The extreme risk spillovers between the US and China’s agricultural commodity futures markets

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Abstract. In this study, we investigate the downside and upside risk spillover effects between the same kind of agricultural futures in the Chinese and US markets, taking the value-at-risk (VaR) and conditional value-at-risk (CVaR) as a risk measure, characterized and computed using copula-GARCH approach. We find evidence of a significant positive dependence between the US and Chinese agricultural commodity futures markets. And the empirical results also show that the existence of downside and upside risk spillover effects between variables, especially significant during financial turmoil periods. Market regulators and traders of agricultural futures will benefit by identifying tail dependence and extreme risk spillovers.

1. Introduction

With the integration of the global economy, the linkage between the financial markets of various countries is becoming closer than ever, risk spread from crisis-prone countries to other countries faster and more aggressively. For example, the 2007-2009 subprime crises occurred in the United States, but it quickly spread to other countries and regions, which ultimately led to the global financial crisis. It is not difficult to see that financial risk spillover effect is universal, sufficient attention should be paid in the practice of risk management.

Over the last couple of decades, China's agricultural futures market has achieved remarkable development, the amount of agricultural futures contracts traded are now leading in major derivatives markets. Despite its increasing influence in the world agricultural futures markets, the prices of China’s most important agricultural commodities can only passively follow the international markets and do not have strong international pricing power. Moreover, the US agricultural futures market has been considered as the largest and most representative agricultural futures market in the world, which profoundly affects other futures markets. Nowadays, these two agricultural futures markets have become two crucial financial variables that are intrinsically linked in the global level. As the two largest agricultural futures economies, the risk transfer between agricultural futures in the US and the Chinese markets attracted much attention from market participants and policymakers in the world. In particular, the extreme upward and downward spillover risks are very important for market participants in terms of portfolio diversification, risk management, trading, and hedging strategies. However, even though the systemic risk is an important dimension of contagion that enables the impact of extreme downward and upward movements between markets to be quantified, no study has yet examined systemic risk between the US and Chinese agricultural markets or how this risk changed.
with the onset of the recent crisis. Therefore, the objective of this study is to quantify and test extreme risk spillovers between the US and China’s agricultural futures markets.

Value-at-risk (VaR) is a powerful tool for measures of market risk, which is widely applied to risk management by financial institution and regulators. An alternative risk measure that overcomes VaR’s main drawbacks is conditional value-at-risk (CVaR) developed by Rockafellar and Uryasev [1]. VaR addresses the question: “How bad can things get?” The CVaR addresses the question: “If things go bad, what is the expected loss?” A key point in estimating the portfolio VaR and CVaR is to model the co-movement of returns, i.e., the dependence structure, especially since VaR and CVaR are related to the tail of the distribution. Therefore, firstly, this paper focuses on studying the co-movement between the US and Chinese agricultural futures markets. Second, we examine the downside and upside risk spillover between variables based on information from dependence.

This paper includes five parts: In section 2, we review the related works of literatures. Section 3 introduces the ARMA-GARCH model for marginals and summarizes the methodologies for analyzing dependence and VaR and CVaR. Section 4 describes the data of five pair’s representative agricultural futures prices and analyzes the empirical results. Finally, Section 5 provides the conclusion of the work.

2. Literature review

Some researches in relation to the relationship between the US and China’s agricultural futures markets have been investigated in the past work. Fung et al. [2] were the first to explore the interaction between the US and China’s commodity futures markets. The empirical results indicated that there is a significant spillover effect between the US and Chinese soybean and wheat futures markets and the US commodity futures market act as a leading role in transmitting information to the Chinese market. Similar results were obtained in later studies (Li and Lu [3], Mo and Gupta [4], Jia and Wang et al. [5], Chen and Weng [6]). These studies primarily focus on correlation or information spillover in mean and volatility between commodity futures markets without considering the dependence structure. However, in extreme risk situations, cross-market dependence is often dynamic and nonlinear, and there may be an extreme tail dependency.

