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The effects of drought on stock prices: An industry-specific perspective

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In this study, we examine the effect of drought on industry stock prices using a balanced panel of monthly data for 15 industries classified by China Securities Regulatory Commission in 2012. By combining the results of ordinary least squares (OLS) estimation and quantile regression models, we present a comprehensive evaluation of the relationship between drought and industry stock prices. The OLS regression results generally show that drought is negatively correlated with industry stock prices. However, quantile regression reveals that the effect of drought changes from positive to negative from the lowest to the highest stock price quantile. In addition, drought resistance capacity varies by industry. We further use threshold regression to determine the effects of investor sentiment on the relationship between drought and stock prices and identify two different regimes: low sentiment and high sentiment. In the low sentiment regime, drought has a significant negative effect on industry stock prices, while in the high sentiment regime, drought has a significant positive impact on industry stock prices.

KEYWORDS

drought, quantile regression, threshold regression, industry perspective, stock prices

Introduction

The global climate system is undergoing a major change characterized by global warming. Increasing climate change is becoming one of the main drivers of drought, as it speeds up the global water cycle, making wet areas wetter and dry areas drier (Wanders and Wada, 2015). Disintegrated planning, weak governance, and myopic water management can also lead to socioeconomic drought[1]. As a result, water resource management has become more important and difficult. Undoubtedly, a more detailed understanding of the economic impact of drought, including the identification of at-risk industries and the mechanisms contributing to drought hazards, are key steps toward a stronger risk-based approach to drought management. In a relatively efficient market, the

1 Socioeconomic drought refers to conditions whereby the water demand outstrips the supply, leading to societal, economic, and environmental impacts (Hayes et al., 2011; Zseleczky and Yosef, 2014).

10.3389/fenvs.2022.978404

impact of a disaster such as drought should be reflected by changes in short-run stock prices, which indicate market views on expected changes in the value of assets (Beatty and Shimshack, 2010; Balvers et al., 2017; Ding et al., 2022). In this study, the effect of drought is approached from the perspective of its effect on industry stock prices.

According to the Chinese Ministry of Water Resources, although China is rich in fresh water resources, its per-capita water resource level is only around a quarter of the global level. Consequently, China is one of 13 countries considered "water-poor" worldwide. This issue is exacerbated by the uneven distribution of China's water resources, which is characterized by greater water availability in southern areas but a higher distribution of cultivated land in northern areas. More than 400 of China's 660 cities face water shortages (i.e., two-thirds of cities have insufficient water supply)[2]. Regions across China exhibit significant cross-sectional variations in climate. Together with regional diversity, climate change has exacerbated the uneven distribution of water resources, thus increasing the disconnect between supply and demand in northern China and perpetuating regional drought in southern China. In addition, China is both a big agricultural country and an industrial country. Agriculture is most vulnerable to drought. Industrial production process is often accompanied by water pollution, which making the problem of drought and its impact more serious. A wrong or lack of intervention is likely to trigger socioeconomic drought. China's geographic vastness, distinct industrial and climatological features provide a unique setting for a study on the economic impact of drought in an Asian country and enable new insights.

Initially, we estimate drought trends using the Palmer Drought Severity Index (PDSI)[3], a widely used resource in climatology studies on drought (Palmer, 1965; Dai, 2011; Trenberth et al., 2014). Our sample comprises the monthly stock return data of 15 industries from 2000 to 2014. We then analyze the effect of drought by industry to account for industry heterogeneity, as this effect depends on both the industry's water demand and the upstream and downstream water demands. From the perspective of the capital market on the economic impact of drought, we successively examine the responses of stock prices in different quantiles and the role of investor sentiment. We mainly use the quantile regression model to study the effect of drought on the conditional distribution of industry stock prices. The weather-related literature reveals that climate factors can affect stock prices by influencing investor sentiment (Kamstra et al., 2000; Hirshleifer and Shumway, 2003; Kamstra et al., 2003; Lu and Chou, 2012; Schmittmann et al., 2015) and that investor sentiment can lead to asymmetric stock price reactions (Chen et al., 2013; Ni et al., 2015). Inspired by this earlier work, we introduce the threshold regression model and find a threshold effect of investor sentiment on the relationship between drought and industry stock prices.

The OLS regression results generally show that drought is negatively correlated with industry stock prices. However, quantile regression reveals that the effect of drought changes from positive to negative from the lowest to the highest stock price quantile. In addition, drought resistance capacity varies by industry. We further use threshold regression to determine the effects of investor sentiment on the relationship between drought and stock prices and identify two different regimes: low sentiment and high sentiment. In the low sentiment regime, drought has a significant negative effect on industry stock prices, while in the high sentiment regime, drought has a significant positive impact on industry stock prices.

This study makes two contributions to the literature. First, by using data from China, a unique setting, to analyze whether and how drought affects stock prices, we contribute to a poorly explored area of research on the effects of climatological factors, climate change, and environmental disasters on economic factors. Second, we present the first industry-wide analysis of the effects of drought on stock prices. Previous studies in this area mainly focus on specific industries, such as agriculture, mining, and real estate (Bonnafous et al., 2017; Farzanegan et al., 2019; Hong et al., 2019), which usually have large water demand and undoubtedly are affected directly by drought. The potential effects of drought on other industries have received little attention. Our study addresses this gap in the literature.

The remainder of this paper is organized as follows. Section 2 describes the channels from drought to industry stock prices. Section 3 presents our data. Section 4 includes an introduction and demonstration of the model and discussion of the empirical results. Section 5 presents the robustness test. The final section contains our concluding remarks.

Why does drought affect industry stock prices?

Drought has direct and indirect economic effects on agriculture and non-agriculture industries through soil moisture, rivers,

2 http://www.ches.org.cn/ches/kpyd/szy/201703/t20170303_879724.htm.

3 The Palmer Drought Index (PDSI) is based on the relationship between water supply and demand. A situation wherein the local water supply falls short of demand is defined as drought; otherwise, it is considered humid. Water supply data are relatively easy to obtain and are usually expressed by precipitation. In contrast, water demand calculations are more complex because they involve the influences of temperature, soil properties, land use, and other factors. To solve this problem, Palmer put forward the concept of "climatically appropriate for existing conditions," defined water demand as "climatically appropriate precipitation," and use the difference between actual precipitation and climatically appropriate precipitation to determine water profit and loss status. The PDSI considers not only the current water supply and demand but also the influence of previous dry and wet conditions and their durations on the current drought situation. Although this index is not perfect, it is the most widely used and readily available resource for climate studies (Alley, 1984).

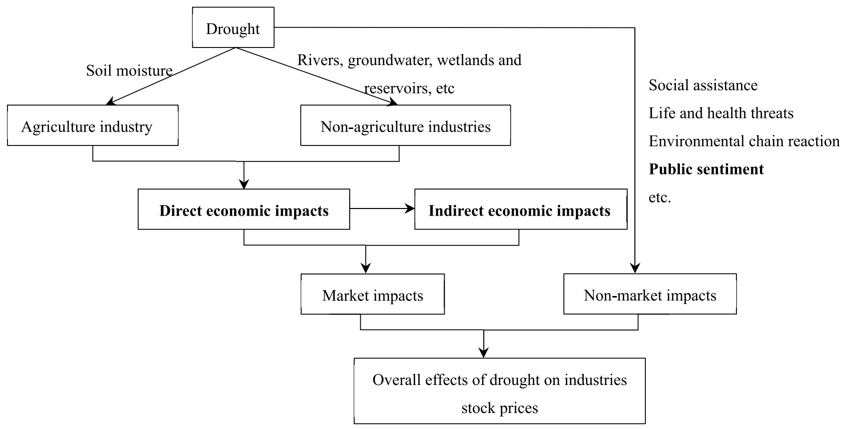

FIGURE 1
An overview of drought effects on industry stock prices.

groundwater, wetlands and reservoirs. In an efficient market, these effects will be reflected in industry stock prices. We call this phenomenon the market impacts of the drought on industry stock prices. From a non-market point of view, government departments and civil society organizations assist affect industries and individuals. For individuals, in addition to the risk of property loss, drought and the environmental chain reaction also brings threats to life and health. These consequences affect investor sentiment, which in turn feeds into risk-taking behavior and stock prices. In short, the effects of drought on industry stock prices can be divided into market and non-market levels. Among them, we focus on two more specific components, the economic impact and investor sentiment. Figure 1 is an overview of drought effects on industries stock prices.

A market-oriented perspective

It is a common practice in the literature to classify the economic effects of natural hazards, including drought into direct and indirect categories (Parker et al., 1987; Cochrane, 2004; Rose, 2004; Van der Veen, 2004). However, a unified and clear definition of the two categories is lacking. Defining the direct effects of drought as physical damage to buildings, crops and natural resources without considering large-scale economic damage does not meet the practical needs of drought economic impact assessment. Therefore, we follow Cochrane (2004), Rose (2004) and Ding et al. (2011) to expand the direct effects of drought to include both physical damage and consequences such as business disruption and unemployment. The indirect impacts are defined as the interaction between industries and the cost of transaction.

For direct effects, agriculture is the most vulnerable industry to drought. Inadequate soil moisture results in crop failure. The economic losses and distribution caused by negative supply shocks of agricultural products depend on the market structure and the supply-demand relations. Farmers can get compensation by buying insurance, or transfer economic losses through high prices. In extreme cases, they can even profit from drought. However, offsets are widespread across vast territories. That is, higher crop prices will attract the inflow of crops from non-arid areas, which curbing local crop prices increase.

Drought also has a direct economic impact on non-agricultural industries by affecting rivers, groundwater, wetlands and reservoirs. Utilities such as water management and water supply need to pay for a balance between supply and demand. In the tourism industry, the development space of forest, grassland, ice and snow, and wetland becomes smaller. The safety and accessibility of the shipping industry are threatened by the drying up of rivers. Other industries are more or less directly affected by drought due to water and environmental needs.

