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AGRIBUSINESS

The shocks and integrations of COVID-19 pandemic on Chinese agricultural markets: comparative empirical evidence from China and other countries

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ABSTRACT: We use the ARIMA-GARCH model to estimate the shocks of COVID-19 on Chinese agricultural markets and utilize the ARDL-ECM model to estimate the integration relationships between Chinese and international agricultural markets which are based on the effective market hypothesis theory and daily trading data of US, UK, China and India. The main study findings showed that COVID-19 has a significant negative impact on agricultural product market, specifically, India suffered with the greatest negative impact, followed by the UK, the US and China. Further, this study results revealed that Chinese grain markets that are considered strategic places have not been separated from international markets, but there still exist segmentation phenomena among non-strategic agricultural markets.
Key words: COVID-19, shocks and integrations, agricultural futures market, agricultural investment, risk hedging.

Os choques e integrações da pandemia da COVID-19 nos mercados agrícolas chineses: evidências empíricas comparativas da China e de outros países

RESUMO: Utilizamos o modelo ARIMA-GARCH para estimar os choques da COVID-19 nos mercados agrícolas chineses e utilizamos o modelo ARDL-ECM para estimar as relações de integração entre os mercados agrícolas chineses e internacionais que se baseiam na teoria da hipótese de mercado eficaz e nos dados comerciais diários dos EUA, Reino Unido, China e Índia. As principais conclusões do estudo mostram que a COVID-19 tem um impacto negativo significativo no mercado de produtos agrícolas, especificamente, a Índia sofreu o maior impacto negativo, seguida pelo Reino Unido, pelos EUA e pela China. Além disso, os resultados deste estudo revelam que os mercados chineses de cereais, considerados locais estratégicos, não foram separados dos mercados internacionais, mas ainda existem fenômenos de segmentação entre os mercados agrícolas não estratégicos.
Palavras-chave: COVID-19, choques e integrações, mercado futuro agrícola, investimento agrícola, cobertura de risco.

INTRODUCTION

Since the outbreak of COVID-19, major grain producing countries such as Russia, India, Kazakhstan, Serbia, Egypt, and Vietnam have adopted policies to restrict or prohibit agricultural exports for different periods of time, leading to panic in global hoarding of food, increased prices of bulk agricultural products, severely damaged agricultural production and agricultural market cycle. According to the statistics of the Food and Agriculture Organization (FAO) in 2020, a variety of adverse factors such as COVID-19 lead to a grain reduction of more than 20% globally, 44 countries are experiencing food shortages, more than 690 million people are starving, and humanity may be facing the worst food security crisis in nearly 50 years.

Under such circumstances, can the agricultural market resist the shocks of COVID-19 and reflect the relationship between market supply and demand? In the era of comprehensive development of the global financial derivatives market, the agricultural futures market can answer this question. It plays an extremely important role in hedging precipitous risks, for example: during the financial crisis in 2008, the US transferred and dispersed real economic risks to the world through futures markets (MENSI et al., 2022). According to the statistics of the International Monetary Fund (IMF), the financial crisis made the global banking industry lose a total of 2.28 trillion dollars, but the US only borne 39% of it, and other countries shared 61%. In 2020, the trading volume of the global futures market has increased by 43.10%, among them, the increase in

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agricultural product futures accounted for 5.10%, highlighting the importance of risk management in the futures market in difficult economic times. Currently, it is an important stage to test the ability of the agricultural futures market to hedge against the risks of COVID-19. If they are effective, then agricultural production will be restored, the prices of agricultural products will stabilize, and the growth of the agricultural economy will be promoted.

In this paper, Chinese agricultural futures markets are the main research object, and agricultural futures markets of the United States, Britain and India are selected as the comparative research object. We attempted to answer two questions: First, the ability of Chinese agricultural futures market to withstand the shock of the COVID-19 epidemic compared with the international ones. Second, are the Chinese agricultural future markets fragmented or integrated with other agricultural future markets during the spread of the epidemic?. The study reported that during the peak period of the epidemic, India suffered with the greatest negative impact, followed by the UK, the US and China. Chinese grain futures markets, oilseeds and oilmarkets, and cotton markets are not separated from the other markets, but there is a separation between Chinese sugar market and the timber market from other markets. This research can help China to strengthen the monitoring, judgment, and early warning of risks in global trade, adjust the cooperation quality and investment structure in foreign countries, adapt international trade rules, and realize independent food security in the post-epidemic era.

Theoretical analysis

The futures market is the most important information distribution and risk management market in the modern market system, it collects various risk factors that affect the current or future market fluctuations and has an important price discovery and risk hedging function for the spot market (WORKING, 1948). Since the efficient market hypothesis was proposed by (FAMA, 1970), scholars started to evaluate the market efficiency in three forms, weak, semi-strong, and strong. Some scholars studied market efficiency through the level of market integration, which refers to the internal dynamics of the market (GARCÍA-HIERNAUX et al., 2016). The long-term integration relationship between markets would change positively or negatively due to the impact of major events.

Weak form efficiency of futures market

The development and evolution of the US futures market is the main reason for the weakening of commodity price volatility after the 1870s, and the early (1877-1900) grain futures market has achieved price discovery efficiency (SANTOS, 2002). KRISTOUFEK & VOSVRDA (2014) using the methods of long-term memory, fractal dimension and approximate entropy to study the market efficiency of 25 commodity futures in the US, they reported that the level of market efficiency from high to low is: energy, soft commodities, grains, metals and livestock. However, conclusions from (CONSUEGRA & GARCI-VERDUGO, 2017; DOU et al., 2022) are different; they construct a social welfare loss model and found that the efficiency of soft commodities, livestock, grains, and oil markets present different characteristics in different time periods, during the entire investigation period from 1975 to 2015, the livestock futures market is the most efficient, but after 2008, the efficiency level of the oil futures market has been significantly improved.

In the UK, the most strongest futures market is metals futures market, FIGUEROLA-FERRETTI & GONZALO (2010) proved that the UK metal futures market can aggregate all liquid market information by constructing two arbitrage pricing models (equilibrium price model with finite/infinite supply elasticity). SHELDON (1987) tested whether the soybean, potato, and pork futures markets conformed to the random walk form through the martingale process and spectral methods; the results showed that the overall operation of the three markets are weak and inefficient, and they are not weakly efficient markets. AULTON et al. (1997) considered that due to factors such as biological attributes, quality, storage period, trade volume and contract maturity, the efficiency level of the UK agricultural futures market “varies by variety”.

In the process of China’s transition from a planned economy to a market economy, the futures market already has functions of price discovery and risk aversion (WANG & KE, 2005). Judging from market activity and price fluctuations, China’s futures market does not appear to be overreacted to information (LIU et al., 2020). Affected by factors such as spot market dependence, contract maturity, and trading activity, China’s corn and soybean futures markets are the most efficient, while the wheat futures market is relatively inefficient (JU & YANG, 2018).

Overall, there is only one-way bootstrap relationship for the Granger causality test between the Indian agricultural futures market and the spot market, but the cotton futures market is relatively efficiently (PRADHAN et al., 2021). MOHANTY & MISHRA (2020) used the random walk hypothesis and the variance ratio test to study the efficiency of agricultural futures markets before and after the merger of the Forward Market Committee of India (FMC) and the Securities and Exchange Board of India (SEBI) in 2015. The results showed that; although, the level of market supervision and risk management have been improved after the merger, as a whole it is still in a weak and ineffective state, which may be affected by insufficient market competition environment, limited market liquidity, and incomplete infrastructure.

