



# Dynamic Volatility Spillover Among Chinese Black Series Futures Under Structural Breaks

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**Abstract:** This paper explores the dynamic volatility spillovers among five major futures in China, including rebar, hot-rolled coils, iron ore, cooking coal and coke. We employ the Dynamic Conditional Correlation (DCC) GARCH model to examine the volatility spillover effects among the markets considering structural breaks invariance. We used a modified Iterated Cumulative Sum of Squares (ICSS) algorithm to detect the structural breaks. The empirical results show there are strong correlations across the black series futures market. Especially, the relation between rebar and hot-rolled coils, coke and cooking coal is more closely than other pairs. This research provides insight into the information transmission in black series futures market, which is meaningful to market participants making hedging and trading strategies. This study extends the literature by investigating the dynamic linkage among five kinds of black series futures.

**Keywords:** *Dynamic spillovers, structural breaks, black series futures, DCC, GARCH*

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## INTRODUCTION

As an important indicator to measure the progress of a country's industrial modernization, the steel industry is significant to a country's economy. Until 2018, the yearly output of crude steel in China arrived 928 million tones, accounted for the half of the world's total steel production. The huge demand and output of steel triggered the development of many industries, especially the upstream industry which are connected to the steel metallurgy like iron ore, cooking coal and coke. Since 2009, the rebar was issued by SHFE, a series of black futures were listed in DCE and SHFE respectively. With the listing of iron ore futures in 2013, a complete futures hedging platform of steel production chain has been formed.

The black series futures cover the steel-related commodities. Rebar and hot rolled coils are the final steel products, iron ore is the basic composition of them. Coke is the essential material in steel metallurgical which is the product of coking coal after volatilization at high temperature, the steel industry is the main consumer of coke. Cooking coal is also the source of fuel power. As the booming development in steel industry, it has attracted large number of investors. Due to the instability in policy and economic, black series shows the violent volatility, it increases the uncertainty in return. While futures market provides a benchmark price for transactions on the spot, study the dynamic correlation among markets can help investor to understand information transmission mechanism among these markets.

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It's significant to market participants make hedge and trade strategies to decrease risk and policy makers improve the regulatory measures.

This study extends the literature by investigating the dynamic linkage among five kinds of black series futures. For this purpose, we adopt the DCC model of Engle (2002) to detect the volatility spillover across the markets. This classic model is usually used to study the time-varying correlation between different assets (e.g., (Behmiri, Manera, & Nicolini, 2019; Carvalho, 2018; Du, Elkamhi, & Ericsson, 2019; Fałdziński & Pietrzak, 2015; Kinata, 2016)). However, Hillebrand (2005), and Mikosch and Stărică (2004) point out that if ignore the structural change points in the sample, the result of GARCH effect will appear spurious persistence, the estimated autoregressive parameters will be bias. Therefore, we take the change points into consideration in this study. Inclan and Tiao (1994) proposed the ICSS algorithm to capture the change of variance. Sansó, Carrion, and Aragó (2020) found that when the conditional variance obeys a non-independent process such as the GARCH process, the IT statistics of ICSS model may be greatly overestimated, then the modified ICSS model is developed. First, we employ the Kappa-2 (k-2) of the modified ICSS to test the change point among five futures. Then we adopt the DCC GARCH model allowing the structural breaks as dummy variables in variance to identify the dynamic correlation across the markets.

This paper is organized as follows: section 2 reviews the literature which relevant to black series futures market and research methods. Section 3 and 4 describe the analytical method, data and preliminary analysis. Section 5 discuss the empirical result and section 6 provide the conclusion.

## LITERATURE REVIEW

Numerous researching on dynamic linkage among futures markets have been studied, most of them are focus on agriculture, energy and precious metal industry. Due to the late start of Chinese futures market, most black series futures have been issued in recent years, the studies on these futures is relatively scarce. Most studies have focused on the relationship between futures and spot. J. Zhou (2010) analyzed the relationship between steel futures and spot by employing Vector Error Correction Model (VECM) and EGARCH model, found exist long term equilibrium relationship and bidirectional spillover between rebar spot and futures. Xiao (2014) have done the research on the relationship between coke spot and futures, showed the strong relationship between spot and futures. Kim and Lim (2019) applied VECM model research the price discovery mechanism and bivariate EGARCH (1, 1) model studied the volatility spillover between spot and futures market by using 7 kinds steel-related futures which are listed on Chinese futures market, found wire rod, coking coal, coke and silico-manganese exist bidirectional spillover and rebar spillover from spot to futures. Huang (2017) found futures market of coke, cooking coal and rebar plays a leading role in price discovery, coke owns the strongest price discovery function followed by cooking coal and rebar. This study applied the Granger causality test, VECM model, Johansen cointegration test and variance decomposition.

