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Examining the predictive information of CBOE OVX on China's oil futures volatility: Evidence from MS-MIDAS models

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Abstract
This study evaluates whether CBOE crude oil volatility index (OVX) owns forecasting ability for China's oil futures volatility using Markov-regime mixed data sampling (MS-MIDAS) models. In-sample empirical result shows that, OVX can significantly lead to high future short-term, middle-term and long-term volatilities with regard to Chinese oil futures market. Moreover, our proposed model, the Markov-regime MIDAS with including the OVX (MS-MIDAS-RV-OVX), significantly outperforms the MIDAS and other competing models. Unsurprising results further confirm that OVX indeed contain predictive information for oil realized volatility (especially significant and robust in middle-term and long-term horizons) and regime switching is useful to deal with the structural break within the energy market. We carry out economic value analysis and discuss OVX's asymmetric effects concerning different trading hours and good (bad) OVX, and find OVX performs better in day-time trading hours and the good OVX is more predictive for the oil futures RV than the bad OVX. The further discussion also confirms our previous conclusions are robust during the highly volatile period of the COVID-19 pandemic.

1. Introduction
Always known as the king of commodity by industry insiders, crude oil is directly or indirectly used in all industries because of its extensive participation in our everyday life. Thus, fluctuations of crude oil play an important role in the development of the commodity and even the national economy, which attracts plenty of researchers to carry out related explorations [23,28,40,44,50,55]. For instance, Gong et al. [23] demonstrated that higher oil price has brought negative effects to the global economy. Mo et al. [44] find oil price can promote economic growth in the long run. Under this condition, a totally different oil future comes out in China and has made more progress internationally. Rolled out on March 26, 2018 and tailor-made for international investors, the yuan-denominated oil futures is the first international futures to be listed in China. Compared with the other two famous benchmark oil futures (e.g., WTI and Brent), China's oil futures own several typical features. First, China's oil futures are settled in yuan while the other two futures are settled in dollars. Second, China's oil futures contract is based on oil with higher sulfur content, while the other two are based on all light low-sulfur oil. Third, the trading time of China's oil futures are different, which are day trading hours between 9:00am and 11:30am, 1:30pm and 3:00pm local time and night trading hours from 9:00pm to 2:30am the next day.

This milestone step is of special significance for China from following perspectives. According to the Shanghai futures exchange, the listing of Chinese crude oil future is conducive to the formation of a price system that reflects the supply and demand relationship between China and the Asia-pacific crude oil market. Remaining the world's largest importer of crude oil, however, China did not have discourse power in the pricing of international crude oil market. This milestone step makes up for this disadvantage, and further increase China’s comprehensive national strength and core competitiveness to a certain extent. Till now, China's oil futures is capable of taking a place the global crude market in the near future and research on the

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1 https://www.chinadaily.com.cn/a/201903/27/WS5c9b088fa3104842260b2db4.html
2 https://www.wsj.com/articles/chinas-oil-futures-give-new-york-and-london-a-run-for-their-money-11553679002.
INE oil futures holds significant importance for China.

Proposed by the Chicago Board of Options Exchange (CBOE), OVX is an immediate measurement of investors’ uncertainty of future crude oil prices changes, which makes OVX an interesting uncertainty index for investors, policy makers and scholars. OVX is popularly applied in the volatility forecasting of different markets, for instance, clean energy equity markets [2,17], China’s stock markets [3], China’s commodity markets [27], metal markets [18,19], Bitcoin prices [4,15]. From the stands of literature, with regards to the oil markets, some studies [1,12,26,34,36] have also investigated the predictable ability of CBOE OVX on forecasting international oil markets volatility (e.g., WTI and Brent). For instance, Lv [36] evaluates whether OVX is helpful for forecasting the WTI futures volatility based on the HAR-RV models. They find that OVX indeed positively affects oil futures RV and the larger OVX has more powerful performance than smaller ones. Haugom et al. [26] examine whether OVX is capable of forecasting RV in the WTI futures market, and verify that adding OVX to the HAR-RV model makes the model better fit RV time series. Ji and Fan (2016) examine the interdependence such as direction, dynamics, magnitude and asymmetry relationship between WTI and OVX by applying a time-varying parameter (TVP) GARCH model. They find that the interdependence between the OVX and WTI RV returns is significantly negative, and the time-varying results show that it is not always negative. Chen et al. [12] utilize GARCH-type models to prove that CBOE OVX owns predictive ability for WTI and Brent market. They verify that adding OVX to the GARCH-type model improves forecasting accuracy even in longer predictive periods of 5 and 20 days.

With regards to the China’s crude oil futures market, researches on this market are rare. As far as we know, till now, there are nearly five literature about this newly emerging crude oil futures [27]; Chen et al., 2019 [54]; Li et al., 2020; Yang and Zhou, 2020). More specifically, Ji and Zhang (2019) give a relatively comprehensive introduction about China’s crude oil futures. Chen et al. (2019) detect the pricing efficiency of China’s crude oil futures and find the crude oil futures market has very weak-form efficiency. Wang et al. [54] investigate China’s crude oil futures price returns based on the multifractal characteristics, and they find the multifractality degree of China’s crude oil futures is greater than WTI but weaker than Brent. Yang and Zhou (2020) investigate the return and volatility transmission between China’s crude oil futures and international crude oil futures markets. Li et al. (2020) examine the relationships between Chinese crude oil futures and its two underlying crude oil spots from the perspective of hedging. However, the research on China’s crude oil's volatility is extremely rare and we tryto investigate the relationship between OVX and China’s oil futures volatility in this paper.

