Mixed-frequency forecasting of crude oil volatility based on the information content of global economic conditions

Afees A. Salisu[a,b], Rangan Gupta[c], Elie Bouri[d], Qiang Ji[e,f*]

[a] Department for Management of Science and Technology Development, Ton Duc Thang University, Ho Chi Minh City, Vietnam

[b] Faculty of Business Administration, Ton Duc Thang University, Ho Chi Minh City, Vietnam.

[c] Department of Economics, University of Pretoria, Pretoria, 0002, South Africa.

[d] USEK Business School, Holy Spirit University of Kaslik, Jounieh, Lebanon.

[e] Institutes of Science and Development, Chinese Academy of Sciences, Beijing 100190, China

[f] School of Public Policy and Management, University of Chinese Academy of Sciences, Beijing 100049, China

[*] Corresponding author, associate professor at Institutes of Science and Development, Chinese Academy of Sciences. Email: jqwxnjq@163.com/jqwxnjq@casipm.ac.cn.

Abstract: This paper subjects six alternative indicators of global economic activity to empirically examine their relative predictive powers in the forecast of crude oil market volatility. GARCH-MIDAS approach is constructed to accommodate all the relevant series at their available data frequencies, thereby circumventing information loss and any associated bias. We find evidence in support of global economic activity as a good predictor of energy market volatility. Our forecast evaluation of the various indicators places a higher weight on the newly developed indicator of global economic activity which is based on a set of 16 variables covering multiple dimensions of the global economy, whereas other indicators do not seem to capture. Furthermore, we find that accounting for any inherent asymmetry in the global economic activity proxies improves the forecast accuracy of the GARCH-MIDAS-X model for oil volatility. The results leading to these conclusions are robust to multiple forecast horizons and consistent across alternative energy sources.

Keywords: Energy markets volatility, global economic conditions, mixed frequency, GARCH-MIDAS model

1 INTRODUCTION

The recent financialization of the commodity market in general, and oil and energy sectors in particular has led to increased participation of hedge funds, pension funds, and insurance companies in the oil market, thus rendering oil a profitable alternative investment in the portfolio decisions of financial institutions (Bampinas & Panagiotidis, 2015, 2017; Bonato, 2019; Luo et al., 2020; Zhu et al., 2020). Hence, accurate estimates of oil-price volatility are of vital importance to oil traders. Naturally, there exists a large literature on forecasting the volatility of daily oil returns.

An elaborate review of the literature is beyond the scope of this paper, but we provide below a broad summary of the studies by focusing on the three most prominent approaches: (1) traditionally, oil market volatility has been modelled through univariate and multivariate versions of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, as well as the Markov-switching multifractal (MSM) model (see, e.g., Degiannakis & Filis, 2017; Gkillas et al., 2020; Lux et al., 2016, for detailed reviews). In general, studies in this literature find that the univariate GARCH-type models outperform their multivariate counterparts, and this outperformance remains significant even if daily exogenous predictors are included. Moreover, within the univariate GARCH models, more often than not, it is the standard version that outperformed other more complicated variations in this category. But the power of the MSM model for the majority of the times across forecasting horizons and sub-samples relative to the various univariate GARCH models is well recognized; (2) a shared characteristic of the above line of research is that they rely on oil-price returns at a daily frequency and forecast the daily conditional oil-price volatility. Nevertheless, as pointed out by McAleer and Medeiros (2008), intraday data containing rich information can lead to more accurate estimates and forecasts of daily volatility. Given this, various types of high-frequency predictors associated with financial and commodity markets, metrics of uncertainties, and behavioral variables have been incorporated into the Heterogeneous Autoregressive (HAR) model of Corsi (2009) to improve forecasts of the realized volatility of oil relative to the benchmark HAR model (see, e.g., Bonato et al., 2020; Chen et al., 2020; Luo et al., 2019; Ma et al., 2019, for a detailed discussion of this literature), and (3) finally, borrowing from the recent literature on the role of economic activity, that is, low frequency macroeconomic variables, on the volatility of stock markets (Asgharian et al., 2013; Conrad & Loch, 2015; Engle et al., 2013; Fang et al., 2020), a parallel literature has also emerged for forecasting oil volatility based on economic activity using the generalized autoregressive conditional heteroskedasticity (GARCH) variant of mixed data sampling (MIDAS), that is, the GARCH-MIDAS model (see, e.g., Nguyen & Walther, 2020; Pan et al., 2017; Wei et al., 2017; Yin & Zhou, 2016). The GARCH-MIDAS avoids the loss of information that would have resulted by averaging the daily volatility to a lower monthly frequency (Clements & Galvão, 2008; Das et al., 2019). Instead, the main idea behind this model is that volatility is not just volatility but that there are different components to volatility, namely, one pertaining to short-term fluctuations and the other to a long-run component, with the latter likely to be affected by economic activity as stressed by Kilian (2010), Baumeister and Peersman (2013), and Greenberg (2016).

Given the financialization of the oil market, and borrowing from the literature on stock markets, we can conjecture a negative relationship between economic conditions and oil market volatility (Conrad et al., 2014), just as observed for stock markets (see, e.g., Engle & Rangel, 2008; Rangel & Engle, 2011). The underlying theoretical channel can be elaborated as follows. The present value model of asset prices (Shiller, 1981a, 1981b) can be used to show that asset market volatility, and hence oil volatility due to financialization, depends on the volatility of cash flows and the discount factor. Given that worsening of global economic conditions (such as in crises periods) affects the volatility of variables that reflect future cash flows by generating economic uncertainty (Bernanke, 1983) and the discount factor (Schwert, 1989), one can hypothesize a negative relationship between economic conditions and oil and energy markets volatilities.

Against this backdrop, the objective of our analysis is to forecast oil return volatility based on a new measure of global economic conditions, developed by Baumeister et al. (2020), to forecast prices and production of oil and energy markets. This index covers conditions of real economic activity, commodity (excluding precious metals and energy) prices, financial indicators, transportation, uncertainty, expectations, weather, and energy market-related indicators, with the importance of these variables stressed individually in the GARCH-MIDAS literature of oil market volatility (Liu et al., 2019; Nguyen & Walther, 2020; Yu & Fang, 2018). 1 Hence, it essentially encapsulates the various measures that capture the economic conditions of the world economy (not just in the United States), as discussed above, to forecast oil market volatility.

Given that this global economic conditions index (GECON) is available at a monthly frequency, we rely on the GARCH-MIDAS model to help predict oil market volatility on a daily basis (to avoid loss of information). Note that, in our context, the GARCH-MIDAS model is the preferred framework, since MSM-MIDAS models have not yet been developed, though they would be ideal to forecast energy market volatility (given the superior performance of the MSM models relative to the GARCH framework). At the same time, daily data-based HAR-type models too, where realized volatility (RV) estimates are derived from intraday data, do not allow for predictors at lower frequency, as would be the case in our context. This in turn would require the usage of reverse-MIDAS regressions recently developed by Foroni et al. (2018), which could indeed be an area of future research. Of course, we could obtain RV at monthly frequency from daily data and use a monthly version of the HAR-RV model, but then this would not allow us to produce daily forecasts. In light of these issues, high-frequency forecasting of the volatility of energy markets based on the GECON index does indeed make the GARCH-MIDAS approach preferable over alternative methods.

The decision to forecast oil market volatility at a daily frequency is not only due to the underlying statistical need to provide more accurate measures of volatility (Ghysels et al., 2019) 2 but also because high-frequency forecasts are important for investors in terms of making timely portfolio decisions, given that daily volatility forecast features prominently in the context of Value-at-Risk (VaR) estimates (Ghysels & Valkanov, 2012). At the same time, the variability of oil prices is also a concern from a policy perspective, as oil-price volatility has been shown to impact economic activity negatively, because it captures macroeconomic uncertainty (Elder & Serletis, 2010; van Eyden et al., 2019). Hence, high-frequency forecasts of oil market uncertainty would help policymakers to predict in real time, that is, nowcast, the future path of low-frequency domestic real activity variables, using MIDAS models (Banbura et al., 2011), and in the process allow them to develop appropriate and early policy responses to prevent possible recessions.

Although the focus of the current research is on forecasting both spot and futures of West Texas Intermediate (WTI) and Brent crude oil market volatilities using GECON, we also predict the volatility of natural gas and heating oil. In addition, we forecast the volatility of the returns of all the three energy markets using five alternatives, but narrower, measures of global economic activity (primarily associated with output) that have been used in the GARCH-MIDAS literature of oil (and stock volatility) discussed above for the sake of comparison. Because oil market is affected by a wide array of variables, our presumption is that GECON will be able to improve the accuracy of oil market volatility forecastability, compared with the other measures of global economic activity, as highlighted for oil returns by Baumeister et al. (2020).

To the best of our knowledge, this study is the first attempt to forecast the daily volatility of energy prices using a broad index of global economic conditions (GECON) based on a GARCH-MIDAS approach. In this regard, our study compliments the recent work of Salisu et al. (2020), which highlights the important predictive role of the GECON index for volatility of precious metals, also based on a GARCH-MIDAS framework, which has also become popular for predicting volatility of gold and other precious metals in recent times (Fang et al., 2018). The remainder of the paper is organized as follows: Section 2 discusses the data, whereas Section 3 outlines the econometric framework; Section 4 presents the empirical results from the in-sample and out-sample predictive analyses, with Section 5 concluding the paper.

2 DATA AND PRELIMINARY ANALYSES

Conventionally, the return, rather than the price, series is used in the analysis of volatility to circumvent the unit root problem. Thus, in this study, we employ the spot and futures price returns of four energy sources (WTI, Brent, heating oil, and natural gas) and six economic activity proxies (GECON, real commodity price factor [RCPF], global steel production factor [GSPF], real shipping cost factor [RSCF], Kilian's index [KINDX], and OECD+6NME industrial production [OECDIP]). As stated earlier, the energy returns and economic activities are in daily and monthly frequencies, respectively. The energy price data were sourced from DataStream, whereas the economic activity proxies were obtained from two research databases (sites.google.com/site/cjsbaumeister/research and econweb.ucsd.edu/~jhamilton/). Several proxies (RCPF, GSPF, and RSCF) were directly provided to us by Professor Baumeister.

