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University of Pretoria
Department of Economics Working Paper Series

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Thanoj K. Muddana
San Francisco State University
Komal S.R. Bhimireddy
San Francisco State University
Anandamayee Majumdar
San Francisco State University
Rangan Gupta
University of Pretoria
Working Paper: 2024-21
May 2024

Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Forecasting Gold Returns Volatility Over 1258-2023: The Role of Moments

Thanoj K. Muddana*, Komal S.R. Bhimireddy**, Anandamayee Majumdar*** and Rangan Gupta****

Abstract

We analyze the role of leverage, lower and upper tail risks, skewness and kurtosis of real gold returns in forecasting its volatility of over the annual data sample of 1258 to 2023. To conduct our forecasting experiment, we first fit Bayesian time-varying parameters quantile regressions to real gold returns, under six alternative prior settings, to obtain the estimates of volatility (as inter-quantile range), lower and upper tail risks, skewness and kurtosis. Second, we forecast the derived estimates of conditional volatility using the information contained in leverage of gold returns, tail risks, skewness and kurtosis using recursively estimated linear predictive regressions over the out-of-sample periods. We find strong statistical evidence of the role of the moments-based predictors in forecasting gold returns volatility over the short- to medium term, i.e., till one- to five-year ahead, when compared to the autoregressive benchmark. Our results have important implications for investors and policymakers.

Keywords: Time-varying parameters quantile regressions; Bayesian inference; Real gold returns; Moments; Volatility forecasting; Linear predictive regressions

JEL Codes: C22, C53, Q02

* Department of Mathematics, San Francisco State University, California, USA. Email: tmuddana@sfsu.edu.
** Department of Mathematics, San Francisco State University, California, USA. Email: kbhimireddy@sfsu.edu.
*** Department of Mathematics, San Francisco State University, California, USA. Email: amajumdar@sfsu.edu.
**** Corresponding author. Department of Economics, University of Pretoria, Pretoria, South Africa. Email: rangan.gupta@up.ac.za.

1. Introduction

The “safe haven” property of gold is well-recognized (Boubaker et al., 2020; Salisu et al., 2022a, 2023), wherein during periods of heightened risks in other financial (stocks, bonds and (crypto)currencies) markets, gold provides portfolio-diversification benefits. Naturally, forecasting volatility of gold returns is of interest to investors for devising hedging strategies, as well as, in the pricing of related derivatives. Understandably, there exists a large literature that has aimed to forecast gold volatility (see, Salisu et al. (2020, 2022b), Gupta and Pierdzioch (2021), Gupta et al. (2023a), and Gabauer et al. (forthcoming) for detailed reviews). While the predictive role of various macroeconomic, financial and behavioural variables have been analysed in this process, with the advent of intraday data, the information content of accurately estimated (realized) moments of gold prices (Gkillas et al., 2020; Bouri et al., 2021; Demirer et al., 2021) in forecasting its daily (realized) volatility over the last two and a half decades have been strongly highlighted in many papers, even over and above economic drivers (see, for example, Demirer et al. (2019), Asai et al. (2019, 2020), Bonato et al. (2021), Gupta and Pierdzioch (2022), Luo et al. (2022), and references cited therein). The underlying reason behind the success of these moments, such as leverage (only negative returns), tail risks, skewness and kurtosis, emanates from the fact that these statistics of gold prices provides an empirical proxy for rare disasters (associated with not only financial crises, but also natural disasters, geopolitical events, and even outbreak of contagious diseases (Balcilar et al., 2022; Bouri et al., 2022)), which are known to explain asset price movements (Rietz, 1988; Longstaff and Piazzesi, 2004; Barro, 2006, 2009; Barro and Ursúa, 2012).

Against this backdrop, the objective of this paper is to take a historical perspective, by analyzing the role of leverage, tail risks, skewness and kurtosis or real gold returns in forecasting its volatility over the longest available annual data sample of 1258 to 2023, which ensures us in avoiding, the so-called, “sample-selection bias.” At the same time, the role of disaster events, as reflected by the moments, being rare, warrants the need to look at long spans of data (Ćorić, 2018, 2021). This exercise, is not only of importance to investors, but also policymakers, as gold returns volatility is known to be a metric for global uncertainty (Salisu et al., 2022c), and its accurate forecasting would allow the design of appropriate monetary and fiscal policy responses in preventing recessionary outcomes.

