Extreme Climate and Agricultural Product Price Volatility: Empirical Evidence from the Futures Market

Zishuo Lian[1*], Surui Zhang[1,a], Yawen Lin[1,b], Qianting Ma[1,c], Rong Sun[2,d]

[1]College of Finance, Nanjing Agricultural University, Nanjing, China
[2]School of Accounting, Nanjing Audit University, Nanjing

*Lzs02921@outlook.com, [a]m13921211052@163.com, [b]lyw369059@163.com, [c]mqt2626@njau.edu.cn, [d]rong0728sun@163.com

Abstract. As the frequency of extreme climate events escalates, the financial systems face significant challenges. This paper empirically examines the effects of extreme climate on the volatility of agricultural product futures prices by constructing a network of agricultural product futures. The findings reveal three key impacts: First, extreme climate conditions increase the uncertainty in agricultural product futures supply and investor market expectations, significantly affecting the volatility of futures prices. Second, extreme climate enhance the volatility of agricultural product futures prices by increasing network clustering. Third, the effects of extreme climate on the volatility of agricultural product futures prices are significant in autumn due to seasonal heterogeneity. This paper unveils the mechanisms through which extreme climate impacts agricultural product futures price volatility, offering insights and policy recommendations to relevant sectors for mitigating the effects of extreme climate on the agricultural futures market.

Keywords: Agricultural Product Futures; Extreme Climate; Shannon Entropy; Network Clustering; Seasonal Heterogeneity

1 Introduction

Extreme climate change is considered one of the most significant challenges of the 21st century. The report released by the United Nations Intergovernmental Panel on Climate Change (IPCC) in 2022 notes that, under the influence of extreme climate changes, "China will be among the regions most affected." Currently, China's agricultural market has been severely affected by multiple climatic disasters. In 2021 alone, the "extraordinary heavy rainfall" in Henan affected an area of 1,021.4 thousand hectares, with 179.8 thousand hectares experiencing total crop failure. The frequent occurrence of extreme climate events poses severe challenges to natural ecosystems, public health, and economic development, while also exacerbating the uncertainty in the financial system, threatening financial stability, and hindering economic progress (FSB 2020) [1].

The construction of complex networks and the measurement of financial market system stability using network entropy have gained widespread attention among scholars.

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Wang et al. (2023) [2] utilized transfer entropy to calculate the correlation network matrix of interbank risk contagion, demonstrating that interbank systemic risks significantly increased following the outbreak of the pandemic. In the futures market, Niu and Hu (2021) [3] combined transfer entropy with the data decomposition technique CEEMDAN, confirming the presence of highly active assets that produce stronger spillover and contagion effects during the market information overflow process.

The agricultural futures market, one of the earliest futures markets, plays a pivotal role in society (Ahumada & Cornejo, 2016) [4]. Predicting the prices of agricultural product futures not only helps investors achieve considerable returns but also plays a critical role in devising hedging strategies (Luo et al., 2022) [5]. Beckmann and Czudaj (2014) [6] utilized the GARCH-in-mean VAR model and discovered that speculative influences on one market could spread to others, increasing the volatility of agricultural product futures markets. Degiannakis et al. (2022) [7] argue that studying the behavior of agricultural product prices and their volatility is crucial, as it assists policy bodies in preparing for periods of high price volatility or in designing preventative policies. Few scholars have explored the impact of agricultural product futures price volatility from the perspective of complex networks.

Extreme climate events, which deviate significantly from the average climate state and statistically represent low-probability occurrences. These events have a substantial impact on society and the environment. They have profound effects on the global economy. Sampson (2017) [8] showed that increases in the intensity and frequency of extreme climate events directly cause reductions in crop yields, endangering food security. According to Monasterolo (2020) [9], climate change is now considered a significant source of risk for financial systems. Zhou et al. (2023) [10] noted that natural disasters and climate change risks generally diminish the profitability and risk-sharing capacity of insurance companies, the stability of banks and credit supply, and the returns and stability of stock and bond markets. Despite extensive literature on the impact of extreme climate on financial stability, the influence of extreme climate on the volatility of agricultural product futures prices has not yet been adequately addressed.