Hailing from the existing literature, two obvious features need to be extremely emphasized here, which really motivate us to carry out this research. The first is that most literature focus on the volatility of international oil markets such as WTI and Brent, and research on China’s oil futures market is extremely rare. Second, the existing researches mainly focus on HAR-RV or GARCH-type models and few literatures apply MIDAS models to predict oil RV. However, we pick MIDAS models to predict oil futures RV for following reasons. First, MIDAS-RV model is capable of better reflecting heterogeneity than the HAR-RV model because HAR-RV model is a special evolution from the MIDAS-RV model [20,31]; 2009). In addition, MIDAS-RV model is popularly applied and practical application. Further confirm that MIDAS models obtain more powerful forecasting performances than other models [3, 38, 45]. For instance, Santos and Ziegelmann [49] find MIDAS prediction is superior to several multi-period volatility forecasting models such as HAR, MIDAS and their combination methods. Ma et al. [38] find the MIDAS-RV may better reflect heterogeneity than the HAR-RV model. As far as we know, only two literature predict intraday oil futures volatility relying on MIDAS framework [16,42]. Furthermore, the result of structural breaks test show structural breaks indeed exist in China’s oil futures markets, which makes regime switching reasonable to be considered in our model.

In addition, Kuck and Schweikert [30] and Uddin et al. [52] demonstrate that regime switching is more efficient to forecast the oil market volatility. Therefore, this paper purposely investigates the predictability of OVX on China’s oil futures volatility using novel Markov-regime mixed data sampling (MS-MIDAS) models.

In order to seek for the potent relationship between OVX on China’s oil futures volatility, we carry out the empirical analysis as follows. First, we pick MIDAS-RV and its extended models to predict Chinese oil futures RV. The rolling window method is applied and out-of-sample forecasting performances are assessed by Model Confidence Set test (MCS). Second, we investigate the economic value of our proposed models. Third, we apply a plenty of robustness checks to evaluate our results including such as alternative realized measures (RR), alternative lags of OVX, alternative lags (kmax), out-of-sample R². Furthermore, we investigate the asymmetric effects of OVX with regards to different trading hours and good RV bad RV. Finally, we further discuss OVX’s predictability during the highly volatile period of the COVID-19 pandemic.

Contributions of our article can be deemed from the following aspects. First, the yuan-denominated oil futures are of special significance for China from theoretical and practical perspectives. However, raw literature concentrate on Chinese oil futures and MIDAS model, maybe due to the fact that Chinese oil futures newly comes to the market. Thus, to fill this gap, we choose MIDAS models to do the predictive evaluation about COBE OVX’s predictability on Chinese oil futures RV.

Second, the structural breaks test shows Chinese oil futures market indeed owns structural breaks, which makes it is reasonable for us to consider regime switching in our proposed models. Therefore, we are the first to investigate whether OVX owns forecasting ability for China’s oil futures volatility based on MS-MIDAS models.

Third, we discuss the asymmetric effects of OVX. Against the special background of China’s oil futures market, we consider day-time and over-night trading hours and evaluate whether OVX has different predictive performances. In addition, we compare different effects of bad and good OVX on Chinese oil futures market as well.

Fourthly, considering the startling impact that the COVID-19 pandemic has brought to the industry of global oil and gas, we make further discussion about whether OVX still contains valuable predictive information for Chinese oil market even though during the prevailing of the COVID-19 pandemic.

Several findings are obtained here, In-sample analysis shows that OVX can significantly lead to high future volatility with regard to China’s oil futures market in different horizons. Via out-of-sample analysis, the MS-MIDAS model including OVX stands out in the model set, implying that considering the combination of OVX information and regime switching together can achieve more satisfying predictive performance, especially significant and robust in medium-term and long-term horizons. Moreover, we find the economic gains of MS-MIDAS-RV-OVX model are the largest among our proposed models. Furthermore, we also find OVX performs better in day-time trading hours and the good OVX is more predictive for the oil futures RV than the bad OVX. During the COVID-19 pandemic, similar findings are also obtained. What’s more, these results are especially significant and robust in horizons of medium-term and long-term. The remainder of our article is presented as follows. Next part makes a brief presentation of the realized
measurement, benchmark and the related predictive models. Section 3 shows descriptive statistics such as the mean, standard error, skewness and kurtosis of variables. Section 4 shows the predictive results from in-sample, out-of-sample prediction, economic value and robustness checks. Section 5 presents the discussion about OVX’s asymmetric effects. Section 6 presents discussion about COVID-19 pandemic. Section 7 concludes the paper.

2. Methodology

2.1. Realized volatility

Produced by Andersen and Bollerslev [5], RV holds the advantages of non-parametric and easier computation [41]. Following Meddahi et al. [41], for a certain trading day t, the squared intraday high-frequency returns can be constructed as:

$$RV_t = \sum_{j=1}^{M} r_{ij}^2,$$

where $r_{ij}$ represents the jth intraday return of day t, M presents the amounts of observations.

According to Barndorff-Nielsen and Shepherd [9], RV can be presented as follows, when $\Delta \rightarrow 0$:

$$RV_t \rightarrow \int_0^t \sigma^2(s) ds + \sum_{0<s\leq t} k^2(s),$$

where $\int_0^t \sigma^2(s) ds$ is the integrated variance (IV) which can be calculated by realized bi-power variation (BPV) as follows:

$$BPV_t = \mu^{-2} \sum_{j=2}^{1/\Delta} \left| r_{ij} \right| r_{ij-1},$$

where $\mu = \sqrt{2/\pi} \approx 0.7979$. $\sum_{0<s\leq t} k^2(s)$ presents the jump components.

