Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Forecasting China’s crude oil futures volatility: New evidence from the MIDAS-RV model and COVID-19 pandemic

Zhonglu Chen, Yong Ye, Xiafei Li

School of Economics and Management, Southwest Jiaotong University, Chengdu, China

ARTICLE INFO

Keywords:
China’s crude oil futures volatility
MIDAS
Jump
Leverage effect
COVID-19 pandemic

ABSTRACT

In this study, we focus on the role of jumps and leverage in predicting the realized volatility (RV) of China’s crude oil futures. We employ a standard mixed data sampling (MIDAS) modeling framework. First, the in-sample results indicate that the jump and leverage effects are useful in predicting the RV of Chinese crude oil futures. Second, the out-of-sample results suggest that jump has very significant predictive power at the one-day-ahead horizon while the leverage effect contains more useful information for long-term predictions. Moreover, our results are supported by a number of robustness checks. Finally, we find new evidence that the prediction model that considers the leverage effect has the best predictive power during the COVID-19 pandemic.

1. Introduction

China crude oil futures listed on the Shanghai Futures Exchange Shanghai International Energy Trading Center on March 26, 2018, were aimed at global investors and to facilitate convenient trading, settlement and delivery of crude oil futures. Both parties to the transaction can use RMB as the transaction currency to directly conduct related transactions and settlement, thereby simplifying the transaction process, improving transaction efficiency, and further promoting the development of China’s crude oil futures. It is the first crude oil futures contract in China and the first in the world to be denominated in RMB. Ji and Zhang (2019) detail the characteristics of Chinese crude oil futures. An increasing number of industrial production companies, market participants and media are paying attention to Chinese crude oil futures.

Volatility forecasts play an important role in risk management, asset pricing, and portfolios, and methods of improving the accuracy of volatility prediction represent an important and difficult issue (see, e.g., Ji and Guo, 2015; Rossi and Fantazzini, 2015; Wang et al., 2016; Degiannakis and Filis, 2017; Ma et al., 2017; Wang et al., 2018a; Ma et al., 2019; Zhang et al., 2019b; Bai et al., 2020; Liang et al., 2020a; Liang et al., 2020b; Wei et al., 2020; Zhang et al., 2020; Zhang et al., 2021). In addition, numerous studies have examined the factors that affect oil prices (see, e.g., Elder et al., 2013; Zhang and Cao, 2013; Sèvi, 2014; Wang et al., 2016; Zhang, 2017; Jing et al., 2018; Wang et al., 2018b; Zhang et al., 2019a). Following Buncic and Gisler (2017), and they stress the importance of jumps and leverage in predicting global stock market volatility. However, relatively limited research has focused on the realized volatility forecasting of Chinese crude oil futures. This study mainly investigates the role of jumps and leverage in predicting the realized volatility of China’s crude oil futures. First, we employ the MIDAS model of Ghysels et al. (2007) as a benchmark model to model and predict China’s oil futures price RV, and the proposed model is referred to as MIDAS-RV. Second, we can obtain the MIDAS-RV-CJ and MIDAS-RV-L models by adding jump and negative returns to the MIDAS-RV model, respectively. Third, we employ prevailing evaluation methods of model confidence set (Hansen et al., 2011) to assess out-of-sample predictions. Finally, we perform a number of robustness checks, including different $k_{\text{max}}$, out-of-sample $R^2$, and alternative benchmark models.

Our study contributes to the literature from three perspectives. First, our paper is closely linked to recent literature on the detection of China’s crude oil volatility predictability. Wang et al. (2021) investigate the prediction ability of jump, jump intensity, and leverage effect for China’s crude oil futures employing different kinds of HAR-type models. However, we use a benchmark model that is better than HAR. We employ the MIDAS-RV and extension models to predict the RV of Chinese crude oil futures with high-frequency data. Second, we investigate the role of jumps and leverage in predicting the RV of Chinese crude oil futures. The empirical results indicate that the MIDAS-RV-CJ model exhibits more accurate forecasts at the one-day-ahead horizon while the MIDAS-RV-L model can perform better at long-term predictions. Third, we explore the economic value performance of the prediction models.
Table 1
Descriptive statistics.

|        | RV   | CJ  | Return |
|--------|------|-----|--------|
| Mean   | 2.476| 0.553| -0.006 |
| Std.dev| 1.912| 0.997| 0.010  |
| Skewness| 2.336| 2.661| -2.521 |
| Kurtosis| 7.385| 8.965| 7.223  |

Jarque-Bera 1342.676*** 1910.955*** 1365.114***
Q (5) 250.376*** 19.562*** 6.116***
Q (22) 481.928*** 70.603*** 17.130***
ADF -13.717*** -19.697*** -20.118***

Notes: This table represents descriptive statistics for all variables used in this study. The whole sample period is from March 26, 2018, to January 21, 2020, and contains 431 observations. *** Significant at the 1% level.

and find that the MIDAS-RV-CJ model has the highest average expected utility. Taking into account the particularity of the COVID-19 pandemic, we further use samples during the COVID-19 epidemic to conduct an out-of-sample prediction analysis and find that the leverage effect is the best predictor of the COVID-19 pandemic. Our conclusions have important applications for investment decisions during the COVID-19 pandemic.