To explore how extreme climate affects the volatility of agricultural product futures prices, this paper utilizes data from 2016 to 2022 on 18 major agricultural products. By constructing a network of agricultural product futures, this study investigates the impact of extreme climate on the volatility of these prices. The marginal contributions of this paper are primarily threefold. Firstly, by employing network entropy to depict the volatility of agricultural product futures prices, this paper provides novel theoretical support for assessing such volatility. Secondly, this paper examines how extreme climate influences the network of agricultural product futures, thereby affecting their price volatility, offering new theoretical insights into the mechanisms by which extreme climate impacts this volatility. Thirdly, the paper focuses on exploring the heterogeneity characteristics of different seasonal markets during extreme climate events. This analysis is instrumental in guiding policies to guard against seasonal fluctuations in futures prices.

The structure of this paper is as follows. Section II will engage in theoretical analysis and research hypotheses. Section III will design empirical research. Section IV analyzes the empirical results. Section V conducts further analyses. Section VI summarizes the paper and offers policy recommendations.

2 Theoretical Analysis and Research Hypotheses

Based on market supply and demand theory, the volatility of commodity prices is influenced by the supply-demand dynamics. The occurrence of extreme climate events can lead to a reduction in agricultural output, subsequently affecting the supply-demand balance and triggering fluctuations in agricultural markets and prices (Chatzopoulos et al., 2020) [11]. The Expectational Hypothesis Theory suggests that more frequent extreme climate events severely impact investors' market expectations and investment strategies, intensifying the volatility of futures prices (Peri, 2017) [12]. Based on this, we propose the following research hypothesis:

H1: Extreme climate events increase the price volatility of agricultural product futures within the correlation network.

Systemic Risk Theory emphasizes that in the agricultural product futures market, extreme climate events can cause supply chain disruptions, affecting multiple related markets and products (Hui-Min LI et al., 2021) [13]. Such impacts can alter the close connections between different agricultural products within the futures correlation network, exacerbating the risk exposure of these relationships and increasing overall market volatility. Behavioral finance posits that extreme climate events trigger panic and irrational reactions among market participants (Guo et al., 2023) [14], particularly in highly concentrated networks where the contagion effects of emotions and behaviors are more pronounced, leading to excessive price reactions and high volatility. Thus, we propose the following research hypothesis:

H2: Extreme climate events enhance the price volatility of agricultural product futures by altering network clustering.

Seasonal Cycle Theory asserts that seasonality is a critical factor in the agricultural product futures market, as the growth cycles, planting, and harvesting periods directly impact prices. Agricultural production experiences varying fluctuations across the seasons of spring planting, summer growth, autumn harvesting, and winter storage. The occurrence of extreme climate events in different seasons affects the supply and demand of agricultural products to varying degrees, often more frequently in specific seasons, thus leading to seasonal heterogeneity in price volatility (Ceglar & Toreti, 2021) [15]. Based on this, we propose the following research hypothesis:

H3: There is seasonal heterogeneity in the impact of extreme climate on the volatility of agricultural product futures prices.

3 Empirical Study Design

3.1 Agricultural Product Futures Correlation Network Model

In the agricultural product futures network, nodes represent each type of agricultural product futures, while edges denote the correlation degree of price volatility between two agricultural products. Let N denote the number of agricultural product futures, T the study period, Δt the time span between two adjacent agricultural product futures networks, and denotes the length of the price time series used to construct an agricultural product futures network. Using the sample data from day $\left[1,\tau\right]$, the first agricultural product futures network is constructed where the daily return series of agricultural product futures i and j are $Y_i\left(1\right)$ and $Y_j\left(1\right)\left(i,j=1,2\ldots,N\right)$ respectively, constructing $M=INT[(T+\vartriangle t-\tau)/\vartriangle t]$ agricultural product futures networks (where X denotes the integer part of $INT\left(X\right)$) .The m-th network is denoted as $G^m(V,E), m=1,2,\ldots,M$, and the correlation coefficient of prices in the m-th network for agricultural product futures is calculated as Eq (1).

$$\rho_{ij}(m)=\frac{\langle Y_i(m)Y_j(m)\rangle-\langle Y_I(m)Y_j(m)\rangle}{\sqrt{(\langle Y_i^2(m)\rangle-\langle Y_i(m)\rangle^2)(\langle Y_j^2(m)\rangle-\langle Y_j(m)\rangle^2)}} \tag{1}$$

The return series is calculated using logarithmic returns like Eq (2). $p_i^t(m)$ represents the closing price of agricultural product futures i on day t .