Embrechts and Mcneil et al. [7] clarified the limitations of correlation-based models and noted the related advantages of copula model. Copula-based models have been widely used to examine the dependence structure across financial markets. In the recent study, Wu et al. [8] studied the co-movement between oil prices and exchange rates using the copula-GARCH model, with time-varying dependence parameters. The finding shows that the dependence between financial returns is time-varying. Bai and Lam [9] applied Conditional copula-GARCH model to estimate dynamic conditional dependence structure between liquefied petroleum gas freight rate, product price arbitrage and crude oil price. Different types of copula with time-invariant and time-varying were considered. There is evidence of conditional time-varying dependence between markets and the dependence is higher in markets downturns. Moreover, in the study on risk spillover, the static and time-varying copulas are usually used to study the spillover effects by combining the methods of risk measure. For example, Wang and Chen et al. studied the risk of foreign exchange portfolio using VaR and CVaR based on GARCH-copula model. And Jin [10] utilized a CoVaR-copula approach to examine the downside and upside risk spillovers from China to Asian stock markets.

As above mentioned, capturing dependence is very important when we estimating the portfolio VaR and CVaR. To our best knowledge, no study has investigated the relationship between the US and Chinese agricultural futures markets by quantifying and testing upside and downside risk. In response to lack in the literature, the bivariate static and time-varying copulas functions are employed to capture dependence structure between the US and China’s agricultural futures markets, with focus on five agricultural commodities, i.e., soybean meal, corn, soybean oil, soybean and cotton, which occupy critical positions in the Sino-US agricultural markets. Furthermore, from the copula results, we can provide quantitative evidence for the impact of extreme movements between markets.
3. Methodology
We conduct the modelling of this study as follows: i) the appropriate marginal distribution for each futures return series is received by fitting ARMA-GARCH model; ii) estimating different static and time-varying copula parameters that characterize the dependence between bivariate variables; iii) the extreme risk measure based on dependence between the futures is examined.

3.1. The model for marginal distribution and copula approach
Firstly, the appropriate marginal distributions for the copula model are required. To estimate the marginal distribution of the US and Chinese agricultural commodity futures return series, the univariate ARMA (p, q)-GARCH (1, 1) process is applied to achieve this goal in this study. Just as its name implies, the ARMA-GARCH model is a combination of ARMA and GARCH models: i.e. in an ARMA process, the error term follows a GARCH process. An ARCH specification is for conditional mean and a GARCH specification is for conditional variance.

\[ r_t = \phi_0 + \sum_{j=1}^{p} \phi_j r_{t-j} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}, \]  
\[ \varepsilon_t = h_t^{1/2} z_t, \]  
\[ h_t = \omega_0 + \beta_h h_{t-1} + \alpha \varepsilon_{t-1}^2, \]

where Equation (1) is ARMA (p, q) model, \( r_{t-j} \) is an autoregressive term of \( r_t \). \( p \) and \( q \) are lag orders and where \( \phi_j \) and \( \theta_i \) are autoregressive (AR) and moving average (MA) coefficients, respectively. The volatility of return is explained through a simple GARCH (1, 1) process, given by Equation (2) and (3). \( h_t \) is conditional variance, where \( \omega_0, \beta_1, \alpha > 0 \) and \( \alpha + \beta_1 < 1 \) are sufficient to ensure conditional variance \( h_t > 0 \). Where \( z_t \) is independent and identically distributed (i.i.d) innovation variable that follows a Hansen’s skewed-t density distribution to capture heavier tail and asymmetries for futures returns in our study. The density of the skewed-t distribution can be expressed as follows:

\[ f(z_t; \lambda, \nu) = \begin{cases} 
bc(1 + \frac{1}{\nu-2} \left( \frac{bz_t + a}{1-\lambda} \right)^2)^{-\left(\nu+1\right)/2} z_t < -a/b \\
bc(1 + \frac{1}{\nu-2} \left( \frac{bz_t + a}{1+\lambda} \right)^2)^{-\left(\nu+1\right)/2} z_t \geq -a/b 
\end{cases} \]  

where \( \lambda \) and \( \nu \) denote the asymmetry parameter and degree of freedom; \( a, b, c \) are constants, obtaining by \( a = 4\lambda c \left( \frac{\nu - 1}{\nu - 3} \right), b = 1 + 3\lambda^2 - a^2, c = \Gamma \left( \frac{\nu + 1}{2} \right) / \sqrt{\pi (\nu - 2) \Gamma \left( \frac{\nu}{2} \right)} \).

