Asian Economic and Financial Review
ISSN(e): 2222-6737
ISSN(p): 2305-2147
DOI: 10.55493/5002.v15i12.5755
Vol. 15, No. 12, 1908-1928.

URL: www.aessweb.com

Do global investors weather the storm? Evidence from mainland China and Hong Kong stock markets

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Article History
Received: 2 June 2025
Revised: 15 October 2025
Accepted: 31 October 2025
Published: 25 November 2025

Keywords
Bear and bull markets
Extreme weather events
GJR-GARCH model
Institutional investors
Meteorological variables
Stock market behavior.

JEL Classification:
G14; G41; C58; Q54.

ABSTRACT

This study examines the influence of extreme weather events on stock market behavior in China, focusing on the Shanghai and Hong Kong Stock Exchanges. This article's hypothesis is that local weather affects individual investors in Shanghai more significantly due to their short-term, speculative trading habits. In contrast, institutional investors in Hong Kong are less influenced by short-term considerations due to their long-term strategies and access to resources. The Glosten-Jagannathan-Runkle Generalized AutoRegressive Conditional Heteroskedasticity (GJR-GARCH) estimator can test the hypothesis under different market conditions and volatility clustering. The analysis utilizes daily financial and meteorological data from January 1, 2009, to December 31, 2023. The GJR-GARCH estimator incorporates variables such as air pressure, humidity, sunshine hours, and temperature. The results show that extreme weather has a more pronounced effect on the Shanghai market than the Hong Kong market. Furthermore, extreme weather events influence stock turnover and volatility more than stock returns, reflecting shifts in investment behavior. The hypothesis is further tested to determine whether it remains valid during bull and bear markets, which are emotionally charged periods. The hypothesis still holds, albeit with less pronounced effects. Thus, extreme weather can impact stock market performance, with the composition of investors playing a significant role.

Contribution/ Originality: This study contributes to the literature by demonstrating how extreme weather events influence stock market behavior. A GJR-GARCH model incorporates detailed weather variables and shows that extreme weather has a greater impact on the Shanghai market compared to the Hong Kong stock market because of the Shanghai market's higher concentration of local investors, regardless of market conditions.

1. INTRODUCTION

The weather's effect on people's mental well-being extends beyond the weather's impact on the physical environment. The evidence indicates that atmospheric conditions impact mood and behavior (Dowling & Lucey, 2005). People are happier (Schwarz & Clore, 1983) and have greater life satisfaction (Kämpfer & Mutz, 2013) on sunny days than on rainy ones. Suicides also tend to rise during warmer periods (Burke et al., 2018; Cheng et al., 2021). Thus, weather could impact investors' psychological well-being and influence their decision-making and investment behavior.

The study of weather on stock market behavior begins with the Efficient Market Hypothesis (EMH). EMH proposes that in an efficient capital market, stock prices reflect all new information available to investors (Fama, 1998;

Malkiel, 2003). Investors can under- or overreact to information, leading to stock return anomalies. However, investment behavior and strategies tend to evolve over time, correcting most anomalies in the long run. Several behavioral finance theories have challenged the EMH, such as herding behavior, which suggests that investors align their decisions with the majority and do not rely solely on their judgment (Scharfstein & Stein, 1990). Another phenomenon that can challenge the EMH is whether weather influences investment behavior that drives stock prices.

Several researchers explored the link between weather and stock market behavior. For example, Saunders (1993) found that sunlight has a positive influence on investors' moods, which in turn boosts their optimism and risk tolerance levels. Similarly, Hirshleifer and Shumway (2003) and Dowling and Lucey (2005) found that meteorological conditions were associated with higher stock returns. Furthermore, Lu and Chou (2012); Shahzad (2019), and Wang, Lin, and Lin (2012) found that weather influences the Chinese stock market. Symeonidis, Daskalakis, and Markellos (2010) found an inverse relationship between cloudiness and nighttime length, as well as US stock market volatility. Lastly, Sheikh, Shah, and Mahmood (2017) reported mixed findings on weather and stock returns and volatility in six Asian markets, while Trombley (1997) and Krämer and Runde (1997) were unable to replicate Saunders (1993) findings. In sum, the evidence of the weather's influence on stock markets remains inconsistent and fragmented across various global stock markets.

The fragmentation and inconsistency of the literature raise the question of whether particular market conditions are driving the results, such as the composition of local versus institutional investors. For instance, the Shanghai Stock Exchange primarily caters to local Chinese citizens, with limited foreign participation. Local individual investors contribute approximately 86% of the trading volume (China Securities Depository and Clearing, 2024) while overseas ownership was 27.5% in September 2024. In contrast, the Hong Kong Stock Exchange is a major global financial hub, with institutional investors contributing 65% of the total market turnover, while local Chinese investors account for 30%. Accordingly, extreme weather conditions may impact local Chinese investors more than international ones.

Given differences in investor composition, we hypothesize that the influence of extreme weather on stock market behavior is more pronounced in mainland China, where local investors dominate, than in Hong Kong[1], which has a higher composition of institutional and international investors. To test this hypothesis, the impact of extreme weather on both markets is analyzed using recent financial and meteorological data. The meteorological data includes temperature, pressure, humidity, and sunshine hours, while stock returns, turnover rate, and volatility measure stock market performance. This study also accounts for market conditions, as investment behavior changes depending on whether the market is experiencing a bear or bull market. Investors' fear and uncertainty heighten during a bear market, while bull markets foster overconfidence and exuberance. Thus, we further hypothesize that weather continues to impact market behavior, even during emotionally charged times, such as bull and bear markets.

This study addresses another limitation in the weather-finance literature: researchers often rely on local weather data to represent entire markets. For example, Chang, Chen, Chou, and Lin (2008) used only New York City's weather for the New York Stock Exchange, while Lu and Chou (2012) and Shahzad (2019) selected specific cities, such as Shanghai, Shenzhen, Hong Kong, and Taipei. Although these studies capture local weather effects, Mainland China spans a vast geographical area with varying weather patterns that may influence investors differently. Chinese investors trading on the Shanghai Stock Exchange may reside far from the city of Shanghai. To address this issue, composite extreme weather variables are constructed to reflect the diverse meteorological conditions of mainland China.

This study contributes to the literature by examining how extreme weather influences investment behavior in the Shanghai and Hong Kong stock markets, which differ in their composition of retail and institutional investors. While Shahzad (2019) and Jiang, Kang, Cheong, and Yoon (2019) have compared weather effects across regional

[1] Hong Kong refers to the Hong Kong Special Administrative Region (SAR) of the People's Republic of China.

markets, including Shanghai, Shenzhen, Hong Kong, and Taiwan, they have overlooked the differing behavior of investor composition. This study addresses that gap by hypothesizing that weather would have a greater impact in Shanghai, where local retail investors dominate, than in Hong Kong, where institutional and international investors dominate. International investors are less likely to be influenced by local weather conditions. This study's findings support this hypothesis, which holds across both bull and bear market conditions.