The remainder of the paper is organized as follows. We present the methodology and data in Section 2. Section 3 presents the full-sample estimation, out-of-sample prediction results and long-term prediction results. In Section 4, we perform robustness checks. Section 5 shows the economic value test, the empirical results of the use of an expanded sample and the out-of-sample forecasting performance during the COVID-19 pandemic. Finally, Section 6 concludes the paper.

2. Methodology and data

2.1. Prediction models

In this study, we utilize the standard MIDAS model proposed by Ghysels et al. (2007) as the benchmark model. The MIDAS-RV model can be expressed by the following equation:

\[ RV_t = \beta_0 + \beta_1 \sum_{i=1}^{\kappa_{\text{max}}} b(k, \theta^{RV}) RV_{t-i} + \epsilon_t. \]  

where \( RV_t = \sum_{j=1}^{F} r_{j,t} \), \( r_{j,t} \) indicates the \( j \)th intraday return at Day \( t \) and \( F \) indicates the number of observations. \( RV_{t-k} \) represents the lags \( t-k \) of \( RV \). In this paper, we choose \( \kappa_{\text{max}} \) that is equal to 22. The weight \( b(k, \theta^{RV}) \) can be written as follows:

\[ b(k, \theta^{RV}) = f \left( \frac{k}{\kappa_{\text{max}}} \frac{\theta^{RV}_{1}}{\theta^{RV}_{2}} \right) \left/ \sum_{k=1}^{\kappa_{\text{max}}} f \left( \frac{k}{\kappa_{\text{max}}} \frac{\theta^{RV}_{1}}{\theta^{RV}_{2}} \right) \right. \]  

where \( f(a, b) = a^{a-1} (1 - z)^{b-1} / \varphi(a - b) \) and \( \varphi(a, b) = \Gamma(a) \Gamma(b) / \Gamma(a + b) \). According to the studies of Santos and Ziegelmann (2014) and Conrad and Loch (2015), we assign the parameter \( \theta_1 \) of the weighting scheme to 1. Therefore, the weighted values are only dependent on the parameter \( \theta_2 \), which should be larger than 1 to ensure nonnegative volatilities. To investigate the role of jumps, we design the MIDAS-RV-CJ model, defined as follows:

\[ RV_t = \beta_0 + \beta_1 \sum_{i=1}^{\kappa_{\text{max}}} b(k, \theta^{RV}) CRV_{t-k} + \beta_2 \sum_{i=1}^{\kappa_{\text{max}}} b(k, \theta^{CRV}) CJ_{t-k} + \epsilon_t. \]  

We also consider the leverage effect of the MIDAS-RV model to design the MIDAS-RV-L model, which is given as follows:

\[ RV_t = \beta_0 + \beta_1 \sum_{i=1}^{\kappa_{\text{max}}} b(k, \theta^{RV}) RV_{t-k} + \beta_2 \sum_{i=1}^{\kappa_{\text{max}}} b(k, \theta^{RV}) r_{t-k} + \epsilon_t. \]  

where \( r_{t-k} = \min(r_{t-k}, 0) \), which includes the leverage effect and is helpful to explore the impact of lagged negative returns on future China crude oil RV.

2.2. Data

We collect the 5-min high-frequency data of China’s crude oil futures main contract from the Shanghai International Energy Exchange. The whole sample period is from March 26, 2018, to January 21, 2020, and contains 431 observations. We report the standard descriptive statistics for all variables in Table 1. Based on the statistical results, we find that
all the time series of these variables are stationary. In addition, we plot the evolution of 5-min crude oil futures daily RV, jump, and negative return over the full sample in Fig. 1.

3. Empirical results

3.1. Full-sample estimation results

We report the full-sample estimation results of all prediction models in Table 2. It is evident that the values of \( \beta_3 \) for the three prediction models are negative and significant at the 1% level, and the values of \( \beta_1 \) for the three models are significantly positive. We find that the estimated result of \( \beta_2 \) is positive and significant at the 1% level, implying that the jump will lead to high fluctuation of the next day. Second, from the estimation results of the MIDAS-RV-L model, the estimated value of \( \beta_1 \) is \(-37.679\) and significant at the 5% level, suggesting that the leverage effect also has a significant impact on Chinese crude oil futures volatility. Therefore, the in-sample results indicate that the jump and leverage effects are useful in predicting the RV of Chinese crude oil futures.