| Name          | Copula               | Tail dependence |
|---------------|----------------------|-----------------|
| Gaussian      | \( C_{G} \)          | No tail dependence \( \lambda_u = \lambda_l = 0 \) |
| Student-t     | \( C_{ST} \)         | Symmetric tail dependence \( \lambda_u = \lambda_l = 2t_{u+1}^{-1}(\sqrt{\nu} + 1)^{-1}/(\sqrt{1+p}) \) |
| Frank         | \( C_{F} \)          | No tail dependence \( \lambda_u = \lambda_l = 0 \) |
| Clayton       | \( C_{CL} \)         | Asymmetric tail dependence: \( \lambda_u = \lambda_l = 2^{-1/\delta}, \lambda_{u} = 0 \) |
| Rotated Clayton | \( C_{RC} \)         | Asymmetric tail dependence: \( \lambda_u = \lambda_l = 2^{-1/\delta}, \lambda_{u} = 0 \) |
| Gumbel        | \( C_{G} \)          | Asymmetric tail dependence: \( \lambda_u = \lambda_l = 2^{-1/\delta}, \lambda_{u} = 0 \) |
| Rotated Gumbel | \( C_{RG} \)         | Asymmetric tail dependence: \( \lambda_u = \lambda_l = 2^{-1/\delta}, \lambda_{u} = 0 \) |

Notes: The table presents copula functions considered in this study and their features of tail dependence. More details can be seen in Joe [12] and Nelsen [13].

To characterize different dependence structure between the US and Chinese agricultural futures markets, Table 1 summarizes a variety of bivariate copula specifications. The application of copula functions is useful to assess the probability that two markets experience joint extreme upward and
downward movements by examining the upper and lower tail dependencies. An attractive feature of the copula is that it allows us to model separately the marginals and the dependence structure from a pair of variables’ joint distribution. Sklar’s theorem states that there exists a copula function for a given joint distribution function. The joint density function for bivariate copula is written as

\[
f_{X,Y} = c(u,v)f_X(x)f_Y(y)
\]

where \(c(u,v)\) denotes the copula density and \(f_X(x)\) and \(f_Y(y)\) are the marginal densities of the variables \(X\) and \(Y\), respectively.

To account for dynamic dependence, the variation of parameters in a copula specification is allowed. Hence, the time-varying dependence coefficients for the bivariate Normal and \(t\) copulas are represented according to an ARMA \((p, q)\) process [14]:

\[
\rho_t = \Lambda(\psi_0 + \psi_1 \rho_{t-1} + \psi_2 \frac{1}{q} \sum_{j=1}^{q} \Phi^{-1}(u_{t-j})\Phi^{-1}(v_{t-j}))
\]

where \(\Lambda(x)\) is the logistic transformation modified to maintain the value of \(\rho_t\). \(\Phi^{-1}(x)\) is a standard normal quantile function for Gaussian copula. For Student-\(t\) copula, it is replaced by \(t_\nu^{-1}(x)\).

Similarly, we consider the parameter dynamics for the Gumbel and its rotated version (180 degrees) are assumed to follow the ARMA \((p, q)\) process described by:

\[
\delta_t = \omega + \beta \delta_{t-1} + \alpha \sum_{j=1}^{q} |u_{t-j} - v_{t-j}|
\]

The dynamic parameters dependence for Clayton copula is expressed as:

\[
\tau_t = \omega + \beta \tau_{t-1} + \alpha \sum_{j=1}^{q} |u_{t-j} - v_{t-j}|
\]

3.2. Measurements for Downside and Upside Risk Spillover

We analyze risk spillovers between the US and Chinese agricultural futures markets by examining risks related to long and short positions in agricultural futures portfolios. The VaR risk measure reflects the maximum investment losses at a certain quantile level over a given horizon. Following the Pan and Zhang [15], for a confidence level \(1 - \alpha\), we use the left and right \(\alpha\)-quantile of returns given by \(Pr(r_t \leq VaR_{\alpha,t}) = Pr(r_t \geq VaR_{1-\alpha,t}) = \alpha\) to quantify downside and upside VaR, they are respectively estimated as:

\[
VaR_{\alpha,t} = \mu_t + t_{\nu\alpha}^\alpha(\alpha)\sigma_t
\]

\[
VaR_{1-\alpha,t} = \mu_t + t_{\nu\alpha}^{-1}(1-\alpha)\sigma_t
\]

where \(t_{\nu\alpha}^{-1}(\alpha)\) is the \(\alpha\)-quantile of the skewed-t distribution in Equation (4), and \(\mu_t\) and \(\sigma_t\) are the conditional mean and standard deviation of returns, respectively.