The remainder of this paper is structured as follows: Section 2 reviews the research literature, while Section 3 describes the data and methodology. Section 4 discusses the empirical results and findings, and Section 5 concludes the paper.

2. LITERATURE REVIEW

The literature review identifies which weather variables to focus on, establishes the hypothesis, and explains how market states can influence investors' behavior.

2.1. Weather's Effect on Stock Market Performance

Saunders (1993) and Wright and Bower (1992) were the first to link weather-induced mood to stock market performance. They found that sunshine, humidity, temperature, wind, seasonal changes, and daylight saving time influence investors' moods, judgments, and investment decisions. These findings challenge the efficient market hypothesis (EMH), which posits that investors act rationally and that asset prices reflect market information (Fama, 1970). Thus, asset prices should reflect systematic risk, rather than weather-induced mood factors.

Saunders (1993) connected the cloud cover of New York City to the AMEX/DJIA/NYSE returns from 1927 to 1989. He found that stock prices rose more on sunny days than on cloudy ones. Hirshleifer and Shumway (2003) found a positive correlation between sunshine and stock returns in 26 major stock exchanges. Nevertheless, they observed that neither rain nor snow had any effect on stock market returns. They established the first empirical evidence that weather conditions influenced investors' moods and decision-making.

Researchers continued this research strand, establishing a connection between weather conditions and stock returns. Dowling and Lucey (2005) observed that good weather led to higher Irish stock returns. Goetzmann, Kim, Kumar, and Wang (2015) determined that New York cloud cover reduced stock returns and raised institutional selling. Keef and Roush (2007) found that higher temperatures reduced Australian stock returns, while cloud cover and wind speed had no effect. Cao and Wei (2005) found a negative correlation between stock returns and temperature in the US, Canada, Britain, Germany, Sweden, Australia, Japan, and Taiwan. This relationship strengthened during the winter, suggesting that heightened apathy during the summer is associated with lower stock returns. Lastly, Zhang, Dai, Wang, and Lau (2023) found that high temperatures and global warming reduce the downside risk spillover in the US commodities markets, while cloud cover, precipitation, and runoff raise it by increasing crop yields and improving equipment reliability.

Several researchers found weak effects or mixed results of the weather's impact on stock market performance. Krämer and Runde (1997) and Trombley (1997) failed to replicate Saunders' (1993) work in the German and US stock markets. Tufan and Hamarat (2004) found no effect in the Istanbul Stock Exchange. However, several researchers found mixed effects. Sheikh et al. (2017) established that weather influenced India's stock market returns while affecting volatility in Pakistan, Bangladesh, and Sri Lanka. Their study examined the relationship between barometric pressure, cloudiness, humidity, temperature, visibility, and wind speed and stock market returns and volatilities. Lastly, Kathiravan, Selvam, Venkateswar, and Balakrishnan (2021) found that temperature negatively affected the returns of the Shanghai and Singaporean stock markets, while wind speed positively (negatively) influenced the Singaporean (Indian) stock market returns.

Researchers studying the impact of weather on mainland China also yielded mixed results. Lu and Chou (2012) found that weather had no effect on stock index returns but significantly influenced stock turnover and volatility between 2003 and 2008. Stock market volatility was negatively correlated with cloudiness but positively correlated with humidity, air pressure, and wind. Chang, Nieh, Yang, and Yang (2006) reported that temperature and cloud cover negatively influenced stock returns in the Taiwanese stock market, whereasWang et al. (2012) found no effect on stock returns when using sunshine hours, precipitation, and temperature. Wang et al. (2012) found that sunshine hours and temperature increased the volatility of Taiwanese stocks. Lastly, Shahzad (2019) found that the Shanghai and Hong Kong stock returns were not sensitive to temperature, whereas the Shenzhen and Taiwan regions were positively affected. Humidity reduced volatility in most markets, while wind increased it. His findings suggested that the Shanghai and Hong Kong markets are more efficient than those in Shenzhen and Taiwan.

The last strand of literature relates to extreme weather. Kang, Jiang, Lee, and Yoon (2010) observed that extreme weather conditions, including humidity, sunshine, and temperature had a significant influence on A-share returns but not on B-share returns. Nevertheless, extreme weather events impacted the return volatility of A- and B-shares. He and Ma (2021) further showed that Chinese firm-level stock returns decrease with exposure to extreme temperatures. Peters, Wang, and Sanders (2023) found that extreme rainfall lowered GDP growth in Chinese cities. In France, Peillex, El Ouadghiri, Gomes, and Jaballah (2021) found that trading volumes in the French stock market fell significantly on hot days. Kruttli, Tran, and Watugala (2025) also connected extreme weather events, such as hurricanes, increase in implied volatility while reducing the expected return of US stocks. Lastly, Altin (2024) showed that extreme weather events induce anomalies in the US stock market, further challenging the EMH.

The evidence on weather effects is mixed and largely outdated. This study revisits the topic using more recent data, focusing on extreme weather events that affect investors' behavior in the Hong Kong and Shanghai stock markets. Extreme weather can cause investors to alter their decision-making and investment strategies. The research literature also highlights the importance of incorporating various stock market indicators, such as returns, turnover, and volatility, alongside weather variables, including extreme temperatures, humidity, pressure, and sunshine hours.

2.2. Behavioral Differences Between Individual and Institutional Investors

The mainland Chinese and Hong Kong exchanges differ in key aspects. The mainland Chinese exchanges were established in 1990, and domestic investors can trade A-shares denominated in the renminbi. Chinese investors face stricter capital controls and increased restrictions on foreign investment. These regulatory controls and restrictions increase sensitivity to local policy and economic conditions in mainland markets. On the other hand, the Hong Kong Stock Exchange was founded in 1891 and allows institutional and international investors to trade in H-shares. The Hong Kong market has consistently attracted international investors, being more influenced by global factors and international investor sentiment (Yeh & Lee, 2000).

Investor composition can influence market behavior and lead to short-term fluctuations in the market. Retail investors dominate the Chinese stock markets, although institutional participants increased from 18% in 2019 to 24.6% in 2021 (Shanghai Advanced Institute of Finance, 2022). Between 2016 and 2019, retail investors on the Shanghai Stock Exchange held stocks for an average of 40 days, while institutional holdings averaged 109 days. In comparison, US investors held stocks for about 90 days on average for both groups.

Institutional investors differ significantly from Chinese retail investors. They tend to make more selective and long-term-focused trades due to their greater expertise and resources (Barber & Odean, 2008; Kaniel, Saar, & Titman, 2008). On the other hand, Chinese retail investors often hold stocks for short periods, trade frequently, speculate, buy losers, and sell winning stocks. Furthermore, Li, Rhee, and Wang (2017) found that individual investors often exhibit herding behavior with greater sensitivity to public news. Lastly, Yeh and Lee (2000) observed that the Hong Kong market responded more to bad news than to good news, whereas investors in Shanghai and Shenzhen reacted more to good news.

