Dynamic Correlation between Chinese Commodity Futures and the US Stock Market during the Covid-19 Pandemic

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Abstract

Due to the significant damage of Covid-19 on global financial markets, investors are considering diversifying risk and taking the hedging strategy based on commodity futures. This paper carried out a preliminary analysis of the S&P 500 daily price and returns to define the sample period from January 3 to June 30 in 2020. Then, the descriptive analysis on the S&P 500 and 35 Chinese commodity futures is conducted. Finally, the dynamic correlations of the US stock market and Chinese commodity futures are found through the DCC GARCH model. This paper finds that although Chinese commodity markets are negatively affected by the Covid-19, there are three futures that have stable and positive returns to diversify risks, including Corn, Corn Starch, and Polished Round-grained Rice. Also, among different correlation results, Rb negatively correlates with the US stock index during the whole sample period, which is suitable for hedge strategy.

Keywords: Covid-19, US Stock Market, Chinese Commodity Markets, Futures, Dalian Commodity Exchange, Shanghai Futures Exchange, Diversify Risk, Hedge, DCC GARCH.

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Introduction

Because of the highly contagious and fatal of Covid-19, governments made policies that banned citizens from going outside the houses and requiring strict quarantines, which resulted in limited or shutdown of business activities. The policies and news about deaths and cases of the Covid-19 drive investors to be pessimistic about the market, leading to stock market volatility increases and liquidity decreases (Ftiti et al., 2021). Due to Covid-19 has significantly damaged the financial markets globally, there is a growing consensus among investors and portfolio managers that they should alter their goal from profit maximization to a more sustainable one. They paid attention to commodity investments because of the role of a potentially viable hedge strategy and risk diversification to decrease the risk in the pandemic.

The severe influence of Covid-19 has led to a large number of studies on Covid-19's impact on stock markets and commodity markets. Covid-19 pandemic has significant negative effects on stock returns in the Chinese market and increased stock price volatility during two months after January 2020 (Al-Awadhi, 2020); according to Mazur et al. (2021) and Albulescu (2021), the pandemic also increased the stock market volatility in the US from March 2020 to May 2020. Thus, investors demand to reduce their portfolio risk by increasing investment in other categories, including the commodity market. Besides stock markets being damaged, global commodity markets are also seriously affected by the pandemic. Umar conducted two studies about the impacts of the Covid-19 on the global commodity markets (from January 2020 to July 2020 and to April

2021, respectively) and found that the virus badly influences both volatilities of prices and dynamic returns of certain commodities. Meanwhile, Umar also concluded that there are several commodities can be applied in the hedging strategy. Thus, the conclusion supports the consensus that commodities can be viewed as alternative investments by investors for diversification during the uncertainty period. Based on Umar et al. (2021), investors and managers are willing to substitute more vulnerable equities with commodities for hedging and risk management strategies.

Although the performance of the global commodity markets is not attractive, Chinese markets work unexpectedly during the Covid-19 pandemic. According to Ma et al. (2021), after the financial crisis of 2008, China's economy continued to grow while the global economy began to contract; China's economic growth presented an outstanding resilience which can have high-quality development facing external shocks. Sansa (2020) also mentioned that China's financial markets stayed stable and strong compared with other world financial markets during the Covid-19 pandemic. Moreover, research showed some supportive results to the previous opinion, especially for the Chinese commodity markets. Although Chinese natural resource commodity prices became more volatile from January 2019 to April 2021 (Ma et al., 2021), Lin and Zhang (2020) found that exports of grain, oil, and medical herbs increased from January to February 2020. Also, Jia et al. (2021) concluded that most Chinese commodity prices declined less than 3 percent, meaning Covid-19 has a relatively small or temporary effect on most of the commodity markets in China.

The impact of Covid-19 on the international, American, and Chinese stock markets and commodity markets has been studied and addressed. However, the literature has not yet duly addressed how stock markets and commodity markets correlate and which commodity markets can be applied in risk diversification and hedge strategy. This study tries to fill the gaps by examining the dynamic correlation between several Chinese commodity futures and the American stock markets during the Covid-19 period. More specifically, this study investigated certain Chinese commodity futures that can be employed to diversify risks or as a hedge factor during the pandemic.

The rest of this paper is organized as follows. The next section provides a literature review on the studies about the relationship between the stock market and commodity market using historical data; recent studies about the impact of Covid-19 on the stock markets and commodity markets, separately. Section 3 describes the DCCGARCH methodology. Section 4 presents results and findings. Section 5 reports the conclusion. Section 6 shows contributions and limitations.

Literature review

The relation of stock markets and commodity markets

Scholars and researchers have provided extensive literature on the impact of Covid-19 on the stock markets and commodity markets, and some of them stressed the value of commodities in hedging. Some literature revealed the relationship between the stock market and commodity market considering historical events and data. Thuraisamy et al. (2013) investigated spillover effects between 14 Asian equity market volatility, including China. They focused on the volatility of crude oil and gold futures in those countries before and after the crisis. The study used the bivariate BEKK-GARCH model, which can analyze volatility interaction between the equity markets and commodity futures, with daily data obtained from Bloomberg. Examined results asserted that mature equity markets, the Japanese market, tend to have spillover effects on commodity markets; by contrast, immature markets have a tendency to spill over from crude oil and gold markets to equity markets. The most helpful content from Thuraisamy's study for this paper is that a table illustrates the volatility of commodity and equity markets together, which proves that the volatilities of the two cross-market items are comparable and supports the basis of this paper.

Using a similar approach, the GARCH model and Dynamic Conditional Correlation GARCH (DCC-GARCH) model, Ding (2021) investigated the dynamic correlation of the stock market and seven commodity markets in the US to find the co-movement of commodity volatilities after commodity financialization. The results unveil that among different commodity markets, there is an asymmetrical capital attracting mechanism, and market volatilities of gold, sugar, and wheat markets largely differentiated from the pre-financialization period. It is worth mentioning that Ding explained that the GARCH model is a popular methodology to measure and predict commodity volatility, which supports the methodology employed by the writer for the volatility analysis.

In addition, another study by Junttila et al. (2018) looks into the correlation of the equity returns and commodity market focus on gold and oil in the US during the historical stock market crisis periods. They emphasized the hedge function of the commodities, which is the same purpose as this research. Using the Dynamic conditional correlation model, which Ding also employed, the study unveils crude oil futures and stock returns have a more positive correlation on each other in the financial turmoil. The study also found that the correlation of gold futures was negative in that period, which showed gold is more attractive in cross-market hedging than crude oil. The finding is helpful in drawing the importance of considering gold commodity from the hedging perspective and insignificance of the crude oil.

The three studies provide ideas of methodologies to analyze the relationship or the correlation of stock markets and commodity markets, from which the third study is the closest to this paper. However, Junttila analyzed the dynamic correlation of the US stock market and gold and Crude oil commodity futures, while this paper connects the US stock market with several Chinese commodity futures in more categories. Also, the results of dynamic correlation between different markets in two countries during the

Covid-19 period might be different from the historical financial crises.

The impacts of Covid-19 on Chinese and US stock markets

Besides studying periods before the Covid-19 pandemic, scholars have a growing interest in the impacts of Covid-19 on the stock markets and commodity markets. There are some studies about how Covid-19 influences the stock market in China and the US. The study of Zhang (2021) examined how the Covid-19 pandemic influenced the Chinese oil stock market. The study applied the autoregressive conditional heteroskedasticity (ARCH) models, commonly used to analyze energy market volatility, to find that the pandemic increased oil stock price volatility, but the persistence of fluctuation is weak in China. According to Devpura & Narayan (2020), oil price volatility can be used to predict stock market returns and affect industrial production. Based on this knowledge and Zhang's result, Covid-19 has weak long-term effects on the Chinese stock market, and the Chinese stock market recovered after the short-term shock or the peak of Covid-19.

For the same country, Al-Awadhi (2020) analyzed the Covid-19 virus influence on the aggregated stock market. After employing the panel regression approach, the estimated results unveil that Covid-19 has significant negative effects on Chinese stock returns, which seems not to match Zhang's finding. However, there is a considerable difference between the two studies in that they used different sample periods. Zhang's study covers from July 8, 2019, to July 5, 2021, while Al-Awadhi only covers nearly three months from January 10, 2020, to March 16, 2020. Thus, based on the fundings of Zhang and Al-Awadhi and their different sample periods, it is evident that the sample period is significant for this research, and impacts of the pandemic are different in small intervals among the long-term. Moreover, both of them used regression methodology to evaluate the stock market volatility. In addition, Zhang used the oil stock price index, *oilindex*, obtained from the China Stock Market & Accounting Research database; Al-Awadhi employed the Hang Seng Index and Shanghai Stock Exchange Composite Index.