Conditional Value at Risk (CVaR) is a risk assessment measure that quantifies the size of the tail loss. As an improvement of deficiencies of VaR, Artzner et al. [16] argued that CVaR can quantify the expected losses that occur beyond the VaR level. Generally, the conventional tool of risk measurement may underestimate the minimum risk levels for a given goal. The copula-based CVaR approach is to provide a better insight to make up for deficiencies. It can be calculated as follows:

\[
CVaR_t = \mu_t + \sigma_t \left[ \frac{1}{\nu} \int_0^\gamma xt_{\nu}^{-1}(x)dx \right]
\]

The downside and upside CVaR of futures returns with confidence level of \(1 - \gamma\) are defined as \(\gamma\)-quantile of the conditional probability distribution:

\[
Pr(r_t \leq CVaR_{\gamma,t}) = \gamma
\]

\[
Pr(r_t \geq CVaR_{1-\gamma,t}) = \gamma
\]

4. Data and empirical results

4.1. Data

Using the data of the daily closing prices for agricultural futures mentioned above in this study from 9th January 2006 to 31st July 2018, from the Thomson Reuters DataStream database. The prices of soybean meal, corn, soybean oil, and No.1 soybean futures are obtained from Dalian Commodity Exchange (DCE) in Chinese markets and Chicago Board of Trade (CBOT) in the US markets. And the
Chinese cotton futures are from Zhengzhou Commodity Exchange (ZCE), the US cotton futures are from Intercontinental Exchange (ICE, U.S.). All futures prices are adjusted to USD/Ton, and we transform each price data into logarithmic returns, \( \ln \left( \frac{P_t}{P_{t-1}} \right) \) before being used for analyzing.

Econometricians have informed that the regression of non-stationary time series may produce a spurious regression. The unit root test is used to check stationarity of the collected data. The standard tests for unit root have ADF-Test [17], PP-Test [18] and KPSS test [19]. Hansen [20] proposed a better way for unit root test is to consider stationary covariates in an otherwise conventional ADF framework. Using covariates also allows to some extent to couple unit root testing and economic theory.

**Table 2.** Descriptive statistics for five agricultural commodity futures price returns.

|                  | Soybean meal | Corn | Soybean oil | Soybean | Cotton |
|------------------|--------------|------|-------------|---------|--------|
| **Panel A: US markets** |              |      |             |         |        |
| Mean             | 0.000        | -0.000 | 0.000       | 0.000   | 0.000  |
| Maximum          | 0.075        | 0.087 | 0.074       | 0.065   | 0.095  |
| Minimum          | -0.254       | -0.245 | -0.072      | -0.141  | -0.271 |
| Std.dev.         | 0.018        | 0.019 | 0.014       | 0.016   | 0.018  |
| Skewness         | -1.352       | -0.648 | 0.079       | -0.792  | -1.157 |
| Kurtosis         | 18.133       | 13.399 | 5.450       | 9.367   | 20.619 |
| Jarque-Bera      | 32258*       | 14989* | 823*        | 5876*   | 43102* |
| ADF              | -56.030*     | -56.130* | -56.341*    | -56.555* | -54.600* |
| PP               | -56.018*     | -56.121* | -56.357*    | -56.551* | -54.610* |
| KPSS             | 0.101        | 0.247 | 0.349       | 0.245   | 0.0653 |
| CADF             | -15.984*     | -15.722* | -16.751*    | -15.763* | -16.374* |

|                  | Soybean meal | Corn | Soybean oil | Soybean | Cotton |
|------------------|--------------|------|-------------|---------|--------|
| **Panel B: Chinese markets** |              |      |             |         |        |
| Mean             | 0.000        | 0.000 | 0.000       | 0.000   | 0.000  |
| Maximum          | 0.084        | 0.122 | 0.105       | 0.137   | 0.084  |
| Minimum          | -0.148       | -0.164 | -0.111      | -0.102  | -0.173 |
| Std.dev.         | 0.014        | 0.010 | 0.013       | 0.010   | 0.010  |
| Skewness         | -1.469       | -1.614 | -0.231      | 0.299   | -1.600 |
| Kurtosis         | 18.888       | 62.986 | 10.085      | 20.547  | 39.811 |
| Jarque-Bera      | 35633*       | 492587* | 6880*       | 42077*  | 186362* |
| ADF              | -54.343*     | -56.112* | -56.633*    | -53.370* | -49.470* |
| PP               | -54.725*     | -56.150* | -56.701*    | -53.400* | -49.871* |
| KPSS             | 0.105        | 0.522 | 0.342       | 0.385   | 0.165  |
| CADF             | -9.674*      | -16.851* | -15.576*    | -16.972* | -14.352* |

