The impact of COVID-19 on the interdependence between US and Chinese oil futures markets

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Abstract
The oil futures market plays a vital role in the global financial system, especially after the negative future oil price rose during the COVID-19 pandemic. This paper investigates the COVID-19 impact on the interdependence between the US and Chinese oil futures markets by extending the dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity (DCC-GARCH) models with incorporating COVID-19 variables and by applying vector autoregression (VAR) models. Our study reveals that the COVID-19 pandemic enhanced the long-run correlation between the two oil markets. In contrast, daily changes in pandemic severity had a negative effect on the short-term transient correlation. Our results show that COVID-19 changed the one-direction causality from the US oil market to the Chinese market in the pre-COVID period to a bidirectional causal relation between the two markets during the COVID period. It strengthened the volatility spillover effect from the Chinese to US markets. These findings are helpful to regulators’ monitoring oil supply chain risk and investors’ cross-market hedging of spillover risks from a systematic risk perspective.

Keywords
COVID-19 effect, DCC-GARCH, oil futures markets, VAR model

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1 | INTRODUCTION

With the financialization of commodity markets, during the last several decades, the linkage between different commodity futures markets has become a focal research point in the existing literature (see Ding et al., 2021; Tang & Xiong, 2012). In particular, Pindyck and Rotemberg (1990) develop the excess comovement hypothesis and examine the comovement of commodity returns and find that the heredity effect is one driving factor for the comovement of different commodity markets. Vansteenkiste (2009) adopts 32 commodities from 1957 to 2007 for the empirical test, revealing that the global demand, exchange rate, and real interest rates play significant roles in determining commodity price comovements. Byrne et al. (2013) also provide evidence that the real interest rate is a determinant of commodity price comovements. Recent works, including Zhang and Ding (2018), Zhang et al. (2018, 2019), Ding and Zhang (2020), Zhang and Ding (2021), demonstrate that the liquidity effect is a key determinant for the comovement of prices, returns and volatilities across different commodity futures markets on a daily frequency basis.
The above studies on the intermarket linkage only focus on the connectedness between futures markets with different commodity types. On the other hand, increasing trade among different nations and the globalization of financial markets has also contributed to the connectedness among cross-border commodity markets (Yang & Zhou, 2020). Under the influence of a strong external shock, such interdependence between different international commodity markets could accelerate risk spillover (Alquist et al., 2020; Melvin & Sultan, 1990; Song et al., 2018; Webb et al., 2016), which might lead to extreme events, such as negative oil futures prices at the start of the COVID-19 pandemic in the spring of 2020 and cross-broader supply chain disruption due to the pandemic lockdown. Thus, understanding the international linkages of commodity futures markets could help regulators to stabilize the global commodity supply chain. Furthermore, a clear understanding and ability to predict futures return linkages and risk transmissions among international commodity futures markets is highly relevant to investors when formulating effective international portfolio investment and hedging strategies.

Since the global financial crisis in 2008, many studies have paid attention to the impacts of external events or crises in the market linkages between developed and emerging markets (H. Li & Majerowska, 2008; Wang et al., 2020; Wu et al., 2017). Nevertheless, these works are mainly concerned about international stock market linkages. Little work has been done on the international commodity market linkage during public crises. We have noticed earlier works on price comovement between US and Canadian wheat futures markets (Booth et al., 1998) and price cointegration between London and Shanghai copper futures markets (X. Li & Zhang, 2008). Recent works (Cui et al., 2022, Yang & Zhou, 2020) have examined return and volatility links between international crude oil and Chinese commodity futures markets. However, the above works have not investigated the impacts of public events on such cross-border commodity market linkages. The outbreak of global pandemic at the beginning of 2020 has switched the crude oil futures market from a stable regime to a volatile regime (Liu & Lee, 2021). Furthermore, crude oil futures exhibit a different price overreaction behavior compared to other commodities during the COVID-19 pandemic (Borgards et al., 2021). Recent work (Zhang & Mao, 2022) showed that COVID-19 has enhanced the connectedness between US and Chinese stock markets. As stock markets and oil futures markets usually impact each other, the goal of this paper is to scrutinize the impact of COVID-19 on the interdependence between the US and Chinese oil futures markets.