Few researchers have investigated how weather induces behavioral differences between institutional and retail investors. For example, Shahzad (2019) found that the returns of the Shenzhen and Taiwanese stock markets were more sensitive to weather than those of the Shanghai and Hong Kong markets. However, he did not attribute the behavioral difference between retail and institutional investors. Jiang et al. (2019) found that extreme weather events had a significant impact on the returns of the Shenzhen stock market, but not on those of the Hong Kong stock market. They also discovered that extremely low temperatures increased Shenzhen market returns, but this relationship weakened in 2012 after Chinese A-shares were opened to foreign investors.

The evidence suggests that investment behavior in Hong Kong is less sensitive to extreme weather conditions than that of local Chinese investors. Many Hong Kong investors reside abroad and are unlikely to be influenced by local weather. Hong Kong investors are generally better informed, more rational, and more sophisticated than retail Chinese investors. Accordingly, the hypothesis is developed below.

H_1: Extreme weather factors significantly affect the Shanghai stock market more than the Hong Kong stock market because of investor composition.

2.3. Economic Conditions Affecting Investors' Behavior

The prevailing market state can influence investors' behavior. Investors are more likely to take risks in bull markets, which they perceive as low-risk, and less likely to do so in bear markets, which they perceive as high-risk (Isen & Patrick, 1983). Furthermore, heightened uncertainty can amplify the impact of mood on decision-making (Forgas, 1995; Slovic, Finucane, Peters, & MacGregor, 2002). Nevertheless, few researchers have attempted to investigate how the weather impacts the stock market during different market states.

Market states can shape how weather influences investors' behavior. For example, Wang, Shih, and Jang (2018) investigated the weather's impact on the stock markets in Hong Kong, Japan, and Taiwan regions during bull and bear markets. They found no significant correlations between weather factors and stock market returns during bull markets. They concluded that bull markets fueled optimism and overconfidence, which nullified the weather's impact. However, less cloud cover and lower temperatures resulted in higher returns in the Taiwan region and Japanese markets during bear markets. The good weather raised investors' optimism and appetite for risk, as well as their stock purchases. Furthermore, humidity was positively correlated with market returns in the Hong Kong and Japanese markets during bear markets. Lastly, Jiang, Gupta, Subramaniam, and Yoon (2021) found that extremely high temperatures significantly lowered Shenzhen stock returns, while bear markets strengthened this relationship. Their findings suggested that poor weather amplifies investors' pessimism and selling behavior.

Prevailing market states can significantly influence investors' sentiment. This study examines bear and bull markets to assess the impact of weather conditions during market downturns and recoveries. Given the dominance of institutional investors, the hypothesis is expanded to include H2.

H_2: The Hong Kong stock market is less sensitive to weather conditions during a bull or bear market than the Shanghai stock market.

3. DATA AND METHODOLOGY

This section defines the variables, data sources, and model construction. It also explains how composite extreme weather variables are constructed to account for China's large geographical area and diverse meteorological conditions.

3.1. The Market, Weather, and Control Variables

The data comprises daily meteorological and stock market data from January 1, 2009, to December 31, 2023. The start date was chosen after the 2008 Global Financial Crisis, as central banks aggressively stabilized the financial markets, resulting in a rapid recovery. A crashing market could bias parameter estimates while masking the effects of weather on the stock markets. The end date reflects the latest available data used in the study. The weather data is collected from the China Meteorological Data Service Center (CMDC) and the Hong Kong Observatory. The daily stock market data comes from WIND and Bloomberg. Lastly, linear interpolation is used to impute missing data.

Stock market returns, share turnover, and volatility are measures used to assess the impact of extreme weather events on market behavior. The stock market return (RET) is calculated as the difference in the natural logarithm of the stock index between two consecutive days or $\text{RET} = \ln(\text{index}_t) - \ln(\text{index}_{t-1})$. Turnover (TUR) is computed as the daily trading volume divided by the number of outstanding shares or $\text{TUR} = \text{trading volume}_t$ / number of outstanding shares. Share turnover (TUR) reflects the market's trading activity level. Lastly, the volatility (VOL) quantifies the extent of stock price movements. Volatility is calculated as the difference between the highest and lowest indices of the trading day, normalized by the average of these two indices or $\text{VOL} = (\text{index}_\text{h} - \text{index}_\text{l})/[(\text{index}_\text{h} + \text{index}_\text{l})/2]$. Although turnover and volatility are related, turnover measures the frequency of trades and thus reflects liquidity, while volatility refers to the magnitude of price fluctuations. A volatile stock is inherently riskier than a stable one. Table 1 summarizes the descriptions and variable sources.

Table 1. The variables' descriptions and sources.

Variables	Description	Source
Stock market variables		
RET	Daily stock market index return (SSE and HIS)	WIND, Bloomberg, Authors' own computation
TUR	Daily turnover rate	WIND, Bloomberg, Authors' own computation
VOL	Daily stock return volatility	WIND, Bloomberg, Authors' own computation
Weather variables		
TEM	Mean air temperature, given in degrees Celsius (℃)	China Meteorological Data Service Center, Hong Kong Observatory
HUM	Mean humidity or moisture represents the percentage of water vapor in the atmosphere, given in percentage (%)	China Meteorological Data Service Center, Hong Kong Observatory
PRES	Sea level pressure, given in hectopascal (hPa)	China Meteorological Data Service Center, Hong Kong Observatory
SUN	Sunshine - Duration of sunshine in a day, given in hours	China Meteorological data service center, Hong Kong observatory
Control variables		
FW	Fall and winter, labeled as one if the date is between September 21 and March 20, zero otherwise	Authors' computation
MON	Monday, defined as one if Monday, zero otherwise	Authors' computation
JAN	January is defined as one if January, zero otherwise	Authors' computation
SAD	Seasonal Affective Disorder	Authors' computations
INT	The 10-year government yield for mainland China and Hong Kong	Bloomberg

Temperature, humidity, pressure, and sunshine hours comprise the weather variables. Warm temperatures are shown to stimulate positive moods in people (Howarth & Hoffman, 1984), which may, in turn, influence their investment behavior. Furthermore, the Affect Infusion Model posits that investors' positive moods could lead to better evaluations, overly optimistic expectations, and decreased risk aversion (Forgas, 1995). Conversely, the Mood Maintenance Hypothesis proposes that individuals who feel good behave conservatively, as they maintain their upbeat mood while raising their risk aversion (Isen & Patrick, 1983). Furthermore, a non-behavioral hypothesis posits that pleasant weather conditions may reduce market liquidity due to higher opportunity costs associated with favorable weather conditions (Schmittmann, Pirschel, Meyer, & Hackethal, 2015). This hypothesis suggests that individuals tend to opt for outdoor or leisure activities during pleasant weather, while reducing their trading activity and liquidity. These theories predict opposite behaviors in response to good weather, which makes it difficult to predict how pleasant weather affects stock market investment.

