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The Impact of COVID-19 on Commodity Options Market: Evidence from China

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Abstract
Considering the severe economic impact of COVID-19, this study examines COVID-19’s influence on the Chinese commodity market. The literature shows that COVID-19’s influence in China during its abatement period has not been well investigated. We address this issue by the intraday analysis of the volatility from 16 commodity options contracts in the Chinese commodity options market over the period 2019-2021. We demonstrate that while the pandemic eased in China after its initial outbreak, it still significantly affected the volatility of Chinese agricultural commodities options. In contrast, its impacts on the volatility of options for petrochemicals, ores, and metals are negligible. This pattern reflects the role of pandemic-led supply disruptions affecting agricultural commodity prices as necessities, contributing to higher price volatility relative to non-agricultural commodities, which are less volatile.

Keywords: COVID-19, Commodity options, High-frequency data, Realized volatility

JEL classification: G13, G15, O53.

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Highlights

• We analyze the impact of COVID-19 on the volatility of the options commodity market.
• We compare the pre-outbreak period with the period in which the pandemic recedes.
• We focus on the 16 futures options contracts to test the epidemic impact.
• Well-controlled COVID-19 affects only agricultural commodities.
• Such results are related to agricultural commodities as necessities.

1 Introduction

From the end of January 2020, the coronavirus disease 2019 (COVID-19) has not only become a fierce global storm attacking public health but also quickly spread to the global financial markets. A collapse in the world economy is caused by lockdowns, massive travel restrictions, and other measures taken by many countries to slow down the spreading of the pandemic. For example, U.S. stocks fused four times in just ten days. The Dow Jones index fell by 23% in the first quarter, the FTSE 100 index in the U.K. fell by 25%, the DAX index in Germany fell by 25%, and the Korean stock market fell by 20%, all of which were recorded the most significant quarterly decline since the 1987 financial crisis. However, China’s swift economic coping strategies have reversed the situation and brought about a strong rebound in the economy. In late 2020 and early 2021, the epidemic situation in China is already minimal. At the time of the COVID-19 sweeping the whole world, China may be the only major economy to maintain a positive growth rate in 2020. Despite the economic headwinds, has the impact of the epidemic disappeared? If not, is the epidemic at this point a systemic or non-systemic risk to the overall economic system? What are potential risks easily overlooked? Therefore, it is necessary and exciting to investigate the epidemic impact on the Chinese financial market under this background to answer these questions.

The commodity market is one of the lifelines of the national economy because livelihood materials and industrial raw materials are primarily traded in this market. For example, crude oil, as one of the essential commodities, the drastic changes in oil price would directly lead to the market’s concern about the uncertainty of the future. Besides, recent studies reaffirm that the commodity market is strongly associated with other financial markets and can also affect the global economy (see, e.g.
Furthermore, with the rapid development of the commodity derivatives market, the relationship between the commodity market and other markets has become increasingly diversified and complex, becoming a risk source that cannot be ignored in the economic system. As an important part of the commodity market, the commodity option is one of the most dynamic risk management tools in the current capital market (see, e.g, Bollerslev and Ole Mikkelsen (1996); Christensen and Nielsen (2007); Christensen, rregaard Nielsen and Zhu (2010)). The commodity option underlying is a commodity, such as cotton and soybean in agricultural products, copper in metals, iron ore in ores, etc. A commodity option is an excellent financial instrument for commodity risk hedging and management, and volatility plays a significant role in it because it not only is an important indicator of option pricing but also can measure market risk and affect the stability of the commodity market (see, e.g. Chen and Ewald (2017); Feunou and Okou (2019); Xu, Xiao and Zhang (2020)).

Different from most existing studies using low-frequency data, this paper focuses on high-frequency data analysis. In most low-frequency studies, GARCH and stochastic volatility type models are commonly used to model and forecast financial volatility. While the enhancement of the availability of high-frequency data brings a new dimension to volatility modeling on financial assets in recent twenty years (see Andersen et al. (2006), Barndorff- Nielsen and Shephard (2006), A˘ıt-Sahalia and Jacod (2014), Degiannakis et al. (2020)). There are increasing literature using high sampling frequency because lower sampling frequency may result in information loss (see Hansen and Lunde (2006), Bandi and Russell (2006)). For example, by the use of high-frequency data, Erdemlioglu, Petitjean and Vargas (2021) and Anag- nostidis, Fontaine and Varsakelis (2020) studied the prediction of financial market risk and the monitoring of moral hazard in financial markets, respectively.