Some studies have done to arbitrage strategy in black series futures. L. Zhou (2017) chose iron ore rebar and coke research the arbitrage strategies. This study employed cointegration test found among them exist long-term stable cointegration relationship and by using Jarque-Bera statistics, determined the best arbitrage strategies. Besides, Li (2014) done the research about the arbitrage of cooking coal, iron ore and rebar futures, shows the rebar and cooking coal, rebar and coke have strong correlation. Su (2017) tested the correlation coefficient between black futures and spot employed Copula-GARCH model and estimated the hedge ratio of a single variety using minimum variance and use the BEKK GARCH model to predict the variance and covariance of returns.

Some literatures in correlation of black future shows the strong relationships across them. Q. Wang, Hang, Su, and Zhou (2018) examined the dynamic correlation in black series futures in short-term, medium term and long-term and the DCC-GARCH-t model are employed. Then applied Granger causality in risk test to measure the risk contagion. Research found there is a positive dynamic correlation between black futures, the dynamic correlation is largest during the medium-term time scale. Cooking coal futures and coke futures have the highest correlation, the complexity of the infection will increase as the length of the time scale increases. The spread of "black" futures is synchronized. Q. Wang, Dai, and Zhou (2020); J. Wang and Zheng (2019) used the Vector Autoregressive (VAR) model and Granger causality test to investigate the linkage across futures and spot of iron ore and coke. They found the iron ore spot have significant impact on coke futures, the spillover from coke futures to spot is not strong, it proves that Chinas coke futures are not mature enough. Q. Wang et al. (2020) analyzed the co-movement between coke, cooking coal and pig iron. Johansen cointegration test and Granger causality test are applied. This study found a bidirectional spillover exist in coke, cooking coal and pig iron market, the pig iron is the main factor that impact the coke price.

Mangy literatures adopt DCC GARCH model to test the dynamic correlation between different assets. Traditional studies assume that the volatility of the asset return is a stable process, however, financial markets will face large shocks, which may lead to structural changes in asset returns and cause high volatility persistence. Rapach and Strauss (2008) use the modified ICSS algorithm to study the structural changes in the variance of the 8 US dollar exchange rate and combined change points with GARCH model to conduct in-sample test and out-of-sample test on the series. They pointed out allowing the structural breaks could improve the volatility forecast accuracy. Güloğlu, Kaya, and Aydemir (2016) investigated the dynamic linkage among Latin American stock markets with the consider of structural breaks. They set the change point as a dummy variable and put it into the variance equation. Xie and Zhao (2012) applied Bai and Perron test and modified ICSS algorithm to detect the change point in RMB exchange rate. Then introduce structural breaks points into the GARCH family model, compare the changes of parameter estimates before and after considering the change point. Mensi, Hammoudeh, and Yoon (2015) apply ICSS algorithm to detected structural breaks in U.S. dollar exchange rate, WTI, Brent, kerosene, gasoline and propane. Then took change point into bivariate DCC EGARCH model to compare the correlation with and without change point.

**METHODOLOGY**

**Modified Iterated Cumulative Sums of Squares (ICSS) Algorithm**

To detect the structural breaks, we apply Kappa-2 (k-2) statistics of modified ICSS algorithm. Inclan and Tiao (1994) proposed iterated cumulative sums of squares (ICSS) algorithm to identify discrete points of variance, the IT statistics is defined as:

$$IT = \sup |(T/2)^{0.5} D_k| \tag{1}$$

$$D_k = ( C_k / C_T ) - k / T \tag{2}$$

$$C_k = \sum_{t=1}^k z_t^2, k = 1, 2, \dots, T \text{ and } z_t \sim i.i.d. (0, \sigma^2) \tag{3}$$

Obviously,  $D_0 = D_T = 0$ . The null hypothesis of this algorithm is that the unconditional variance  $z_t$  is a constant at time  $k$ , the alternative hypothesis is existing unconditional variance structure breaks at a certain point. When null hypothesis is rejected, it points that the maximum value of  $(T/2)^{0.5} D_k$  is greater than the critical value,  $k$  is the structural break point.  $\sup |W^*(r)|$  is standard Brown Bridge distribution, expression is  $W^*(r) = W(r) - rW(1)$ .

When the conditional variance of the time series meets the conditions in the dependent process, the IT statistics of model may overestimate, to overcome this problem, modified ICSS algorithm was proposed by Sansó et al. (2020), the functions show as:

$$AIT = \sup |(T/2)^{0.5} G_k| \tag{4}$$

Where

$$G_K = \lambda^{-0.5} [C_k - (k/T)C_T] \tag{5}$$

$$\hat{\lambda} = \hat{\gamma}_0 + 2 \sum_{i=1}^m [1 - l(m+1)^{-1}] \hat{\gamma}_l \tag{6}$$

$$\hat{\gamma}_l = T^{-1} \sum_{t=l+1}^T (e_t^2 - \hat{\sigma}^2) (e_{t-1}^2 - \hat{\sigma}^2) \tag{7}$$

$$\hat{\sigma}^2 = T^{-1} C_T \tag{8}$$

The  $1 - l(m+1)^{-1}$  is a Bartlett lag window, so AIT depends on the choice of  $m$  and the asymptotic distribution of AIT is also the distribution of  $\sup |W^*(r)|$  which under general conditions.