Notes: Std.Dev. is the standard deviations. Jarque-Bera is \( \chi^2 \) statistics for the test of normality. ADF, PP and KPSS denote the statistic of Augmented Dickey-Fuller, the Phillips-Perron unit root tests, and the KPSS test, respectively. CADF is covariate ADF test. * represents significance at the 1% level.

Table 2 provides the descriptive statistics of futures return series. The value of skewness indicates that the return series for most of the agricultural commodity futures in the US and Chinese markets show negative skewness, which means their price returns exist downside risk or have a probability of negative return. The Kurtosis of all data series is greater than 3, which imply that agricultural futures returns have a probability distribution function with heavier tails. The values of the Jarque-Bera test are significant at 1% level, further confirming all data series do not follow a normal distribution. Thus, the assumption of shewed-t is appropriate in this paper. Moreover, according to the statistics of ADF, PP unit root tests, the KPSS stationary test, and CADF test, the return series of all the agricultural commodity futures considered are found to be stationary.

4.2. **Marginal model results**

The ARMA (p,q)-GARCH (1,1) model in Equation (1)-(3) for each agricultural futures return is estimated by considering different autoregressive and moving average lags p and q ranging from 0 to a maximum lag of 10. The optimal model is selected according to taking minimum Akaike information criterion (AIC) values and the results are reported in Table 3.
The parameter estimates for mean display AR and MA coefficients. All of variables are significant, which means there is serial dependence. As for volatility, the highly significant GARCH parameters give an indication of persistent volatility. We also can see that the asymmetry effects are significant for all return series. The degrees of freedom parameters for the skewed-t distribution indicate that error terms are not normal, which consistent with the results provided by descriptive statistics. We also check the goodness-of-fit of marginal models. The Ljung-Box statistics provide no evidence of serial correlation and ARCH tests show ARCH effects remain in residual terms. Furthermore, we test uniformity for the transformed marginals of these residuals using the Kolmogorov-Smirnov (KS) test. These preliminary results indicate that most marginal distribution models are not mis-specified, so the dependence structure between the US and Chinese agricultural futures markets can be correctly characterized by copula model.

Table 3. Estimates of marginal distribution models.