Mazur et al. (2021) and Albulescu (2021) focus on the Covid-19 impacts on the US stock market. The sample period of Mazur's study is short, only covering March 2020, but the conclusion is inspirable that while some stock values fall dramatically, the stocks of "natural gas, food, healthcare, and software" earn high positive returns. The result increases the possibility that American investors pay attention to these categories, and it is necessary to consider these terms in the Chinese commodity markets, which American investors could consider taking as hedging. By applying a simple Ordinary Least Squares (OLS) regression, the result of Albulescu's study unveils that the pandemic increased the US financial markets' volatility, from March 11, 2020, to May 15, 2020. This matches with the assumption of this research that Covid-19 has a significant negative influence on the US financial market and illustrates the potential that American investors might want to diversify their risk by investing in the Chinese markets and increases the value of this research. In addition, there is one surprising point by comparing the studies related to the US stock market that each study uses a different index to represent the US stock market volatility. Junttila used S&P500 Composite Total Return Index, and Ding used S&P500. Mazur applied the Standard and Poor's (S&P) 1,500, while Albulescu used the S&P 500 realized volatility (RV) directly. Albulescu explained that RV data is more formative than other financial volatility metrics, which were obtained from the S&P Dow Jones Indices database. It is essential because the choice of the US stock market index is a determinative variable to the conclusion of this paper.

Moreover, Sansa (2020) analyzed Covid-19's impact on the Chinese and US stock markets from March 1, 2020, to March 25, 2020, which is a short interval. Through simple Regression in Double Log and Semi Log-Linear Models, Sansa concluded that Covid-19 increased both financial market volatilities, which matches the result of Albulescu. Also, Sansa used the Shanghai Stock Exchange to show the Chinese stock market volatility, the same as Al-Awadhi. Sansa also mentioned a claim in the introduction part supported by its analysis results indicates that China's financial markets remain strong and stable compared to other world financial markets during the Covid-19 pandemic, which matches the conclusion of Zhang. This finding is crucial to prove the second assumption of this research that the Chinese financial market is relatively stable and can recover effectively during the Covid-19 pandemic, and increases the attractiveness of the Chinese commodity markets to American investors.

The impacts of Covid-19 on commodity markets

There are also many peer-reviewed articles analyzing the impacts of Covid-19 on the commodity markets. The writer found three pieces of literature focused on the global view and three articles focused on the Chinese commodity markets. Umar et al. (2021) undertook two studies on the international commodity markets. Umar illustrates the volatility of five commodities (energy commodities, agricultural products, livestock commodities, precious metals, and nonprecious metals) and their coherence with Covid-19. The result of the study via wavelet coherence and wavelet phase difference techniques unveils that the low coherence intervals show several commodities are attractive to offer diversification benefits based on the three levels of coherence. Although the detailed commodities are not given in the study, the conclusion supports this research powerfully by showing the certainty that several commodities are helpful in applying the hedging strategy.

Another study of Umar focuses on Softs, Grains, and Livestock commodity indexes and their dynamic return and volatility connectedness. The results obtained via the recent time-varying parameter vector autoregression (TVP-VAR) methodology reveal that both dynamic returns and volatility connectedness were significantly influenced by the Covid-19 pandemic; markets have significant differences in the level of the return connectedness measure. Besides Umar's two studies, Shaikh and Huynh (2021) also analyzed the impact of Covid-19 on the global markets. Their study contains the global equity market, commodities, and FX market in the commodity market section; they employed time series-based regression models and concluded from a different aspect that commodity options act as the best hedge against COVID-19, which provides firm support and direction for this paper. The time spans of the two Umar's studies covered are from January 21, 2020, to the end of July 2020 and from January 1, 2020, to April 30, 2021, respectively; Shaikh and Huynh used a sample period from January 2018 to March 2020.

The last three pieces of literature are concentrated on the Chinese commodities during the

Covid-19 pandemic. Lin and Zhang (2020) analyze the agricultural commodity exports in China from January–February of 2020 through a firm-level survey in the Fujian province. The survey results unveil that the average agricultural business declined in the exports, but the exports of grain, oil, and medical herbs even increased. Although the data obtained represent a partial Chinese commodity, one of the three major agricultural provinces in China, the categories of grain, oil, and medical herbs are worthy of attention in this research.

While Lin and Zhang analyzed the export volumes of the agricultural commodities, Ma et al. (2021) and Jia et al. (2021) focus on commodity price volatility. More specifically, Ma studied the causal linkage of economic growth and commodity prices, focusing on natural resources. Similar to Umar's wavelet analyses, Ma applied three approaches, the wavelet power spectrum, and the wavelet coherence approaches, and the frequency domain causality test, to analyze the causal linkage of economic growth and natural resources commodity prices from January 1, 2019, to April 1, 2021. They found that the natural resource commodity price is more volatile than the economic performance, especially at the peak of Covid-19 in China. They also found only in the medium-run, the economic performance was significantly influenced by the natural resource commodity price volatility. It is impressive that Ma's study divided the period of the Covid-19 pandemic into three intervals and showed that investors should pay more attention to using a hedging strategy in the medium interval.

Jia illustrates interactions of international oil price, COVID-19, and economy in China.

After applying the China Energy-Economy-Environment Analysis model, the study results indicated that most commodities prices declined less than 3%. Thus, the influence of Covid-19 on the Chinese commodity market is relatively small. Among all categories, agriculture is the least affected, matching with the finding of Lin and Zhang's study, while the real estate industry is the most affected. The result supports the third aspect of assumptions for this paper that the Chinese commodity market is attractive to consider as a hedging strategy.

The main novelty of this paper is to analyze the dynamic conditional correlation between Chinese commodity markets and the US stock market during the Covid-19 pandemic period from the risk diversification and hedging perspective. Also, this research aims to find a specific interval of the stock market crisis in the US to highlight the value of Chinese commodities serving in hedging. Finally, this research will give details on which Chinese commodities are stable used in diversifying risk and the hedging strategy to investors.

Methodology

Dynamic Conditional Correlation Model

This paper applies the dynamic conditional correlation GARCH model (DCC GARCH) to investigate the time-varying conditional correlations between the US stock market index and several Chinese commodity futures during the Covid-19 pandemic. The following DCC GARCH model specification has been designed based on theoretical knowledge and the literature presented.

DCC GARCH model assumes that the conditional returns are normally distributed with zero means, and the matrix of the time-varying variance can be decomposed as

$$H_t = D_t P_t D_t, \tag{1}$$

where H_t is the time-varying variance-covariance matrix, P_t is a time-varying correlation matrix, and D_t is the diagonal matrix of time-varying conditional standard deviations ($D_t = diag\left[\sqrt{h_{i,t}^2}\right]$). The diagonal matrix of time-varying standard deviations can be obtained through estimating a univariate GARCH more, given

$$h_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \, h_{t-i}^2, \tag{2}$$

where h_t^2 represents the time-varying conditional variance of the S&P 500 and commodity futures in this paper. α comes from the ARCH model, and β comes from the univariate GARCH model. After the estimation for each series, the correlation is given

$$Q_t = (1 - a - b)pbar + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1}, \tag{3}$$

where ε are standardized residuals, p bar is the unconditional correlation matrix of ε. a, b are parameters that meet the condition $a + b < 1$ while a presents the immediate impact of disturbance on conditional volatility, and b presents the persistence of the conditional volatility across time. The P_t can be simplified as

$$P_t = diag\{Q_t\}^{-1} Q_t diag\{Qt\}^{-1}, \tag{4}$$

where

$$diag\{Q_t\}^{-1} = \begin{bmatrix} 1/\sqrt{q_{iit}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1/\sqrt{q_{nnt}} \end{bmatrix}. \tag{5}$$

The parameters need to be maximized to approach the real world using maximizing likelihood logarithm based on the likelihood function

$$L = -\frac{1}{2}\sum_{t=1}^{T}(nln\pi + \ln(detH_t) + \varepsilon_t H_t^{-1} \varepsilon_t^T. \tag{6}$$

Finally, the time-varying conditional correlations are calculated by

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t} q_{jj,t}}}, \tag{7}$$

where $q_{i,j,t}$ is the covariance between S&P 500 returns and commodity futures returns at time t, and $q_{ii,t} q_{jj,t}$ are conditional variance estimates at time t.