Semi-strong form efficiency of futures market

The impact of financial risks on the agricultural futures market has periodic and cyclical characteristics, and the uncertainty risks from 2010 to 2015 caused a significant negative impact on the US corn and soybean markets, but the impact on the wheat futures market was not significant (GOZGOR et al., 2016). Energy risks such as the oil crisis have a significant shock on the agricultural futures market. From 2006 to 2016, the US agricultural futures market took on crude oil market risks driven by rapidly growing energy demand in emerging economies (ALGIERI et al., 2017). Some scholars considered that monetary policy, trade frictions, agricultural support policy, and government information announcements lead to the loss of agricultural futures market efficiency (ALAM & GILBERT, 2017; HOFFMAN et al., 2015; INDRIAWAN et al., 2021); however, MAKKONEN et al. (2021) used quantile regression method to study the impact of macroeconomic, policy, and extreme climate change on agricultural futures markets; they reported that, compared with other factors, climate risks are the most important factor impacting the agricultural futures market. This view can also be supported by (ATEMS & SARDAR, 2021) and (CASHIN et al., 2017) who studied the shock of El Niño on agricultural market prices.

During the period of sharp fluctuations in crude oil market prices, China's soybean, corn, cotton, and palm oil futures markets also produced significant negative profit margins (LIU et al., 2020), among which the economic crop market was more fragile (ZHANG & QU, 2015). The economic policy uncertainty during the financial crisis in 2008, the post-crisis era in 2011 and the stock market disaster period in 2015 had both positive and negative impacts on Chinese agricultural futures prices. Among them, the 2015 stock market disaster had the longest duration and the highest impact on the futures market (XIAO et al., 2019). Although, there are herd behavior and price bubbles in the futures market during major risk events, contracts of different varieties respond differently, the price bubble in the Chinese agricultural futures market is generally controllable, which is a limited arbitrage market (LI et al., 2017; MAO et al., 2020).

Integration relationships of futures market

DAWSON & SANJUÁN (2006) reported that there was a long-term integration relationship between the wheat futures markets of the US and Canada from 1974 to 2001, and the US agricultural export promotion programs in 1985 and 1995 contributed to the integration in both countries. AYADI et al. (2021) used the DCC-GARCH model and International Capital Asset Pricing Model (ICAPM) to study the impact of global financial crisis, Irish banking crisis, European financial crisis and Brexit crisis on the integration relationship among the agricultural futures markets of the US, Western Europe and BRIC countries.

In terms of China, the first point of view is that there is a high degree of integration between the domestic and foreign agricultural product futures markets. Due to the existence of the transmission delay effect, the impact of international prices on the Chinese market will reach maximum at a certain point in the future (ARNADE et al., 2017; GE et al., 2010; ZHANG & LIU, 2020). The second view is that the international and Chinese agricultural futures market does not show a significant integration relationship, but the reform and opening policy has strengthened the spillover effect of international price fluctuations on the Chinese market, and the degree of integration is gradually increasing. Although, the two types of study have produced different results, they all illustrate the disadvantages and drawbacks of the separation of the Chinese market from the international market, affirming the positive impact of price synergy on economic growth, and advocating for increasing the openness of the agricultural market to foreign countries.

MATERIALS AND METHODS

Data sources and description

Select the daily closing prices of agricultural futures markets as time series; the number of varieties included in the US, the UK, China, and India is respectively 15, 4, 23 and 6. Corn, soybean, indica rice, wheat, soybean oil, soybean meal, sugar No. 11, cotton No. 2, wood, orange juice, C-type coffee, cocoa, live cattle and feed cattle are included in the America agricultural future time series that traded on the Chicago Mercantile Exchange (CME). Wheat, sugar, cocoa and coffee are included in the UK agricultural future time series that traded on the Intercontinental Exchange (ICE). Corn, corn starch, soybean NO.1, soybean NO.2, early indica rice, japonica rice, late indica rice, japonica rice, common wheat, strong wheat, soybean oil, soybean meal, rapeseed oil, sugar, cotton, cotton yarn, palm oil, plywood, fiberboard, natural rubber, egg, apple and date are included in Chinese agricultural future time series that traded on the Dalian Commodity Exchange (DCE) and the Zhengzhou Commodity Exchange (CZCE). Cotton, seed cotton, palm oil, castor oil, cardamom and mint oil is included in India agricultural future time series which traded on the Multi Commodity Exchange of India Ltd (MCX).

First, establish the comprehensive index of the agricultural futures market, which refers to the calculation method of the stock markets. Many international institutions use this method to reflect commodity price indices (such as Goldman Sachs Commodity Index, GSCI; Dow Jones-UBS Commodity Index; Rogers International Commodity Index; etc.). Its calculation Equation is as follows:

$$R_t = 100 * \mathrm{Ln}\frac{P_t}{P_{t-1}} \tag{1}$$

Where R_t is the return rate of the entire agricultural futures market of each country, the comprehensive market return rates of the US, the UK, China and India are respectively denoted as R_{Us}, R_{Uk}, R_{Ch} and R_{In}. Where P_t represents the composite price index of the agricultural futures market on the *t* day, after taking the logarithm, it can be expressed as:

$$\mathrm{Ln}P_t = \sum_{i=1}^{n} \mathrm{Ln}\frac{P_i Q_i}{Q_t} \tag{2}$$

Where $\mathrm{Ln}P_t$, P_{it}, Q_{it} and Q_t respectively represent the logarithm of the comprehensive price index, closing price, trading volume and total market transaction volume of all varieties on the t day.

Table 1 reports the descriptive statistics, which are the maximum, median, minimum, mean, standard deviation, skewness, and kurtosis for the US, the UK, China, and India agricultural futures market from 1 April 2019 to 22 November 2021. China has the highest mean (0.029) which means that on average the market has the highest return, at the same time, India has the largest standard deviation (0.912) which implies that the market has the greatest risk. The UK has the lowest average return, and the US is the least risky. In terms of skewness and kurtosis, the time series data showed the distribution characteristics of sharp peak and fat tail.

Model setting

First, establish the time window of the event study. Generally, the estimate window is longer than 120 days and the event window is determined by the purpose of the investigation and the influence of the event (KOTHARI & WARNER, 2007). The selected time range is from 1 April 2019 to 26 February 2020 to investigate the shocks of COVID-19 pandemic, and from 1 January 2020 to 22 November 2021 to investigate market integration.

ARIMA-GARCH model

We take 30 January 2020 as the cut-off point, because on this day the World Health Organization (WHO) officially declared that the world enters an international emergency. We defined the events window as 30 days from January 15, 2020 to February 26, 2020, which indicates the time interval is [-10,20], and the event estimation window is 200 trading days from April 1, 2019 to January 14, 2020, which indicates the time interval is [-191,-9]. On this basis, expected returns of agricultural futures markets in the absence of COVID-19 are estimated , and the ARIMA-GARCH model can be expressed as:

$$E(R_t) = C + \varphi_1 R_{t-1} + \varphi_2 R_{t-2} + \ldots + \varphi_p R_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \tag{3}$$

Where $E(R_t)$ is the expected return rate of agricultural futures market on the *t* day, C is a constant, φ_p and θ_q are parameters to be estimated, and the residual ε_t follows an independent and identically distributed white noise process.