3.2. Out-of-sample prediction results

In this paper, we employ the rolling window approach to generate out-of-sample predictions, while the out-of-sample prediction length is 130. To assess the forecasting quality, we use the following two loss functions:

\[
QLIKE = \frac{1}{q} \sum_{t=q+1}^{\infty} \left( \ln \left( \frac{\hat{RV}_t}{RV_t} \right) \right)^2 . \tag{5}
\]

\[
MSE = \frac{1}{q} \sum_{t=q+1}^{\infty} \left( RV_t - \hat{RV}_t \right)^2 . \tag{6}
\]

where \( m \) and \( q \) denote the length of the in-sample estimation period and out-of-sample evaluation period, respectively. It is well known that the MCS test of Hansen et al. (2011) is widely used in many studies of forecasting volatility (see, e.g., Wei et al., 2015; Rossi and Fantazzini, 2015; Gong and Lin, 2017). The MCS test is very useful for determining whether the forecasting model used has a statistically significant difference in out-of-sample prediction performance without specifying a benchmark model. We select a 25% significance level to ascertain the MCS p values. Instances in which the MCS p value is larger than 0.25 are highlighted in bold. Instances in which the MCS p value is equal to 1 are highlighted in bold and underlined, implying that this prediction model exhibits the best forecasting performance. We report the MCS p values in Table 3. We find that the MIDAS-RV and MIDAS-RV-L models cannot survive in MCS because their p values are less than 0.25 at one-day-ahead predictions. Obviously, only the MIDAS-RV-CJ model can pass the MCS test and yield the largest p values of 1 under the two loss functions of QLIKE and MSE, implying that the MIDAS-RV-CJ model exhibits the best predictions. These results provide evidence that a jump is very important at one-day-ahead predictions. The possible reason is that some news of international crude oil price is closely related to the volatility of Chinese crude oil future prices, and investors will make investment portfolios based on the news of international crude oil. Investors are also more sensitive when markets take big jumps. As a result, models that take into account jumps perform better when predicting volatility over the next day.

3.3. Long-term prediction results

Some market participants may focus on long-term prediction performance. However, we report the long-term prediction results in Table 4. We consider three horizons: 5-day-ahead (one week), 10-day-ahead (two weeks), and 22-day-ahead (one month). First, for 5-day-ahead predictions, we observe that the MIDAS-RV-L model yields the largest MCS p values under QLIKE and MSE; however, the MIDAS-RV and MIDAS-RV-CJ models perform poorly. Second, for 10-day-ahead predictions, we find that the MIDAS-RV model can pass the MCS test under the loss function of MSE, and the MIDAS-RV-L model still yields the largest MCS p values under QLIKE and MSE. Third, for 22-day-ahead prediction, the MIDAS-RV-L model has the best predictive power. Therefore, we can conclude that the leverage effect is more useful for long-term predictions.

4. Robustness checks

To ensure that our results are robust, we perform many tests in this section, including different \( k^{max} \), out-of-sample \( R^2 \), alternative benchmark model, and direction-of-change test. In addition, these robustness test methods are also widely used in financial forecasting research (see, e.g., Yang et al., 2015; Tian et al., 2017; Li et al., 2020a; Li et al., 2020b; Wen et al., 2020; Zhang et al., 2020; Li et al., 2021; Lu et al., 2021; Zhang et al., 2021).

4.1. Different \( k^{max} \)

In the previous empirical analysis, we set \( k^{max} \) to 22. Different \( k^{max} \) values may lead to completely different results. Therefore, we additionally consider two \( k^{max} \) values of 44 and 66. Table 5 summarizes the MCS p values for different \( k^{max} \). We observe that only the MIDAS-RV-CJ model can survive in MCS and yield the largest MCS p values under QLIKE and MSE, implying that the MIDAS-RV-CJ model exhibits higher prediction accuracy at a one-day-ahead horizon. In short, our results are robust to different \( k^{max} \) values.

1 For more information about MCS, please refer to Hansen et al. (2011).
**Table 4**

MCS p values for long-term predictions.

| Prediction models | H = 5                  | H = 10                  | H = 22                  |
|-------------------|------------------------|------------------------|------------------------|
|                   | QLIKE | MSE | SeimQ | Range | Range | Range | Range | Range | Range | Range | Range | Range |
| MIDAS-RV          |        |     |       | 0.0831 | 0.0831 | 0.0274 | 0.0724 | 0.1136 | 0.1367 | 0.6004 | 0.6004 | 0.1202 | 0.1202 | 0.4686 | 0.4686 |
| MIDAS-RV-CJ       | 0.0042 | 0.0022 | 0.0023 | 0.0009 | 0.0001 | 0.0000 | 0.0008 | 0.0011 | 0.0010 | 0.0003 | 0.0003 | 0.0646 | 0.0646 |
| MIDAS-RV-L        | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |

Notes: This table summarizes the MCS p values for long-term predictions (i.e., H = 5, H = 10, and H = 22). Instances in which the MCS p value is greater than 0.25 are highlighted in bold. Instances in which the MCS p value is equal to 1 are highlighted in bold and underlined, and they imply that this prediction model exhibits the best forecasting performance. The out-of-sample prediction length is 130.