This paper aims to examine whether the pandemic exerts an impact on the volatility of the Chinese commodity options market during the waning of the pandemic. To answer this question, we propose to explore the epidemic’s impact on volatility by studying the Chinese commodity options market. For this purpose, we conduct the following analysis. Firstly, the realized volatility is calculated at four types of high-frequency data (1-min, 5-min, 15-min, and 30-min) from the commodity futures market. Then, options prices based on these volatilities will be given by the Black (1976) model. After that, the performance of different sampling
frequencies will be proposed by comparing the MAE\(^1\) (Mean Absolute Error) and RMSE\(^2\) (Root Mean Squared Error) of different sampling frequencies, which are computed from the model-based options prices and market prices. Finally, we compare the performance of MAE and RMSE before the pandemic with the corresponding performance during the waning of the epidemic, and then the impact of COVID-19 on the volatility of the Chinese commodity options market during the slowdown period can be inferred.

The paper will contribute to the literature by filling three main gaps. Firstly, it shed novel light on the volatility effect of an exogenous and systematic shock on the commodity market in the post-pandemic era. Many studies focus on COVID-19 as an emergency event to study the impact of the epidemic on the financial or economic field and the corresponding response. For example, Akhtaruzzaman et al. (2021) examined the role of gold as a hedge or safe-haven asset in the COVID-19 crisis and Funke and Tsang (2020) constructed a dynamic-factor-based indicator to measure the Chinese monetary policy response to the pandemic. However, they do not study the impact of the pandemic on the financial or economic field when the epidemic waned, which is the focus of this paper.

Secondly, it provides a new perspective on the study of volatility in the commodity market from an options view. Commodity futures prices are the commodities market’s most authoritative and widely used reference price system. Therefore, a large number of studies of volatility in commodity markets are based on commodity futures (see, e.g. Joseph, Sisodia and Tiwari (2014); Ouyang and Zhang (2020); Nguyen and Walther (2020)). Based on commodity futures markets, commodity options markets can perform additional and enhanced functions, such as faster price discovery and more accurate volatility forecasting based on implied volatility. However, options markets not only have the characteristics of futures markets (for example, market structure) but are also more complex (for example, the volatility smile), so there are fewer studies examining commodity volatility from an options perspective.

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\(^1\) The mathematical expression for MAE is \(\frac{1}{m} \sum_{i=1}^{m} |x_i - y_i|\), where \(m\) is the number of observation, \(x_i\) and \(y_i\) are estimated and real value, respectively.

\(^2\) The mathematical expression for RMSE is \(\sqrt{\frac{1}{m} \sum_{i=1}^{m} (x_i - y_i)^2}\), where \(m\) is the number of observation, \(x_i\) and \(y_i\) are estimated and real value, respectively.
Finally, although the Chinese commodity options market is very young, it is developing rapidly and is becoming an increasingly important financial market in China. Therefore, it contributes not only to the literature presenting evidence from the Chinese commodity options market but also to the literature relating COVID-19 to the financial markets.

The remainder of this paper is structured as follows. Section 2 introduces the classical model in pricing futures options. Data and empirical results of the impact of COVID-19 on the volatility of Chinese commodity options are presented in Section 3. Section 4 is the conclusion.

2 Model

Black (1976) presented a model which is suitable for futures options. Similar to the Black-Scholes model (see Black and Scholes (1973)), most of the Black (1976) models assumptions are gross oversimplifications. Hence, the Black (1976) model is actually not good in the representation of reality. Plenty of advanced and complex models are developed for pricing futures options based on expanding the assumption of the Black (1976) model. However, the complexity of the model is not a criterion for evaluating the quality of the model. Even options are highly leveraged and nonlinear on the underlying, Black (1976) model can still capture the quickly changing options prices quite well to some extent. More importantly, the weaknesses of the Black (1976) model are well understood and the results from the model are intuitively sensible. Therefore, the Black (1976) model is actually widely used in practice.

Black (1976) model assumes the futures price follows the lognormal process, the European call price $C$ and the European put price $P$ for a futures options are given as follows,

$$\begin{align*}
C &= e^{-rT} \left[ F_0 N(d_1) - KN(d_2) \right] \\
P &= e^{-rT} \left[ KN(-d_2) - F_0 N(-d_1) \right]
\end{align*}$$

where

$$\begin{align*}
d_1 &= \frac{\ln(F_0 / K) + \sigma^2 T / 2}{\sigma \sqrt{T}} \\
d_2 &= \frac{\ln(F_0 / K) - \sigma^2 T / 2}{\sigma \sqrt{T}} = d_1 - \sigma \sqrt{T}
\end{align*}$$
and $F_0$ is the futures price, $K$ is the strike price, $r$ is the interest-free rate, $T$ is the time to maturity, $\sigma$ is the volatility of the futures price, $N(\cdot)$ is the cumulative probability distribution function for a standardized normal distribution.