Although the variables have different start and end dates, we restrict our data sample to a range between April 21, 2006, and August 31, 2018. This is to ensure a balanced data sample, to serve as a basis for comparison of the predictability of the six contending economic activities. Our analysis is presented in two phases: the main estimation, which involves predicting energy (spot and future) price volatility for WTI and Brent, using each of the six economic activity proxies; and additional analyses, which involve the remaining two energy (spot and future) price volatilities and the economic activity proxies. This serves as a form of sensitivity analysis.

We provide a brief description of the real economic activities incorporated in the prediction of energy price volatility. KINDX is based on single-voyage dry-cargo freight rates (Kilian, 2009). The founding intuition is that deviations from linear time trend changes in real shipping costs can capture the cyclical component of demand for industrial commodities. As the established link between the shipment of raw industrial materials and future production of manufacturing goods, KINDX is used to proxy the state of the global business cycle (Kilian, 2009). Hamilton (2019) faults the isolation of the cyclical component of real shipping costs by the removal of a deterministic linear time trend on the basis of lack of data support. Hence, we have adopted a month-on-month growth rate of the index.

Another proxy of real economic activity, the RSCF, was proposed by Baumeister et al. (2020). The RSCF is derived from an unbalanced panel of disaggregated data, a cross-section of 61 freight rates for individual shipping routes, for a set of industrial commodities (coal, iron ore, and fertilizer).

The world industrial production index (OECD) (Baumeister & Hamilton, 2019) is measured by the physical volume of output generated in the industrial sector and is considered to be a closer representation of the traditional concept of economic activity. An updated monthly version—OECDIP—which includes OECD countries as well as six emerging markets (Brazil, China, India, Indonesia, the Russian Federation, and South Africa), was constructed using a similar methodology as used by the OECD (Baumeister & Hamilton, 2019).

The RCPF is an extraction of the global factor relating to business cycle fluctuations from the monthly growth rates of real prices of 23 basic industrial and agricultural commodities used as inputs in the production of final goods, excluding precious metals (Alquist et al., 2019).

The GSPF is obtained from monthly global steel production by taking cognisance of the structural break problem of aggregation caused by alterations in the number of reporting countries. This follows from Ravazzolo and Vespignani's (2020) suggestion that steel is a relevant component for construction, transportation, and manufacturing in many industries and is also a relatively homogenous globally and freely traded commodity (see Baumeister et al., 2020, and Table 2 for further explanation of these indices).

Moving away from indices that only attempt to capture the cyclical component of global real economic activity, which is thus restricted, we consider a more encompassing index: GECON (Baumeister et al., 2020). This index is derived by applying the expectation–maximization algorithm to 16 indicators associated with commodity prices, economic activity, financial indicators, transportation, uncertainty and expectation measures, weather, and energy-related indicators (Baumeister et al., 2020).

Table 1 presents the summary statistics and the preliminary analysis of the data used in the present study. The energy spot and futures price returns are considered respectively in the first and second pane, whereas the economic activity proxies are presented in the third pane. The WTI spot price has the highest returns, whereas natural gas has the lowest. For futures prices, Brent and natural gas have the highest and lowest returns, respectively. The energy returns have a relatively similar spread as their standard deviation hovers around 0.2 and 0.3 for both spot and futures price returns. The energy spot price returns appear to be skewed negatively (Brent, heating oil, and natural gas) and positively (WTI). The stance is not the same with respect to futures price returns as natural gas and WTI skewness values are different from those of the spot prices. All the energy spot and futures price returns exhibit excess kurtosis and are, thus, leptokurtic. The realized volatility of the energy proxies is all positively skewed and exhibit excess kurtosis.

TABLE 1. Summary statistics and preliminary analysis

	Mean	SD	Skewness	Kurtosis	N	ARCH(5)	ARCH(10)	ARCH(20)	Q(5)	Q(10)	Q(20)	$Q^2(5)$	$Q^2(10)$	$Q^2(20)$
Energy price returns														
Spot prices														
BRENT	−1.55E-04	0.03	−2.61	110.08	3915	122.65***	69.61***	51.26***	26.44***	97.55***	208.10***	553.42***	743.84***	1142.90***
Heating	−1.41E-04	0.02	−0.3	9.86	3915	91.89***	53.35***	29.39***	3.35	4.68	21.5	683.23***	1005.20***	1409.30***
Natural gas	−2.27E-04	0.02	−1.3	101.16	3915	0.37	0.39	4.77***	0.21	0.38	22.88	1.8	3.61	95.48***
WTI	3.71E-06	0.03	1.07	39.73	3913	211.96***	167.03***	140.18***	35.88***	55.93***	98.88***	1456.00***	2877.10***	3880.30***
Future prices														
BRENT	−1.03E-04	0.02	−0.69	18.57	3915	57.54***	47.72***	38.16***	7.18	22.28**	52.73***	379.89***	804.97***	1626.80***
Heating	−2.22E-04	0.02	−0.15	11.87	3670	94.73***	71.39***	39.69***	23.10***	28.38***	33.56**	626.76***	1225.00***	1606.20***
Natural gas	−3.52E-04	0.03	0.53	7.92	3915	22.88***	18.94***	11.66***	8.94	14.08	22.9	150.85***	297.21***	475.17***
WTI	−2.14E-04	0.03	−2.27	63.11	3725	63.89***	49.23***	31.90***	38.80***	47.84***	93.61***	421.37***	774.98***	978.21***
Realized volatility														
Spot prices														
BRENT	4.55E-04	6.44E-04	4.48	28.08	1987	2.86**	201.91***	101.44***	13.58**	756.75***	973.02***	14.772**	1050.80***	1566.30***
Heating	3.99E-04	3.81E-04	2.27	9.23	1987	10.39***	80.59***	50.44***	5.73	524.50***	560.48***	57.86***	719.60***	842.52***
Natural gas	3.41E-04	1.18E-03	6.19	47.06	1987	0.11	65.85***	49.05***	15.75***	482.05***	585.83***	0.57	499.86***	577.82***
WTI	5.64E-04	9.50E-04	4.22	24.52	1987	57.55***	117.16***	64.71***	123.62***	757.98***	1051.20***	385.11***	1156.60***	1444.80***
Future prices														
BRENT	4.43E-04	6.24E-04	3.55	16.73	1987	32.50***	75.52***	55.98***	53.41***	518.46***	653.11***	202.60***	790.13***	1311.30***
Heating	3.89E-04	4.15E-04	2.90	13.09	1987	60.33***	75.02***	48.75***	23.98***	496.50***	542.79***	283.60***	794.06***	988.22***

Natural gas	1.03E-03	1.16E-03	3.93	24.22	1987	0.33	60.93***	44.15***	13.58**	416.18***	443.07***	1.72	473.29***	490.05***
WTI	5.44E-04	8.24E-04	3.91	21.28	1987	37.45***	91.71***	60.90***	23.89***	461.43***	666.09***	272.28***	1131.20***	1669.80***
Economic activities														
GECON	−1.26E-01	0.54	−3.41	18.99	180	0.75	0.41	0.31	1.86	7.31	25.77	1.07	1.09	1.18
GSPF	−2.33E-03	0.69	−0.52	5.49	160	19.08***	9.49***	5.11***	20.93***	37.97***	105.67***	57.01***	66.70***	71.39***
KINDX	−5.66E-01	22.65	−0.63	5.25	173	3.28***	2.08**	0.95	7.35	15.65	22.37	17.79***	20.66**	23.27
OECDIP	1.44E-01	0.76	−2.81	17.47	178	1.72	1.17	0.62	16.01***	18.16**	27.74	5.03	5.14	5.5
RCPF	2.88E-02	0.54	−1.32	10.28	160	3.27***	1.62	0.82	10.021*	17.993*	28.11	16.48***	21.27**	23.93
RSCF	−3.36E-02	0.95	−0.75	6.35	160	5.95***	4.17***	1.87**	8.83	25.25***	36.13**	28.99***	48.66***	53.19***

Note: Global economic conditions indicator (GECON), real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX), and OECD+6NME industrial production (OECDIP).

* Statistical significance at 10%.

** Statistical significance at 5%.

*** Statistical significance at 1%.

We also find some degree of heteroscedasticity and autocorrelation up to at least lag 20. On the economic activity proxies, with a mean ranging from −2.33E-03 to 2.88E-02, KINDX appears to be the most volatile economic activity proxy. All the economic activity proxies are negatively skewed and leptokurtic, whereas all except GECON exhibited some degree of heteroscedasticity and autocorrelation up to at least lag 20. The observed data characteristics are suited for the GARCH-MIDAS framework.

3 METHODOLOGY

We rely on the modeling framework that accommodates mixed data frequencies to analyze the role of global economic conditions in forecasting energy market volatility. Our choice of model is informed by the available data frequency for the relevant series, where daily frequency is available for the energy series considered (i.e., crude oil, heating, and natural gas), whereas the highest available frequency for the various measures of global economic conditions is monthly frequency. We favor the GARCH-MIDAS model, which is suitable for high-frequency dependent (energy) and low-frequency independent (global economic conditions) variables. 3

One of the attractions of this model is its ability to combine data occurring naturally in different frequencies and, thus, help to overcome the problem of information loss and, consequently, estimation bias that results from aggregation or disaggregation that most models, dependent on uniform frequency, are likely to cause. In other words, the model incorporates all the available information into the estimation process and may, therefore, offer better predictability than other models that do not. The GARCH-MIDAS model 4 is, therefore, considered appropriate given that our predicted variables—WTI, Brent, heating oil, and natural gas—occur daily, whereas the predictor variable is a monthly occurring variable: global economic activity.