For indirect effects, the direct effects of drought on an industry spread upstream or downstream. In the shipping industry, for example, 2.93 billion tons of goods pass along the Yangtze River in 2019, including large quantities of iron ore, thermal coal and mining and construction materials[4]. Poor transportation of thermal coal will aggravate electricity shortage, while shortages of iron ore and mining materials will affect manufacturing, real estate and mining industries. The increase in raw material prices is expected to pass through the price transfer, but is also likely to cause a decline in income. Any form of economic losses will influence the economic decisions of

4 Website of the Ministry of Transport of the People's Republic of China: https://www.mot.gov.cn/.

market participants in the next stage, thus driving a new round of economic impacts.

A sentiment-oriented perspective

A number of psychological results show that natural disasters have a great influence on sentiment (Nolen-Hoeksema and Morrow, 1991; Krug et al., 1998; Jha et al., 2021). The space-time character of drought should be considered when analyzing its impacts on sentiment. Spatially, drought affects sentiment in arid area and non-arid area through different mechanisms. Direct and indirect gains and losses of assets, as well as life and health crises, may be the main channels through which drought affects the sentiment of arid communities (Bica et al., 2017). Finance can be the savior or the oppressor. Financial Insurance promotes risk-sharing, but insurance contracts and intermediaries are usually designed to prevent subsequent renegotiations (Diamond and Rajan, 2001; Agarwal et al., 2017). When uninsured disasters occur, economic losses are usually concentrated in a small group of people, leading to dissatisfaction and negative emotions (Chetty et al., 2020; Mongey et al., 2021). However, insurance measures may also be ineffective in compensating for property losses and mitigating negative sentiment. Gennaioli et al. (2020) show that insurance claims are often disputed and lead to non-payment or reduced payment. Government aid can act as a backstop and stabilize market sentiment (Jha et al., 2021). In addition, drought may have a positive emotional impact on those who profit from it, such as producers of drought resistance devices and farmers outside the disaster zone.

Social media has changed the way the public engages in disasters and other mass emergencies (Palen and Hughes, 2018). People outside the disaster area can easily communicate sentiment with people in the disaster area through social media, and get witness texts, photos, videos, maps and other information about the disaster. Bica et al. (2017) find that locals are more focused on human suffering and losses, while non-locals are more concerned about recovery and relief efforts. Individual orientations reflected by different positions and concerns produce different sentiments (Bravo-Marquez et al., 2014). Sentiment analysis through machine learning using social media data has become a popular topic in recent years. Yoo et al. (2018) argue that real-time generated content in social media includes information about social issues and events such as natural disasters. They developed the Polaris system to use the real-time information to analyze and predict the emotional trajectories of users. Neppalli et al. (2017) use Twitter data to visualize users' emotions around hurricanes, and then analyze their emotional communication.

From the timeline, public sentiment is evolving at different stages of disaster development. Gruebner et al. (2017) use social media data to surveilla New York population mental health after disasters. They find 24 sentiments spatial clusters. Among them, sadness and disgust are the most prominent sentiments. Anger, confusion, disgust and fear clusters appear pre disaster, surprise is found peri disaster, and sadness emerges post disaster. Han and Wang (2019) use microblog data to analyze people's sentiments during the flood in Shouguang City, China in 2018, and detect nine sentiments. They prove that these sentiments have different time trends.

The psychological literature shows that affective states induce emotional congruence bias in risk decision making, which is expressed as a preference for risk in positive sentiments, and risk aversion in negative sentiments (Yuen and Lee, 2003; Schulreich et al., 2014; Otto et al., 2016). This phenomenon is also fully supported by clinical observations. People with depression tend to ignore the positive aspects, while people with mania tend to ignore the potentially negative consequences of their actions (Beck, 2008; Edition, 2013; Huys et al., 2015). Inspired by this, behavioral economics and finance researchers have identified events that appear to affect asset prices, particularly stock prices, through their impacts on the affective state of investors. Edmans et al. (2007) find a significant stock market decline after soccer losses. Frieder and Subrahmanyam (2004) believe that stock prices are boosted by anticipation and optimism ahead of Patrick's Day and Rosh Hashanah. Lepori (2015) finds that endings of hit teleplay trigger negative emotions in viewers, leading to a drop in stock prices. Saunders (1993) confirms that weather-related sentiment has a significant effect on stock prices. The average stock price on a sunny day is higher than on a cloudy one. Bassi et al. (2013) provide further experimental evidence that sunshine and good weather promote risk-taking through sentiment channel.

In summary, the drought can affect industry stock prices through economic impact and investor sentiment. Given China's vast territory, people's complex positions and emotions, and the complex space-time nature of the drought, we cannot accurately predict the size and direction of drought impacts on industry stock prices. Therefore, it becomes a major problem to be studied in this paper. Another question we are interested in is whether the effects of drought vary depending on investor sentiment.

Data and variables

Sample selection and data sources

Our sample comprises a monthly balanced panel of data from 15 industries classified as follows by the China Securities Regulatory Commission in 2012: agriculture, forestry, animal husbandry, and fishery (AFAHF); mining (Min); manufacturing (Man); electricity, heat, gas, and water production and supply (EHGWPS); construction (Con); wholesale and retail (W&R); transportation, storage, and postal services (TSPS);

accommodation and catering (A&C); information transmission, software, and information technology services (ITS); finance (Fin); real estate (RE); leasing and business services (LBS); water, environment, and public facilities management (WEPFM); culture, sports, and entertainment (CSE); and comprehensive industry (Com). The data span the 2000–2014 period. Economic and financial data are obtained from the China Securities Market and Accounting Research database. As a quantitative measure of drought, PDSI data are taken from the website of the National Center for Atmospheric Research.

Variables

Industry stock return is the dependent variable and drought trend is the independent variable. We first calculate the industry stock return (*Indreturn*) by weighting the monthly stock return of A-share listed companies in a given industry by the circulating market value and subtracting the risk-free interest rate as follows:

$$Indreturn_{it} = \frac{\sum_n w_{nt} r_{nt}}{\sum_n w_{nt}} - R_t \tag{1}$$

where subscripts i, t, and n represent the industry, time, and number of companies in the industry, respectively. w_{nt} is the outstanding market value of stock n at time t-1. The monthly stock return of each company (r_{it}) is defined as the ratio of the comparable closing price on the last trading day of each month, considering the reinvestment of cash dividends, to the corresponding value of the previous month, minus 1. The risk-free rate (R_t) is based on the 3-month time deposit rate. The industry classification of each company follows the industry classification rules set by the China Securities Regulatory Commission (CSRC) in 2012. We set the following two types of company stock returns as missing values: stocks whose prices rise by 300% or more in 1 month and fall by 50% or more in the next month (rise and then fall), and stocks whose prices have risen by more than 1000% in a month. Finally, all stock prices are winsorized at the 1st and 99th percentiles to reduce the impact of outliers on our results. We focus on A-shares because they account for 99.5% of total market capitalization; in contrast, B-share stocks are small and illiquid. The circulation market value-weighted return heavily weights large and more liquid stocks, which alleviates the disturbance caused by outlying small firms.

As the drought trend (*Trend*) is calculated based on the PDSI index, it is beneficial to understand the ranges and trends of the PDSI values at the sample sites. The PDSI usually falls between −4 and 4; values greater than 0 indicate the degree of moisture, while lower values indicate the degree of dryness. Table 1 presents the correspondence between the PDSI values and drought severity. Figure 2 plots the time series of monthly PDSI values for China from 1930 to 2014 with a fitted trend line. The PDSI fluctuates violently within a range of roughly −6 to 6. The downward-sloping fitted trend line indicates the increasing drought trend in China. The average PDSI from 1930 to 2014 is −1.096, compared with −2.774 during the sample period of 2000–2014; thus, the drought situation in China has changed from slight to moderate drought. Together with the short-term violent fluctuations, these data demonstrate that China is affected by long-term drought and threatened by short-term floods.

We focus on the impact of the long-term drought trend because it has greater economic value and policy guidance implications. Following Hong et al. (2019), we measure *Trend* as

$$PDSI_t = a + bt + cPDSI_{t-1} + \varepsilon. \tag{2}$$

This AR(1) model is augmented with a deterministic time trend t. The coefficient b of the deterministic time trend is the parameter of interest that captures the long-term drought trend. We define *Trend* as equal to b. A smaller value of *Trend* indicates a more serious long-term drought trend. The recursive window method is applied to estimate the above model. $Trend_t$ is estimated using PDSI data from January 1990 to month t. In addition to considering the impact of quarterly precipitation differences, we use two alternative measures of drought in the robustness test. One measure is the drought index calculated based using the entire Box–Jenkins iterative process; the other is the lag period drought index.

We introduce some control variables according to the actual situation and the relevant theoretical model. First, we include the 36-month moving average PDSI (*PDSI36*) in the control variables to capture the short-term drought effect. As shown in Figure 2, China faces long-term drought problems but short-term flood hazards.

Our analysis of industry stock prices is based mainly on the Fama–French three-factor model. Therefore, we add the market factor (*RP*), the size factor (*SMB*), and the book-to-market factor (*HML*) to the control variables.

RP is the difference between the monthly A-share market return and the monthly risk-free interest rate. The monthly market return rate is calculated using the weighted average method for the market value of circulation, and cash dividend reinvestment is considered.

SMB is the difference between the monthly returns of a small-cap stock portfolio and a large-cap stock portfolio. Portfolio division is based on the Fama 2 × 3 portfolio division method. The monthly return of the portfolio is calculated using the weighted market value of circulation.

HML is the difference between the monthly returns of a combination of the high book-to-market ratio and the low book-to-market ratio. The portfolio division is based on the

TABLE 1 The correspondence between PDSI values and drought degree.

PDSI value	Drought degree	PDSI value	Drought degree
≤−4	Extreme drought	0.5–1	Initial moisture
−4 to −3	Severe drought	1–2	Slight moisture
−3 to −2	**Moderate drought**	2–3	Moderate moisture
−2 to −1	Slight drought	3–4	Heavy moisture
−1 to −0.5	Initial drought	≥4	Extreme moisture
−0.5 to 0.5	normal		

This table reports the correspondence between PDSI values and drought degree. The bold part shows the drought situation of our sample period.

