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Weather Shocks and Stock Market Performance: Insights from China's Agricultural Sector

By

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In recent decades, global climate change has resulted in a notable increase in the frequency and severity of extreme weather events worldwide, including in China, presenting considerable challenges for agricultural companies. For agricultural companies, these events signify heightened market risks related to production and operations, impacting financial markets. This study employs event study methodology and the Fama–French three-factor model to analyze the abnormal impacts of extreme rainfall and high-temperature events on agricultural stock returns in China from 2013 to 2023. This research finds a significant negative impact on the stock prices of agricultural companies within a short-term window (11 days) around extreme weather events, especially on the day before the event. Furthermore, the study finds that the market's reaction varies with the severity of weather disasters. Our research suggests that policymakers should recognize the consequences of such events on the stock market and adopt the following policies: strengthen corporate climate risk management, developing financial products related to climate risk, enhancing climate risk information disclosure, and bolstering government support and policy guidance.

Keywords: Climate Change, Extreme Weather, Agricultural Companies, Stock Returns, Event Study, Fama–French three-factor model

1 Introduction

In the contemporary era, climate risks have emerged as a focal issue of concern among global policymakers and the financial sector, posing substantial challenges to the sustainability of economies and societies across the globe (Antoniuk & Leirvik, 2024). The relentless progression of global climate change and ongoing global warming has unmistakably increased the frequency and severity of extreme weather events (Bourdeau-Brien & Kryzanowski, 2017). A World Meteorological Organization report highlights that, in the first twenty years of the 21st century, the world incurred economic losses of 2.97 trillion dollars due to climate-related natural disasters. Between 2000 and 2019, recorded disasters reached 6,681, significantly higher than the 3,656 events documented from 1980s to 2000s (Smith, 2021).

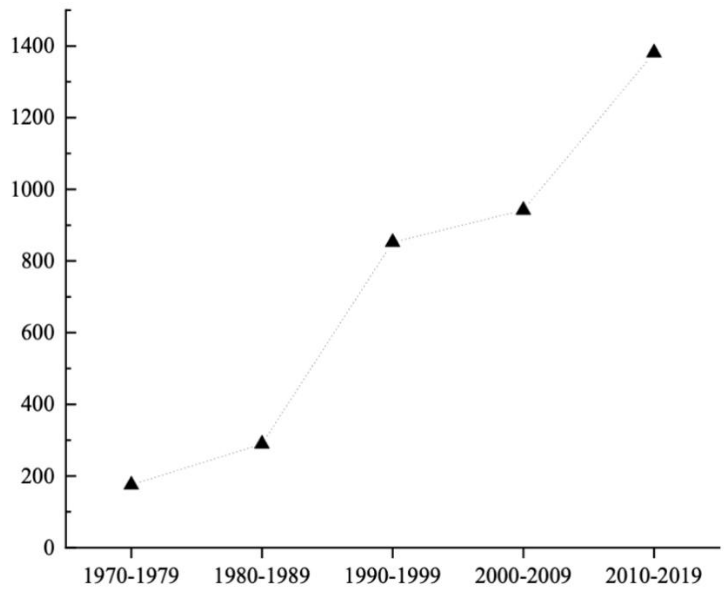

Figure 1: Global Economic Losses Due to Disasters (in billions of USD)

Extreme weather events profoundly impact the expansive territory of China. According to data from the Centre for Research on the Epidemiology of Disasters (CRED), between 2010 and 2019, the direct economic losses from natural disasters in Mainland China accounted for

16.89% of the total global losses. Fu et al. (2023) unveil annual rice yield reductions in China due to extreme precipitation events amounting to approximately 16.09 million tons, which has led to an approximate 8% decrease in the country's rice production over the past two decades, the world's second-largest economy, China's GDP reached 17.52 trillion dollars by the end of 2023. China's agricultural production has been severely damaged by the rising frequency of extreme weather events, especially during the severe high-temperature droughts of 2022, which resulted in substantial economic losses. In response to these challenges, the Chinese government has initiated several measures to establish a green financial system to meet climate change demands.

Nevertheless, a crucial question remains: "How do climate risks influence the performance of stock markets?" The objective of this study extends beyond examining the direct effects of climate risks on agricultural output and explores the impact of extreme weather events on the stock prices of enterprises closely related to the agricultural sector.

2 Research Significance

This study aims to provide a theoretical perspective for comprehending the intricate relationship among climate risk, agriculture, and the financial system.

Firstly, this research adopts an integrated classification of climate events, categorizing heavy rainfall and high temperatures as statistically defined by the China Meteorological Administration. For example, the China Meteorological Administration defines a rainfall event as 'torrential rain' when the precipitation reaches 50 millimeters or more in 24 hours, and as a 'heatwave' event when the daily maximum temperature reaches or exceeds 35°C. The foundational dataset provided by the official department facilitates a more precise assessment of the impact that different types and intensities of climatic events have on the share prices of companies involved in the agricultural sector.

Furthermore, this methodology enhances the precision in quantifying climate risk impacts and offers more comprehensive guidelines for risk management, thus providing a solid foundation for adaptive decision-making within financial markets.

Additionally, the innovative dimension of this research is evident in its application of diverse methodologies, incorporating short-term event analysis methods, market models, and the Fama-French three-factor model. This methodological variety facilitates a thorough exploration of the complex effects of climate change on the agricultural finance sector from different angles. Meanwhile, it also reveals more detailed and multi-layered impact mechanisms, offering a comprehensive research perspective.

Furthermore, this study distinctly focuses on publicly listed agricultural companies, examining the effects of extreme climate events on their stock prices, significantly enriching the existing body of literature. While the majority of existing studies concentrate on the direct impacts of climate change on agricultural output and revenue, this research broadens these impacts into the financial sphere, providing fresh insights into the influence of climate risks on the entire financial ecosystem (Bai et al., 2022; Khan et al., 2023; Xie et al., 2020).