### DCC GARCH Model

To investigate the dynamic spillover in black series futures, the DCC-GARCH model is applied. In this model, we allow the structural breaks as dummy variables to univariate GARCH process. The DCC-GARCH model is used to construct the time-varying correlations among variables which was proposed by Engle (2002). The modeling steps are as follows:

The mean equation is defined as:

$$r_{i,t} = \mu_{i,t}(\theta) + \varepsilon_{i,t}, \quad \varepsilon_{i,t} | \Omega_{t-1} \sim N(0, H_t) \quad (9)$$

where  $r_{i,t}$  is return of rebar, hot rolled coils, iron ore, coke and cooking coal at time  $t$ .  $\mu_{i,t}(\theta)$  is the conditional  $5 \times 1$  mean vector of  $r_{i,t}$ .  $\varepsilon_{i,t}$  is a sequence of random variables.

Then estimates the conditional variance  $h_{i,t}$  with univariate GARCH (1,1) process. The structural breaks are considered in this model and the change points are brought into the variance equation as dummy variables.

$$h_{i,t} = \omega + \alpha_1 \varepsilon_{i,t-1}^2 + \beta_1 h_{j,t-1} + \gamma_i D_{i,t} \quad (10)$$

where  $D_{i,t}$  represents a vector of dummy variables for black series futures at time  $t$ .  $D_{i,t} = 1$  when  $t > t_{i,v}$ ,  $i$  is the time of structural breaks, otherwise it is zero.

The conditional variance-covariance matrix is defined as:

$$H_t = D_t R_t D_t \quad (11)$$

where  $D_t$  is a diagonal matrix of square root conditional variances,  $R_t$  is a  $t \times \frac{N(N-1)}{2}$  matrix containing the time-varying conditional correlations.

$$D_t = \text{diag} \left( h_{11,t}^{\frac{1}{2}}, \dots, h_{NN,t}^{\frac{1}{2}} \right)' \quad (12)$$

$$R_t = \text{diag} \left( q_{11,t}^{-\frac{1}{2}}, \dots, q_{NN,t}^{-\frac{1}{2}} \right) Q_t \text{diag} \left( q_{11,t}^{-\frac{1}{2}}, \dots, q_{NN,t}^{-\frac{1}{2}} \right)$$

where  $Q_t = (q_{ij,t})$  is a  $N \times N$  symmetric positive definite matrix is given by

$$Q_t = (1 - \alpha - \beta) \bar{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1} \quad (13)$$

where  $u_t$  is the  $N \times 1$  vector of standardized residuals,  $\bar{Q}$  is the  $N \times N$  unconditional variance matrix of  $u_t$ , and  $\alpha$  and  $\beta$  are nonnegative scalar parameters satisfying  $\alpha + \beta < 1$ .

The main purpose of this study is researching the dynamic correlation among black series futures. Through  $H_t$ , the dynamic correlations can be obtained by:

$$\rho_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{ii,t}} \sqrt{h_{jj,t}}} \quad (14)$$

## DATA AND PRELIMINARY ANALYSIS

### Data

In this study, the five varieties of black futures are examined. The span of sample is from 21st March 2014 to 11th May 2020, including 1496 observations. Black series futures contracts include rebar (RB), hot rolled coils (HC), iron ore (IO), cooking coal (JM) and coke (J) which are trade on Shanghai Futures Exchange (SHFE) and Dalian Commodity Exchange (DCE) respectively. The data considers the continuous daily closing price which the prices expressed in YUAN/Ton and the data are collected from wind database.

Figure 1 displays the daily price trend of the five black series futures from 2014 to 2020. It exhibits the similar trend among five commodities, especially rebar (RB) and hot rolled coils (HC) showing a highly consistent co-movement, they have almost the same trend and price. Besides, compared with iron ore (IO), hot rolled coils (HC), rebar and cooking coal (JM) are more volatile during the sample period. In 2014, impacted by dollar index rise, global commodities enter bear market and impact by the insufficient domestic demand and overcapacity in the steel industry, the Platts 62% iron

ore index slipped at the beginning of the year caused coal and steel industry varieties supply and demand imbalance. This led the decreasing trend of steel industry and this trend continued to 2015. Then as the government strengthened supervision of black-based futures, the market showed a slight downward trend. In 2018, trade war between US and China began, cause panic in futures markets, futures market volatility but whole market overall is stable.

