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Forecasting Oil and Gold Volatilities with Sentiment Indicators Under Structural Breaks

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Abstract: This paper contributes to the literature on forecasting the realized volatility of oil and gold by (i) utilizing the Infinite Hidden Markov (IHM) switching model within the Heterogeneous Autoregressive (HAR) framework to accommodate structural breaks in the data and (ii) incorporating, for the first time in the literature, various sentiment indicators that proxy for the speculative and hedging tendencies of investors in these markets as predictors in the forecasting models. We show that accounting for structural breaks and incorporating sentiment-related indicators in the forecasting model does not only improve the out-of-sample forecasting performance of volatility models but also has significant economic implications, offering improved risk-adjusted returns for investors, particularly for short-term and mid-term forecasts. We also find evidence of significant cross-market information spilling over across the oil, gold, and stock markets that also contributes to the predictability of short-term market fluctuations due to sentiment-related factors. The results highlight the predictive role of investor sentiment-related factors in improving the forecast accuracy of volatility dynamics in commodities with the potential to also yield economic gains for investors in these markets.

Keywords: Crude oil, realized volatility forecast, Infinite Hidden Markov model, structural break, speculation.

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1. Introduction

The severity of the global financial crisis as well as the prolonged European sovereign debt crisis have highlighted the risks associated with portfolios comprised of conventional financial assets (Balcilar et al., 2017; Lau et al., 2017; Muteba Mwamba et al., 2017). This in turn has triggered an interest in alternative investment opportunities, particularly in the commodity market (Bampinas and Panagiotidis, 2015; Bahloul et al., 2018), as investors seek diversification opportunities by supplementing their traditional portfolios with positions in commodities, oil in particular. Due to the recent financialization of the commodity market (Tang and Xiong, 2012; Silvennoinen and Thorp, 2013; Bonato, 2019), which has resulted in an increased participation of hedge funds, pension funds, and insurance companies in commodity investments, crude oil is now considered a profitable alternative instrument in the portfolio decisions of financial institutions (Büyükşahin and Robe, 2014; Antonakakis et al., 2018; Bonato et al., 2020a). Not surprisingly, the market size of crude oil investments stands at $1.7 trillion per year at current spot prices, with 34 billion barrels produced each year and over 1.7 trillion barrels of crude oil in remaining reserves.[1] At the same time, the role of gold as a traditional 'safe haven' is well-established (Baur and Lucey, 2010; Baur and McDermott, 2010; Balcilar et al., 2016; Bilgin et al., 2018; Bouoiyour et al., 2018). Accordingly, the market for gold is now the world's largest metal market in terms of US dollar, valued at $170 billion per year at current spot prices with a production of over 3,200 tons per annum (World Gold Council). Given the growing interest in these strategic commodities, either as an alternative diversification tool or as a safe haven to protect investment value during uncertain times, accurate forecasts of gold and oil market volatilities are of paramount importance to investors in the pricing of related derivatives and for devising portfolio allocation strategies (Asai and McAleer, 2015; 2017; Chang et al., 2018a, b).

[1] U.S. Energy Information Administration (EIA); BP Statistical Review of World Energy.

In academic research, a large number of studies have examined forecasting the daily conditional volatilities of gold and oil based on univariate and multivariate models from the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family, which has also included mixed frequency data sampling (MIDAS)-GARCH specifications to accommodate lower data frequency predictors as well as Markov-switching multifractal models (for detailed literature reviews, see Lux et al., 2016; Degiannakis and Filis, 2017; Fang et al., 2018; Salisu et al., forthcoming). In a comprehensive survey, McAleer and Medeiros (2008) highlight that rich information contained in intraday data can produce more accurate estimates and forecasts of daily (realized) volatility. In light of this, an increasing number of studies has focused on predicting the realized volatility of the gold and oil markets derived from intraday data using the Heterogeneous Autoregressive (HAR)-type model developed by Corsi (2009).[2] This emerging strand of literature has incorporated a wide array of predictors, including high-frequency macroeconomic and financial variables as well as more recently developed uncertainty and risk proxies.

We contribute to the literature from two novel perspectives. The first contribution relates to the evidence that forecasting realized volatility with HAR-type models beyond a one day-ahead horizon becomes problematic if structural breaks are present in the observed data (Raggi and Bordignon, 2012; Yang and Chen, 2014; Ma et al., 2018a, 2018b). Given this evidence, and building on the recent works of Luo et al. (2019, 2020), we utilize the Infinite Hidden Markov (IHM) switching model based on hierarchical Dirichlet processes as well as the IHM variant with a constant conditional mean (IHMC) of the HAR framework in a forecasting application to intraday data for WTI oil and gold futures. IHM-based forecasting models allow us to accommodate unknown breakpoints in volatilities due to possibly uncaptured factors or

[2] See for example, Asai et al. (2019, 2020), Bonato et al. (2020b, 2020c), Bouri et al. (2020, forthcoming), Demirer et al. (2019, 2020, forthcoming a, forthcoming b), Gkillas et al. (2020a, 2020b), Nguyen and Walther (2020), and references cited therein for earlier studies in this regard.

events, which is an important consideration in providing accurate forecasts, particularly at intermediate and long horizons.

The second contribution of our study is to incorporate, for the first time in the literature, various sentiment proxies that proxy for the speculative and hedging tendencies of investors in these markets as predictors in forecasting models. The use of investor sentiment in the forecasting context is motivated by well-established evidence from the equity and currency markets that links investor sentiment to short-run price fluctuations and anomalies (e.g. Wang, 2004; Baker and Wurgler, 2006; Frazzini and Lamont, 2008 and Antoniou et al., 2013; Huang et al., 2015; Demirer and Zhang, 2019, among others). To that end, following Lucia et al. (2015), we derive the speculative and hedging indicators from trading volume and open interest information obtained from futures contract transactions and examine the predictive role of these investor sentiment proxies in forecasting the realized volatility of the oil and gold markets over and above the higher moments derived from intraday data, including volatility jumps, realized skewness, and realized kurtosis. To the best of our knowledge, this is the first paper to forecast the realized volatility of gold and oil based on individual and cross-market speculation and hedge ratios using the IHM-based modification of the HAR model.

Our results show that the IHM-HAR and IHMC-HAR models identify clear structural breaks in WTI oil and gold volatility dynamics, essentially indicating the presence of external forces that drive unknown structural breaks in volatility. Furthermore, we find that the speculative and hedging indicators capture valuable predictive information over the realized volatility in both markets, particularly in the short-run, over and above the information contained in the realized measures obtained from the intraday data. We argue that the short-run predictability of return volatility in these commodities due to speculative and hedging indicators could be a manifestation of the time-variation in traders' risk preferences. Finally, our results suggest that the majority of cases that allow for structural breaks and include the speculation and hedging indicators as predictors in the volatility models not only yield improved out-of-sample forecasting performance in a statistical sense but also improve the economic performance of the models, particularly for short-term and mid-term forecasts. The results therefore provide support for well-established evidence regarding the role of sentiment-related factors over subsequent price patterns—yet in the context of volatility forecasting in commodities.

The remainder of the paper is organized as follows: Section 2 describes the data and the estimation of the various higher moments; Section 3 outlines the models and the methodologies; Section 4 presents the econometric results; and Section 5 concludes the paper.

2. Data and Higher Moments

2.1. Data

We use intraday data on gold and WTI oil futures that are traded at NYMEX over a 24-hour trading day (pit and electronic) to construct daily measures of returns (*r*), standard realized volatility (*RV*), volatility jumps (*RJ*), realized skewness (*RSK*), and realized kurtosis (*RKU*). The futures price data, in continuous format, is obtained from www.kibot.com. Close to the expiration of a contract, the position is rolled over to the next available contract, provided that the activity has increased. Daily returns are computed as the end of day (New York time) price difference (close to close). In the case of intraday returns, five-minute prices are obtained via last-tick interpolation, and five-minute returns are then computed by taking the log-differences of these prices, which, in turn, are used to compute the realized moments, as discussed below. Our data covers the period of 3 January, 2012 to 16 May, 2017, with the start and end dates being driven by data availability at the time of writing this paper.

In addition to the realized measures of *RJ*, *RSK*, and *RKU* obtained from the intraday data, we also use the speculative (*spec*) and hedge (*hedging*) ratios for gold, WTI, and S&P 500 futures as additional predictors to forecast the realized volatility for gold and WTI oil.

Following Lucia et al. (2015), we derive the speculative and hedging ratios from trading volume and open interest information obtained from the futures contract transactions. Building on Garcia et al. (1986), the speculative behaviour in a given market is defined in terms of the ratio of the trading volume to the open interest such that higher values for this ratio indicate the relative importance of speculative activity in the market with respect to hedging activity. This ratio measures the number of contracts traded relative to the size of the outstanding positions in the market based on the assumption that speculators engage in short-term positions, thus resulting in faster trading volume growth relative to the open interest (Robles et al., 2009).[3] Similarly, following Lucia and Pardo (2010), hedging activity is measured by the ratio of the change in the open interest during a given period to the trading volume during that period. Lucia and Pardo (2010) argue that the net positions opened (or closed) during a given period may more accurately reflect the activity of a hedger, and a high (or close to one) value of this ratio may be interpreted as low speculative activity in the contract. Naturally, the correlation between *spec* and *hedging* ratios is expected to be negative.