The significance of this paper is threefold. First, oil is important to both the US and China, the two largest oil consumption countries worldwide. Although China is a major oil importer worldwide, only very recently in the spring of 2018 China launched oil futures trading in the Shanghai Future Exchange. The linkage between the US and Chinese oil futures markets, especially during the COVID-19 pandemic, lacks a thorough understanding. Second, international oil markets are vital to financial and economic stability worldwide, as numerous studies indicate that oil prices have a strong linkage to international stock markets (Ghosh & Kanjilal, 2016), to other commodity prices (Sun et al., 2021) and economic factors, such as GDP and interest rates (Lian et al., 2020; Urom et al., 2021). Finally, the COVID-19 pandemic is a dramatic public crisis that has affected almost all aspects of the worldwide economy and commodity price volatilities (Zhang & Wang, 2021), especially oil futures prices, which move in an extremely volatile way. Therefore, investigation of the impacts of COVID-19 on US and Chinese oil futures markets' return and volatility spillover effects is important to understand the effect the pandemic had on the world economy.

Regarding our research methodologies, we first investigated the impact of COVID-19 on the dynamic correlation of two futures returns by extending dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity (DCC-GARCH) models and incorporating COVID influencing variables. We used the Granger test to study the causality relation among two markets before and after the outbreak of COVID-19. Finally, we analyzed the impact of COVID-19 on the risk spillover effect across the US and Chinese oil futures markets using the impulse and response function and the variance decomposition method under the vector autoregression (VAR) model framework.

This study conveys five main contributions to the existing literature with the following findings. First, COVID-19 has significantly strengthened the long-run equilibrium correlation between the US and Chinese oil futures returns but has a negative effect on short-term instantaneous correlation. Second, from the Granger test, the causality relationship between the two markets changes from one-directional US to Chinese causality before the outbreak of COVID-19 to a bidirectional causal relation after the COVID-19 outbreak. Third, the response of Chinese oil futures from the US oil market's impulsive shock lasts a longer number of days than the US response to the Chinese shock in the pre-COVID period. In contrast, these two responses from the other market's shock lasted almost the same number of days during the COVID period. In addition, such cross-market impulse-response effects became stronger and more persistent during the COVID period than during the pre-COVID period. Finally, from variance decomposition analysis, the volatility spillover effect from the Chinese oil market to the US market became stronger after the COVID-19 outbreak, even though the spillover effect from the US oil market to the Chinese market was still dominant.
The above findings imply that the linkage between the US and Chinese oil futures markets became stronger after the outbreak of COVID-19 because the US oil futures traders followed information from the Chinese oil market more closely during the COVID period than during the pre-COVID period. Such enhanced information transmission from the Chinese market to the US market during the COVID period is consistent with the following facts. COVID-19 was initially found in China, a world manufacturing center and major oil importer, and supply chain disruptions due to the pandemic lockdown in China led to a huge negative impact on global commodity markets and the worldwide economy. Furthermore, China is one of a few countries that controlled the spread of COVID-19. The Chinese economy plays a vital role in stabilizing global supply chains and commodity markets, while the rest of the world is severely impacted by the COVID-19 pandemic.

The remainder of this paper is organized as follows: Section 2 presents the data and descriptive statistics. Section 3 scrutinizes the COVID-19 impact on the dynamic correlation between the US and Chinese oil markets by extending the DCC-GARCH models with the inclusion of COVID-19 variables. Section 4 develops VAR models to study the impact of COVID-19 on causality and spillover effects across two markets. Section 5 concludes our paper.

2 DATA AND DESCRIPTIVE STATISTICS

We consider the daily closing prices for NYMEX’s oil in the US and oil futures in the Shanghai Futures Exchange (SFE) in China, which started to trade on March 26, 2018. Normally, futures contracts are combined using the nearest futures approach to become a continuous contract. In particular, the data of a futures contract with nearest maturity (usually in 1 month) has been used until its expiration and then the subsequent contract is used continuously until its expiration, and so on.

The outbreak of COVID-19 was announced on January 17, 2020. We select the period from March 26, 2018, to January 17, 2020, as the pre-COVID period and from January 18, 2020, to July 2, 2021, as the ongoing COVID-19 period. We use oilus and oilc to represent US and Chinese oil futures prices. We convert Chinese oil futures prices from RMB to US dollars to be consistent with US oil futures prices in currency. Table 1 displays the descriptive statistics for US and Chinese oil futures prices for both pre-COVID and ongoing-COVID periods. We observed that in both periods, the mean prices for US oil futures were lower than those for Chinese oil futures, while the standard deviations for US oil futures were higher than those for Chinese oil futures. More importantly, we find that both US and Chinese oil prices decreased by approximately 30%, while standard deviations increased by approximately 100% after the outbreak of COVID-19. This indicates that COVID-19 has significantly impacted the demand for oil in a negative direction, while it dramatically increases the price risk. Table 2 displays the descriptive statistics for US and Chinese oil futures returns for both periods.