This study examines the impact of extreme weather events on investment behavior. Equation 1 defines Shanghai's (SSE) higher temperature dummy variable. A dummy variable is created for extreme temperatures, which equals one if that day had a temperature in the top 25th percentile and zero otherwise[2]. A dummy variable is similarly created for Hong Kong. Lastly, lower temperatures may influence investment behavior differently than hot weather. Accordingly, a dummy variable is created separately for daily temperatures lower than the 25th percentile for Shanghai. The Shanghai lower temperature threshold is shown in Equation 2. Hong Kong is similarly created.

$$TEM_{SSE}^{75} = \begin{Bmatrix} 1 & if\ temperature_t \geq 75\ percentile \\ & 0 \quad otherwise \end{Bmatrix} \quad (1)$$

$$TEM_{SSE}^{25} = \begin{Bmatrix} 1 & if\ temperature_t \leq 25\ percentile \\ & 0 \quad otherwise \end{Bmatrix} \quad (2)$$

Humidity is the second weather variable, representing the percentage of water vapor in the atmosphere. Humidity has mixed effects on mood. High humidity can cause physical discomfort to some investors, while others find warm and humid weather relaxing or pleasant. Furthermore, investors' perception of humidity varies depending on local weather conditions. For example, investors residing in dry areas may welcome high humidity, whereas investors in humid regions find it uncomfortable. Accordingly, dummy variables are created for extreme humidity in the top 25th percentile and for humidity in the bottom 25th percentile for both Hong Kong and Shanghai.

The third weather variable is atmospheric pressure. High pressure is associated with calm, fair weather, while low pressure is associated with cloudiness, precipitation, and wind. Storms and typhoons typically occur during periods of low atmospheric pressure. These events can disrupt economic activities and create uncertainty in financial markets. Furthermore, low air pressure may induce feelings of gloominess and fatigue, potentially leading to negative sentiment. Accordingly, a dummy variable is created for atmospheric pressure in the top 25th percentile and zero otherwise for both Hong Kong and Shanghai. Then, another dummy variable is created for atmospheric pressure in the bottom 25th percentile for both exchanges.

The fourth weather variable is sunshine hours, representing the duration of sunshine in a day. Sunshine can boost positive moods and alleviate negative sentiments, particularly in regions with limited sunlight during fall and winter. Exposure to sunshine triggers the release of serotonin, a neurotransmitter that elevates a person's mood, promotes happiness, and increases energy. Conversely, insufficient sunlight could lead to higher melatonin secretion, a hormone that induces sleepiness and sluggishness. Reduced sunlight exposure decreases serotonin levels and could contribute to depression. Thus, dummy variables are created for sunshine hours in the top 25th percentile for both Hong Kong and Shanghai, as well as another dummy variable for the bottom 25th percentile.

This study accounts for extreme weather events in a large country with diverse meteorological conditions. Mainland China spans 9.3 million square kilometers and is divided into five time zones. Local investors are spread across China, with 63% of the trading volume on the Shanghai stock market originating from Beijing, Guangdong, Jiangsu, Shanghai, and Zhejiang. Table 2 shows the descriptive statistics for the weather variables in the five provinces. Guangdong has a higher average temperature than Beijing because it lies farther south. Accordingly, residents in Guangdong would have a higher temperature threshold than those in Beijing.

The composite dummy weather variables are constructed from the five provinces, where any extreme weather event in one of the provinces is included in the composite measure. Equation 3 illustrates how the composite weather variable is calculated, utilizing extremely high temperatures in mainland China. The reasoning is that investors in a particular province can respond to extreme weather, triggering a rally (or dip) that diffuses to investors in other provinces through herding behavior. Lastly, Hong Kong is an urban area and does not require this composite measure. Nevertheless, the weather in Hong Kong is included in Table 2 for comparison.

$$TEM_{composite}^{75} = TEM_{Beijing}^{75} \cup TEM_{\text{Guangdong}}^{75} \cup \cdots \cup TEM_{\text{Zhejiang}}^{75} \quad (3)$$

[2] Cheema, Faff, and Szulczyk (2022) used the dummy variable technique to determine whether extreme market drops drive investors toward safe-haven assets.

Table 2. Descriptive weather statistics for mainland China and Hong Kong.

Statistic	Province	TEMP	HUM	PRES	SUN
	Beijing	-13.30	8.00	986.20	0.00
	Guangdong	4.60	27.00	985.70	0.00
	Jiangsu	-4.50	20.00	986.40	0.00
	Shanghai	-4.60	23.00	986.40	0.00
	Zhejiang	-3.20	17.00	982.70	0.00
Minimum	Hong Kong	7.40	29.00	992.20	0.00
	Beijing	13.77	51.65	1012.47	6.82
	Guangdong	22.34	78.47	1005.18	4.48
	Jiangsu	17.77	71.88	1015.48	4.79
	Shanghai	18.11	70.35	1015.73	4.11
	Zhejiang	18.15	71.92	1011.09	4.63
Mean	Hong Kong	23.93	78.01	1012.73	5.06
	Beijing	15.00	52.00	1012.30	8.00
	Guangdong	23.50	80.00	1005.20	4.30
	Jiangsu	18.30	72.00	1015.60	5.00
	Shanghai	18.70	71.00	1015.90	3.70
	Zhejiang	18.80	73.00	1011.20	4.60
Median	Hong Kong	24.80	79.00	1012.70	5.10
	Beijing	34.50	100.00	1040.00	14.10
	Guangdong	32.30	100.00	1026.60	12.30
	Jiangsu	36.20	100.00	1042.00	13.00
	Shanghai	35.70	100.00	1042.00	12.40
	Zhejiang	35.70	100.00	1037.40	12.80
Maximum	Hong Kong	32.20	99.00	1032.60	12.40
	Beijing	11.37	19.94	10.45	3.98
	Guangdong	6.09	11.24	6.80	3.76
	Jiangsu	9.11	13.36	9.28	4.09
	Shanghai	8.76	14.08	9.09	3.78
	Zhejiang	8.99	14.53	9.12	4.08
Std. Dev.	Hong Kong	5.11	10.25	6.35	3.85
	Beijing	-0.22	0.04	0.12	-0.48
	Guangdong	-0.57	-0.92	0.06	0.18
	Jiangsu	-0.12	-0.32	0.09	0.12
	Shanghai	-0.12	-0.27	0.07	0.36
	Zhejiang	-0.13	-0.39	0.10	0.18
Skewness	Hong Kong	-0.53	-0.98	-0.02	0.05
	Beijing	-1.31	-0.94	-0.95	-0.95
	Guangdong	-0.65	1.30	-0.62	-1.44
	Jiangsu	-1.10	-0.27	-0.98	-1.47
	Shanghai	-1.08	-0.30	-0.96	-1.29
	Zhejiang	-1.09	-0.40	-0.97	-1.47
Kurtosis	Hong Kong	-0.68	1.81	-0.61	-1.47

Additional variables are added to control for stock market anomalies and seasonal effects. The fall-winter (FW) is a dummy variable, set to 0 if the day lies between March 20 and September 21 and 1 otherwise. This variable captures the effect of winter on investment behavior since cold, rainy weather may affect investors' sentiment. The Monday (MON) Effect is that investors believe a trend will continue on Monday if the stock market is up (down) on Friday. Accordingly, a dummy variable equals one for Monday and zero for all other days. The January (JAN) Effect refers to investors buying stock in January, which raises stock prices after they sold their stocks in December, having incurred tax losses. The dummy variable equals one for January and zero for all other months. Berument and Kiymaz (2001); Dicle and Levendis (2014) and Gultekin and Gultekin (1983) for a thorough discussion of these variables, furthermore, a rising (falling) interest (INT) rate causes investors to reduce (boost) their investments, decreasing (raising) stock prices[3]. Lastly, Seasonal Affective Disorder (SAD) warrants a detailed discussion due to its complexity.