2.2. Higher Moments

2.2.1. Realized Volatility Estimator

An advantage of using intraday data is that we are also able to compute measures of higher moments, such as realized volatility, volatility jumps, realized skewness, and realized kurtosis, which can be utilized as predictors in the model. The first measure we consider is the classical estimator of realized volatility, i.e., the sum of squared intraday returns (Andersen and Bollerslev, 1998), which is expressed as

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

where $r_{t,i}$ is the intraday $M \times 1$ return vector and $i = 1, \ldots, M$ is the number of intraday

[3] In an application of this measure to the oil futures market, Chan et al. (2015) show that the oil futures market was dominated by uninformed speculators in the post-financialization period.

returns.

2.2.2. Volatility Jump Estimator

A number of studies, including Barndorff-Nielsen and Shephard (2004), Huang and Tauchen (2005), and Andersen et al. (2007), have documented the presence of volatility jumps in higher frequency time series. Barndorff-Nielsen and Shephard (2004) show that realized volatility converges into permanent and discontinuous (jump) components as

$$\lim_{M \to \infty} RV_t = \int_{t-1}^{t} \sigma^2(s)ds + \sum_{j=1}^{N_t} k_{t,j}^2, \tag{3}$$

where N_t is the number of jumps within day t, and $k_{t,j}$ is the jump size. This specification suggests that RV_t is a consistent estimator of the integrated variance $\int_{t-1}^{t} \sigma^2(s)ds$ plus the jump contribution. The asymptotic results of Barndorff-Nielsen and Shephard (2004, 2006) further show that

$$\lim_{M \to \infty} BV_t = \int_{t-1}^{t} \sigma^2(s)ds \tag{4}$$

where BV_t is the realized bipolar variation defined as

$$BV_t = \mu_1^{-1}\left(\frac{N}{M-1}\right)\sum_{i=2}^{M}\left|r_{t,i-1}\right|\left|r_{i,t}\right| = \frac{\pi}{2}\sum_{i=2}^{M}\left|r_{t,i-1}\right|\left|r_{i,t}\right| \tag{5}$$

and

$$\mu_a = E(|Z|^a), Z{\sim}N(0,1), a > 0. \tag{6}$$

Having defined the continuous component of the realized volatility, a consistent estimator of the pure jump contribution can then be expressed as

$$J_t = RV_t - BV_t \tag{7}$$

In order to test the significance of the jumps, we adopt the following formal test estimator proposed by Barndorff-Nielsen and Shephard (2006)

$$JT_t = \frac{RV_t - BV_t}{(v_{bb} - v_{qq})\frac{1}{N}QP_t} \tag{8}$$

where QP_t is the Tri-Power Quarticity defined as

$$TP_t = M_{\mu_{4/3}^{-3}} \left(\frac{M}{M-1}\right) \sum_{i=3}^{M} |r_{t,i-2}|^{4/3} \, |r_{t,i}|^{4/3} \quad (9)$$

which converges to

$$TP_t \to \int_{t-1}^{t} \sigma^4(s) ds \quad (10)$$

even in the presence of jumps. $v_{bb} = \left(\frac{\pi}{2}\right)^2 + \pi - 3$ and $v_{qq} = 2$. Note that, for each t, $JT_t \sim N(0,1)$ as $M \to \infty$.

As can be seen in Equation (25), the jump contribution to RV_t is either positive or null. Therefore, in order to avoid negative empirical contributions, we follow Zhou and Zhu (2012) and re-define the jump measure as

$$RJ_t = \max(RV_t - BV_t; 0) \quad (11)$$

2.2.3. Realized Skewness and Realized Kurtosis

We compute the realized skewness, *RSK*, and realized kurtosis, *RKU*, as measures of the higher-moments of the daily return distribution computed from the intra-day returns. Like Amaya et al. (2015), we consider *RSK* as a measure of the asymmetry of the daily return distribution and *RKU* as a measure that accounts for extremes. Given the intraday returns and realized volatility estimates, realized skewness (*RSK*) on day *t* is computed as

$$RSK_t = \frac{\sqrt{N} \sum_{i=1}^{N} (r_{i,t})^3}{RV_t^{3/2}} \quad (12)$$

while realized kurtosis (*RKU*) on day *t* is given by

$$RKU_t = \frac{N \sum_{i=1}^{N} (r_{i,t})^4}{RV_t^2} \quad (13)$$

The scaling of *RSK* and *RKU* by $(N)^{1/2}$ and *N*, respectively, ensures that their magnitudes correspond to daily skewness and kurtosis.

Table A1 in the Appendix presents descriptive statistics and preliminary tests of variables associated with the WTI oil futures (Panel A), gold futures (Panel B), and S&P 500 futures (Panel C). As shown in Panels A and B, the mean *RV* for WTI futures (3.3) is much higher than for gold futures (0.75), suggesting that the oil market experiences greater price fluctuations when compared with the gold market, as also confirmed by the higher mean value of *RJ* for the oil market. Examining the speculative rations, we observe that, while the mean values of the speculation ratios for WTI and gold futures are similar, they are much higher than for that of S&P 500 futures. At the same time, the average value of the hedge ratios for WTI and gold are close to 0, revealing that the two-sided hedge activities in these markets are evenly matched. Meanwhile, the average value of the same for the S&P 500 futures is negative, suggesting that the opposite-side of hedge activities dominates the sample period for equities.

All variables are found to exhibit high-peak and fat-tail properties. The Jarque-Bera (JB) statistics significantly reject the null hypothesis of a normal distribution for all variables. In addition, the results of the Ljung-Box Q-statistic suggest a significant autocorrelation and long memory property for almost all variables. Finally, the ADF statistic for all the variables confirms stationarity and, hence, suggests that no further transformation is required for the predictors of RV. In addition to the descriptive statistics in Table A1, the time series plots presented in Figure A1 in the Appendix highlight that *RV*, *RJ*, *RSK*, and *RKU*, as well as the speculation and hedge ratios, are non-constant, with their magnitudes evolving over time.

3. Models and Methodologies

3.1. Specifications

Having described the data and the computation of the higher-moments, we now turn to the discussion of the models and methodologies. In particular, we outline the HAR-RV model of Corsi (2009) and its various extensions, which also incorporates structural breaks using the infinite hidden Markov switching process. Specifically, we estimate the following alternative specifications for forecasting the RV of oil and gold:

M1. $$\log(\mathrm{RV}_t) = \beta_0 + \beta_1 \log(\mathrm{RV}_{t-1}) + \beta_2 \log(\mathrm{RV}_{t-1:t-5}) + \beta_3 log(\mathrm{RV}_{t-1:t-22}) + u_t \tag{14}$$

M2. $\log(\mathrm{RV}_t) = \beta_0 + \beta_1\log(\mathrm{RV}_{t-1}) + \beta_2\log(\mathrm{RV}_{t-1:t-5}) + \beta_3 log(\mathrm{RV}_{t-1:t-22}) +$

$\beta_4 log(RJ_{t-1} + 1) + RSK_{t-1} + RKU_{t-1} + u_t$ (15)

M3 (WTI). $\log(\mathrm{RV}_t) = \beta_0 + \beta_1\log(\mathrm{RV}_{t-1}) + \beta_2\log(\mathrm{RV}_{t-1:t-5}) + \beta_3 log(\mathrm{RV}_{t-1:t-22}) +$

$\beta_4 log(RJ_{t-1} + 1) + RSK_{t-1} + RKU_{t-1} + spec\_wti_{t-1} + hedge\_wti_{t-1} + u_t$ (16)

M3 (Gold). $\log(\mathrm{RV}_t) = \beta_0 + \beta_1\log(\mathrm{RV}_{t-1}) + \beta_2\log(\mathrm{RV}_{t-1:t-5}) + \beta_3 log(\mathrm{RV}_{t-1:t-22}) +$

$\beta_4 log(RJ_{t-1} + 1) + RSK_{t-1} + RKU_{t-1} + spec\_gold_{t-1} + hedge\_gold_{t-1} + u_t$ (17)

M4. $\log(\mathrm{RV}_t) = \beta_0 + \beta_1\log(\mathrm{RV}_{t-1}) + \beta_2\log(\mathrm{RV}_{t-1:t-5}) + \beta_3 log(\mathrm{RV}_{t-1:t-22}) +$

$\beta_4 log(RJ_{t-1} + 1) + RSK_{t-1} + RKU_{t-1} + spec\_wti_{t-1} + hedge\_wti_{t-1} +$

$spec\_gold_{t-1} + hedge\_gold_{t-1} + u_t$

(18)

M5. $\log(\mathrm{RV}_t) = \beta_0 + \beta_1\log(\mathrm{RV}_{t-1}) + \beta_2\log(\mathrm{RV}_{t-1:t-5}) + \beta_3 log(\mathrm{RV}_{t-1:t-22}) +$

$\beta_4 log(RJ_{t-1} + 1) + RSK_{t-1} + RKU_{t-1} + spec\_wti_{t-1} + hedge\_wti_{t-1} +$

$spec\_gold_{t-1} + hedge\_gold_{t-1} + spec\_sp500_{t-1} + hedge\_sp500_{t-1} + u_t$

(19)

Note that, in these formulations, $RV_{t-1:t-h}$ with h = 5 and 22 corresponds to the average RV over a week and month, respectively, with the aim of capturing the long-memory and multi-scale behaviour of oil and gold RVs.