The returns on energy (WTI, Brent, heating oil, and natural gas) prices are generated as log returns and technically defined as $r_{i,t} = ln(P_{i,t}) - ln(P_{i-1,t})$, where $P_{i,t}$ is the ith day energy price in the tth month; $t = 1,\ldots,T$ and $i = 1,\ldots,N_t$ indicate monthly and daily frequencies, respectively, and N_t indicates the number of days in any given month t. The GARCH-MIDAS model for the daily energy price returns comprises two components: a constant unconditional mean and a conditional variance part, defined as

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

and

$$\varepsilon_{i,t} | \Phi_{i-1,t} \sim N(0,1) \tag{2}$$

where μ denotes the unconditional mean of the energy price return. The conditional variance part in 1 is decomposed into short- and long-run components, such that the short-run component ($h_{i,t}$) is characterized by a higher frequency and follows the GARCH(1,1) process, whereas the long-run volatility is captured by τ_t. The notation $\Phi_{i-1,t}$ denotes the information that is available at day $i - 1$ of month t. The conditional variance is, therefore, defined as

$$h_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_i} + \beta h_{i-1,t} \tag{3}$$

where α and β represent ARCH and GARCH terms, respectively, satisfying the following conditions: $\alpha > 0$, $\beta \geq 0$, and $\alpha+\beta < 1$. Following Engle et al. (2013) specification, which puts everything in the daily frequency without loss of the GARCH-MIDAS features, the initial monthly varying long-term component (τ_t) is structured to daily frequency—τ_i, because the days across months t are rolled back without keeping track of it and given as

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) X_{i-k}^{(rw)} \tag{4}$$

where the superscript "rw" indicates that a rolling window framework 5 is implemented; m denotes the long-run component constant; θ represents the MIDAS slope coefficient that indicates the predictability of the incorporated predictor variable X_{i-k}; the weighting scheme $\phi_k(\omega_1, \omega_2) \geq 0,\ \ k = 1,\ldots,K$ must sum to one for the identification of the model's parameters; based on the Akaike Information criterion (AIC) and the Bayesian information criterion (BIC), we choose the optimal lag-length $K = 12$ which corresponds to one MIDAS years, to filter the secular component of the MIDAS weights.

Hinging on the flexibility and popularity as portrayed by Colacito et al. (2011), the two-parameter beta polynomial weighting scheme is transformed to a one-parameter beta polynomial weighting scheme. Here, ω_1 is set to one, whereas $\omega_2 = \omega$, in a bid to obtain an optimal weighting function that is monotonically decreasing (Engle et al., 2013). The weighting function is defined as

$$\begin{aligned} \phi_k(\omega_1, \omega_2) &= \frac{[k/(K+1)]^{\omega_1-1} \times [1-k/(K+1)]^{\omega_2-1}}{\sum_{j=1}^{K} [j/(K+1)]^{\omega_1-1} \times [1-j/(K+1)]^{\omega_2-1}} \\ &\Leftrightarrow \phi_k(\omega) \frac{[1-k/(K+1)]^{\omega-1}}{\sum_{j=1}^{K} [1-j/(K+1)]^{\omega-1}} \end{aligned} \tag{5}$$

where the weights are positive and sum to unity, whereas the restriction, $\omega > 1$, is imposed to ensure that recent observations are assigned higher weights.

For the in-sample predictability analysis, we test whether θ is significantly different from zero, such that a rejection of the null would imply that futures energy return volatility can be influenced by the current state of economic conditions. The sign obtained after estimation tells us the direction of the relationship, and can be explained either way. For instance, a positive relationship suggests that an improvement in economic activity increases trading in the energy market, which, by extension, increases its volatility. Conversely, a negative relationship implies that higher economic activity reduces overall uncertainty, which reduces oil market uncertainty. We consider a heterogeneous autoregressive (HAR) model, which is to be compared with our benchmark GARCH-MIDAS model variant. The model is specified as

$$y_t = \beta^{(0)} + \sum_{k=1}^{K} \beta^{(k)} y_{t-1}^{(k)} + u_t \tag{6}$$

where $y_{t-1}^{(k)} = 1 \Big/ m_k \sum_{i=1}^{m_k} y_{t+1-i}$ represent squared returns which is used to proxy realized volatility, $\beta = (\beta^{(0)}, \beta^{(1)}, \ldots, \beta^{(K)})$ are the coefficients to be estimated, ($m_1 = 1$, $m_2 = 5$ & $m_3 = 20$)

are pre-specified values representing the sampling frequency, such that they correspond to 1 day, 1 week, and 1 month, given that our study deals with the daily frequency.

We also comparatively examine the in-sample and out-of-sample forecast performance of the GARCH-MIDAS models for the alternative economic activity indices, as well as the HAR model with realized volatility using 50% of the full data sample. We employ a relative QLIKE loss function and the Diebold and Mariano test. Following Patton (2011), we define the QLIKE loss

$$\text{function as}\, QLIKE = \sum_{t=1}^{T}\left({rv_t}/{\hat{\sigma}_t^2} - log\left({rv_t}/{\hat{\sigma}_t^2} \right) - 1 \right) \tag{7}$$

where rv_t is the realized volatility at time t; $\hat{\sigma}_t^2$ is the conditional volatility from our GARCH-MIDAS and HAR models. Subsequently, a relative QLIKE statistic is computed by taking the ratio between our preferred GARCH-MIDAS variant (GARCH-MIDAS-GECON) and other contending GARCH-MIDAS and HAR models. A value less than one would indicated outperformance of our preferred model over the contending models. The Diebold and Mariano (1995) statistic is also herein employed, to formally ascertain the statistical significance of the difference in the forecast precisions of any given pair of competing models. The test statistic is specified as

$$DM\,Stat = \frac{\bar{d}}{\sqrt{V(d)/T}} \sim N(0,1) \tag{8}$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the sample mean of the loss differential $d_t \equiv g(\varepsilon_{it}) - g(\varepsilon_{jt})$ with $g(\varepsilon_{it})$ and $g(\varepsilon_{jt})$ representing the loss functions of the forecast errors, ε_{it} and ε_{jt}, which are associated with the two forecasts, $\hat{r}_{it}$ and $\hat{r}_{jt}$, respectively, and $V(d_t)$ is the unconditional variance of d_t. The null hypothesis asserts relative equality of the forecast accuracy of the paired competing models, such that $E[d_t] = 0$. The rejection of this null hypothesis would imply that the forecast accuracy of the two competing models is statistically different.

4 RESULTS AND DISCUSSION

We begin our analyses with the crude oil volatility. Thereafter, we examine other energy sources, including heating oil and natural gas. The result comprises the predictability stance of the different economic activity proxies for crude oil volatility (using both spot and futures prices for WTI and Brent) and forecast evaluation (using the Diebold & Mariano, 1995, statistic). The predictability result (see Table 2) is based on the full data sample, whereas we consider 50% of the full data sample for forecast performance evaluation (see Table 3). This is in a bid to ensure that the results are not sensitive to the sample period that is employed. Nonetheless, we also provide a predictability result based on a 50% data sample in the appendix (see Tables A1 and A2). In the forecast evaluation, three out-of-sample forecast horizons [$h = 60$, $h = 120$, and $h = 180$ days ahead] are considered. The rolling window approach is adopted, wherein one-day ahead forecasts are generated iteratively over the entire specified out-of-sample horizon. Upon confirmation of predictability, the performance of the contending economic activity proxies is examined.

TABLE 2. The predictability of economic conditions in crude oil market volatility

Energy price	Economic activity	μ	α	β	θ	w	m
Spot prices							
WTI	GECON	5.01E-04 [3.19E-04]	3.65E-02*** [4.54E-03]	9.53E-01*** [5.64E-03]	−5.93E-02*** [7.29E-03]	1.57E+01*** [3.59E+00]	4.05E-04*** [4.15E-05]
	RCPF	1.28E-04 [2.88E-04]	6.14E-02*** [3.01E-03]	9.04E-01*** [5.22E-03]	2.01E-02*** [8.90E-04]	4.84E+00*** [1.16E-02]	2.59E-04*** [1.15E-05]
	GSPF	5.58E-04* [3.11E-04]	6.58E-02*** [4.26E-03]	9.15E-01*** [6.12E-03]	2.27E-02*** [1.77E-03]	5.00E+00*** [1.08E-02]	3.59E-04*** [2.80E-05]
	RSCF	6.40E-04** [3.03E-04]	9.90E-02*** [7.38E-03]	8.86E-01*** [7.44E-03]	5.13E-02*** [9.17E-03]	4.98E+00*** [1.67E-02]	5.26E-04*** [9.39E-05]
	KINDX	5.26E-04* [2.97E-04]	9.84E-02*** [6.81E-03]	8.96E-01*** [6.89E-03]	1.67E-02** [7.32E-03]	5.05E+00*** [1.14E-02]	8.92E-04** [3.92E-04]
	OECDIP	4.65E-04 [3.26E-04]	5.63E-02*** [5.17E-03]	9.37E-01*** [5.62E-03]	−2.97E-02*** [7.94E-03]	1.31E+01*** [3.74E+00]	5.54E-04*** [1.12E-04]
BRENT	GECON	2.51E-04 [2.99E-04]	3.01E-02*** [4.28E-03]	9.66E-01*** [4.80E-03]	−4.99E-02*** [9.41E-03]	1.32E+01*** [3.76E+00]	3.55E-04*** [5.88E-05]
	RCPF	2.85E-04 [2.94E-04]	3.39E-02*** [3.74E-03]	9.65E-01*** [3.79E-03]	−4.21E-02*** [1.24E-02]	4.56E+00*** [7.66E-01]	4.19E-04*** [1.16E-04]
	GSPF	5.29E-04** [2.42E-04]	1.08E-01*** [5.81E-03]	8.43E-01*** [5.37E-03]	4.83E-02*** [2.51E-03]	4.97E+00*** [2.75E-03]	2.09E-04*** [1.09E-05]
	RSCF	1.92E-04 [2.99E-04]	3.91E-02*** [4.51E-03]	9.59E-01*** [4.64E-03]	−4.23E-02** [1.71E-02]	1.10E+00*** [2.33E-01]	4.59E-04*** [1.28E-04]
	KINDX	−7.66E-04 [7.65E-04]	5.03E-02*** [3.73E-03]	9.00E-01*** [8.04E-03]	3.22E-02*** [2.31E-04]	5.00E+00*** [1.21E-02]	1.87E-03*** [1.41E-05]
	OECDIP	2.04E-04 [2.98E-04]	3.66E-02*** [3.90E-03]	9.61E-01*** [4.00E-03]	−2.56E-02*** [9.26E-03]	6.54E+00*** [2.21E+00]	4.51E-04*** [1.19E-04]
Future prices							
WTI	GECON	3.87E-04 [3.16E-04]	3.77E-02*** [5.06E-03]	9.53E-01*** [6.32E-03]	−5.62E-02*** [8.69E-03]	1.50E+01*** [3.93E+00]	3.88E-04*** [4.45E-05]
	RCPF	4.70E-04* [2.42E-04]	8.18E-02*** [5.01E-03]	9.05E-01*** [5.75E-03]	1.29E-02*** [1.64E-03]	4.87E+00*** [2.01E-02]	1.67E-04*** [2.12E-05]
	GSPF	5.41E-04* [2.83E-04]	9.34E-02*** [6.66E-03]	8.86E-01*** [7.94E-03]	2.17E-02*** [2.43E-03]	5.09E+00*** [1.94E-02]	3.43E-04*** [3.85E-05]
	RSCF	4.90E-04* [2.96E-04]	1.03E-01*** [8.13E-03]	8.85E-01*** [8.03E-03]	5.25E-02*** [1.14E-02]	4.98E+00*** [1.67E-02]	5.38E-04*** [1.17E-04]

