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COVID-19 impact on commodity futures volatilities

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ABSTRACT

COVID-19 pandemic has affected almost all aspects of the global economy, especially commodity futures markets, due to the disruption risk of global supply chains from the pandemic lockdown. This paper extends ARMA-GARCH models to investigate the pandemic impact on both long-run and short-term volatilities of four major commodity futures. Model-fitting results reveal that the pandemic event has enhanced long-run volatilities for all futures returns, while the daily COVID-19 infection speed has mixed effects on short-term (instantaneous) volatilities. Our extended models and research findings are useful in global supply chain risk management, commodity options trading and regulators’ supervision of inflation risk.

1. Introduction

Volatility forecasting for commodity futures is highly important in various activities, including hedging, trading, and regulating (Ding et al., 2019; Ding et al., 2020). Business profitability is highly dependent on risk management strategies to hedge futures cash flow uncertainty. Commodity price shocks and fluctuations are key risks for companies with global supply chains. Commodity traders often use commodity options to hedge commodity futures price risks. Volatility forecasting is the key to accurately predicting commodity option prices since underlying futures volatility dynamics drive their price moves. Commodity price shocks also affect people’s lives since commodity prices are closely related to the consumer price index (CPI). Thus, commodity futures volatility forecasting can help regulators formulate effective inflation control measures. The ongoing COVID-19 pandemic has impacted almost every aspect of the global economy, especially supply chain disruption or supply-demand mismatches, which sends shock waves to commodity futures markets, such as negative oil futures prices in the spring of 2020.

Since COVID-19 became a global pandemic, many studies have been done on the impact of the pandemic on financial markets. Bai et al. (2021) find that COVID-19 has a positive long-term impact on the volatilities of major stock markets, including the U.S., UK, China, and Japan. On the other hand, such pandemic impact could be reduced through government measures, as evidenced from the Asia-Pacific stock markets (Izani et al., 2020). Zhang and Hamori (2021) find that long-term COVID-19 impacts on oil and stock markets are more significant than the 2008 global financial crisis. Several studies have shown that COVID-19 has increased volatility spillover effects between stock and energy markets (Cui et al., 2021; Si et al., 2021; Liao et al., 2021). The contagion effect of the COVID-19 pandemic has been evidenced on gold and cryptocurrencies (Corbet et al., 2020).

In summary, the existing studies have mainly studied the impact of COVID-19 on stock market volatility and volatility spillover between different financial markets. The impact on commodity futures volatility has not been researched comprehensively. The purpose of the paper is to study the impacts of COVID-19 on both the long-run and instantaneous volatilities of commodity futures by establishing volatility forecasting models incorporating the pandemic effect.

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Our models are extensions of ARMA-GARCH models, which have the advantages of no need for exogenous variables to predict volatilities. ARMA-GARCH models are used extensively in forecasting volatilities in different areas, including finance, real estate and weather (Liu et al., 2019; Apergis et al., 2020; Zou et al., 2020). Our models are fitted to futures returns of oil, soybean, copper and gold, which are the most actively traded representative futures in energy, agricultural, industrial and precious metal commodity classes, respectively, with a data period from Jan 1, 2019 to June 30, 2021.

Our model results show that the pandemic has increased long-run volatilities across all four commodity futures. In contrast, the impact of daily infection speed on instantaneous volatilities is mixed, with a positive impact on copper and gold and a negative effect on oil and soybean. Such mixed results could be due to different commodity trading purposes of consumption or investment, regulators’ price control measures and supply-demand mismatches, all of which could lead to different traders’ responses and price sensitivities to supply chain disruption risk from the pandemic lockdown.

The remainder of this paper is organized as follows. Section 2 builds methodology. Section 3 presents data and descriptive statistics. Section 4 gives the model-fitting results and their implications. Section 5 concludes.

2. Methodology

We extend the ARMA(m,n)-GARCH(p,q) model to include variables that can characterize the COVID-19 event and its severity change. In the model, ARMA(m,n) describes the mean equation for futures returns, and the volatility equation will include COVID-19 variables under the GARCH(p,q) framework. The ARMA model has a major advantage in that it does not need exogenous variables to forecast the mean return because lag returns can capture it.