3.2. Methodologies

3.2.1. ***Infinite Hidden Markov-Switching Heterogenous Autoregressive Realized Volatility (IHM HAR-RV) Model***

The HAR-RV models above can be written into a general linear regression model:

$$y_t = X_t\beta + u_t, u_t \sim N(0, \sigma^2) \quad (20)$$

where N(.) is the Gaussian distribution, and σ^2 is the variance for the residuals. Conventional HAR-RV models are specified with constant coefficients and variances. However, the recent literature suggests that considering structural breaks improves the forecast accuracy in HAR-

RV models as the high-frequency data-based realized volatilities of financial assets are always subject to unknown structures (Bollerslev et al., 2015; Tian et al., 2017). Therefore, we extend the HAR-RV models by incorporating structural breaks, whereby we model the coefficients and variance using the IHM switching process.

For the IHM HAR-RV model, the variation in the coefficients and variances are governed by the same Markov state variable, s_t, and s_t follows the infinite hidden Markov switching process as follows:

$$\beta_{s_t} \sim N(\beta_0, \Sigma_0), {\sigma_{s_t}}^2 \sim IG(\phi_0, \nu_0) \tag{21}$$

$$s_t | s_{t-1}, \{p_k^s\}_{k=1}^{\infty} \sim p_{s_{t-1}}^s \tag{22}$$

$$p_k^s | \mathrm{c}^s, \rho^s, \pi^s \sim DP(\mathrm{c}^s, (1-\rho^s)\pi^s + \rho^s \delta_i) \tag{23}$$

$$\pi^s \,|\, \gamma^s \sim SBP(\gamma^s) \tag{24}$$

In the infinite hidden Markov switching process, the coefficients, β_{s_t}, are sampled from the normal distribution with parameters β_0 and Σ_0. The variances, ${\sigma_{s_t}}^2$, follow the inverse-Gaussian distribution with parameters ϕ_0 and ν_0. The regime indicator, s_t, depends on the infinite state parameter, p_k^s, which follows the Dirichlet process (DP) according to Fox et al. (2011). The DP process is determined by the positive concentration parameter c and the base distribution G_0, which has the form $G_0 = (1-\rho)\pi + \rho\delta_i$. The parameter π in the DP process is obtained from a stick-breaking process, as detailed in Sethuraman (1994). ρ is the hyperparameters for the DP process.

We also analyse an alternative version of the IHM HAR-RV model, where the coefficients are assumed to be time-invariant and only the variances are driven by the IHM switching process, which we denote as the IHMC HAR-RV model as follows:

$$\beta \sim N(\alpha_c, \Sigma_c), {\sigma_{s_t}}^2 \sim IG(\phi_0, \nu_0) \tag{25}$$

$$s_t \mid s_{t-1}, \{p_k^s\}_{k=1}^{\infty} \sim p_{s_{t-1}}^s \tag{26}$$

$$p_k^s|\mathrm{c}^s, \rho^s, \pi^s \sim DP(\mathrm{c}^s, (1-\rho^s)\pi^s + \rho^s\delta_i) \tag{27}$$

$$\pi^s|\gamma^s \sim SBP(\gamma^s) \tag{28}$$

The Markov Chain Monte Carlo (MCMC) approach is employed for estimations of parameters in the IHM-HAR-RV and IHMC-HAR-RV models. The posterior means of the parameters are obtained from 10000 simulations after 5000 simulations of burn-in.

3.2.2. Out-of-Sample Evaluation: Statistical and Economic evaluations

In this section, we further evaluate the out-of-sample forecast performances for our alternative models. We select 1/3 observations as the out of sample and employ the recursive forecast method to obtain the short-term ($h = 1$), mid-term ($h = 5$), and long-term ($h = 22$) out-of-sample forecasts, corresponding to one-day, one-week, and one-month ahead, respectively.

For the one-step-ahead forecasts, we obtain the realized volatility forecast by re-estimating each volatility forecast model with rolling in-sample observations. For the multi-step forecasts, referring to Marcellino et al. (2006), we select both direct forecasts and iterated forecasts. The forecasting of cumulative h-day ahead realized volatility $RV_{t+1:t+h|t} = \frac{1}{h}\sum_{i=1}^{h} RV_{t+i|t}$, $h = 5, 22$ is estimated similar with the one-step-ahead forecasts, while replaces the daily accumulated realized volatility with weekly or monthly horizon in the models.

In this paper, we construct 15 switching and non-switching models for forecasting by combing two IHM switching models with different HAR-RV models. The density forecast results is evaluated according to the log-marginal likelihood statistic. Following Patton (2011), Mean Square Error (MSE) and Quasi-likelihood (QLIKE) loss functions are employed for unbiasedness evaluation, while the P-statistic is used to measure the variance proportion explained by the forecasts (Blair et al., 2001). Moreover, the Model Confidence Set (MCS) developed by Hansen et al. (2011) is employed to test the significance of forecast performances among various volatility models. We implement the MCS using the stationary bootstrap based on Hansen et al. (2011).

Besides forecast accuracy, market participants are also concerned with the economic gains from the volatility forecasts. Therefore, economic significance of forecasting models also cannot be ignored. A mean-variance utility is defined as follows:

$$U(R_p) = E(R_p) - \frac{1}{2}\gamma Var(R_p) \tag{29}$$

where γ is the risk-aversion rate, R_p is the return of the portfolio, $E(R_p)$ is the expected portfolio return, and $Var(R_p)$ is the expected portfolio variance.

According to Campbell and Thompson (2008) and Neely et al. (2014), the optimal weight that is allocated to the commodity futures at time *t + 1* should be:

$$\hat{w}_t = \frac{1}{\gamma}\left(\frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}^2}\right) \tag{30}$$

where $\hat{r}_{t+1}$ is the forecast return, which is approximated by taking the moving average of returns over the past T1 days, with T1 being the length of the in-sample period. $\hat{\sigma}_{t+1}^2$ is the forecast variance of the excess return. We employ the moving average of the excess return with the rolling window of 256 trading days (one-year) to proxy the forecast excess return $\hat{r}_{t+1}$.

The portfolio return at time t is then given by

$$R_{p,t+1} = \hat{w}_t r_{t+1} + r_{t+1}^f \tag{31}$$

where r_{t+1} and r_{t+1}^f are the excess return of the commodity futures and the risk-free return at time *t + 1*, respectively. In this paper, we employ the return of a five-year US Treasury note as the return of the risk-free asset.

In the case of direct multi-step forecasts, the results for the multi-step forecast models are averaged over all possible weekly horizons (e.g., Monday to Monday, Tuesday to Tuesday, etc.) and monthly horizons (e.g., the first day of a month, the second day of a month, etc.)

following Luo et al. (2020).

In this paper, we use the economic value of Δ such that $\sum_{t=T_1+1}^{T} U(r_{pt}^{k}) = \sum_{t=T_1+1}^{T} U(r_{pt}^{l} - \Delta)$ for two different portfolios, p_1 and p_2 to evaluate the economic significance of forecasting models. Larger value of Δ means a risk-averse investor would like to sacrifice more returns to switch from model l to model k. The economic values is determined by using quadratic utility with risk aversion γ as follows.

$$U(r_{pt}, \gamma) = (1 + r_{pt}) - \frac{\gamma}{2(1+\gamma)}(1 + r_{pt})^2 \tag{32}$$

Similar to most previous literature, two levels of risk aversion, i.e., a mild risk aversion rate of $\gamma=1$ and strong risk aversion rate of $\gamma=10$ are considered for risk aversion level robustness test.

4. Empirical Findings

4.1. In-Sample Analysis

Figures 1 and 2 visualize the posterior distribution of the number of regimes (left column) and the heat maps (right column) depicting the hidden Markov structure for WTI oil and gold, respectively. In Panel A, the IHM-MAR-M5 model refers to the Infinite Hidden Markov-switching heterogenous autoregressive realized volatility model, which incorporates a regime-switching framework wherein the variation in the coefficients and variances is governed by a Markov state variable. The IHMC-HAR-M5 model in Panel B refers to the case in which the coefficients are assumed to be time-invariant, and only the variances are driven by the IHM switching process. M5 refers to the predictive model structure described in Equation (18). Lighter colours in the heat maps indicate a higher likelihood of observations being in the same regime, while darker colours indicate a lower likelihood (Hou, 2017; Luo et al., 2019).

In Figure 1 Panel A, the results for the IHM-HAR-M5 model indicate a high likelihood for two observations to be in the same regime, while there are also time periods for which there is a greater likelihood for two observations to be in different regimes (indicated by the dark lines). In contrast, when all parameters are held constant and only the variance is allowed to switch, the results for the IHMC-HAR-M5 model in Panel B clearly show that the frequency of observations with a high likelihood of being in different regimes increases. Clearly, these findings support the presence of distinct regimes in the data. Comparing the findings for WTI and gold in Figures 1 and 2, respectively, we observe that gold has a higher likelihood for two observations being in different regimes, with the IHMC-HAR-M5 model (only allowing for variance to switch) also increasing the likelihood of different regimes. The increased frequency is particularly apparent from 2015 onwards for WTI and from 2014 onwards for gold.