In this model, all parameters can be obtained from the market except volatility. In order to obtain the value of volatility, realized volatility is implemented. Generally, dividing each trading day into $N$ period, the realized volatility (RV) is defined as followed,

$$RV_t = \sum_{j=1}^{N} r_j^2$$

where

$$r_j = \ln p_j - \ln p_{j-1}, (j=1,2,\ldots,N),$$

$r_j$ is the futures return at time $j$ and $p_j$ is the futures price at time $j$. After that, the value of volatility in the Black (1976) model can be obtained by taking the square root of $RV_t$ and annualizing the result.

### 3 Data and Empirical Results

#### 3.1 Data

In the high-frequency field, Andersen and Bollerslev (1998) firstly proposed a new evaluation method for the measurement of volatility, namely realized volatility, that is, taking the sum of squares of intraday returns. This method is model-free and does not require complex parameter estimation. Realized volatility approach is used to estimate the volatility. Many researchers have proved this method to have advantages over low-frequency volatility. For example, compared with volatility calculated with low-frequency data, Corsi, Fusari and La Vecchia (2013) and Majewski, Bormetti and Corsi (2015) proved that realized volatility could give a better performance in giving a value for options. Many studies also applied realized volatility in the Chinese futures market. Liu and Wan (2012) investigated the dynamics of daily volatility of Shanghai fuel oil futures prices by realized volatility. Yang et al. (2017) studied the realized volatility of agriculture futures in China by HAR model with bagging and combination methods. Wen, Wang and Zhang (2021) also explored the predictability of high-frequency return in the Chinese oil futures market. However, few studies applied realized volatility to the Chinese commodity options market since this market is very young.

However, when it comes to high-frequency data, the problem of market

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3 The first commodity option to land in China was in March 2017.
Market microstructure\(^4\) is raised. Generally, the higher the sampling frequency of the data, the more market information is obtained and the smaller the error in the measurement of realized volatility. Taking market microstructure into account, Ait-Sahalia, Mykland and Zhang (2005) tried to find an accurate volatility by investigating the noise of market microstructure from different sampling frequencies. However, their method requires high demand on both econometrics technique and data storage space. Moreover, the result that comes from their method may not be acceptable. For example, according to their method, a frequency of 1 minute and 30 seconds is theoretically optimal. However, in practice, this value may not be as intuitive as 1 minute or 5 minutes is the optimal sample frequency. Therefore, the realized volatility from their method can be highly inaccurate.

While, many other researchers focus on taking the method of comparing a fixed number of different frequencies (tick-by-tick, 5-min, 15-min and 30-min) to find the most accurate volatility based on S&P500 or some individual stocks. (see Bandi, Russell and Yang (2008), Allen, McAleer and Scharth (2011) Jou, Wang and Chiu (2013), Christoffersen et al. (2014), Çelik and Ergin (2014), Liu, Patton and Sheppard (2015) and Naimoli, Gerlach and Storti (2022), Çelik and Ergin (2014) and Liu, Patton and Sheppard (2015))

The main contract of futures will be considered in this paper because this type of contract is the most active. In order to consider the impact of the epidemic when the epidemic is not severe, two futures contracts with the exact underlying but different expiration times will be considered, which active period is from 02/12/2019 to 23/01/2020 and 01/12/2020 to 22/01/2021, respectively, that is, one is the main contract before the outbreak, and the other one is the main contract one year after the outbreak. There are two other advantages of choosing these two sample periods. First, it can exclude the influence of structure problems from futures or options contracts. Second, it can exclude the influence of seasonal factors on commodities.\(^5\) During these two periods, weekends and other non-trading days are omitted, which means that the trading days are considered to be continuous and 38 days for each futures contract. The interest-free rate is 0.05\(^6\) for these two periods.

\(^4\) Market microstructure investigates the mechanism of price discovery and how prices adjust to new information.

\(^5\) The first problem is common in futures or options contracts. For example, different contracts have different expired times. The second problem is common in commodities, especially in agricultural commodity products. For example, the price of apples during harvest season is relatively low.