| Soybean meal | Corn | Soybean oil | Soybean | Cotton |
|-------------|------|-------------|---------|--------|
| US | CHN | US | CHN | US | CHN | US | CHN | US | CHN |
| Mean | | | | | | | | | |
| $\varphi_0$ | 0.000 | 0.000 | 0.000 | -0.000 | -0.000 | 0.001* | 0.000* | 0.000 | 0.000 | 0.000 |
| $\varphi_1$ | -0.572* | 1.938* | 1.368* | -0.977* | -0.179* | -0.686* | 0.729* | -0.091* | -1.418* | 0.390* |
| $\varphi_2$ | -0.045* | -1.712* | -1.450* | -0.571* | 0.408* | -0.384* | -0.798* | -0.114* | -2.069* | -0.407* |
| $\varphi_3$ | -0.572* | 0.660* | 0.198* | -0.571* | 0.408* | -0.384* | 0.439* | 0.461* | -1.301* | 0.987* |
| $\varphi_4$ | -0.983* | 0.322* | 0.685* | -0.774* | 0.650* | -0.801* | 0.744* | 0.744* | -0.869* | 0.000* |
| $\varphi_5$ | -0.577* | -0.024* | -0.891* | 0.187* | 0.931* | 0.038* | | | | |
| $\varphi_6$ | 0.577* | -1.881* | -1.351* | 0.996* | 0.179* | 0.686* | -0.739* | 0.113* | 1.438* | -0.309* |
| $\varphi_7$ | 0.053* | 1.642* | 1.408* | 0.601* | -0.398* | 0.389* | 0.786* | 0.108* | 2.103* | 0.379* |
| $\varphi_8$ | 0.576* | -0.627* | -1.296* | -0.126* | 0.117* | -0.480* | -0.414* | -0.441* | 1.360* | -0.950* |
| $\varphi_9$ | 0.993* | -0.397* | -0.653* | 0.765* | -0.650* | 0.779* | -0.773* | 0.922* | -0.077* | 0.000* |
| $\varphi_{10}$ | 0.624* | -0.875* | -0.160* | -0.942* | 0.0345* | 0.000* | | | | |
| Variance | | | | | | | | | |
| $\omega_0$ | 0.000 | 0.000* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Alpha1 | 0.005* | 0.182* | 0.056 | 0.003* | 0.034* | 0.085* | 0.043* | 0.314* | 0.059* | 0.191* |
| Beta1 | 0.944* | 0.817* | 0.940* | 0.996* | 0.959* | 0.915* | 0.949* | 0.685* | 0.925* | 0.808* |
| Asymmetry | 0.994* | 0.977* | 1.010* | 0.982* | 1.067* | 1.004* | 0.955* | 1.011* | 1.008* | 1.019* |
| Tail | 4.685* | 2.335* | 4.920* | 2.283* | 10.687* | 2.283* | 4.530* | 2.368* | 4.646* | 2.714* |
| Loglik | 8854 | 10211 | 8736 | 12056 | 9569 | 10453 | 9419 | 11253 | 8929 | 11650 |
| Q2(1) | [0.737] | [0.795] | [0.955] | [0.148] | [0.781] | [0.033] | [0.310] | [0.629] | [0.489] | [0.981] |
| Q2(5) | [0.937] | [0.743] | [0.986] | [0.309] | [0.688] | [0.115] | [0.686] | [0.925] | [0.577] | [0.995] |
| Q2(9) | [0.983] | [0.883] | [0.998] | [0.616] | [0.740] | [0.285] | [0.864] | [0.981] | [0.743] | [0.999] |
| ARCH(3) | [0.833] | [0.279] | [0.615] | [0.781] | [0.258] | [0.675] | [0.613] | [0.681] | [0.924] | [0.737] |
| ARCH(5) | [0.883] | [0.634] | [0.879] | [0.938] | [0.390] | [0.966] | [0.710] | [0.890] | [0.710] | [0.966] |
| ARCH(7) | [0.959] | [0.813] | [0.967] | [0.998] | [0.540] | [0.987] | [0.879] | [0.959] | [0.899] | [0.993] |
| KS | [0.836] | [0.010] | [0.580] | [0.089] | [0.373] | [0.000] | [0.005] | [0.663] | [0.425] | [0.244] |

Notes: This table shows the parameters of marginal model with skewed-t distribution. Loglik denotes log-likelihood. P values for these tests are reported in squared brackets. Q2 is Ljung-Box p-value for serial correlation. ARCH test is to check the existence of ARCH effects. The KS means Kolmogorov-Smirnov test for uniformity. * and ** indicates significance at 1% and 5% level, respectively.

4.3. Static and time-varying copula model results
After modelling the marginal distribution models, we convert the standardized residuals from the marginal models into the uniform [0,1] to estimate the static and time-varying version of the bivariate copula models. We judge the ability of static and time-varying copulas to explain the dependence between futures by minimum AIC for competing models.

Panel A and Panel B of Table 4 report the estimated parameters of the static and time-varying copulas for the selected agricultural futures pair, respectively. The empirical results demonstrate that there is positive and significant dependence for these five agricultural futures between the US and China’s markets. Particularly, compared with other futures commodities, we find that there is the lowest dependence between Chinese and American corn futures. The relative lower dependence
between the US and Chinese corn futures may be interpreted by the bilateral relationship that caused by the trade patterns. Chen and Weng [6] mentioned that China has always been a net exporter of corn, and the United States did not become a major country of Chinese corn import until 2010. A comparison of AIC values for static and time-varying copulas indicates that static copula is better able to capture tail dependence between Sino-US soybean meal, corn and soybean futures, while time-varying copula provides a better fit for soybean oil futures. According to the best-fit copula, we know that all markets except for the cotton futures market have lower tail dependence due to the time-varying Gaussian copula with tail independence for cotton futures. Hence, if extreme downward movement occurs for futures prices in the US or Chinese markets, they will react sharply each other.