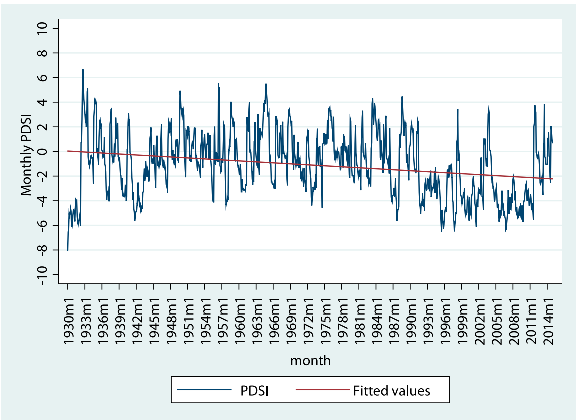

FIGURE 2
Historical PDSI for China. This figure plots the time series of monthly PDSI value for China. The sample period is from January of 1930 to December of 2014. The PDSI value is displayed on the blue line. The red line is the fit line.

Fama 2 × 3 portfolio division method. The monthly return of the portfolio is calculated using the weighted market value of circulation.

Summary statistics

Table 2 describes the statistical results, including the means, medians, standard deviations, skewness, kurtosis, and results of tests of normal distribution and stability. These data are intended to facilitate a preliminary understanding of the properties and distribution of industry stock returns and the key variables used in this study. As shown in Table 2, stock returns in various industries have similar statistical characteristics, and mean industry stock prices and associated SDs fluctuate widely. All of the stock return series are fat-tailed and right-skewed, suggesting asymmetry. The Jarque–Berra test provides further evidence that the stock returns in nearly all industries are not normally distributed. The last column of Table 2 presents the results of the augmented Dickey–Fuller test. All of the time series, including *Trend* and *PDSI36*, are stationary.

Empirical results

Degree and structure of dependence

We use the classical ordinary least-squares (OLS) multiple linear model and quantile regression model to examine the effect of drought on stock prices by industry. The basic model is as follows:

$$y_t = a + bx_t + \varepsilon_t, \tag{3}$$

where y_t represents the industry stock return $(indreturn_t)$ and x_t is a vector consisting of the explanatory variable $(Trend_t)$ and the control variables mentioned above.

The OLS method gives the conditional mean of the target variable as

$$E(y_t|x_t) = a + bx_t. \tag{4}$$

The conditional expectation $E(y_t|x_t)$ indicates the concentrated trend of the conditional distribution of $y_t|x_t$; however, we focus on the influence of $Trend_t$ on the whole conditional distribution of $y_t|x_t$.

Quantile regression, as proposed by Koenker and Bassett (1978), provides comprehensive information about the conditional distribution of $y_t|x_t$. For a given x_t, the conditional quantile function y_t at quantile τ is defined as

$$Q_\tau(y_t|x_t) = a_\tau + b_\tau x_t + F_{\varepsilon_t}^{-1}(\tau), \tag{5}$$

where F_{ε_t} is the distribution function of the error term ε_t. The estimated coefficient $\widehat{b_\tau}$ of the quantile regression is given by the following function:

$$\widehat{b_\tau} = arg \min_{a_\tau, b_\tau \in \mathbb{R}} \sum_{t=1}^{T} \rho_\tau(y_t - (a_\tau + b_\tau x_t)), \tag{6}$$

where T is the sample size and ρ_τ is the check function, defined as $\rho_\tau(\varepsilon) = (\tau - 1)\varepsilon$ if $\varepsilon < 0$ and $\rho_\tau(\varepsilon) = \tau\varepsilon$ otherwise. Because the

TABLE 2 Summary statistics.

Industry	*N*	Min	Mean	Med	Max	Std	Skew	Kurt	JB	ADF
AFAHF	180	−0.262	0.015	0.008	0.256	0.097	0.151	3.112	0.780	−2.362***
Min	180	−0.286	0.019	0.011	0.300	0.097	0.214	3.965	8.368**	−4.319***
Man	180	−0.239	0.019	0.020	0.301	0.087	0.078	3.771	4.644*	−3.706***
EHGWPS	180	−0.223	0.014	0.010	0.364	0.087	0.385	4.752	27.462***	−4.216***
Con	180	−0.235	0.014	0.012	0.386	0.098	0.590	4.285	22.845***	−3.139***
W&R	180	−0.250	0.018	0.012	0.323	0.091	0.274	3.720	6.135**	−3.262***
TSPS	180	−0.253	0.013	0.010	0.257	0.083	0.129	3.949	7.257**	−3.759***
A&C	180	−0.297	0.016	0.010	0.295	0.101	0.169	3.151	1.028	−3.148***
ITS	180	−0.256	0.016	0.011	0.358	0.089	0.223	4.452	17.318***	−3.184***
Fin	180	−0.272	0.014	0.008	0.357	0.096	0.559	4.730	31.824***	−3.614***
RE	180	−0.261	0.019	0.011	0.364	0.103	0.529	4.161	18.498***	−4.162***
LBS	180	−0.222	0.018	0.013	0.274	0.090	0.230	3.172	1.805	−4.043***
WEPFM	180	−0.234	0.012	0.006	0.440	0.097	0.798	5.422	63.104***	−3.629***
CSE	180	−0.279	0.019	0.007	0.382	0.115	0.361	3.693	7.518**	−5.549***
Com	180	−0.239	0.016	0.012	0.400	0.098	0.332	3.968	10.328***	−3.766***
Trend	180	−0.378	−0.096	−0.090	0.116	0.115	−0.801	2.936	289.520***	−2.800***
PDSI36	180	−4.578	−3.093	−3.434	−0.279	1.233	0.564	2.064	241.750***	−2.090**

This table reports the summary statistics of each industries' stock returns and drought related indicators, including the means, medians, SDs, skewness, kurtosis, and results of tests of normal distribution and stability. Our sample period is 2000–2014. The 15 industries are Agriculture, forestry, animal husbandry and fishery (AFAHF); Mining (Min); Manufacturing (Man); Electricity, heat, gas and water production and supply (EHGWPS); Construction (Con); Wholesale and retail (W&R); Transportation, storage and postal services (TSPS); Accommodation and catering (A&C); Information transmission, software and information technology services (ITS); Finance (Fin); Real estate (RE); Leasing and business services (LBS); Water, environment and public facilities management (WEPFM); Culture, sports, and entertainment (CSE); Comprehensive industry (Com). JB is the Jarque-Berra test statistic, and the null hypothesis of the test is that variables obey normal distribution. ADF is the augmented Dickey-Fuller test statistic, and the null hypothesis of this test is that unit roots exist. ***, ** and * imply the rejection of the null hypothesis in the case at 1, 5 and 10% levels of significance, respectively.

objective function of quantile regression cannot be differentiated, we usually use the linear programming method to calculate $\widehat{b_\tau}$. Furthermore, we apply a bootstrap method to estimate the quantile regression model, thus avoiding the hypothesis of identically distributed errors and accounting for heteroscedasticity.

Table 3 reports our empirical results. Column (1) presents the results of the OLS estimation and columns (2) to (8) list the results of the quantile regression estimation. For brevity, we report only the coefficients of *Trend*. Notably, the OLS and quantile regression estimations are distinct, with relatively fewer significant values in the OLS regression. We first focus on column (1). Among the 15 coefficients of *Trend*, only one is negative and is not significant. However, 4 of the 14 positive coefficients are significant. Because *Trend* is negatively correlated with the degree of drought, positive coefficients of *Trend* indicate that drought poses downside risks to stock prices in various industries, with significant risks in the AFAHF, Man, Fin, and WEPFM industries. A study by the National Academy of Sciences (1999) classifies the effects of drought as direct, such as "physical destruction of buildings, crops and natural resources," and indirect, such as "consequences of such destruction, such as temporary unemployment and business disruption." The Man, WEPFM, and particularly AFAHF industries have high water demand and are more directly affected by drought (Deschênes and Greenstone, 2007). In contrast, the effect of drought on the Fin industry reflects more indirect costs related to drought-related business disruptions and backward and forward multiplier economic effects, such as non-performing loans.

Quantile regressions can comprehensively reveal the effect of drought on industry stock prices. Columns (2) to (8) of Table 3 reveal that in addition to the four industries listed above, another six industries are affected by drought to various degrees. The strongest effects are observed in the RE and LBS industries, which are both widely associated with other industries. The RE industry is affected by many upstream industries, such as steel, cement, machinery, and home decoration. The LBS industry affects many downstream industries because it includes a wide range of areas, such as business management services, legal consulting, market management, advertising services, conferences and exhibitions, and other business services. As a result, these industries are affected more severely by droughts through subtle, indirect mechanisms involving industrial chains.

Lines 4, 7, and 8 of Table 3 demonstrate that drought does not significantly affect the EHGWPS, TSPS, and A&C industries. This phenomenon may be attributable to various factors, including an active governmental intervention policy and the nature of company ownership. As mentioned above, China's drought problem is local, not global; dry and wet conditions not