2.2. The benchmark MIDAS model

We apply MIDAS-type models to predict RV of oil futures, and our benchmark model from Ghysels et al. [21] can be expressed as follows.3

Model 1: MIDAS-RV.

$$RV_{t,t+h} = \beta_0 + \beta_1 \sum_{k=1}^{k_{\text{max}}} b(k, \theta_{RV}) RV_{t-k} + \epsilon_{t+h},$$

where $RV_{t,t+h} = 1/b(RV_{t,t+1} + RV_{t,t+2} + \ldots + RV_{t,t-\Delta h})$, and $RV_{t,t}$ denotes lags (t-k) of RV. For instance, $RV_{t-1}$ represents the lag one of RV. In this paper, $k_{\text{max}}$ is equal to 50.

Following Ghysels et al. [20], Ghysels et al. [21]; and Ghysels and Valkanov [22], the weights $b(k, \theta_{RV})$ can be defined as follows:

$$b(k, \theta_{RV}) = f\left(\frac{k}{k_{\text{max}}}, \theta_1, \theta_2\right) / \sum_{l=1}^{l_{\text{max}}} f\left(\frac{k}{k_{\text{max}}}, \theta_1, \theta_2\right),$$

where $f(x, y, z) = x^{y-1} (1-x)^{z-1} / \beta(y, z)$ and $\beta(y, z)$is defined as $\beta(y, z) = \Gamma(y) \Gamma(z) / \Gamma(y+z)$. Following Ma et al. [38], $\theta_1$ within the function $b(k, \theta_{RV})$ is set to be 1. Thus, it is the parameter $\theta_2$ that only determines the weighted values of RV lags. We choose this model as the benchmark and do further evaluations on its forecasting ability on oil futures volatility with the extended models.

We mainly try to evaluate whether CBOE OVX owns valuable predictive information for China’s oil futures volatility based on MIDAS models in our study. As abovementioned, few studies focus on the relationship between OVX and China’s oil futures volatility from a quantitative aspect. Therefore, we naturally add OVX as an additional variable to the basic MIDAS model and construct following model, which is defined as:

Model 2: MIDAS-RV-OVX.

$$RV_{t,t+h} = \beta_0 + \beta_1 \sum_{k=1}^{k_{\text{max}}} b(k, \theta_{RV}, \theta_{OVX}) RV_{t-k} + \epsilon_{t+h},$$

Uddin et al. [52] and Yu and Song (2018) have verified that models with regime switching may be more efficient to bring improvement to doing predictions in energy market, especially the oil market. To detect whether structural breaks point exist within Chinese oil futures market, we apply the structural break test proposed by Lavielle and Teyssire [31]. The result shows that structural break obviously exists in China’s oil futures market. To detect whether structural breaks point exist within Chinese oil futures market, it is reasonable for us to consider regime switching in the benchmark MIDAS model. Following the previous studies (e.g. Ref. [39,51], we consider two regimes, high and low volatility, to improve to do predictions in energy market, especially the oil market.

Model 3: MS-MIDAS-RV.

$$RV_{t,t+h} = \beta_{0,5} + \beta_{1,5} \sum_{k=1}^{k_{\text{max}}} b(k, \theta_{RV}, \theta_{OVX}) RV_{t-k} + \epsilon_{t+h},$$

where $\epsilon_{5} \sim (0, \sigma_{\epsilon}^2)$, $\beta_{0,5}$, $\beta_{1,5}$, are state parameters, and unobserved state variable $S_t$ is driven by different conditions with transition probabilities. $S_t = 1$ represents a low-volatility state, which means

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3. The code is available upon request.
the oil market enjoys lower stability under this circumstance. $S_t = 1$ represents a high-volatility state and it has relatively large conditional variance, in which the market has fierce fluctuation. Following Shi and Ho [51] and Ma et al. [39]; $S_t$ owns a fixed two-state Markov process, and its matrix of fixed transition probability is:

$$
\begin{bmatrix}
0.01 & 1 - 0.01 \\
1 - 0.11 & 0.11
\end{bmatrix},
$$

(8)

where

$$p_{00} = p(S_t = 0|S_{t-1} = 0),$$

$$p_{11} = p(S_t = 1|S_{t-1} = 1),$$

To have a closer look at whether OVX can have different performances during high or low volatility period, we naturally built MS-MIDAS-RV-OVX (Model 4).

Model 4: MS-MIDAS-RV-OVX.

$$RV_{t+h} = \beta_{0,S_t} + \beta_{1,S_t} \sum_{k=1}^{k_{\text{max}}} b(k, \theta_1^{RV}, \theta_2^{RV}) RV_{t-k} + \gamma_{1,S_t} \sum_{k=1}^{k_{\text{max}}} b(k, \theta_1^{OVX}, \theta_2^{OVX}) OVX_{t-k} + \epsilon_{h}$$

(11)

Information for the typology of the four models discussed in this paper is summarized in Table 1.

### Table 1

| Model   | Model name          | Equation         | Component(s) included          |
|---------|---------------------|------------------|--------------------------------|
| Model 1 | MIDAS-RV            | Equation (4)     | Benchmark model                |
| Model 2 | MIDAS-RV-OVX        | Equation (6)     | OVX index                      |
| Model 3 | MS-MIDAS-RV         | Equation (7)     | Regime switching               |
| Model 4 | MS-MIDAS-RV-OVX     | Equation (11)    | Regime switching - OVX index   |

### Table 2

| Statistics | RV | OVXd | OVXw | OVXm |
|------------|----|------|------|------|
| Observations | 423 | 423  | 423  | 423  |
| Mean       | 2.864 | 9.437 | 43.777 | 129.150 |
| Std.dev    | 3.174 | 20.694 | 98.063 | 187.955 |
| Skewness   | 4.410 | 4.380 | 4.645 | 4.645 |
| Kurtosis   | 28.314 | 19.298 | 21.540 | 59.439 |
| Jarque-Bera | 15146.025*** | 7743.659*** | 9485.574*** | 64014.580*** |
| Q (5)      | 281.651*** | 1751.075*** | 1680.400*** | 1065.756*** |
| Q (22)     | 443.106*** | 3227.844*** | 2800.687*** | 1568.371*** |

**Notes:** This table shows the descriptive statistics for all variables, including time series of RV and OVX. The whole sample period ranges from March 27, 2018 to April 16, 2020 containing 423 trading days. Following Jarque and Bera (1987), we set the null hypothesis of normal distribution for each variable. Ljung and Box (1978) propose the Ljung-Box statistic called Q(n), in our study, we test the 5th and 22nd order serial correlation. Asterisk ***, ** and * denote rejections of null hypothesis at 1%, 5% and 10% level. In this table, p value less than 0.1 are meaningful.