Since financial time series usually show the phenomenon of fluctuation cluster, the residual after ARIMA modeling may have the ARCH effect, so it is necessary to establish the GARCH model of error variance to estimate the relationship between the conditional variance of the error term and the past error term over time, which can be expressed as:

$$\sigma_t^2 = \mathrm{Var}(\varepsilon_t | I_{t-1}) = \alpha_0 + \sum_{i=1}^{p'} \alpha_i \sigma_{t-i}^2 + \sum_{i=1}^{q'} \beta_j \varepsilon_{t-j}^2 \tag{4}$$

Finally, the *T* test is performed on the abnormal return rate AR_t and cumulative abnormal return rate CAR_t .

$$AR_t = R_t - E(R_t) \tag{5}$$

$$CAR_t[t_1, t_2] = \sum_{t=t_1}^{t_2} AR_t \tag{6}$$

The cumulative abnormal return rates of the US, the UK, China and India are denoted as CAR_{us}, CAR_{uk}, CAR_{ch} and CAR_{in} . If CAR is significantly 0, it indicates that the event has no influence on the market. If the CAR is significantly negative, it indicates that the event has a negative effect on the market, leading to a price decline and abnormal losses. If the CAR

Table 1 - Descriptive statistics.

Variables	-----Max-----	---Median---	-----Min-----	-----Mean-----	------SD------	--Skewness--	---Kurtosis---
R_{Us}	2.961	0.011	-2.862	0.025	0.685	-0.835	15.363
R_{Uk}	3.744	0.008	-2.643	0.020	0.743	0.201	15.523
R_{Ch}	2.894	0.014	-3.075	0.029	0.733	0.603	26.163
R_{In}	3.855	0.029	-3.038	0.024	0.912	0.362	19.144

is significantly positive, it indicates that this event has a positive effect on the market, promoting price increase and abnormal profits.

ARDL-ECM Model

The selected varieties of contracts can be classified into four categories: grains, oilseeds and oil, soft commodities, and forest products. The autoregressive distributed lag model (ARDL) is used to test the integration relationship between different futures markets. This model is suitable for variables of the same order of single integer (I(0) or I(1)) or a mixture of I(0) and I(1). When there is an endogeneity problem between the variables, unbiased estimation of the model can be effective.

There are three steps of the Bounds Test. Step 1: it can be estimated by the F statistics to judge if there exist the integration relationship between variables. If the value of the F statistic is greater than the upper boundary value, the null hypothesis that there is no integration relationship between variables is rejected; if the value of the F statistic is less than the lower boundary value, the null hypothesis that there is no integration relationship between variables cannot be rejected; if the value of F statistic is in the interval between the lower boundary value and the upper boundary value, it is impossible to judge whether there is an integration relationship between variables (PESARAN et al., 2001). Step 2, if the variables exist the co-integration in the long-run, the maximum likelihood method can be used to estimate the elasticity. Step 3, the ECM model can be used to estimate the speed of adjustment coefficient in the short-run.

Grain Market Integration Relationship

The ARDL model to test the integration relationship between the China-US corn, China-US indica rice, and China-US-UK wheat markets can be expressed as follows:

$$R_{Ch\_n} = C_1 + \sum_{i=1}^{k} a_i R_{Ch\_n\ (t\text{-}k)} + \sum_{i=1}^{k} b_i R_{Us\_n\ (t\text{-}k)} + \varepsilon_{t1} \quad (7)$$

$$R_{Ch\_r} = C_2 + \sum_{i=1}^{k} c_i R_{Ch\_r\ (t\text{-}k)} + \sum_{i=1}^{k} d_i R_{Us\_r\ (t\text{-}k)} + \varepsilon_{t2} \quad (8)$$

$$R_{Ch\_w} = C_3 + \sum_{i=1}^{k} e_i R_{Ch\_w\ (t\text{-}k)} + \sum_{i=1}^{k} f_i R_{Us\_w\ (t\text{-}k)} + \sum_{i=1}^{k} g_i R_{Uk\_w\ (t\text{-}k)} + \varepsilon_{t3} \quad (9)$$

Oilseeds and oil markets integration relationship

The ARDL model to test the integration relationship between the China-US soybean, China-US soybean oil, and China-India palm oil markets can be expressed as follows:

$$R_{Ch\_b} = C_4 + \sum_{i=1}^{k} h_i R_{Ch\_b\ (t\text{-}k)} + \sum_{i=1}^{k} h_i R_{Us\_b\ (t\text{-}k)} + \varepsilon_{t4} \quad (10)$$

$$R_{Ch\_o} = C_5 + \sum_{i=1}^{k} j_i R_{Ch\_o\ (t\text{-}k)} + \sum_{i=1}^{k} l_i R_{Us\_o\ (t\text{-}k)} + \varepsilon_{t5} \quad (11)$$

$$R_{Ch\_m} = C_6 + \sum_{i=1}^{k} m_i R_{Ch\_m\ (t\text{-}k)} + \sum_{i=1}^{k} n_i R_{Us\_m\ (t\text{-}k)} + \varepsilon_{t6} \quad (12)$$

$$R_{Ch\_p} = C_7 + \sum_{i=1}^{k} o_i R_{Ch\_p\ (t\text{-}k)} + \sum_{i=1}^{k} p_i R_{In\_p\ (t\text{-}k)} + \varepsilon_{t7} \quad (13)$$

Soft commodities markets integration relationship

The ARDL model to test the integration relationship between China-US-UK sugar and China-US-India cotton markets can be expressed as follows:

$$R_{Ch\_s} = C_8 + \sum_{i=1}^{k} q_i R_{Ch\_s\ (t\text{-}k)} + \sum_{i=1}^{k} r_i R_{Us\_s\ (t\text{-}k)} + \sum_{i=1}^{k} s_i R_{Uk\_s\ (t\text{-}k)} + \varepsilon_{t8} \quad (14)$$

$$R_{Ch\_c} = C_9 + \sum_{i=1}^{k} t_i R_{Ch\_c\ (t\text{-}k)} + \sum_{i=1}^{k} u_i R_{Us\_c\ (t\text{-}k)} + \sum_{i=1}^{k} v_i R_{In\_c\ (t\text{-}k)} + \varepsilon_{t9} \quad (15)$$

Forests markets integration relationships

The ARDL model to test the integration relationship between the Chinese-US timber markets can be expressed as follows:

$$R_{Ch\_t} = C_{10} + \sum_{i=1}^{k} w_i R_{Ch\_t\ (t-k)} + \sum_{i=1}^{k} x_i R_{Us\_t\ (t-k)} + \varepsilon_{t10} \quad (16)$$

RESULTS AND DISCUSSION

Unit root test results

The ADF method is used to test the stationarity of the variables, and the trend item is selected according to the AIC information criterion. The test results showed that the R_{Us}, R_{Uk}, R_{Ch} and R_{In} are stationary at the 1% significance level. The data conform to the modeling conditions of ARIMA (p，d，q) , after one difference (d =1) transformation, the ARIMA model can be transformed into an ARMA model (p, q) with p-order auto-regression term and q-order moving average term.

The Shock of COVID-19 on Chinese and Other Agricultural Markets

Estimation results of ARIMA-GARCH model

Empirical content is implemented by Stata15.0 software. The ARIMA optimal models of R_{Us}, R_{Uk}, R_{Ch} and R_{In} are respectively ARIMA(1,1,1), ARIMA(2,1,2), ARIMA(1,1,1) and ARIMA(2,1,2) which are judged by ACF, PACF and SBC information guidelines. The GARCH (1, 1) model based on the generalized error distribution (GED distribution) has the best fitting effect, the coefficients of the variance equations are all greater than 0, and the sum of the coefficients is less than 1, which satisfies the parameter requirements of the model. The ARCH-LM test with lag order of 1-10 is carried out on the residual series of the equations, and the results showed that the residual series of the GARCH (1, 1) model does not have ARCH effect, the estimation of the variance equation is accurate and reliable (Table 2).