	KINDX	3.45E-04 [2.97E-04]	8.64E-02*** [6.90E-03]	9.10E-01*** [7.04E-03]	1.99E-02** [1.01E-02]	5.02E+00*** [1.87E-02]	1.06E-03** [5.37E-04]
	OECDIP	2.91E-04 [3.16E-04]	5.03E-02*** [5.04E-03]	9.45E-01*** [5.19E-03]	−3.59E-02*** [1.02E-02]	9.44E+00*** [2.22E+00]	5.33E-04*** [1.41E-04]
BRENT	GECON	3.21E-04 [2.97E-04]	3.19E-02*** [4.30E-03]	9.62E-01*** [5.29E-03]	−4.80E-02*** [8.11E-03]	1.26E+01*** [3.64E+00]	3.31E-04*** [4.40E-05]
	RCPF	3.06E-04 [2.31E-04]	7.88E-02*** [6.05E-03]	9.21E-01*** [5.03E-03]	−2.16E-03 [3.72E-03]	5.88E+00*** [2.00E+00]	2.45E-05 [4.19E-05]
	GSPF	−6.62E-04** [2.60E-04]	4.15E-02*** [1.92E-03]	9.00E-01*** [4.87E-03]	1.24E-02*** [3.91E-04]	5.04E+00*** [7.47E-03]	2.05E-04*** [6.48E-06]
	RSCF	4.85E-04* [2.90E-04]	9.01E-02*** [6.64E-03]	8.96E-01*** [7.14E-03]	1.87E-02*** [3.32E-03]	4.62E+00*** [1.84E-02]	4.16E-04*** [7.41E-05]
	KINDX	1.16E-04 [6.55E-04]	7.45E-02*** [7.25E-03]	9.20E-01*** [8.46E-03]	9.47E-02*** [3.18E-02]	4.94E+00*** [1.01E-02]	5.01E-03*** [1.68E-03]
	OECDIP	2.12E-05 [6.33E-04]	5.00E-02*** [3.31E-03]	9.00E-01*** [5.31E-03]	1.00E-01*** [5.89E-05]	5.00E+00*** [3.57E-03]	1.29E-03*** [4.68E-07]

Note: Global economic conditions indicator (GECON), real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX), and OECD+6NME industrial production (OECDIP). Values in square brackets are the associated standard errors of the estimated parameters.

* Statistical significance at 10%.

** Statistical significance at 5%.

*** Statistical significance at 1%.

TABLE 3. Forecast evaluation using QLIKE and Diebold–Mariano statistics (WTI and Brent)

Energy	Economic activity	Spot prices				Future prices			
		***h* = 30**	***h* = 60**	***h* = 120**	***h* = 180**	***h* = 30**	***h* = 60**	***h* = 120**	***h* = 180**
WTI	RCPF	0.823*** [16.554]	0.874*** [9.965]	0.786*** [19.352]	0.751*** [23.347]	1.192 [−16.803]	1.650 [−19.329]	1.512 [−19.081]	1.593 [−20.230]
	GSPF	0.863*** [15.031]	0.848*** [13.683]	0.777*** [25.170]	0.739*** [27.984]	0.970*** [17.377]	0.852*** [19.418]	0.758*** [30.499]	0.694*** [29.506]
	RSCF	0.830*** [10.058]	0.889*** [7.876]	0.715*** [17.894]	0.612*** [25.184]	1.013 [9.627]	0.982*** [7.652]	0.678*** [17.266]	0.539*** [23.832]
	KILIAN	0.797*** [13.557]	0.863*** [9.055]	0.760*** [19.655]	0.709*** [25.312]	0.886*** [15.136]	0.926*** [8.179]	0.850*** [11.077]	0.867*** [10.602]
	OECDIP	0.742*** [12.243]	0.750*** [15.701]	0.743*** [21.231]	0.720*** [29.997]	0.851*** [4.915]	0.792* [11.422]	0.806*** [10.123]	0.772*** [15.709]
	HAR	1.144 [3.794]	0.402*** [7.075]	0.310*** [10.545]	0.388*** [9.914]	0.940*** [4.237]	0.408*** [6.842]	0.288*** [10.203]	0.361*** [8.990]
Brent	RCPF	1.969 [9.518]	1.314 [9.311]	1.263 [7.807]	1.171 [10.586]	0.934*** [16.129]	0.934*** [9.027]	0.753*** [16.781]	0.824*** [15.701]
	GSPF	2.244 [9.162]	2.053 [2.517]	1.463 [1.953]	1.451 [1.851]	0.909*** [29.010]	0.801*** [43.419]	0.712*** [62.629]	0.749*** [35.775]
	RSCF	1.265 [9.151]	1.205 [6.592]	0.837*** [10.276]	0.837*** [10.806]	0.869*** [20.964]	0.860*** [10.734]	0.770*** [18.661]	0.808*** [21.047]
	KILIAN	1.323 [9.352]	1.216 [7.745]	0.866*** [7.295]	0.872*** [6.718]	0.835*** [20.115]	0.824*** [11.395]	0.774*** [14.263]	0.848*** [14.062]
	OECDIP	0.931 [−1.248]	0.876*** [4.432]	0.815*** [8.067]	0.808*** [10.934]	0.054*** [172.429]	0.046*** [90.517]	0.036*** [130.877]	0.036*** [190.582]
	HAR	0.666*** [4.249]	0.367*** [6.994]	0.342*** [12.255]	0.348*** [11.418]	0.860*** [6.050]	0.400*** [7.612]	0.204*** [10.847]	0.274*** [8.087]

Note: Real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX), OECD+6NME industrial production (OECDIP) are separately predictors in the GARCH-MIDAS model; and HAR is heterogeneous autoregressive model. Each cell contains the relative QLIKE statistics and Diebold–Mariano (DM) test values in square brackets. The relative QLIKE and the DM tests are used to compare different variants of the GARCH-MIDAS (listed on the rows) and the HAR model with a GARCH-MIDAS model that incorporates GECON as a predictor variable, using the squared error and QLIKE loss functions. Statistical significance at 1%, 5%, and 10% levels are used in the table to show cases where the relative QLIKE is less than one and the DM statistic is positive and significant. Hence, significance implies preference of the GARCH-MIDAS-GECON over the row listed GARCH-MIDAS and HAR model constructs.

* Statistical significance at 10%.

** Statistical significance at 5%.

*** Statistical significance at 1%.

4.1 The role of economic conditions in crude oil market volatility

As noted previously, we begin the analyses with the crude oil market. Table 2 presents the GARCH-MIDAS parameters where each of the economic activity proxies is incorporated in the volatility of crude oil market for both spot (upper pane) and futures (lower pane) of WTI and Brent. These parameters include the unconditional mean for crude oil (μ); ARCH term (α); GARCH term (β); the slope coefficient (θ) that gives an indication of the predictability stance of monthly economic activity for daily crude oil volatility; adjusted beta polynomial weight (w); and the long-run constant term (m). With the exception of the unconditional mean, we find all the parameters to be statistically significant across the various economic activities (except for the θ coefficient of KINDX for WTI spot and RSCF for Brent futures), crude oil spot, and futures prices. For the ARCH and GARCH terms, which give some information on the short-run component of the model in terms of persistence, we find a high degree of volatility persistence, which also exhibits mean-reverting characteristics, since the sum of the ARCH and GARCH terms is less than unity.

Imperatively, although the impact of shocks to crude oil (WTI and Brent) volatility is likely to take longer to decay completely, the impact of such shocks would not be permanent. We confirm this stance consistently across economic activity proxies and crude oil spot and futures prices. The adjusted beta weight coefficients are found to be statistically significant and greater than one across the two crude oil proxies and economic activity proxies, which is an indication that immediate past observations are assigned larger weights than far apart lag observations. The secular component emanating from the model with GECON appears to consistently track the volatility of the energy (spot and future) prices more than the other economic activity proxies (see Figure 1). This may be suggestive of the precision of the adjusted beta weight associated with the model incorporating GECON over the other economic activity proxies.