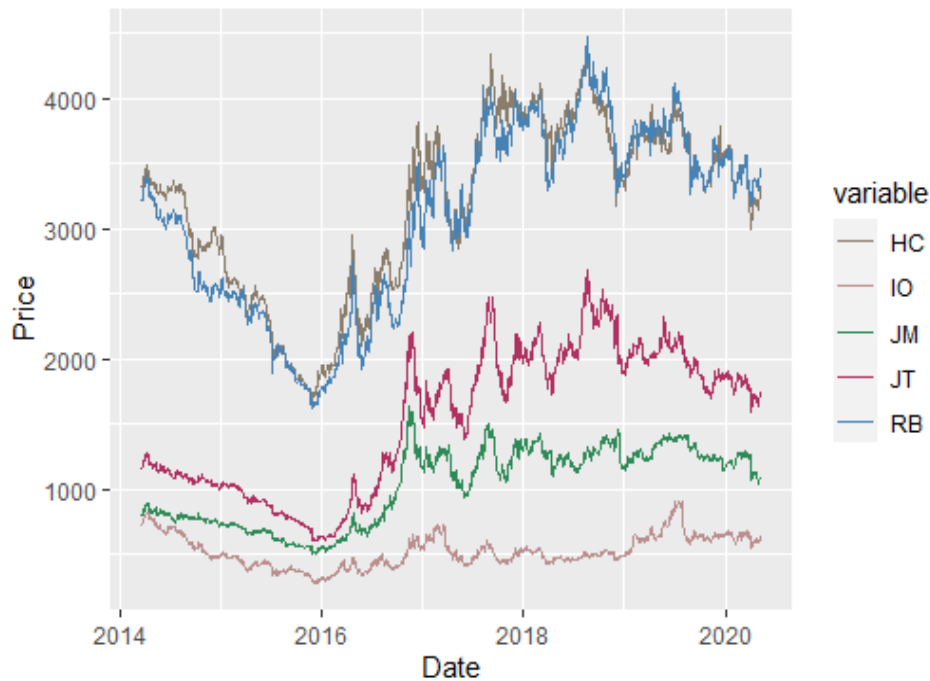


Figure 1 Price of Five Black Series Futures from 2014 to 2020

**Preliminary Analysis**

In this study, we use daily returns of futures to measure the volatilities in prices. The data will be processed as log difference:

$$r_{i,t} = \ln p_{i,t} - \ln p_{i,t-1}, i = 1, 2, 3 \dots \tag{15}$$

Where  $r_{i,t}$  is the corresponding logarithmic return of hot rolled coils (HC), rebar (RB), iron ore (IO), coke (J) and cooking coal (JM) at time  $t$ ,  $p_{i,t}, p_{i,t-1}$  is the corresponding price of futures at the time  $t$  and  $t-1$ .

Table 1 shows the descriptive statistics on daily returns of hot rolled coils (HC), rebar (RB), iron ore (IO), coke (J) and cooking coal (JM). Coke (J) have the highest average of return while hot rolled coils (HC) return is lowest. The standard deviation statistics of returns exhibit that iron ore (IO) is most volatile, followed by cooking coal (JM), coke (J), rebar (RB). Hot rolled coils (HC) is most stable among five markets. All skewness value of return is negative, showing a left skew in series and the excess kurtosis value of return indicates all series are leptokurtic distribution. Besides, the Jarque-Bera statistics reject the null hypothesis, means the returns of all series are not normal distribution, indicating all series are peaked distributions and fat tails. By applying Ljung Box test, it evident there are serial correlation, white noise of null hypothesis is rejected. The result of ARCH LM test reject the null hypothesis of absence ARCH effect, prove that all return series have heteroscedasticity. Thus, the use of a GARCH-based approach is appropriate for modeling some stylized facts such as fat tails, clustering volatility, persistence for the five black series futures returns.

Table 2 reports unit root test for the return of series. ADF test (Dickey & Fuller, 1979), PP tests (Phillips & Perron, 1988) and the KPSS test (Kwiatkowski, Phillips, Schmidt, Shin, et al., 1992) are applied. ADF test and PP test are strongly reject the null hypothesis of existing unit root whereas KPSS accept the null hypothesis of series is stationary. It evident all return series are stationary process.

Table 1 DESCRIPTIVE STATISTICS FOR FUTURES RETURNS

	HC	RB	IO	J	JM
Mean	0.000001	0.000047	-0.000101	0.000262	0.000197
Maximum	0.064064	0.066527	0.073636	0.091116	0.134672
Minimum	-0.081322	-0.097041	-0.182879	-0.156212	-0.145089
Std.Dev	0.016364	0.017115	0.023389	0.020464	0.020675
Skewness	-0.43301	-0.31023	-0.84685	-0.65444	-0.72038
Kurtosis	3.50060	3.63274	4.96344	5.32919	8.09672
JB	813.9454***	850.1050***	1720.252***	1883.446***	4228.216***
Q (12)	250.2***	186.55***	35.907***	129.16***	73.945***
ARCH LM (10)	107.83***	85.827***	27.553***	79.147***	38.851***

Note: \*\*\*indicates reject the null hypothesis of at the 1% significance level; JB refers to statistics of the Jarque-Bera test and Q (12) is Ljung-Box Q statistic of return with 12 lags.