$$Y_i^t(m)=ln\,p_i^t(m)-ln\,p_i^{t-1}(m) \tag{2}$$

Subsequently, $\rho_{ij}(m)$ is transformed into the corresponding distance metric $d_{ij}(m)$ like Eq (3); then the appropriate transformations are made to construct m-th agricultural product futures networks $G^m(V,E)$ that reflect the complex price fluctuation correlation patterns of N agricultural product futures from $[1+(m-1)\vartriangle t,(m-1)\vartriangle t+\tau]$ days like Eq (4).

$$d_{ij}(m)=\sqrt{2(1-\rho_{ij}(m))} \tag{3}$$

$$w_{ij}(m)=exp(-d_{ij}(m)) \tag{4}$$

Network topology features include the clustering coefficient. Drawing on prior research (Liu et al., 2022) [16], the clustering coefficient for weighted networks are constructed as Eq (5):

$$C=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\sum_{j,k}w_{ij}w_{jk}w_{ki}}{\max_j(w_{ij})\sum_{j,k}w_{ij}w_{ki}}\right) \tag{5}$$

Network entropy describes the level of system stability, where higher network entropy indicates stronger stability of the agricultural product futures correlation network system. A random matrix is obtained through the following formula Eq (6):

$$p_{ij}(m)=\frac{w_{ij}(m)}{\sum_{j=1}^{N}w_{ij}(m)} \tag{6}$$

Random matrix $p_{ij}(m)$ i row can serve as a transition probability distribution. Using Shannon entropy formula, the Shannon entropy HSS_{it} of a firm i in the agricultural product futures network m, as Eq (7):

$$HSS_{it}(m) = -\sum_{j=1}^{N} p_{ij}(m) \log p_{ij}(m) \tag{7}$$

3.2 Baseline Regression Model

The frequent occurrence of extreme climate events poses significant shocks to the financial system. This study aims to analyze the intrinsic connection between extreme climate events and the volatility of agricultural product futures prices, delving into how extreme climates influence this volatility. To test the empirical hypotheses, the following baseline regression model is constructed:

$$SAF_{i,t} = \alpha_0 + \alpha_1 Cl_{i,t} + \sum \alpha Control_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{8}$$

Here, i represents a specific agricultural product future, t denotes the period, covering 28 quarters from Q1 2016 to Q4 2022. The dependent variable $SAF_{i,t}$ is the price volatility of the i-th agricultural product futures in period t, and the independent variable $Cli_{i,t}$ is the number of times the i-th product was impacted by extreme climate events during t. $Control_{i,t}$ includes both micro and macroeconomic control variables that could influence the volatility of agricultural product futures prices, γ_i and δ_t represent individual fixed effects for agricultural product futures and year fixed effects, respectively, and $\varepsilon_{i,t}$ is the random error term.

Drawing from previous literature settings and data availability (K Anderson & A Strutt, 2014) [17], the following control variables were selected: micro-level controls include the logarithm of open contracts volume (*lnOCV)* reflecting market participants' expectations and attitudes, and the logarithm of trading volume (*lnVOL*) indicating market activity; macro-level controls include the logarithm of Gross Domestic Product (*lnGDP*) representing overall economic conditions, population total in logarithm (*lnPop*), inflation rate (*IR*), and average exchange rate (*AER*).

3.3 Data Sources and Descriptive Statistics

This study bases its analysis on data for Chinese agricultural product futures prices up to Q4 2022. It excludes data from non-trading days and agricultural products with severe data omissions due to suspensions. Eighteen types of agricultural product futures were retained. Price-related data for these futures were sourced from the Dalian Commodity Exchange and the Zhengzhou Commodity Exchange. Extreme climate data was obtained from monthly alert reports issued by the China Meteorological Administration National Warning Release System. Control variables were sourced from the National Bureau of Statistics, the OECD database, and the World Bank. Descriptive statistics for each variable are reported in Table 1.

Table 1. Descriptive Statistics

Variables	Obs.	Mean	Std.	Min	Max
$SAF_{i,t}$	504	2.7851	0.0208	2.6540	2.8904
$Cli_{i,\ t}$	504	10.5266	0.9271	9.0512	11.8824
lnOCV	504	11.4164	2.6902	1.6045	14.7583
lnVOL	504	11.0798	3.1755	1.7736	14.7779
lnGDP	504	12.3234	0.1754	11.9939	12.6617
lnPop	504	11.8528	0.0060	11.8390	11.8584
IR	504	1.9948	0.9896	-0.1090	4.9566
AER	504	6.7164	0.2344	6.3474	7.1296