Lastly, this study provides valuable insights for policymakers and financial practitioners regarding the various mechanisms of climate change that impact the agricultural financial market. It also equips financial institutions with actionable strategies for addressing and managing climate-related risks, contributing to green and sustainable finance growth.

3 Literature Review

3.1 The Impact of Climate Risks on the Economy

The impact of climate risks on the global economic and financial system has emerged as a prominent topic in multiple research disciplines. The impact of climate risks on the economic system is usually divided into two categories: transformation risks and physical risks(Clapp et al., 2017). Transformation risks focus on the transition of the economy to a low-carbon model, including the adoption of new technologies, the formulation of climate policies, and the evolution of production and consumption patterns. These changes challenge high-emission enterprises and their financial supporters (Antoniuk & Leirvik, 2024; Carney, 2015; Chabot & Bertrand, 2023). Physical risks stem from sustained weather patterns and sudden extreme weather events caused by climate change, directly impacting the economic system and financial assets (Antoniuk & Leirvik, 2024; Carney, 2015; Chabot & Bertrand, 2023). Against this backdrop, change initially focused on the study of transformation risks(Bressan & Romagnoli, 2021). Svartzman et al. (2021) investigated the emergence of new systemic financial risks associated with climate change and the transition toward a low-carbon economy. Their findings underscored the need for central banks to participate in formulating policies to mitigate climate change.

Battiston et al. (2021) conducted a study on the propagation of climate policy risks spread through the financial system, revealing that the timing of climate policies is crucial. Early and stable timing can adjust asset values smoothly and avoid systemic risks(Roncoroni et al., 2021). Wang et al. (2023) assessed the effect of climate policies on the fund market from direct and indirect risk contagion channels. The study demonstrated that indirect risk contagion amplified the adverse impact of climate policies on investment fund markets. In recent years, physical risks have been gradually gaining attention(Bressan & Romagnoli, 2021; Chabot & Bertrand, 2023). Research results from Burke et al. (2015) suggest that climate warming may exacerbate global inequality and significantly reduce global economic output. Likewise, Acevedo et al. (2020) also found that countries with hot climates have been significantly negatively affected by climate warming, mainly manifested in reduced investment, labor productivity, deterioration in human health, and lower agricultural and industrial output. In addition, Nakamura et al. (2013) concluded that personal consumption decreased significantly after disasters. As for the company level, Huang et al. (2018) research unveiled that disasters such as major storms, floods, and heat waves affected companies' profits and cash flow.

Scholars have also conducted a series of explorations and studies on more specific systemic financial factors. For example, Monasterolo (2020) discussed climate-related financial risks, priced climate risks in investor portfolios, and calculated the maximum loss they might cause systemic risk. Kedward et al. (2022) examined the approaches central banks and financial regulatory agencies adopted to manage biodiversity financial risks associated with climate finance. Their research suggests that financial regulatory agencies can prevent financing for commercial activities harmful to climate and biodiversity.

These existing studies usually focus on the macro impact of weather disasters on the economy. However, few studies delve into their direct relationship with stock market performance(U-Din et al., 2022). As the lifeblood of modern economic growth, the performance of the securities market is synchronized to national prosperity. Controlling the risk factors in the stock market is crucial for ensuring national stability and improving public welfare. Current research indicates climate disasters, such as hurricanes, droughts, and floods, exert a non-negligible impact on stock market returns and macroeconomics(Bourdeau-Brien & Kryzanowski, 2017; U-Din et al., 2022; Worthington, 2008). Lanfear et al. (2019) study revealed that hurricanes landing in the United States have had a significant abnormal impact on stock returns and liquidity, particularly affecting portfolios with smaller market values, higher book-to-market ratios, and more significant momentum more sensitively. U-Din et al. (2022) found that due to global warming, the frequency and intensity of extreme weather events in Canada have increased, and these weather disasters have had a significant negative impact on the Canadian stock market, especially in the IT and financial industries. Saunders (1993) identified that weather events can affect investors' sentiment, an effect likely manifested in stock returns. He reported that the return rates of the New York Stock Exchange index tend to exhibit negativity on overcast days(Saunders, 1993).

However, disaster events such as hurricanes, droughts, and floods are often not identified and classified until a few days after they occur, a delay that poses a challenge to the timely response of financial markets(Bourdeau-Brien & Kryzanowski, 2017; U-Din et al., 2022). More importantly, these extreme events frequently result from the cumulative effect of daily climatic conditions, e.g., continuous high temperatures or rainstorms, indicating that a sole focus on disastrous events may adequately capture the full potential impact of climate change on the economic and financial system(IPCC, 2012). In the field of regional economic impacts, West and Lenze (1994) pioneeringly proposed in 1994 that the consequences of natural disasters are primarily regional. Strobl (2011) identified that disaster events significantly impact the economy at the regional level, yet these effects scatter thoroughly at the national level. However, one study argues that precipitation, temperature, sunshine, and wind speed do not affect Australia's overall market returns (Worthington, 2008). The findings of Worthington et al.(2008) might be attributable to the influence of weather events limited to specific industries. Consequently, this research intends to focus on the agricultural sector as the primary focus of investigation.

All the above studies provide theoretical support for this study, focusing on local agricultural companies listed in various provinces in China. Existing studies have reflected from various angles the multifaceted and multilevel impact of climate disasters on the financial system. However, current research still lacks sufficient focus on everyday climatic conditions. Therefore, this study seeks to proactively identify and assess climate risks in advance by focusing on daily climate data in the provinces of China, particularly precipitation and temperature. This approach enhances the specificity and timeliness of risk assessments, improving our comprehension of the impacts of these daily weather events on the stock market.