\(^6\) The 5-year LPR(Loan Prime Rate) is 4.65% for these two periods in China. We have set the interest-free rate at 0.05 for simplification of calculation, which will not affect the final result of this paper.
According to the characteristics of the Chinese commodity futures market, it should be noticed that if there is a transaction on the night before the trading day, the opening time of the trading day is 21:00 on the previous day, and the closing time is 15:00 on the trading day.

Taking trading volume, trading value, open interest, liquidation and representativeness into consideration, eight underlying(sixteen futures contract) are chosen to be examined in this paper, that is, sugar(SR005, SR105), cotton(CF005, CF105), soybean meal(M2005, M2105), corn(C2005, C2105), PTA(TA005, TA105), iron ore(I2005, I2105), copper(CU2002, CU2102), natural rubber(RU2005, RU2105). In order to compare the performance of different sampling frequencies from the futures options perspective, the at-the-money call options 7 for corresponding futures contracts, and four different frequency samplings of each futures contract, i.e., 1-min, 5-min, 15-min, 30-min, are employed to construct the panel data in the empirical study.

Samples with the same underlying but different sampling frequency are similar in characteristics such as mean, median, maximum, and minimum; the main difference is the number of observations. Hence, Table 1 describes observations for futures contracts. Table 2 and table 3 describe some features of futures options for non-epidemic period and epidemic period respectively. The reason why the observations in table 1 are quite different from the observations in table 2 and table 3 is that observations in table 1 are futures’ minute data to measure the realized volatility and calculate the daily options price. In contrast, observations in table 2 and table 3 are options’ daily data to compare with the previously calculated options price. The strike price is chosen to be close to the underlying price at the beginning of the transaction from the sample period.

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7 Generally, at-the-money options are the most actively traded in the market. The reason for this is that the direction for at-the-money options is difficult to determine and is most speculative as the buyer makes a profit when it turns in-the-money options, and the seller makes a profit when it turns out-of-the-money option. It is hard to find an at-the-money option as its definition in reality. In practice, we find an option with a strike price that is closest to the price of the underlying as an at-the-money option. Put options are also examined, and the result is similar to the call options. Therefore, the at-the-money call options are chosen in this paper for consideration.
Table 1: Descriptive Statistics of Observations, 02/12/2019-23/01/2020 and 01/12/2020-22/01/2021

|          | SR    | CF    | M     | C     | TA    | I     | CU    | RU    |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|
| Observations from 02/12/2019-23/01/2020 |       |       |       |       |       |       |       |       |
| 1min     | 13351 | 13351 | 13141 | 13141 | 13351 | 13141 | 17581 | 13141 |
| 5min     | 2640  | 2640  | 2598  | 2598  | 2640  | 2598  | 3486  | 2598  |
| 15min    | 880   | 880   | 866   | 866   | 880   | 866   | 1162  | 866   |
| 30min    | 459   | 459   | 452   | 452   | 459   | 452   | 600   | 452   |
| Observations from 01/12/2020-22/01/2021 |       |       |       |       |       |       |       |       |
| 1min     | 13262 | 13262 | 13262 | 13262 | 13262 | 17822 |       |       |
| 5min     | 2622  | 2622  | 2622  | 2622  | 2622  | 3534  | 2622  |       |
| 15min    | 874   | 874   | 874   | 874   | 874   | 1178  | 874   |       |
| 30min    | 456   | 456   | 456   | 456   | 456   | 608   | 456   |       |

Note: Descriptive statistics of futures price observations in the whole sample. The reason why different underlying within the same sampling frequency in the same period has different observations is that different underlying has different trading hours at night. The observations of the same underlying in different periods are also different; the reason is that the trading hours are changed at night according to the adjustment of the commodity exchanges. Data are available through Wind.

3.2 Empirical Results of Realized Volatility

As indicated before, the realized volatility can be calculated by different sampling frequencies according to equation (1). The results of realized volatility for different sampling frequencies are shown in figure 1 to figure 8. For comparison, the 5-day historical volatility of 16 futures prices will be used as a benchmark.

Figure 1 presents the results of different realized volatilities and 5-day historical volatility of the sugar futures contract (SR005 and SR105). As can be seen, the trends of all realized volatilities, calculated from different sampling frequencies, are similar. Moreover, although the results of 1-min, 5-min, 15-min, and 30-min realized volatility differ from the 5-day historical volatility, they are very close. 5-day historical volatility is used as a benchmark; however, it does not mean that 5-day historical volatility can represent the actual market volatility. Treating 5-day historical volatility as a benchmark test that realized volatility is roughly correct. Furthermore, the value of mean volatility for 1-min, 5-min, 15-min, 30-min and 5-day historical are 0.12, 0.11, 0.1, 0.09 and 0.12 for the contract SR005, respectively. The value of mean volatility for 1-min, 5-min, 15-min, 30-min and 5-day historical are 0.15, 0.14, 0.13, 0.13 and 0.16 for the contract SR105, respectively. Compared with the value for the different contracts with the same sampling frequency, it can be easily found that the volatility was higher when the epidemic happened.
Table 2: Descriptive Statistics, 02/12/2019-23/01/2020