Let \( D \) be a dummy variable, which is 0 before the pandemic and 1 during the pandemic. Denote \( C_t \) as the new COVID-19 cases that were reported to the WHO on day \( t \). We define \( \Delta_t = \frac{C_t - C_{t-1}}{C_{t-1}} \) as the percentage change of new cases. Then, \( \Delta_t \) measures the dynamic change in the severity of the COVID-19 pandemic. In other words, \( \Delta_t \) indicates the speed of COVID-19 infection.

Now, we establish the first model to describe whether the COVID-19 event can influence the long-run variance after we control the GARCH(p,q) effect, which is defined as:

\[
\begin{align*}
    y_t &= c + \sum_{i=1}^{m} a_i y_{t-i} + \sum_{j=1}^{n} \beta_j \varepsilon_{t-j} + \varepsilon_t \\
    \varepsilon_t &= \sigma_t \cdot \varepsilon_t \\
    \sigma_t^2 &= w + \gamma D + \sum_{k=1}^{p} \mu_k \sigma_{t-k}^2 + \sum_{j=1}^{q} \lambda_j \varepsilon_{t-j}^2
\end{align*}
\]

where \( y_t \) is the futures return at time \( t \);
\( \varepsilon_t \) is the residual of the mean Equation (1) at time \( t \);
\( \sigma_t \) is the volatility at time \( t \);
\( \varepsilon \) is standard normal white noise with \( E(\varepsilon) = 0, \text{Var}(\varepsilon) = 1 \) and \( \text{Cov}(\varepsilon, \varepsilon_t) = 0 \);
\( w \) is the long-run equilibrium variance before the pandemic; and
\( w + \gamma \) is the long-run equilibrium variance during the pandemic.

Therefore, \( \gamma \) measures the impact of the COVID-19 event on the long-run equilibrium variance.

Then, we build the second model to capture the impact of COVID-19 infection speed dynamically \( \Delta_t \) on the time-dependent futures variance \( \sigma_t^2 \), which is defined as:

\[
\begin{align*}
    y_t &= c + \sum_{i=1}^{m} a_i y_{t-i} + \sum_{j=1}^{n} \beta_j \varepsilon_{t-j} + \varepsilon_t \\
    \varepsilon_t &= \sigma_t \cdot \varepsilon_t \\
    \sigma_t^2 &= w + \gamma D + \sum_{k=1}^{p} \mu_k \sigma_{t-k}^2 + \sum_{j=1}^{q} \lambda_j \varepsilon_{t-j}^2 + \theta D \Delta_{t-1}
\end{align*}
\]

Comparing the variance Equation (3) in the first model, the variance Equation (6) in the second model has an additional term \( \theta D \Delta_{t-1} \). The coefficient \( \theta \) measures the amount of increase (or decrease) if the infection speed \( \Delta_{t-1} \) on the last day increases by 1% during the COVID-19 pandemic \( (D = 1) \).

In both models, \( |\sum_{i=1}^{m} a_i| < 1 \) is required to guarantee the stationarity of the return series \( \{y_t\} \). Furthermore, we require \( w > 0, \mu_k > 0, \lambda_i > 0 \) and \( 0 < \sum \mu_k + \sum \lambda_i < 1 \) to make \( \sigma_t^2 > 0 \) and \( (\varepsilon_t) \) a stationary process. The variance Equation (3) or (6) decomposes the variance of the residual at time \( t \) into three or four components: the long-run equilibrium variance \( w + \gamma D \), the impact from past volatility information \( \sum_{k=1}^{p} \mu_k \sigma_{t-k}^2 \) and the influence from recent residual information \( \sum_{j=1}^{q} \lambda_j \varepsilon_{t-j}^2 \) without considering the impact of the pandemic transmission speed, or \( \theta D \Delta_{t-1} \) if we consider the infection speed impact on the futures volatility at time \( t \).
3. Data and descriptive statistics

We consider the daily closing prices for four commodity futures: NYMEX’s oil, CBOT’s soybean, COMEX’s copper, and gold from Jan 1, 2019 to June 30, 2021. There are two reasons for selecting these four commodities for our study of futures volatilities. First, they have the longest trading history in exchanges to avoid the extreme price volatility problem due to a lack of trading. Second, they represent most actively traded (highest trading volumes) futures in four different commodity classes: energy, agricultural, industrial metal and precious metal classes.