**Table 5**

MCS p values for different $k^{max}$.

| Prediction models | Panel A: $k^{max} = 44$ | Panel B: $k^{max} = 66$ |
|-------------------|------------------------|------------------------|
|                   | QLIKE | SeimQ | MSE | Range | Range | Range | Range |
| MIDAS-RV          | 0.0191 | 0.0191 | 0.0533 | 0.0533 |          |        |        |
| MIDAS-RV-CJ       | 1.0000 | 1.0000 | 1.0000 | 1.0000 |          |        |        |
| MIDAS-RV-L        | 0.0128 | 0.0203 | 0.0193 | 0.0107 |          |        |        |
| MIDAS-RV          | 0.0159 | 0.0159 | 0.0743 | 0.0107 |          |        |        |
| MIDAS-RV-CJ       | 1.0000 | 1.0000 | 1.0000 | 1.0000 |          |        |        |
| MIDAS-RV-L        | 0.0005 | 0.0004 | 0.0202 | 0.0109 |          |        |        |

Notes: This table summarizes the MCS p values for different $k^{max}$. Instances in which the MCS p value is greater than 0.25 are highlighted in bold. Instances in which the MCS p value is equal to 1 are highlighted in bold and underlined, and they imply that this prediction model exhibits the best forecasting performance. The out-of-sample prediction length is 130.

**Table 6**

Out-of-sample $R^2$.

| Prediction models | $R^2$ (%) | MSPE-Adj. | p value |
|-------------------|-----------|-----------|---------|
| MIDAS-RV-CJ       | 3.284**   | 2.043     | 0.021   |
| MIDAS-RV-L        | −4.236    | −2.254    | 0.987   |

Notes: This table shows the out-of-sample $R^2$ results. Positive $R^2_{OOS}$ values indicate that this prediction model exhibits superior predictive power than the benchmark model of the MIDAS-RV model. ** Significant at the 5% level.

**4.2. Out-of-sample $R^2$**

In this subsection, we use alternative evaluation of out-of-sample $R^2$ ($R^2_{OOS}$), defined as:

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T} (RV_{m+k} − \bar{RV}_{m+k})^2}{\sum_{t=1}^{T} (RV_{m+k} − \bar{RV}_{m+k,bench})^2}$$

(7)

where $RV_{m+k}$, $\bar{RV}_{m+k}$ and $\bar{RV}_{m+k,bench}$ are the actual RV, forecast RV, and benchmark RV of Day $m + k$, respectively, and the definitions of $m$ and $q$ are consistent with those in the loss functions QLIKE and MSE. Positive $R^2_{OOS}$ values indicate that this prediction model exhibits superior predictive power than the benchmark model of the MIDAS-RV model. From the results of Table 6, we find that the $R^2_{OOS}$ value of the MIDAS-RV-CJ model is 3.384% and significant at the 5% level, while the $R^2_{OOS}$ value of the MIDAS-RV-CJ model is negative. In other words, our results are robust based on the out-of-sample $R^2$ test.

**4.3. Alternative benchmark model**

In this subsection, we employ the heterogeneous autoregressive realized volatility model of Corsi (2009) as an alternative benchmark model. Mathematically, the HAR-RV model is defined as follows:

$$RV_t = β_0 + β_1RV_{t−1} + β_2RV_{t−5/2} + β_3RV_{t−22/2} + ϵ_t.$$  

(8)

$$RV_t'_{h−1} = \frac{1}{h}(RV_{t−1} + \ldots + RV_{t−h−1})$$  

(9)

where $RV_{t−1}$, $RV_{t−5/2}$, and $RV_{t−22/2}$ indicate the daily, weekly, and monthly HAR components, respectively. Naturally, we can obtain the HAR-RV-CJ and HAR-RV-L models by adding jump and negative return to the HAR-RV model. Table 7 shows the MCS p values when we use an alternative benchmark model of HAR-RV at one-day-ahead predictions. It can be seen that under two loss functions of QLIKE and MSE, the MIDAS-RV-CJ model has the largest MCS p values of 1. However, other competing models fail to enter the MCS with a significance level of 25%. In summary, when we consider HAR-type models, our MIDAS-RV-CJ model can still considerably improve the prediction accuracy of Chinese crude oil futures volatility at a one-day-ahead horizon (see Table 7).

**4.4. Direction-of-change test**

In this subsection, we further use the direction-of-change (DoC) ratio to evaluate the ability of the forecasting models to forecast the direction of change in China’s oil futures volatility. We assume that $p_t$ is a dummy variable. If the predictive direction of volatility of the model is correct at Day $t$, then take 1; otherwise, 0.

**Table 8**

DoC test.

| Forecasting models | SR (%) | stat. value | p value |
|-------------------|--------|-------------|---------|
| MIDAS-RV          | 0.6589*** | 3.6991 | 0.0001 |
| MIDAS-RV-CJ       | 0.7364*** | 5.4191 | 0.0000 |
| MIDAS-RV-L        | 0.6744*** | 4.0584 | 0.0000 |

Notes: This table shows the results of the direction-of-change test. *** Significant at the 1% level.
Notes: The tale reports the in-sample estimation results using an expanded sample. The prediction models during the COVID-19 pandemic, the constant Sharpe ratio is 0.4, and the risk aversion coefficient is 2.