SAD, or "winter depression," occurs during the fall and winter. The symptoms include fatigue, loss of interest, difficulty concentrating, and drowsiness due to reduced sunlight exposure. The decrease in sunlight is calculated for darker months as $SAD_t = FW_t \times (H_t - 12)$. The H_t represents the duration of daylight hours on a particular day, while FW is the dummy variable for the Fall-Winter season.

The H_t represents a day's duration from sunrise to sunset at a location on the Earth, given the latitude (L) in the northern hemisphere. The latitude (L) for Shanghai (Hong Kong) is 31.25 (22.3) degrees. The H_t is calculated using spherical trigonometry, as shown in Equation 4, and was first introduced by Forsythe, Rykiel Jr, Stahl, Wu, and Schoolfield (1995). Since the Earth changes its tilt as it revolves around the sun, Equation 5 calculates the sun's declination angle (ϕ) in radians given the revolution angle (θ). At last, Equation 6 calculates the revolution angle from the day of the year or Julian (J). A $Julian_t$ represents a single day in a year, ranging from 1 to 365 for non-leap years and 366 for leap years, which begins on January 1.

$$H_t = 24 - \frac{24}{\pi} cos^{-1}\left(\frac{sin\left(0.8333\cdot\frac{\pi}{180}\right)+sin\left(\frac{L\pi}{180}\right)\cdot sin\phi}{cos\left(\frac{L\pi}{180}\right)\cdot cos\phi}\right) \quad (4)$$

$$\phi = sin^{-1}\left(0.39795 \cdot \cos(\theta)\right) \quad (5)$$

$$\theta = 0.2163108 + 2 \cdot tan^{-1}[0.9671396 \cdot \tan(0.00860 \cdot [J - 186])] \quad (6)$$

3.2. Unit Roots and Descriptive Statistics

The analysis employs the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which requires all variables to be stationary. Standard unit root tests are performed, including the Augmented Dickey-Fuller (ADF), the Phillips-Perron (PP), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The dummy variables are excluded from the unit root tests since they are stationary as they alternate between 0 and 1. The three tests indicate that the interest rates in Hong Kong and Shanghai have unit roots in Table 3. Thus, interest rates are differenced to make them stationary, as shown in the table. The three tests suggest that stock returns and SAD are stationary. However, the KPSS test indicates that stock turnover and volatility exhibit unit roots, while the ADF and PP tests do not. Therefore, we conclude that all variables are stationary.

Table 3. The unit root tests.

Test	Stock returns	Stock turnover	Stock volatility	SAD	Δ Interest rate
Hong Kong					
ADF	**-16.016*** **	**-9.766*** **	**-7.609*** **	**-10.509*** **	**-12.21*** **
PP	**-3602.1*** **	**-2734.2*** **	**-3206.1*** **	**-22.85** **	**-1547.7*** **
KPSS	0.256	**2.002*** **	**3.228*** **	0.041	0.142
Shanghai					
ADF	**-14.807*** **	**-4.173*** **	**-6.797*** **	**-9.9529*** **	**-14.017*** **
PP	**-3548.0*** **	**-102.12*** **	**-2543.4*** **	**-23.301** **	**-3212.6*** **
ADF	0.092	**2.322*** **	**4.250*** **	0.043	0.226

Note: Statistical significance indicates stationarity for the ADF and PP, while the KPSS indicates a unit root. ***, **, * indicate statistical significance at 1% and 5%. Bold indicates statistical significance.

Table 4 shows the descriptive statistics for the dependent and control variables. The dummy variables are excluded for convenience. The stock returns (RET) and interest rate difference (ΔINT) have means and medians close to zero. Their skewness is close to zero, with a kurtosis of less than 6. However, the stock turnover (TUR) and volatility (VOL) exhibit positive skewness, indicating a rightward skew. Their kurtosis is also relatively high,

[3] Linear interpolation is used to expand weekly yields into daily yields because the daily 10-year bond yield is not available.

indicating that some trading days experienced extreme positive (or negative) returns. Consequently, the default distribution for the GARCH maximum likelihood function is the skewed normal.

Table 4. Descriptive statistics of the dependent and control variables.

Statistic	Exchange	RET	TURN	VOL	ΔINT
Minimum	Shanghai	-0.0887	0.0022	0.0025	-0.1606
	Hong Kong	-0.0657	0.0549	0.0000	-0.1643
Mean	Shanghai	0.0001	0.0081	0.0153	0.0000
	Hong Kong	0.0000	0.2329	0.0135	0.0005
Median	Shanghai	0.0005	0.0066	0.0124	0.0000
	Hong Kong	0.0003	0.2108	0.0116	0.0000
Maximum	Shanghai	0.0594	0.0413	0.1063	0.2082
	Hong Kong	0.0869	3.0688	0.0794	0.1543
Std. Dev.	Shanghai	0.0133	0.0054	0.0103	0.0257
	Hong Kong	0.0134	0.1078	0.0075	0.0235
Skewness	Shanghai	-0.8384	2.3806	2.7356	0.1783
	Hong Kong	0.0611	8.5711	2.2442	0.0313
Kurtosis	Shanghai	5.7164	6.6963	11.9423	4.5957
	Hong Kong	2.7587	176.4557	9.3652	5.8457

3.3. Determining the Market State

The hypothesis requires that bull or bear markets be identified to demonstrate that the hypothesis holds regardless of the market state. Two moving averages (MAs) are calculated with moving window sizes of 50 and 200. The 200-day (50-day) MA reflects long-term (short-term) trends in the market (Murphy, 1999). Investors drive up stock prices when the 50-day moving average exceeds the 200-day moving average, a characteristic of a bull market. A bear market is the opposite, as investors sell off their holdings, driving stock prices down as the 50-day moving average dips below the 200-day moving average.