Table 4. Copula estimates for the US and China’s agricultural futures returns.

| Copula          | Soybean meal | Corn  | Soybean oil | Soybean | Cotton |
|-----------------|--------------|-------|-------------|---------|--------|
| **Panel A: Time-invariant Copulas** |              |       |             |         |        |
| i). Gaussian    |              |       |             |         |        |
| ρ              | 0.13*(0.01)  | 0.05*(0.01) | 0.16*(0.01) | 0.14*(0.01) | 0.14*(0.01) |
| AIC            | -57.63       | -6.78 | -101.72     | -66.1   | -60.91 |
| ii). Student’s t|              |       |             |         |        |
| ρ              | 0.13*(0.02)  | 0.05*(0.02) | 0.17*(0.02) | 0.14*(0.02) | 0.14*(0.02) |
| v              | 9.09*(1.68)  | 15.56*(3.88) | 21.52*(7.22) | 18.28*(5.99) | 19.16*(6.61) |
| AIC            | -90.21       | -24.71 | -109.71     | -74.82  | -68.72 |
| iii). Frank     |              |       |             |         |        |
| δ              | 0.78*(0.1)   | 0.25*(0.09) | 1.09*(0.09) | 0.83*(0.1) | 0.79*(0.1) |
| AIC            | -51.21       | -3.58  | -103.38     | -58.63  | -52.92 |
| iv). Clayton’s  |              |       |             |         |        |
| α              | 0.18*(0.01)  | 0.05*(0.01) | 0.15*(0.01) | 0.15*(0.01) | 0.13*(0.00) |
| AIC            | -86.3        | -8.19  | -68.96      | -60.1   | -40.71 |
| v). Rotated Clayton |         |       |             |         |        |
| α              | 0.11*(0.02)  | 0.05*(0.01) | 0.17*(0.01) | 0.13*(0.01) | 0.15*(0.01) |
| AIC            | -25.08       | -9.25  | -81.51      | -45.19  | -56.13 |
| vi). Gumbel     |              |       |             |         |        |
| δ              | 1.07*(0.01)  | 1.03*(0.01) | 1.09*(0.01) | 1.08*(0.01) | 1.08*(0.01) |
| AIC            | -45.25       | -14.71 | -88.39      | -53.67  | -68.63 |
| vii). Rotated Gumbel |         |       |             |         |        |
| δ              | 1.1*(0.01)   | 1.03*(0.01) | 1.09*(0.01) | 1.08*(0.01) | 1.08*   |
| AIC            | -97.37       | -15.31 | -84.47      | -68.45  | -50.65 |
| **Panel B: Time-varying copulas** |              |       |             |         |        |
| viii). TVP-Gaussian |         |       |             |         |        |
| ψ_0           | 0.570*(0.12) | 0.052 (0.12) | -0.003 (0.01) | -0.004 (0.01) | -0.011 (0.01) |
| ψ_1           | -2.026*(0.01) | -0.955 (1.34) | 1.960*(0.05) | 1.985*(0.06) | 1.925*(0.06) |
| ψ_2           | -0.046 (0.14) | 0.125 (0.13) | 0.019*(0.01) | 0.013 (0.02) | 0.056*(0.02) |
| AIC           | -56.922      | -3.875 | -103.902    | -71.979 | -71.248 |
| ix). TVP-Student-t |         |       |             |         |        |
| ψ_0           | 0.234 (0.42) | 0.061** (0.02) | -0.002 (0.01) | 0.186 (0.18) | 0.130 (0.12) |
| ψ_1           | 0.049 (3.28) | 0.006 (2.03) | 1.955* (0.06) | 0.304 (1.48) | 0.515 (1.80) |
| ψ_2           | 0.045 (0.10) | 0.053 (0.08) | 0.021** (0.01) | 0.082 (0.08) | 0.232 (0.15) |
| v             | -0.366 (0.46) | -0.014 (0.35) | -0.685 (2.63) | -0.032 (0.15) | -0.044 (0.07) |
| ψ_3           | -0.102* (0.01) | -0.064* (0.00) | 0.011 (0.07) | -0.078* (0.00) | -0.067* (0.00) |
| ψ_4           | -0.401 (0.32) | -0.019 (0.62) | -1.302 (1.21) | -0.391* (0.11) | -0.080 (0.13) |
| AIC           | -84.612      | -16.490 | -111.204    | -70.276 | -67.627 |
| x). TVP-Clayton |         |       |             |         |        |
| ω             | 0.0142 (0.17) | -1.559 (0.66) | 0.1775 (0.12) | 0.361* (0.12) | 0.399 (0.21) |
| β             | -0.211 (0.63) | 2.313 (1.81) | 0.636* (0.13) | 0.601* (0.03) | 0.620* (0.06) |
| α             | 0.381 (0.50) | -2.544 (2.06) | -0.176 (0.45) | -0.965 (0.90) | -0.747 (0.69) |
| AIC           | 96.825       | 10.555  | 78.526      | 73.232  | 56.095 |
| xi). TVP-Gumbel |         |       |             |         |        |
| ω             | -3.531 (0.62) | 0.006 (0.78) | 0.004 (0.99) | 0.004 (7.01) | -0.000 (1.12) |
| β             | 2.972 (061)  | 0.002 (0.70) | -0.004 (0.99) | -0.004 (6.98) | -0.000 (1.08) |
| α             | 1.943 (0.23) | -0.028 (1.65) | 0.000 (0.29) | -0.000 (1.14) | 0.000 (0.38) |
| AIC           | 6.100        | 4.267   | -7.456      | 6.174   | 6.648  |