To conduct our forecasting experiment, we take a two-step approach. As the only data frequency available for gold prices over our sample period is annual, computing the realized moments using higher-frequency is not possible. To tackle this issue, we rely on a quantile regression approach (Koenker and Bassett, 1978), whereby this method is designed to estimate the conditional quantiles of an endogenous variable (gold returns). However, realizing the possibility of structural changes (which we show below to exist in the gold returns using formal statistical tests), we actually estimate quantile regressions featuring time-varying parameters to obtain robust statistical inference and calculations of the underlying moments from the conditional quantiles, following Pfarrhofer (2022). Once we obtain the relevant estimates of the conditional quantiles (under alternative Bayesian priors), we are able to derive metrics of volatility (inter-quantile range), upper and lower tail risks, skewness and kurtosis, besides leverage (i.e., negative gold returns only), and utilize the calculated moments to forecast volatility based on a linear predictive regression model, which is recursively-estimated over the out-of-sample period to produce multi-horizon forecasts.

To the best of our knowledge, this is the first attempt to forecast gold returns volatility based on its underlying moments, derived from Bayesian time-varying parameter quantile regressions, covering over seven centuries, i.e., 766 years of data. The remainder of the paper is organized as follows: Section 2 outlines the data and the basics of the econometric methodologies, while Section 3 presents the results from the forecasting exercise, with Section 4 concluding the paper.

2. Data and Econometric Methodologies

2.1. Real Gold Price

For the price of gold, we use annual data of nominal prices (in British pounds) of gold starting in 1257 till 2023, which is the earliest date of data availability, and is retrieved from MeasuringWorth.[1] The nominal price of gold is transformed into its real counterpart by deflating with the Consumer Price Index (CPI) of the United Kingdom derived from a database maintained by the Bank of England called: "A Millenium of Macroeconomic Data for the UK".[2]

Computation of log-returns implies that our effective sample covers 1258 to 2023 for real gold returns, with the fluctuating data plotted in Figure 1, and summarized in Table 1. The data is

[1] https://www.measuringworth.com/datasets/gold/.
[2] https://www.bankofengland.co.uk/statistics/research-datasets.

clearly non-normal, as suggested by the strong rejection of the null of normality under the Jarque-Bera test, due to positive skewness and excess kurtosis. The non-normalness of real gold log-returns serves as a preliminary need to look at a quantiles-based model, besides the underlying requirement of obtaining the moments. Furthermore, the Bai and Perron (2003) tests of multiple structural breaks applied to an ordinary least squares (OLS) estimation of real gold log-returns on a constant yielded four breaks (1377, 1590, 1704, and 1819), and, hence, justified the decision to use a time-varying parameter-quantile regression (TVP-QR) approach to model gold returns, to which we turn to next.

[INSERT FIGURE 1 AND TABLE 1]

2.1. Econometric Models

2.1.1. Time-varying parameters-quantile regression (TVP-QR)

Let $\{y_t\}_{t=1}^{T}$ be a scalar time series, in our case depicting the real log-returns of gold, and $\{x_t\}_{t=1}^{T}$ a K×1-vector of explanatory variables at time $t = 1, \ldots, T$, which may comprise an intercept, observed/latent factors, additional covariates or lags of the endogenous variable. Here, as in Pfarrhofer (2022), we only consider an intercept in the model. A general version of the TVP-QR framework is given by:

$$y_t = x_t'\beta_{pt} + \epsilon_t, \qquad \text{with} \qquad \int_{-\infty}^{0} f_p(\epsilon_t)\, \mathrm{d}\epsilon_t = p. \tag{1}$$

where $q_p(x_t) = x_t'\,\beta_{pt}$ as the pth quantile regression function of y_t conditional on x_t, for $p \in (0, 1)$. The regression coefficients are collected in a K×1-vector $\{\beta_{pt}\}_{t=1}^{T}$, with them varying over time and are specific to the pth quantile. The error term ϵ_t with density $f_p(\bullet)$ has its pth quantile is equal to zero. The density $f_p(\bullet)$ is chosen to be the asymmetric Laplace (AL_p) distribution. In this paper, in addition to TVPs, the Bayesian QR features a time-varying scale parameter similar to a stochastic volatility model. To achieve this, auxiliary variables $v_{pt} \sim \varepsilon(\sigma_{pt})$ which follow an exponential distribution with time-varying scaling σ_{pt}, and $u_t \sim N(0,1)$, are defined.