TABLE 3 Coefficients of Trend in OLS and quantile regressions by industry.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	**QR05**	**QR10**	**QR25**	**QR50**	**QR75**	**QR90**	**QR95**	***N***
AFAHF	**0.073****	**−0.090**	**−0.056**	**0.017**	**0.055****	**0.111****	**0.236*****	**0.308*****	**5**
	(0.035)	**(0.064)**	**(0.045)**	**(0.033)**	**(0.026)**	**(0.045)**	**(0.059)**	**(0.071)**	
Min	0.009	−0.022	−0.028	0.026	0.019	0.002	−0.010	−0.030	0
	(0.032)	(0.043)	(0.040)	(0.033)	(0.042)	(0.055)	(0.068)	(0.103)	
Man	**0.043****	**−0.017**	**0.013**	**0.009**	**0.042***	**0.047****	**0.090*****	**0.110*****	**5**
	(0.018)	**(0.045)**	**(0.033)**	**(0.016)**	**(0.023)**	**(0.020)**	**(0.025)**	**(0.040)**	
EHGWPS	0.019	−0.021	−0.030	−0.015	−0.014	−0.0005	0.086	0.095	0
	(0.032)	(0.050)	(0.046)	(0.037)	(0.031)	(0.042)	(0.074)	(0.073)	
Con	0.056	0.026	−0.054	0.002	0.063*	0.053	0.086	0.078	1
	(0.036)	(0.066)	(0.055)	(0.031)	(0.036)	(0.052)	(0.124)	(0.140)	
W&R	0.018	−0.033	−0.036	−0.005	−0.004	0.044*	0.062	0.070	1
	(0.026)	(0.037)	(0.030)	(0.025)	(0.021)	(0.023)	(0.053)	(0.062)	
TSPS	0.014	−0.092	−0.058	−0.028	−0.010	0.030	0.025	0.075	0
	(0.029)	(0.099)	(0.050)	(0.023)	(0.022)	(0.033)	(0.071)	(0.090)	
A&C	0.019	0.090	−0.003	0.010	0.018	0.029	−0.007	−0.036	0
	(0.033)	(0.065)	(0.042)	(0.040)	(0.033)	(0.055)	(0.088)	(0.091)	
ITS	**0.056**	**−0.017**	**−0.007**	**0.031**	**0.083*****	**0.119****	**0.178***	**−0.027**	**3**
	(0.036)	**(0.047)**	**(0.036)**	**(0.027)**	**(0.031)**	**(0.048)**	**(0.102)**	**(0.187)**	
Fin	**0.054***	**0.092***	**0.063**	**0.080***	**0.074***	**0.015**	**0.013**	**−0.043**	**4**
	(0.030)	**(0.053)**	**(0.061)**	**(0.045)**	**(0.044)**	**(0.049)**	**(0.058)**	**(0.072)**	
RE	**−0.004**	**−0.208*****	**−0.155*****	**−0.090*****	**−0.034**	**0.058**	**0.168****	**0.260*****	**5**
	(0.043)	**(0.055)**	**(0.038)**	**(0.032)**	**(0.031)**	**(0.037)**	**(0.080)**	**(0.096)**	
LBS	**0.029**	**−0.100***	**−0.080***	**−0.031**	**0.021**	**0.095****	**0.157*****	**0.219*****	**5**
	(0.036)	**(0.054)**	**(0.046)**	**(0.040)**	**(0.032)**	**(0.037)**	**(0.057)**	**(0.072)**	
WEPFM	**0.087****	**0.049**	**0.064**	**0.091****	**0.067***	**0.054**	**0.082**	**0.0005**	**3**
	(0.037)	**(0.126)**	**(0.060)**	**(0.044)**	**(0.037)**	**(0.054)**	**(0.112)**	**(0.213)**	
CSE	0.070	0.040	−0.025	0.035	0.060	0.003	0.198	0.396***	1
	(0.059)	(0.122)	(0.093)	(0.060)	(0.052)	(0.096)	(0.132)	(0.145)	
Com	0.033	0.003	0.049	−0.017	0.009	0.041	0.049	0.089	0
	(0.027)	(0.060)	(0.053)	(0.037)	(0.029)	(0.038)	(0.048)	(0.075)	
N	4	3	2	3	6	5	5	5	

This table reports the OLS and quantile regression results of monthly stock returns on the long-term trend of drought by industry. Our sample period is 2000–2014. To save space, we only report the coefficients of *Trend*. From left to right column are the regression results of OLS and quantile regression models on the 5, 10, 25, 50, 75, 90 and 95 quantiles. The rightmost column and the bottom row count the number of significant coefficients by row and column, respectively. The bold part are the industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regressions. Numbers in parentheses are standard errors. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

only follow an uneven spatial distribution but also a highly variable temporal distribution. To address this long-term imbalance in water resource distribution and complement current resources, the government has developed the South-to-North Water Diversion and West-to-East Electricity Transmission projects. The construction of reservoirs, desalination of seawater, prevention and control of water pollution, and protection of the environment have also effectively enhanced the resilience of these industries to drought. Furthermore, resources considered vital to livelihoods and the economy, such as water, electricity, and transportation, are mostly controlled by the state, and thus the stock prices in these industries are more strongly influenced by national policies. The food industry also is not significantly affected by drought for several reasons. First, the allocation of water resources can alleviate the problem of food production at its source. Second, national grain reserves and imported food supplies can be used as needed to address food shortages. Third, policies to control food prices can prevent excessive inflation.

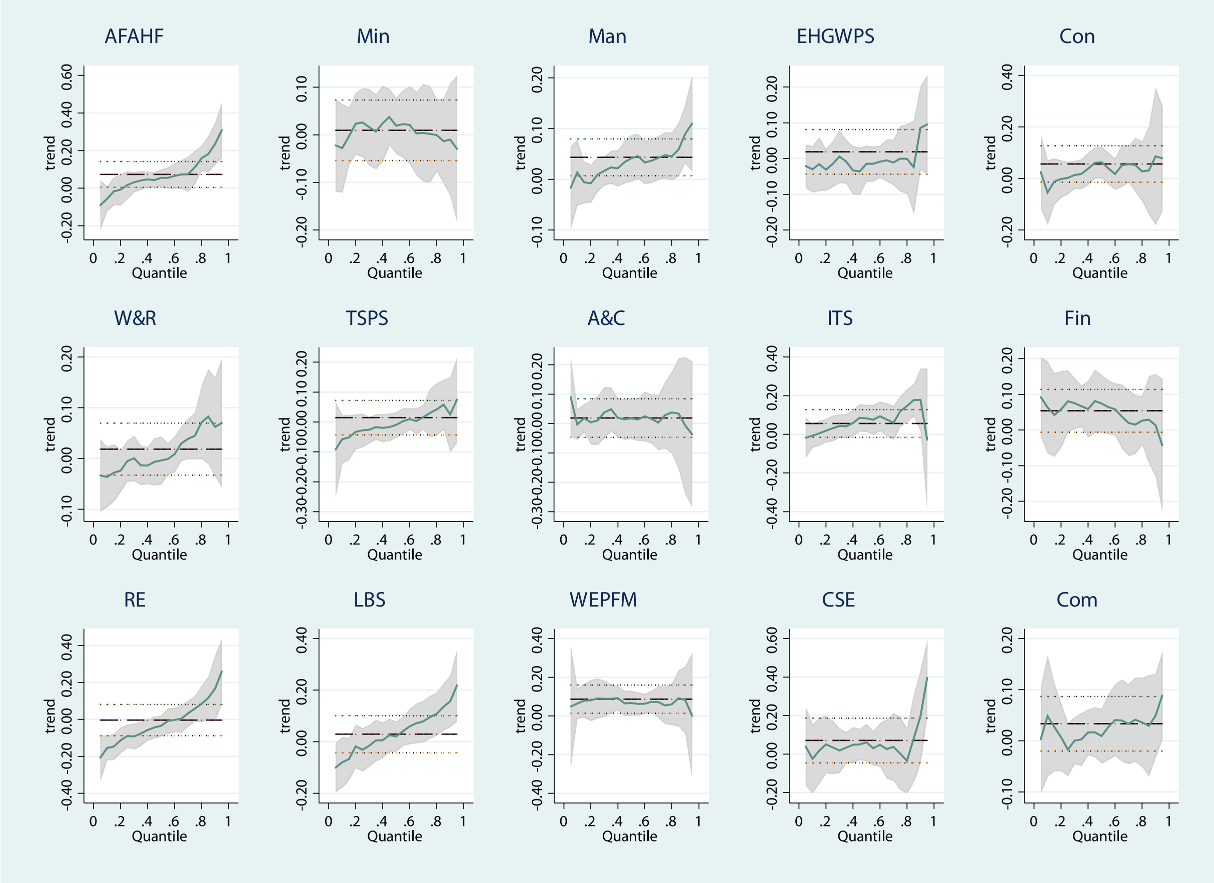

FIGURE 3
Quantile slope coefficients of *Trend*. The blue line is the coefficient values of *Trend*, and the shadow is the corresponding 95% CI. The dotted line is the coefficient value of ordinary least square estimation of *Trend* and its corresponding 95% CI.

The coefficients of *Trend* tend to change from negative to positive from the lowest to the highest stock price quantile. In high quantiles, however, the marginal effect is usually significant. We conclude that co-movement tends to exist in booming markets with high expected returns. A long-term drought trend is not conducive to economic prosperity.

Figure 3 plots changes in the coefficients of *Trend* across quantiles by industry. The 95% confidence interval is indicated by shading. The shift in the basic shape from negative to positive in Figure 3 confirms the overall trend of the coefficients in Table 3. For all industries, the 95% CI widens at both ends of the conditional distribution, indicating that the estimated coefficients are less accurate. The estimated OLS coefficients and 95% CIs (indicated by the dotted line) again demonstrate the superior ability of quantile regression to fully explore the relationship between drought and industry stock prices.

Quantile regression can reveal the effect of drought on the conditional distribution of industrial stock returns. However, a study of the effect of the degree of drought on industrial stock prices is also interesting and can provide more information about the dependence and structure of the relationship between these variables. We build model (7) as follows:

$$\mathrm{Indreturn}_t = \alpha_0 + \beta_1 Trend_t + \beta_2 Dum_t + \boldsymbol{\theta}' \boldsymbol{x}_{it} + \varepsilon_{it}, \qquad (7)$$

where subscript t represents the month and $\boldsymbol{x}_{it}$ represents the control variables, which include $PDSI36_t$, RP_t, SMB_t, and HML_t. Dum_t is a dummy variable that equals 1 when the PDSI of month t is smaller than the mean PDSI of the sample period from January 1990 to month t, and 0 otherwise. Thus, a Dum_t value of 1 represents drought conditions that are more severe than the historical average (i.e., extreme).