The IHM-HAR and IHMC-HAR models identify clear structural breaks in the WTI and gold volatility dynamics, essentially indicating the presence of external forces that drive unknown structural breaks in volatility. While the identification of such external forces is beyond the scope of our study, these forces could include macroeconomic, political, or other exogenous shocks. Nevertheless, our results show that WTI has fewer hidden structural breaks than gold, possibly due to the role of gold as a traditional safe haven, making this commodity more reactive to changes in market states. For WTI, both the IHM-HAR-M5 and IHMC-HAR-M5 models identify possible structural breaks at the end of 2014 and 2015, with the IHMC-HAR-M5 model also identifying potential breaks at the end of 2016 for WTI. In the case of gold, the IHM-HAR-M5 model identifies possible structural breaks between March 2013 and August 2013, December 2014, January 2016, and November 2016. In the IHMC-HAR-M5 model for gold, there are periods of about two months in duration that show a higher chance of structural breaks, around December 2014, June 2015, March 2016, and December 2016. Overall, the analysis of the regime dynamics suggests the presence of distinct market states that govern volatility dynamics in these commodities, indicating support for the IHM-based models utilized in the forecasting analysis.

4.2. Out-of-Sample Forecasting

We now turn our attention to the results from the forecasting exercise. Table 1 reports the forecast precision evaluation results for WTI oil futures according to the Mincer-Zarnowitz-R^2 (MZ- R^2) statistic, the MSE and QLIKE loss functions according to Patton (2011), as well as the P-statistic according to Blair et al. (2001). Panels A, B, and C report the findings for the short-term ($h = 1$), mid-term ($h = 5$), and long-term ($h = 22$) out-of-sample forecasts, respectively. In each panel, the benchmark HAR model is reported for each of the five models (M1, …, M5) described in Equations 14–18. The benchmark model is then compared with the IHM-HAR model, which incorporates a regime-switching process that governs the variation in the coefficients and variances, and the IHMC-VAR model, in which the coefficients are assumed to be time-invariant and only the variances are driven by the IHM switching process.

For the short-term ($h = 1$) WTI volatility forecasts reported in Panel A, the HAR-M3 model, which includes lagged *RV*, *RJ*, *RSK*, and *RKU* as well as the speculation and hedge ratios of the WTI futures, is found to consistently yield the highest forecast precision among all the forecast models according to all four evaluation statistics. As suggested by the MCS results, the HAR-M3 and HAR-M5 models with and without breaks are always included in the MCS at a 75% confidence level based on the MSE loss function and are included in the MCS at a 90% confidence level based on the QLIKE loss function, suggesting that including speculation and hedge indicators of WTI improve the forecasts of WTI volatility. These findings suggest that behavioural factors related to speculative and hedging tendencies by traders capture predictive information regarding short-term volatility dynamics. Indeed, the evidence from stock markets already establishes a link between behavioural factors and short-term momentum and reversals in stock returns (e.g. Dasgupta et al., 2011; Singh, 2013; Brown et al., 2014; Demirer et al., 2015; Chen and Demirer, 2018, among others). Accordingly, it can be argued that the predictive power of behavioural factors over short-run volatility dynamics could be due to possible mis-pricing in the commodity market driven by sentiment-related factors.

In the case of the mid- and long-term forecasts reported in Panels B and C, we observe that the IHM-HAR-M1 model (the benchmark model combined with the IHM structure) has the highest forecast precision among all the competing models based on all four evaluation statistics. According to the MCS results, only the IHM-HAR-M1 model is included in the MCS at a 75% confidence level for the mid-term and long-term forecasts, suggesting it has better forecast performance when compared to the other models. Moreover, the HAR models combined with the IHM structure improve the forecast precision of the benchmark HAR model for all the forecast steps. These findings provide support for the visual inferences obtained from Figure 1 in that incorporating a regime switching process that governs the variation of the coefficients and variances in the forecasting model clearly improves the out-of-sample predictive accuracy compared to the static alternatives, particularly for mid- to long-term forecast horizons. These findings also support those for the short-term forecasts in Panel A in that the predictive information contained in the speculative and hedging indicators are primarily confined to short-term market forecasts, which is likely due to the information these indicators capture regarding volatility dynamics driven by over/underreaction to news that eventually subsides in the intermediate and long run.

The statistical evaluation results for gold futures reported in Table 2 yield somewhat similar inferences to those obtained for WTI oil. The MSE and QLIKE loss results as well as the p-statistic support the IHM-HAR-M4 model, i.e., the model that incorporates the speculation and hedge ratios for oil and gold futures. The out-of-sample superiority of the IHM-based model is in line with the regime statistics reported in Figure 2, providing support for the presence of market regimes that govern the variation of model coefficients and variances. Furthermore, the outperformance of the model that incorporates the speculative and hedging indicators for both the oil and gold markets in Panel A provides further support for the predictive information these behavioural factors capture with short-term volatility patterns over and above the information contained in the realized measures obtained from intraday data. Considering the finding in Demirer et al. (2019) that time-varying risk aversion contains significant predictive information over gold market volatility, the short-run predictability of the return volatility in these commodities due to speculative and hedging indicators could be a manifestation of the time-variation in traders' risk preferences. Nevertheless, the findings are further supported by the MCS results that the HAR-M4 and HAR-M5 models with and without breaks are included in the MCS at a 75% confidence level based on both MSE and QLIKE loss functions for the one-step forecasts, suggesting that including speculation and hedge ratios of WTI and S&P futures achieves higher forecast precision for short-term forecasts.

In the case of the mid- and long-term forecasts reported in Panels B and C, we observe that the IHM-HAR framework is consistently the best model according to all four evaluation statistics. These results show that combining the IHM structure with the HAR models improves the forecast precision of the corresponding HAR models, which is in line with the visual inferences obtained from Figure 2, highlighting the importance of regime dynamics over gold market volatility patterns. In all, the results show that including individual speculation and hedge ratios as well as those of the S&P futures improves the volatility forecasts for both WTI and gold futures, particularly in the short run, suggesting that these behavioural indicators capture predictive information over and above that included in the realized measures obtained from intraday data. Moreover, combining the IHM structure with the HAR models is found to improve the forecast precision of the corresponding HAR models, highlighting the role of market regimes in volatility dynamics.

The predictive role of the speculative and hedging activity indicators, particularly for the short-run volatility forecasts, is indeed in line with the growing evidence from the stock and currency markets that links investor sentiment to short-run price fluctuations and anomalies (e.g. Wang, 2004; Baker and Wurgler, 2006; Frazzini and Lamont, 2008 and Antoniou et al., 2013; Huang et al., 2015; Demirer and Zhang, 2019, among others). Considering that investor sentiment is closely related to risk aversion (e.g. Bams et al., 2017) and speculative tendencies are linked to investor sentiment (e.g. Lemmon and Ni, 2011; Blasco et al., 2012), one can argue that the arrival of new information to the market increases speculative and/or hedging activity among traders, which, in turn, leads to short-term fluctuations in the oil market that subside once the information is fully processed by market participants or uncertainty clears. It is, however, interesting that there is also significant cross-market information that spills over from the gold and stock markets that also contributes to the predictability of these short-term market fluctuations due to sentiment-related factors.

4.3. Economic Implications

In addition to the statistical evaluations presented thus far, we compare the investment performance of different volatility forecast models based on various out-of-sample performance metrics, including the mean return, Sharpe ratio, and economic gains based on a mild ($\gamma = 1$) and strong risk aversion rate ($\gamma = 10$) in the utility function (Equation 33). These performance metrics evaluate the economic significance of volatility forecast models in the context of portfolio optimization. We consider two types of economic values based on two types of benchmark models. Particularly, EV1 refers to the economic values of different HAR models with infinite hidden Markov switching structures against the corresponding benchmark HAR models (with different predictor sets), and EV2 refers to the economic values of different HAR models with infinite hidden Markov switching structures against the benchmark HAR model. Tables 3 and 4 show the results of economic evaluations in terms of the portfolio return and the economic values of various HAR models for the one-step, five-step and 22-step forecasts for WTI oil and gold volatility, respectively. The results from the mild and strong risk aversion rates are presented in Panels A and B, respectively.

Examining the findings for WTI futures in Table 3, we observe that, for the short-term forecasts, the IHM-HAR-M3, IHM-HAR-M4, and IHM-HAR-M5 models rank in the top three among all forecast model specifications in terms of the out-of-sample return, Sharpe ratio, and economic value. Particularly, the IHM-HAR-M3 model yields the highest out-of-sample annualized returns of 3.590% ($\gamma = 1$) and 1.711% ($\gamma = 10$), followed by the IHM-HAR-M5 model, yielding out-of-sample annualized returns of 3.581% ($\gamma = 1$) and 1.710% ($\gamma = 10$). The Sharpe ratio is consistent with the above results, suggesting that these three models that incorporate speculative and hedging indicators offer more stable portfolio returns compared to the other models. In terms of the mid-term forecasts and given the mild risk-aversion rate, the IHM-HAR model has the highest out-of-sample return (2.501%) and Sharpe ratio (0.284), followed by the IHM-HAR-M3 model and IHM-HAR-M5 model with out-of-sample returns of 2.495% and 2.463%, respectively. For the long-term forecasts, the IHMC-HAR model, IHM-HAR-M2 model, and IHMC-HAR-M4 model perform the best, with out-of-sample returns of 2.295%, 2.292%, and 2.265%, respectively. Under strong risk aversion rates, the results are similar—yet only with smaller magnitudes.