The model in (1) can be written as:

$$y_t = x_t'\beta_{pt} + \theta_p v_{pt} + \tau T_p \sqrt{\sigma_{pt} v_{pt}}\, u_t, \quad \theta_p = \frac{1-2p}{p(1-p)}, \; \tau_p^2 = \frac{2}{p(1-p)}. \tag{2}$$

Let $\tilde{y}_{pt} = (y_t - \theta_p v_{pt})/(\tau_p\sqrt{\sigma_{pt} v_{pt}})$ and $\tilde{x}_{pt} = \left(\tau_p\sqrt{\sigma_{pt} v_{pt}} I_K\right)^{-1} x_t$ with I_K denoting an identity matrix of size K. Conditional on v_{pt} and σ_{pt} , (2) can be written as a standard TVP regression:

$$\tilde{y}_{pt} = \tilde{x}'_{pt}\beta_{pt} + u_t, \quad u_t \sim N(0,1). \tag{3}$$

Finally, time-variation in the quantile-specific regression coefficients and the logarithmic scale parameters are introduced via standard random walk state equations as follows:

$$\beta_{pt} = \beta_{pt-1} + \eta_{pt}, \ \ \eta_{pt} \sim N\left(0, \Omega_{pt}\right), \tag{4}$$

$$\log\left(\sigma_{pt}\right) = \log\left(\sigma_{pt-1}\right) + e_{pt}, \ \ e_{pt} \sim N\left(0, \varsigma_p^2\right), \tag{5}$$

with $K \times K$-matrix $\Omega_{pt} = diag\ (\omega_{p1,t}, \ldots, \omega_{pK,t})$ collecting independent state innovation variances on its diagonal and ς_p^2 corresponding to the state innovation variance of the scale parameters.

Time-variation for the kth coefficient in β_{pt} is governed by $\omega_{pk,t}$ for $k = 1, \ldots, K$. The three priors we look into in this regard are the inverse Gamma distribution (iG), static horseshoe (shs), and dynamic horseshoe (dhs), wherein, in the first case, time variation is disregarded by relying on a constant specification, and time-varying degree of shrinkage without and with persistence are considered under the latter two respectively. The set-up is completed by assuming iG priors for the case of a time-invariant scale parameter (TIS) of the AL_p distribution, and on the state innovation variance of the logarithmic time-varying process (TVS) of the scale parameter. The resulting posterior distributions and details on the sampling algorithm are provided in Pfarrhofer (2022).

Disregarding a number of draws as burn-in, the Markov chain Monte Carlo (MCMC) algorithm delivers draws from the desired posterior distributions. We discard the initial 3000 draws as burn-in and use each third of the 9000 subsequent draws for posterior and predictive inferences.[3] Specifically speaking, using the Bayesian TVP-QR, we obtain the fitted values of real gold log-returns ($\widehat{\tilde{y}_{pt}}$) at the quantiles, i.e., p = 0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95,

[3] In this regard, we utilize the R codes corresponding to Pfarrhofer (2022), available at: https://github.com/mpfarrho/tvp-qr.

and 0.99, to obtain our estimates of lower (LTR) and upper (UTR) tail risks, skewness (SKEW) and kurtosis (KURT), to forecast volatility, i.e., the inter-quantile range (IQR), as will be discussed in detail below, under six prior settings of: iG-TIS, iG-TVS, shs-TIS, shs-TVS, dhs-TIS, and dhs-TVS.

2.1.2. Predictive regression model

To forecast volatility (IQR), we utilize the following linear predictive regression model, based on $\{z_t\}_{t=1}^{T}$, which is a M×1-vector of predictors at time t = 1, . . . , T, with the regression coefficients represented by a M×1-vector $\{\gamma_t\}_{t=1}^{T}$:

$$IQR_{t+h} = z_t'\gamma_t + \varepsilon_{t+h} \tag{6}$$

where, IQR (=$\widehat{\tilde{y}_{0.90}} - \widehat{\tilde{y}_{0.10}}$) is our metric of real gold log-returns volatility with ε_{t+h} denoting the disturbance term, where h (= 1, 2, ….,10) is the forecast horizon. IQR_{t+h} is basically the cumulative sum of IQR over the forecast horizon. z includes lags of the IQR, as determined by the Schwarz Information Criterion (SIC), leverage (i.e., a time series involving the periods that correspond to only negative real gold log-returns: LEV), LTR, UTR, SKEW and KURT. Note that, following Gupta et al. (2023b), LTR = $\widehat{\tilde{y}_{0.05}}$; UTR = $\widehat{\tilde{y}_{0.95}}$; SKEW= $(\widehat{\tilde{y}_{0.90}} + \widehat{\tilde{y}_{0.10}} - 2\widehat{\tilde{y}_{0.50}})/(\widehat{\tilde{y}_{0.90}} - \widehat{\tilde{y}_{0.10}})$, and; KURT = $(\widehat{\tilde{y}_{0.99}} - \widehat{\tilde{y}_{0.01}})/(\widehat{\tilde{y}_{0.75}} - \widehat{\tilde{y}_{0.25}})$. Our benchmark model simply involves lags of IQR using SIC, with the optimal leg-length being: 2, 2, 6, 3, 4, and 3, under iG-TIS, iG-TVS, shs-TIS, shs-TVS, dhs-TIS, and dhs-TVS, respectively.