Table 4 shows the regression results produced by model (7), classified by industry. In all industries, the coefficients of *Trend* remain positive, again proving that a trend of long-term drought is not conducive to an increase in industry stock prices, as shown in Table 3. However, a discussion of Table 4 should focus on the coefficient estimates of Dum_t, which are negative but not significant in only 2 of 15 industries. In contrast, 6 of the

10.3389/fenvs.2022.978404

TABLE 4 The impact of different degrees of drought on industry stock price.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	AFAHF	**Min**	**Man**	**EHGWPS**	**Con**	**W&R**	**TSPS**	**A&C**	**ITS**	**Fin**	**RE**	**LBS**	**WEPFM**	**CSE**	**Com**
Trend	0.079**	0.038	0.061***	0.021	0.082**	0.041	0.029	0.043	0.058	0.052	0.017	0.051	0.092**	0.074	0.032
	(0.037)	(0.034)	(0.019)	(0.034)	(0.038)	(0.027)	(0.031)	(0.035)	(0.039)	(0.032)	(0.046)	(0.039)	(0.040)	(0.063)	(0.029)
Dum	0.004	0.017**	0.010**	0.001	0.015*	0.014**	0.009	0.014*	0.001	−0.001	0.012	0.013*	0.003	0.002	−0.001
	(0.008)	(0.007)	(0.004)	(0.007)	(0.008)	(0.006)	(0.007)	(0.007)	(0.008)	(0.007)	(0.010)	(0.008)	(0.008)	(0.013)	(0.006)
PDSI36	−0.006*	−0.005	−0.004**	−0.002	−0.001	0.001	0.003	0.002	0.001	−0.004	0.002	0.003	−0.003	−0.001	−0.002
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.006)	(0.003)
RP	0.921***	1.091***	0.981***	0.920***	1.035***	0.963***	0.912***	0.941***	0.890***	1.058***	1.099***	0.917***	0.990***	0.939***	1.036***
	(0.041)	(0.037)	(0.021)	(0.037)	(0.042)	(0.030)	(0.034)	(0.039)	(0.043)	(0.036)	(0.050)	(0.043)	(0.044)	(0.070)	(0.032)
SMB	0.741***	−0.343***	0.432***	0.239***	0.296***	0.511***	0.123**	0.859***	0.410***	−0.625***	−0.101	0.309***	0.451***	0.808***	0.631***
	(0.068)	(0.062)	(0.035)	(0.062)	(0.069)	(0.050)	(0.057)	(0.064)	(0.071)	(0.059)	(0.084)	(0.071)	(0.072)	(0.115)	(0.053)
HML	−0.256**	0.092	−0.116**	0.466***	0.278**	−0.234***	0.133	−0.232**	−0.304***	0.047	−0.413***	−0.387***	−0.170	−0.195	−0.175**
	(0.111)	(0.101)	(0.058)	(0.101)	(0.113)	(0.082)	(0.093)	(0.105)	(0.116)	(0.097)	(0.136)	(0.116)	(0.118)	(0.188)	(0.086)
Constant	−0.010	−0.011	−0.004	−0.003	−0.004	0.005	0.010	0.004	0.016*	0.004	0.014	0.017*	−0.001	0.008	0.003
	(0.010)	(0.009)	(0.005)	(0.009)	(0.010)	(0.007)	(0.008)	(0.009)	(0.010)	(0.008)	(0.012)	(0.010)	(0.010)	(0.016)	(0.007)
N	180	180	180	180	180	180	180	180	180	180	180	180	180	180	180
R-squared	0.806	0.841	0.936	0.800	0.801	0.880	0.817	0.838	0.749	0.849	0.742	0.758	0.779	0.606	0.885

This table reports the regression results of different degrees of drought and industry stock prices. Our sample period is 2000–2014. Dum_t is a dummy variable. When the PDSI index of month t is smaller than the mean of PDSI index of the sample period from January 1990 to month t, it is 1, otherwise it is 0. In this way, a value of 1 for Dum_t represents extreme drought conditions that are more severe than the historical average. The last two rows show the goodness of fit and sample size. Numbers in parentheses are SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

13 positive coefficient estimates are significant, corresponding to Min, Man, Con, W&R, A&C, and LBS. These regression results show that extreme drought drives up stock prices in these industries, possibly because of market speculation. The PDSI index trend in Figure 2 suggests that China faces frequent droughts and floods, and extreme droughts usually do not persist. Furthermore, the literature proposes that stock prices have the characteristics of mean reversion (Kim et al., 1991; Barberis et al., 1998; Gropp, 2004). In a drought, industry stock prices fall as climatological conditions worsen. When either drought conditions or stock prices reach a certain threshold, investors expect an immediate reversal and increase their investment, leading to a positive correlation between extreme drought and industry stock prices.

Regimes of investor sentiment

The results of quantile regression show that drought has a complex effect on industry stock returns. This relationship may be affected not only by fundamental factors but also by irrational factors, such as investor sentiment. The signs of the coefficients of *Trend* in each quantile are inconsistent, indicating that the relationship between drought and industry stock returns may be nonlinear due to variable investor sentiment. Therefore, we consider the threshold effect of investor sentiment. To avoid error caused by an artificial division of the investor sentiment interval, we use the threshold panel model developed by Hansen (1999). This model can be used to specify the threshold variable, namely investor sentiment, and endogenously divide the intervals according to the characteristics of the data, allowing a study of the relationship between drought and industry stock returns in different sentiment regimes.

We first focus on a single threshold model and expand it to a multi-threshold model. The single threshold model is set as follows:

$$\mathrm{Indreturn_{it}} = \alpha_i + \boldsymbol{\theta}'\boldsymbol{x_{it}} + \delta_1 \mathrm{Trend_t} \mathrm{I}(\mathrm{TO_{it}} \le \tau_1) + \delta_2 \mathrm{Trend_t} \mathrm{I}(\mathrm{TO_{it}} > \tau_1) + \varepsilon_{it}. \tag{8}$$

Unlike the empirical evidence above, our threshold model (8) is based on panel data of industry stock returns: subscript i represents the various industries and t is the month. $Indreturn_{it}$ and $Trend_t$ remain the dependent and independent variables, respectively. $\boldsymbol{x_{it}}$ represents the control variables, including $PDSI36_t$, RP_t, SMB_t, and HML_t. TO_t is the threshold variable that represents investor sentiment. Following Baker et al. (2012) and Huang et al. (2015), we use the turnover rate to measure investor sentiment, given the positive correlation between these variables. τ_1 is a specific threshold value and $I(\cdot)$ is an indicator function. Finally, α_i reflects the individual effects of the industry, such as the life cycle, location preference, natural ecological attributes, and other unobservable factors. Of these industry effects, the natural ecological attributes are not easily changed in a short time. Some industries exist harmoniously with nature, whereas others inevitably cause harm to the environment. For example, the mining industry tends to pollute water and damage vegetation, thereby increasing the probability of drought. Various government departments have imposed environmental protection requirements on the mining industry. These policies have increased production costs in this industry, which are ultimately reflected in stock prices. To address these variations, we study the threshold effect of investor sentiment using an individual fixed effect model that can control the effects of unobservable factors, such as natural ecological attributes, that are difficult to change in the short term but can affect both drought and stock returns.

To obtain the parameter estimator, we subtract the intra-group mean from each observation to eliminate the individual effect α_i. The transformed model is as follows:

$$Indreturn^*_{it} = \delta_1 \mathrm{Trend}^*_t \mathrm{I}(\mathrm{TO_{it}} \le \tau_1) + \delta_2 \mathrm{Trend}^*_t \mathrm{I}(\mathrm{TO_{it}} > \tau_1) + \boldsymbol{\theta}'\mathbf{x}^*_{it} + \varepsilon^*_{it}. \tag{9}$$

Coefficients δ_1 and δ_2 correspond to the different regimes. Given the threshold value τ_1, we can obtain the parameter estimates $\hat{\delta}_1(\tau_1)$ and $\hat{\delta}_2(\tau_1)$ and the residual sum $\mathrm{SSR}(\tau_1)$ of model (9). Finally, by minimizing $\mathrm{SSR}(\tau_1)$, we obtain the estimated value $\hat{\tau}_1$ and parameters $\hat{\delta}_1(\hat{\tau}_1)$ and $\hat{\delta}_2(\hat{\tau}_1)$. Next, we perform two tests to determine whether the threshold effect is significant and whether the estimated threshold value is equal to the actual value. For the first test, the null hypothesis states that there is no threshold effect, H_0: $\delta_1 = \delta_2$, and the corresponding alternative hypothesis is H_1: $\delta_1 \neq \delta_2$. The test statistic is

$$\mathrm{F} = \frac{SSR^* - \mathrm{SSR}(\hat{\tau}_1)}{\hat{\sigma}^2}, \tag{10}$$

where SSR^* is the square sum of the residuals of the model under the null hypothesis. $\hat{\sigma}^2 = \frac{\mathrm{SSR}(\hat{\tau}_1)}{\mathrm{n(T-1)}}$ is the uniform estimation of the variance of the disturbance term, n is the sample size, and T is the length of time. The larger the value of $SSR^* - \mathrm{SSR}(\hat{\tau}_1)$, the more SSR increases with constraints; further, the likelihood of rejection of the null hypothesis H_0: $\delta_1 = \delta_2$ increases. Under the null hypothesis, the threshold value τ_1 is unrecognizable, so the F statistic has a nonstandard distribution. The bootstrap method can be used to obtain the asymptotic distribution and p value. For the second test, the null hypothesis states that the estimated threshold value is equal to its actual value, H_0: $\hat{\tau}_1 = \tau_0$. The corresponding likelihood ratio test statistic is

$$LR(\tau_1) = \frac{\mathrm{SSR}(\tau_1) - \mathrm{SSR}(\hat{\tau}_1)}{\hat{\sigma}^2}. \tag{11}$$

If $\hat{\tau}_1 = \tau_0$ is true, then the statistic also has a nonstandard distribution. However, its cumulative distribution function is

TABLE 5 Threshold effect test of investor sentiment.

	H0	H1	Fstat	Prob	Crit10	Crit5	Crit1
Full sample	Liner	Single	35.84	0.000	11.677	15.046	21.742
	Single	Double	23.71	0.100	23.542	34.303	55.909
The first subsample	Liner	Single	29.44	0.000	11.107	13.747	22.221
	Single	Double	7.23	0.623	21.153	25.245	38.709
The second subsample	Liner	Single	18.23	0.003	9.593	12.784	16.304
	Single	Double	8.79	0.277	12.311	14.852	20.673

This table reports the threshold effect test results of investor sentiment in three samples. Our sample period is 2000–2014. The full sample is the monthly stock return panel data of 15 industries. The first subsample includes industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regression in Table 3. The other industries are included in the second subsample. This table shows the original hypothesis, alternative hypothesis, F statistic, probability value, and critical values at 10, 5 and 1% from left to right columns.