In terms of the two types of economic values, the economic values against the corresponding HAR models (EV1) suggest that combining the IHM switching structure improves the forecast performances of the corresponding HAR models at all forecast horizons. Particularly, the IHM-type models yield greater economic values compared to the IHMC-type models. The economic values against the basic HAR model (EV2) suggest that the specified HAR models have better portfolio performances when compared with the basic HAR model for the short-term and mid-term forecasts. The results also suggest that the HAR models allowing for breaks outperform the HAR models that have a linear structure. Accordingly, the analysis of economic performance metrics suggests that accounting for sentiment-related indicators does not only improve the forecasting performance of volatility models but also has significant economic implications, offering improved risk-adjusted returns for traders.

Table 4 presents the economic evaluation results for gold futures. The results for gold generally confirm the findings for WTI, although gold is found to yield much higher returns compared to the portfolios that include positions in WTI oil. Given the mild risk-aversion rate of $\gamma = 1$ in Panel A, the M4 and M5 models that include speculative and hedging indicators for all market segments are found to yield the highest mean out-of-sample returns, with 22.9778% (HAR-M5), 19.0463% (IHM-HAR-M5), and 16.2949% (IHM-HAR-M4) in the short-, medium-, and long-runs, yielding reward-to-risk ratios (Sharpe) of 0.1481, 0.2849, and 0.5543, respectively. We observe similar results for the strong risk aversion case presented in Panel B, albeit with smaller magnitudes. In the case of the EV1 metric, we observe that only the IHMC-HAR-type models have better forecast performances when compared to the corresponding HAR models, implied by the positive EV1 for the short-term forecasts. Meanwhile, both the IHMC-HAR-type models and IHM-HAR-type models have positive economic values against the corresponding HAR models, and the IHM-HAR-type model is found to achieve higher economic values for the mid- and long-term forecasts. The economic values against the basic HAR model (EV2) suggest that most of the specified HAR models have better portfolio performances when compared with the basic HAR model at all forecast horizons.

In all, our results suggest that, for the majority of the cases, allowing for structural breaks and including the speculation and hedging indicators as predictors in volatility models not only yield improved out-of-sample forecasting performance in a statistical sense but also improve the economic performance of the models, particularly for short-term and mid-term forecasts. The findings thus present support for the role of sentiment-related factors over mis-pricing and anomalous patterns in stock and currency markets (e.g. Wang, 2004; Baker and Wurgler, 2006; Frazzini and Lamont, 2008 and Antoniou et al., 2013; Huang et al., 2015; Demirer and Zhang, 2019, among others), suggesting that the predictive power of sentiment-related indicators can in fact be exploited to extract economic gains by including these indicators in the forecasting models. In earlier studies on equity markets, Brown and Cliff (2005) and Baker and Wurgler (2006) relate sentiment to the comovement in the demand shocks of noise traders, which, in turn, results in persistent mispricing. Baker and Wurgler (2006) further argue that subsequent market correction results in the predictability of contrarian patterns as sentiment dissipates in the long run. Accordingly, one can argue that the predictive power of sentiment indicators over volatility patterns in these strategic commodities is a manifestation of the possible mis-pricing of these assets due to the arrival of new information and/or a disposition effect that affects the trading tendencies of investors towards assets based on their past performance (e.g., Odean, 1998). Nevertheless, the economic analysis of the forecasts clearly suggests that accounting for structural breaks and incorporating forecasting models with sentiment indicators can help investors improve the risk-adjusted performance of their investment portfolios.

5. Conclusion

Given the emerging evidence regarding the role of the strategic commodities of crude oil and gold as an alternative diversification/hedging tool for traditional equity investors, the accurate forecasting of return volatility in these assets has significant implications in terms of both valuation and investment. This paper contributes to the literature on volatility forecasting in these commodities from two novel perspectives. First, considering the argument that forecasting realized volatility with HAR-type models beyond a one day-ahead horizon becomes problematic if structural breaks are present in the observed data, we utilize the Infinite Hidden Markov (IHM) switching model based on hierarchical Dirichlet processes in a forecasting application to intraday data for WTI oil and gold futures. Second, we incorporate, for the first time in the literature, various sentiment indicators that proxy for the speculative and hedging tendencies of investors in these markets as predictors in the forecasting models.

Our findings suggest that accounting for structural breaks and incorporating sentiment-related indicators in the forecasting model does not only improve the forecasting performance of volatility models but also have significant economic implications, offering improved risk-adjusted returns for traders. The predictive information contained in the speculative and hedging indicators is primarily confined to short-term volatility forecasts, likely due to the information these indicators capture regarding volatility dynamics driven by over/underreaction to news that eventually subsides in the intermediate and long run. Considering the finding in Demirer et al. (2019) in that time-varying risk aversion contains significant predictive information over gold market volatility, we argue that the short-run predictability of return volatility in these commodities due to speculative and hedging indicators could be a manifestation of the time-variation in traders' risk preferences. Interestingly, we also find evidence of significant cross-market information spilling over across the oil, gold, and stock markets that also contributes to the predictability of short-term market fluctuations due to sentiment-related factors. The results highlight the predictive role of investor sentiment-related factors in improving the forecast accuracy of volatility dynamics in commodities with the potential to also yield improved risk-adjusted returns for investors in these markets. In future research, it would be interesting to examine the role of external factors that drive regime shifts in volatility patterns and whether or not volatility regimes play a role in the predictive ability of the speculation and hedging indicators we document.

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Table 1. Forecast precision evaluations for WTI oil volatility at different forecast horizons

	Panel A: h=1				**Panel B:** h=5				**Panel C:** h=22			
	MZR2	MSE	QLIKE	P statistic	MZR2	MSE	QLIKE	P statistic	MZR2	MSE	QLIKE	P statistic
HAR-M1	0.7228	3.4671**	0.0993*	0.8574	0.6851	3.2162	0.0807	0.8405	0.4419	5.0524	0.1078	0.6795
IHM-HAR-M1	0.7251	3.4698**	0.1000*	0.8573	0.9383	0.6354**	0.0120**	0.9685	0.9709	0.2361**	0.0033**	0.9850
IHMC-HAR-M1	0.7162	3.6679**	0.1018	0.8491	0.6582	4.0262*	0.0979	0.8003	0.2850	7.0231	0.1466	0.5545
HAR-M2	0.7211	3.4872**	0.0991*	0.8566	0.6865	3.1998	0.0803	0.8405	0.4502	4.9756	0.1068	0.6843
IHM-HAR-M2	0.7240	3.4976**	0.0997*	0.8562	0.9157	0.8567*	0.0146	0.9685	0.9558	0.3526	0.0050	0.9776
IHMC-HAR-M2	0.7144	3.6909**	0.1023	0.8482	0.6580	4.0151*	0.0971	0.8003	0.2863	6.9205	0.1452	0.5610
HAR-M3	0.7253	3.3538**	0.0965**	0.8621	0.6972	3.1004	0.0787	0.8462	0.4682	4.8298	0.1075	0.6936
IHM-HAR-M3	0.7230	3.4108**	0.0978*	0.8597	0.9196	0.8137*	0.0150	0.9596	0.9470	0.4413	0.0049	0.9720
IHMC-HAR-M3	0.7171	3.4884**	0.0987*	0.8565	0.6644	3.9815*	0.0971	0.8026	0.3079	6.2648	0.1440	0.6026
HAR-M4	0.7223	3.3956**	0.0977*	0.8603	0.6954	3.1222	0.0793	0.8452	0.4710	4.7873	0.1072	0.6963
IHM-HAR-M4	0.7213	3.4321**	0.0980*	0.8588	0.9185	0.8272*	0.0154	0.9590	0.9414	0.4785	0.0053	0.9696
IHMC-HAR-M4	0.7152	3.5105**	0.0996	0.8556	0.6614	3.9986*	0.0978	0.8017	0.3178	6.0446	0.1436	0.6165
HAR-M5	0.7207	3.4145**	0.0975*	0.8596	0.6923	3.1513	0.0800	0.8437	0.4699	4.7679	0.1088	0.6975
IHM-HAR-M5	0.7231	3.4071**	0.0973**	0.8599	0.9212	0.8012*	0.0156	0.9603	0.9525	0.3771	0.0052	0.9761
IHMC-HAR-M5	0.7157	3.5020**	0.0995*	0.8560	0.6590	4.0248*	0.0982	0.8004	0.2839	7.4716	0.1426	0.5260

Note: This table presents the forecast precision evaluation results according to the Mincer-Zarnowitz-R^2 (MZ- R^2) statistic, the MSE and QLIKE loss functions according to Patton (2011), as well as the P-statistic according to Blair et al. (2001). The MSE and QLIKE statistics marked with ** suggest the corresponding models are included in the MCS at a 75% confidence level, and those marked with * suggest the corresponding models are included in the MCS at a 95% confidence level. Panes A, B, and C report the findings for the one-step, five-step and 22-step forecasts, respectively, for realized volatility.