4 Baseline Regression Analysis

4.1 Baseline Regression Analysis

Following the model settings described earlier, the baseline regression results are shown in Table 2. Column (1) presents the results of regressing agricultural product futures price volatility on extreme climate events. The coefficient estimate for Cli is significant at the 5% level, indicating a positive impact of extreme climate on the volatility of agricultural product futures prices. Columns (2) and (3) include results with micro-level and macro-level control variables added, respectively, and column (4) shows the results with both micro and macro control variables included. The inclusion of control variables increases the goodness of fit and enhances the explanatory power of the regression model, confirming the effectiveness and appropriateness of incorporating these variables. After adding control variables, the coefficient of Cli is significantly positive at the 10% level in all three cases, affirming that extreme climate enhances the volatility of prices within the agricultural product futures correlation network. Thus, H1 is validated.

Table 2. Baseline Regression Results

	SAF (1)	*SAF* (2)	*SAF* (3)	*SAF* (4)
Cli	0.0024**	0.0014*	0.0018*	0.0013*
	(0.0010)	(0.0008)	(0.0009)	(0.0008)
lnVOL		0.0022*		0.0023*
		(0.1258)		(0.0013)
lnOCV		-0.0026**		-0.0262**
		(0.0013)		(0.0013)
lnGDP			0.0307***	0.0042
			(0.011)	(0.0064)
lnPop			-0.6370**	-0.1733
			(0.2605)	(0.1909)
IR			0.0020	0.0018*

			(0.0011)	(0.0009)
AER			0.0058	-0.0025
			(0.0049)	(0.0030)
Cons	2.7600	2.7745***	9.8945***	4.7897**
	(0.0154)	(0.0092)	(2.9442)	(2.194)
N	504	504	504	504
R^2	0.0523	0.2408	0.1175	0.2479

(Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.)

4.2 Robustness Test

The study conducts robustness tests by replacing the dependent variable and altering the computation method of the core explanatory variable, with specific data obtained from the formulas mentioned earlier. The regression results are displayed in Table 3. Initially, the dependent variable was replaced with Renyi entropy to measure the volatility of agricultural product futures prices. Column (1) shows the results without control variables, and column (2) includes control variables. The results indicate that the core explanatory variable Cli is significant at the 1% level without control variables and at the 5% level with control variables, demonstrating the robustness of the baseline regression results. Subsequently, the explanatory variable was replaced for further robustness tests. Given the significant and widespread impact of extreme precipitation on the growth of agricultural products within the context of extreme climate events, the study substitutes the core explanatory variable with the occurrence of extreme precipitation events. Column (3) presents the results without control variables, and column (4) includes control variables. The coefficient for EP is significant at the 10% level, confirming the robustness of the baseline regression results and further validating H1.

Table 3. Robustness Test Results

	SAFR (1)	*SAFR* (2)	*SAF* (3)	*SAF* (4)
EP			0.0011*	0.0009*
			(0.0007)	(0.0005)
Cli	0.0047***	0.0029**		
	(0.0018)	(0.0013)		
Controls	NO	YES	NO	YES
Individual Fixed	YES	YES	YES	YES
N	504	504	504	504
R^2	0.1243	0.3033	0.0806	0.2479

(Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.)

5 Further Analysis

5.1 Mechanism Analysis

This paper considers the clustering coefficient as a mediating variable to test the impact mechanism of extreme climate on the volatility of agricultural product futures prices. Following the two-step method used by Semrau and Sigmund (2012) [18], the mediating effect model is constructed as follows:

$$C_{\mathrm{i,t}} = \theta_0 + \theta_1 Cli_{i,t} + \theta \sum Control_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{9}$$

$$SAF_{\mathrm{i,t}} = \beta_0 + \beta_1 C_{i,t} + \beta \sum Control_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{10}$$

In equations (9) and (10), $C_{i,t}$ represents the clustering coefficient of agricultural product futures i in period t. We focus on the significance of the coefficients in equations (9) and (10). When both β_1 and θ_1 are significant, a positive mediation effect is indicated. Column (1) in Table 4 shows the results of regressing the clustering coefficient C on the number of extreme climate events Cli, and column (2) shows the results of regressing the volatility of agricultural product futures prices SAF on the clustering coefficient C. In the regression of C on Cli, the coefficient of Cli is significant at the 1% level, indicating a positive impact of extreme climate on the clustering coefficient. In the regression of SAF on C, the coefficient of C is significant at the 10% level, suggesting that the clustering coefficient positively affects the volatility of agricultural product futures prices. Thus, H2 is confirmed.