TABLE 6 Threshold regression results of investor sentiment.

	Full sample		The first subsample		The second subsample	
	Liner	Single	Liner	Single	Liner	Single
Trend	0.039***	0.034***	0.048***	0.042***	0.030***	0.024***
	(0.007)	(0.006)	(0.011)	(0.011)	(0.008)	(0.006)
		−0.288***		−0.356**		−0.109***
		(0.075)		(0.097)		(0.029)
PDSI36	−0.002*	−0.0004	−0.002	−0.0001	−0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RP	0.985***	0.977***	0.984***	0.972***	0.986***	0.965***
	(0.018)	(0.017)	(0.030)	(0.029)	(0.024)	(0.023)
SMB	0.313**	0.304**	0.229	0.215	0.387**	0.383**
	(0.108)	(0.107)	(0.171)	(0.169)	(0.141)	(0.139)
HML	−0.116*	−0.103	−0.243***	−0.225**	−0.005	0.029
	(0.065)	(0.066)	(0.065)	(0.069)	(0.095)	(0.090)
Constant	0.005**	0.007***	0.007	0.010**	0.004	0.009**
	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)
Threshold		**52.3**		**52.0**		**21.9**
95% CI		[50.5, 53.7]		[50.7, 55.6]		[20.6, 22.0]
R^2	0.739	0.743	0.739	0.746	0.743	0.747
N	2700	2700	1260	1260	1440	1440

This table reports the linear and threshold regression results of investor sentiment in three samples. Our sample period is 2000–2014. The full sample is the monthly stock return panel data of 15 industries. The first subsample includes industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in linear regression and quantile regression in Table 3. The other industries are included in the second subsample. The last four rows show the threshold value, 95% CI of the threshold value, goodness of fit and sample size. Numbers in parentheses are SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

$(1 - e^{-x/2})^2$, so its critical value can be calculated directly. The statistic LR can be used to calculate the CI of τ_1. The above model assumes that there is only one investor sentiment threshold. From an econometric perspective, however, there may be multiple thresholds. By assuming a known value of estimated τ_1 in the single threshold model and then searching for τ_2, the single threshold model can be easily extended to a scenario with multiple thresholds.

We also divide the sample according to the empirical results in Table 3 to better test the threshold effect of investor sentiment. We divide the sample using a cut-off value of 3 for the total significant number of *Trend* coefficients in the OLS regression and quantile regression of an industry. Industries with a cut-off value greater than 3 comprise the first sub-sample, which includes AFAHF, Man, ITS, Fin, RE, LBS, and WEPFM. Drought has a significant effect on these industries, and it thus increases the probability of observing the threshold effect of investor sentiment. The remaining industries comprise the second sub-sample; here, drought has a lesser effect, so the evidence of a threshold effect of investor sentiment may not be observed. Table 5 presents the *F*-statistics, probability values, and critical values at the 10, 5, and 1% levels for each test of each sample. We use a bootstrap method to calculate the critical *F*-statistic value. The bootstrap number is 300.

In the test of the linear model, the *F*-statistics for the whole sample, the first and the second sub-sample are 35.84, 29.44, and 18.23, each of which rejects the null hypothesis at a 1% level of significance. However, the null hypothesis is not rejected in all samples during the test of the single-threshold model. Therefore, the single-threshold model is suitable for studying the threshold effect of investor sentiment on the relationship between drought and industry stock returns.

To verify the robustness of the results, we present the estimation results for both the linear model and the single-threshold model in Table 6, which also lists the regression results of the full sample and the subsamples. All of the linear models show positive coefficients of *Trend*, again verifying the results of OLS regression for each industry in Table 3. In other words, the correlation between drought and stock prices is generally negative. After the threshold feature is introduced, the SD of the model error decreases and the determinable coefficient increases, indicating that this feature captures at least some of the nonlinear components of the variable relationship. We first focus on the full sample. The estimated threshold value of 52.3 falls within the 95% CI [50.5,53.7], indicating that the estimated threshold value is consistent with the true value. We can sample into a low sentiment regime ($TO \leq 52.3$) and a high sentiment regime ($TO > 52.3$). In the low sentiment regime, the coefficient of *Trend* is 0.034, which means that drought has a significant negative effect on industry stock prices in this regime. This result is consistent with the fact that drought is not conducive to economic development. In the high sentiment regime, the coefficient of *Trend* is −0.288, which is significant at the 1% level. In other words, the effect of the drought on industry stock prices shifts from negative to positive. This phenomenon reflects the irrational or speculative behavior of investors. The regression results in Table 6 are consistent with the findings of research on the effect of investor sentiment on the stock market (Brown and Cliff, 2005; Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006; Kaplanski and Levy, 2010; Mian and Sankaraguruswamy, 2012). Consistently, these studies demonstrate that when investor sentiment is high, investors tend to have a high propensity toward speculation and thus overvalue risky assets such as stocks. The reverse is true during low sentiment periods, as investors' pessimism leads them to undervalue stocks.

The results of regression are the same in the subsamples as in the whole sample. Specifically, as investor sentiment shifts from low to high, the correlation between drought and industry stock prices shifts from negative to positive. The first subsample has a threshold value of 52.0, which is very close to that of the whole sample. Although we also observe a significant threshold effect of investor sentiment in the second subsample, its threshold value of 21.9 is less than half of the corresponding values of the whole sample and the first subsample. Therefore, the effect of drought on industry stock prices is more likely to be distorted by investor sentiment in the second subsample, although we note that the effect of drought on industry stock prices is smaller in the second than in the first subsample. In the low sentiment regime, the coefficients of *Trend* are 0.034, 0.042, and 0.024 in the whole sample, first subsample, and second subsample, respectively. In the high sentiment regime, the coefficient of *Trend* in the second subsample is −0.109, which is approximately half of the corresponding value in the full sample which is −0.288 and one-third of that in the first subsample which is −0.356. These results are consistent with the results of regression in Table 3, which demonstrate drought has a less significant effect on industry stock prices in the second subsample. In summary, the results of regression of the threshold model confirm the influence of the investor sentiment threshold on the relationship between drought and industry stock prices.

Robustness checks

Consideration of differences in quarterly precipitation

China has a pronounced monsoon climate, with seasonal variations in precipitation. According to the China Meteorological data network[5], precipitation is more frequent in the second and third quarters than in the first and fourth quarters. This pattern may affect estimation of the drought trend. To determine whether our regression results are affected by this phenomenon, we add quarter dummy variables to the long-term drought trend measurement model:

$$PDSI_t = a + bt + cPDSI_{t-1} + d_1D_1 + d_2D_2 + d_3D_3 + \varepsilon. \quad (12)$$

This AR(1) model is augmented with a deterministic time trend t and quarter dummies. D_1, D_2, and D_3 are the dummy variables for the first, second, and third quarters, respectively. The coefficient of the deterministic time trend in model (12) is the alternative measure of the long-term drought trend.

Table 7 shows the OLS and quantile regression results of individual industries based on this alternative measure of *Trend*. Again, the OLS regression results show a negative correlation between drought and industry stock prices, and this relationship is significant in four industries, although Fin is replaced with ITS.

5 http://data.cma.cn/.

TABLE 7 Robustness check I: OLS and quantile regressions considering quarterly precipitation difference.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	**QR05**	**QR10**	**QR25**	**QR50**	**QR75**	**QR90**	**QR95**	***N***
AFAHF	**0.085****	**−0.096**	**−0.059**	**0.025**	**0.061****	**0.124****	**0.208*****	**0.328*****	**5**
	(0.038)	**(0.074)**	**(0.052)**	**(0.038)**	**(0.030)**	**(0.052)**	**(0.063)**	**(0.076)**	
Min	0.016	−0.028	0.004	0.027	0.031	0.002	−0.010	−0.030	0
	(0.035)	(0.050)	(0.045)	(0.037)	(0.044)	(0.062)	(0.067)	(0.110)	
Man	**0.049****	**−0.009**	**0.016**	**0.011**	**0.037**	**0.049****	**0.076*****	**0.112*****	**4**
	(0.020)	**(0.047)**	**(0.036)**	**(0.019)**	**(0.024)**	**(0.023)**	**(0.027)**	**(0.043)**	
EHGWPS	0.021	−0.021	−0.029	−0.017	−0.018	−0.015	0.107	0.100	0
	(0.035)	(0.058)	(0.055)	(0.044)	(0.035)	(0.044)	(0.080)	(0.079)	
Con	0.060	0.030	−0.011	0.005	0.064	0.059	0.081	0.089	0
	(0.039)	(0.072)	(0.064)	(0.034)	(0.041)	(0.064)	(0.141)	(0.159)	
W&R	0.019	−0.034	−0.038	−0.006	−0.005	0.046*	0.067	0.072	1
	(0.028)	(0.039)	(0.034)	(0.028)	(0.024)	(0.025)	(0.058)	(0.071)	
TSPS	0.017	0.157	−0.024	−0.019	−0.011	0.028	0.028	0.083	0
	(0.032)	(0.118)	(0.065)	(0.025)	(0.024)	(0.036)	(0.072)	(0.088)	
A&C	0.014	0.088	−0.006	0.014	0.014	0.008	−0.008	−0.041	0
	(0.036)	(0.071)	(0.042)	(0.044)	(0.039)	(0.061)	(0.098)	(0.098)	
ITS	**0.073***	**−0.017**	**0.010**	**0.037**	**0.088*****	**0.133****	**0.216****	**0.207**	**4**
	(0.040)	**(0.058)**	**(0.042)**	**(0.031)**	**(0.033)**	**(0.055)**	**(0.100)**	**(0.176)**	
Fin	0.045	0.087	0.027	0.067	0.040	−0.013	0.013	−0.053	0
	(0.033)	(0.059)	(0.068)	(0.048)	(0.052)	(0.052)	(0.067)	(0.106)	
RE	**−0.010**	**−0.228*****	**−0.176*****	**−0.118*****	**−0.037**	**0.063**	**0.160***	**0.273****	**5**
	(0.047)	**(0.062)**	**(0.039)**	**(0.033)**	**(0.033)**	**(0.043)**	**(0.086)**	**(0.110)**	
LBS	**0.032**	**−0.102***	**−0.089***	**−0.032**	**0.024**	**0.096****	**0.149****	**0.224*****	**5**
	(0.040)	**(0.061)**	**(0.051)**	**(0.044)**	**(0.036)**	**(0.041)**	**(0.062)**	**(0.080)**	
WEPFM	**0.096****	**0.040**	**0.070**	**0.084***	**0.079****	**0.061**	**0.088**	**0.0005**	**3**
	(0.041)	**(0.126)**	**(0.061)**	**(0.050)**	**(0.040)**	**(0.062)**	**(0.123)**	**(0.196)**	
CSE	0.086	0.047	−0.024	0.039	0.072	0.024	0.250*	0.393***	2
	(0.064)	(0.130)	(0.102)	(0.068)	(0.062)	(0.106)	(0.143)	(0.143)	
Com	0.037	0.003	0.057	−0.019	0.010	0.044	0.084	0.106	0
	(0.030)	(0.063)	(0.060)	(0.040)	(0.031)	(0.039)	(0.051)	(0.079)	
N	4	2	2	2	3	5	6	5	