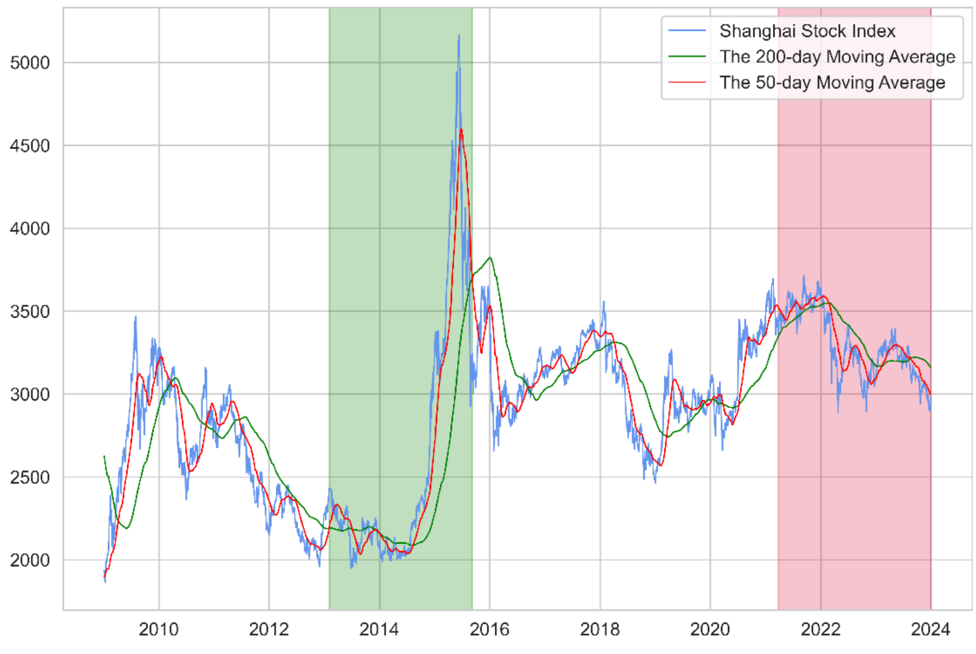

Figure 1. The Shanghai Stock Index (HSI) with bull (Green) and bear (Red) markets identified.

The trading rule is applied to determine the market state. The trading rule indicates that the Shanghai index experienced a bull market between February 4, 2013, and September 8, 2015, as shown by the green area in Figure 1. This area includes several episodes of a bear market in 2013 because the GARCH(1,1) analysis requires a minimum of 500 observations to minimize biases in parameter estimation (Hwang & Valls Pereira, 2006). Furthermore, the

Shanghai stock market experienced a bear market between March 26, 2021, and December 31, 2023, denoted by the reddish area. Figure 2 illustrates that the Hong Kong stock market experienced a bull market from January 21, 2016, to July 13, 2018, and a bear market from March 26, 2021, to December 31, 2023. Consequently, the bear markets coincide for both markets, whereas the Shanghai market experienced a bull market before Hong Kong.

Alt text: The Shanghai Stock Index is plotted between 2009 and 2023. The 50-day and 200-day moving averages are also plotted, with the bull (bear) market shaded green (red).

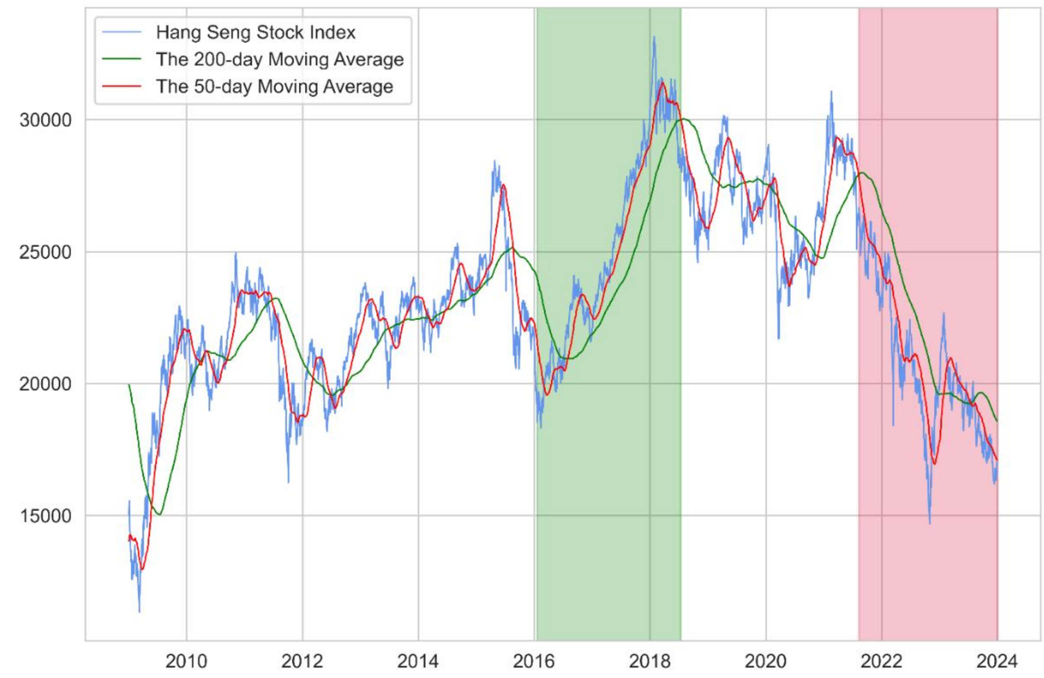

Figure 2. The Hang Seng Index (HSI) with bull (Green) and bear (Red) markets identified.

Alt text: The Hang Seng Index is plotted between 2009 and 2023. The 50-day and 200-day moving averages are also plotted, with the bull (bear) market shaded green (red).

3.4. The Empirical Model

Equation 7 models the relationship between the dependent variable, y_t, at time t, and the weather and control variables. The dependent variable is stock returns (RET), turnover (TUR), or volatility (VOL), while the Hong Kong and Shanghai stock markets are estimated separately.

$$y_t = \mu + \sum \delta_j WEATHER_{j,t}^{75} + \sum \theta_k WEATHER_{k,t}^{25} + \sum \rho_{\mathrm{m}} CONTROL_{m,t} + \varepsilon_t \quad (7)$$

Where $WEATHER^{75}$ denotes the dummy variable for extreme temperature, humidity, air pressure, and sunshine hours in the top 25th percentile, while $WEATHER^{25}$ is for the bottom 25th percentile, CONTROL comprises the control variables, including Seasonal Affective Disorder (SAD), Fall-Winter (FW), Monday (MON), January (JAN), and interest rate difference (ΔINT). The μ defines the mean, while ε_t is the error term at time *t* and includes the conditional heteroscedasticity.

The Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) model (Glosten, Jagannathan, & Runkle, 1993) estimates Equation 7. The GJR-GARCH is commonly used in financial analysis because it effectively handles asymmetric shocks and improves the accuracy of volatility modeling (Aliyev, Ajayi, & Gasim, 2020; Cheema et al., 2022; Nugroho et al., 2019). The error term reflects a Gaussian white noise (z_t) process via $\varepsilon_t = \sigma_t \cdot z_t$ with the condition variance defined in Equation 8.