Table 2. Forecast precision evaluations for gold volatility at different forecast horizons

	Panel A: h=1				**Panel B:** h=5				**Panel C:** h=22			
	MZR2	MSE	QLIKE	P statistic	MZR2	MSE	QLIKE	P statistic	MZR2	MSE	QLIKE	P statistic
HAR-M1	0.2218	0.1582**	0.1513	0.6026	0.1650	0.0828*	0.1049	0.5760	0.0346	0.0452	0.0871	0.4287
IHM-HAR-M1	0.2534	0.1503**	0.1502	0.6224	0.7613	0.0256**	0.0188**	0.8687	0.9488	0.0021**	0.0030**	0.9737
IHMC-HAR-M1	0.2100	0.1613**	0.1541	0.5946	0.1348	0.0873*	0.1156	0.5526	0.0277	0.0474	0.0973	0.4008
HAR-M2	0.2272	0.1561**	0.1476*	0.6078	0.1739	0.0819*	0.1023	0.5806	0.0385	0.0451	0.0862	0.4293
IHM-HAR-M2	0.2359	0.1535**	0.1471*	0.6142	0.7267	0.0285*	0.0215	0.8538	0.9285	0.0029	0.0041	0.9639
IHMC-HAR-M2	0.2189	0.1587**	0.1496*	0.6014	0.1431	0.0861*	0.1125	0.5591	0.0272	0.0473	0.0965	0.4016
HAR-M3	0.2265	0.1564**	0.1488	0.6070	0.1783	0.0815*	0.1016	0.5825	0.0498	0.0447	0.0838	0.4351
IHM-HAR-M3	0.2588	0.1488**	0.1467*	0.6262	0.7156	0.0292*	0.0211	0.8505	0.9195	0.0032	0.0042	0.9597
IHMC-HAR-M3	0.2207	0.1586**	0.1503*	0.6016	0.1451	0.0860*	0.1122	0.5596	0.0359	0.0466	0.0944	0.4106
HAR-M4	0.2282	0.1546**	0.1441**	0.6115	0.1817	0.0814*	0.1017	0.5831	0.0536	0.0448	0.0844	0.4337
IHM-HAR-M4	0.2570	0.1486**	0.1430**	0.6267	0.7300	0.0279*	0.0204	0.8573	0.9201	0.0032	0.0043	0.9601
IHMC-HAR-M4	0.2203	0.1569**	0.1459**	0.6058	0.1495	0.0856*	0.1117	0.5616	0.0356	0.0466	0.0942	0.4106
HAR-M5	0.2246	0.1553**	0.1444**	0.6097	0.1721	0.0826*	0.1036	0.5768	0.0506	0.0452	0.0855	0.4285
IHM-HAR-M5	0.2262	0.1554**	0.1433**	0.6096	0.7154	0.0287*	0.0212	0.8528	0.9221	0.0031	0.0044	0.9610
IHMC-HAR-M5	0.2148	0.1579**	0.1463**	0.6032	0.1318	0.0878*	0.1147	0.5504	0.0332	0.0466	0.0949	0.4106

Note: See notes in Table 1.

Table 3. The economic evaluations for WTI oil RV

Model	Panel A: γ=1				Panel B: γ=10			
	r	SR	EV1	EV2	r	SR	EV1	EV2
				h=1				
HAR	3.476	0.102	0.000	0.000	1.700	0.499	0.000	0.000
IHM-HAR	3.533	0.105	0.058	0.058	1.705	0.504	0.006	0.006
IHMC-HAR	3.505	0.101	0.029	0.029	1.703	0.491	0.003	0.003
HAR-M2	3.492	0.103	0.000	0.017	1.701	0.498	0.000	0.002
IHM-HAR-M2	3.539	0.105	0.048	0.064	1.706	0.503	0.005	0.007
IHMC-HAR-M2	3.492	0.101	-0.001	0.015	1.701	0.489	0.000	0.002
HAR-M3	3.511	0.105	0.000	0.037	1.703	0.508	0.000	0.004
IHM-HAR-M3	3.590	0.108	0.079	0.116	1.711	0.512	0.008	0.012
IHMC-HAR-M3	3.530	0.104	0.018	0.054	1.705	0.501	0.002	0.006
HAR-M4	3.523	0.104	0.000	0.048	1.704	0.502	0.000	0.005
IHM-HAR-M4	3.556	0.106	0.034	0.082	1.708	0.507	0.004	0.009
IHMC-HAR-M4	3.521	0.103	-0.002	0.046	1.704	0.495	0.000	0.005
HAR-M5	3.535	0.105	0.000	0.060	1.706	0.503	0.000	0.006
IHM-HAR-M5	3.581	0.107	0.046	0.107	1.710	0.508	0.005	0.011
IHMC-HAR-M5	3.548	0.104	0.013	0.073	1.707	0.497	0.001	0.008
				h=5				
HAR	2.219	0.149	0.000	0.000	1.573	1.046	0.000	0.000
IHM-HAR	2.501	0.200	0.284	0.284	1.601	1.244	0.029	0.029
IHMC-HAR	2.271	0.139	0.052	0.052	1.578	0.962	0.005	0.005
HAR-M2	2.219	0.149	0.000	0.000	1.573	1.046	0.000	0.000
IHM-HAR-M2	2.455	0.192	0.241	0.238	1.597	1.218	0.025	0.025
IHMC-HAR-M2	2.275	0.140	0.059	0.056	1.579	0.963	0.006	0.006
HAR-M3	2.227	0.147	0.000	0.007	1.574	1.034	0.000	0.001
IHM-HAR-M3	2.495	0.198	0.271	0.279	1.601	1.235	0.028	0.029
IHMC-HAR-M3	2.268	0.138	0.041	0.048	1.578	0.954	0.004	0.005
HAR-M4	2.238	0.148	0.000	0.018	1.575	1.031	0.000	0.002
IHM-HAR-M4	2.434	0.192	0.199	0.217	1.594	1.224	0.021	0.022
IHMC-HAR-M4	2.276	0.138	0.039	0.057	1.579	0.950	0.004	0.006
HAR-M5	2.253	0.148	0.000	0.033	1.576	1.029	0.000	0.003
IHM-HAR-M5	2.463	0.194	0.212	0.246	1.597	1.222	0.022	0.025
IHMC-HAR-M5	2.283	0.138	0.030	0.063	1.579	0.950	0.003	0.007
				h=22				
HAR	2.176	0.311	0.000	0.000	1.564	2.101	0.000	0.000
IHM-HAR	1.957	0.335	-0.221	-0.221	1.542	2.371	-0.023	-0.023
IHMC-HAR	2.295	0.307	0.119	0.119	1.575	1.989	0.012	0.012
HAR-M2	2.173	0.312	0.000	-0.003	1.563	2.109	0.000	0.000
IHM-HAR-M2	1.940	0.327	-0.234	-0.237	1.540	2.345	-0.024	-0.025
IHMC-HAR-M2	2.292	0.307	0.119	0.116	1.575	1.991	0.012	0.012
HAR-M3	2.106	0.294	0.000	-0.070	1.557	2.063	0.000	-0.007
IHM-HAR-M3	1.942	0.329	-0.165	-0.235	1.540	2.353	-0.017	-0.024
IHMC-HAR-M3	2.238	0.301	0.133	0.062	1.570	1.993	0.014	0.006
HAR-M4	2.096	0.289	0.000	-0.081	1.556	2.039	0.000	-0.008
IHM-HAR-M4	1.940	0.328	-0.157	-0.238	1.540	2.350	-0.016	-0.025
IHMC-HAR-M4	2.265	0.301	0.170	0.089	1.572	1.974	0.018	0.009
HAR-M5	2.083	0.286	0.000	-0.094	1.554	2.029	0.000	-0.010
IHM-HAR-M5	1.950	0.329	-0.134	-0.227	1.541	2.351	-0.014	-0.024
IHMC-HAR-M5	2.244	0.305	0.162	0.068	1.570	2.013	0.017	0.007

Note: This table shows the results of economic evaluation in terms of the portfolio return and economic values of various HAR models for the one-step, five-step and 22-step forecasts for WTI oil volatility. r is the portfolio return. EV1 refers to the economic values of different HAR models with infinite hidden Markov switching structures against the corresponding benchmark HAR models (with different predictor sets), and EV2 refers to the economic values of different HAR models with infinite hidden Markov switching structures against the benchmark HAR model. We consider two types of risk-aversion rate $\gamma=1$ and $\gamma=10$ in Panels A and B, respectively.

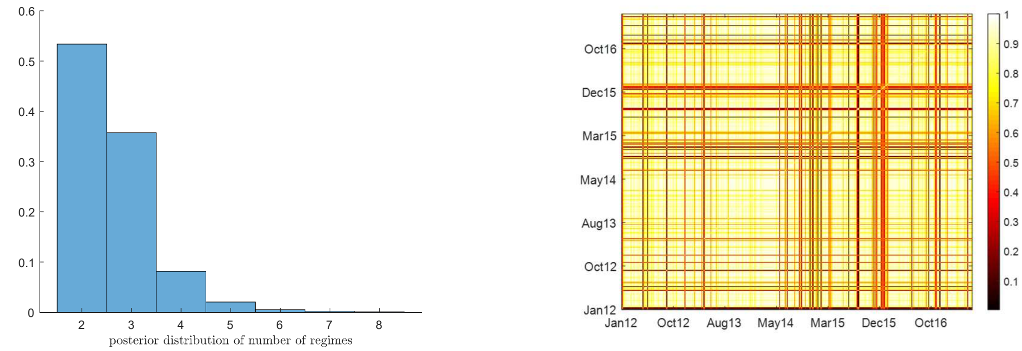
Table 4. The economic evaluations for Gold RV