Table 2 UNIT ROOT TEST FOR RETURN OF FIVE BLACK FUTURES

	HC	RB	IO	J	JM
ADF	-39.62088 ***	-39.04276***	-36.33249 ***	-38.48552***	-42.29768***
PP	-39.64125***	-39.04169***	-36.32532***	-38.52221***	-42.22872***
KPSS	0.158455	0.152966	0.162878	0.147794***	0.115867***

Note: \*\*\*indicates reject the null hypothesis of at the 1% significance level.

## EMPIRICAL RESULT

### Structural Breaks Detection

Firstly, we employ kappa-2 (k2) test of modified ICSS algorithm proposed by (Sansó et al., 2020) to detect the change point in return of five black futures. The results are listed in Table 3. It shows that the hot rolled coils (HC), rebar (RB), iron ore (IO) and cooking coal (JM) all experienced two times structural breaks while coke (J) have five times break. As the column of breaks position shown, structural breaks happened in the similar positions in hot rolled coils (HC), rebar (RB), iron ore (IO) and cooking coal (JM). Most structural breaks happened in black series futures are closely related to policies and spot markets. Before 2016, the black series futures market suffered a long-term downturn which last two years because of soft demand and excess capacity in steel market. In this stage, most steel trading companies choose to reduce inventories. Comparing the standard deviation of hot rolled coils (HC), rebar (RB), iron ore (IO) and cooking coal (JM), the volatility of return in these two years are relatively bigger than other periods. The downturn status last until 2016, the supply side policy started in this year. This policy is aiming to adjust the supply and demand structure of commodities, reduce excess capacity. As benefit from supply side policy, since the start of this year, policy effects gradually appear, both the supply and demand sides of the steel industry formed a positive impact on black series commodities, all black futures prices rose sharply. As can be seen from the table3, the breaks happened in all black series market between February and April, especially in March, volatility regime produced in rebar (RB), iron ore (IO) and cooking coal (JM). As the result of modified ICSS algorithm shown, structural breaks of coke (J) mainly concentrate on 2016 which experienced 3 times regime. Its an extraordinary year of coke market. As table shown, the return of coke (J) futures in this year is more volatile. In February, the government promulgated quantitative targets for capacity reduction in steel, coke and coal industry. As the result, coal production declined and steel price increased. This led to purchasing increased in coke. Coke as an intermediate link between coal and steel, unbalance demand and supply resulted its price rocket, thus coke futures entered bull market this year. Accordingly, structural breaks happened frequently in this stage. From table, we can see that several structural breaks happened in the end of



2017. It is due to environmental protection policies which started in November of this year. Many cities have taken measures to restrict steel production during the heating season. As supply responds lagging to changes in demand, the black market stopped falling and rebounded. This policy also contributed a structural break to coke futures in 2018.

These change points in variance could lead to bias estimate. In order to fit volatility in black series market better, we take structural breaks into consideration in the process of dynamic correlation detection.

Table 3 *STRUCTURAL BREAKS FOR FIVE BLACK FUTURES*

Series	Position	Period	Std.
HC	467	2014.03.21-2016.02.19	0.02143
	886	2016.02.20-2017.11.06	0.00021
		2017.11.06-2020.05.11	0.00046
RB	477	2014.03.21-2016.03.04	0.01135
	876	2016.03.05-2017.10.23	0.02312
		2017.10.24-2020.05.11	0.00484
IO	476	2014.03.21-2016.03.03	0.00922
	886	2016.03.04-2017.11.06	0.01200
		2017.11.07-2020.05.11	0.00083
J	501	2014.03.21-2016.04.08	0.00853
	532	2016.04.09-2016.05.24	0.03108
	640	2016.05.25-2016.11.03	0.01240
	706	2016.11.04-2017.02.13	0.01803
	1165	2017.02.14-2018.12.25	0.00840
JM		2018.12.26-2020.05.11	0.00598
	496	2014.03.21-2016.03.31	0.03643
	921	2016.04.01-2017.12.25	0.00830
		2017.12.26-2020.05.11	0.00842

**Analysis of Dynamic Correlation under Structural Breaks**

To estimate the dynamic correlation coefficient more accurately, the dummy variables are considered to represent structural breaks and are incorporated into the DCC GARCH model. Table 4 shows the estimate result of DCC-GARCH model across the black series futures. As shown in panel A of estimate result of univariate GARCH (1,1), the ARCH and GARCH terms of all series are significant which prove that series have volatility clustering and the sum of ARCH and GARCH terms are close to one, this indicates the return of black futures have high volatility persistent. Panel B displays the result of DCC, the coefficients of  $\beta$  are relatively large which indicate that the impact of shock lasts long across the black futures market.  $\alpha$  and  $\beta$  are both positive and significance at the 1% level, it indicates the DCC model is stationary.