Dickey–Fuller (ADF) test proved that at the 1% significance level, there is no hint of unit root, which gives an evident sign that all the data series are stationary in levels.

Fig. 2 presents the graphical information of oil RV and OVX index during our sample period. At a glance of Fig. 2, we observe that Chinese oil futures RV, OVX, almost have the similar volatility trajectory and possess similar spikes.

### 4. Empirical design

#### 4.1. In-sample analysis

It is of vital importance that in-sample forecasting is capable of predicting, and the predictive information of benchmark and extended models is contained in Table 3. Several findings indeed draw our attentions. Firstly, the coefficient parameters for RV within all the models are all significant at the 1% significance level, reflecting the past oil realized volatility can cause a higher volatility in the future. Besides, the parameter estimates of OVX in the MIDAS-RV-OVX model is remarkably positive at the 10% significance level in the mid-term horizon ($h = 5$) and remarkably positive at the 5% significance level in the long-term horizon ($h = 20$), indicating that OVX can predict oil market volatility especially in medium- and long-term horizons.

Interestingly, from the coefficient values of MS-MIDAS-RV and MS-MIDAS-RV-OVX models, we find that the impacts of OVX are different to predict future oil realized volatility under high and low volatility regimes. More specifically, the impacts of OVX on predicting the oil RV are larger during low volatility regimes than high volatility regimes. Several possible reasons can be used to explain OVX’s predictive power for China’s oil futures market. Firstly, OVX itself is a benchmark for international oil price volatility. Second, China’s oil future market plays an more and more active part in the international market, for instance, compared with 2018, it has 120% year-on-year increase in opening accounts overseas and its dealers are distributed up to 19 countries in 5 continents. Most importantly, Chinese oil futures is keeping step with other international oil markets, specifically, it owns 86.2% correlation with WTI, 92.6%
correlation with Brent and 94.1% correlation with Oman.\textsuperscript{5}

4.2. Out-of-sample analysis

There is no doubt that out-of-sample predictive ability is of vital significance for volatility forecasting, owing to it is capable of reflecting the model’s future prediction performance which the market participants really focus on. To avoid the overlapping of data, we apply rolling window approach to do the prediction and make out-of-sample prediction maintain an unchangeable length (in our paper, it is 300 observations.).

4.2.1. Out-of-sample evaluated method

There is no doubt that out-of-sample predictive ability is of vital importance in volatility forecasting, because of its capacity to reflect the model’s future prediction performance. To keep step with Patton [46]; As a result, the QLIKE and MSE loss functions were applied to carry out out-of-sample evaluation. These two loss functions are defined as follows:

\begin{equation}
\text{QLIKE} = L^{-1} \sum_{m=1}^{L} \left( \ln(\overline{RV}_L) + \frac{RV_m}{\overline{RV}_L} \right), \tag{12}
\end{equation}

\begin{equation}
\text{MSE} = L^{-1} \sum_{m=1}^{L} \left( \frac{RV_m - \overline{RV}_L}{\overline{RV}_L} \right)^2, \tag{13}
\end{equation}

where $\overline{RV}_L$ indicates the out-of-sample forecasting realized volatility from the forecasting model, while $RV_m$ is the actual volatility during the same period. $L$ represents the length of evaluation period.

To further confirm the models’ predictive performance, we combine Model Confidence Set (MCS) of Hansen et al. [25] and the loss functions we have discussed above (QLIKE and MSE expression from Equations (12) and (13)) to determine which model can be kept in the set. In line with (Chkili et al., 2014), We also pick $\alpha = 0.25$ to be our confidence level and obtain a model set, which contains models having more excellent predictive ability over the eliminated ones. In other words, if a model with a MCS $p$-value larger than 0.25, it can stay in the best model set and this model indeed possess a relatively satisfactory predictive performance for China’s oil futures RV. Moreover, stationary bootstrap\textsuperscript{6} method is picked to evaluate the interpretation of the MCS test $p$-value.

4.2.2. Out-of-sample forecasting results

The proposed models’ predictive ability from MCS test is exhibited in Table 4. Several findings are uncovered here. From the results of MIDAS-RV-OVX and MS-MIDAS-RV-OVX model, we find OVX owns information to predict oil futures RV and the MCS test $p$-value of the MS-MIDAS-RV-OVX is always larger than 0.25 and nearly equal to 1 especially during medium-term and long-term horizons. In other words, MS-MIDAS-RV-OVX model has better performance in the best model set. This result shows the combination of OVX and regime switching indeed contain predictive information for China’s oil futures, especially during medium-term and long-term periods. Moreover, OVX is a measurement for market’s expectation for future 30-day crude oil price volatility, which maybe the reason why OVX is more significant and robust during medium-term and long-term periods. The reasons for the satisfying predictive performance of MS-MIDAS-RV-OVX model can be that OVX itself is a benchmark for international oil price volatility and regime switching is really helpful for dealing with structural breaks in the energy market. This indeed trigger our deeper thinking that, although Chinese crude oil futures are settled in RMB, the

\textsuperscript{5} These numbers can be obtained from http://www.ine.cn/news/area/2801.html.