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (8)$$

The GJR-GARCH can model volatility clustering, handle leptokurtic returns, and account for the leverage effect. The leptokurtic time series reflects higher or lower returns, i.e., fat tails, relative to the normal distribution. Lastly, the indicator variable in Equation 9 captures the leverage effect when good (bad) news influences the dependent variable $\gamma>0$ ($\gamma<0$).

$$I_{t-1} = \begin{Bmatrix} 0 & if\ y_{t-1} \geq \mu \\ 1 & if\ y_{t-1} < \mu \end{Bmatrix} \quad (9)$$

The GJR-GARCH (1,1) is estimated with parameters α and β. These variables determine the overall persistence, $\alpha + \beta + 0.5 \cdot \gamma$, which indicates how volatility shocks persist into the future. If persistence is close to one, it suggests that shocks persist. The volatility term is used in two different contexts. The GARCH volatility is referred to as variance volatility, while stock volatility refers to the measure of how much a stock's price fluctuates over a specific period.

4. EMPIRICAL RESULTS

Section 4.1 tests the hypothesis for the full sample, while Sections 4.2 and 4.3 determine whether the hypothesis holds in bull and bear markets.

4.1. Weather's Impact on the Stock Markets

Table 5 presents the GJR-GARCH results for the Shanghai and Hong Kong stock markets from January 1, 2009, to December 31, 2023. The analysis reveals that only one weather variable, higher temperature ($TEMP^{75}$), has a significant impact on stock returns in Shanghai, whereas no weather variables are significant for Hong Kong. Thus, higher temperatures lead to increased stock returns in Shanghai. The interest rate differences (ΔINT) have a positive impact on both markets, and the fall-winter (FW) variable is significant for Hong Kong. Lastly, the beta, $\hat{\beta}$, indicates long-lasting volatility in the variance equation, while a small alpha, $\hat{\alpha}$, suggests minimal investor reaction to new information. Only the $\hat{\gamma}$ *is* statistically significant for the Hong Kong market, indicating that investors react positively to good news. Both time series exhibit persistent variance, as indicated by $\hat{\alpha} + \hat{\beta} + 0.5 \cdot \hat{\gamma}$.

Table 5. GARCH Estimations for the full dataset.

Variables	Mainland China						Hong Kong					
	Returns		Turnover		Stock Volatility		Returns		Turnover		Stock Volatility	
	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.
$\hat{\mu}$	-0.4804	-0.6763	**5.7913*** **	**45.7138**	**12.7311*** **	**27.0700**	0.1287	0.2596	**212.9827*** **	**73.4528**	**11.51*** **	**41.94**
TEM^{25th}	-0.1881	-0.3211	**0.3338*** **	**3.2574**	0.3750	0.9120	0.1066	0.1813	**11.6769*** **	**3.0987**	**-0.7659** **	**-2.4168**
TEM^{75t}	**1.1849** **	**2.1319**	-0.0076	-0.0767	**-0.6591* **	**-1.7134**	-0.0662	-0.1142	**6.9824** **	**2.0127**	0.2455	0.7478
HUM^{25th}	-0.1409	-0.3663	**0.1188** **	**1.9946**	**0.5663** **	**2.2204**	-0.2128	-0.4119	**-6.1536** **	**-2.0804**	0.2742	1.0132
HUM^{75th}	0.3979	0.9169	**0.1515** **	**2.3759**	0.2883	1.0101	0.0606	0.1105	-2.4791	-0.8035	0.2220	0.7785
$PRES^{25th}$	-0.8629	-1.5342	**-0.1569* **	**-1.6458**	-0.4182	-1.1080	-0.3813	-0.7316	3.0756	0.9583	-0.0973	-0.3419
$PRES^{75th}$	0.5486	0.9318	0.1489	1.6284	**1.0757*** **	**2.7423**	0.6273	1.0133	-4.3616	-1.1882	0.4343	1.3862
SUN^{25th}	-0.4067	-1.0295	-0.0708	-1.2401	-0.1581	-0.5955	-0.0589	-0.1124	-0.3652	-0.1248	0.0534	0.1978
SUN^{75th}	0.2456	0.5888	-0.0441	-0.7745	**-0.7355*** **	**-2.7926**	0.1764	0.3706	3.2917	1.2401	-0.3301	-1.3216
FW	-0.1378	-0.2210	**-0.3232** **	**-2.5192**	0.0276	0.0626	-0.4893	-0.8208	6.6282	1.6353	0.2814	1.0260
MON	0.5304	1.2547	**0.1918*** **	**3.5374**	**1.0089*** **	**3.5998**	-0.2569	-0.5594	**-13.4667*** **	**-5.5232**	0.0431	0.1794
JAN	0.5559	0.6845	0.2295	1.3966	0.7908	1.6445	**1.4742* **	**1.9096**	**16.6769*** **	**3.0008**	**1.0567*** **	**2.7080**
SAD	-0.2424	-0.5258	-0.0516	-0.4878	**1.6870*** **	**5.2864**	0.0338	0.0496	**19.4953*** **	**3.9681**	**0.2108** **	**2.0652**
ΔINT	**22.9269*** **	**3.2607**	-0.0297	-0.0311	**-10.7800** **	**-2.2489**	**15.3628* **	**1.8207**	-47.1135	-0.8688	6.9957	1.5308
$\hat{\omega}$	0.0000	0.3425	**0.0000*** **	**23.3158**	**0.0000*** **	**175.8975**	**0.0000* **	**1.9015**	**0.0030*** **	**18.7997**	**0.0000*** **	**35913.56**
$\hat{\alpha}$	**0.0645* **	**1.7260**	**0.6927*** **	**16.4452**	**0.0903*** **	**14.1822**	**0.0170*** **	**2.9063**	**1.0000*** **	**15.6785**	**0.2111*** **	**10.6296**
$\hat{\beta}$	**0.9278*** **	**22.4308**	**0.3148*** **	**12.9118**	**0.8930*** **	**208.2008**	**0.9304*** **	**98.0183**	0.0330	1.5206	**0.7146*** **	**51.1766**
$\hat{\gamma}$	0.0049	0.3900	**-0.1747*** **	**-4.3383**	**-0.0815*** **	**-12.6537**	**0.0730*** **	**5.4548**	**-0.5846*** **	**-7.1772**	**-0.2171*** **	**-10.6271**
Persistence	0.9947		0.9202		0.9425		0.9840		0.7407		0.8171	
OBS	3645		3645		3645		3707		3707		3707	

Note: The maximum likelihood function of the GJR-GARCH(1,1) uses a skewed normal distribution. The parameter estimates are scaled by 1×10^3 except for the variance parameter estimates because stock returns vary to the thousandths. $WEATHER^{75th(25th)}$ denotes extreme high (low) weather conditions. ***, **, * indicate statistical significance at 1%, 5% and 10%. Bold indicates statistical significance.