The logarithmic return is applied to get the returns of the settlement prices,

$$r_t = 100 * [\ln(P_t) - ln(p_{t-1})],$$

where P_t and p_{t-1} are weekly prices series in the periods t and t-1.

Data Collection

The datasets consist of daily observations for the S&P 500 to represent the US stock prices index, which is obtained from Bloomberg in the unit of CHY. For the Chinese commodity markets, this paper uses daily data of several categories derived from Dalian Commodity Exchange (DCE), including the agricultural and industrial commodities, and

Shanghai Futures Exchange (SFE), including metal, energy, and chemical commodity futures. The sample period is the first half-year of 2020, from January 2 to June 28 in 2020. There are 18 futures from the Dalian exchange and 17 from the Shanghai exchange, with three futures excluded due to partial unavailable data. The material employed in this paper is Microsoft Excel, which is convenient to conduct the DCC GARCH model and data visualization.

To define the sample period, a preliminary analysis of the S&P 500 is an efficient approach since the sample period is when the US stock market was shocked by the Covid-19 pandemic. Figure 1 shows the index movement from 2019/7/1 to 2020/10/1, showing a dramatic decline of the index from February to April in 2020 and gradually recovering in the next months. To cover the relatively longer period than the large decline and following recovering period, the sample period is defined from January 3 to June 30 in 2020. Figures 2 and 3 show the time series of returns of the S&P 500 index and equity volatility applying the GARCH model during the sample period.

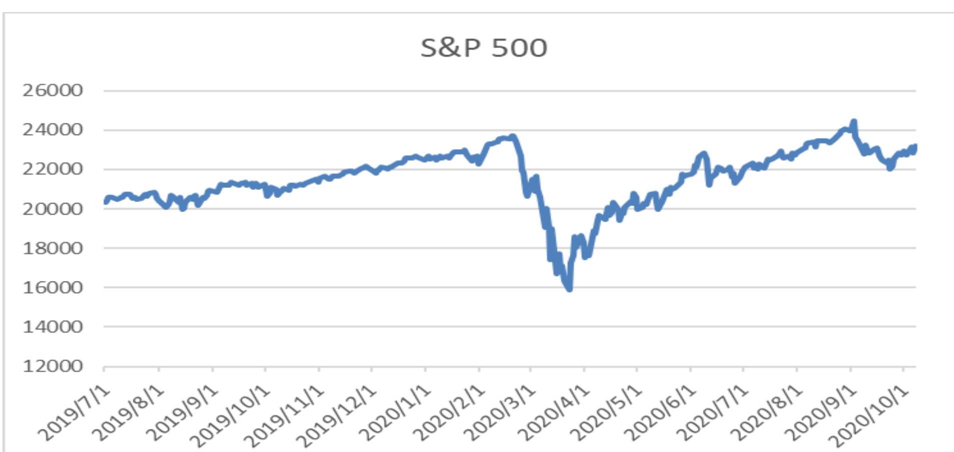

Fig. 1 S&P 500 index. Source: Bloomberg.

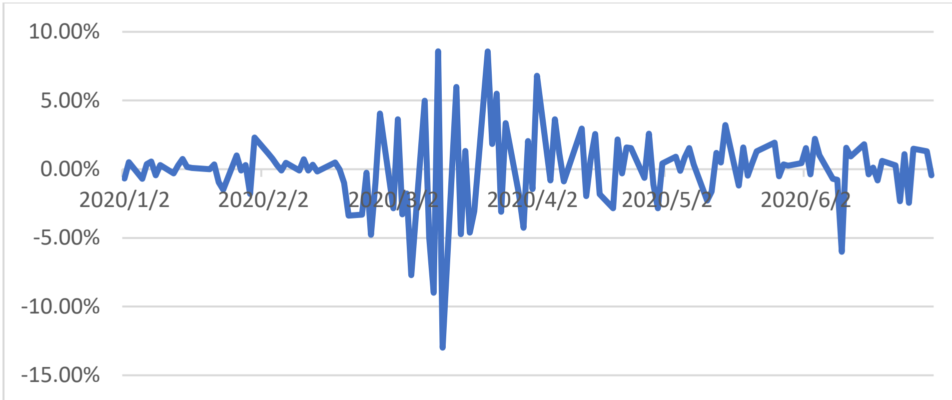

Fig. 2. Return of S&P 500 index.

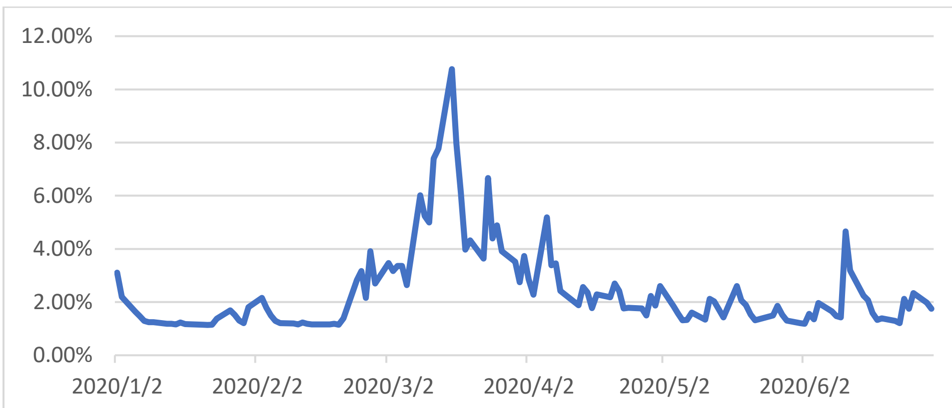

Fig. 3. GARCH model result of S&P 500 index return.

Figures 2 and 3 illustrate that the volatility of S&P 500 return increased rapidly during the first half of March 2020, with some lower peaks in the following months. Therefore, the author surmises that American investors would worry about their equity return mainly starting from March 2020, which is an essential month to observe in the dynamic correlation analysis.

Results and Findings

Descriptive Statistics

The table1 in the appendix reports the descriptive statistics for the return series of S&P 500 and all commodity futures (futures above the black line are available in the DCE, and others starting from the Cu are available in the SFE). From January 3 to June 30, 2020, the average daily return on S&P 500 is negative 0.023%, with a minimum daily return of negative 12.99% and a maximum of 8.58%. The average return for six months shows that S&P 500 is affected weakly by Covid-19; however, the index is affected seriously by the pandemic, shown in figure 1. Therefore, a deeper analysis of returns of S&P 500 should be carried out, which separate the periods within the six months. In table 2, the averages and standard deviations of five different periods of S&P 500 are presented, from which the average daily return is negative 0.61% in February and March with the 0.04 standard deviation, while the average daily return is negative 1.15% in March with 0.056 standard deviation. Thus, the US stock market is significantly influenced by the Covid-19 that the market gave large negative returns with increased volatility, especially in February and March in 2020, which matches with the finding of Albulescu (2021).

The daily average returns of Chinese commodity futures are also provided in table 1 in the appendix, and the analysis of them is shown in the table3. From the table3, half of commodity futures average returns in DCE are positive. In contrast, only two out of 17 commodity futures average returns in SFE are positive, showing that metal, energy, and chemical futures provided in the SFE are more negatively affected by the Covid-19 than agricultural and industrial commodities. The negative daily average returns of commodity futures also show that the Chinese commodity markets are also negatively affected by the Covid-19, and some futures even have larger negative returns than S&P 500. Here is a question that why the author did not separate the sample period and focus on the February March period to compare the returns of the two markets. The reason is that it is not very significant to prove whether Chinese commodity futures can have higher positive returns than the US stock index in a short period. Hence, the author compared the two series in the sample period to show some values of Chinese commodity futures to investors.

In table 3, the average daily return of S&P 500 and Chinese futures, there are 17 futures returns (nearly half) are lower than the S&P 500's returns. Therefore, it is difficult to conclude that the performance of Chinese commodity markets is better than the US stock markets during the Covid-19 from the average return respect. However, in the standard deviation respect, there are only four future returns that are more volatile than S&P 500, which shows the Chinese commodity market is relatively more stable than the US stock market in the covid-19 pandemic, matching the results of Sansa's study (2020). What is noteworthy is that several commodity futures have both positive returns and low standard deviations (less than 0.01), including Corn, Corn Starch, and Polished Round-grained Rice. These three commodity futures that can generate stable and positive returns during the Covid-19 pandemic are suitable choices for investors.