3.2 The Impact of Climate Risks on the Agricultural Sector

As one of the most sensitive and vulnerable economic sectors, agriculture has particularly evident climate risk impacts. Most existing research focuses on the direct impact of climate change on agricultural output and income. For example, Schlenker and Roberts (2009) found that when temperatures reach 32 degrees Celsius, corn, soybeans, and cotton output declines sharply. Costinot et al. (2016) research showed that the impact of climate shocks on agricultural markets depends on the average level of shocks and their spatial distribution. Xie et al. (2020) research showed that most countries' annual average crop production will decrease in response to climate change. They forecasted that by 2050, corn and soybean production in the United States, Argentina, and Brazil will experience significant negative impacts. Rising and Devineni (2020) studied six major crops in the United States, including barley, corn, cotton, soybeans, rice, and wheat, and found that extreme temperatures caused by climate change will reduce the average yield of these crops and decrease the total agricultural profit. Focusing on China, the nation has long contended with climate risks including heavy rainfall, heat waves, and droughts. (Ke & Wen, 2009). Piao et al. (2010) research found that since 1960, China's climate has warmed significantly, increasing the frequency of heat waves. They predicted that the frequency of heat waves and extreme rainfall in most parts of China may further increase (Piao et al., 2010).

Regarding research on China's agriculture, scholars generally assert that climate change significantly affects China's agricultural production through temperature and precipitation(Tao et al., 2008; Xie et al., 2020). For example, Tao et al. (2008) research showed that even after considering countermeasures, a degree Celsius increase in temperature would lead to a 6.1% to 18.6% decrease in rice production. Regarding the stock market, research by Lin and Wu (2023) on listed companies in different industries in China found that disclosing information related to climate risks could mitigate future stock price crash risks. This mitigating effect was more conspicuous in listed companies in agriculture, forestry, animal husbandry, and fisheries. These studies provide strong support for the selection of indicators in this study. However, significant gaps persist in the existing literature on the impact of climate risks on agricultural companies in the financial market, especially in transitioning these risks into specific impacts on the vulnerability of China's agricultural companies and financial system. Through this unique perspective, this article explores the impact of climate change on Chinese agricultural companies and their performance in the financial market, focusing on the mechanism of extreme weather events affecting the stock prices of institutions closely related to the agricultural sector.

4 Theoretical Framework and Research Methodology

4.1 Interaction Between Climate Risk and Stock Performance

The occurrence of natural disasters triggered by climate change directly impinges on agricultural production, thereby influencing agricultural enterprises' stock prices and market valuations. These enterprises can employ strategies like technological innovation, diversification of crops, and leveraging insurance mechanisms to mitigate the impacts of climate risk.

In this study, a theoretical framework has been developed to understand the impact of climate risk on the stock prices of publicly listed agricultural companies. This framework assesses the effect of climate change on the stock prices of publicly listed agricultural companies. Extreme weather events directly affect the output and revenue capabilities of agricultural companies. These direct impacts manifest in companies' financial statements, influencing investor perceptions of the company's stock and affecting its price. Additionally, demand for insurance and loans also experiences an impact. The rise in extreme climate events escalates the claims for agricultural insurance and boosts the demand for insurance products and loans.

Agricultural companies on the stock market may seek increased insurance protection and financial backing to navigate climate risks, which influence their capital structure and financial expenses and affect stock prices.

Concerning indirect impacts, the repercussions of climate change on agricultural production may pervade through the entire macroeconomy, attenuating economic activity, reducing consumer purchasing power, and consequently impacting publicly traded agricultural companies' sales and profitability prospects. This indirect influence heightens market uncertainty, potentially causing fluctuations in stock prices.

4.2 Research Methodology

In terms of methodology, this research will utilize the short-term event analysis methods in conjunction with the Fama-French three-factor model to explore the effects of extreme weather events on the stock prices of China's agricultural sector-related publicly listed companies.

Financial research has widely used event analysis, market models, and the Fama-French three-factor model. Scholars primarily use event analysis to estimate the impact of specific events on stock prices. Wai Kong Cheung (2011) applied standard event analysis to explore the impact of including or deleting stocks in the Dow Jones Sustainability World Index on stock returns, risks, and liquidity. Oehler et al. (2017) explored the short-term abnormal stock returns of UK-listed companies in a five-day event window before and after the Brexit referendum through short-term event analysis. They found that the degree of internationalization of a company is a crucial pricing factor in the face of country-specific risk events. In climate event research, Lanfear et al. (2019) tested the abnormal impacts on stock returns and portfolios during five different window periods before and after hurricane events in the North Atlantic of the USA. Market models are classic models used in the financial sector to analyze stock market behavior by establishing a relationship between stock returns and overall market returns, identifying the impact of specific events on individual stocks or the overall market. For example, Ewing et al. (2006) used market models to study the impact of Hurricane Floyd and related news on the market value of insurance companies. Lasfer et al. (2007) compared the performance of developed and emerging markets in the face of stock market crashes using market models. These studies provide references for this study, using the Fama-French three-factor model. The three-factor model was proposed by Fama and French (1993) and can comprehensively explain the differences in stock returns. The three-factor model has been widely applied in research on China's A-share market, with many articles examining its application in predicting China's stock price movements(Drew et al., 2003; Jiao & Lilti, 2017; Liu et al., 2019). These existing studies provide theoretical model support for this study. This study integrates event research, market models, and the Fama-French three-factor model to construct an innovative multi-method research strategy. This comprehensive research methodology enables a multidimensional and in-depth analysis of how climate change affects the stock market related to agriculture, while simultaneously elucidating the nuanced and multilayered mechanisms of climate risks. Specifically, the design steps of the experiment are as follows.