3 COVID-19 IMPACT ON OIL FUTURES RETURN CORRELATIONS

We estimate the dynamic correlations between US and Chinese oil futures risks by employing the DCC-GARCH model proposed by Engle (2002). Let D be a dummy variable that takes the value of 0 for the pre-COVID period and the value of 1 for the ongoing COVID period. We also denote \( w_t \) as the new COVID-19 cases that were reported to the WHO on Day \( t \). Then, we propose the following model to investigate the COVID-19 impact on the covariance dynamics between two oil futures returns:

\[
\text{Cov}_t = \alpha_0 + \alpha_1 D + \sum_{k=1}^{p} \mu_k \text{Cov}_{t-k} + \sum_{l=1}^{q} \lambda_l \varepsilon_{t-l} \varepsilon_{t-l} - \delta D w_{t-1},
\]

(1)

| Period           | Variables | Obs | Mean        | Std. dev. | Min  | Max  | p1   | p99  | Skew. | Kurt.   |
|------------------|-----------|-----|-------------|-----------|------|------|------|------|-------|---------|
| Pre-COVID period | Oilu      | 430 | 60.70205    | 6.819217  | 42.53| 74.96| 45.88| 74.11| 0.0955| 2.1408  |
|                  | Oilc      | 430 | 68.12963    | 5.953947  | 51.90| 85.61| 55.42| 82.39| 0.2483| 2.5345  |
| Ongoing-COVID    | Oilu      | 341 | 46.80443    | 14.11402  | 10.01| 75.23| 13.78| 73.66| −0.088| 2.5362  |
|                  | Oilc      | 341 | 49.00791    | 11.50703  | 29.94| 72.39| 32.46| 72.00| 0.495 | 1.844   |
where Covt is the covariance of US and Chinese oil futures returns on Day t, \( \varepsilon_{t-1} \) is the residual from US oil return based on the DCC-GARCH model, \( \varepsilon_t \) is the residual from Chinese oil return based on the DCC-GARCH model, and \( \alpha_0, \alpha_1, \mu_k, \lambda_l, \theta \) are coefficients.

In the above model, \( \alpha_1 \) indicates the impact of COVID-19 on long-run covariance, while \( \theta \) presents the COVID-19 impact on short-term covariance.

We further define Corrt = \( \frac{Cov_t}{\sigma_t \sigma_t} \) as the dynamic correlation between US and Chinese oil futures return. Now we propose the correlation model as following:

\[
Corrt = \beta_0 + \beta_1 D + \sum_{k=1}^{p} \gamma_k Corrt-k + \sum_{l=1}^{q} \delta_l \frac{\varepsilon_{t-l} \varepsilon_{t-l-1}}{\sigma_t \sigma_{t-l}} + \theta' Dw_{t-1}. \tag{2}
\]

where \( \sigma_t \) is the standard deviation of the US oil futures returns at Day t and \( \sigma_t \) is the standard deviation of the Chinese oil futures returns at Day t. In the above model, \( \beta_1 \) indicates the impact of COVID-19 on long-run correlation, while \( \theta' \) presents the COVID-19 impact on short-term transient correlation.

Figures 1 and 2 deliver the covariance and correlation evolutions between US and Chinese oil futures returns from March 26, 2018, to July 2, 2021. From Figure 1 and Figure 2, we find that there is a huge covariance spike at the beginning of March 2020 when the WHO announced the beginning of the pandemic, and the correlation became much more volatile during the COVID-19 period. The Model (1) covariance fitting results in Table 3 show that the coefficient for the dummy variable D is positively significant, and the coefficient for \( Dw_{t-1} \) is insignificant. Table 4 presents the correlation fittings results for Model (2) which show the coefficient for the dummy variable D is also positively significant, but for the coefficient for \( Dw_{t-1} \) is negatively significant. This finding reveals that the COVID-19 pandemic strengthened the linkage between the two oil futures markets from a long-run perspective. In contrast, the daily new COVID-19 cases had little impact on covariance or has negatively significant impact on short term (transient) correlation. Since US and China had very different COVID severity and prevention measures, the negative (or insignificant) impact of COVID-19 on the transient correlations (or covariances) could be the reflection of difference in short term oil demand under the different pandemic effect on daily business activities in the two countries.