|                | SR005c5400 | CF005c13200 | M2005c27500 | C2005c19000 | TA005c48000 | I2005c60000 | CU2002c47000 | RU2005c12500 |
|----------------|------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Mean           | 265.39     | 561.32      | 70.87       | 38.20       | 234.89      | 64.14       | 1919.94     | 857.58      |
| Median         | 207.25     | 561.50      | 74.50       | 37.00       | 234.89      | 63.96       | 2085.00     | 853.50      |
| Maximum        | 498.00     | 1293.00     | 97.50       | 61.00       | 346.00      | 84.20       | 2789.00     | 1097.00     |
| Minimum        | 162.50     | 317.00      | 25.50       | 150.00      | 150.00      | 21.10       | 504.00      | 408.00      |
| Std. Dev.      | 282.59     | 1293.00     | 150.00      | 150.00      | 150.00      | 21.10       | 504.00      | 408.00      |
| Skewness       | -0.50      | -1.24       | -1.01       | 2.87        | 2.37        | -0.38       | 0.71        | -0.01       |
| Kurtosis       | 2.87       | 61.00       | 61.00       | 61.00       | 61.00       | 61.00       | 61.00       | 61.00       |
| Observations   | 38.00      | 38.00       | 38.00       | 38.00       | 38.00       | 38.00       | 38.00       | 38.00       |

Note: Descriptive statistics of daily futures options prices in a non-epidemic period. The reason why the trading day of PTA options and iron ore options is not 38 days is that the trading time of PTA options started on 16/12/2019, and the trading time of iron ore options started on 09/12/2019. Copper options only have 35 trading days because the maturity of this options contract is 20/01/2020. Data are available through Wind.

Table 3: Descriptive Statistics, 01/12/2020-22/01/2021

|                | SR105c5100 | CF105c14600 | M2105c3200 | C2105c2680 | TA105c3550 | I2105c840 | CU2102c25700 | RU2105c15500 |
|----------------|------------|-------------|------------|------------|------------|------------|-------------|--------------|
| Mean           | 225.18     | 808.50      | 235.38     | 110.00     | 372.88     | 188.50     | 1977.63     | 716.63       |
| Median         | 228.50     | 760.50      | 171.50     | 86.25      | 356.50     | 208.85     | 1891.00     | 702.00       |
| Maximum        | 393.00     | 1232.00     | 573.50     | 217.50     | 561.00     | 296.50     | 3288.00     | 1272.00      |
| Minimum        | 101.00     | 500.00      | 69.50      | 35.50      | 182.00     | 86.25      | 1450.00     | 494.00       |
| Std. Dev.      | 211.02     | 157.54      | 64.48      | 100.94     | 57.72      | 141.12     | 444.12      | 159.42       |
| Skewness       | -0.34      | -1.02       | -0.26      | 0.32       | -0.33      | 0.47       | 2.09        | 3.13         |
| Kurtosis       | 0.37       | 0.33        | 0.65       | 0.51       | 0.18       | -0.90      | 1.42        | 1.59         |
| Observations   | 38.00      | 38.00       | 38.00      | 38.00      | 38.00      | 38.00      | 38.00       | 38.00        |

Note: Descriptive statistics of daily futures options prices in epidemic period. Data are available through Wind.

Figure 1: Realized volatilities and Historical volatility: SR005 on the left, SR105 on the right
Figure 2: Realized volatilities and Historical volatility: CF005 on the left, CF105 on the right

The results of different realized volatilities and 5-day historical volatility of the cotton futures contract (CF005 and CF105) are presented in Figure 2. Similar results with the sugar futures contract can be found in the cotton futures contract, except in the term of the mean of different volatility. The value of mean volatility for 1-min, 5-min, 15-min, 30-min and 5-day historical are 0.18, 0.16, 0.15, 0.14 and 0.13 for the contract CF005, respectively; the value of mean volatility for 1-min, 5-min, 15-min, 30-min and 5-day historical are 0.18, 0.16, 0.15, 0.14 and 0.19 for the contract CF105, respectively. It can be seen that except the 5-day historical volatility of the cotton futures contract after the epidemic is higher than the contract before the epidemic, the results of other high-frequency sampling volatility of cotton futures contract after the epidemic are the same as the cotton future contract before the epidemic.