Table 10
In-sample analysis using an expanded sample.

| Prediction models | MIDAS-RV | MIDAS-RV-CJ | MIDAS-RV-L |
|-------------------|----------|-------------|------------|
| $\hat{\nu}$      | –1.425 *** | –2.640 *** | –2.625 *** |
| $\hat{\theta}$    | 0.830 *** | 0.695 ***   | 0.712 ***  |
| $\beta$           | 26.049 *** | 31.977 ***  | 19.828 *** |
| $\gamma$          | –5.160 *** | –16.757 ** |
| LogL              | –422.460 | –422.340    | –414.980   |

Notes: The tale reports the in-sample estimation results using an expanded sample. The expanded sample period is from March 26, 2018, to April 30, 2021, and contains 751 observations.

\[
p_i = \begin{cases} 
  1 & \text{if } RV_i > RV_{i-1} \text{ and } \hat{RV}_i > RV_{i-1} \\
  1 & \text{if } RV_i < RV_{i-1} \text{ and } \hat{RV}_i < RV_{i-1} \\
  0 & \text{otherwise}
\end{cases}
\]  

(10)

Mathematically, the DoC rate can be computed as $1/\sum_{i=m+1}^{q} p_i$. Then, the nonparametric test of Pesaran and Timmermann (1992) is used to examine the null hypothesis that the DoC ratio of a target model is smaller than that of a random walk. Obviously, the direction prediction accuracy of all models is very good, exceeding 65% (see Table 8). Moreover, the MIDAS-RV-CJ model can produce the best directional prediction accuracy, reaching more than 73%.

5. Extensions

In this section, we first explore the economic value performance of the prediction models, and second, we conduct an empirical test using an expanded sample. Finally, we study the prediction performance of the prediction models during the COVID-19 pandemic.

5.1. Economic value

In this subsection, we further evaluate the economic value of each forecasting model using a mean-variance utility method introduced by Bollerslev et al. (2018). We follow the influential study of Bollerslev et al. (2018), which relies exclusively on volatility forecasts to quantify utility benefits. Mathematically, the reported utility is defined as follows:

\[
U \left( \hat{RV}_{i+1} \right) = \frac{1}{q} \sum_{j=1}^{q} \frac{\left( \sqrt{RV_{i+1}^2 - 2 RV_{i+1}} \right)}{q}.
\]  

(11)

where the definitions of $m$ and $q$ are consistent with those in the above loss functions. Following the work of Bollerslev et al. (2018), the annualized Sharpe ratio and coefficient of relative risk aversion are set to $SR = 0.4$ and $\gamma = 2$, respectively. The results of the averaged expected utility are shown in Table 9. We find that the MIDAS-RV-CJ model has the highest average expected utility at 3.3307, 3.3472, and 3.3453 when $k_{\text{max}} = 22$, $k_{\text{max}} = 44$, and $k_{\text{max}} = 66$, respectively.

Table 11
MCS test results using an expanded sample.

| Prediction models | QUIKE | MSE |
|-------------------|------|-----|
|                  | Range | SeimQ | Range | SeimQ |
| Panel A: $k_{\text{max}} = 22$ | MIDAS-RV | 0.1345 | 0.1360 | 0.2116 | 0.3671 |
|                  | MIDAS-RV-CJ | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
|                  | MIDAS-RV-L | 0.1345 | 0.1360 | 0.5803 | 0.5803 |
| Panel B: $k_{\text{max}} = 44$ | MIDAS-RV | 0.1318 | 0.1165 | 0.1870 | 0.3196 |
|                  | MIDAS-RV-CJ | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
|                  | MIDAS-RV-L | 0.1318 | 0.1165 | 0.5055 | 0.5055 |
| Panel C: $k_{\text{max}} = 66$ | MIDAS-RV | 0.1399 | 0.1210 | 0.1891 | 0.3341 |
|                  | MIDAS-RV-CJ | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
|                  | MIDAS-RV-L | 0.1399 | 0.1210 | 0.5233 | 0.5233 |

Notes: This table shows the MCS p values using an expanded sample. Instances in which the MCS p value is greater than 0.25 are highlighted in bold. Instances in which the MCS p value is equal to 1 are highlighted in bold and underlined, and they imply that this prediction model exhibits the best forecasting performance. Panels A, B, C show the results of different $k_{\text{max}}$ values.