Model	Panel A: γ=1				Panel B: γ=10			
	r	SR	EV1	EV2	r	SR	EV1	EV2
				h=1				
HAR	21.8447	0.1447	0.0000	0.0000	3.5365	0.2338	0.0000	0.0000
IHM-HAR	21.6286	0.1447	-0.2229	-0.2229	3.5149	0.2347	-0.0232	-0.0232
IHMC-HAR	21.9955	0.1440	0.1526	0.1526	3.5516	0.2321	0.0159	0.0159
HAR-M2	22.4322	0.1479	0.0000	0.6228	3.5953	0.2367	0.0000	0.0648
IHM-HAR-M2	22.3562	0.1483	-0.0770	0.5457	3.5877	0.2376	-0.0080	0.0568
IHMC-HAR-M2	22.4645	0.1473	0.0308	0.6537	3.5985	0.2356	0.0032	0.0680
HAR-M3	22.6582	0.1472	0.0000	0.8539	3.6179	0.2346	0.0000	0.0889
IHM-HAR-M3	22.2693	0.1473	-0.4015	0.4514	3.5790	0.2364	-0.0418	0.0470
IHMC-HAR-M3	22.4173	0.1459	-0.2553	0.5980	3.5938	0.2335	-0.0266	0.0622
HAR-M4	22.6760	0.1468	0.0000	0.8703	3.6196	0.2339	0.0000	0.0906
IHM-HAR-M4	22.2110	0.1462	-0.4835	0.3856	3.5731	0.2347	-0.0503	0.0401
IHMC-HAR-M4	22.6523	0.1463	-0.0266	0.8436	3.6173	0.2333	-0.0028	0.0878
HAR-M5	22.9778	0.1481	0.0000	1.1900	3.6498	0.2348	0.0000	0.1238
IHM-HAR-M5	22.4017	0.1478	-0.5973	0.5907	3.5922	0.2366	-0.0621	0.0615
IHMC-HAR-M5	22.7763	0.1473	-0.2125	0.9767	3.6297	0.2343	-0.0221	0.1016
				h=5				
HAR	17.0330	0.2792	0.0000	0.0000	3.0544	0.4965	0.0000	0.0000
IHM-HAR	18.6770	0.2837	1.7230	1.7230	3.2188	0.4852	0.1792	0.1792
IHMC-HAR	17.6818	0.2784	0.6771	0.6771	3.1193	0.4871	0.0704	0.0704
HAR-M2	17.2816	0.2809	0.0000	0.2600	3.0793	0.4964	0.0000	0.0270
IHM-HAR-M2	18.8315	0.2846	1.6249	1.8860	3.2343	0.4851	0.1690	0.1962
IHMC-HAR-M2	17.7913	0.2798	0.5318	0.7921	3.1302	0.4883	0.0553	0.0824
HAR-M3	17.5137	0.2810	0.0000	0.5024	3.1025	0.4937	0.0000	0.0522
IHM-HAR-M3	18.7031	0.2838	1.2463	1.7505	3.2214	0.4850	0.1296	0.1821
IHMC-HAR-M3	17.8228	0.2797	0.3223	0.8251	3.1334	0.4879	0.0335	0.0858
HAR-M4	17.6697	0.2798	0.0000	0.6650	3.1181	0.4898	0.0000	0.0692
IHM-HAR-M4	18.9370	0.2839	1.3293	1.9967	3.2448	0.4828	0.1383	0.2077
IHMC-HAR-M4	17.9656	0.2792	0.3088	0.9744	3.1477	0.4852	0.0321	0.1013
HAR-M5	17.8552	0.2816	0.0000	0.8598	3.1366	0.4907	0.0000	0.0894
IHM-HAR-M5	19.0463	0.2849	1.2496	2.1124	3.2557	0.4833	0.1300	0.2197
IHMC-HAR-M5	18.0745	0.2814	0.2291	1.0895	3.1586	0.4879	0.0238	0.1133
				h=22				
HAR	14.7463	0.5972	0.0000	0.0000	2.8206	1.0983	0.0000	0.0000
IHM-HAR	16.1220	0.5569	1.4353	1.4353	2.9582	0.9791	0.1492	0.1492
IHMC-HAR	15.7432	0.5973	1.0401	1.0401	2.9203	1.0686	0.1081	0.1081
HAR-M2	14.6764	0.5943	0.0000	-0.0729	2.8136	1.0955	0.0000	-0.0076
IHM-HAR-M2	16.2913	0.5556	1.6860	1.6128	2.9751	0.9727	0.1752	0.1676
IHMC-HAR-M2	15.6553	0.5965	1.0212	0.9481	2.9115	1.0700	0.1062	0.0986
HAR-M3	14.7699	0.5941	0.0000	0.0244	2.8230	1.0915	0.0000	0.0025
IHM-HAR-M3	16.2327	0.5562	1.5268	1.5514	2.9693	0.9753	0.1587	0.1612
IHMC-HAR-M3	15.9230	0.5982	1.2039	1.2284	2.9383	1.0642	0.1252	0.1277
HAR-M4	14.8426	0.5903	0.0000	0.1000	2.8302	1.0827	0.0000	0.0104
IHM-HAR-M4	16.2949	0.5543	1.5162	1.6166	2.9755	0.9706	0.1576	0.1680
IHMC-HAR-M4	15.8740	0.5977	1.0768	1.1771	2.9334	1.0648	0.1120	0.1224
HAR-M5	14.7949	0.5914	0.0000	0.0504	2.8255	1.0864	0.0000	0.0052
IHM-HAR-M5	16.2394	0.5544	1.5077	1.5583	2.9699	0.9722	0.1567	0.1620
IHMC-HAR-M5	15.8720	0.5980	1.1244	1.1749	2.9332	1.0654	0.1169	0.1222

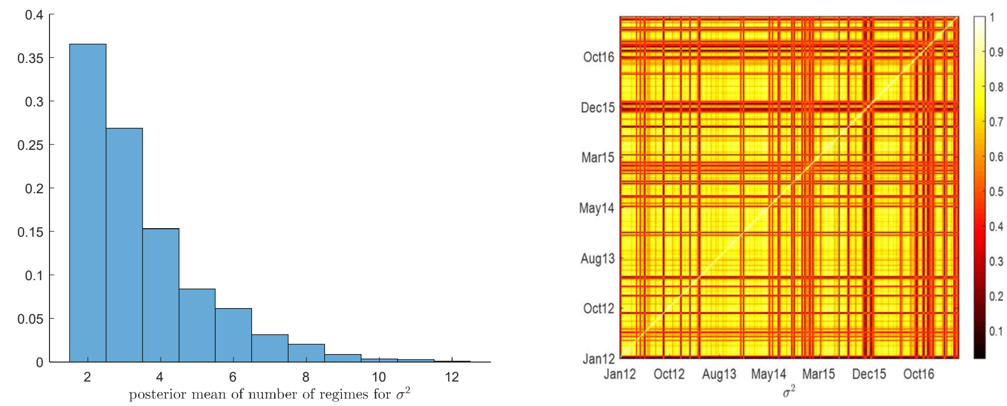
Note: See notes in Table 3

Figure 1. Posterior mean of number of regimes and heat map of regimes for the WTI sample.

Panel A: IHM-HAR-M5 model



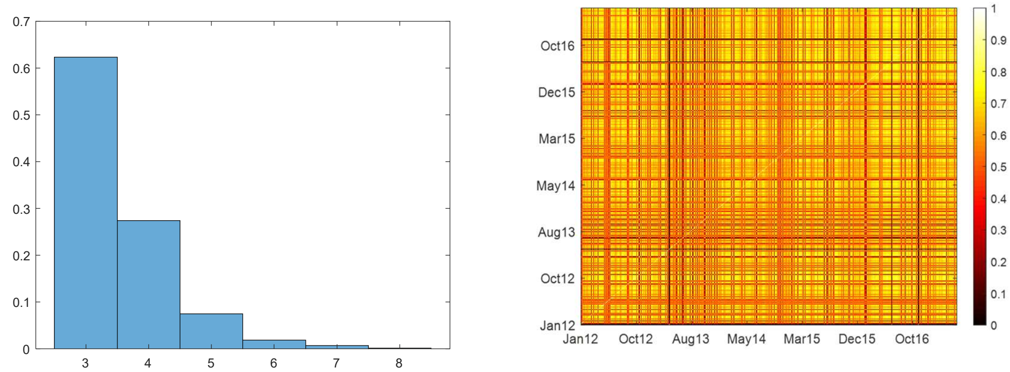
Panel B: IHMC-HAR-M5 model



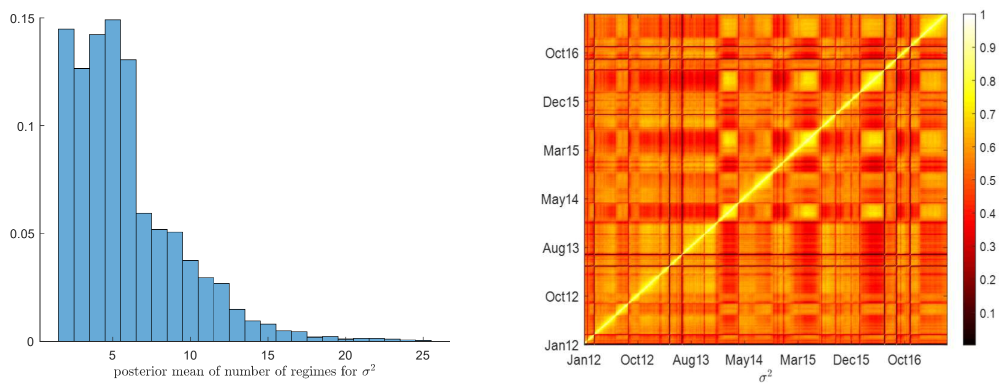
Note. The IHM-MAR-M5 model in Panel A refers to the Infinite Hidden Markov-Switching Heterogenous Autoregressive Realized Volatility model which incorporates a regime-switching framework in which the variation of the coefficients and variances are governed by a Markov state variable. The IHMC-HAR-M5 model in Panel B refers to the alternative specification in which the coefficients are assumed to be time-invariant, and only the variances are driven by the IHM switching process. M5 refers to the predictive model structure described in Equation (18).