Figure 3 shows the performance of different high-frequency sampling volatilities and the 5-day historical volatility of the soybean meal futures contract (M2005 and M2105). The performances of all volatilities in their corresponding futures contracts are similar, and the gap between them is also not very big. The value of mean volatility for 1-min, 5-min, 15-min, 30-min and 5-day historical are 0.13, 0.11, 0.09, 0.09 and 0.10 for the contract M2005, respectively and the value of mean volatility for 1-min, 5-min, 15-min, 30-min and 5-day historical are 0.23, 0.21, 0.21, 0.2 and 0.21 for the contract M2105, respectively. The volatility of soybean meal futures contract after the epidemic is higher than that before the epidemic.
Figure 3: Realized volatilities and Historical volatility: M2005 on the left, M2105 on the right

Figure 4: Realized volatilities and Historical volatility: C2005 on the left, C2105 on the right

Figure 4 presents the performance of different high-frequency sampling volatilities and the 5-day historical volatility of the corn futures contract (C2005 and C2105). Except for the 1-min of the C2005 contract, the performance of other volatilities in their corresponding futures contracts is relatively close. The result of the 1-min realized volatility of the C2005 contract is very different because the 1-min price of the futures contract of the C2005 is very volatile. In other words, the 1-min price data of the C2005 is too noisy and may require a more advanced method to calculate realized volatility. The value of mean volatility for 1-min, 5-min, 15-min, 30-min and 5-day historical are 0.12, 0.08, 0.07, 0.06, 0.06 for the contract C2005, respectively and the value of mean volatility for 1-min, 5-min, 15-min, 30-min and 5-day historical are 0.15, 0.13, 0.12, 0.12, 0.11 for the contract C2105, respectively. It can also be found that the volatility becomes higher
during the epidemic.

Figure 5: Realized volatilities and Historical volatility: TA005 on the left, TA105 on the right

Figure 5 provides the performance of different high-frequency sampling volatilities and 5-day historical volatility of the PTA futures contract (TA005 and TA105). The performances of all volatilities in their corresponding futures contracts are quite similar. The value of mean volatility of 1-min, 5-min, 15-min, 30-min and 5-day historical for the contract TA005 are 0.19, 0.16, 0.14, 0.13 and 0.15, respectively and the value of mean volatility of 1-min, 5-min, 15-min, 30-min and 5-day historical for the contract TA105 are 0.27, 0.23, 0.22, 0.22 and 0.22, respectively. It can be seen that the volatility of the PTA futures contract is higher in the period of the epidemic.

Figure 6 exhibits the performance of different high-frequency sampling volatilities and 5-day historical volatility of the iron ore futures contract (I2005 and I2105). The performances of all volatilities in their corresponding futures contracts are also quite similar. The value of mean volatility of 1-min, 5-min, 15-min, 30-min and 5-day historical for the contract I2005 are 0.28, 0.22, 0.2, 0.19 and 0.22, respectively. The value of mean volatility of 1-min, 5-min, 15-min, 30-min and 5-day historical for the contract I2105 is 0.47, 0.43, 0.4, 0.37 and 0.37, respectively. It can be found that the volatility of the iron ore futures contract was significantly higher in the period of the epidemic.
Figure 6: Realized volatilities and Historical volatility: I2005 on the left, I2105 on the right

Figure 7: Realized volatilities and Historical volatility: CU2002 on the left, CU2102 on the right

The performance of different realized volatilities and 5-day historical volatility of the copper futures contract (CU2002 and CU2102) is established in Figure 7. The same result with the iron ore futures contract can be found in the copper futures contract. The value of mean volatility of 1-min, 5-min, 15-min, 30-min and 5-day historical for the contract CU2002 are 0.09, 0.08, 0.08, 0.07, and 0.08, respectively. The value of mean volatility of 1-min, 5-min, 15-min, 30-min and 5-day historical for the contract CU2102 are 0.17, 0.15, 0.15, 0.14 and 0.16, respectively. It can be found that the volatility of the copper futures contract during the epidemic has almost doubled compared to that of the non-epidemic period.
Figure 8 displays the performance of different high-frequency sampling volatilities and the 5-day historical volatility of the natural rubber futures contract (RU2005 and RU2105). The performances of all volatilities in their corresponding futures contracts are quite similar, which is similar to the above-mentioned futures contract. The value of mean volatility for 1-min, 5-min, 15-min, 30-min and 5-day historical are 0.22, 0.19, 0.18, 0.16 and 0.16 for the contract RU2005, respectively and the value of mean volatility for 1-min, 5-min, 15-min, 30-min and 5-day historical are 0.31, 0.28, 0.27, 0.28 and 0.34 for the contract RU2105, respectively. It can also be found that the volatility of the natural rubber futures contract increased significantly during the period of the epidemic.