4.2.1 Design Steps of the Event Analysis Methods

The delimitation of estimation and event windows remains a subject of considerable debate in event study methodology. This study defines the estimation window as a fixed period from

240 to 11 trading days before the event day, representing a trading year. As indicated by data from the European Centre for Medium-Range Weather Forecasting, while mainstream global weather forecasting models can predict weather conditions with a 90% accuracy up to five days in advance, their accuracy drops to about 40% for forecasts made ten days ahead. This sharp decline in forecasting reliability reflects the rationale for setting the estimation window to end 11 trading days before the event, encompassing 240 trading days, to avoid the market prematurely anticipating the event. As for the event window, this study contemplates three distinct temporal frames to assess the potential impacts of extreme weather events during their occurrence: one trading day before and after, three trading days, and five trading days. We use the returns from the subsequent trading day as a proxy for firms with no trading data available on the event day. The estimation window, defined as the period from 240 to 11 trading days before the event, is utilized to analyze normal and abnormal returns. The computation of normal returns establishes the expected performance in the absence of the event, with any deviations construed as ARs. Subsequently, CARs are aggregated to evaluate the aggregate impact of climatic events on stock prices. The individual stock returns are calculated using daily stock returns that consider reinvestment of cash dividends. In contrast, the market returns are based on each sub-market's daily market returns (weighted by circulating market value), also considering the reinvestment of cash dividends.

This study utilizes the market model to estimate normal returns, regressing historical stock returns against a market index to ascertain their interrelation. Therefore, stocks' abnormal return (AR) at that time was the actual return minus the expected return based on the market model. The study calculates Average Abnormal Returns (AARs) within the event window by averaging the abnormal returns of all considered stocks. Cumulative Average Abnormal Returns (CAAR) are then determined by summing the AARs across the event window.

The regression formula for the market model is expressed as:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$$

The parameters α_i and β_i of the market model are determined through least squares regression analysis, where $\varepsilon_{i,t}$ represents the error term.

Abnormal Returns:

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t})$$

In this formula, $R_{i,t}$ signifies the actual return of stock i at time t, $\hat{\alpha}_i + \hat{\beta}_i R_{m,t}$ symbolizes the expected return of stock i, $\hat{\alpha}_i$ denotes the expected return of the stock, and $\hat{\beta}_i$ indicates the stock's return sensitivity to market returns. $R_{m,t}$ represents the abnormal return, indicating the stock's sensitivity to public information.

4.2.2 Design Steps the Fama-French Three-Factor Model

The Fama-French three-factor model (FF3) is utilized to estimate the excess returns of stock repurchases as follows:

$$R_{it} - R_{ft} = a_i + b_i(R_{mt} - R_{ft}) + c_i SMB_t + d_i HML_t + \varepsilon_{it}$$

In this model, R_{it} signifies the return rate of stock i at time t; $R_{mt} - R_{ft}$ represents the market risk premium, where R_{ft} is the risk-free return rate at time t, based on the benchmark annual fixed deposit rate announced by the central bank, and R_{mt} denotes the daily market return rate weighted by circulating market value; SMB_t is the market value factor, indicating the difference in returns ratio between small and large market capitalization stock portfolios at time t, weighted by circulating market value; HML_t refers to the book-to-market value ratio factor, indicating the return ratio difference between portfolios with high and low book-to-market ratios at time t, weighted by circulating market value.

By fitting the stock returns ratio during the estimation window with the parameters in the formula, calculated the expected return ratio for each trading day within the window period, denoted as $E(R_{it})$:

$$E(R_{it}) = \hat{a}_i + \hat{b}_i(R_{mt} - R_{ft}) + \hat{c}_i SMB_t + \hat{d}_i HML_t + \varepsilon_{it}$$

The daily excess return AR_{it} and the cumulative excess return $CAR(t_1, t_2)$ within a specific window period are calculated:

$$AR_{it} = R_{it} - E(R_{it})$$

$$CAR_{it}(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it}$$

Arithmetic averaging of AR_{it} and $CAR(t_1, t_2)$ across various sample companies within the same event window yields the average excess return rate AAR_t and average cumulative excess return rate $CAAR(t_1, t_2)$:

$$AAR_t = \frac{1}{n}\sum_{i=1}^{n} AR_{it}$$

$$CAAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AAR_t$$

AAR_t takes the mean of the abnormal returns for all stocks in the sample on a given day t, providing a snapshot of the average effect of the event on the sampled stocks for that day. $CAAR(t_1, t_2)$ aggregates the daily average abnormal returns over the event period, offering a single measure of the overall average effect of the event across all sampled stocks.

3.2.2 T-test

A T-test is conducted for analysis, with the statistic as follows:

$$T_{AAR} = \frac{AAR_t}{S(AR_{it})/\sqrt{n}}$$

$$T_{CAAR} = \frac{CAAR(t_1, t_2)}{S(CAR_{it}(t_1, t_2))/\sqrt{n}}$$

T-tests are frequently employed in event studies to determine whether specific occurrences have statistically significant effects on company stock returns. In this analysis, the T-test facilitates an examination of the potential significance of extreme weather events on the stock performance of agricultural companies.

5 Data and Empirical Strategy

This study utilizes three principal datasets. The first dataset encompasses 24-hour precipitation data from 8 AM to 8 AM the following day, along with the highest temperature readings of the day for capital cities across 31 provinces in China, spanning from January 1, 2013, to December 31, 2023, sourced from the China Meteorological Administration database. The second dataset includes daily closing stock prices of 46 agriculture-related companies listed on the Shanghai and Shenzhen stock exchanges and headquarters location information for these companies. The Wind database provides data for all trading days within the specified period. Additionally, the study considers only the events that occurred during the trading days of stocks that were suspended, not yet listed, or delisted during this period. The third dataset includes the Fama-French three-factor model-related data, comprising the market risk premium factor, size factor, and book-to-market ratio factor for the A-share market of the Shanghai and Shenzhen stock exchanges, acquired from the CSMAR database.