Test results of CAR

According to Equations (5) and (6), the normal return rate of agricultural futures markets is predicted, the CAR is calculated, and the T test is performed. The test results showed that in the window of [-10, -6], all CAR values are positive, indicating that the epidemic information has not been transmitted to the agricultural futures markets. However, on the fifth day before the event, the Chinese agricultural futures market produced negative abnormal profit margins, while the others were still positive. The reason for the difference is that on the sixth day before the event, China officially announced the city lockdown measures in Wuhan city, the news transferred to financial markets quickly, resulting in a decline in market profit margins. Whereas, the message delivery in international markets is slow, there is no significant impact on market earnings of the US, UK or India. In the event window of [-10, -1], the CAR values of the Chinese agricultural futures market decreased by 16.9%, and the other markets were not negatively impacted.

The reversal happened on the day before the official announcement by the WHO, the CAR values of the US, UK, China, and India are -7.55%, -6.58% ,-9.61%, and -2.00%, and these numbers dropped to -12.92%, -9.66%, -11.87%, and -7.33% on the event day. In the following 5 days, the four markets had the same trend, the CAR values of the US, UK, China and India were -49.65%, -47.82%,-39.22% and -34.23%. In the window of [6,10], the confidence in the Chinese market gradually retreated and the decline rate of market returns slowed, but the other three countries still maintained the decline trend as in the earlier stage. In the window of [11,15], the rate of market losses has slowed slightly in the US, UK and China, but the negative impact of the Indian market increased, the CAR value decreased to -48.16%, and this situation continued to the next period. In the window of [16,20], the CAR value of the Indian market decreased to -59.90%, while the shock in the US, UK and China gradually decreases with CAR values of -46.32%, -44.57% and -14.32%, which indicates that the information transmission speed of the Indian market is lower than other countries. During the whole period, the CAR values of the four countries from small to large are as follows: India (-49.55%) < The US < (-47.08%) < The UK (-45.35%) < China (-43.99%) (Table 3).

The integration relationships between Chinese and other agricultural markets

Results from the ARDL model for integration

Grain markets integration relationship

To test the null hypothesis of co-integration, the first step is to determine whether there is a relationship between the variables over the long term using bound tests. The Equation (7) ~ (9) that tests the integration relationship with F statistics of 11.04, 7.02 and 6.69, which are higher than the upper critical value for 1%, 10%, and 10% of table 4. Hence, the null hypothesis was rejected, confirming the existence of integration among China-US corn market, China-US indica market and China-US-UK wheat market.

Table 2 - ARIMA-GARCH model estimation results.

	-------Variable-------	------Coefficient------	------Std. Error------	----GED Statistic----	--------P-value--------
$E(R_{Ch})$	C	0.014	0.202	-0.467*	0.052
	AR (1)	-0.276	0.013	38.207***	0.000
	MA (1)	0.177	0.310	119.002***	0.005
	α_0	0.030	0.001	4.426*	0.073
	ARCH (1)	0.057	0.309	9.553***	0.005
	GARCH (1)	0.929	0.001	84.521*	0.082
$E(R_{Us})$	C	0.026	0.411	0.603***	0.000
	AR (1)	0.301	0.129	-29.980***	0.000
	MA (1)	0.202	0.456	-99.866**	0.036
	α_0	0.011	0.000	3.054**	0.012
	ARCH (1)	0.043	0.311	11.956***	0.000
	GARCH (1)	0.932	0.001	90.857**	0.041
$E(R_{Uk})$	C	0.011	0.310	0.621***	0.000
	AR (10)	0.263	0.243	-29.730**	0.031
	AR (2)	0.121	0.222	-79.901***	0.000
	MA (1)	-0.194	0.121	7.029***	0.003
	MA (2)	-0.233	0.009	1339.053***	0.000
	α_0	0.032	0.011	4.101***	0.000
	ARCH (1)	0.017	0.009	6.506***	0.000
	GARCH (1)	0.954	0.014	49.710***	0.000
$E(R_{In})$	C	0.013	0.419	0.453***	0.000
	AR (1)	-0.301	0.409	19.920*	0.060
	AR (2)	0.276	0.220	-47.208***	0.000
	MA (1)	0.110	0.178	-10.988***	0.001
	MA (2)	0.308	0.011	-1205.068***	0.000
	α_0	0.0300	0.071	11.923**	0.032
	ARCH (1)	0.045	0.019	12.320***	0.000
	GARCH (1)	0.921	0.014	59.090***	0.000

Note: ***, ** and * represent significant at the significance level of 1%, 5% and 10%, respectively.

Oilseeds and Oil Markets Integration Relationship

The Equation (10) ~ (13) that tests the integration relationship with F statistics of 8.97, 9.34, 6.49 and 6.93, which are greater than the upper critical value for 5%, 5%, 10% and 10% from table 4. Therefore, the null hypothesis was rejected, confirming the existence of integration between the China-US soybean market, China-US soybean oil market, the China-US soybean meal market and the China-India palm oil market.

Soft commodities markets integration relationship

Equation (14) tested the integration relationship with F statistics of 3.57, which is less than the lowest critical value for 10% from table 4. Therefore, the null hypothesis was accepted, which confirmed the nonexistence of integration between the China-US-UK sugar market.

The Equation (15) tests the integration relationship with F statistics of 6.02, which is greater than the upper critical value for 5% from table 4. Hence, the null hypothesis was rejected, which confirmed the existence of integration among the China-US-India cotton market.

Forest products markets integration relationship

Equation (16) tested the integration relationship with F statistics of 4.71, which is less than the lower critical value for 10% from table 4. Hence, the null hypothesis was accepted, confirming the nonexistence of integration between China-US wood market (Table 4).

Table 3 - Test results of CAR values.

Windows	--US--	t-Stats	P-Value	-UK-	t-Stats	P-Value	China	t-Stats	P-Value	India	t-Stats	P-Value
[-10, -6]	0.063	1.760*	0.077	0.055	1.915*	0.065	0.043	1.771*	0.063	0.039	1.400	0.255
[-5, -5]	0.020	2.399**	0.045	0.036	1.065	0.355	-0.059	-2.370**	0.033	0.034	1.602	0.147
[-5, -1]	0.049	4.655***	0.001	0.044	2.012**	0.065	-0.119	-3.031***	0.000	0.035	1.671*	0.091
[-10, -1]	0.029	2.908***	0.000	0.036	3.087***	0.000	-0.169	-3.823***	0.000	0.029	1.134	0.106
[-1, -1]	-0.076	-4.281***	0.000	-0.066	-14.199***	0.001	-0.096	-4.982***	0.001	-0.020	-2.553**	0.079
[0, 0]	-0.129	-5.092***	0.000	-0.097	-13.753***	0.000	-0.119	-5.433***	0.000	-0.073	-3.810***	0.000
[1, 1]	-0.131	-5.558***	0.000	-0.101	-15.959***	0.000	-0.122	-5.983***	0.001	-0.084	-4.557***	0.005
[1, 5]	-0.497	-14.961***	0.001	-0.478	-30.625***	0.001	-0.392	-12.430**	0.052	-0.342	-17.446***	0.000
[6, 10]	-0.520	-14.647***	0.000	-0.485	-29.655***	0.003	-0.253	-11.381***	0.003	-0.391	-19.507***	0.006
[11, 15]	-0.507	-12.537***	0.002	-0.461	-27.752***	0.000	-0.179	-10.907***	0.005	-0.482	-21.203***	0.001
[16, 20]	-0.463	-11.981***	0.004	-0.446	-20.670***	0.000	-0.143	-12.026***	0.000	-0.599	-25.291***	0.007
[0, 10]	-0.518	-11.351***	0.000	-0.480	-25.579***	0.001	-0.341	-14.920***	0.001	-0.371	-20.980***	0.000
[11, 20]	-0.487	-17.872***	0.006	-0.466	-25.902***	0.000	-0.152	-13.659***	0.000	-0.569	-32.091***	0.000
[0, 20]	-0.500	-20.660***	0.000	-0.479	-28.449***	0.000	-0.289	-17.802***	0.000	-0.519	-31.092***	0.001
[-10, 20]	-0.471	-16.900***	0.000	-0.453	-26.056***	0.001	-0.434	-16.650***	0.000	-0.496	-29.051***	0.000