We select March 12, 2020 as the starting date for the COVID-19 pandemic, as declared by the WHO. Then, the dummy variable \( D = 0 \) before this date and \( D = 1 \) after that. The daily return is defined as \( R_t = \ln \left( \frac{P_t}{P_{t-1}} \right) \times 100\% \), where \( P_t \) and \( P_{t-1} \) are the closing prices at day \( t \) and day \( t - 1 \), respectively.

Table 1 lists the descriptive statistics of daily returns for four commodity futures, displaying thin peak and thick tail distributions. Since all J-B statistics are greater than 3, their return distributions deviate from normal distributions. Therefore, GARCH models are necessary and suitable to describe the evolution of futures volatilities. We further conduct ADF stationarity tests for these four futures return series. Since all ADF values are less than 1% critical values, as shown in Table 2, all return series are stationary processes, necessary for subsequent model building.

4. Model fittings and implications

We first determine the ARMA \((m, n)\) model for the mean equation. Lag numbers \( m \) and \( n \) are chosen using autocorrelations (AC) and partial autocorrelations (PAC) for the return time series. Then, we use the AIC, AC and HQC criteria to determine the best-fitted model. Smaller AIC, SC and HQC are better than the fitted model is. After the mean equation, ARMA \((m, n)\) is determined, we test the ARCH effect for the residuals \( \varepsilon_t \). The variance equation GARCH \((p, q)\) could be determined only if \( \varepsilon_t \) exhibits the ARCH effect. The GARCH \((p, q)\) model is determined similarly to ARMA \((m, n)\) by using AC and PAC functions together with AIC, SC and HQC criteria.

We take copper futures as an example to establish the first model described by Equations (1), (2), and (3). The autocorrelation and partial autocorrelation functions for copper returns time series are shown in Table 3. We can determine lag numbers preliminarily at most 1 in the ARMA \((m, n)\) model. Furthermore, from the AIC, SC and HQC statistics for ARMA \((1,0)\), ARMA \((0,1)\) and ARMA \((1,1)\) in Table 4, we find that the best-fitted model is ARMA \((1,0)\) since its AIC, SC and HQC are smallest among the three models.

Table 5 shows that residuals for ARMA \((1,0)\) are not autocorrelated, while variances of residuals exhibit the ARCH effect, as Table 6 shows. Then, we build the COVID-19 adjusted GARCH \((p, q)\) model as in Equation (3). Like the construction of the mean Equation (1), we determine that the best-fitted model for the variance Equation (3) is GARCH \((0,1)\) using AC and PAC functions together with AIC, SC and HQC criteria. Table 7 gives the ARMA \((1,0)\)-GARCH \((0,1)\) model coefficients with the COVID-19 long-run impact on copper futures volatilities. The variance equation for copper futures is given by:

\[
\sigma_t^2 = 0.0000916 + 0.000111 \times D + 0.176615 \times \varepsilon_{t-1}^2
\]  

\[
(7)
\]

From Table 7, all coefficients are significant at the 5% level except the constant term in the mean equation. Finally, from Table 8, we find that the residuals in the ARMA \((1,0)\)-GARCH \((0,1)\) model do not have an ARCH effect, as both p values for F and chi-square statistics exceed the 10% level. Therefore, after including the GARCH model, the residual ARCH effect is eliminated.

We apply the above model building procedure to the other three commodity futures: soybean, oil, gold. Table 9 gives the model summary for the first type of model as Equations (1), (2), and (3) with COVID-19 impact on the long-run variance of all four commodity futures. Table 10 shows the model fitting results for the second type of model as Equations (4), (5), and (6) to include the additional impact of COVID-19 infection spread on the short-term transient variance with the control of its long-run impact.