\textsuperscript{6} About the MCS $p$-value computation, more technical details can be found in Hansen et al. [25].
Table 3
In-sample estimation results.

|                | Model 1 | Model 2 | Model 3 | Model 4 |
|----------------|---------|---------|---------|---------|
| Panel A: h = 1 | \(\beta_0\) | -1.721*** | -1.686 | -1.997*** | -1.743*** |
|                | \(\beta_{0S}\) | -1.200*** | -2.445*** |         |         |
|                | \(\beta_1\) | 0.797*** | 0.675*** | 0.765*** | 0.523*** |
|                | \(\gamma_1\) | 0.141 | 0.461*** | 0.293*** |         |
|                | \(\gamma_{1S}\) | 0.321* |         |         |         |
| \(p^{10}\)    | 0.996 | 0.996 |         |         |         |
| \(p^{11}\)    | 1.000 | 1.000 |         |         |         |
| Panel B: h = 5 | \(\beta_0\) | -3.060*** | -2.065*** | -4.754*** | -5.947*** |
|                | \(\beta_{0S}\) | -2.915*** | -3.571*** |         |         |
|                | \(\beta_1\) | 0.629*** | 0.487*** | 0.367*** | 0.443*** |
|                | \(\gamma_1\) | 0.359* | 0.594*** | 0.932*** |         |
|                | \(\gamma_{1S}\) | 0.019 |         |         |         |
| \(p^{10}\)    | 0.923 | 0.940 |         |         |         |
| \(p^{11}\)    | 0.955 | 0.961 |         |         |         |
| Panel C: h = 20 | \(\beta_0\) | -6.611*** | -7.930*** | -9.807*** | -13.193*** |
|                | \(\beta_{0S}\) | -5.442*** | -2.431*** |         |         |
|                | \(\beta_1\) | 0.203*** | 0.212*** | 0.221*** | 0.954*** |
|                | \(\gamma_1\) | 0.384*** | 0.623*** | 0.660*** |         |
|                | \(\gamma_{1S}\) | 0.163 |         |         |         |
| \(p^{10}\)    | 0.975 | 0.971 |         |         |         |
| \(p^{11}\)    | 0.974 | 0.972 |         |         |         |

Notes: This table shows the parameter estimation results from an in-sample perspective. \(\beta_0\) is the constant term, \(\beta_i\) and \(\gamma_j\) present the coefficient of RV and OVX respectively, \(S_0\) and \(S_i\) indicate the low and high volatility respectively, \(p^{10}\) and \(p^{11}\) are the probability value of the transition matrix. Different horizons h = 1, 5, 20 are shown in Panel A, B, C as well. Asterisk ***, ** and * denote rejections of null hypothesis at 1%, 5% and 10% level. In this table, p value less than 0.1 are meaningful.

Table 4
Results of MCS test.

| Forecasting models | QLIKE | SeimQ | MSE | Range | SeimQ |
|-------------------|-------|-------|-----|-------|-------|
| Panel A: h = 1    |       |       |     |       |       |
| MIDAS-RV          | 0.0748 | 0.0517 | 0.8417 | 0.8892 |
| MIDAS-RV-OVX      | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| MS-MIDAS-RV       | 0.0748 | 0.0289 | 0.4699 | 0.6597 |
| MS-MIDAS-RV-OVX   | 0.3092 | 0.3092 | 0.8471 | 0.8892 |
| Panel B: h = 5    |       |       |     |       |       |
| MIDAS-RV          | 0.0954 | 0.0449 | 0.6194 | 0.4028 |
| MIDAS-RV-OVX      | 0.0954 | 0.0449 | 0.6194 | 0.4028 |
| MS-MIDAS-RV       | 0.0954 | 0.0449 | 0.6194 | 0.4028 |
| MS-MIDAS-RV-OVX   | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Panel C: h = 20   |       |       |     |       |       |
| MIDAS-RV          | 0.0008 | 0.0073 | 0.0028 | 0.0184 |
| MIDAS-RV-OVX      | 0.0053 | 0.0167 | 0.0094 | 0.0445 |
| MS-MIDAS-RV       | 0.6794 | 0.6794 | 1.0000 | 1.0000 |
| MS-MIDAS-RV-OVX   | 1.0000 | 1.0000 | 1.0000 | 1.0000 |

Notes: This table shows the results of MCS test, and the p-value is calculated according to the range and semi-quadratic (SeimQ) statistics. Two criteria, i.e., QLIKE and MSE are adapted. The p-values > 0.25 and p-values – 1 are overstriking and underlined. Different horizons h = 1, 5 and 20 are shown in Panel A, B, C. In this table, the MCS test p-value of indicates a better prediction.

Commodity financialization makes the prediction of Chinese crude oil futures still need to seriously consider the international crude oil risks.

4.3. Economic value analysis

It is undeniable that out-of-sample predictive performance is of vital significance for volatility forecasting. However, as “Economic Man”, it cannot be neglected that market investors keep their eye closely on the economic value of the proposed model. In this part, following Guidolin and Na [24]; Neely et al. (2014), Bollerslev et al. [11] and Mei et al. [42]; we apply a mean-variance utility method to detect the economic value of our proposed models. This function reflects an investor’s assets assignments between oil futures and a risk-free asset. The utility function can be presented as:

\[ U_t(t) = E_r (w_t ' r_t + r_f) - \frac{1}{2} \gamma \text{Var} (w_t ' r_t + r_f), \]

where \(w_t\) is the optimal weight of Chinese oil futures, \(r_t\) is the excess return \(r_t = r_t - r_f\), \(r_f\) is the oil futures return, and \(r_f\) is the risk-free rate (here we apply the three-month Shanghai Interbank Offered Rate (SHIBOR)). \(\gamma\) is a risk aversion coefficient. \(w_t ' r_{t-1} + r_{f-1}\) can be used to define portfolio return. On the \((t+1)\)th day, the ex-ante optimal weight of Chinese oil futures can be calculated by the function below:

\[ w_t^* = \frac{1}{\gamma} \left( r_{t+1} + r_{f-1} \right)^{-1}. \]

where \(RV_{t+1}\) stands for the prediction of Chinese oil futures’ excess return on the \((t+1)\)th day, which can be obtained from historical average returns. Furthermore, \(RV_{t+1}\) are volatility forecasts of oil futures excess returns from our proposed models. We set the \(w_t^* \in [-1.5, 1.5]\) following Zhang et al. [60]. The certainty equivalent return (CER) can be written as,

\[ CER_p = \mu_p - \frac{\gamma}{2} \overline{RV}_{t-1}{^2}. \]