From the above analysis of the results, two conclusions can be drawn. Firstly, in most cases, the performance of realized volatility for different sampling frequencies is good, that is, the realized volatility results from the original calculation method can be trusted. Secondly, the volatility of the selected sample contracts during the epidemic period is generally higher than that before the epidemic. This result is consistent with common sense, proving that this paper’s realized volatility is reliable.
3.3 Empirical Results of Options prices

As showed before, with volatility obtained, the future call options prices can easily be calculated by equation (1). The results of different sampling frequencies for different underlying are presented in Figure 9 to Figure 16.

Figure 9: Options prices obtained from Model and Market: SR005 on the left, SR105 on the right

Figure 10: Options prices obtained from Model and Market: CF005 on the left, CF105 on the right

As seen from the above figures, except for the futures options prices of corn, the options prices obtained by different sampling frequencies of all other futures contracts are roughly the same as the market price. Indeed, not all the options prices results are very close to the market prices. However, this paper aims to compare the performance of different sampling frequencies and the impact of the epidemic rather than to explore the accuracy of the model. In this regard, the results from Figure 9 to Figure 16 can already illustrate that the Black (1976) model is fully competent.
Figure 11: Options prices obtained from Model and Market: M2005 on the left, M2105 on the right

Figure 12: Options prices obtained from Model and Market: C2005 on the left, C2105 on the right

Figure 13: Options prices obtained from Model and Market: TA005 on the left, TA105 on the right
Figure 14: Options prices obtained from Model and Market: I2005 on the left, I2105 on the right

Figure 15: Options prices obtained from Model and Market: CU2002 on the left, CU2102 on the right

Figure 16: Options prices obtained from Model and Market: RU2005 on the left, RU2105 on the right
3.4 Comparison with Market Price

As mentioned before, the market price of the at-the-money futures call options contract is treated as the benchmark for comparison. The effectiveness of the different sampling frequencies and the comparison between model price and market price are given in Figures 17 to Figure 24.

Figure 17: The performance of SR005 and SR105 during epidemic period and non-epidemic period: MAE on the left, RMSE on the right

Figure 17 shows the validity of different sampling frequencies and comparison for the sugar futures options contract. As can be seen, both in MAE and RMSE, the optimal sampling frequency is the 1-min sample before the epidemic, while the optimal sampling frequency becomes the 5-min sample after the epidemic. Moreover, it can be noticed that the relationship between different sampling frequencies has changed after the epidemic in terms of validity. For example, the performance of MAE and RMSE for different sampling frequencies during the non-epidemic exhibits a concave curve. In contrast, the performance during the epidemic appears to be a convex curve.

The effectiveness of different sampling frequencies and comparison for the cotton futures options contract is shown in Figure 18. It can be concluded that the optimal sampling frequency is the 1-min sample during the epidemic in both MAE and RMSE. In contrast, the performance of different sampling frequencies before the epidemic is similar. Besides, the performance of MAE and RMSE for different sampling frequencies before the epidemic seems like a straight line, while the performance after the epidemic looks like a diagonal line.

Figure 19 gives the validity of different sampling frequencies and comparison for the soybean meal futures options contract. As shown in the above Figure, both in MAE and RMSE, the optimal sampling
frequency is the 5-min sample before the epidemic. In contrast, the optimal sampling frequency becomes the 1-min sample after the COVID-19 occurred. In addition, it can also be found that the relationship between different sampling frequencies has changed after the epidemic. Furthermore, MAE and RMSE during the epidemic period are significantly bigger than during the non-epidemic period.

Figure 18: The performance of CF005 and CF105 during epidemic period and non-epidemic period: MAE on the left, RMSE on the right

Figure 19: The performance of M2005 and M2105 during epidemic period and non-epidemic period: MAE on the left, RMSE on the right
Figure 20: The performance of C2005 and C2105 during epidemic period and non-epidemic period: MAE on the left, RMSE on the right.