### TABLE 2  Descriptive statistics for US and Chinese oil futures returns

| Period               | Variables | Obs | Mean  | Std. Dev. | Min   | Max   | p1    | p99  | Skew. | Kurt. |
|----------------------|-----------|-----|-------|-----------|-------|-------|-------|------|-------|-------|
| Precovid-19 period   | \( R^u \) | 429 | -0.003 | 0.02169   | -0.0823 | 0.1326 | -0.0695 | 0.0453 | -0.077 | 7.663 |
|                      | \( R^c \) | 429 | -0.00004 | 0.0159   | -0.0656 | 0.0737 | -0.0426 | 0.0365 | -0.124 | 4.867 |
| Ongoing-covid-19 period | \( R^u \) | 341 | 0.001 | 0.062   | -0.602 | 0.32 | -0.28 | 0.22 | -2.529 | 34.814 |
|                      | \( R^c \) | 341 | 0 | 0.026 | -0.098 | 0.107 | -0.087 | 0.075 | -0.262 | 6.037 |

**Figure 1** The covariance evolutions between US and Chinese oil futures returns from March 26, 2018, to July 2, 2021.
4.1 VAR models

Before we built the VAR models, we conducted ADF tests for the stationarity of oil futures returns for US and Chinese markets. Table A1 shows the ADF test results, which indicate that both futures returns were stationary time series in both the pre-COVID and ongoing-COVID periods. Here the daily returns are calculated as:

$$R_t = \ln P_t - \ln P_{t-1},$$
where \( p_t \) and \( p_{t-1} \) are the oil prices on Days \( t \) and \( t-1 \), respectively. We denote \( R_t^u \) and \( R_t^c \) for US and Chinese oil futures returns at Day \( t \).

Next, we used LR statistics and FPE, AIC, HQIC, and SBIC information measures to determine the optimal number of VAR lags. Table A2 presents the above five measures for different lags for the pre-COVID and ongoing-COVID periods. From Table A2, we find that optimal lags were 3 for the pre-COVID period and 4 for the ongoing-COVID period. Then, we establish VAR models as follows:

**pre-COVID period VAR model:**

\[
\begin{pmatrix}
R_t^u \\
R_t^c
\end{pmatrix} = \begin{pmatrix}
-0.13 & 0.012 \\
0.515 & -0.17
\end{pmatrix} \begin{pmatrix}
R_{t-1}^u \\
R_{t-1}^c
\end{pmatrix} + \begin{pmatrix}
-0.039 & 0.065 \\
0.262 & -0.096
\end{pmatrix} \begin{pmatrix}
R_{t-2}^u \\
R_{t-2}^c
\end{pmatrix} + \begin{pmatrix}
-0.064 & 0.071 \\
0.116 & 0.044
\end{pmatrix} \begin{pmatrix}
R_{t-3}^u \\
R_{t-3}^c
\end{pmatrix}
\]

**ongoing-COVID period VAR model:**

\[
\begin{pmatrix}
R_t^u \\
R_t^c
\end{pmatrix} = \begin{pmatrix}
0.000 \\
0.001
\end{pmatrix} + \begin{pmatrix}
-0.12 & 0.464 \\
0.218 & 0.141
\end{pmatrix} \begin{pmatrix}
R_{t-1}^u \\
R_{t-1}^c
\end{pmatrix} + \begin{pmatrix}
-0.212 & 0.144 \\
-0.009 & 0.1
\end{pmatrix} \begin{pmatrix}
R_{t-2}^u \\
R_{t-2}^c
\end{pmatrix} + \begin{pmatrix}
-0.203 & 0.011 \\
-0.02 & -0.109
\end{pmatrix} \begin{pmatrix}
R_{t-3}^u \\
R_{t-3}^c
\end{pmatrix} + \begin{pmatrix}
0.091 & 0.21 \\
0.054 & 0.014
\end{pmatrix} \begin{pmatrix}
R_{t-4}^u \\
R_{t-4}^c
\end{pmatrix}
\]

Roots of the VAR comparison matrix were all within the unit circle for the pre-COVID and ongoing-COVID periods, respectively. Therefore, our VAR systems were stable in both periods.