This research posits that climate risk impacts agriculture, subsequently influencing the stock prices of agriculture-related enterprises. Specifically, the study hypothesizes a negative correlation between extreme weather events and the stock prices of listed agricultural companies in China. The China Meteorological Administration classified the following events as extreme weather occurrences:

(1) daily precipitation from 8 AM to 8 AM the next day ranging between 50-99.9 millimeters;

(2) daily precipitation from 8 AM to 8 AM the next day exceeding 100 millimeters;

(3) the highest daily temperature reaching between 35°C and 36.9°C;

(4) the highest daily temperature exceeding 37°C.

Within this framework, Event 1 occurred 751 times, Event 2 occurred 196 times, Event 3 occurred 3450 times, and Event 4 occurred 628 times in 11 years.

6 Empirical Results Analysis

The empirical analysis in this thesis examines the abnormal returns of agricultural companies before and after extreme weather events. This section first presents the findings related to abnormal returns under various climatic conditions, followed by discussing the robustness checks conducted. (Note: ***: p-value <0.01; **: p-value <0.05; *: p-value <0.1)

6.1 Abnormal Return Patterns After the Shock

This study begins by analyzing the market model with the estimation window (-240, -11), reporting on the tests of AARs and CAARs within the event window (-5, 5) for four events in Table 1. The results indicate that extreme weather events can cause adverse market effects. Specifically, the AARs according to the market model the day before the events were -0.3482%, -0.4737%, -0.1707%, and -0.2340%, all passing the 1% significance level. This result suggests that investors had negative market expectations before the extreme weather events, potentially influenced by prior knowledge obtained from weather forecasts. On the day of the event, none of the four events achieved statistical significance, potentially due to the influence of inconsistent market expectations and emotional responses, resulting in deviations of actual market behaviors from those anticipated. In the 3-5 trading days following the event, all four types of events displayed significantly negative AARs, which can primarily be attributed to extreme weather events leading to reduced crop yields or damaged farmland. These impacts could affect corporate financial statements, and quantifying the associated losses may necessitate an extended period. Consequently, investors' expectations regarding the company's future profitability might continue to be negatively impacted, potentially leading to substantial negative returns in the days after the event.

	Event1			Event2			Event3			Event4		
Day	AAR(%)	t value	p value	AAR(%)	t value	p value	AAR(%)	t value	p value	AAR(%)	t value	p value
-5	0.0175	0.1868	0.8518	-0.0311	-0.1548	0.8772	-0.0734	-1.4789	0.1393	-0.2650	-3.2029	0.0014***
-4	0.1113	1.2465	0.2130	0.0824	0.8218	0.4123	0.0148	0.2976	0.7661	0.0087	0.1061	0.9155
-3	-0.0340	-0.4024	0.6875	-0.2734	-1.7743	0.0778*	-0.0945	-1.9414	0.0523*	0.0048	0.0594	0.9526
-2	-0.1376	-1.7039	0.0889*	-0.2326	-1.8654	0.0638*	-0.0766	-1.6456	0.0999*	0.0573	0.6813	0.4958
-1	-0.3482	-3.9168	0.0001***	-0.4737	-1.9962	0.0475**	-0.1707	-3.8542	0.0001***	-0.2340	-2.9193	0.0036***
0	0.0552	0.5689	0.5696	0.0473	0.8632	0.3892	-0.0067	-0.1311	0.8957	0.096	1.0981	0.2724
1	-0.0933	-1.0231	0.3067	0.1473	1.0599	0.2907	0.0549	1.0944	0.2739	0.1389	1.5568	0.1198
2	0.0754	0.8799	0.3793	-0.1097	-0.5108	0.6102	0.0044	0.0912	0.9274	-0.1650	-1.8202	0.0690*
3	-0.3210	-3.4643	0.0006***	-0.1043	-1.0576	0.2918	-0.3591	-7.2104	0.0000***	-0.2551	-3.1051	0.0020***
4	-0.0577	-0.6418	0.5213	-0.3371	-1.0668	0.2876*	-0.1134	-2.3832	0.0172**	-0.2727	-3.3245	0.0009***
5	-0.1752	-1.9381	0.0531*	-0.1537	-0.8382	0.4031	-0.0423	-0.8558	0.3921	0.0354	0.4342	0.6643
Window	CAAR	t value	p value	CAAR	t value	p value	CAAR	t value	p value	CAAR	t value	p value
[-5, 5]	-0.7606	-3.8337	0.0001***	-1.239	-3.0676	0.0025***	-0.8627	-4.8752	0.0000***	-0.8507	-3.0099	0.0027***
[-3, 3]	-0.7187	-3.8837	0.0001***	-0.9343	-2.4059	0.0171**	-0.6483	-4.5703	0.0000***	-0.3571	-1.5625	0.1185
[-1, 1]	-0.3713	-2.4705	0.0137**	-0.2762	-0.8934	0.3728	-0.1226	-1.3626	0.1731	0.0009	0.0053	0.9957
[0, 3]	-0.2495	-1.5257	0.1275	-0.0109	-0.0317	0.9747	-0.3065	-2.6318	0.0085***	-0.1852	-1.0386	0.2992
[0, 5]	-0.4464	-2.4256	0.0155**	-0.4314	-1.1505	0.2515	-0.4622	-3.2610	0.0011***	-0.4225	-1.9092	0.0565*

Table 1: Test results of AAR and CAAR of the market model within the (-240, -11) estimation window (%)