Figure 2 Posterior mean of number of regimes and heat map of regimes for the gold sample.

Panel A: IHM-HAR-M5 model



Panel B: IHMC-HAR-M5 model



Note. See notes to Figure 1.

APPENDIX:

Table A1. Summary Statistics

	Mean	Std. Dev.	Skewness	Kurtosis	JB statistic	Ljung-Box, Q(5)	Ljung-Box, Q(10)	Ljung-Box, Q(20)	ADF
					Panel A: WTI Crude oil				
RV	3.30	3.94	3.13	15.59	11215.90***	4032.18***	6998.48***	11562.84***	-8.64***
Jump	0.05	0.21	9.39	124.47	856677.19***	68.22***	124.01***	177.14***	-21.08***
RSK	0.01	1.62	0.60	7.76	1368.12***	11.40**	13.24	27.06	-26.00***
RKU	11.76	12.39	4.63	31.09	49628.70***	26.70***	45.65***	90.88***	-27.29***
Spec	0.44	0.15	0.82	3.73	183.53***	2627.22***	3650.76***	6435.85***	-13.32***
Hedge	0.00	0.02	-0.45	4.27	136.80***	149.46***	187.99***	288.83***	-19.63***
					Panel B: Gold				
RV	0.75	0.84	10.98	215.53	2588811.30***	641.12***	802.86***	945.41***	-17.04***
Jump	0.01	0.04	7.93	93.27	476371.73***	6.91	18.50**	34.68**	-25.98***
RSK	0.11	1.79	0.45	9.10	2156.27***	9.07	9.93	14.86	-27.15***
RKU	13.60	15.25	4.22	25.95	33890.00***	15.40***	27.73***	53.94***	-27.06***
Spec	0.44	0.16	1.71	9.83	3310.80***	832.46***	1029.76***	1115.74***	-15.67***
Hedge	0.00	0.03	-0.07	3.80	37.35***	76.92***	83.93***	113.76***	-20.96***
					Panel C: S&P 500				
Spec	0.08	0.08	2.93	12.07	6612.58***	1755.72***	1771.03***	1886.02***	-12.12
Hedge	-0.09	1.55	-11.63	166.13	1539825.58***	1.24	2.37	5.34	-26.58

Note: *** suggests the corresponding values are significant at the 1% confidence level. *RV*, *RJ*, *RSK*, and *RKU* refer to the standard realized volatility, volatility jumps, realized skewness, and realized kurtosis, respectively, obtained from intraday data. *Spec* and *Hedge* denote the speculation and hedge ratios, respectively, obtained from gold, WTI, and S&P 500 futures.

Figure A1. Data Plots:

Figure A1(a): WTI-Related Variables

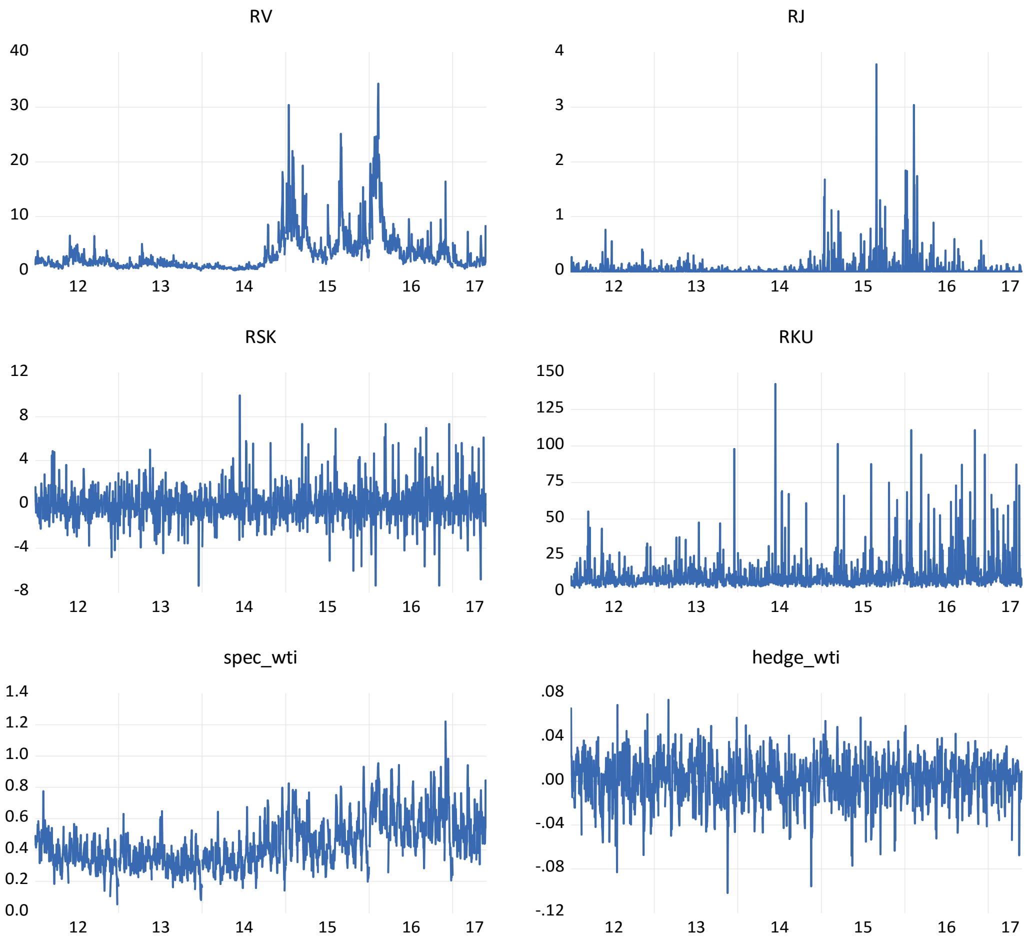


Figure A2(b): Gold-Related Variables

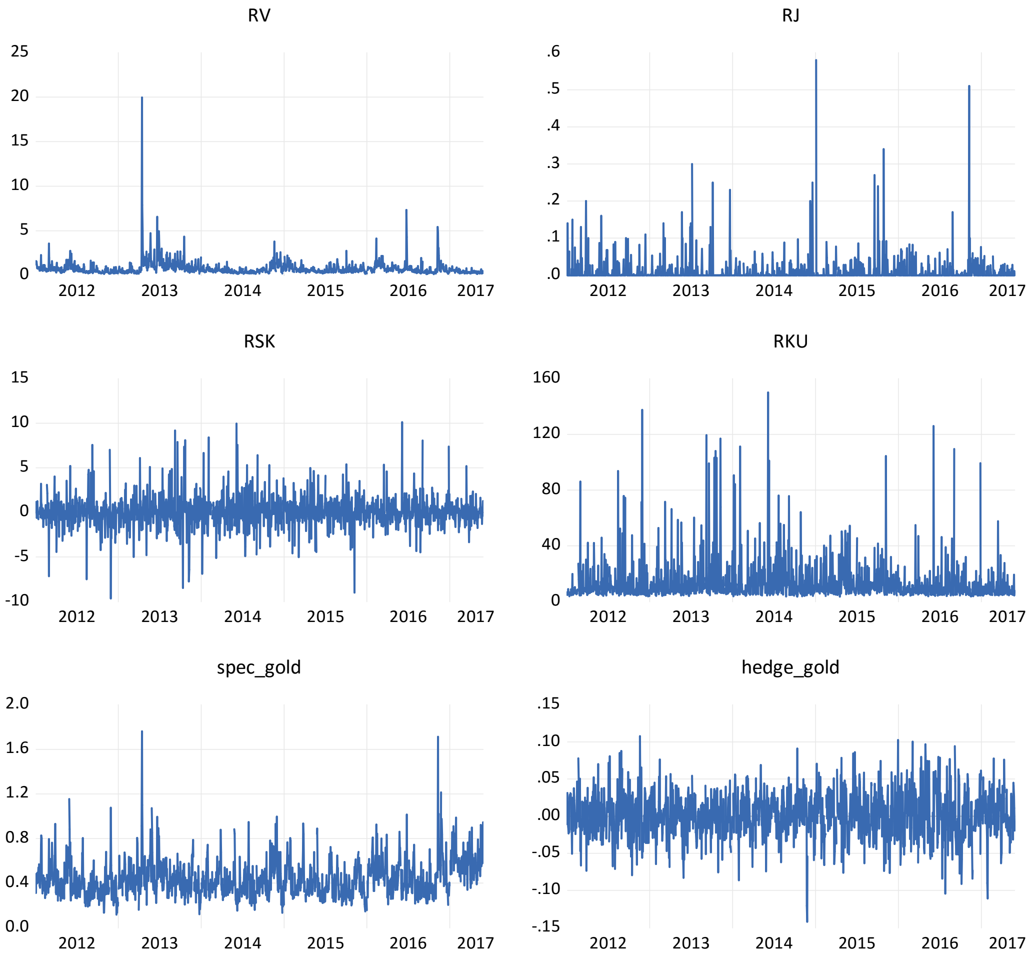


Figure A3(c): S&P500-Related Variables