The results of economic value analysis are reported in Table 5. The portfolio performance can be evaluated by the value of CER. First, comparing MIDAS-RV with MIDAS-RV-OVX model, CER gains are always larger than that of MIDAS-RV model, suggesting OVX indeed contain predictive information for risk-free rate.

Notes: The data can be obtained from http://www.reset.cn.
China’s oil futures. Second, we find that CER gains of MS-MIDAS-RV-OVX model are the largest among our proposed models during different horizons. This result shows the combination of OVX and regime switching indeed contain predictive information for China’s oil futures, and its predictive performance is more significant and robust during medium-term and long-term periods. In other words, the results from economic value analysis are consistent with out-of-sample results.

4.5. Various robustness tests

4.5.1. Alternative realized measures
To further identify whether our above-mentioned results are robust or not, this section presents the application of realized kernel (RK), another commonly used variance estimator of Barndorff-Nielsen et al. [8]; and it can be expressed as follows:

\[
\text{RK}_n = \frac{1}{H} \sum_{j=-H}^{H} k\left(\frac{j}{H+1}\right)'_{ij},
\]

where \(k(x)\) is the Parzen kernel function, and \(H\) is a bandwidth parameter [7]. Several findings are presented here. From Table 6, we find that MIDAS-RV-OVX passed MCS test in all horizons, suggesting OVX indeed offers improvement to the forecasting of oil alone. Moreover, MS-MIDAS-RV-OVX didn’t passed MCS test in short-term horizon, showing that considering the combination of OVX information and regime switching together is helpful for forecasting China’s oil futures market volatility and it has more satisfying predictive performance in the medium-term and long-term horizons. Therefore, these findings are consistent with what we have observed from out-of-sample results.

4.5.2. Alternative lags of OVX
We try to test different lags of variable’s effects on the predicting performance of the models. Out-of-sample forecasting design choose 1 lag of OVX, and in this part, we choose 2 lags of OVX and further check the robustness of the models. Table 7 presents the results. We find that MS-MIDAS-RV-OVX model passed the MCS test in medium-term, and long-term horizons, showing the introduction of OVX and regime switching have more satisfying predictive performance. These results further confirm that our out-of-sample results are really robust.

4.5.3. Alternative lags
In this section, alternative \(k_{\text{max}}\) value is chosen as another robustness check method. We initially choose the value of \(k_{\text{max}}\) to be 50. Differently, following Breitung and Roling (2015), Ma et al. [38]; we set \(k_{\text{max}}\) equal to 40 and \(60^{\circ}\) in this part, and further carry out out-of-sample prediction. The results of alternative \(k_{\text{max}}\) values are presented in Table 8. We find MS-MIDAS-RV-OVX model robustly has more satisfying predictive performance than other models when adopting the different \(k_{\text{max}}\) values (40 and 60) within different horizons especially in medium-term and long-term periods, suggesting that the combination of OVX and regime switching owns the best forecasting performance. These findings are consistent with what we have observed from out-of-sample results.

4.5.4. Alternative evaluation method
In this section, we try to apply another evaluation method to detect whether OVX contains valuable predictive information for forecasting the volatility within China’s oil futures market. In this part, we apply out-of-sample \(R^2\), denoted as \(R^2_{\text{out}}\), to detect the notable distinction in predictive ability among models. Following Paye [48]; Wang et al. [56] and Liang et al. [33]; we also apply this statistic, which is defined as:

\[
R^2_{\text{out}} = 1 - \frac{\sum_{i=1}^{M} \left( R^j_t - \hat{R}^j_t \right)^2}{\sum_{i=1}^{M} \left( R^j_t - \hat{R}^j_0 \right)^2},
\]

where \(R^j_t\) is the actual realized range-based volatility, \(\hat{R}^j_t\) is the estimation from model \(j\), and \(j\in\{1, 2, 3, 4\}\). This statistic measures the related model have an excellent predictive performance over the benchmark model.

| Table 7 | The result of alternative lags of OVX with the MCS test. |
|------------------|------------------|------------------|------------------|------------------|
| Forecasting models | QLIKE | MSE |
| Range | SeimQ | Range | SeimQ |
| --- | --- | --- | --- |
| Panel A: \(h = 1\) | | | | |
| MIDAS-RV | 0.0859 | 0.0528 | 1.0000 | 1.0000 |
| MIDAS-RV-OVX | **1.0000** | **1.0000** | **0.9922** | **0.9901** |
| MS-MIDAS-RV | 0.0859 | 0.0596 | **0.8269** | **0.9213** |
| MS-MIDAS-RV-OVX | 0.2020 | 0.2020 | **0.9922** | **0.9901** |
| Panel B: \(h = 5\) | | | | |
| MIDAS-RV | 0.1107 | 0.0492 | **0.4408** | **0.2861** |
| MIDAS-RV-OVX | 0.1107 | 0.0492 | **0.4408** | **0.2427** |
| MS-MIDAS-RV | 0.1107 | 0.0682 | **0.4408** | **0.2960** |
| MS-MIDAS-RV-OVX | **1.0000** | **1.0000** | **1.0000** | **1.0000** |
| Panel C: \(h = 20\) | | | | |
| MIDAS-RV | 0.0058 | 0.0144 | 0.0163 | 0.0544 |
| MIDAS-RV-OVX | 0.0056 | 0.0202 | 0.0162 | 0.0518 |
| MS-MIDAS-RV | **1.0000** | **1.0000** | **0.8269** | **0.9213** |
| MS-MIDAS-RV-OVX | **1.0000** | **0.8269** | **1.0000** | **0.9901** |