Estimation results of ARDL-ECM model coefficient

The long-run and short-run effects on grain markets

The optimal lag orders of the ARDL models for corn, indica rice and wheat markets are ARDL(1,1), ARDL(1,1) and ARDL(1, 1, 1), and the ECM models are as follows:

$$\Delta R_{Ch\_n} = C'_1 + \sum_{i=1}^{k} a'_1 \Delta R_{Ch\_n\ (t-k)} + \sum_{i=1}^{k} b_i' \Delta R_{Us\_n\ (t-k)} + \varepsilon'_{t1}$$

$$\sum_{i=1}^{k} b_i' \Delta R_{Us\_n\ (t-k)} + \varepsilon'_{t1} \qquad (17)$$

$$\Delta R_{Ch\_r} = C'_2 + \sum_{i=1}^{k} c'_i \Delta R_{Ch\_r\ (t-k)} + \sum_{i=1}^{k} d'_i \Delta R_{Us\_r\ (t-k)} + \varepsilon'_{t2} \qquad (18)$$

$$\Delta R_{Ch\_w} = C'_3 + \sum_{i=1}^{k} e'_i \Delta R_{Ch\_w\ (t-k)} + \sum_{i=1}^{k} f'_i \Delta R_{Us\_w\ (t-k)} + \sum_{i=1}^{k} g'_i \Delta R_{Uk\_w\ (t-k)} + \varepsilon'_{t3} \qquad (19)$$

The elasticity of China-US corn market is -0.13 in the long-run, and the error correction coefficient between ΔR_{Ch_n} and ΔR_{Us_n} is -0.22, thus, when there is a divergence in the China-US corn markets, they can achieve integration at the convergence speed of 22%. The elasticity of China-US indica market is 0.29 in the long-run, and the error correction coefficient between ΔR_{Ch_r} and ΔR_{Us_r} is -0.15, thus, when there is a divergence in the China-US indica markets, they can achieve integration at the convergence speed of 15%. The elasticity of China-US wheat market is -0.17 in the long-run, and the error correction coefficient between ΔR_{Ch_w} and ΔR_{Us_w} is -0.12, thus, when there is a divergence in the China-US wheat markets, they can achieve integration at the convergence speed of 12%. The elasticity of China-UK wheat market is -0.13 in the long-run, and the error correction coefficient between ΔR_{Ch_w} and ΔR_{Uk_w} is -0.13, thus, when there is a divergence in the China-UK wheat markets, they can achieve integration at the convergence speed of 13% (Table 5).

The long-run and short-run effects on oilseeds and oil markets

The optimal lag orders of the ARDL models for soybean, soybean oil, soybean meal and palm oil markets are ARDL(1,0), ARDL (1,0), ARDL (1,0) and ARDL (1,1), and the ECM models are as follows:

$$\Delta R_{Ch\_b} = C'_4 + \sum_{i=1}^{k} h'_i \Delta R_{Ch\_b\ (t-k)} + \sum_{i=1}^{k} h'_i \Delta R_{Us\_b\ (t-k)} + \varepsilon'_{t4} \qquad (20)$$

$$\Delta R_{Ch\_o} = C'_5 + \sum_{i=1}^{k} j'_i \Delta R_{Ch\_o\ (t-k)} + \sum_{i=1}^{k} l'_i \Delta R_{Us\_o\ (t-k)} + \varepsilon'_{t5} \qquad (21)$$

$$\Delta R_{Ch\_m} = C'_6 + \sum_{i=1}^{k} m'_i \Delta R_{Ch\_m\ (t-k)} + \sum_{i=1}^{k} n'_i \Delta R_{Us\_m\ (t-k)} + \varepsilon'_{t6} \qquad (22)$$

Table 4 - ARDL bounds test for Integration.

Significance level	----------------10%----------------		----------------5%----------------		----------------1%----------------	
Critical values	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
	5.59	6.26	6.56	7.30	8.74	9.63
F-Bound test	Corn: F_7=11.037; indica rice: F_8=7.022; Soybean: F_{10}=8.966; Soybean oil: F_{11}=9. 338; Soybean meal: F_{12}=6.491; Palm oil: F_{13}=6.927; Wood: F_{16}=4.712					
Significance level	----------------10%----------------		----------------5%----------------		----------------1%----------------	
Critical values	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
	4.19	5.06	4.87	5.85	6.34	7.52
F-Bound test	----------------------------Wheat: F_9=6.691; Sugar: F_{14}=3.565; Cotton: F_{15}=6.023----------------------------					

$$\Delta R_{Ch\_p} = C'_7 + \sum_{i=1}^{k} o'_i \Delta R_{Ch\_p\ (t-k)} + \sum_{i=1}^{k} p'_i \Delta R_{In\_p\ (t-k)} + \varepsilon'_{t7} \quad (23)$$

The results showed that the elasticity of China-US soybean market is -0.20 in the long-run, and the error correction coefficient between ΔR_{Cn_b} and ΔR_{Us_b} is -0.18, thus, when there is a divergence in the China-US soybean markets, they can achieve integration at the convergence speed of 18%. The elasticity of China-US soybean oil market is -0.21 in the long-run, and the error correction coefficient between ΔR_{Cn_o} and ΔR_{Us_o} is -0.12, thus, when there is a divergence in the China-US soybean oil markets, they can achieve integration at the convergence speed of 12%. The elasticity of China-US soybean meal market is 0.18 in the long-run, and the error correction coefficient between ΔR_{Cn_m} and ΔR_{Us_m} is -0.10, thus, when there is a divergence in the China-US soybean meal markets, they can achieve integration at the convergence speed of 10%. The elasticity of China-India palm oil market is -0.21 in the long-run, and the error correction coefficient between ΔR_{Cn_p} and ΔR_{In_p}

Table 5 - Long-run and short-run coefficients of grain markets.