On the predictability stance, we test the hypothesis that the MIDAS slope coefficient (θ) is statistically different from zero, such that a rejection of the null will imply predictability of the corresponding economic activity for crude oil volatility; otherwise, there is no stance of predictability. Consequently, we find predictability of the economic activity proxies for crude oil proxies, regardless of whether spot or futures price returns is used, given that the slope parameter (θ) is found to be statistically significant. The only cases of unconfirmed predictability of economic activity for crude oil-price volatility is RCPF in the volatility of Brent futures.

In addition, we find the nexus between economic activity and crude oil volatility to be mixed for GARCH-MIDAS model incorporating RCPF and RSCF, consistently negative for the GARCH-MIDAS models incorporating GECON and OECDIP (except for Brent crude futures), regardless of the crude oil volatility being considered; and positive for GARCH-MIDAS model incorporating GSPF and Kilian index. Interestingly, the consistent negative relationship between volatility and economic activity (especially, GECON and OECDIP), is in line with the channels identified in the introduction, associated with cash flow and the discount factor.

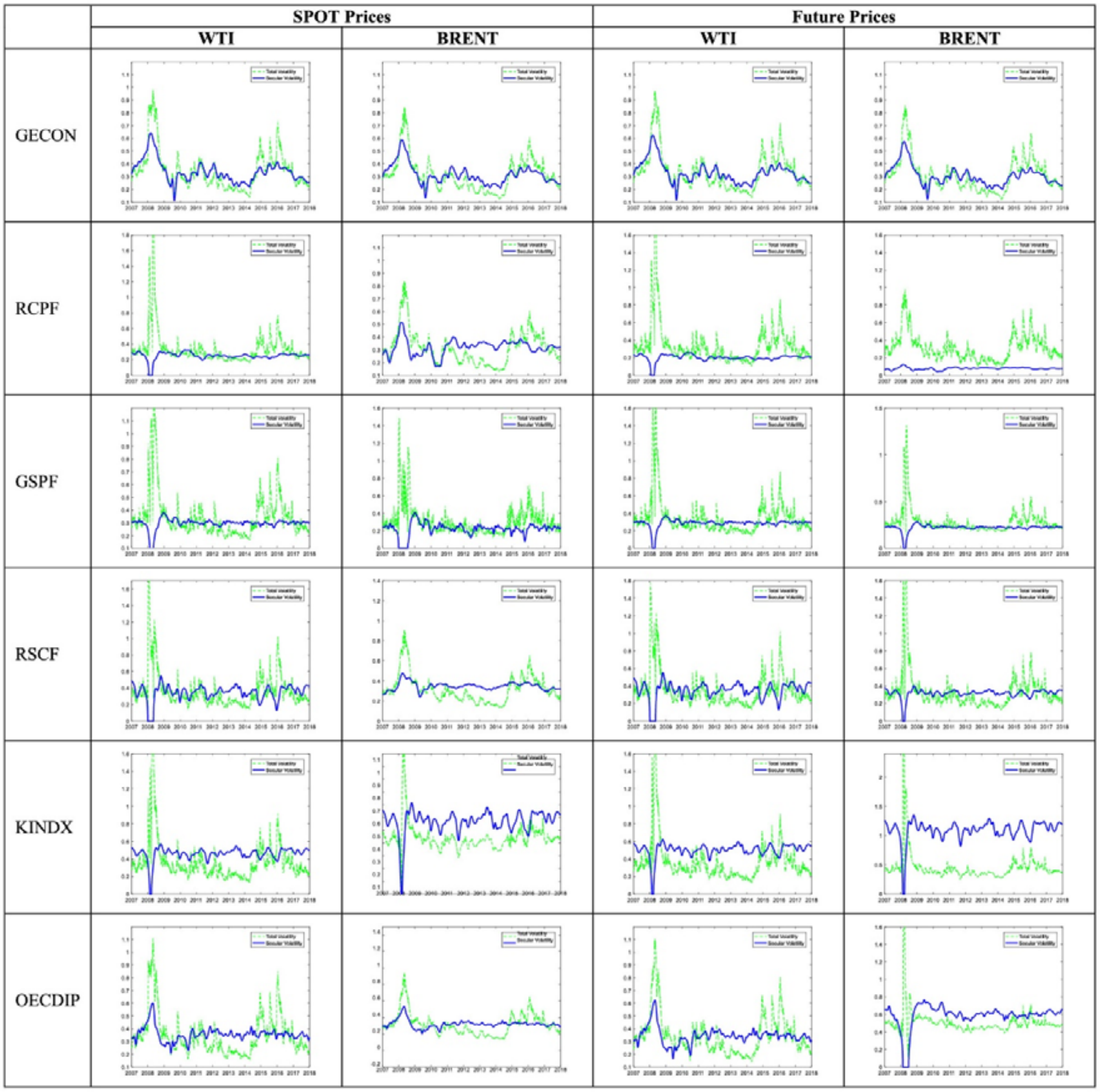

FIGURE 1. Estimated volatility for WTI and Brent corresponding to economic activity proxies

4.2 Out-of-sample forecast evaluation

Following from the established predictability of economic activity for crude oil volatility, we further consider the out-of-sample performance of the GARCH-MIDAS predictive model that incorporates any pair of crude oil (spot or future) volatility and economic activity at each point. This is a bid to ascertain which of the economic activity proxies predicts the corresponding crude oil volatility more precisely, with the least forecast error. Consequently, for each crude oil volatility proxy, there are six different GARCH-MIDAS models and a HAR model construct, thus leading to a total of 56 models comprising different pairs of predicted and predictor variables, as well as the HAR model with realized volatility. Also, four forecast horizons are considered, which include $h = 30$, $h = 60$, $h = 120$, and $h = 180$ days ahead. Using the relative QLIKE loss function and the Diebold and Mariano statistic for the paired models comparison, we consider the GARCH-MIDAS model with GECON as the predictor variable to be our benchmark model, and pair same with each GARCH-MIDAS model variants with other economic activity proxies, as well as the HAR model with realized volatility. For any pair of the benchmark model and a competing model, we expect a QLIKE value less than one, and a positive and statistically significant DM values for our benchmark model to be preferred and adjudged as a data-supported model with the higher precision between the contending pair. We consider only 50% of the data sample for the forecast evaluation, using a rolling window estimation on the long-run component, such that the long-run component varies daily. The results for the model predicting WTI and Brent spot and futures volatility are presented in Table 3.

We find the GARCH-MIDAS model with GECON as the predictor variable for WTI (both for spot and futures), in comparison with the other competing GARCH-MIDAS model constructs and the HAR model with realized volatility, to mostly have lower QLIKE values as well as positive and statistically significant DM statistics when a 30-days-ahead forecast horizon is considered, except in the cases of HAR for WTI spot and RCPF for WTI futures (negatively significant). However, the out-performance of GECON over all the competing models is found when the forecast horizon is increased to 60, 120, and 180 days (except for RCPF under WTI futures). Consequently, the GECON proxy records a higher precision in predicting the WTI spot and futures volatility across all specified forecast horizons. The out-performance of the GECON proxy over the other economic activity proxies transcends the crude oil proxy considered, as a consistently similar result is obtained in the case of Brent (especially, for futures), and across the forecast horizons. More interestingly, is the out-performance of the GARCH-MIDAS-GECON model over the HAR-RV model, regardless of the crude oil proxy and forecast horizon considered. This brings to bear a statistical confirmation that incorporating GECON as a predictor in the GARCH-MIDAS model for energy return volatility would improve forecast precision over the GARCH-MIDAS model that ignores the same.

Overall, we find the GECON to be the most preferred economic activity proxy for predicting spot and futures WTI and Brent return volatility. This is in addition to its confirmed in-sample predictability, which is not sensitive to the crude oil volatility being modelled. Consequently, the GECON provides a more precise estimate of the relationship between crude oil volatility and economic activity. This feat confirms the standpoint of Baumeister et al. (2020), whose contribution is attributable to the GECON. They do not only argue against using the previous indices that capture only the cyclical component of economic activities (therefore, failing to measure the global economic conditions properly), but also construct an alternative index that reasonably reflects global economic activity. It is, therefore, not surprising that the GECON of Baumeister et al. (2020) consistently out-performs other indices and possesses a higher precision in the predictability of the return of crude oil.

In sum, our study provides empirical evidence to support the preference of the GECON over other indices, particularly when dealing with the predictability of global variables, such as oil price and possibly other variables whose behavior are susceptible to global macroeconomic shocks. Our finding complements a similar work by Baumeister et al. (2020), focusing on the energy market and global economic activity, albeit with a different approach and objective. We focus on energy market volatility using a mixed-frequency approach, rather than returns, as the former measures uncertainty in the market, which is a more important factor when making investment decisions.

4.3 Additional analysis

We follow similar trends as with the main estimation to examine two additional energy sources—heating oil and natural gas—further as a robustness check for the sensitivity of the predictive performance of the six economic activity proxies. In this case, we only consider 50% of the data sample for the predictability (see Tables A1 and A2) and forecast evaluation (Table 4). We do not discuss the predictability results in detail here as the sections corresponding to WTI and Brent crude volatility are similar to those of the full sample discussed in the main estimation, showing the predictability of economic activity for crude oil volatility. Thus, we focus on which economic activity would produce the most precise in-sample predictability (see Figure 2) and out-of-sample forecast for the return volatility of the energy market considered—in this case, heating oil and natural gas. The relative QLIKE and the DM results, presented in Table 4, are also under similar section as the main estimation: spot and futures return volatility for heating oil and natural gas with 30-, 60-, 120-, and 180-days-ahead forecast horizons.