### 4.2 | Granger causality tests

Table 5 lists four Granger causality tests for the US and Chinese oil futures returns in two periods. We discover the fact that US oil futures return moves are a Granger cause for Chinese oil futures return moves but not in the reverse direction before the outbreak of COVID-19. However, the two markets become a mutual Granger cause for each other regarding the return move during the COVID period.
This interesting finding could be explained as follows. China is one of a few countries that contained COVID-19, while the rest of the world is under the active spread of the virus. Therefore, China plays a more significant role as the world manufactory center and the critical player in the world supply chain during the COVID period than during the pre-COVID period due to the pandemic lockdown in most countries. Thus, global investors are more sensitive to Chinese oil demand during the COVID period than during the pre-COVID period. Consequently, the Chinese oil futures market is also a Granger cause for the US oil futures market and vice versa after the outbreak of COVID-19.

### 4.3 Impulse and response analysis

Impulse and response analyses were undertaken for the US and Chinese oil futures returns VAR systems to study the response of one oil market return when the other market return was under a one standard deviation shock, before and after the COVID-19 outbreak in China.

Figures 3 and 4 show impulse and response functions for US and Chinese oil futures returns for pre-COVID and ongoing-COVID periods. From Figure 3, we observe the following. In the pre-COVID period, Chinese oil futures returns jump to 0.01 in response to the US return shock of 0.02. In contrast, US oil futures returns jump to approximately 0.005 in response to a positive 0.01 shock in Chinese futures returns. Moreover, the Chinese market has a daily delay in responding to US impulse shocks, and this response lasts approximately 6 days. In comparison, the US response to Chinese impulse shocks lasts only 3 days. This asymmetric impulse and response between the two markets is in consistent with our finding in Section 4.2 that the US oil market was a Granger cause for the Chinese market before the outbreak of COVID-19. The slower response of the Chinese market to the US shock than the US response to the shock from the Chinese market also reveals that the Chinese oil futures market is not as efficient as the US oil futures market.

During the COVID period in Figure 4, one-standard deviations of impulsive shocks are 0.06 for the US market and 0.02 for Chinese oil futures, which are much more than their one-standard deviations of 0.02 for the US market and 0.01 for the Chinese market in the pre-COVID period. This indicates that COVID-19 has brought more uncertainty to both oil futures markets, such as the negative oil futures price at the beginning of the pandemic. Furthermore, each market's response to the impulsive shock from the other market lasts 8 days, which is more than the lasting days in the pre-COVID period. The above results show that the outbreak of COVID-19 caused a dramatic shock move to people's perceptions of the world economy. Both the US and Chinese oil futures markets responded with their volatilities in a strong and persistent way.

Finally, the similar impulse and response patterns from the two markets during the COVID period are in consistent with our results in Section 4.2. Both US and Chinese oil futures returns are a Granger cause to each other after the outbreak of COVID-19.

### 4.4 Variance decomposition of standard errors

Variance decomposition of standard errors for the two oil futures VAR systems will give a detailed decomposition of the standard error of each oil return into percentage contributions from the variations of both futures returns. These variance decompositions give a quantitative comparison of how strongly the US market affects the Chinese market and vice versa. Tables 6 and 7 display the variance decomposition results for each oil return's standard error in the pre-COVID and ongoing-COVID periods, respectively, from which we can make the following observations. The standard errors of Chinese oil market returns can be attributed to US market variations with contributions of 50% and
25% in the pre-COVID and ongoing COVID periods, respectively. On the other hand, the standard errors of US oil returns have 5% and 10% contributions from Chinese markets before and after the outbreak of COVID 19. Therefore, the increased influence of the Chinese market on the US market confirms the findings from the Granger causality test in Section 4.2. The results demonstrate that the increase Chinese impact on the US market after the COVID-19 outbreak is due to the change in one-direction causality from the US market to the Chinese market in the pre-COVID period to the bidirectional causal relation between the two oil futures markets during the COVID-19 period.

Finally, from the results of Granger tests, impulse and response analysis and variance decomposition in Section 4, we can infer that COVID-19 has made the interdependence between the US and Chinese oil markets significantly strong, which is also indicated by the correlation analysis in Section 3.

5 | CONCLUSIONS

This paper has investigated the impact of COVID-19 on the interdependence between the US and Chinese oil futures markets. The study of the pandemic impact on dynamic cross-market correlations is carried out by extending DCC-GARCH models to incorporate COVID-19 influencing variables. The impact of the pandemic on causality and spillover effects between two oil futures markets has been analyzed by the Granger test, impulse and response functions, and variance decomposition method under the VAR framework.
**Figure 4** Impulse and response functions in the ongoing COVID-19 period