Table 5 gives the basic statistical features of the dynamic correlation among return of black series futures which include 10 pairwise statistics. Overview, there are strong linkage across the black series market. The correlation coefficients are more than 0.5 in most pairs. On average, the correlations between hot rolled coils (HC) and iron ore (IO), hot rolled coils (HC) and coke (J), rebar (RB) and iron ore (IO), rebar (RB) and coke (J), iron ore (IO) and coke (J) are similar, their correlation coefficients are fluctuating around 5. At the same time, rebar (RB) and hot rolled coils (HC) shows strong correlation between them, the highest value is over 0.9, coke and cooking coal also have high linkage that the average correlation is 0.664996. On the contrary, the conditional correlation between hot rolled coils (HC) and cooking coal (JM), rebar (RB) and cooking coal (JM) and coke (J) and cooking coal (JM) are relatively low, the lowest correlation between them could be negative.

Figure 2 exhibits the time varying correlations which obtain from DCC GARCH estimates. We can see that the within the sample interval, the correlation of all paired black futures fluctuated in a large range. Combined with the statistics in Table 5, the gap between the maximum and minimum values of correlations coefficient could exceed 0.7

in hot rolled coils (HC) and cooking coal (JM), rebar (RB) and cooking coal (JM). Besides, the difference between maximum and minimum in other pairwise is over 0.5 in most cases. As the result of standard deviation terms show that the overall dynamic correlation coefficient between futures is relatively stable, the standard deviation statistical values are between 0.05 to 0.08. The dynamic correlation between iron ore (IO) and coke (J) is most violate. In figures, most pairs dynamic correlation coefficients oscillate in the interval between 0.4-0.6 and 0.5-0.7, except rebar (RB) and hot rolled coils (HC), it displays a high degree of correlation. This illustrates that the price volatility in any futures of hot rolled coil (HC) and rebar (RB) will have a significant impact on the price of another and this volatility may spread to the entire black futures market, triggering changes in other black futures.

Table 4 ESTIMATES RESULT OF DCC GARCH MODEL

	HC	RB	IO	J	JM
Panel A: estimates of the univariate GARCH(1,1)					
Const (m)	-0.000095***	-0.000417***	-0.000534***	-0.000619***	-0.000197***
Const (v)	0.000000	0.000000	0.000004	0.000000	0.000000
ARCH (1)	0.082471***	0.067016***	0.031478***	0.078304***	0.081658***
GARCH (1)	0.880768***	0.890238***	0.958970***	0.888299***	0.864520***
Panel B: estimates of the DCC model					
$\alpha$	0.045211***				
$\beta$	0.797020***				
$\alpha + \beta$	0.842231				

Note: \*\*\*indicates reject the null hypothesis of at the 1% significance level.

Table 5 STATISTICS OF CONDITIONAL DYNAMIC CORRELATION

	$\rho_{HC-RB}$	$\rho_{HC-IO}$	$\rho_{HC-J}$	$\rho_{HC-JM}$	$\rho_{RB-IO}$
Mean	0.834168	0.585283	0.584377	0.461620	0.631814
Maximum	0.945302	0.771159	0.805471	0.686647	0.796403
Minimum	0.449884	0.0713256	0.271082	-0.190650	0.237479
Std.Dev	0.0513795	0.0621740	0.0589944	0.0718531	0.0633477
Skewness	-3.32083	-1.61221	-1.01166	-2.10318	-2.03999
Kurtosis	15.0389e	7.56177	3.57374	13.3379	7.42310
	$\rho_{RB-J}$	$\rho_{RB-JM}$	$\rho_{IO-J}$	$\rho_{IO-JM}$	$\rho_{J-JM}$
Mean	0.615153	0.498541	0.528268	0.439993	0.664996
Maximum	0.818689	0.708977	0.766083	0.643676	0.815546
Minimum	0.270951	-0.025197	0.0838300	-0.123584	0.0893369
Std.Dev	0.0580313	0.0691530	0.0717885	0.0780878	0.0760498
Skewness	-1.27092	-1.67945	-1.76986	-2.07381	-3.02821
Kurtosis	4.98331	8.03248	7.55467	8.73354	13.2237