The benchmark and full (with moments) models are both recursively estimated using OLS over the alternative out-of-sample periods, with the detail discussion outlined in the next segment.

3. Empirical Findings

In this section we discuss the findings from our forecasting exercise. A crucial aspect of any forecasting experiment involves the determination of the split of the entire sample period into in- and out-of-samples. In this regard, the starting point of the out-of-sample, over which the benchmark and model with moments for IQR are recursively estimated, corresponds to the first break point derived using the Bai and Perron (2003) tests of multiple structural breaks applied to the benchmark model under each of the six prior set-ups. To be precise, the starting points of out-samples till 2023 for the forecasting exercises are: 1391, 1391, 1464, 1391, 1378, and 1378 for the models with prior-settings of iG-TIS, iG-TVS, shs-TIS, shs-TVS, dhs-TIS, and dhs-TVS, respectively. Understandably, the corresponding in-sample periods cover 1257-1390, 1257-1390, 1257-1463, 1257-1390, 1257-1377, and 1257-1377, wherein the full model and the benchmark, which is nested in the former, are estimated for the first time, before being repeatedly estimated using an expanding-window to produce robust multi-step-ahead forecasts accounting for parameter changes due to other breaks over the out-of-samples. In this context, note that, the break dates of the benchmark model of IQR using iG-TIS, iG-TVS, shs-TIS, shs-TVS, dhs-TIS, and dhs-TVS were: 1391, 1598, 1868; 1391, 1609, 1868; 1464, 1910; 1391, 1550, 1681, 1796, 1910; 1378, 1550, 1688, 1802; 1378, 1550, 1682, 1796, 1910, respectively.

As part of the metric for forecasting performance of the benchmark and the complete model for IQR under the six alternative prior structures, we compare Mean Square Errors (MSEs) across the two models. Given this in Table 2, we report the Relative MSEs (RMSEs), which is basically the MSE from the model with moments relative to the same from the benchmark. Understandably, a value of less than unity, will correspond to the full model outperforming the benchmark which does not involve the moments. When considering the iG-TIS and iG-TVS cases, clearly in the latter case moments produces more accurate forecast for real gold log-returns volatility relative to the benchmark till h=5, compared to only h=1 in the former prior setting, suggesting the importance of incorporating the role of time-varying (stochastic) volatility in the error structure of the TVP-QR framework utilized in the first step to derive estimates of IQR, LTR, UTR, SKEW and KURT. Interestingly, the shs-TIS tends to outperform the benchmark of the IQR till 8-year-ahead, while the shs-TVS model does so up to h=4. These findings highlight time-varying shrinkage of the model parameters incorporated under shs unlike with iG, even when ignoring time-variation in error volatility of the TVP-QR fitted to real gold log-returns. A similar pattern to shs emerges across dhs-TIS and dhs-TVS till horizons six and five, respectively, in terms of outperforming the benchmark. As dhs captures persistence in the shrinkage of the time-varying parameters of the TVP-QR model, the last set of results depicts the role of this feature, even when time-varying volatility in the error process is suppressed.

[INSERT TABLE 2]

In Table 2, we also present the MSE-F test statistic of McCracken (2007). The MSE-F statistic tests whether the MSE for the full (unrestricted) model with the moments is lower than the MSE produced by its nested benchmark (restricted), i.e., without the moments and just the lags of IQR, in a statistically significant manner.[4] As can be seen from this table, in all the instances, across the six prior settings used to obtain the moments, where the forecasts of IQR obtained from LEV, LTR, UTR, SKEW and KURT outperforms the autoregressive benchmark, the gains are statistically significant at the 1% level of significance.