Long-run	--------Variable--------	------Coefficient------	-----------S.E----------	-------t-Statistic-------	--------P-Value--------
China-US corn	$R_{Ch\_n}(-1)$	0.923	0.031	30.246***	0.000
	R_{Us_n}	-0.080	0.031	-2.573**	0.003
Equation (7)	$R_{Us\_n}(-1)$	-0.126	0.020	-6.436***	0.000
	C	28.989	12.557	2.309***	0.045
China-US indica: Equation (8)	$R_{Ch\_r}(-1)$	0.915	0.188	4.867***	0.000
	R_{Us_r}	0.190	0.246	0.775	0.240
	$R_{Us\_r}(-1)$	0.290	0.102	2.837***	0.008
	C	31.071	18.501	1.679*	0.064
China-US-UK wheat: Equation (9)	$R_{Ch\_w}(-1)$	0.928	0.020	45.955***	0.000
	R_{Us_w}	-0.168	0.036	-4.703***	0.000
	$R_{Us\_w}(-1)$	-0.1702	0.020	-8.344***	0.000
	R_{Uk_w}	-0.100	0.062	-1.612	0.133
	$R_{Uk\_w}(-1)$	-0.127	0.056	-2.279**	0.048
	C	-41.558	26.870	-1.547	0.004
Short-run	Variable	Coefficient	S.E	t-Statistic	P-Value
Corn: Equation (17)	ΔR_{Ch_n} & Δ_{RUs_n}	-0.215	0.025	-8.713***	0.0000
Indica: Equation (18)	ΔR_{Ch_r}&ΔR_{Us_r}	-0.154	0.050	-3.101***	0.000
Wheat: Equation (19)	ΔR_{Ch_w}&ΔR_{Us_w}	-0.119	0.029	-4.165***	0.000
	ΔR_{Ch_w}&ΔR_{Uk_w}	-0.101	0.049	-2.055**	0.000

is -0.10, thus, when there is a divergence in the China-India palm oil markets, they can achieve integration at the convergence speed of 12% (Table 6).

The long-run and short-run effects on soft commodities markets

The optimal lag orders of the ARDL models for cotton markets is ARDL (1,1,1), and the ECM model is as follows:

$$\Delta R_{Ch\_c} = C'_9 + \sum_{i=1}^{k} t'_i \Delta R_{Ch\_c\,(t-k)} + \sum_{i=1}^{k} u'_i \Delta R_{Us\_c\,(t-k)} + \sum_{i=1}^{k} v'_i \Delta R_{In\_c\,(t-k)} + \varepsilon'_{t9} \quad (24)$$

The results showed that the elasticity of China-US cotton market is -0.16 in the long-run, and the error correction coefficient between ΔR_{Ch_c} and ΔR_{Us_c} is -0.11, thus, when there is a divergence in the China-US cotton markets, they can achieve integration at the convergence speed of 11%. The elasticity of China-India cotton market is 0.09 in the long-run, and the error correction coefficient between ΔR_{Ch_c} and ΔR_{In_c} is -0.10, thus, when there is a divergence in the China-India cotton markets, they can achieve integration at the convergence speed of 10% (Table 7).

RESULTS AND DISCUSSION

During the peak of the COVID-19, the global agricultural markets suffered heavy losses, and the degree of negative impact from high to low is: India, the US, the UK and China. The CAR values of the markets all showed a trend from positive to negative. Due to the timely prevention and control measures by the Chinese government, the market reversal time point is earlier; hence, there is no severe limit-down situation in the later period. The market trends in the US and the UK are basically the same; before the announcement from the WHO, they were not significantly affected, but within 20 days of the epidemic outbreak, the market return rate dropped sharply. On the 16th day of the event, the negative impacts on the markets of the US, the UK, and China have slowed down, but the opposite situation happened in India, the reason may be that the agricultural futures market in India was less efficient, coupled with the weak awareness and prevention of the epidemic, resulting in a certain lag in the market transmission.

Despite the heavy damage, the Chinese grain markets, the oilseed and oil markets, and the cotton market have not been separated from other markets. Therefore, during the spread of the epidemic; although; some food producing countries introduced policies of agricultural trade restrictions that caused social panic and increased food prices, the impact of these factors on market efficiency was short-lived or limited, which did not stop the trend of integration among large agricultural markets. In particular, the integration trends of the grain market

Table 6 - Long-run and short-run coefficients of oilseeds and oil markets.

Long-run	-----Variable-----	---Coefficient---	-------S.E.-------	t-Statistic	---P-Value---
China-US soybean: Equation (10)	$R_{Ch\_b}(-1)$	0.926	0.015	61.618***	0.000
	R_{Us_b}	-0.200	0.019	-10.432***	0.000
	C	19.378	10.866	1.783*	0.081
China-US soybean oil: Equation (11)	$R_{Ch\_o}(-1)$	0.919	0.030	31.146***	0.000
	R_{Us_o}	-0.2159	0.023	-9.485***	-0.000
	C	37.756	19.002	1.987**	0.041
China-US soybean meal:Equation (12)	$R_{Ch\_m}(-1)$	0.936	0.0410	22.873***	0.000
	R_{Us_m}	0.177	0.033	5.401***	0.000
	C	22.300	12.119	1.840*	0.071
China-India Palm Oil:Equation (13)	$R_{Ch\_p}(-1)$	0.920	0.037	25.137***	0.000
	R_{In_p}	0.180	0.099	1.831*	0.086
	$R_{In\_p}(-1)$	0.192	0.070	2.736**	0.030
	C	23.770	14.037	1.693*	0.041
Short-run	Variable	Coefficient	S.E.	t-Statistic	P-Value
Soybean: Equation (20)	ΔR_{Ch_b}&ΔR_{Us_b}	-0.1840	0.023	-8.000***	0.000
Soybean oil: Equation (21)	ΔR_{Ch_o} & ΔR_{Us_o}	-0.120	0.015	-8.276***	0.000
Soybean meal: Equation (22)	ΔR_{Ch_m} & ΔR_{Us_m}	-0.100	0.020	-5.149***	0.000
Palm oil: Equation (23)	ΔR_{Ch_p} & Δ_{RIn_p}	-0.134	0.058	-2.261*	0.040

Table 7 - Long-run and short-run coefficients of cotton markets.

Long-run	------Variable------	----Coefficient----	---------S.E.---------	t-Statistic （显著水平）	----P - Value----
China-US-India cotton: Equation (15)	$R_{Ch\_c}(-1)$	0.925	0.060	15.499^{***}	0.000
	R_{Us_c}	0.139	0.097	1.432	0.000
	$R_{Us\_c}(-1)$	0.161	0.074	2.160^{**}	0.012
	R_{In_c}	0.101	0.087	1.163	0.111
	$R_{In\_c}(-1)$	0.090	0.051	1.790^{*}	0.075
	C	27.020	19.007	1.422	0.118
Short-run	Variable	Coefficient	S.E	t-Statistic（显著水平）	P - Value
Cotton: Equation (24)	ΔR_{Ch_c} & ΔR_{Us_c}	-0.113	0.023	-4.965^{***}	-0.000
	ΔR_{Ch_c} & ΔR_{In_c}	-0.104	0.049	-2.147^{*}	-0.021

between China and the United States have not been seriously disrupted by the epidemic. This is due to the fact that China has placed great importance on food security and promoted a series of agricultural market-oriented reform policies, which played a positive role in promoting the price mechanism and risk hedging. It can be seen that the China grain futures markets can basically resist the impact of the epidemic and that the prices can stabilize agricultural production.

During the spread of the epidemic, the rate of convergence of prices of China and other countries showed asymmetrical, from high to low is: corn, soybean, indica, soybean oil, wheat, etc. The depth and breadth of the Chinese corn industry chain is relatively high, and the price is closely related to the price of international crude oil which facilitates its rapid response to shocks from external event shocks (MA & HOU, 2019).

However, there is a segmentation phenomenon in the China-US-UK sugar market. The peak of the epidemic is also the tilling and jointing period of sugarcane, the production was reduced due to an unfavorable climate in the main sugarcane producing countries, such as India, Thailand, Pakistan, etc., resulting in large fluctuations in market supply and demand. It may also be related to the development of biological energy in recent years, and the ethanol industry has changed the original price transmission relationship between the sugar industry and the energy market (DRABIK et al., 2015), during the epidemic period, the demand for crude oil and ethanol shrank sharply (GUPTA et al., 2021), and the price difference between China and the United States was greater; therefore, the markets had not yet achieved effective integration.