6.2 Do different types of climate events have different impacts on the results?

6.2.1 Extreme rainfall events

The analysis suggests that if extreme precipitation events impact the production and operations of agricultural enterprises, the market will reevaluate the value of the related companies both before and after such events. The study has tested the market model using two estimation windows, [-240, -11] and [11, 240], and Table 2 demonstrates the impact of extreme rainfall events on the stock prices of agricultural companies. We found that both types of extreme rainfall events elicited significant adverse market effects on the day before the event. However, Event 1 showed significant negative AARs on the third and fifth days following the event. Remarkably, event 2 had a lower negative AAR than Event 1 the day before the event. For instance, using the [-240, -11] estimation window, Event 1's AAR was -0.3482%, while Event 2's AAR was -0.4737%, both significant at the 5% confidence level. These results suggest that extreme precipitation events (⩾ 100 mm) amplify the adverse market effects, with agricultural listed companies experiencing lower abnormal returns with more significant precipitation amounts. The primary reason is that investors assess companies' risks and prospects based on the precipitation levels, affecting stock performance. After the event, the AAR trends for events with different precipitation levels showed divergence: Event 1 exhibited significant negative returns on the third and fifth days post-event, whereas Event 2 only showed significant negative returns on the fourth day. This varied pattern indicates that as the severity of the disaster changes, the market adjusts agricultural companies' stock prices correspondingly.

The potential explanation for this outcome is as follows:

Firstly, the market and investors gradually absorb and adjust to the direct adverse effects, such as crop damage and farmland flooding, typically caused by extreme rainfall.

Secondly, the government may extend more aid for higher-level precipitation events, and companies may receive more insurance payouts, influencing market expectations for agricultural company stock prices.

Notably, within the event window [-3, 3], the CAAR values are significantly negative, consistently passing significance tests at the 5% or 1% levels. This persistent negative CAAR demonstrates that the adverse market effects induced by extreme precipitation events exhibit considerable durability, affecting investors' perceptions and valuations of agricultural enterprises far beyond the immediate aftermath of the events.

The CAAR test results within specific event windows reveal that the CAAR for agricultural listed companies triggered by Event 1 reaches its minimum within the (-3, 3) window and rebounds within the (-5, 5) window, passing the significance test. Meanwhile, the CAAR for agricultural listed companies caused by Event 2 is negative within the (-3, 3) window and passes the significance test. The consistency of the conclusions across both estimation windows underscores the robustness of the empirical results of this study.

	Event1 [-240,-11]		Event1 [11,240]		Event2 [-240,-11]		Event2 [11,240]	
Day	AAR(%)	t value	AAR(%)	t value	AAR(%)	t value	AAR(%)	t value
-5	0.0175	0.1868	0.2106	2.2932**	-0.0311	-0.1548	-0.0494	-0.2532
-4	0.1113	1.2465	0.1096	1.3058	0.0824	0.8218	0.0794	0.4192
-3	-0.0340	-0.4024	-0.0300	-0.3593	-0.2734	-1.7743*	-0.2091	-1.3397
-2	-0.1376	-1.7039*	-0.2127	-2.4741**	-0.2326	-1.8654	-0.2063	-1.1627
-1	-0.3482	-3.9168***	-0.2807	-3.1019***	-0.4737	-1.9962***	-0.3252	-2.0848**
0	0.0552	0.5689	-0.1535	-1.5483	0.0473	0.8632	0.0360	0.1755
1	-0.0933	-1.0231	-0.1669	-1.8578*	0.1473	1.0599	0.2456	1.4166
2	0.0754	0.8799	-0.1267	-1.4084	-0.1097	-0.5108	-0.1246	-0.8348
3	-0.3210	-3.4643***	-0.4399	-4.4507***	-0.1043	-1.0576	-0.1666	-0.9707
4	-0.0577	-0.6418	-0.0096	-0.1132	-0.3371	-1.0668*	-0.2399	-1.4850
5	-0.1752	-1.9381*	-0.1519	-1.7820*	-0.1537	-0.8382	-0.1308	-0.8197
Window	CAAR	t value	CAAR	t value	CAAR	t value	CAAR	t value
[-5, 5]	-0.5373	-2.7082***	-0.6786	-3.3684***	-0.5566	-1.3289	-0.6786	-1.7336*
[-3, 3]	-0.7187	-3.8837***	-1.2191	-6.3748***	-0.9343	-2.4059**	-0.6899	-1.8175*
[-1, 1]	-0.3713	-2.4705**	-0.5373	-3.6889***	-0.2762	-0.8934	-0.0505	-0.1637
[0, 3]	-0.2495	-1.5257	-0.8202	-4.5392***	-0.0109	-0.0317	0.0045	0.0132
[0, 5]	-0.4464	-2.4256**	-0.9552	-4.8572***	-0.4314	-1.1505	-0.2976	-0.8149

Table 2: AAR and CAAR test results for extreme rainfall events (%)

6.2.2 Extreme High-Temperature Events

The result shows that extreme high-temperature events can affect the production and operations of agricultural enterprises, prompting a market reassessment of the involved companies' valuations around the time of these events. Table 3 indicates that negative market impacts were observed the day before the events for both Event 3 and Event 4, with AARs of -0.1707% and -0.2340%, respectively, within the [-240, 11] estimation window, and both were statistically significant. Like precipitation events, weather forecasts appear to influence investor behavior in the context of high-temperature events. Upon comparing two high-temperature events, the study revealed that the lower extreme temperature events (35℃-36.9℃) elicited negative AARs 3-4 days before the event, achieving a 10% significance level with an AAR of -0.0945%. On the contrary, the market effects for the more severe temperature events (⩾37℃) were significantly negative five days before the event, reaching an AAR of -0.2650%. The AAR trend also shows moderate extreme temperature events (35℃-36.9℃) gradually weakened before the event day. These findings indicate significant differences in the market effects induced by moderate extreme temperature events (35℃-36.9℃) compared to more severe events (⩾37℃). A possible explanation is that the temperature range of 35℃-36.9℃ is more prevalent in certain regions, leading investors to regard such conditions as typical potentially and anticipate sustained detriment to the operations of agricultural firms. Temperatures ranging from 37℃ to 40℃ are less common, necessitating a period for investors to evaluate whether such conditions will exert a lasting impact. Consequently, adjustments in stock prices may only manifest after a delay as the market reflects this assessment. Three days after the event, the AARs for the two types of events reached -0.3591% and -0.2551%, respectively, and both were significant at the 1% level. The potential reason for this outcome might be that temperatures of ⩾37℃ are considered extreme in many areas perceived by investors as exceptional. The market may view extremely high temperatures as short-term incidents rather than ongoing climate change. Accordingly, the long-term impact on agricultural companies might be considered minimal. Therefore, when temperatures exceed 37 degrees, the negative market reaction induced by extremely high temperatures is not as prominent as that for events with 35-37 degrees. Additionally, CAAR test results within specific event windows suggest that compared to extreme temperature events (⩾37℃), moderate extreme temperature events (35℃-36.9℃) pose a more significant risk to the operations of agricultural firms. Consequently, the CAARs for agricultural listed companies affected by moderate extreme temperature events (35℃ -36.9℃) are negative in the (-3, 3) and (-5, 5) window periods and all pass the 1% significance test. The findings indicate that discrepancies in stock price performance following extreme temperature shocks can be attributed to variations in investors' reaction times and their assessments of the impact of different temperature ranges.