Table 12
MCS test results during the COVID-19 pandemic.

| Prediction models | QUIKE | MSE |
|-------------------|------|-----|
|                  | Range | SeimQ | Range | SeimQ |
| Panel A: $k_{\text{max}} = 22$ | MIDAS-RV | 0.3051 | 0.3913 | 0.0886 | 0.0806 |
|                  | MIDAS-RV-CJ | 0.3913 | 0.3913 | 0.0886 | 0.0806 |
|                  | MIDAS-RV-L | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Panel B: $k_{\text{max}} = 44$ | MIDAS-RV | 0.3170 | 0.3957 | 0.1020 | 0.1222 |
|                  | MIDAS-RV-CJ | 0.4416 | 0.4416 | 0.1140 | 0.1222 |
|                  | MIDAS-RV-L | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Panel C: $k_{\text{max}} = 66$ | MIDAS-RV | 0.3051 | 0.3913 | 0.0886 | 0.0806 |
|                  | MIDAS-RV-CJ | 0.3913 | 0.3913 | 0.0886 | 0.0806 |
|                  | MIDAS-RV-L | 1.0000 | 1.0000 | 1.0000 | 1.0000 |

Notes: This table shows the MCS p values during the COVID-19 pandemic. The out-of-sample forecast period is from January 3, 2020, to April 30, 2021. Panels A, B, C show the results of different $k_{\text{max}}$. Instances in which the MCS p value is greater than 0.25 are highlighted in bold. Instances in which the MCS p value is equal to 1 are highlighted in bold and underlined, and they imply that this prediction model exhibits the best forecasting performance.

$k_{\text{max}}$ is equal to 22, 44, and 66, respectively. This evidence also tells market participants of China’s crude oil futures that more consideration of the impact of jumps can bring good economic value performance.

5.2. Expanded sample

The outbreak of the COVID-19 pandemic has severely affected the operation of the global economy, and all walks of life have been severely impacted. Financial or energy-related research during the COVID-19 pandemic has become an important hot topic (see, e.g., Ashraf, 2020; Goodell, 2020; Li et al., 2020; Sharif et al., 2020). Therefore, we use samples that include this period for further analysis. The expanded sample period is from March 26, 2018, to April 30, 2021, and contains 751 observations. Table 10 shows the in-sample estimation results using an expanded sample. We find that all parameters are significant, which is basically consistent with the conclusions in Table 2. Table 11 shows the MCS p values using an expanded sample. Obviously, even if our sample period includes the period of the COVID-19 pandemic, the MIDAS-RV-CJ model is still the best model. Therefore, our results are robust to the use of an expanded sample.
leverage is more intuitive. Table 13 shows the out-of-sample economy regressed, and the continuous bad market had a great impact Second, during the COVID-19 pandemic, instability increased, the abnormal jumps because they may contain more impact information. Normal and moderate leverage is considered by investors to be normal most of the time. Investors are more sensitive to price volatilities most of the time. Investors are more sensitive to abnormal jumps because they may contain more impact information. Second, during the COVID-19 pandemic, instability increased, the economy regressed, and the continuous bad market had a great impact on investors, causing investors to panic. At this time, the volatility jump information is second because the negative return corresponding to the leverage is more intuitive. Table 13 shows the out-of-sample R² results during the COVID-19 pandemic. We observe that regardless of the value of K, the MIDAS-RV-L model can produce a significantly positive R²OOS value. This result reaffirms that the leverage effect is the best predictor of the COVID-19 pandemic.

5.3. Out-of-sample forecasting performance during the COVID-19 pandemic

In this subsection, we focus on investigating the prediction performance of the prediction model during the COVID-19 pandemic. Table 12 reports the MCS test results during the COVID-19 pandemic. We observe that when K is equal to 22, 44, and 66, the MIDAS-RV-L model can generate the largest MCS p values of 1 under the two loss functions of QLIKE and MSE, implying that this prediction model is the best model during the COVID-19 pandemic. Why is the predictive power of the leverage effect stronger during the COVID-19 pandemic? This is an interesting question. The possible reasons are that during the period of economic prosperity or stability, a continuous bad market rarely occurs. Normal and moderate leverage is considered by investors to be normal most of the time. Investors are more sensitive to abnormal jumps because they may contain more impact information. Second, during the COVID-19 pandemic, instability increased, the economy regressed, and the continuous bad market had a great impact on investors, causing investors to panic. At this time, the volatility jump information is second because the negative return corresponding to the leverage is more intuitive. Table 13 shows the out-of-sample R² results during the COVID-19 pandemic. We observe that regardless of the value of K, the MIDAS-RV-L model can produce a significantly positive R²OOS value. This result reaffirms that the leverage effect is the best predictor of the COVID-19 pandemic.

6. Conclusions

This study mainly investigates the role of jumps and leverage in predicting the realized volatility (RV) of China’s crude oil futures. We employ the MIDAS-RV model as a benchmark model and design the MIDAS-RV-CJ and MIDAS-RV-L models. We collect the 5-min high frequency data of China’s crude oil futures main contract from the Shanghai International Energy Exchange. First, the in-sample results indicate that the jump and leverage effects are useful in predicting the RV of Chinese crude oil futures. Second, based on the QLIKE and MSE loss functions, the MCS test results suggest that jump has very significant predictive power at one-day-ahead horizon out-of-sample predictions while the leverage effect contains more useful information for long-term predictions. Finally, our results are supported by a number of robustness checks, including different k_max values of 44 and 66, out-of-sample R², alternative benchmark model of HAR-RV, and Direction-of-Change test.