The estimated secular component from GARCH-MIDAS-GECON model tracks the volatility of the heating oil and natural gas (spot and future) prices more closely than the models with other economic activity proxies (see Figure 2). This is similar to the stance with WTI and Brent price, and is also suggestive of the precision of the adjusted beta weight in the GARCH-MIDAS-GECON model over the other economic activity proxies. For the four specified out-of-sample forecast horizons, we find an overwhelming out-performance of GECON over the other economic activity proxies and the HAR model realized volatility in forecasting the return volatility for heating oil (whether spot or futures). Except for the few cases of where GARCH-MIDAS-GECON was significantly outperformed by other contending models, especially at forecast horizons 30 and 60,, the former (GARCH-MIDAS-GECON) again proves to be the most preferred global economic activity proxy for modeling energy (spot and future) market volatility, as it consistently out-performs other economic activity proxies, as well as the HAR-RV model, across the specified out-of-sample forecast horizons. This further confirms its superiority over all others as it hinges on the incorporation of all possible information compared with variants of economic activity proxies that only attempt to capture the cyclical component. Our predictability results, in addition to the observed forecast performance, show the importance of accommodating all plausible economic activity information when modeling energy market volatility; hence, the preference for the GECON.

On the importance of accounting for leverage effect in the short-term volatility function of the GARCH-MIDAS as suggested by Pan and Liu (2018) and Wang et al. (2020), we partially decomposed our economic activity proxies into positive (assuming one when economic activity is greater than zero, and zero otherwise) and negative (assuming one when economic activity is less than zero, and zero otherwise), and incorporate them separately in our GARCH-MIDAS model. We subject the resulting forecasts of the conditional volatility to the evaluation by the relative QLIKE and the DM statistics. The results are presented in Table 5, with interpretation following as previously defined. Our findings across the energy price volatility proxies and forecast horizons suggest that negative and positive economic activity proxies cannot be modelled much in the same way, as we find statistically significant difference in the performance of the positive and negative economic activity proxy, with preference in favor of the latter. Hence, accounting for leverage, and by extension asymmetry effect would improve upon the forecast of the GARCH-MIDAS-GECON model in the forecast of energy price volatility.

TABLE 4. Forecast evaluation using QLIKE and Diebold–Mariano statistics (heating oil and natural gas)

Energy	Economic activity	Spot prices				Future prices			
		h **= 30**	***h*** **= 60**	***h*** **= 120**	***h*** **= 180**	***h*** **= 30**	***h*** **= 60**	***h*** **= 120**	***h*** **= 180**
Heating oil	RCPF	0.854*** [40.687]	0.794*** [18.299]	0.642*** [23.146]	0.678*** [22.467]	0.046*** [298.000]	0.034*** [351.426]	0.031*** [314.570]	0.035*** [242.299]
	GSPF	0.854*** [37.464]	0.777*** [26.641]	0.660*** [25.338]	0.671*** [25.602]	0.835*** [32.377]	0.742*** [36.636]	0.613*** [58.285]	0.671*** [46.383]
	RSCF	0.843*** [41.328]	0.795*** [16.038]	0.691*** [18.613]	0.719*** [19.700]	0.829*** [24.577]	0.799*** [14.918]	0.695*** [21.635]	0.779*** [22.020]
	KILIAN	0.826*** [32.672]	0.765*** [16.148]	0.666*** [18.254]	0.675*** [20.641]	0.756*** [34.884]	0.696*** [21.482]	0.599*** [35.037]	0.647*** [40.348]
	OECDIP	0.814*** [25.087]	0.746*** [44.415]	0.641*** [31.633]	0.653*** [31.848]	0.787*** [9.704]	0.708*** [20.663]	0.659*** [26.071]	0.719*** [30.531]
	HAR	1.607 [1.295]	1.624*** [2.317]	0.514*** [7.788]	0.455*** [8.849]	0.762*** [7.920]	0.383*** [10.550]	0.203*** [17.507]	0.236*** [18.340]
Natural gas	RCPF	9.465 [33.931]	0.356*** [60.334]	0.104*** [106.418]	0.099*** [124.600]	1.258 [−1.556]	1.361 [−4.612]	1.437 [−9.295]	1.352 [−9.528]
	GSPF	21.378 [20.809]	1.006 [32.635]	0.206*** [56.924]	0.198*** [72.740]	0.903*** [−3.092]	0.738*** [3.945]	0.777*** [7.875]	0.774*** [12.286]
	RSCF	1.229 [66.280]	0.123*** [123.968]	0.044*** [153.810]	0.042*** [185.019]	1.031 [1.415]	0.955*** [4.948]	0.895*** [12.019]	0.831*** [17.714]
	KILIAN	0.272*** [150.703]	0.045*** [244.510]	0.019*** [152.154]	0.018*** [169.673]	1.045 [1.552]	1.013 [1.596]	1.018*** [2.398]	0.910*** [7.305]
	OECDIP	1.895 [40.424]	1.116 [29.912]	0.338*** [53.974]	0.325*** [60.072]	0.152*** [87.439]	0.206*** [63.433]	0.157*** [81.878]	0.141*** [107.652]
	HAR	5.862 [80.903]	0.918*** [63.738]	0.284*** [81.899]	0.280*** [108.460]	0.132*** [11.402]	0.165*** [20.249]	0.189*** [29.000]	0.205*** [33.439]

Note: Real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX), OECD+6NME industrial production (OECDIP) are separately predictors in the GARCH-MIDAS model; and HAR is heterogeneous autoregressive model. Each cell contains the relative QLIKE statistics and Diebold–Mariano (DM) test values in square brackets. The relative QLIKE and the DM tests are used to compare different variants of the GARCH-MIDAS (listed on the rows) and the HAR model with a GARCH-MIDAS model that incorporates GECON as a predictor variable, using the squared error and QLIKE loss functions. Statistical significance at 1%, 5%, and 10% levels are used in the table to show cases where the relative QLIKE is less than one and the DM statistic is positive and significant. Hence, significance implies preference of the GARCH-MIDAS-GECON over the row listed GARCH-MIDAS and HAR model constructs.

* Statistical significance at 10%.

** Statistical significance at 5%.

*** Statistical significance at 1%.

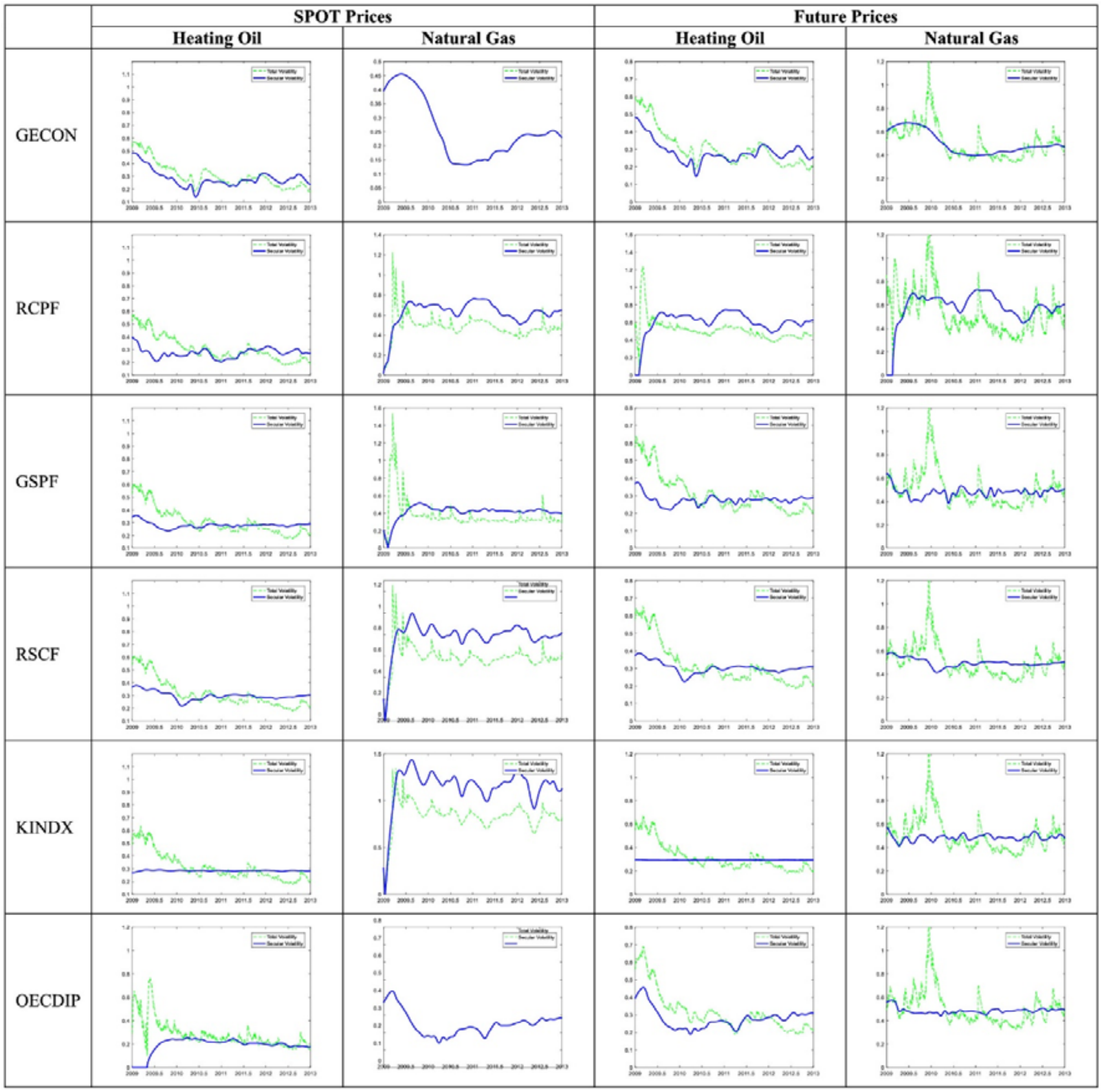

FIGURE 2. Estimated volatility for heating oil and natural gas corresponding to economic activity proxies

TABLE 5. Forecast evaluation for GARCH-MIDAS model with negative and positive asymmetry using relative QLIKE and Diebold–Mariano statistics