The results demonstrate that extreme climate positively influences the volatility of agricultural product futures prices by increasing network clustering. A network with high clustering indicates significant complex interconnections among agricultural product futures within it. In such a correlation network, agricultural product futures as nodes are densely connected with other futures. These connections represent the volatility correlations among agricultural product futures. When network clustering is enhanced, these connections become tighter, and even minor fluctuations in any agricultural product futures can quickly propagate through the network, impacting other related futures. Due to the tight interconnections among agricultural product futures, volatility can spread more rapidly in a highly clustered network. The volatility can disperse throughout the entire network, enhancing the volatility of agricultural product futures prices.

Table 4. Mechanism Analysis Results

	C	*SAF*
	(1)	(2)
C		0.1823*
		(0.1097)
Cli	0.0042***	
	(0.0007)	

Controls	YES	YES
Individual Fixed	YES	YES
N	504	504
R^2	0.3864	0.2616

(Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.)

5.2 Heterogeneity Analysis

This paper further explores the impact of extreme climate on the price volatility of agricultural product futures across different seasons. Autumn is the main season for the maturity and harvest of most crops; extreme climate events during this season can lead to significant reductions in agricultural output, thereby affecting market supply. Accordingly, the 18 types of agricultural product futures analyzed in this study are categorized into two groups based on the harvest season: autumn and summer. Twelve are classified as autumn agricultural product futures, four as summer, and products like eggs and palm oil are available throughout the year. This classification allows for baseline regression analysis of price volatility for these three categories in response to extreme climate events.

The regression results are presented in Table 5, where column (1) represents autumn agricultural product futures, column (2) represents summer agricultural product futures, and column (3) represents year-round agricultural product futures. The coefficient of *Cli* in column (1) is significant at the 10% level, indicating that extreme climate events have a more pronounced effect on the price volatility of autumn agricultural product futures compared to those of summer and year-round. Specifically, while extreme climate events also occur in summer, this season is not the primary harvest period for most crops. Consequently, the impact of such events on market supply and market expectations is relatively minor, and these futures tend to occupy more peripheral positions within the correlation network, with less pronounced clustering effects. Therefore, the volatility of summer agricultural product futures prices is less significantly affected by extreme climate events. In contrast, most agricultural products mature and are harvested in autumn, forming tight connections within the correlation network. Autumn often witnesses a higher frequency of extreme climate conditions, leading to drastic reductions in crop yields, directly impacting market supply and, consequently, triggering price volatility. Thus, the impact of extreme climate on autumn agricultural product futures prices is notably more significant.

Table 5. Heterogeneity Analysis Results

	Aut	*Sum*	*All*
	(1)	(2)	(3)
Cli	0.0015*	0.0010	0.0006
	(0.0009)	(0.0020)	(0.0017)
Controls	YES	YES	YES

Individual Fixed	YES	YES	YES
N	333	107	56
R^2	0.2270	0.2343	0.2310

(Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.)

6 Conclusions and Policy Recommendations

In recent years, as the frequency of extreme climate events has continuously risen, researchers have begun to explore their impact on the volatility of agricultural product futures prices. Utilizing quarterly data from 2016 to 2022 for 18 types of agricultural product futures from the Zhengzhou Commodity Exchange and the Dalian Commodity Exchange, this paper constructed a correlation network of agricultural product futures to empirically test the impact of extreme climate on price volatility. The empirical results demonstrate that: firstly, extreme climate increases the uncertainty of agricultural product futures supply and investor expectations, significantly affecting the volatility of these prices. Secondly, extreme climate enhances the volatility of agricultural product futures prices by increasing network clustering. Thirdly, due to seasonality, extreme climate has a significant impact on the volatility of autumn agricultural product futures prices.

To control and reduce the impact of extreme climate events on the volatility of agricultural product futures prices, the following policy recommendations are proposed. Firstly, governments and relevant financial institutions should collaborate to establish a climate risk management framework that includes real-time monitoring and early warning of different extreme climate events. This would enable farmers and investors to make more rational production and risk management decisions, thereby reducing the impact of extreme climate on the volatility of agricultural product futures prices. Secondly, policymakers should improve information disclosure standards to enhance market transparency and reduce issues of information asymmetry, thus increasing the effectiveness and stability of the agricultural product futures market. Thirdly, promote the development of agricultural insurance by encouraging insurance companies to develop agricultural insurance products related to extreme climate. Offering differentiated risk protection services for different seasons can enhance the sustainability of agricultural production and minimize the volatility of agricultural product futures prices.

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