	Event3 [-240,-11]		Event3 [11,240]		Event4 [-240,-11]		Event4 [11,240]	
Day	AAR(%)	t value	AAR(%)	t value	AAR(%)	t value	AAR(%)	t value
-5	-0.0734	-1.4789	0.0109	0.2347	-0.2650	-3.2029***	-0.2781	-3.6710***
-4	0.0148	0.2976	-0.0676	-1.6615*	0.0087	0.1061	-0.0458	-0.6637
-3	-0.0945	-1.9414*	-0.0134	-0.3173	0.0048	0.0594	0.0764	1.1057
-2	-0.0766	-1.6456*	-0.1177	-2.9082***	0.0573	0.6813	0.0252	0.347
-1	-0.1707	-3.8542***	-0.1472	-3.7798***	-0.2340	-2.9193***	-0.2195	-3.1146***
0	-0.0067	-0.1311	-0.0428	-0.9978	0.096	1.0981	-0.0323	-0.4494
1	0.0549	1.0944	-0.1592	-4.2877***	0.1389	1.5568	-0.2395	-3.5662***
2	0.0044	0.0912	-0.1929	-4.9785***	-0.1650	-1.8202*	-0.2448	-3.3218***
3	-0.3591	-7.2104***	-0.4098	-9.6675***	-0.2551	-3.1051***	-0.2666	-3.8097***

4	-0.1134	-2.3832**	-0.0531	-1.3175	-0.2727	-3.3245***	-0.2018	-2.8819***
5	-0.0423	-0.8558	0.1057	2.5381**	0.0354	0.4342	0.1238	1.8495*
Window	CAAR	t value	CAAR	t value	CAAR	t value	CAAR	t value
[-5, 5]	-0.8627	-4.8752***	-0.6315	-6.9267***	-0.8507	-3.0099***	-0.5321	-3.6368***
[-3, 3]	-0.6483	-4.5703***	-0.9324	-11.2142***	-0.3571	-1.5625	-0.7870	-5.8437***
[-1, 1]	-0.1226	-1.3626	-0.3163	-5.2637***	0.0009	0.0053	-0.4372	-4.4487***
[0, 3]	-0.3065	-2.6318***	-0.7298	-10.2856***	-0.1852	-1.0386	-0.7235	-6.1392***
[0, 5]	-0.4622	-3.2610***	-0.7700	-10.1895***	-0.4225	-1.9092*	-0.7908	-5.5360***

Table 3: AAR and CAAR test results for extreme temperature events (%)

6.3 Analysis Based on the Fama-French Three-Factor Model

This study conducted analyses using the Fama-French three-factor model within the estimation window of [-240, -11]. Compared with the market model, AARs presented in Table 4 on the day before the events were recorded at -0.3682%, -0.7420%, -0.1309%, and -0.2732%, each achieving the 1% significance test. Nonetheless, according to the Fama-French model, the negative impact of Event 1 was transient, registering significance only on the trading day following the event, with an Average Abnormal Return (AAR) of -0.1761%. For Events 2, 3, and 4, the magnitude and direction of the abnormal returns predicted by the Fama-French model were similar to those of the market model, indicating that the Fama-French model offers consistent explanatory power for the negative impacts of these events. Event 2 exhibited the most significant negative abnormal return before the event, which may be attributed to the market participants' higher anticipation of negative impacts from the event or a greater sensitivity to such types of events. Following the events, the CAARs for all four events were consistently significant within the [-3, 3] and [-5, 5] windows, suggesting that the adverse effects of these events are enduring and not merely transient shocks to the market, potentially affecting investors' long-term profitability expectations for agricultural enterprises. The Fama-French model results consider factors beyond company-specific and market risks, confirming the impacts of extreme weather disaster events on the market performance of agricultural enterprises as indicated in the market model.