The timber markets between China and the US are fragmented which may be related to the different scenarios of logging, construction and real estate industries in two countries. During the spread of the epidemic, the supply and demand in the US timber market was out of balance. The blockade measures led to idleness and interruptions in the logging and the construction industry. The inventory of timber was lower and the supply was insufficient. After the epidemic stabilized, the demand for the real estate market surged and the prices of wood skyrocketed. At the same time, the inventory is well stocked and the real estate market is strictly controlled, and there has not been a sharp rise or fall in timber prices in China.

CONCLUSION

COVID-19 has changed the investment pattern of the agricultural market, and international investment is flowing to markets expected to be more stable. It is foreseeable that the Chinese agricultural market will face a situation of coexistence of opportunities and risks in the post-epidemic era. In response to current and future agricultural risks, China should continue to adhere to the food security strategy to ensure stable prices and sufficient supply of domestic agricultural products. China should monitor the interference of international hot money on the domestic financial market and derivatives market and prevent price bubbles caused by excessive speculation. In the process of the international market cycle of agricultural products, it is necessary to strengthen the monitoring, assessment, and early warning of market risks, optimize the structure of foreign investment in agricultural resources, and expand food supplies around the world. To meet commodity pricing and risk management needs, China should strengthen its participation and cooperation in international agricultural trade, financial derivatives trade, and bilateral or multilateral investment.

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DECLARATION OF CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHORS' CONTRIBUTIONS

All authors contributed equally to the conception and writing of this manuscript. All authors critically revised the manuscript and approved of the final version.

REFERENCES

ALAM, M. R.; GILBERT, S. Monetary policy shocks and the dynamics of agricultural commodity prices: evidence from structural and factor-augmented VAR analyses. **Agricultural Economics**, v.48, n.1, p.15-27, 2017. Available from: <https://doi.80599.net/10.1111/agec.12291>. Accessed: Feb. 11, 2019. doi: 10.1111/agec.12291.

ALGIERI, B. et al. A tale of two tails: Explaining extreme events in financialized agricultural markets. **Food Policy**, v.69, p.256-269, 2017. Available from: <https://doi.80599.net/10.1016/j.foodpol.2017.05.004>. Accessed: May, 9, 2019. doi: 10.1016/j.foodpol.2017.05.004.

ARNADE, C. et al. Agricultural price transmission: China relationships with world commodity markets. **Journal of Commodity Markets**, v.7, p.28-40, 2017. Available from: <https://doi.80599.net/10.1016/j.jcomm.2017.07.001>. Accessed: Jul. 15, 2020. doi: 10.1016/j.jcomm.2017.07.001.

ATEMS, B.; SARDAR N. Exploring asymmetries in the effects of El Niño-Southern Oscillation on US food and agricultural stock prices. **The Quarterly Review of Economics and Finance**, v.81, p.1-14, 2021. Available from: <https://doi.80599.net/10.1016/j.qref.2021.04.013>. Accessed: Apr. 14, 2022. doi: 10.1016/j.qref.2021.04.013.

AULTON, A. J. et al. Efficiency tests of futures markets for UK agricultural commodities. **Journal of Agricultural Economics**, v.48, n.3, p.408-424, 1997. Available from: <https://doi.80599.net/10.1016/j.qref.2021.04.013>. Accessed: Jul. 14, 2011. doi: 10.1111/j.1477-9552.1997.tb01162.x.

AYADI, A. et al. Equity-commodity contagion during four recent crises: Evidence from the USA, Europe and the BRICS. **International Review of Economics & Finance**, v.76, p. 376-423, 1997. Available from: <https://doi.80599.net/10.1016/j.iref.2021.06.013>. Accessed: Jul. 14, 2011. doi: 10.1016/j.iref.2021.06.013.

CASHIN, P. et al. Fair weather or foul? The macroeconomic effects of El Niño. **Journal of International Economics**, v.106, p.37-54, 1997. Available from: <https://doi.org/10.1016/j.jinteco.2017.01.010>. Accessed: Jan. 1, 2017. doi: 10.1016/j.jinteco.2017.01.010.

CONSUEGRA, M; GARCI-VERDUGO, J. Measuring the functional efficiency of agricultural futures markets. A**ustralian Journal of Agricultural and Resource Economics**, v.61, n.2, p.232-246, 2017. Available from: <https://doi.80599.net/10.1111/1467-8489.12196>. Accessed: Feb. 16, 2019. doi: 10.1111/1467-8489.12196.

DAWSON, P.; SANJUÁN, A. I. Structural breaks, the export enhancement program and the relationship between Canadian and US hard wheat prices. **Journal of Agricultural Economics**, v.57, n.1, p.101-116. 2006. Available from: <https://doi.80599.net/10.1111/j.1477-9552.2006.00034.x>. Accessed: Feb. 16, 2019. doi: 10.1111/j.1477-9552.2006.00034.x.

DOU, Y. et al. Dynamic linkages between economic policy uncertainty and the carbon futures market: Does Covid-19 pandemic matter? **Resources Policy**, v.75, p.102455. 2021. Available from: <https://doi.org/10.1016/j.resourpol.2021.102455>. Accessed: Jan. 6, 2022. doi: 10.1016/j.resourpol.2021.102455.

DRABIK, D. et al. The Economics of Brazil's Ethanol-Sugar Markets, Mandates, and Tax Exemptions. **American Journal of Agricultural Economics**, v.97, n.5, p.1433-1450, 2015. Available from: <https://doi.80599.net/doi:10.1093/ajae/aau109>. Accessed: Dec. 6, 2019. doi: 10.1093/ajae/aau109.

FAMA, E. F. Efficient capital markets: A review of theory and empirical work. **The Journal of Finance**, v.25, n.2, p.383-417, 1970. Available from: <https://doi.org/10.2307/2325486>. Accessed: Dec. 6, 2020. doi: 10.2307/2325486.

FIGUEROLA-FERRETTI, I.; GONZALO, J. Modelling and measuring price discovery in commodity markets. **Journal of Econometrics**, v.158, n.1, p.95-107, 2010. Available from: <https://doi.80599.net/10.1016/j.jeconom.2010.03.013>. Accessed: Dec. 6, 2020. doi: 10.1016/j.jeconom.2010.03.013.

GARCÍA-HIERNAUX, A. et al. Market integration dynamics and asymptotic price convergence in distribution, **Economic Modelling**, v.52, Part B, p.913-925,2016.Available from: <https://doi.org/10.1016/j.econmod.2015.10.029>. Accessed: Jul. 6, 2023. doi: 10.1016/j.econmod.2015.10.029.

GE, Y. et al. Cotton market integration and the impact of China's new exchange rate regime. **Agricultural Economics**, v.41, n.5, p.443-451, 2010. Available from: <https://doi.80599.net/10.1111/j.1574-0862.2010.00456.x>. Accessed: Dec. 6, 2017. doi: 10.1111/j.1574-0862.2010.00456.x.

GOZGOR, G. et al. Commodity markets volatility transmission: Roles of risk perceptions and uncertainty in financial markets. Journal of International Financial Markets, **Institutions and Money**, v.44, n.5, p.35-45, 2016. Available from: <https://doi.80599.net/10.1016/j.intfin.2016.04.008>. Accessed: Jun. 6, 2020. doi: 10.1016/j.intfin.2016.04.008.