One must realize that, it is not possible to compare the findings across the prior-settings in terms of deciding on what is the best model when it comes to forecasting IQR of real gold returns based on its derived moments, as the underlying estimate of the conditional volatility differs. But we can safely say that, except for the case of iG-TIS, moments can produce accurate forecasts for real gold log-returns volatility over the short- to medium-run, with time-variation and its persistence involving parameter shrinkage playing important roles, even more than the underlying nature of stochastic volatility of the errors in the TVP-QR, when computing the conditional estimates of volatility and its moments of real gold log-returns. In any event, to gain some insight as to what might be the most relevant model for real gold log-returns to utilize for the purpose of obtaining the moments, we looked at the full-sample fits at the conditional median, i.e., p=0.50, of the Bayesian TVP-QR models under iG-TIS, iG-TVS, shs-TIS, shs-TVS, dhs-TIS, and dhs-TVS, and found that the MSEs are: 133.9299, 133.2372, 134.0049, 134.0201, 133.7264, and 134.2596, respectively. This suggested that at the normal state of real gold log-returns, i.e., at the conditional median, the best model is the IG-TVS, followed closely by the dhs-TIS.[5] Using this information, and the results reported in Table 2, we can then suggest that indeed IQR is forecastable in a statistically accurate manner with the information of the moments at least till 5-year ahead – a finding that aligns with the fact that economic losses are at its strongest in the first few years following rare disaster-related shocks (Ćorić and Škrabić Perić, 2023).

4. Conclusion

The objective of this paper is to analyze the role of leverage, tail risks, skewness and kurtosis or real gold returns in forecasting its volatility over the annual data sample of 1258 to 2023.

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[4] The MSE-F test is designed to accommodate for nestedness across the two competing models. The statistic is formally given as: $(T\text{-}R\text{-}h+1)\times(MSE_0/MSE_1\text{-}1)$, where MSE_0 (MSE_1) is the MSE from the restricted or benchmark (unrestricted or full) model, T is the total sample size, R is number of observations used for estimation of the model from which the first forecast is formed (i.e. the in-sample portion of the total number of observations), and h the forecasting horizon.

[5] When we look at relatively bearish and bullish gold markets at p=0.25 and 0.75, our results for the in-sample performance of the Bayesian TVP-QR model under the six prior settings continued to suggest the best fit for the prior settings of iG-TVS. Specifically speaking, under iG-TIS, iG-TVS, shs-TIS, shs-TVS, dhs-TIS, and dhs-TVS, the MSEs at p=0.25(0.75) are: 161.8381 (163.2265), 157.4114 (160.4385), 162.8762 (164.1333), 158.8050 (160.4644), 162.6659 (164.5052), and 158.6311 (161.1871), respectively.

For this purpose, we undertook a two-step approach. First, we fit Bayesian time-varying parameters quantile regressions to real gold returns, under six alternative prior settings, to obtain the estimates of volatility i.e., the inter-quantile range, lower and upper tail risks, skewness and kurtosis. Second, we forecast the derived estimates of conditional volatility using the information contained in leverage of gold returns, tail risks, skewness and kurtosis using recursively estimated linear predictive regressions over the out-of-sample periods. We find strong statistical evidence, in five out of the six prior structures defining the Bayesian models of gold returns, of the role of the moments-based predictors in forecasting gold returns volatility over the short- to medium term, i.e., till one- to five-year ahead, when compared to the alternative autoregressive benchmarks.

Forecasting gold returns volatility is of interest to investors for devising hedging strategies, given its “safe haven” role. Naturally, the fact that gold returns volatility can be accurately forecasted over short- to medium-run based on leverage, tail risks, skewness and kurtosis of real gold returns over the longest data sample available, thus avoiding any possibility of sample- selection bias, should be a valuable findings for investors in making optimal portfolio decisions in the face of rare disaster risks. At the same time, disaster risks reflected in the moments driving gold returns volatility -a metric of uncertainty, should carry valuable policy-related information. This is because the recessionary effects of rare disaster risks are likely to be prolonged via its link with the variability in gold prices in the future, to which the policymakers can respond in a timely-fashion by enhancing the size and persistence of expansionary monetary and fiscal policies to reduce the likelihood of deep economic losses.

As part of future research, contingent on data availability, it would be interesting to perform such an analysis on historical data of other commodities as well, for the sake of comparability with our findings associated with real gold returns volatility.