Figure 20 displays the validity of different sampling frequencies and comparison for the corn futures options contract. As indicated before, there is a problem with the 1-min sample in computing realized volatility; hence it is difficult to determine which sampling frequency is the best. However, if the 1-min sample is excluded, it can also be found that the optimal sampling frequency is changed from the 5-min sample during the non-epidemic period to the 15-min sample during the epidemic period from the views of RMSE. In addition, a bigger MAE and RMSE can also be found in the period of epidemic except for the 1-min sample.

Figure 21 presents the validity of different sampling frequencies and comparison for the PTA futures options contract. In terms of MAE, the optimal sampling frequency is the 5-min sample and has not changed since the epidemic happened. The result in Figure 21 is very interesting because the relationship between the two before and after the epidemic seems to move up in parallel. However, both MAE and RMSE are bigger during the non-epidemic period than during the epidemic period, which is beyond expectation. The reason may be caused by the PTA options product just launched, and the corresponding market is not well-developed, resulting in sharp price fluctuations.
Figure 21: The performance of TA005 and TA105 during epidemic period and non-epidemic period: MAE on the left, RMSE on the right.

Figure 22: The performance of I2005 and I2105 during epidemic period and non-epidemic period: MAE on the left, RMSE on the right.

Figure 22 shows the validity of different sampling frequencies and comparison for the iron ore futures options contract. As can be seen, the performance of MAE and RMSE in the I2005 and I2105 contracts is similar to the result obtained from the case of the PTA futures options contract. The difference is both MAE and RMSE are bigger during the epidemic period than in the non-epidemic period.

Figure 23 displays the validity of different sampling frequencies and comparison for the copper futures options contract. It is unclear which sampling frequency is optimal from the side of MAE. However, from the view of RMSE, the optimal sampling frequency keeps the same before and after the epidemic, that is, the 5-min sample. Moreover, it can also be seen that MAE and RMSE are significantly bigger during the epidemic.
The effectiveness of different sampling frequencies and comparison for natural rubber futures options contract is presented in Figure 24. From the view of MAE, with a decrease in frequency, the MAE performs worse both in the non-epidemic and epidemic periods. Also, the same result can be found that MAE and RMSE are significantly bigger in the period of the epidemic than in the non-epidemic period.

In conclusion, three findings can be obtained by comparing the model and market prices. Firstly, except for PTA futures options contracts, sugar futures options contracts, and cotton futures options contracts, other contracts clearly show that the gap between the prices obtained by the Black (1976) model and the market prices is increasing during the
epidemic. This phenomenon indicates that the Black (1976) model may have missed some important factors in the case of an epidemic. Therefore, in situations with similar catastrophes, more advanced models are needed to improve the accuracy of options pricing. Secondly, the results of Figure 17 to Figure 24 reveal that the volatility noise of agricultural products changes more than that of non-agricultural products at different frequencies after the epidemic. Finally and most importantly, it can be inferred that when the epidemic has no impact on non-agricultural products, it still impacts agricultural products. For example, in this paper, regarding which sampling frequency is optimal, the epidemic may impact agricultural products (sugar, cotton, soybean meal, and corn). However, it has little impact on petrochemicals (PTA, natural rubber\(^8\)), ores (iron ore) and metals (copper). The reason may be that agricultural products are more susceptible to the conditions of logistics and storage during the epidemic period.

4 Conclusion

This paper examines the impact of the COVID-19 pandemic during the mitigation period on the volatility of the Chinese commodity market. Focusing on the intraday data of 16 commodity options contracts, we first calculate the realized volatility at four different sampling frequencies. Then, we extract the options prices from the Black (1976) model by substituting these volatilities. Finally, the impact of the pandemic during the waning period can be found by MAE and RMSE.

The main findings can be summarized as follows. Firstly, when the epidemic is not severe, it still significantly impacts agricultural options, but it has almost no impact on petrochemicals, ores, and metals. Therefore, the epidemic’s impact on necessities is more significant than non-necessities. Secondly, from the perspective of market microstructure and the result of optimal sample frequency, it can be concluded that investors are more worried about the price of agricultural products during the epidemic. Finally, although the Chinese commodity options market is very young, it is not much different from other mature markets because the classical options pricing model can also be applied in the Chinese commodity options market.

The findings of this paper enable investors to better understand the risks of different commodities in the environment of significant disasters and

\(^8\) Although natural rubber is an agricultural product, its price is mainly affected by synthetic rubber, which is a product of petroleum.
provide empirical support to financial regulators in formulating investment and regulatory policies for commodity products, especially agricultural products. Moreover, the paper illustrates an application of intraday data for a high-frequency hedging strategy to predict the volatility of the commodity market, which applies to market research reports with futures and corresponding futures options and thus benefits the financial practitioners and institutions.

**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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