This table reports the OLS and quantile regression results based on the alternative measure of the long-term trend of drought, which considering quarterly precipitation difference. To save space, we only report the coefficients of Trend. From left to right column are the regression results of OLS model and quantile regression models on the 5, 10, 25, 50, 75, 90 and 95 quantiles. The rightmost column and the bottom row count the number of significant coefficients by row and column, respectively. The bold part are the industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regressions. Numbers in parentheses are SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

The results of quantile regression demonstrate that more than half of the industries are significantly affected by drought, and this effect is usually positive when stock prices are low and negative when prices are high. The coefficient estimation accuracy is higher at high stock price quantiles. The AFHAF, Man, ITS, RE, and LBS industries are most affected by drought, similar to the results shown in Table 3. In summary, the OLS and quantile regression results are in line with our previous findings.

As shown in Table 8, the results of the threshold effect reveal a single-threshold effect in the whole sample and the first subsample but a double-threshold effect in the second subsample. Table 9 reports both the linear and threshold regression results. The results of linear regression still show a negative correlation of drought with stock prices. No significant changes are observed in the results of threshold regression in either the whole sample or the subsamples. Despite the double-threshold effect in the second subsample, the regression results do not differ substantially from those in Table 6. Specifically, the threshold values in the second subsample are 16.3 and 18.5. At turnover rates higher

TABLE 8 Robustness check Ⅰ: Threshold effect test of investor sentiment considering quarterly precipitation difference.

	H0	H1	Fstat	Prob	Crit10	Crit5	Crit1
Full sample	Liner	Single	35.84	0.000	11.649	12.986	19.172
	Single	Double	23.71	0.100	23.687	30.644	41.112
The first subsample	Liner	Single	31.73	0.003	12.988	16.581	24.591
	Single	Double	3.09	0.887	19.824	25.362	36.092
The second subsample	Liner	Single	22.04	0.000	10.167	12.127	15.538
	Single	Double	9.27	0.067	8.194	9.659	13.178
	Double	Triple	4.69	0.613	15.707	21.777	31.558

This table reports the threshold effect test results of investor sentiment in three samples based on the alternative measure of the long-term trend of drought. Our sample period is 2000–2014. The full sample is the monthly stock return panel data of 15 industries. The first subsample includes industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regression in Table 7. The other industries are included in the second subsample. This table shows the original hypothesis, alternative hypothesis, F statistic, probability value, and critical values at 10, 5 and 1% from left to right columns.

TABLE 9 Robustness check Ⅰ: Threshold regression results of investor sentiment considering quarterly precipitation difference.

	Full sample		The first subsample		The second subsample		
	Liner	Single	Liner	Single	Liner	Single	Double
Trend	0.039***	0.034***	0.047**	0.040**	0.033***	0.036***	0.033***
	(0.007)	(0.006)	(0.013)	(0.013)	(0.007)	(0.007)	(0.006)
		−0.288***		−0.352**		−0.077**	−0.076**
		(0.075)		(0.107)		(0.033)	(0.033)
							−0.376***
							(0.077)
PDSI36	−0.002*	−0.0005	−0.001	0.0002	−0.002*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RP	0.985***	0.977***	0.972***	0.959***	0.994***	0.974***	0.970***
	(0.018)	(0.017)	(0.032)	(0.029)	(0.023)	(0.021)	(0.021)
SMB	0.313**	0.304**	0.371**	0.359**	0.275	0.270	0.266
	(0.108)	(0.107)	(0.113)	(0.108)	(0.168)	(0.168)	(0.167)
HML	−0.116*	−0.103	−0.292***	−0.271***	0.001	0.027	0.030
	(0.065)	(0.066)	(0.050)	(0.060)	(0.084)	(0.080)	(0.081)
Constant	0.005**	0.007***	0.007	0.011**	0.004	0.008**	0.009***
	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)
Threshold		52.3		51.9		16.3	16.3, 18.5
95% CI		[50.5, 53.7]		[50.5,53.2]		[15.0, 16.6]	[14.8,16.6], [18.3,18.7]
R^2	0.739	0.743	0.767	0.776	0.726	0.731	0.732
N	2700	2700	1080	1080	1620	1620	1620

This table reports the linear and threshold regression results of investor sentiment in three samples based on the alternative measure of the long-term trend of drought. Our sample period is 2000–2014. The full sample is the monthly stock return panel data of 15 industries. The first subsample includes industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regression in Table 7. The other industries are included in the second subsample. The last four rows show the threshold value, 95% CI of the threshold value, goodness of fit and sample size. Numbers in parentheses are robust SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

than 16.3, the impact of drought on stock prices changes from negative to positive, and this positive impact becomes stronger at turnover rates higher than 18.5. Once again, these results demonstrate that the threshold effect of investor sentiment is more likely to distort the relationship between drought and stock prices in the second subsample. A comparison of the subsamples shows that drought has a greater negative effect on the first subsample but nearly identical positive effects on both subsamples, and the second subsample has a significantly lower threshold value. In summary, our main findings are not altered

TABLE 10 Robustness check II: OLS and quantile regressions based on Trend calculated by Box-Jenkins process.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	QR05	QR10	QR25	QR50	QR75	QR90	QR95	*N*
AFAHF	**0.060****	**−0.074**	**−0.043**	**0.006**	**0.046****	**0.090****	**0.171*****	**0.240*****	**5**
	(0.027)	**(0.050)**	**(0.038)**	**(0.028)**	**(0.021)**	**(0.035)**	**(0.044)**	**(0.054)**	
Min	0.015	−0.018	−0.017	0.020	0.023	0.029	−0.005	−0.028	0
	(0.025)	(0.032)	(0.031)	(0.026)	(0.030)	(0.043)	(0.057)	(0.082)	
Man	**0.038*****	**−0.009**	**0.010**	**0.007**	**0.035****	**0.044*****	**0.075*****	**0.090*****	**5**
	(0.014)	**(0.031)**	**(0.025)**	**(0.013)**	**(0.017)**	**(0.015)**	**(0.020)**	**(0.030)**	
EHGWPS	0.014	−0.016	−0.020	−0.016	−0.016	0.004	0.069	0.084	0
	(0.025)	(0.034)	(0.030)	(0.029)	(0.025)	(0.032)	(0.058)	(0.056)	
Con	0.051*	0.020	−0.042	0.002	0.054*	0.051	0.065	0.095	2
	(0.028)	(0.051)	(0.048)	(0.026)	(0.029)	(0.038)	(0.092)	(0.111)	
W&R	0.022	−0.025	−0.020	−0.004	0.002	0.049***	0.050	0.060	1
	(0.020)	(0.028)	(0.025)	(0.020)	(0.017)	(0.017)	(0.039)	(0.049)	
TSPS	0.012	−0.068	−0.048	−0.028	−0.008	0.025	0.057	0.116*	1
	(0.023)	(0.052)	(0.032)	(0.017)	(0.018)	(0.023)	(0.045)	(0.061)	
A&C	0.019	0.080	−0.002	0.008	0.013	0.017	0.010	−0.020	0
	(0.026)	(0.051)	(0.034)	(0.035)	(0.026)	(0.041)	(0.070)	(0.072)	
ITS	**0.046**	**−0.012**	**−0.005**	**0.019**	**0.069*****	**0.097****	**0.132***	**0.134**	**3**
	(0.028)	**(0.036)**	**(0.025)**	**(0.021)**	**(0.024)**	**(0.038)**	**(0.079)**	**(0.150)**	
Fin	**0.046***	**0.070**	**0.053**	**0.063***	**0.059***	**0.016**	**0.010**	**0.004**	**3**
	(0.023)	**(0.045)**	**(0.046)**	**(0.033)**	**(0.034)**	**(0.037)**	**(0.044)**	**(0.058)**	
RE	**0.004**	**−0.159*****	**−0.122*****	**−0.078*****	**−0.017**	**0.044**	**0.124****	**0.203*****	**5**
	(0.033)	**(0.043)**	**(0.032)**	**(0.026)**	**(0.025)**	**(0.030)**	**(0.056)**	**(0.074)**	
LBS	**0.027**	**−0.074***	**−0.062***	**−0.022**	**0.020**	**0.077*****	**0.111****	**0.163*****	**5**
	(0.028)	**(0.042)**	**(0.034)**	**(0.030)**	**(0.025)**	**(0.028)**	**(0.043)**	**(0.050)**	
WEPFM	**0.068****	**0.051**	**0.052**	**0.073****	**0.053***	**0.049**	**0.072**	**0.0003**	**3**
	(0.029)	**(0.120)**	**(0.052)**	**(0.036)**	**(0.029)**	**(0.041)**	**(0.089)**	**(0.182)**	
CSE	0.059	0.030	−0.020	0.031	0.054	0.025	0.193*	0.299***	2
	(0.046)	(0.096)	(0.070)	(0.044)	(0.041)	(0.079)	(0.102)	(0.107)	
Com	0.026	0.002	0.037	−0.014	0.009	0.020	0.052	0.066	0
	(0.021)	(0.045)	(0.039)	(0.028)	(0.025)	(0.031)	(0.036)	(0.049)	
N	5	2	2	3	6	5	6	6	

This table reports the OLS and quantile regression results of monthly stock returns on the long-term trend of drought by industry. Our sample period is 2000–2014. To save space, we only report the coefficients of Trend. From left to right column are the regression results of OLS model and quantile regression models on the 5, 10, 25, 50, 75, 90 and 95 quantiles. The rightmost column and the bottom row count the number of significant coefficients by row and column, respectively. The bold part are the industries significantly affected by drought, i.e. there are at least three coefficients of *Trend* are significant in OLS regression and quantile regressions. Numbers in parentheses are SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

by considering the quarterly effects in our calculation of the long-term drought trend.