Notes: The table represents the estimates for different copula models for the US and China’s agricultural futures returns. The minimum AIC value (in bold) suggests the best copula fit. *and ** indicate significance at 1% and 5% level, respectively.
4.4. Risk spillover effects between the US and China’s agricultural futures

Using the estimates of marginal models and the best pair-copula, we then simulate the simulated data in order to compute the downside and upside VaR and CVaR values of each agricultural futures return at the 99% (α=0.01). We note that the downside and upside VaR and CVaR for each pair are computed under the equally weighted assumption, and their values are plotted in Figure 1. Graphically, the downside and upside VaR and CVaR between all agricultural futures pairs are dynamics and show the same trend over time, albeit with deference in magnitude across futures. Apparently, the impact of the uncertain crisis events is reflected by abrupt changes.

![Figure 1. Upside and downside value-at-risk (VaR) and conditional value-at-risk (CVaR) between the US and China’s agricultural futures markets.](image)

More specifically, it is observed that the empirical values of portfolio CVaR for downside risk are significantly below portfolio VaR values in all markets, and their differences are reflected in different sizes across futures markets. We also find that for an equally weighted agricultural futures portfolio, the downside CVaR values for corn and soybean oil futures displayed relatively lower than other three futures, which is consistent with the degree of dependence from copula results. Particularly, we also observed that the risk spillovers between corn futures markets significantly increased during the period of 2013-2014 which may correspond to Sino-US GMO corn event. And for cotton futures, reserve
policy and direct subsidy policy implemented by the Chinese government in 2011-2013 and 2014, respectively, causing the large fluctuation of cotton price. Thus, when investors explore potential investment opportunities in China or the US agricultural futures markets, they should consider avoiding the downside risks resulted by extreme changes hold their portfolios. For these investors, hedging downside risk spillovers implies to hold short positions for a portfolio of the futures. With respect to upside risk, we find the estimating risk of futures portfolio is largest for soybean meal futures, which means that soybean meal futures will receive a more positive impact when markets are during the extreme upwards movements periods. In the case of this scenario, investors should consider taking a long instead of short positions.

Moreover, the VaR and CVaR values of all agricultural futures remain high at the end of our sample period, especially for soybean futures, indicating that the volatility of the US and Chinese markets is higher recently. The main reason may be Sino-US trade war, because the soybean futures own the highest degree of marketization, price fluctuated greatly. These results coincide with the growing linkages in terms of trade and investment movements between the US and Chinese commodity futures markets.

5. Conclusions
This paper analyzes risk spillovers between the US and China's agricultural futures markets by combining the static and time-varying copula model with measures for risk. We obtained several conclusions as follows: First of all, our findings indicate that the correlation between the US and Chinese agricultural futures markets appears significant positive. Besides, the dependence structure differs across agricultural futures as they exhibit different tail dependence features. Moreover, there are significant upside and downside risk spillovers between Chinese and American agricultural markets, particularly in an uncertain economic situation. Our findings also show that the existence of tail dependence between the US and Chinese agricultural futures returns requires market practitioners to take into account both dependence structures and extreme spillover risks, which have important implications in managing asset risk and improving trading strategies.

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