**Table 6** Variance decomposition results in the pre-COVID-19 period

| Step | Decomposition for Ru | Decomposition for $R^c$ |
|------|-----------------------|--------------------------|
|      | $R^u$ | $R^c$ | $R^u$ | $R^c$ |
| 1    | 0.952 | 0.048 |       |       |
| 2    | 0.953 | 0.047 | 0.491 | 0.509 |
| 3    | 0.952 | 0.048 | 0.501 | 0.499 |
| 4    | 0.952 | 0.048 | 0.498 | 0.502 |
| 5    | 0.952 | 0.048 | 0.499 | 0.501 |
| 6    | 0.952 | 0.048 | 0.499 | 0.501 |
| 7    | 0.952 | 0.048 | 0.5  | 0.5   |
| 8    | 0.952 | 0.048 | 0.5  | 0.5   |
Our research shows that the COVID-19 pandemic enhanced the long-run correlation between US and Chinese oil futures returns, while the daily new cases of COVID-19 had little or negative effect on short-term transient correlation. Furthermore, we demonstrated that COVID-19 has also enhanced the causal relation from one-directional causality (from the US to China) to bidirectional causality between the two futures markets. In addition, the Chinese oil futures market’s response to US market impulsive shocks lasted longer than the US response to Chinese shocks in the pre-COVID period. On the other hand, however, both markets’ responses to the other market’s impulse lasted a similar amount of time during the COVID-19 period. Finally, COVID-19 has also significantly increased the volatility spillover effect from the Chinese oil market to the US oil market.

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DATA AVAILABILITY STATEMENT
These data were derived from the following commercial data provider WIND available in the public domain: https://www.wind.com.cn/newsite/data.html

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### TABLE 7  Variance decomposition results in the ongoing COVID-19 period

| Step | Decomposition for $R^u$ | Decomposition for $R^c$ |
|------|-------------------------|-------------------------|
|      | $R^u$ | $R^c$ | $R^u$ | $R^c$ |
| 1    | 0.918 | 0.082 | 0 | 1 |
| 2    | 0.906 | 0.094 | 0.256 | 0.744 |
| 3    | 0.906 | 0.094 | 0.248 | 0.752 |
| 4    | 0.907 | 0.093 | 0.249 | 0.751 |
| 5    | 0.904 | 0.096 | 0.249 | 0.751 |
| 6    | 0.903 | 0.097 | 0.252 | 0.748 |
| 7    | 0.903 | 0.097 | 0.253 | 0.747 |
| 8    | 0.903 | 0.097 | 0.253 | 0.747 |
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**APPENDIX A**

Tables A1 and A2

**TABLE A1** ADF tests for stationary of futures returns

| Period             | Variable | ADF Value | p Value | Stationarity |
|--------------------|----------|-----------|---------|-------------|
| Precovid-19 period | $R_u$    | −23.39    | 0       | Stable      |
|                    | $R_c$    | −18.101   | 0       | Stable      |
| Ongoing-Covid-19   | $R_u$    | −19.357   | 0       | Stable      |
|                    | $R_c$    | −13.951   | 0       | Stable      |
### TABLE A2  Determination of the optimal VAR lags

| lag | LL       | LR    | df  | p     | FPE      | AIC      | HQIC     | SBIC     |
|-----|----------|-------|-----|-------|----------|----------|----------|----------|
|     | Precovid-19 period |       |     |       |          |          |          |          |
| 0   | 2194.62  | 0     | 10.318 | 10.311 | 10.299  |          |          |          |
| 1   | 2331.37  | 273.49| 4     | 0     | 0        | 10.943   | 10.92    | 10.886   |
| 2   | 2352.18  | 41.617| 4     | 0     | 0        | 11.022   | 10.984   | 10.926*  |
| 3   | 2359.5   | 14.637*| 4     | 0.006 | 5.5e-08*| 11.0376*| 10.9849*| 10.904   |
| 4   | 2362     | 5.016 | 4     | 0.286 | 0        | 11.031   | 10.963   | 10.859   |
|     | Ongoing-covid-19 period |       |     |       |          |          |          |          |
| 0   | 1222.61  | 0     | 7.266| 7.256 | 7.243    |          |          |          |
| 1   | 1300.04  | 154.87| 4     | 0     | 0        | 7.703    | 7.67546*| 7.63447*|
| 2   | 1305.56  | 11.037| 4     | 0.026 | 0        | 7.712    | 7.666    | 7.598    |
| 3   | 1312.99  | 14.867*| 4     | 0.005 | 0        | 7.732    | 7.669    | 7.573    |
| 4   | 1317.49  | 8.988 | 4     | 0.061 | 1.5e-06*| 7.73505*| 7.654    | 7.531    |

* Indicates significant at the 1% level