Alternative drought index

Following the literature, we use *Trend* calculated based on the AR(1) model in our main empirical analysis. To improve robustness, we use the Box–Jenkins process to reselect the model, determine the order, and calculate *Trend*. As PDSI is a stationary time series, we calculate the autocorrelation coefficient and partial autocorrelation coefficient to determine the suitability of the ARMA, AR, and MA models. The autocorrelation coefficient tails off to zero, and the partial autocorrelation coefficient is truncated. Although the third-order partial autocorrelation coefficient is significantly different from zero, values above the third order can be considered equal to zero. Therefore, we extend model (2) to the AR(3) model to recalculate *Trend* and repeat our empirical analysis of the economic impact of drought.

TABLE 11 Robustness check III: OLS and quantile regressions based on $Trend_{t-1}$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	QR05	QR10	QR25	QR50	QR75	QR90	QR95	N
AFAHF	**0.067***	**−0.135****	**−0.068**	**0.009**	**0.057****	**0.072**	**0.201*****	**0.248*****	**5**
	(0.035)	**(0.062)**	**(0.044)**	**(0.035)**	**(0.028)**	**(0.049)**	**(0.061)**	**(0.068)**	
Min	0.008	−0.016	−0.030	0.028	0.020	0.006	−0.008	−0.028	0
	(0.032)	(0.044)	(0.042)	(0.035)	(0.047)	(0.052)	(0.070)	(0.101)	
Man	**0.044****	**−0.012**	**−0.012**	**0.007**	**0.040***	**0.054*****	**0.079*****	**0.113*****	**5**
	(0.018)	**(0.042)**	**(0.033)**	**(0.018)**	**(0.022)**	**(0.019)**	**(0.025)**	**(0.039)**	
EHGWPS	0.016	−0.056	−0.048	−0.023	−0.018	−0.001	0.089	0.079	0
	(0.032)	(0.046)	(0.041)	(0.041)	(0.034)	(0.045)	(0.075)	(0.078)	
Con	0.055	0.027	−0.052	0.003	0.058	0.055	0.085	0.114	0
	(0.036)	(0.059)	(0.051)	(0.029)	(0.036)	(0.047)	(0.119)	(0.141)	
W&R	0.021	−0.030	−0.047	−0.006	−0.004	0.043*	0.053	0.053	1
	(0.025)	(0.040)	(0.032)	(0.024)	(0.021)	(0.022)	(0.049)	(0.057)	
TSPS	0.018	−0.126*	−0.035	−0.034	−0.002	0.031	0.073	0.136*	2
	(0.029)	(0.069)	(0.040)	(0.023)	(0.023)	(0.029)	(0.060)	(0.075)	
A&C	0.029	0.092	−0.003	0.006	0.021	0.050	0.019	−0.034	0
	(0.034)	(0.063)	(0.044)	(0.041)	(0.043)	(0.065)	(0.097)	(0.099)	
ITS	0.048	−0.028	−0.022	0.023	0.083**	0.142***	0.124	−0.037	2
	(0.036)	(0.044)	(0.034)	(0.026)	(0.034)	(0.048)	(0.117)	(0.211)	
Fin	**0.061****	**0.103***	**0.064**	**0.078***	**0.084***	**0.022**	**0.010**	**−0.039**	**4**
	(0.030)	**(0.053)**	**(0.055)**	**(0.042)**	**(0.045)**	**(0.054)**	**(0.067)**	**(0.090)**	
RE	**0.005**	**−0.218*****	**−0.153*****	**−0.099*****	**−0.031**	**0.062***	**0.173****	**0.304*****	**6**
	(0.043)	**(0.060)**	**(0.040)**	**(0.031)**	**(0.031)**	**(0.034)**	**(0.072)**	**(0.101)**	
LBS	**0.020**	**−0.121****	**−0.083***	**−0.044**	**0.017**	**0.093****	**0.068**	**0.230*****	**4**
	(0.035)	(0.056)	(0.046)	(0.041)	(0.034)	(0.041)	(0.057)	(0.082)	
WEPFM	0.073**	0.060	0.069	0.089**	0.053	0.045	0.092	0.0005	2
	(0.037)	(0.127)	(0.066)	(0.043)	(0.037)	(0.050)	(0.121)	(0.226)	
CSE	0.062	0.057	−0.026	0.042	0.055	−0.0002	0.205	0.330**	1
	(0.059)	(0.134)	(0.085)	(0.060)	(0.049)	(0.096)	(0.132)	(0.148)	
Com	0.030	−0.010	0.050	−0.020	0.013	0.036	0.038	0.066	0
	(0.027)	(0.065)	(0.054)	(0.035)	(0.032)	(0.039)	(0.047)	(0.081)	
N	4	5	2	3	4	5	3	6	

This table reports the OLS and quantile regression results of monthly stock returns on the long-term trend of drought lagged one period by industry. Our sample period is 2000–2014. To save space, we only report the coefficients of Trend. From left to right column are the regression results of OLS model and quantile regression models on the 5, 10, 25, 50, 75, 90 and 95 quantiles. The rightmost column and the bottom row count the number of significant coefficients by row and column, respectively. The bold part are the industries significantly affected by drought, i.e. there are at least three coefficients of Trend are significant in OLS regression and quantile regressions. Numbers in parentheses are SEs. *, ** and *** denote statistical significance at 10, 5 and 1%, respectively.

Table 10 presents the results of OLS and quantile regression of the relationship between drought and industry stock prices, which are very close to the results in Table 3. OLS regression reveals a negative effect of drought on industry stock prices. Further consideration of the quantile regression results reveals that for almost all of the industries, the effect of drought shifts from positive to negative with the transition from the low to high quantile and is more significant in the high quantile. This evidence shows that drought is not conducive to economic prosperity and has a negative overall effect on industry stock prices. Individually, OLS regression captures the significant effects of drought on the AFAHF, Man, Fin, and WEPFM industries, while quantile regression further captures the significant effects of drought on the ITS, RE, and LBS industries. These results are consistent with our earlier findings.

It is also interesting to study the delayed response of industry stock prices by directly lagging *Trend* by one period. Here, we replace $Trend_t$ with $Trend_{t-1}$ in model (3). Table 11 reports the results of regression between industry stock returns and the lag *Trend*. A comparison of the regression results in Tables 3, 11 reveals similar responses of industry stock prices to drought in the previous period and in the current period, although drought in the previous period has a relatively smaller and less significant effect on industry stock prices. Out of curiosity, we also examine the effect of monthly changes in *Trend* on industry stock prices. However, our empirical results show that this monthly change has no significant effect on the stock prices of various industries, possibly because monthly variations in the long-term drought trend are too small and difficult to detect (data not shown because of space limitations).

Conclusion

In China, drought is a frequent form of natural disaster characterized by a relative long duration and wide range of effects. Increases in global warming and changes to atmospheric circulation patterns have exacerbated the drought trend in China in recent years. This paper uses the PDSI to examine the effects of long-term drought trends on stock prices in various industries from 2000 to 2014.

The structure and strength of the relationship between drought and stock prices vary according to industry. The results obtained using OLS regression models show that drought generally has a negative correlation with industry stock prices. However, our OLS regression models only identify four industries that are significantly affected by drought. The quantile regression model provides a more comprehensive analysis of the relationship between drought and industry stock prices, revealing that drought significantly affects stock prices in 10 of the 15 studied industries to various degrees. The AFAHF, Man, ITS, Fin, RE, LBS, and WEPFM industries are particularly vulnerable to drought. Furthermore, the effect of drought on industry stock prices shifts from positive to negative as the analysis moves from low to high quantiles and is more significant in the high quantiles latter group. This result indicates that drought is not conducive to economic prosperity.

The results from our threshold model based on panel data show that the effects of drought on industry stock prices vary according to the threshold effect of investor sentiment. In the low sentiment regime, drought is negatively correlated with industry stock prices, whereas in the high sentiment regime, this correlation positive. This pattern suggests that investors are overly cautious or pessimistic during periods of low sentiment period, leading to the undervaluation of stocks, whereas they tend to speculate during periods of high sentiment, leading to the overvaluation of stocks.

Our findings have many implications for policy-makers, practitioners, and academics. First, they confirm the industry-based heterogeneity in the economic effect of drought and the threshold effect of investor sentiment. This confirmation will help the government to guide market investors and formulate drought-response policies for specific industries. Second, our findings may help investors to build portfolios that control their risk of exposure to drought. Third, our results demonstrate the need for more in-depth, detailed studies of the economic effect of drought that combine the effects of different scenarios and other factors, such as industry heterogeneity and investor sentiment.

Although the effects of drought are extensive and complex, research on these effects in the field of economics is still in its infancy. Constrained by the availability of data on drought, this paper mainly studies the economic effect of drought from a capital market perspective, focusing on different quantiles of stock prices and the role of investor sentiment. However, the field of economics still holds considerable scope for drought research. When regional drought data collected over longer time spans and at a higher frequency and greater density become easy to obtain, studies based on panel data and time series data can be carried out smoothly. For example, regional drought indicators can be matched to company addresses, enabling the construction of panel data to study the effect of drought at the firm level. Regarding time series, the overall drought index can be used to study the effects of drought on stock price indexes and commodity futures prices and to predict stock price indexes or inform the construction of commodity futures hedging strategies.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: China Securities Market and Accounting Research database National Center for Atmospheric Research.

Author contributions

All authors contribute equally to the paper.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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