Notes: This table exhibits models’ MCS p-values with alternative realized measures (RK). The forecasts for different horizons \(h = 1, 5, 20\) are shown in Panel A, B, C. In this table, the MCS test p-value of 1 indicates a better prediction.

We further examined other lag lengths and the results are very similar.
Following Clark and West [13] and Mei et al. [43], we refer to the MSPE metric to do the evaluation about whether the extended models and benchmark model can exhibit different performances in predicting oil futures RV.

Results are presented in Table 9. First, the $R_{OOS}^2$ of MIDAS-RV-OVX model are all larger than zero in different horizons, showing OVX is able to predict China’s oil futures RV. Second, the $R_{OOS}^2$ of MS-MIDAS-RV model are nearly larger than zero, showing regime switching indeed adds improvement to the forecasting accuracy.

Third, the $R_{OOS}^2$ value of MS-MIDAS-RV-OVX is the largest during the medium-term and long-term periods, showing the consideration of OVX and regime switching together achieves the best forecasting performance, especially more significant and robust in medium-term and long-term horizons. These findings are consistent with what we have observed from out-of-sample results.

### 4.5.5. Recursive (expanding) estimation window

Due to the reality that China’s oil futures oil futures are newly introduced to investors, it is an unchangeable objective fact that the data sample period of China’s oil futures is relatively short. Following Zhang et al. [60] and Ma et al. [37], we apply recursive (expanding) estimation window to do the evaluation, which can minimize loss of freedom and protect the original data information as much as possible. The results of recursive (expanding) estimation window are presented in Table 10. We find that MS-MIDAS-RV-OVX model not only passed the MCS test in all the horizons, but also the p-values of MS-MIDAS-RV-OVX model are all equal to 1. This confirms that the combination of OVX and regime switching in MIDAS framework indeed improve the predictive performance. These results are consistent with our results above mentioned.

### 4.5.6. Controlling VIX

With the integration of the global economy, it’s undeniable that more and more intimate correlations exist between oil market and stock market [6,32,37]. For instance, Asteriou and Bashmakova [6] find oil price beta is negative and statistically significant to stock returns. In this part, we try to control the impact of volatility transmission from stock market and make further evaluation.

Proposed by Chicago Board of Options Exchange (CBOE), VIX...
The results of trading hours with the MCS test.

| Forecasting models | QLIKE  | MSE   | QLIKE  | MSE   | QLIKE  | MSE   |
|--------------------|--------|-------|--------|-------|--------|-------|
|                    | Range  | SeimQ | Range  | SeimQ | Range  | SeimQ |
| Panel A: h = 1     |        |       |        |       |        |       |
| MIDAS-RV-VIX       | 1.0000 | 1.0000| 0.2687 | 0.1584|        |       |
| MIDAS-RV-OVX-VIX   | 0.1242 | 0.1170| 0.1675 | 0.1584|        |       |
| MS-MIDAS-RV-VIX    | 0.1242 | 0.1170| 0.1675 | 0.1584|        |       |
| MS-MIDAS-RV-OVX-VIX| 0.0529 | 0.0455| 1.0000 | 1.0000|        |       |
| Panel B: h = 5     |        |       |        |       |        |       |
| MIDAS-RV-VIX       | 0.1208 | 0.0847| 0.1956 | 0.1262|        |       |
| MIDAS-RV-OVX-VIX   | 0.1208 | 0.0637| 0.1956 | 0.1262|        |       |
| MS-MIDAS-RV-VIX    | 1.0000 | 1.0000| 0.1956 | 0.1262|        |       |
| MS-MIDAS-RV-OVX-VIX| 0.6072 | 0.6072| 1.0000 | 1.0000|        |       |
| Panel C: h = 20    |        |       |        |       |        |       |
| MIDAS-RV-VIX       | 0.0110 | 0.0047| 0.2155 | 0.1613|        |       |
| MIDAS-RV-OVX-VIX   | 0.0189 | 0.0170| 0.2155 | 0.2175|        |       |
| MS-MIDAS-RV-VIX    | 0.5544 | 0.5544| 1.0000 | 1.0000|        |       |
| MS-MIDAS-RV-OVX-VIX| 1.0000 | 1.0000| 0.7108 | 0.7108|        |       |

Notes: This table exhibits models' MCS p-values by adding VIX index, which is constructed similar with OVX. The forecasts for different horizons h = 1, 5 and 20 are shown in Panel A, B, C. In this table, the MCS test p-value of 1 indicates a better prediction.

5. Asymmetric effects

5.1. Different trading hours

Different from international oil futures such as WTI and Brent oil futures which continuously trade for nearly 23 h, Chinese oil futures owns different trading hours. More specially, the day-time trading hours of Chinese oil futures ranges from 9:00am to 15:00pm, with totally 135-min breaks, while the over-night trading hours covers the periods from 09:00pm to 2:30am (the next day) with no breaks. Thus, it remains to be an extremely interesting question that does OVX plays a different role in day-time trading hours and over-night trading hours? If so, which trading hours is more active for OVX’s performance, day-time trading hours or over-night trading hours? In this section, we do evaluation to detect OVX’s asymmetric effects on Chinese oil futures during day-time and over-night trading hours.