In addition, we explore the economic value performance of the prediction models and find that the MIDAS-RV-CJ model has the highest average expected utility. Taking into account the particularity of the COVID-19 pandemic, we further use samples during the COVID-19 epidemic to conduct an out-of-sample prediction analysis and find that the leverage effect is the best predictor of the COVID-19 pandemic. The relevant empirical results of the paper have important applied economic significance. First, investors, market participants, and policy-makers can use the useful predictors found in this study when predicting the RV of China’s crude oil futures. More importantly, by investigating the predicted performance during the COVID-19 epidemic, the new evidence provided has good guiding significance for investors and market participants. The factors found in this article can be used to predict the volatility of China’s crude oil futures more effectively, reduce investment risks, and achieve better returns.

Declaration of competing interest

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

Acknowledgments

This work is supported by the Humanities and Social Science Fund of Ministry of Education of China (21YJA630107).

References

Ashraf, B.N., 2020. Stock markets’ reaction to COVID-19: cases or fatalities? Res. Int. Bus. Finance, 101249.
Bai, L., Wei, Y., Wei, G., Li, X., Zhang, S., 2020. Infectious Disease Pandemic and Permanent Volatility of International Stock Markets: A Long-Term Perspective. Finance Research Letters, 101799.
Bollerslev, T., Hood, B., Huns, J., Pedersen, L.H., 2018. Risk everywhere: modeling and managing volatility. Rev. Financ. Stud. 31, 2729–2773.
Buncic, D., Gider, K.I., 2017. The role of jumps and leverage in forecasting volatility in international equity markets. J. Int. Money Finance 79, 1–19.
Conrad, C., Loch, K., 2015. Anticipating long-term stock market volatility. J. Appl. Econom. 30, 1090–1114.
Corde, F., 2009. A simple approximate long-memory model of realized volatility. J. Financ. Econom. 7, 174–196.
Degiannakis, S., Fila, G., 2017. Forecasting oil price realized volatility using information channels from other asset classes. J. Int. Money Finance 76, 28–49.
Elder, J., Miao, H., Ramchander, S., 2013. Jumps in oil prices: the role of economic news. Energy J. 217–237.
Ghysels, E., Sinko, A., Valkanov, R., 2007. MIDAS regressions: further results and new directions. Econom. Rev. 26, 53–90.
Gong, X., Lin, B., 2017. Forecasting the good and bad uncertainties of crude oil prices using a HAR framework. Energy Econ. 67, 315–327.
Goodell, J.W., 2020. COVID-19 and finance: agendas for future research. Finance Res. Lett., 101512.
Hansen, P.R., Lund, A., Nason, J.M., 2011. The model confidence set. Econometrica 79, 453–497.
Ji, Q., Guo, J.F., 2015. Oil price volatility and oil-related events: an Internet concern study perspective. Appl. Energy 137, 256–264.
Ji, Q., Zhang, D., 2019. China’s crude oil futures introduction and some stylized facts. Finance Res. Lett. 28, 378–380.
Jing, L., Feng, M., Ke, Y., Zhang, Y., 2018. Forecasting the oil futures price volatility: large jumps and small jumps. Energy Econ. 72.
Li, X., Li, B., Wei, G., Bai, L., Wei, Y., Liang, C., 2021. Return connectedness among commodity and financial assets during the COVID-19 pandemic: evidence from China and the US. Resour. Pol. 73, 102166.
Li, X., Wei, Y., Chen, X., Ma, F., Liang, C., Chen, W., 2020c. Which uncertainty is powerful to forecast crude oil market volatility? New evidence. Int. J. Finance Econom. Li, Y., Liang, C., Ma, F., Wang, J., 2020b. The role of the IDEM in predicting European stock market volatility during the COVID-19 pandemic. Finance Res. Lett. 36, 101749.
Liang, C., Li, Y., Ma, F., Wei, Y., 2021. Global equity market volatilities forecasting: a comparison of leverage effects, jumps, and overnight information. Int. Rev. Financ. Anal. 75, 101750.
Liang, C., Tang, L., Li, Y., Wei, Y., 2020a. Which Sentiment Index Is More Informative to Forecast Stock Market Volatility? Evidence from China. International Review of Financial Analysis, 101552.
Liang, C., Wei, Y., Li, X., Zhang, X., Zhang, Y., 2020b. Uncertainty and crude oil market volatility: new evidence. Appl. Econ. 52, 2945–2959.
Lu, X., Ma, F., Wang, J., Zha, B., 2021. Oil shocks and stock market volatility: new evidence. Energy Econ., 105567.
Ma, F., Liao, Y., Zhang, Y., Cao, Y., 2019. Harnessing jump component for crude oil volatility forecasting in the presence of extreme shocks. J. Empir. Finance 52, 40–55.
Ma, F., Wei, Y., Wang, C., He, F., 2017. Forecasting the volatility of crude oil futures using high-frequency data: further evidence. Empir. Econ. 55, 1–26.
Pesaran, M.H., Timmermann, A., 1992. A simple nonparametric test of predictive performance. J. Bus. Econom. Stat. 10, 461–471.
Rossi, E., Fantazzini, D., 2015. Long memory and periodicity in intraday volatility. J. Financ. Econom. 13, 922–961.
Sevi, B., 2014. Forecasting the volatility of crude oil futures using intraday data. Eur. J. Oper. Res. 235, 643–659.