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Figure 1. Plot of Real Gold Log-Returns (1258-2023)

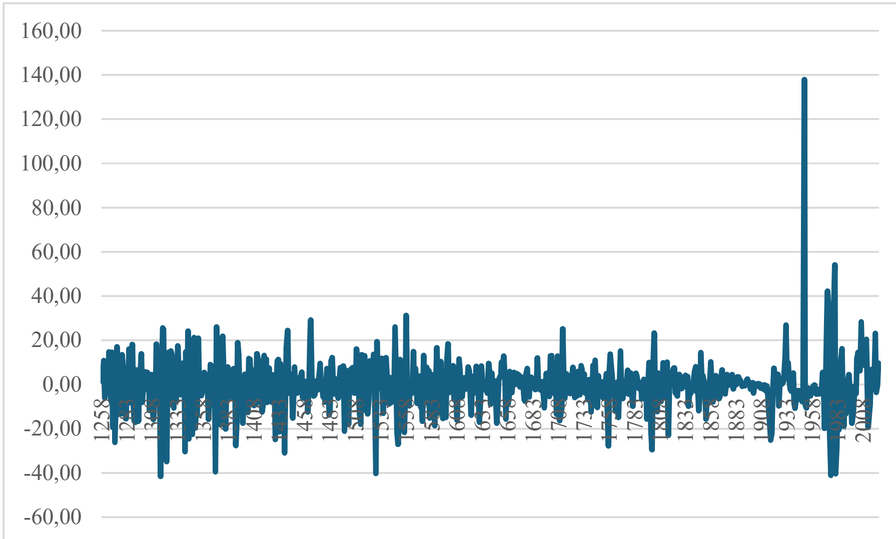

Table 1. Summary Statistics Real Gold Log-Returns (1258-2023; Observations (*N*) = 766)

Statistic	Value
Mean	-0.2778
Median	-0.4350
Maximum	137.9600
Minimum	-41.5800
Standard Deviation	11.5794
Skewness	2.1502
Kurtosis	30.4921
Jarque-Bera (JB)	24713.2700[#]

Note: [#] indicates rejection of the null-hypothesis (of normality) under the JB test.

Table 2. Forecasting results

	h									
Statistic	1	2	3	4	5	6	7	8	9	10
					iG-TIS					
RRMSE	0.7003	1.3480	1.7427	1.6048	1.4559	1.4479	1.4434	1.4037	1.3605	1.3192
MSE-F	270.8432#	-163.1503	-268.9252	-237.4301	-196.9561	-194.2591	-192.6219	-180.0249	-165.5998	-150.9824
					iG-TVS					
RRMSE	0.5625	0.5633	0.5689	0.7254	0.9685	1.0381	1.0578	1.0830	1.1117	1.1412
MSE-F	492.4172#	490.0416#	478.2494#	238.4334#	20.4671#	-23.0445	-34.2491	-47.9750	-62.7867	-77.2013
					shs-TIS					
RRMSE	0.6959	0.6894	0.6831	0.6795	0.6759	0.6713	0.6786	0.8430	1.0174	1.0825
MSE-F	244.7133#	251.9037#	258.8971#	262.7277#	266.5705#	271.7611#	262.3495#	102.9868#	-9.45279	-41.9915
					shs-TVS					
RRMSE	0.734062	0.736679	0.729994	0.736067	1.007012	1.094443	1.106447	1.119258	1.144001	1.173872
MSE-F	229.3253#	225.904#	233.391#	225.9005#	-4.37974	-54.1924	-60.3215	-66.7009	-78.6718	-92.4258
					dhs-TIS					
RRMSE	0.881025	0.838889	0.837808	0.848144	0.859475	0.957686	1.058072	1.095848	1.121139	1.139997
MSE-F	87.23704#	123.8743#	124.6726#	115.126#	104.9678#	28.32181#	-35.126	-55.8902	-68.9357	-78.2268
					dhs-TVS					
RRMSE	0.824578	0.817224	0.818736	0.822771	0.966918	1.07755	1.107303	1.126669	1.14256	1.159384
MSE-F	137.431#	144.2573#	142.5782#	138.5051#	21.96497#	-46.1322	-62.0192	-71.8416	-79.6048	-87.5701

Note: The entries correspond to the Relative Mean Square Error (RMSE) which is the MSE of the unrestricted model of the inter-quantile range (IQR) measuring real gold log-returns volatility including all the moments of real gold log-returns relative to that of the restricted model which incorporates only the lags of the IQR of real gold log-returns volatility for a specific forecast horizon (*h*). The MSE-F statistic tests whether the MSE of the unrestricted model of the inter-quantile range (IQR) of real gold log-returns volatility is statistically lower than that of the restricted model for a specific *h*; # indicates significance of the MSE-F test statistic at the 1% level with a critical value of 3.7830.