The results of our proposed models' predictive performance in different trading hours are presented in Table 12. Several findings can be obtained. First, during the day-time trading hours, the MCS p-values of MS-MIDAS-RV-OVX-VIX model are equal to 1 in the horizons of 5 days and 20 days. This suggests that the combination of OVX and regime switching indeed brings improvement to the models’ forecasting accuracy, especially significant and robust in the medium-term and long horizons. Second, during the over-night trading hours, MIDAS-RV-OVX and MS-MIDAS-RV-OVX passed the MCS test, verifying that OVX really contains predictive information for Chinese oil futures and the consideration of regime switching is also helpful to improve forecasting accuracy. These results are consistent with our previous findings. Most interestingly, comparing the models’ performances in day-time and over-night trading hours, we find OVX is more predictive for China’s oil futures market in the day-time trading hours rather than the over-night trading hours.

5.2. Good and bad OVX

Patton and Sheppard [47] firstly propose the method of decomposing RV into good and bad volatility and evaluate whether downside and upside risk can trigger different effects by using realized semi-variance estimators [7]. This method is popularly applied in volatility forecasting and modeling [10,11,29]. Inspired by them, we classify OVX into good and bad OVX and evaluate whether they have asymmetric performances and they can be presented as:

\[ OVX_+ = OVX_t \cdot I(r_t \geq 0) \]  
\[ OVX_- = OVX_t \cdot I(r_t < 0) \]

where \( I' \) is the indicator function, and \( r_t \) is the return of Chinese oil futures. \( OVX_+ \) (OVX_-) can be calculated as the sum of all available positive (negative) OVX.

In this part, we apply out-of-sample \( R^2 \) test to assess the models’ predictive performance, and MIDAS-RV-OVX is the benchmark model. The good and bad OVX can be denoted as OVXp and OVXn respectively. We add OVXp and OVXn to the benchmark model and obtained MIDAS-RV-OVXp and MIDAS-RV-OVXn model. Similarly, MIDAS-RV-OVXp and MIDAS-RV-OVXn model can be obtained by
adding regime switching. Table 13 presents the results of our proposed models’ predictive performances. Several findings are gained. First, the $R^2_{\text{OOS}}$ of MIDAS-RV-OVXn model and MS-MIDAS-RV-OVX model are all negative through all the horizons, showing the bad OVX does not contribute to the forecasting performance. Second, the $R^2_{\text{OOS}}$ of MIDAS-RV-OVXp model and MS-MIDAS-RV-OVXp model are all larger than zero in the medium-term horizons, suggesting the good OVX is more powerful than the bad OVX to improve the forecasting accuracy, especially robust in the medium-term and long periods.

### 6. The effect of COVID-19 pandemic

It’s worth mentioning the startling outbreak of the COVID-19 pandemic during the sample period, which had great economic impact worldwide and brought fierce threats to the industry of global oil and gas. Volatility has always been a challenging element of the oil and gas market but it is this coronavirus that makes the oil fluctuation been more extreme than it is before. More importantly, the International Energy Agency (IEA) has noted that, both the COVID-19 outbreak and the global oil industry, the part played by China, has changed totally in the last two decades. Moreover, according to IEA, since 2003, China’s oil demand had more than doubled, and by 2019, China’s oil growth accounted for more than 80% of global oil demand growth. Thus, it is such an interesting issue for us to detect whether OVX contain predictive information for China’s oil futures market during the COVID-19 pandemic.

In this section, the predictive sample period ranges from December 08, 2019 to April 16, 2020. And we finally get 77 observations for the COVID-19 pandemic discussion. The results are presented in Table 14. It is unsurprising that the MS-MIDAS-RV-OVX model still stands out in the best model set, which can be observed from the evidence that the p-values of MCS test for the MS-MIDAS-RV-OVX model are all equal to 1 in all horizons. This finding further show the combination of OVX and regime switching is still does good to improve the forecasting accuracy for Chinese oil futures during the highly volatile period of the COVID-19 pandemic. And this result is consistent with our previous findings.

### 7. Conclusions

This article mainly examines the predictive ability of COBE OVX on China’s oil futures volatility on the basis of MS-MIDAS models. Empirical results show that OVX indeed offer improvement to the forecasting accuracy of oil RV. Evidence also implies that regime switching indeed adds improvement to the forecasting accuracy. Moreover, considering the combination of OVX and regime switching owns the best forecasting performance in the MCS test, and performs robustly in various robustness checks of alternative realized measures (RK), alternative lags of OVX, alternative lags ($k_{\text{max}}$), out-of-sample $R^2$, especially during medium-term and long-term horizons.

Moreover, we discuss the economic value of the proposed models and find MS-MIDAS-RV-OVX model significantly owns the largest economic value. In addition, the results about OVX’s asymmetric effects concerning different trading hours and good (bad) OVX further confirm that OVX performs better in day-time trading hours and the good OVX is more predictive for the oil futures RV than the bad OVX. Furthermore, we make further discussion to detect whether OVX still contains valuable predictive information for China’s oil market even though in the prevailing of COVID-19 pandemic. We find that MS-MIDAS-RV-OVX model are always robustly outperforms other models even in this the highly volatile period, implying the combination of OVX and regime switching is really does good to improve the forecasting accuracy even during the COVID-19 pandemic.

### Credit author statement

No conflict of interest exits in the submission of this manuscript, and manuscript is approved by all authors for publication. I would like to declare on behalf of my co-authors that the work described was original research that has not been published previously, and

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9 https://www.eia.gov/.

10 Refer to “In December 2019” in Zhou et al. [61].
not under consideration for publication elsewhere, in whole or in part. The authors listed have approved the manuscript that is enclosed.

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.

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