GUPTA, A. et al. Economic impacts of the COVID−19 lockdown in a remittance-dependent region. **American Journal of Agricultural Economics**, v.103, n.2, p.466-485, 2021. Available from: <https://doi.80599.net/10.1111/ajae.12178>. Accessed: Jan. 5, 2022. doi: 10.1111/ajae.12178.

HOFFMAN, L. A. et al. Forecast performance of WASDE price projections for US corn. **Agricultural Economics**, v.46, p.157-171, 2015. Available from: <https://doi.80599.net/10.1111/agec.12204>. Accessed: Dec. 18, 2018. doi: 10.1111/agec.12204.

INDRIAWAN, I. et al. The impact of the change in USDA announcement release procedures on agricultural commodity futures. **Journal of Commodity Markets**, v.23, p.100149, 2021. Available from: <https://doi.80599.net/10.1016/j.jcomm.2020.100149 >. Accessed: Dec. 29, 2021. doi: 10.1016/j.jcomm.2020.100149.

JU, R. H.; YANG, Z. Assessing the functional efficiency of agricultural futures markets in China. **China Agricultural Economic Review**, v.11, n.2, p.431-442, 2018. Available from: <https://doi.80599.net/10.1108/CAER-03-2018-0056>. Accessed: Oct. 9 2019. doi: 10.1108/CAER-03-2018-0056.

KOTHARI, S.P.; WARNER, J. B. Econometrics of event studies, IN : Handbook of Empirical Corporate Finance, North Holland: Amsterdam, Netherland. 2007. Available from: <https://www.sciencedirect.com/book/9780444532657/handbook-of-empirical-corporate-finance#book-description>. Accessed: Jan. 19, 2018. ISBN: 9780444532657.

KRISTOUFEK, L.; MILOSLAV VOSVRDA. Commodity futures and market efficiency. **Energy Economics**, v.42, p.50-57, 2014. Available from: <https://doi.80599.net/10.1016/j.eneco.2013.12.001>. Accessed: Nov. 20, 2017. doi: 10.1016/j.eneco.2013.12.001.

LI, J. et al. Food price bubbles and government intervention: is China different? **Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie**, v.65, n.1, p.135-157, 2017. Available from: <https://doi.80599.net/10.1111/cjag.12106>. Accessed: Nov. 20, 2018. doi: 10.1111/cjag.12106.

LIU, Q. et al. The market quality of commodity futures markets. **Journal of Futures Markets**, v.40, n.11, p.1751-1766, 2020. Available from: <https://doi.80599.net/10.1002/fut.22115>. Accessed: Jan. 13, 2021. doi: 10.1002/fut.22115.

MA, Z.; HOU, W. J. The interactions between Chinese local corn and WTI crude oil prices: an empirical analysis. **Petroleum Science**, v.16, n.4, p.929-938, 2019. Available from: <https://doi.80599.net/10.1007/s12182-019-0339-1>. Accessed: Jan. 28, 2020. doi: 10.1007/s12182-019-0339-1.

MAKKONEN, A. et al. The effect of temperature anomaly and macroeconomic fundamentals on agricultural commodity futures returns. **Energy Economics**, v.100, p.105377, 2021. Available from: <https://doi.80599.net/10.1016/j.eneco.2021.105377>. Accessed: Dec. 30, 2021. doi: 10.1016/j.eneco.2021.105377.

MAO, Q. et al. Price bubbles in agricultural commodity markets and contributing factors: evidence for corn and soybeans in China. **China Agricultural Economic Review**, v.13, n.1, p.91-122, 2020. Available from: <https://doi.80599.net/10.1108/CAER-10-2019-0190>. Accessed: Dec. 12, 2021. doi: 10.1108/CAER-10-2019-0190.

MENSI, W. et al. Upward/downward multifractality and efficiency in metals futures markets: The impacts of financial and oil crises. **Resources Policy**, v.76, p.102645, 2022. Available from: <https://doi.org/10.1016/j.resourpol.2022.102645>. Accessed: May, 4, 2022. doi: 10.1016/j.resourpol.2022.102645.

MOHANTY, S. K.; MISHRA S. Regulatory reform and market efficiency: The case of Indian agricultural commodity futures markets. **Research in International Business and Finance**, v.52, p.101145, 2020. Available from: <https://doi.80599.net/10.1016/j.ribaf.2019.101145>. Accessed: Dec. 30, 2021. doi: 10.1016/j.ribaf.2019.101145.

PESARAN, M. H. et al. Bounds testing approaches to the analysis of level relationships. **Journal of applied econometrics**, v.13, n.3, p.289-326, 2001. Available from: <https://doi.80599.net/10.1002/jae.616>. Accessed: Dec. 30, 2021. doi: 10.1002/jae.616.

PRADHAN, R. P. et al. The lead–lag relationship between spot and futures prices: Empirical evidence from the Indian commodity market. **Resources Policy**, v.70, p.101934, 2021. Available from: <https://doi.80599.net/10.1016/j.resourpol.2020.101934>. Accessed: Jan. 10, 2022. doi: 10.1016/j.resourpol.2020.101934.

SANTOS, J. Did futures markets stabilise US grain prices? **Journal of Agricultural Economics**, v.53, n.1, p.25-36, 2002. Available from: <https://doi.80599.net/10.1111/j.1477-9552.2002.tb00003.x>. Accessed: Dec. 30, 2021. doi: 10.1111/j.1477-9552.2002.tb00003.x.

SHELDON, I. M. Testing for weak form efficiency in new agricultural futures markets: some UK evidence. **Journal of Agricultural Economics**, v.38, n.1, p.51-64, 1987. Available from: <https://doi.80599.net/10.1111/j.1477-9552.1987.tb01024.x>. Accessed: Dec. 30, 2021. doi: 10.1111/j.1477-9552.1987.tb01024.x.

WANG, H. H.; KE, B. F. Efficiency tests of agricultural commodity futures markets in China. Australian **Journal of Agricultural and Resource Economics**, v.49, n.2, p.125-141, 2005. Available from: <https://doi.80599.net/10.1111/j.1467-8489.2005.00283.x>. Accessed: Jul. 16, 2018. doi: 10.1111/j.1467-8489.2005.00283.x.

WORKING, H. Theory of the inverse carrying charge in futures markets. **Journal of Farm Economics**, v. 30, n.1, p.1-28, 1948. Available from: <https://doi.80599.net/10.2307/1232678>. Accessed: Dec. 17, 2017. doi: 10.2307/1232678.

XIAO, X. et al. Economic policy uncertainty and grain futures price volatility: evidence from China. **China Agricultural Economic Review**, v.11, n.4, p.642-654, 2019. Available from: <https://doi.80599.net/10.1108/CAER-11-2018-0224>. Accessed: Nov. 30, 2020. doi: 10.1108/CAER-11-2018-0224.

ZHANG, C.; QU, X. The effect of global oil price shocks on China's agricultural commodities. **Energy Economics**, v.51, p.354-364, 2015. Available from: <https://doi.80599.net/10.1016/j.eneco.2015.07.012>. Accessed: Nov. 30, 2018. doi: 10.1016/j.eneco.2015.07.012.

ZHANG, X.; LIU, Y. The dynamic impact of international agricultural commodity price fluctuation on Chinese agricultural commodity prices. **International Food and Agribusiness Management Review**, v.23, n.3, p.391-409, 2020. Available from: <https://doi.80599.net/10.22434/IFAMR2019.0172>. Accessed: Dec. 19, 2021. doi: 10.22434/IFAMR2019.0172.