	Spot prices				Future prices			
	h **= 30**	***h*** **= 60**	***h*** **= 120**	***h*** **= 180**	***h*** **= 30**	***h*** **= 60**	***h*** **= 120**	***h*** **= 180**
West Texas intermediate								
GECON	0.964*** [16.376]	0.802*** [14.274]	0.827*** [13.371]	0.834*** [11.821]	0.948*** [18.395]	0.775*** [16.830]	0.821*** [13.261]	0.846*** [11.106]
RCPF	0.608*** [3.708]	0.569*** [7.351]	0.589*** [12.124]	0.664*** [13.667]	0.901*** [30.858]	0.842*** [46.463]	0.819*** [33.596]	0.868*** [20.929]
GSPF	0.998*** [6.294]	0.821*** [10.640]	0.902*** [5.026]	1.146*** [−3.449]	0.701 [−1.267]	0.497*** [3.898]	0.566*** [5.186]	0.689*** [5.825]
RSCF	0.810*** [6.240]	0.703*** [13.099]	0.645*** [23.493]	0.610*** [31.676]	0.843*** [20.881]	0.756*** [30.403]	0.707*** [51.425]	0.679*** [54.703]
KILIAN	-	-	-	-	-	-	-	-
OECDIP	1.235 [0.218]	1.804*** [−7.098]	1.672*** [−9.915]	1.577*** [−13.511]	1.045*** [−7.664]	0.984*** [−3.836]	0.966*** [−2.736]	0.917 [0.945]
Brent crude								
GECON	1.112*** [3.800]	0.884*** [9.072]	1.389 [−0.467]	1.386*** [−2.565]	1.037*** [14.801]	0.965*** [13.051]	1.357* [1.952]	1.223* [1.749]
RCPF	1.037 [−0.043]	0.945*** [4.482]	1.088*** [5.244]	1.070*** [9.206]	1.291*** [−23.422]	1.557*** [−39.401]	1.913*** [−42.554]	2.029*** [−61.696]
GSPF	1.349*** [16.448]	1.063*** [16.908]	0.941*** [20.340]	0.903*** [30.842]	0.947*** [18.821]	0.966*** [7.235]	0.936*** [11.325]	0.880*** [18.990]
RSCF	1.197*** [22.147]	0.947*** [33.023]	0.863*** [42.301]	0.854*** [30.702]	0.913*** [56.094]	0.869*** [39.926]	0.778*** [44.327]	0.769*** [31.419]
KILIAN	-	-	-	-	-	-	-	-
OECDIP	1.502*** [13.547]	1.506*** [1.493]	1.432*** [−3.385]	1.395*** [−2.993]	1.160*** [7.708]	1.462*** [−2.404]	1.331*** [−2.921]	1.261*** [−2.929]
Heating oil								
GECON	1.064*** [10.366]	1.033*** [10.640]	1.439 [−1.094]	1.488*** [−3.832]	1.078*** [10.623]	0.986*** [13.157]	1.489* [−1.694]	1.339*** [−3.458]
RCPF	2.749*** [−44.455]	3.723*** [−81.193]	6.073*** [−91.074]	7.842*** [−90.725]	0.750 [1.034]	0.730*** [4.698]	0.930*** [6.307]	0.869*** [10.799]
GSPF	1.027*** [6.686]	1.041 [1.040]	1.146*** [−4.495]	1.100*** [−3.822]	0.842*** [−5.352]	0.738*** [−1.426]	0.787** [−2.091]	0.917*** [−5.482]
RSCF	0.937*** [25.493]	0.910*** [32.339]	0.878*** [21.417]	0.945*** [13.990]	0.907*** [23.074]	0.861*** [28.877]	0.842*** [33.319]	0.880*** [30.400]
KILIAN	-	-	-	-	-	-	-	-

OECDIP	0.904*** [33.159]	0.888*** [9.268]	1.106** [2.059]	1.098* [1.586]	0.894*** [40.246]	0.851*** [10.389]	1.198*** [2.832]	1.069*** [4.770]	
Natural gas									
GECON	2.270*** [50.613]	2.171*** [88.006]	0.602*** [49.258]	0.592*** [31.999]	1.002*** [2.675]	0.921*** [8.694]	1.074 [−0.004]	1.206*** [−7.239]	
RCPF	0.135*** [−34.488]	3.242*** [−53.833]	3.672*** [−83.695]	3.780*** [−113.124]	1.442*** [−22.998]	1.402*** [−30.384]	1.585*** [−56.627]	1.541*** [−61.426]	
GSPF	0.309*** [−9.877]	0.431*** [−8.418]	0.928*** [−8.261]	0.934*** [−9.281]	0.938 [1.250]	1.011*** [−1.076]	0.891*** [7.101]	0.890*** [11.457]	
RSCF	0.939*** [−77.065]	7.497*** [−111.615]	6.006*** [−168.965]	6.367*** [−179.896]	1.019*** [−32.448]	0.916*** [1.773]	0.623*** [9.950]	0.560*** [16.919]	
KILIAN	-	-	-	-	-	-	-	-	
OECDIP	1.854*** [33.523]	1.706*** [10.504]	0.835*** [12.288]	0.835*** [15.258]	0.926*** [43.172]	0.949*** [20.148]	0.924*** [30.401]	0.926*** [35.018]	

Note: The figures are the ratio of the QLIKE statistics of the negative and positive partial sums of the corresponding economic activity and the Diebold and Mariano statistics in square brackets. Relative QLIKE values less (greater) than unity as well as positive (negative) Diebold and Mariano statistics indicate higher precision in energy forecast using the negative (positive) partial sum than the positive (negative) variant.

* Statistical significance at 10%.

** Statistical significance at 5%.

*** Statistical significance at 1%.

4.4 Economic significance

Here, we move from a statistical-based measure of forecast performance of the competing models to an economic-based forecast performance measure, following from Liu et al. (2019) study. The latter provides additional information as to the economic gains that the inclusion of a predictor variable in a model is likely to have over the model variant that ignores same. In this case, the GARCH-MIDAS model that includes an economic activity proxy (GECON) is compared with the GARCH-MIDAS variant with realized volatility.

Typical mean–variance utility investors always optimize available portfolio by allocating a given share to their choice assets or investment options, in contrast to a risk free asset. The optimal weight, w_t, is determined by

$$w_t = \frac{1}{\gamma}\frac{\theta\hat{r}_{t+1} + (\theta-1)\hat{r}^f_{t+1}}{\theta^2\hat{\sigma}^2_{t+1}} \tag{9}$$

where γ denotes the coefficient of risk aversion; θ is the leverage ratio (Zhang et al., 2018) that is set to 6 and 8, given the assumption that investors usually maintain a margin account at 10% level; $\hat{r}_{t+1}$ is the energy returns forecast at time $t+1$; $\hat{r}^f_{t+1}$ is a risk-free asset (we consider the Treasury bill rate); and $\hat{\sigma}^2_{t+1}$ is the estimate of the return volatility, which is estimated using a 60-day moving window of daily returns. Subsequently, a certainty equivalent return for investors' optimal weight, w_t, as obtained from Equation 7, can be defined as

$$CER = \bar{R}_p - 0.5(1/\gamma)\sigma^2_p \tag{10}$$

where $\bar{R}_p$ and σ^2_p are respectively the mean and variance of the portfolio return in the out-of-sample period; portfolio returns is defined as $R_p = w\theta(r - r^f) + (1 - w)r^f$. The associated portfolio return variance is defined by $Var(R_p) = w^2\theta^2\sigma^2$, where σ^2 denotes the excess return volatility. Consequently, the economic significance determination is obtained by maximizing the objective function of a utility as given in 9 below

$$\begin{aligned} U(R_p) &= E(R_p) - 0.5(1/\gamma)Var(R_p) \\ &= w\theta(r - r^f) + (1-w)r^f - 0.5(1/\gamma)w^2\theta^2\sigma^2 \end{aligned} \tag{11}$$

From the foregoing, we report the portfolio returns, the associated volatility, as well as the certainty equivalent returns and the Sharpe ratio, which is computed as $SP = (R_p - r^f)/\sqrt{Var(R_p)}$. Economic gain is ascertained on the basis of the model construct that yields the maximum returns, CER and SP; and minimum volatility (see Liu et al., 2019). We present the results of the economic significance of including any of the economic activity proxies as predictors in the GARCH-MIDAS framework for predicting energy (spot and futures) returns, when the leverage parameter is set to 6 and 8, with risk aversion level set as 3 (see Table 6).

TABLE 6. Out-of-sample economic gains with leverage ratio value of 6 and 8 (crude oil spot and future prices)

	$\gamma = 3$ and $\theta = 6$								$\gamma = 3$ and $\theta = 8$							
	Spot prices				Future prices				Spot prices				Future prices			
	Return	Volatility	CER	SP	Return	Volatility	CER	SP	Return	Volatility	CER	SP	Return	Volatility	CER	SP
WTI crude																
GECON	**2.220**	**0.461**	**2.220**	**3.206**	2.276	0.462	2.276	3.285	**2.521**	**0.535**	**2.521**	**3.387**	2.583	0.535	2.583	3.470
RCPF	2.060	0.408	2.060	3.155	**2.432**	**0.518**	**2.432**	**3.318**	2.349	0.478	2.349	3.332	**2.752**	**0.596**	**2.752**	**3.507**
GSPF	2.065	0.412	2.065	3.145	2.143	0.422	2.143	3.232	2.354	0.483	2.354	3.323	2.441	0.493	2.441	3.414
RSCF	1.953	0.371	1.953	3.134	1.998	0.370	1.998	3.211	2.231	0.438	2.231	3.305	2.282	0.437	2.282	3.385
KINDX	2.046	0.402	2.046	3.158	2.210	0.440	2.210	3.264	2.334	0.471	2.334	3.334	2.512	0.512	2.512	3.449
OECDIP	2.104	0.426	2.104	3.157	2.230	0.451	2.230	3.256	2.396	0.497	2.396	3.336	2.534	0.524	2.534	3.441
Brent crude																
GECON	**2.910**	**0.480**	**2.910**	**4.135**	**2.762**	**0.581**	**2.762**	**3.566**	**3.281**	**0.553**	**3.281**	**4.354**	**3.119**	**0.668**	**3.119**	**3.763**
RCPF	2.826	0.461	2.826	4.098	2.696	0.558	2.696	3.550	3.189	0.531	3.189	4.315	3.050	0.644	3.050	3.747
GSPF	2.852	0.465	2.852	4.119	2.635	0.540	2.635	3.526	3.218	0.536	3.218	4.335	2.984	0.624	2.984	3.722
RSCF	2.891	0.476	2.891	4.126	2.667	0.552	2.667	3.529	3.264	0.548	3.264	4.347	3.018	0.637	3.018	3.725
KINDX	2.916	0.483	2.916	4.131	2.705	0.563	2.705	3.544	3.290	0.556	3.290	4.353	3.058	0.649	3.058	3.741
OECDIP	2.887	0.476	2.887	4.121	1.213	0.061	1.213	4.724	3.258	0.548	3.258	4.341	1.400	0.092	1.400	4.478
Heating oil																
GECON	**2.592**	**0.439**	**2.592**	**3.844**	**3.337**	**0.636**	**3.337**	**4.126**	**2.926**	**0.506**	**2.926**	**4.050**	**3.759**	**0.730**	**3.759**	4.346
RCPF	2.472	0.404	2.472	3.820	1.607	0.121	1.607	4.486	2.798	0.468	2.798	4.024	1.858	0.164	1.858	**4.473**
GSPF	2.471	0.404	2.471	3.816	3.177	0.587	3.177	4.088	2.797	0.469	2.797	4.021	3.588	0.677	3.588	4.307