	Jan. to June	Feb. to April	Feb. to March	March to April	March
Average	-0.02322%	-0.19768%	-0.61051%	-0.28185%	-1.15034%
Standard deviation	0.02952	0.03790	0.04125	0.04530	0.05592
Variance	0.00087	0.00144	0.00170	0.00205	0.00313

Table 2. Statistics of Five Periods of S&P 500 Returns.

positive daily average return in DCE	9	out of 18
positive daily average return in SFE	2	out of 17
average return lower than S&P500	17	out of 35
standard deviation higher than S&P500	4	out of 35

Table 3. Descriptive Analysis of Chinese Commodity Future Returns

DCC GARCH model Result & Analysis

There are 17 results of the DCC GARCH model, and others failed to find a dynamic correlation between the two variables, which is comprehensible since the stock markets and the commodity markets are in different countries. The following two tables (table 4 and 5) show the dynamic correlations of each commodity futures and S&P 500. In this section, this paper only presents the results of a and b, which are parameters of short-run volatility impact and long-run volatility impact, respectively. The values of other parameters are not significant since they are altered to maximize the log-likelihood.

From the tables 4 and 5, only Coke shows the negative short-run and long-run correlations with S&P500. However, the values of "a" are very small, and the largest one is 0.168, which means the short-term volatility impacts are small. This is because the performance of the US stock market does not strongly correlate to the performance of Chinese commodity markets, which support the idea of using Chinese commodity futures to diversify investors' portfolio to reduce risks. In terms of "b," the persistence of the conditional volatility across time, there are some zeros that mean the Chinese commodity futures do not have a long-term correlation with the S&P 500. This means the returns of the two variables are independent in the long-term, so the futures with zero value of b are also suitable to diversify risks. On the other hand, some futures have some noticeable values of "b," including Corn Starch (0.57), PVC (0.72), Al (0.68), and Ss (0.43), which show that these commodity future returns have a long-run correlation with US stock market, so the investors should pay attention to the movement of S&P500.

Dynamic correlation	a	b
Soybeans2	0.07453	0.20177
Corn Starch	0.00096	0.57148
Fiber Board	0.16822	0.00000
Coke	-0.02974	-0.02123
Hard Coking Coal	0.08057	0.00000
Soybean Meal	0.01238	0.00000
PVC	0.02069	0.71596
Soybean Oil	0.10942	0.00000

Dynamic correlation	a	b
Al	0.01972	0.68398
Au	0.00407	0.00000
Rb	0.01910	0.00000
Ss	0.02244	0.43079
Fu	0.01683	0.00000
Bu	0.02253	0.00000
Ru	0.00178	0.00018
Nr	0.00593	0.00571
Sp	0.12173	0.62868

Table 4 (Left). The Dynamic correlations of commodity Futures in DCE with S&P 500

Table 5 (Right). The Dynamic correlations of commodity Futures in SFE with S&P 500

Graphs of time series dynamic correlations are provided to have a visual presentation and better understand the results. The 17 commodity futures are divided into three groups: the entire positive correlation group, partial positive and partial negative group, and entire negative correlation group. With the goal of applying the DCC GARCH model methodology, finding certain commodity futures that can have a hedge effect for investors during the shocking US stock market period, the author tries to explain the results for most commodity futures and provides some shallow suggestions.

Entire positive correlation group

Figures 4 and 5 show the dynamic correlation between S&P 500 and Corn Starch from DCE and Ru from SFE, respectively. Because during the whole sample period, the correlation is always positive, the two commodity futures cannot work for a hedging strategy. However, in the recovering period of the US stock market, investors can invest in them to offset some losses. Ru has a higher positive correlation accounting for 9.50%, compared to Corn Starch, which is approximately around 4.10% with higher volatility. Thus, Ru can have a higher and relatively stable return in the recovery period.

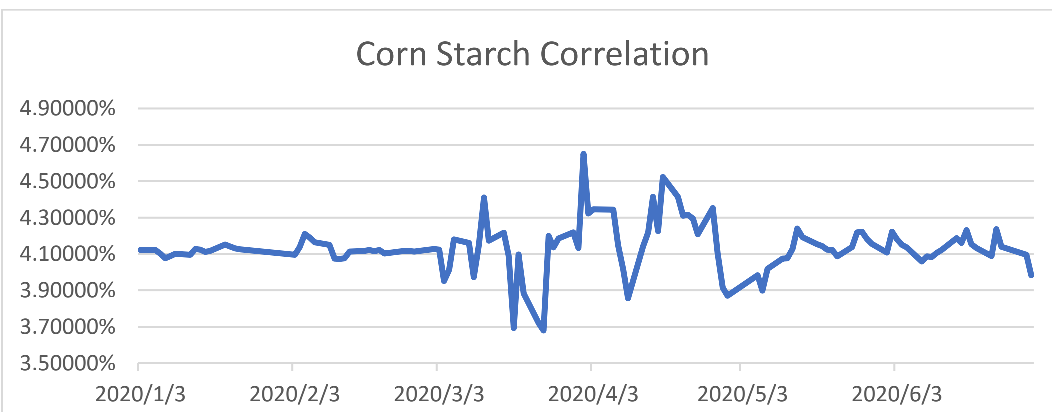

Fig. 4 Dynamic correlation of Corn Starch return and S&P500 return, DCE.

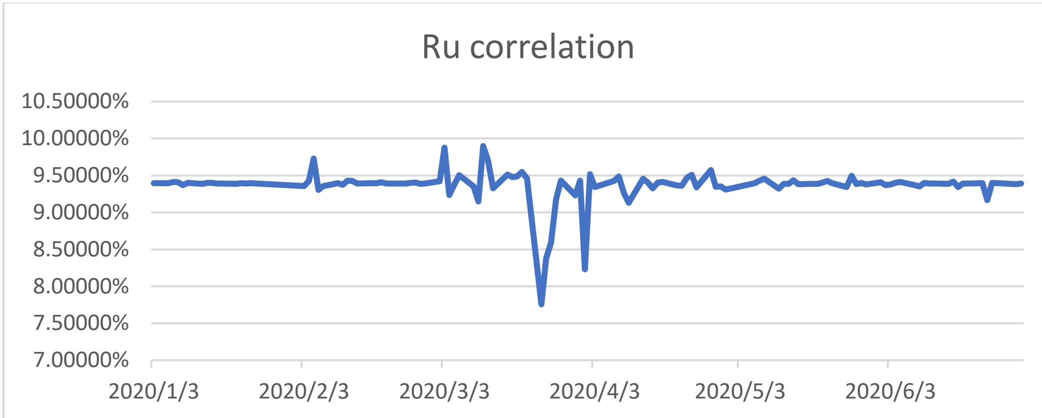

Fig. 5 Dynamic correlation of Ru return and S&P500 return, DCE.

Partial Positive and Partial Negative Group

Most of the commodity futures are divided into partial positive and partial negative groups. The typical results are commodity futures and S&P 500 are positively correlated, excepting some negative relation points in or around March 2020. The author divided these commodity futures into three groups based on the length of volatile periods. Only one or two figures of each group is presented, and other figures can be found in the appendix. (For the reader's convenience, the number of figures are continuous in the three group order though some figures are placed in the appendix).

1. Long volatile periods group

Some Chinese commodity futures' correlations with S&P 500 have relatively longer volatile periods. Figures of Fiber board, Hard Coking Coal, and Soybean oil show that the volatile periods are two months long. Since the correlation is changed daily or does not stay at one side for a period, it is not a good choice to invest in them during the shock period. In terms of their strongness of correlation with the S&P 500, the Fiber board is the strongest, around 15%, while the Soybean Oil is the lowest, just around 5%.