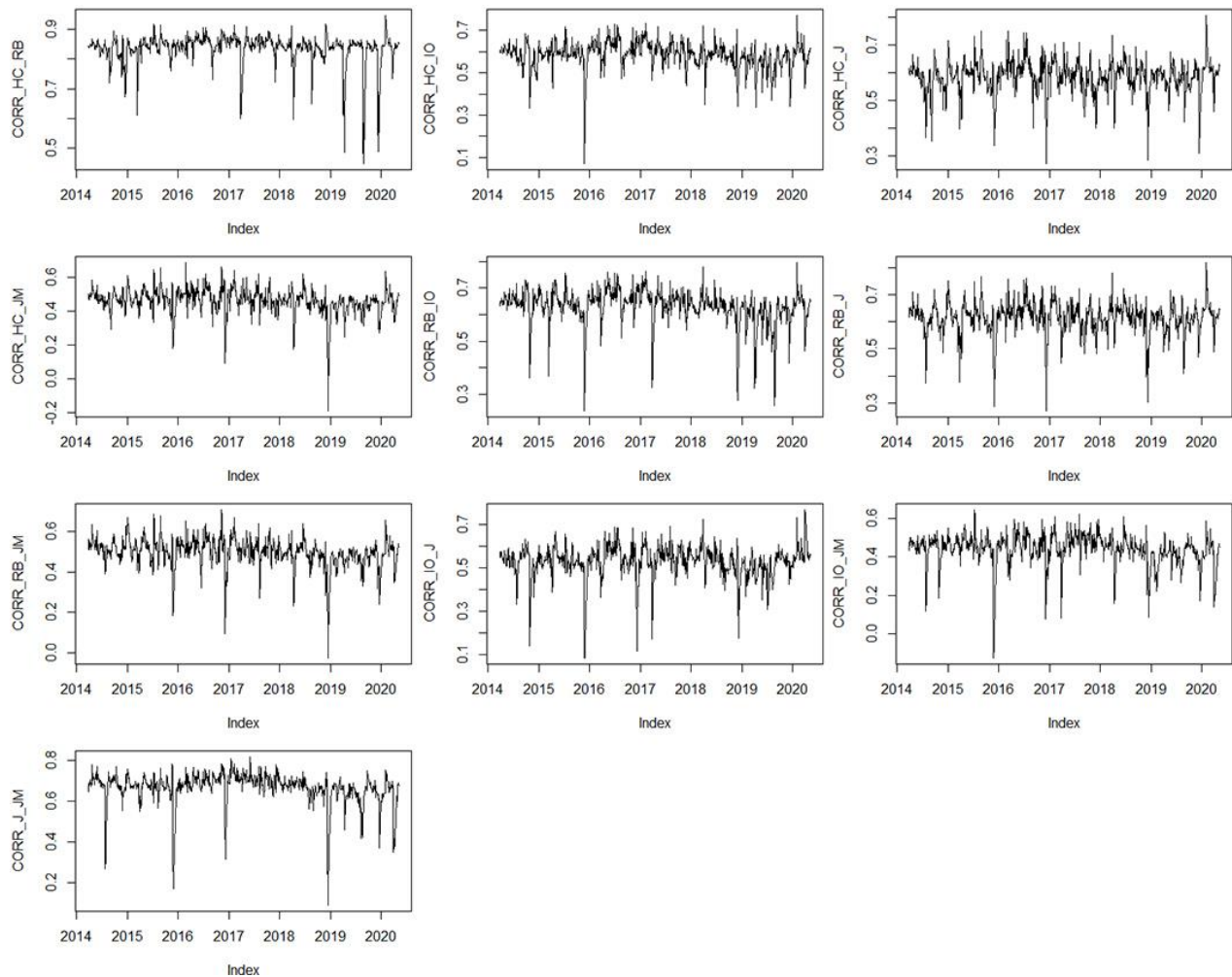


Figure 2 Time Varying Conditional Correlations in 10 Pairwise Black Series futures

## CONCLUSION

This paper examines the DCC in five black series futures market of China by employing DCC GARCH model of Engle (2002). Specially, to decrease the possibility of volatility overestimated, we considered the structural breaks in the GARCH process, the modified ICSS algorithm proposed by Sansó et al. (2020) are applied to detect the change points in series. The results show that coke has the most change points, identifying the coke futures are still in the early stage of development, the market mechanism is not mature. The black series futures market is more volatility during 2014 and 2015 and the timing of several change points corresponds to the implementation of some policies. It's evident that the structural breaks in black series futures of China are closely related to the commodity's supply and demand and also national policies. The study found that black series futures have strong correlations. Rebar and hot rolled coils are highly dependent among all pairwise. Since coke is produced by cooking coal, the test results correspondingly indicate that coke and coking coal futures are closely related. Besides, coking coal is not directly used in metallurgy, it is connected by intermediate commodity coke, therefore except coke, the correlation between cooking coal and other black series futures are relatively weak.

This study provides a better understanding of dynamic volatility transmission mechanism across the black series futures market and can helps investors to develop arbitrage strategies and hedge operating risks. Investors should take cautions to the policies which are related to steel, energy industry and environmental protection. Due to the strong linkage across the black series market, investing in these futures should pay attention to diversify their portfolios to reduce risk. Besides, the market should improve information transmission mechanism to stabilize the market and strengthen market supervision to prevent market manipulation.