Table 13

Out-of-sample R² results during the COVID-19 pandemic.

| Forecasting models | R²OOS (%) | MSPE-Adj. | p value |
|--------------------|----------|-----------|---------|
| Panel A: k max = 22 | -1.3850  | 0.2480    | 0.4021  |
| MIDAS-RV-CJ        | 4.3702***| 2.9023    | 0.0019  |
| MIDAS-RV-L         |          |           |         |
| Panel B: k max = 44 |          |           |         |
| MIDAS-RV-CJ        | 0.0989   | 0.8925    | 0.1861  |
| MIDAS-RV-L         | 4.1194***| 2.8699    | 0.0021  |
| Panel C: k max = 66 |          |           |         |
| MIDAS-RV-CJ        | -1.3850  | 0.2480    | 0.4021  |
| MIDAS-RV-L         | 4.3702***| 2.9023    | 0.0019  |

Notes: This table shows the out-of-sample R² results during the COVID-19 pandemic. The out-of-sample forecast period is from January 3, 2020, to April 30, 2021. Panels A, B and C show the results of different k_max values.
Santos, D.G., Ziegelmann, F.A., 2014. Volatility forecasting via MIDAS, HAR and their combination: an empirical comparative study for IBOVESPA. J. Forecast. 33, 284–299.

Sharif, A., Aloui, C., Yarovaya, L., 2020. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach. Int. Rev. Financ. Anal., 101496.

Tian, F., Yang, K., Chen, L., 2017. Realized volatility forecasting of agricultural commodity futures using the HAR model with time-varying sparsity. Int. J. Forecast. 33, 132–152.

Tian, F., Yang, K., Chen, L., 2021. Forecasting China’s crude oil futures volatility: the role of the jump, jumps intensity, and leverage effect. J. Forecast. 40, 921–941.

Wang, J., Ma, F., Wahab, M., Huang, D., 2021. Forecasting China’s crude oil futures volatility: a heterogeneous volatility spillover GARCH model. J. Forecast. 37.

Wang, Y., Pan, Z., Wu, C., 2018a. Volatility spillover from the US to international stock markets: a heterogeneous volatility spillover GARCH model. J. Forecast. 37.

Wang, Y., Wei, Y., Wu, C., Yin, L., 2018b. Oil and the short-term predictability of stock return volatility. J. Empir. Finance 47, 90–104.

Wang, Y., Wu, C., Li, Y., 2016. Forecasting crude oil market volatility: a Markov switching multifractal volatility approach. Int. J. Forecast. 32, 1–9.

Wei, Y., Liang, C., Li, Y., Zhang, X., Wei, G., 2020. Can CBOE gold and silver implied volatility help to forecast gold futures volatility in China? Evidence based on HAR and Ridge regression models. Finance Res. Lett. 35, 101287.

Wei, Y., Wang, Y., Huang, D., 2010. Forecasting crude oil market volatility: further evidence using GARCH-class models. Energy Econ. 32, 1477–1484.

Wen, D., Wang, Y., Ma, C., Zhang, Y., 2020. Information transmission between gold and financial assets: mean, volatility, or risk spillovers? Resour. Pol. 69, 101871.

Yang, K., Chen, L., Tian, F., 2015. Realized volatility forecast of stock index under structural breaks. J. Forecast. 34, 57–62.

Zhang, D., 2017. Oil shocks and stock markets revisited: measuring connectedness from a global perspective. Energy Econ. 62, 323–333.

Zhang, D., Cao, H., 2013. Sectoral responses of the Chinese stock market to international oil shocks. Emerg. Mark. Finance Trade 49, 37–51.

Zhang, Y., Ma, F., Liao, Y., 2020. Forecasting global equity market volatilities. Int. J. Forecast. 36, 1454–1475.

Zhang, Y., Ma, F., Wang, Y., 2019a. Forecasting crude oil prices with a large set of predictors: can LASSO select powerful predictors? J. Empir. Finance 54, 97–117.

Zhang, Y., Wang, Y., Ma, F., 2021. Forecasting US stock market volatility: how to use international volatility information. J. Forecast. 40, 733–768.

Zhang, Y., Wei, Y., Zhang, Y., Jin, D., 2019b. Forecasting oil price volatility: forecast combination versus shrinkage method. Energy Econ. 80, 423–433.