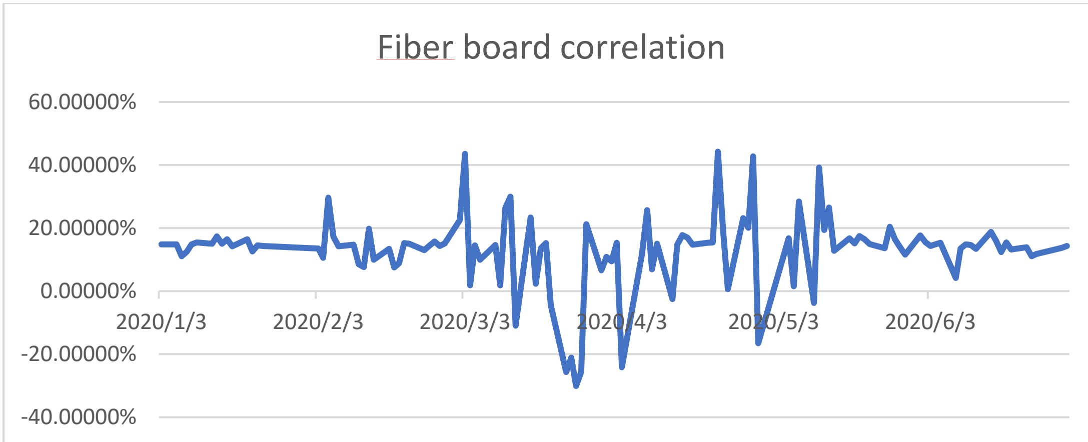

Fig. 6. Dynamic correlation of Fiber Board return and S&P500 return, DCE.

2. Short volatile periods group

Commodity futures which have shorter volatile periods are less affected by the movement of S&P 500 and Covid-19. Usually, the future correlations with the US stock index are positive, but the correlation becomes negative at some points (fig. 9 to 14). However, only some negative correlation points do not mean the futures can have a hedge effect. Also, these negative points are all in the latter half of March 2020, when the S&P 500 volatility is decreased. Therefore, these commodity futures cannot have a hedge effect. On the other hand, their correlation is relatively more stable than futures in the long volatile periods group, so they can have similar effects like the entire positive correlation group to offset some losses. In this point of view, commodity futures that have a stronger correlation with S&P 500 in the stock market recovery period can make profits more effectively. Among the futures in this group, Soybean Meal and Bu have a higher correlation with the index, accounting for around 13% and 15%, respectively. Though lower correlations do not mean the returns of commodity futures are low, investors can make a judgment based on the movement of the US stock market, which is convenient for them.

Coke futures is different from the others in this group in that it has a negative correlation with the S&P 500 in most of the sample period, but in the volatile period, some correlation points become positive. Therefore, Coke might have some hedge effect in the normal circumstance, which means the case that financial markets do not get shocks.

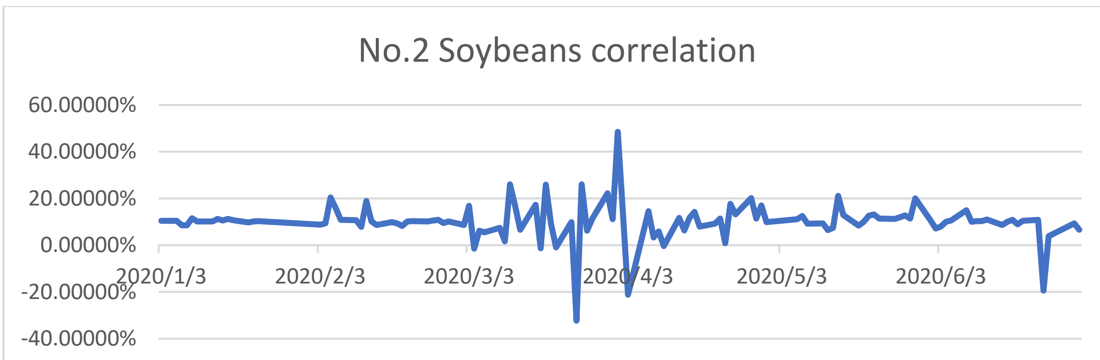

Fig. 9. Dynamic correlation of No.2 Soybeans and S&P500 return, DCE.

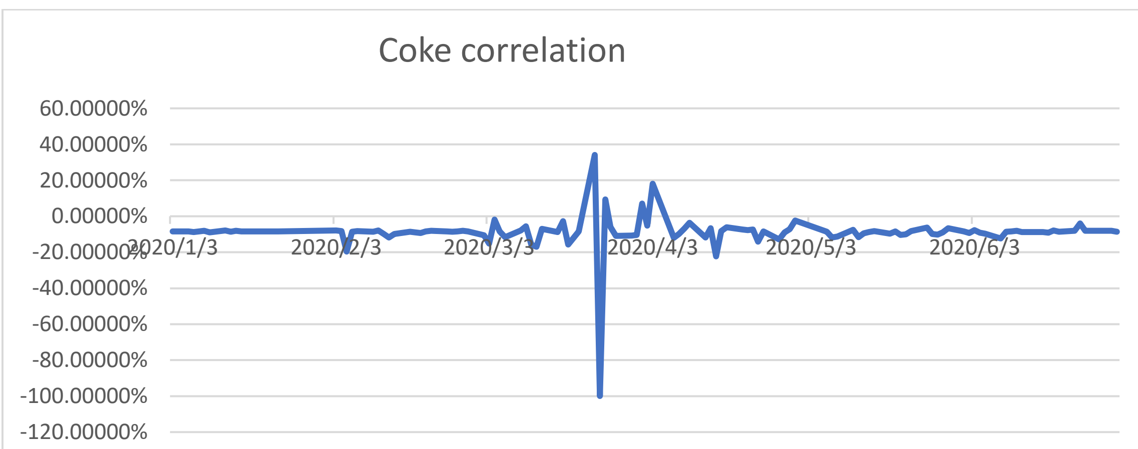

Fig. 15. Dynamic correlation of Coke and S&P500 return, DCE.

3. **Atypical group**

The third group is atypical, which means their correlations with the S&P 500 do not change around the normal correlation value, but they have a slow change process. To be more specific, the correlation changes look like "W" shape or "V" shape. Figure 16 shows the dynamic correlation of PVC and S&P500 return, and during the volatile period, the correlation shape is like a "W." The correlation is decreased to under zero and back to the normal level, and after another dramatic decrease, it gradually goes back to the normal correlation level. Figures 17 to 19 show a "V" shape in the volatile period. In these four futures, the performance of Al is relatively stable and has the highest correlation with S&P 500, accounting for 21%, which also can be used to make some profit in the US stock market recovery period.

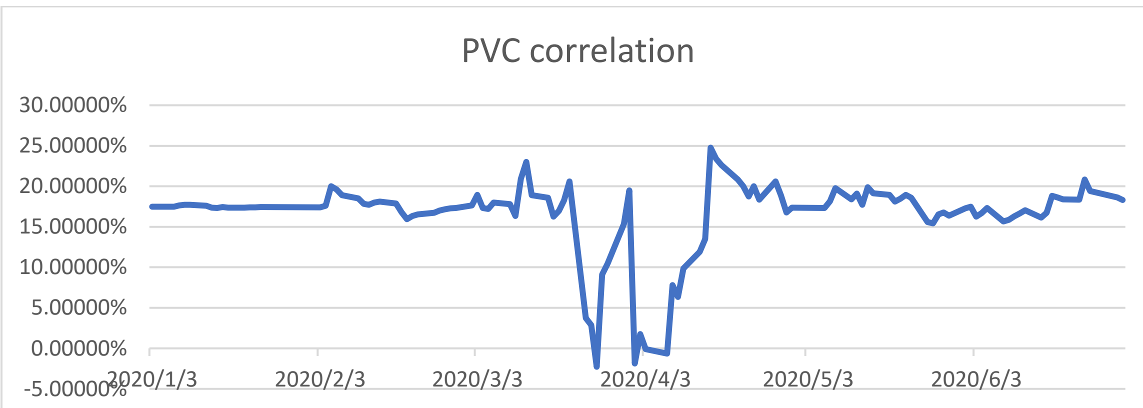

Fig. 16. Dynamic correlation of PVC and S&P500 return, DCE.

