Skewness	0.11	3.26
Kurtosis	13.97	19.22
Start date	January 2, 1969	January 1969
End date	October 31, 2022	December 2019
Frequency	Daily	Monthly
Observations	13522	612
Conditional Heteroscedasticity Test		
$ARCH(5)$	542.12***	16.20***
$ARCH(10)$	298.51***	8.15***
$ARCH(20)$	162.73***	7.09***
Serial Correlation Test		
$Q(5)$	9.17	110.08***
$Q(10)$	24.98***	132.53***
$Q(20)$	50.71***	202.92***
$Q^2(5)$	4439.60***	99.17***
$Q^2(10)$	6321.90***	102.61***
$Q^2(20)$	10012.00***	199.35***
Persistence	-	0.36***

Note: $ARCH(\#)$, $Q(\#)$ and $Q^2(\#)$ are formal tests for ARCH effects, first and higher-order serial correlation, respectively, at the specified lags. ***, **, and* denote the formal tests' statistical significance at 1%, 5%, and 10% levels of significance, respectively. The statistical significance of these tests indicates evidence of the presence of conditional heteroscedasticity and serial correlation.