## REFERENCES

- Behmiri, N. B., Manera, M., & Nicolini, M. (2019). Understanding dynamic conditional correlations between oil, natural gas and non-energy commodity futures markets. *The Energy Journal*, 40(2), 1-32.
- Carvalho, D. (2018). How do financing constraints affect firms equity volatility? *The Journal of Finance*, 73(3), 1139–1182. doi:<https://doi.org/10.1111/jofi.12610>
- Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a), 427–431. doi:<https://doi.org/10.1080/01621459.1979.10482531>
- Du, D., Elkamhi, R., & Ericsson, J. (2019). Time-varying asset volatility and the credit spread puzzle. *The Journal of Finance*, 74(4), 1841–1885. doi:<https://doi.org/10.1111/jofi.12765>
- Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3), 339–350.
- Fałdziński, M., & Pietrzak, M. B. (2015). The multivariate DCC-GARCH model with interdependence among markets in conditional variances equations. *Przegląd Statystyczny. Statistical Review*, 62(4), 397-413.
- Güloğlu, B., Kaya, P., & Aydemir, R. (2016). Volatility transmission among latin american stock markets under structural breaks. *Physica A: Statistical Mechanics and its Applications*, 462, 330–340. doi:<https://doi.org/10.1016/j.physa.2016.06.093>
- Hillebrand, E. (2005). Neglecting parameter changes in GARCH models. *Journal of Econometrics*, 129(1-2), 121–138. doi:<https://doi.org/10.1016/j.jeconom.2004.09.005>
- Huang, Y. Q. (2017). *An empirical study on the price discovery of China's coke, coal and steel futures market* (Master dissertation). Zhejiang Gongshang University, Zhejiang, China.
- Inclan, C., & Tiao, G. C. (1994). Use of cumulative sums of squares for retrospective detection of changes of variance. *Journal of the American Statistical Association*, 89(427), 913–923.
- Kim, K., & Lim, S. (2019). Price discovery and volatility spillover in spot and futures markets: Evidences from steel-related commodities in China. *Applied Economics Letters*, 26(5), 351–357. doi:<https://doi.org/10.1080/13504851.2018.1478385>
- Kinata, E. J. (2016). The effect of market volatility and firm size towards the difference of market reaction around stock-split announcement in Indonesia stock exchange. *Journal of Administrative and Business Studies*, 2(6), 304–313. doi:<https://doi.org/10.20474/jabs-2.6.5>
- Kwiatkowski, D., Phillips, P. C., Schmidt, P., Shin, Y., et al. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54(1-3), 159–178. doi:[https://doi.org/10.1016/0304-4076\(92\)90104-Y](https://doi.org/10.1016/0304-4076(92)90104-Y)
- Li, Q. Y. (2014). *The research of cooking coal, coke, iron ore and rebar futures arbitrage strategy* (Master dissertation). Shanghai Jiao Tong University, Shanghai, China.
- Mensi, W., Hammoudeh, S., & Yoon, S.-M. (2015). Structural breaks, dynamic correlations, asymmetric volatility transmission, and hedging strategies for petroleum prices and USD exchange rate. *Energy Economics*, 48, 46–60. doi:<https://doi.org/10.1016/j.eneco.2014.12.004>
- Mikosch, T., & Stărică, C. (2004). Nonstationarities in financial time series, the long-range dependence, and the IGARCH effects. *Review of Economics and Statistics*, 86(1), 378–390. doi:<https://doi.org/10.1162/003465304323023886>
- Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2), 335–346. doi:<https://doi.org/10.1093/biomet/75.2.335>
- Rapach, D. E., & Strauss, J. K. (2008). Structural breaks and GARCH models of exchange rate volatility. *Journal of Applied Econometrics*, 23(1), 65–90. doi:<https://doi.org/10.1002/jae.976>
- Sansó, A., Carrion, J., & Aragón, V. (2020). Testing for changes in the unconditional variance of financial time series. *Revista de Economía Financiera*, 4, 32-52.
- Su, P. (2017). *The research on hedging of futures black industry Chain: Analysis of price linkage based on combination variety* (Master dissertation). Wuhan University, Wuhan, China.
- Wang, J., & Zheng, Z. Z. (2019). Research on linkage between the futures price of iron ore and coke. *Price Monthly*, 5(11), 1-8.

- Wang, Q., Dai, X., & Zhou, D. (2020). Dynamic correlation and risk contagion between black futures in China: A multi-scale variational mode decomposition approach. *Computational Economics*, 55(4), 1117–1150. doi:<https://doi.org/10.1007/s10614-018-9857-y>
- Wang, Q., Hang, Y., Su, B., & Zhou, P. (2018). Contributions to sector-level carbon intensity change: An integrated decomposition analysis. *Energy Economics*, 70, 12–25. doi:<https://doi.org/10.1016/j.eneco.2017.12.014>
- Xiao, X. X. (2014). *Research on the relationship between coke futures and spot market* (Master dissertation). Harbin Institute of Technology, Harbin, China.
- Xie, C., & Zhao, D. (2012). Do structural breaks influence the characteristics of RMB exchange rate volatility? *South China Journal of Economics*, 9, 102-115.
- Zhou, J. (2010). *Research on the relationship between steel futures and spot market* (Master dissertation). Fudan University, Shanghai, China.
- Zhou, L. (2017). Research on arbitrage of cross - variety based on cointegration: Take black futures as an example price. *Theory & Practice*, 4, 112-115.