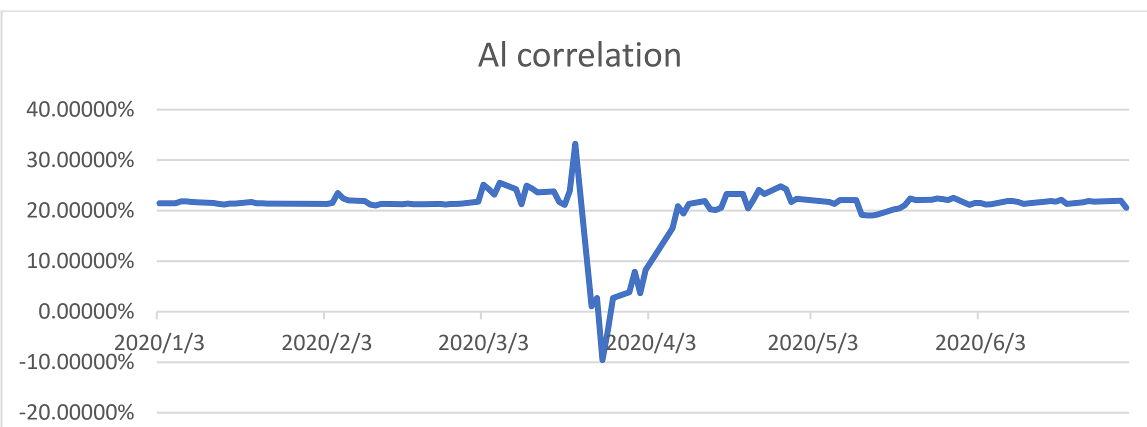

Fig. 17. Dynamic correlation of Al and S&P500 return, SFE.

Entire negative correlation group

There is only one commodity future that negatively correlates with the S&P 500 in the whole sample period, which is Rb from the Shanghai Futures Exchange. Because it has a negative correlation with the index and the correlation is around -10%, it is an appropriate choice to carry out a hedging strategy. Also, the correlation became stronger in the volatile period, increasing its hedging capability. Though there are several days the correlations became weak, they are still negatively correlated; thus, Rb is a suitable commodity future to have hedge effects compared with Coke and other futures.

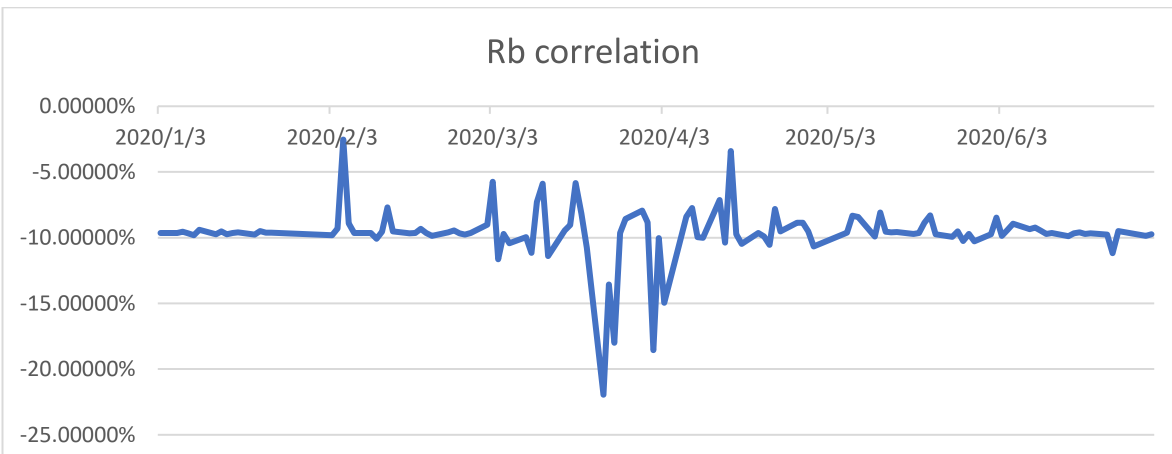

Fig. 4q. Dynamic correlation of Sp and S&P500 return, SFE.

Conclusion

This paper has analyzed the return correlations based on the connection between the US stock markets and several Chinese commodity futures from the Dalian commodity Exchange and Shanghai Futures exchange, focusing on the periods of shocked US stock market due to the Covid-19. For this purpose, a preliminary analysis of the S&P 500 is carried out to define the sample period; a descriptive analysis of the S&P 500 return and several Chinese commodity futures returns is conducted; finally, the Dynamic conditional correlation GARCH model is applied to find the dynamic correlation between the two markets.

The sample period is defined from January to June 2020 based on a dramatic price decline of the S&P 500 and its volatility. Then, the descriptive analysis is conducted and found that the US stock market is significantly negatively affected by the Covid-19, especially in February and March in 2020, where have seriously negative returns with increased volatility; meanwhile, only 11 out of 35 futures have positive average returns in the sample period, which shows that the Chinese commodity markets also negatively affected by the pandemic but most returns of them are more stable than the US stock index. Also, Corn, Corn Starch, and Polished Round-grained Rice, available in the DCE, can generate stable and positive returns during the Covid-19 pandemic and are suitable choices for investors.

Applying the DCC model, two commodity futures positively correlate with the index in the whole sample period. The Ru has a higher and more stable positive correlation with the index than Corn Starch. Most commodity futures have a positive correlation with several negative correlation points in the sample period. Fiber board, Hard Coking Coal, and Soybean oil futures are more sensitive to the shock of the S&P 500, and the index movement has relatively persistent effects on the three commodity futures. Even the volatility of the index decreased, these three futures remained volatile for nearly one month. Most of the futures are not affected by the shock of the index, which are more efficient in spreading the risks for foreign investors. The atypical futures show the "W" or "V" shapes in the volatile period, which means the correlations are relatively abnormal in that period. The Rb commodity future shows the negative correlation in the whole sample period. The correlation became stronger in the volatile period, supporting its suitableness as an element of hedging strategy.

Contributions and Limitations

This paper has some contributions to the previous literature. Firstly, this paper briefly analyzed the performance of Chinese commodity futures in the Dalian Commodity Exchange and Shanghai Futures Exchange during the Covid-19 and found three relatively stable commodity futures with positive returns from January to the end of June in 2020. Secondly, this paper analyzed the co-movement of the different markets in different countries, illustrating the strong potential connection between the American investors and Chinese commodity markets. Thirdly, this paper analyzed the correlations of several commodities futures with S&P 500 in the sample period (volatile periods and the normal circumstance) for investors to make judgments. Fourthly, the finding of a commodity future has a negative correlation with the index provides relevant insights for designing a commodity-based hedge strategy. Rb, available in SFE, has a negative correlation with the index during the entire period, which is suitable to invest taking a hedging strategy. Some futures which have a high correlation with S&P500 are worth consideration in the recovery period of the S&P 500 to earn more positive returns.

There are some limitations to this paper. First, the DCC GARCH model failed to find the correlation between several commodity futures and the index. One possible reason is that the sample period is not long enough, so the model cannot find the correlation processing the data. Another reason is that those Chinese commodity futures do not correlate with the US stock index. Second, the sample period is also not covering a long period of the whole Covid-19 pandemic. This paper only covers the most serious decline period of the US stock market index, but investors might consider whether to keep the hedging strategy in the latter period or not. Third, although the Rb future has a negative correlation with the index during the sample period, it does not mean the future has a hedge effect in the other circumstances. Also, the Rb future might not have a hedge effect in the next stock market shock period. Therefore, the hedge effect of Rb futures needs to be explored and proved.