	Event1		Event2		Event3		Event4	
Day	AAR(%)	t value	AAR(%)	t value	AAR(%)	t value	AAR(%)	t value
-5	0.0593	0.5711	-0.1007	-0.6322	-0.0096	-0.1672	-0.1173	-1.1464
-4	0.1392	1.4340	-0.1517	-1.0469	0.0068	0.1194	-0.0796	-0.8286
-3	-0.0080	-0.0830	-0.2784	-1.8854*	-0.1492	-2.7757***	-0.0848	-0.8926
-2	-0.1238	-1.3478	-0.4028	-2.2431**	-0.0829	-1.5905	0.0776	0.7942
-1	-0.3682	-3.7119***	-0.7420	-4.9243***	-0.1309	-2.6036***	-0.2732	-2.7815***
0	-0.0831	-0.7378	-0.0924	-0.5454	-0.0519	-0.8918	0.0477	0.4475
1	-0.1761	-1.6765*	-0.1662	-1.0046	0.0542	0.9478	0.1037	0.9574
2	0.0208	0.2178	-0.0820	-0.5404	-0.0635	-1.1525	-0.1853	-1.7259*
3	-0.0441	-0.4757	-0.1378	-0.8584	-0.1958	-3.5842***	-0.2146	-2.2028**
4	-0.0099	-0.1028	-0.3724	-2.5039**	-0.1042	-2.0093**	-0.0343	-0.3686
5	-0.0972	-0.9897	-0.1947	-1.1641	-0.0006	-0.0101	0.0282	0.2959
Window	CAAR	t value	CAAR	t value	CAAR	t value	CAAR	t value
[-5, 5]	-0.5822	-2.7716***	-0.8471	-1.8717***	-0.7274	-3.4998***	-0.7319	-2.0235**
[-3, 3]	-0.7108	-3.5735***	-1.6430	-5.0657***	-0.6199	-3.7804***	-0.5289	-1.8586*
[-1, 1]	-0.5959	-3.6323***	-0.9193	-3.8800***	-0.1286	-1.2416*	-0.1218	-0.6191
[0, 3]	-0.2631	-1.4947	-0.4358	-1.7210*	-0.2569	-1.9367*	-0.0339	-0.1699
[0, 5]	-0.3540	-1.7839*	-0.8878	-3.1410***	-0.3616	-2.2579**	-0.2545	-0.9632

Table 3: AAR and CAAR test results by FF3 model (%)

7 Discussion

This research studies the impact of climate risk on the financial market by analyzing the stock performance of companies in the Chinese agricultural sector listed on the stock market before and after extreme weather events. Empirical results display that extreme weather events, including extreme precipitation and extremely high temperatures, significantly negatively impact the stock prices of agricultural listed companies, especially on the day before and 3-5 trading days after the event. This finding confirms the direct impact of climate change risk on the real economy and highlights the financial market's sensitivity and vulnerability to climate risk, offering an intriguing perspective for understanding and responding to climate risks.

Extreme weather events lead to damage in agricultural production, affecting agricultural companies' profit expectations and shareholder wealth, thereby triggering a negative market reaction. This impact is most pronounced in the short term following the event, indicating that the market's response to extreme weather is rapid and sensitive. Furthermore, the effects of various extreme weather events on stock prices differ, potentially due to differences in the severity and frequency of the events and investors' anticipations regarding their impacts. For example, the impact of extreme precipitation on stock prices is more significant when the precipitation is heavy, and the negative impact of extreme high temperatures on stock prices is more pronounced within a specific temperature range.

The following policy recommendations and practical guidance are proposed drawing on the findings of this study:

First, we shall strengthen climate risk management. Considering the profound impact of extreme weather events on companies' stock prices in the agricultural sector, these listed entities should bolster their climate risk management strategies and implement adaptive measures. These could include enhancing crop planting structures, introducing varieties resistant to drought and floods, and fortifying disaster early warning and emergency response mechanisms, all aimed at mitigating the effects of extreme weather on production.

Second, we suggest that financial institutions be encouraged to develop products and services addressing climate risks, such as weather derivatives and agricultural insurance. These tools would assist agricultural enterprises in transferring risk and mitigating the economic impacts of extreme weather events.

Third, the mechanism for disclosing climate risk information should be enhanced. Regulatory agencies should strengthen the requirements for listed companies to disclose such information, compelling them to assess and publicly report the climate risks they encounter and their response measures. This increased transparency will aid investors in making more informed strategic decisions.

Fourth, we shall strengthen government support and policy guidance. The government should develop corresponding support policies and measures, such as technological support and financial subsidies, to help agricultural enterprises improve their disaster resilience and promote green and sustainable finance development through policy guidance. Furthermore, improved weather forecasting and enhanced emergency management measures can be crucial in mitigating the adverse effects of weather-related disasters. (U-Din et al., 2022).

Finally, governments should formulate and implement effective policies and undertake actions related to climate change to curb the human exacerbation of weather disasters, including promoting afforestation and protecting ecosystems.

8 Conclusions

This study presents evidence of the impact of extreme weather disaster events on stock returns in the Chinese market. Notably, in previous research, some researchers have found that weather disaster events significantly affect stock returns(Bourdeau-Brien & Kryzanowski, 2017; U-Din et al., 2022), while others suggest that returns are not affected by these events (Wang & Kutan, 2013; Worthington, 2008). Following previous research findings, this study substantiates the impact of weather disasters on the agricultural industry by analyzing the stock price performance of publicly listed companies within this sector. Specifically, through event study methodology, market models, and the Fama-French three-factor model, this research empirically investigates the effects of daily rainfall and high-temperature types of extreme weather events on the stock prices of agricultural sector companies listed in China. The results indicate that extreme rainfall and high temperatures significantly negatively impact agricultural companies' stock prices, and this impact persists from 1 to 5 days after the event. Compared to high-temperature events, extreme rainfall has a more significant short-term negative impact on agricultural companies. Furthermore, the negative impact on agricultural companies deteriorates as the rainfall intensity increases. The findings of this study also highlight the direct impact of different levels of climate disaster events on the financial market, particularly in the agricultural sector. This insight is crucial for market participants, policymakers, and researchers.

Future research could start with the following intriguing topics.

Firstly, researchers could conduct a comparative analysis of the impact of climate risk on the stock valuations of companies within the agricultural sector across various nations and regions, analyzing the influences of market structure, climate conditions, and adaptability on these valuations. Moreover, future research could broaden the scope to examine the impact of climate risk on other industries integral to the agricultural supply chain, such as the food processing and retail sectors. This expansion would provide a more comprehensive perspective for adapting to climate change and managing associated risks.

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