RSCF	2.509	0.417	2.509	3.817		3.248	0.610	3.248	4.103	2.839	0.482	2.839	4.023		3.666	0.702	3.666	4.323
KINDX	2.473	0.405	2.473	3.817		3.154	0.581	3.154	4.080	2.798	0.469	2.798	4.021		3.563	0.671	3.563	4.297
OECDIP	2.483	0.409	2.482	3.814		3.235	0.606	3.235	4.100	2.810	0.473	2.810	4.019		3.651	0.697	3.651	4.320
Natural gas																		
GECON	**4.653**	**1.053**	**4.653**	4.490		0.922	0.131	0.922	2.425	**5.246**	**1.197**	**5.246**	4.754		1.049	0.158	1.049	2.531
RCPF	1.662	0.136	1.662	4.390		**0.935**	**0.140**	**0.935**	2.383	1.968	0.189	1.968	4.418		**1.064**	**0.167**	**1.064**	2.494
GSPF	2.024	0.233	2.024	4.097		0.885	0.121	0.885	2.413	2.382	0.302	2.382	4.253		1.009	0.147	1.009	2.515
RSCF	1.379	0.003	1.379	**23.153**		0.879	0.121	0.879	2.403	1.498	0.000	1.498	**156.836**		1.003	0.146	1.003	2.505
KINDX	3.367	0.563	3.367	4.426		0.882	0.124	0.882	2.380	3.183	0.469	3.183	4.585		1.005	0.150	1.005	2.484
OECDIP	3.098	0.583	3.098	4.001		0.664	0.051	0.664	**2.733**	3.576	0.689	3.576	4.254		0.761	0.068	0.761	**2.740**

Note: Realized volatility (RV), global economic conditions indicator (GECON), real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX), and OECD+6NME industrial production (OECDIP). For each energy source, there are four measures – Return, Volatility, Certainty equivalent Return (CER) and Sharpe Ratio (SP). The leverage ratio is denoted by θ, with leverage ratio equals one indicating no leverage. We set the leverage ratio to 6 and 8; and set the risk aversion level to 3.

The results in Table 6 show that the GARCH-MIDAS-GECON model provides higher economic gains but with higher risks than the other GARCH-MIDAS model variants, when risk aversion level and leverage ratio are assumed to be 3 and 6, respectively; in the case of WTI (both spot and futures [except for RCPF]). A similar result is observed with respect to natural gas, but not with Brent crude and heating oil, where GARCH-MIDAS-GECON is consistently found to provide higher economic gains but with higher risks. In the case of natural gas, GARCH-MIDAS-GECON does not present economic gains over the GARCH-MIDAS-RCPF when future prices are considered. A consistently observed feat across the energy (spot and futures) is that high returns are associated with high risks.

The results are not markedly different when the leverage parameter is set to 8, with the same risk aversion level. Across all energy sources, the economic gains resulting from GARCH-MIDAS-GECON are mostly greater than those of the GARCH-MIDAS- (RCPF, GSPF, RSCF, KINDX, and OECDIP) model. The associated risks are mostly higher in each of the former than in the latter. From the foregoing, although the incorporation of economic activity proxies provides some economic gains, the associated risk levels are high and insensitive to the choice of leverage ratio, as higher gains are mostly associated with higher risks in both cases; that is, when the leverage ratio is set to either 6 or 8. Imperatively, accounting for economic activity in the predictive model for oil volatility does not only statistically improve prediction but also presents some economic gains, which qualifies such economic activity as a relevant predictor.

5 CONCLUSION

The significant role of global economic activity in the predictability of the future path of energy demand is not new. What is new, however, is how to determine the best indicator among the various alternative indicators for global economic activity. The literature on the subject is replete with the use of world industrial production as a proxy for global economic activity, which does not seem to capture this activity properly. Thus, this study examines the role of global economic activity in the predictability of energy market volatility using six alternative indicators, including one recently developed by Baumeister et al. (2020).

Our interest lies in the volatility of the energy market rather than returns as the former measures the extent of uncertainty in the market, which is a crucial factor when making investment decisions and, by extension, in determining expected/risk-adjusted returns on investment. Given the available data frequencies for the variables of interest (daily energy prices for crude oil, heating oil, and natural gas, and monthly data for the global economic activity), we adopt the GARCH-MIDAS approach. We first analyze crude oil and thereafter extend to other energy sources, namely heating oil and natural gas for robustness. The relative predictive powers of the six alternative indicators of global economic activities are evaluated using multiple out-of-sample forecast horizons based on a 50% data split between the in-sample and out-of-sample forecasts, relying on the rolling window approach to forecasting.

Our predictability results lend support to the negative relationship between global economic activity and crude oil market volatility regardless of whether the spot price or futures price is considered. Further analyses involving heating oil and natural gas offer the same conclusion. Our forecast evaluation of the various indicators validates the use of GECON (Baumeister et al., 2020) as a newly developed indicator of global economic activity when forecasting energy market volatility. These conclusions are robust to multiple forecast horizons and alternative measures of energy sources. We also find some economic gains from incorporating the economic activity proxies, with higher returns being associated with higher risks, which may be invariant to the leverage ratio considered.

Our results have important implications for both investors and policymakers. In particular, by using the information content of the broad measure of economic conditions around the world, investors could accurately forecast the volatility of energy market returns, which could help them to design optimal portfolios, especially under the current extreme situation of deteriorating economic conditions due to the outbreak of COVID-19. Moreover, given that oil market volatility captures economic uncertainty, accurate forecasting would provide information about the future path of the domestic economy contingent on the evolution of uncertainty, which can then be incorporated into mixed-frequency models to produce forecasts of wide ranges of low-frequency variables measuring domestic economic activity, thus allowing the design of appropriate policy responses to prevent the possibility of economic downturns.

In future research, it would be interesting to use GECON, a new measure of global economic conditions, to forecast the volatility of cryptocurrencies along the lines of Walther et al. (2019), which have recently emerged as an important alternative investment option for economic agents, relative to traditional financial assets.

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Biographies

Afees Salisu, PhD, is the current Director and Research Professor of the Centre for Econometric and Allied Research (CEAR), University of Ibadan. He is also affiliated with the Global Humanistic University (GHU) as a University Professor & Doctoral Advisor and Research Fellow of the Institute of Business Research, University of Economics Ho Chi Minh City, Vietnam. He is ranked among Top 5 research economists in the world (see https://ideas.repec.org/f/psa997.html), Top 1 in Africa (https://ideas.repec.org/cgi-bin/rank.cgi?psa997&KxXC) and Top 1 (https://ideas.repec.org/cgi-bin/rank.cgi?psa997&KxXC) in Nigeria based on the ranking by Research Papers in Economics (RePEc) Network which archives the largest database of economists in the world.

Rangan Gupta is a Professor at the Department of Economics, University of Pretoria, South Africa. He completed his PhD in May 2005 from the Department of Economics, University of Connecticut, USA. He then joined the Department of Economics, University of Pretoria, as a Senior Lecturer in August 2005. He obtained his B.Sc. (Honours) degree in Economics from the R.K.M.R. College, Narendrapur, India, and M.Sc. degree in Economics from the University of Calcutta, India. His academic interests are mainly Monetary Theory and Policy, and Time Series Econometrics, and he has authored and co-authored many articles in peer-reviewed journals and book chapters in these areas of research. He is also associated with multiple journals as associate editor and in the editorial boards.

Elie Bouri has been a prolific publisher in the fields of investment, financial markets, risk management, energy finance and economics, and cryptocurrency finance and economics. He has been ranked at number 33 out of 9626 scientists worldwide in the field of Finance by a Stanford-led study. His research has appeared in high impact factor journals such as Journal of Business Ethics and has twice been profiled in the CFA Digest and Forbes, along with others.

Professor Qiang Ji is deputy director of Institute of System Analysis and Management in Institutes of Science and Development, Chinese Academy of Sciences (ISDCAS). He engaged in the research of energy and climate finance, energy strategic management, big data and energy prediction, and published more than 150 articles in peer-reviewed journals. He was selected into Elsevier's list of China's Most Cited Scholars in 2020 and the World's Top 2 Scientists List published by Stanford University. He presides the Excellent Young Scientists Fund of China supported by NSFC. He is the co-founder of China Energy Finance Network, vice president of International Society for Energy Transition Studies and Society for the Studies of Climate Finance. He served as senior editor and associate editor for a series of financial journals, such as International Review of Financial Analysis, Finance Research Letters, International Review of Economics and Finance, and so forth.

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