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Appendix

Descriptive Statistics	Average return	Standard deviation	Variance	MAX return	MIN return
S&P 500	-0.00023	0.02952	0.00087	0.08580	-0.12987
No.1 Soybeans	0.00194	0.01179	0.00014	0.03779	-0.02904
No.2 Soybeans	-0.00065	0.01133	0.00013	0.03023	-0.04725
Corn	0.00081	0.00479	0.00002	0.01165	-0.00964
Corn Starch	0.00053	0.00461	0.00002	0.01193	-0.00902
Ethenylbenzene	-0.00218	0.02312	0.00053	0.06447	-0.08928
Ethylene Glycol	-0.00209	0.01885	0.00036	0.05026	-0.06275
Fiber Board	-0.00068	0.01394	0.00019	0.05713	-0.03910
Iron Ore	0.00103	0.02136	0.00046	0.05709	-0.11047
Coke	0.00003	0.01229	0.00015	0.02286	-0.04469
Egg	0.00033	0.02449	0.00060	0.08289	-0.10679
Hard Coking Coal	0.00000	0.01226	0.00015	0.04346	-0.04282
LLDPE	-0.00054	0.01754	0.00031	0.04933	-0.05882
Soybean Meal	0.00007	0.00874	0.00008	0.03312	-0.03213
RBD Palm Olein	-0.00204	0.01984	0.00039	0.08604	-0.09025
Polypropylene	-0.00020	0.01936	0.00037	0.06974	-0.06249
Polished Round-grained Rice	0.00026	0.00757	0.00006	0.04546	-0.02001
PVC	-0.00047	0.01285	0.00017	0.02955	-0.04688
Soybean Oil	-0.00154	0.01580	0.00025	0.07417	-0.08417
Cu	-0.00014	0.01479	0.00022	0.04047	-0.08381
Al	-0.00023	0.00994	0.00010	0.01853	-0.05101
Zn	-0.00056	0.01230	0.00015	0.03044	-0.04739
Pb	-0.00017	0.01095	0.00012	0.02884	-0.05053
Ni	-0.00066	0.01397	0.00020	0.02947	-0.04902
Sn	0.00021	0.01482	0.00022	0.03897	-0.07333
Au	0.00128	0.01225	0.00015	0.05318	-0.03740
Ag	-0.00006	0.02262	0.00051	0.05723	-0.10427
Rb	-0.00002	0.01187	0.00014	0.02504	-0.07695
Hc	-0.00006	0.01251	0.00016	0.02246	-0.07734
Ss	-0.00073	0.01087	0.00012	0.02986	-0.05416
Sc	-0.00417	0.03150	0.00099	0.07577	-0.10078
Fu	-0.00223	0.02955	0.00087	0.05192	-0.09921
Bu	-0.00157	0.02962	0.00088	0.06487	-0.09267
Ru	-0.00198	0.01676	0.00028	0.03075	-0.08946
Nr	-0.00199	0.01901	0.00036	0.04326	-0.09449
Sp	-0.00037	0.00748	0.00006	0.01766	-0.04336

MAX	0.00194	0.03150	0.00099	0.08604	-0.00902
MIN	-0.00417	0.00461	0.00002	0.01165	-0.12987

Figure 1: Statistical data of S&P 500's and Chinese commodity futures' returns

Long volatile periods group (two more figures)

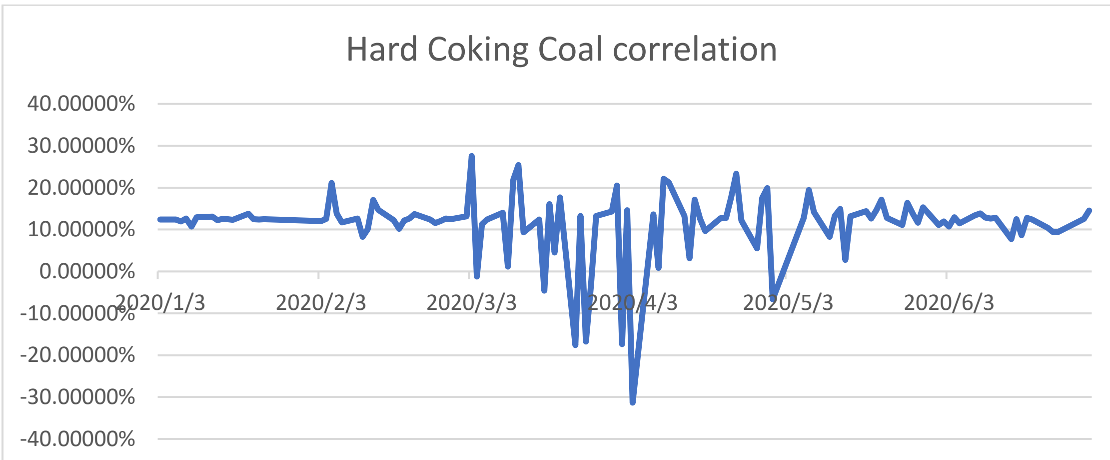

Fig. 7. Dynamic correlation of Hard Coking Coal return and S&P500 return, DCE.

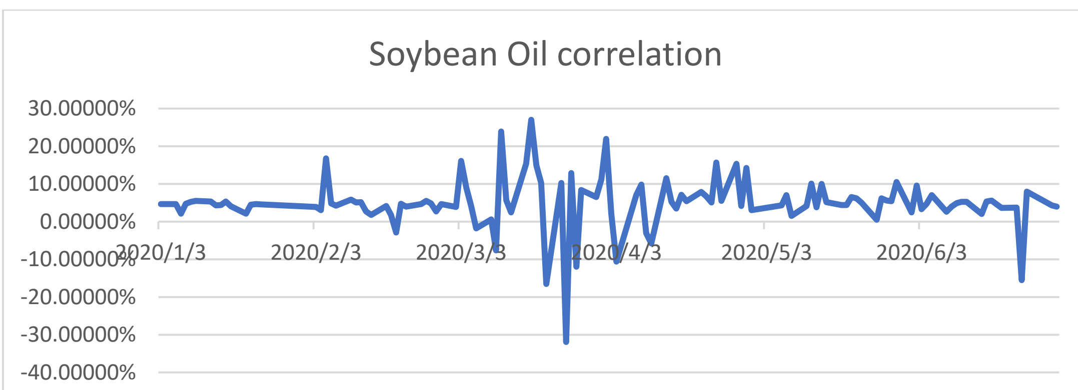

Fig. 8. Dynamic correlation of Soybean Oil return and S&P500 return, DCE.

Short volatile periods group (five more figures)

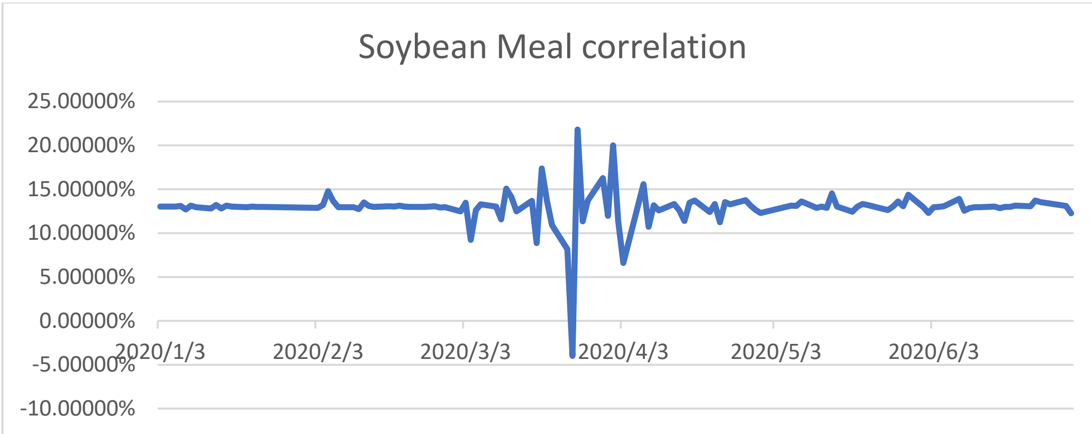

Fig. 10. Dynamic correlation of Soybean Meal and S&P500 return, DCE.

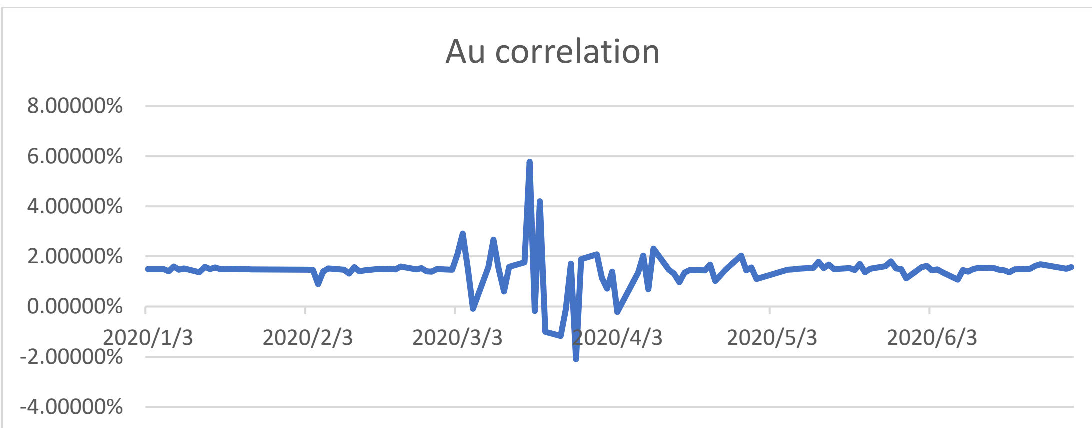

Fig. 11. Dynamic correlation of Au and S&P500 return, SFE.