From Table 9, we find that coefficients for the dummy variable \( D \) are positive in all futures variance equations, which indicates that COVID-19 has increased long-run equilibrium variances across different classes of commodity futures. Thus, the pandemic has brought much more uncertainty to the economy in the long term. Pandemic lockdowns in many parts of the world have created a significant supply chain disruption risk for many commodities and goods, which could lead to their extreme undersupply or oversupply. Dramatic undersupply or oversupply of commodities would move their futures prices in either direction with a huge magnitude, as we observed negative oil futures prices in the spring of 2020 when the pandemic surged in the first wave. Moreover, from the coefficients of \( D \), we observe that the pandemic impacts on long-run variance are the largest in copper futures, followed by soybean, oil and gold in decreasing order. Arguably, copper is an industrial metal concentrated in a few resource-rich countries and is more venerable to supply chain risk due to pandemic lockdowns. Soybean and oil are produced or stored in many parts of the world; thus, they are less subject to supply chain risk. On the other hand, gold is mainly for investment purposes and has the least exposure to supply chain risk and

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**Table 1**

Descriptive statistics of daily returns for four commodity futures.

| Futures varieties | Mean     | Std      | Skewness  | Kurtosis    | J-B        | Probability |
|-------------------|----------|----------|-----------|-------------|------------|-------------|
| Oil               | 0.000751 | 0.040163 | -3.074809 | 45.47936    | 48,283.98  | 0.0000      |
| Soybean           | 0.000699 | 0.012829 | -1.867441 | 30.43785    | 20,287.85  | 0.0000      |
| Copper            | 0.000753 | 0.013609 | -0.302902 | 4.873620    | 102,590.90 | 0.0000      |
| Gold              | 0.000510 | 0.016558 | -0.263793 | 7.865484    | 627.7231   | 0.0000      |
consequently is less affected by the pandemic-induced supply chain breakdown.

Table 10 again displays positive $D$ coefficients and in decreasing order copper, soybean, oil, and gold. However, it is interesting to observe that the coefficients for $D\Delta_{t-1}$ are mixed, positive for copper and gold, and negative for soybean and oil. On the one hand, as
the infection speed $\Delta_t$ increases, the pandemic surge will lead to copper supply chain breaks and futures volatility jumps, which results in a positive $D\Delta_{t-1}$ coefficient. On the other hand, the pandemic surge would also make investors rush to safe assets such as gold. This gold rush movement would lead to gold prices being more volatile on a short time scale, which also leads to a positive $D\Delta_{t-1}$ coefficient. Now let us explain the negative $D\Delta_{t-1}$ coefficients for soybean and oil. Soybean is an agricultural product and is widely available and much more locally produced than copper. Thus, soybean has much less exposure to the pandemic lockdown risk. When the pandemic becomes more severe, the negative $D\Delta_{t-1}$ coefficient for oil could be the result of two competing forces driving the price in the opposite directions. On the one hand, the short-term demand for oil quickly decreases when the pandemic surge speed increases, which creates downward pressure for price moves. On the other hand, accelerating the pandemic surge would make the oil supplier cut down the supply from their expectations of a sharp economic slowdown and make the oil shipping time longer to satisfy quarantine requirements, both of which would create pressure for an upward price move. These two opposite forces could decrease oil futures volatility.

5. Conclusions

This paper explores the impact of the COVID-19 pandemic on both the short-term and long-run volatilities of four major commodity futures, namely, oil, soybean, copper and gold, which represent the most traded futures in their different commodity classes. Our research is carried out by extending ARMA $(m, n)$-GARCH $(p, q)$ models to incorporate COVID-19 influencing variables.

The research shows that the COVID-19 pandemic has increased the long-run volatilities of all four commodity futures with magnitudes in decreasing order of copper, soybean, oil and gold. We furthermore find that the pandemic surge with increased infection speed will increase short-term instantaneous volatilities for copper and gold futures but decrease the instantaneous volatilities for soybean and oil futures with control of the COVID-19 impact on their long-run volatilities. This mixed effect on short-term volatilities of different commodity futures could be because different classes of commodities have different purposes of usages, supply and demand natures, and government measures for price stabilization, all of which result in their different responses and sensitivities to supply chain disruption risk from pandemic lockdowns. Our newly established models and research findings are useful in global supply chain risk management, commodity options trading and regulators’ supervision of inflation risk, especially under the current or future public crisis.

Statement

All authors have seen and approved the final version of the manuscript being submitted. We warrant that the article is the authors’ original work, hasn’t received prior publication and isn’t under consideration for publication elsewhere.
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