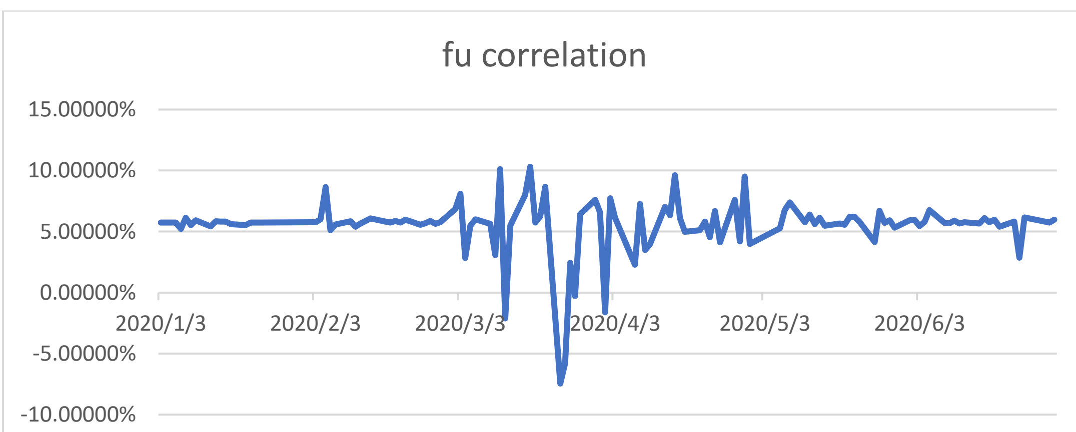

Fig. 12. Dynamic correlation of Fu and S&P500 return, SFE.

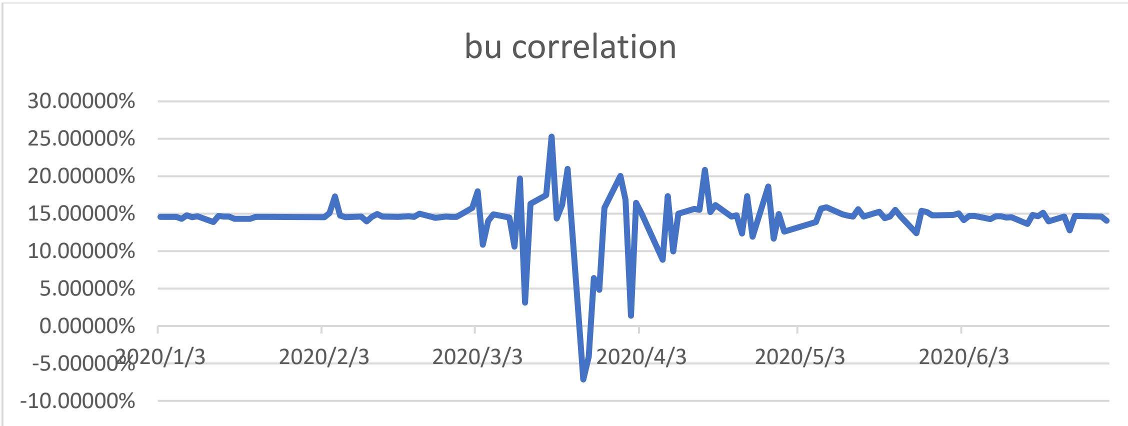

Fig. 13. Dynamic correlation of Bu and S&P500 return, SFE.

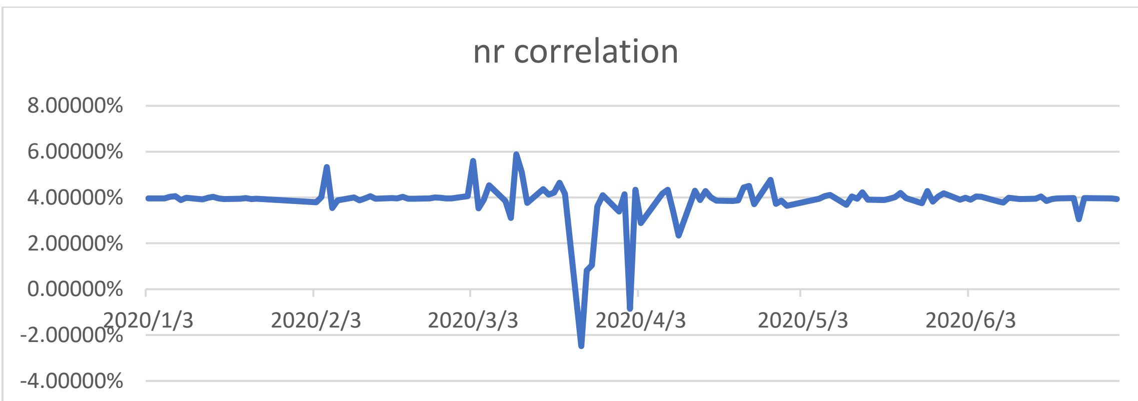

Fig. 14. Dynamic correlation of Nr and S&P500 return, SFE.

Atypical Group (two more figures)

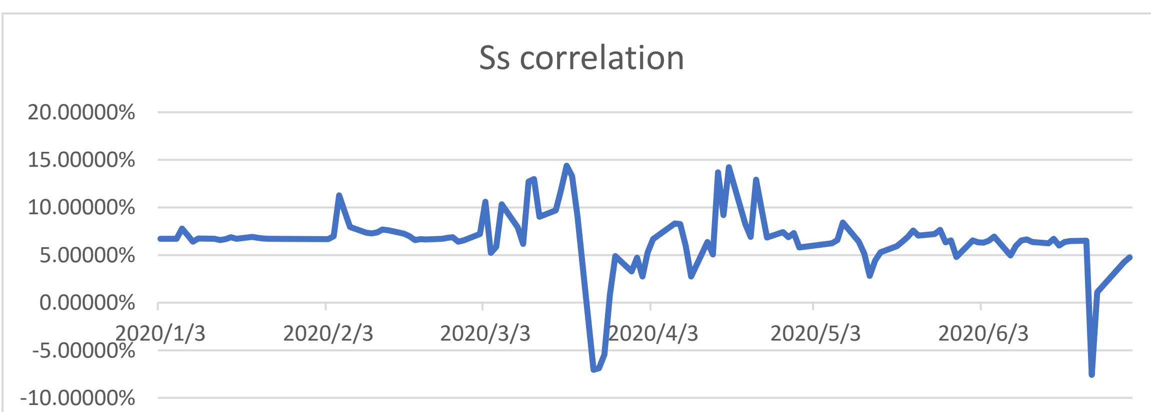

Fig. 18. Dynamic correlation of Ss and S&P500 return, SFE.

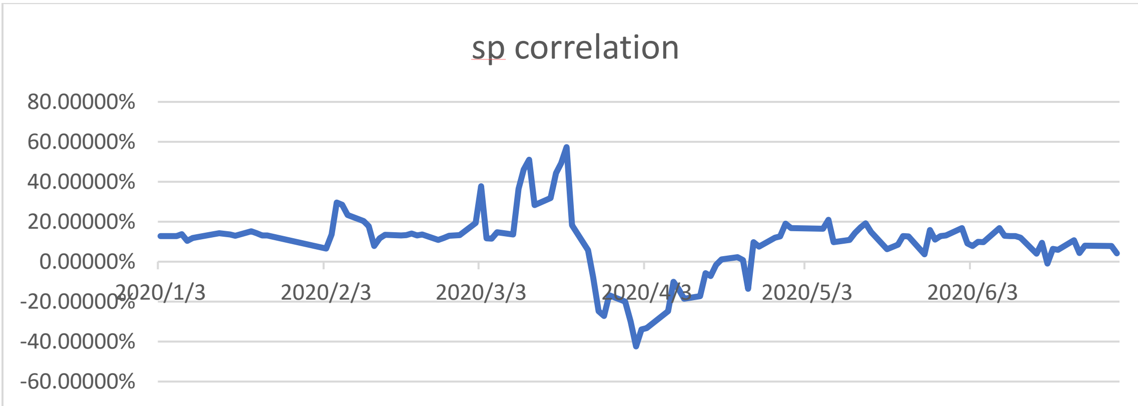

Fig. 19. Dynamic correlation of Sp and S&P500 return, SFE.