The stock turnover reveals a significantly different response to weather. In Shanghai, low extreme weather events for temperature ($TEMP^{25}$) and humidity thresholds (HUM^{25} and HUM^{75}) are statistically significant and raise the turnover rate, while low pressure ($PRES^{25}$) is statistically significant and decreases stock turnover. In Hong Kong, extreme temperatures ($TEMP^{25}$ and $TEMP^{75}$) are statistically significant and raise stock turnover, while lower humidity (HUM^{25}) lowers turnover. Furthermore, Shanghai investors respond to the Fall-Winter (FW) period by lowering turnover, while Monday (MON) raises volatility. Meanwhile, Hong Kong investors react to the MON, JAN, and SAD variables. Ironically, SAD influences stock turnover despite being based on Hong Kong's latitude. Some international investors residing in Australia and New Zealand experience summer when Hong Kong residents are in winter. Lastly, the variance components change for the GJR-GARCH. The betas are small, while the alphas have a larger effect, suggesting that investors respond to new information. Both gammas are negative and statistically significant, indicating that investors respond to bad news. Nevertheless, the overall persistence remains large for both stock exchanges.

For stock volatility, the Shanghai market is affected by multiple weather variables. The high temperature (TEM^{75}) and high sunlight hours (SUN^{75}) lower volatility, while $PRES^{75}$ and HUM^{25} raise volatility. Meanwhile, the lower temperature threshold (TEM^{25}) in Hong Kong lowers volatility. The Monday (MON) and SAD variables, as well as the interest rate difference (ΔINT), affect the Shanghai stock market, while the January (JAN) variable affects the Hong Kong stock market. Lastly, all GJR-GARCH variance components are statistically significant, with larger betas than alphas, indicating persistent variance volatility. The gammas are negative for both markets, indicating investors respond to bad news. Lastly, the overall persistence remains large for both stock exchanges.

Extreme weather has a significant impact on the Shanghai stock market but a minimal influence on the Hong Kong market, supporting the hypothesis that extreme weather affects individual investors more than it does institutional investors. Lastly, stock returns show minimal responsiveness to weather, whereas stock turnover reacts more prominently.

4.2. Weather's Impact During Bull Markets

This section determines whether the hypothesis holds during bull markets in the Shanghai and Hong Kong Stock Exchanges. Bull markets are typically characterized by investors' confidence and excessive exuberance. The Hong Kong bull market spanned from January 21, 2016, to July 13, 2018, while the Shanghai bull market lasted from February 4, 2013, to September 8, 2015.

The results in Table 6 indicate that weather has a less significant impact on bull markets than on the entire sample. The upper threshold for sunshine hours (SUN^{75}) is statistically significant and positively affects stock returns in the Shanghai stock market, whereas no weather variables are significant for the Hong Kong market. The January (JAN) effect is significant and raises returns for Hong Kong. Furthermore, the variance parameters reflect similar trends with low alphas and high betas for both exchanges, indicating persistent variance volatility. For Hong Kong, the gamma is positive and significant, indicating that investors react positively to good news. Thus, investors' exuberance during a bull market overcomes some of the effects of the weather variables.

Table 6. GARCH Estimations for the bull markets.

Variables	Mainland China						Hong Kong					
	Returns		Turnover		Stock Volatility		Returns		Turnover		Stock Volatility	
	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.
$\hat{\mu}$	-0.8000	-0.4477	**4.4101*** **	**18.4090**	**15.0936*** **	**21.8747**	-1.4088	-1.5261	**204.9045*** **	**40.2512**	**11.6685*** **	**22.2327**
TEM^{25th}	-1.5396	-0.9151	0.1300	0.5170	0.7094	1.0011	0.5456	0.4542	8.5869	1.0796	0.0974	0.1536
TEM^{75t}	1.1888	0.8635	**1.0619*** **	**5.1200**	**-2.0617*** **	**-3.3208**	0.6957	0.6813	**18.1609*** **	**2.6405**	0.6736	1.0957
HUM^{25th}	-0.7583	-0.7290	0.0389	0.3148	-0.4349	-0.8173	-0.5996	-0.5981	-6.5180	-1.1754	-0.4060	-0.7397
HUM^{75th}	1.0103	0.8225	0.2148	1.6273	-1.0664	-1.5720	1.3664	1.3045	-3.6042	-0.6595	**-1.4766*** **	**-2.6826**
PRES^{25th}	-1.8411	-1.4297	**-1.0902*** **	**-5.3457**	-0.7799	-1.1364	0.9639	0.9948	-3.5419	-0.5602	**-1.4969*** **	**-2.7776**
PRES^{75th}	1.5458	0.9240	-0.2485	-1.1769	**2.1050** **	**2.4032**	0.5565	0.4653	-7.0395	-0.9442	**1.2767** **	**2.0540**
SUN^{25th}	-0.5164	-0.4555	-0.0463	-0.3620	0.1683	0.2979	0.8749	0.8599	3.8795	0.6881	0.4607	0.8757
SUN^{75th}	**2.4387** **	**2.2978**	-0.0111	-0.0952	-0.4510	-0.7735	0.9459	0.9665	4.5385	0.7713	-0.4240	-0.7618
FW	-1.0044	-0.5929	**1.3827*** **	**5.4022**	-0.6263	-0.8711	0.7524	0.6593	5.4782	0.7928	-0.5736	-0.8705
MON	1.3543	1.1774	-0.0114	-0.1105	0.3492	0.4949	1.4057	1.4943	**-9.8426***	**-1.6697**	-0.2807	-0.5837
JAN	-3.2804	-1.4210	**-1.0058*** **	**-3.3288**	-1.3217	-1.3994	**4.7053*** **	**3.0224**	-21.8918	-1.3557	-0.7295	-0.7084
SAD	-1.0949	-0.7743	**0.9321*** **	**4.1491**	**1.2506***	**1.8571**	1.0288	0.7292	-7.9920	-0.9029	0.7469	0.9011
INT	-10.1799	-0.7098	1.3719	0.8617	-0.6796	-0.0885	-20.9712	-1.1739	**-269.5826*** **	**-2.5152**	-4.6795	-0.4699
$\hat{\omega}$	0.0000	0.4015	**0.0000*** **	**5.6676**	**0.0000*** **	**817.6745**	**0.0000*** **	**192.5995**	**0.0020*** **	**6.8468**	**0.0000*** **	**7.2653**
$\hat{\alpha}$	**0.0956** **	**2.5808**	**0.9258*** **	**9.5317**	**0.2020*** **	**4.3625**	0.0000	0.0000	**0.7336*** **	**3.4638**	**0.1419** **	**1.9805**
$\hat{\beta}$	**0.9140*** **	**24.3218**	**0.1207*** **	**3.2128**	**0.8103*** **	**25.3749**	**0.8525*** **	**51.5327**	0.0000	0.0000	**0.0000**	0.0000
$\hat{\gamma}$	-0.0213	-0.9733	**-0.4345*** **	**-3.3844**	**-0.3890*** **	**-8.7165**	**0.1408*** **	**3.4913**	**-0.3960** **	**-2.0676**	**0.9829*** **	**3.8611**
Persistence	0.9990		0.8294		0.8178		0.9229		0.5356		0.6334	
OBS	629		629		629		609		609		609	

Note: The maximum likelihood function of the GJR-GARCH(1,1) uses a skewed normal distribution. The parameter estimates are scaled by 1×10^3 except for the variance parameter estimates because stock returns vary to the thousandths. WEATHER$^{75th(25th)}$ denotes extreme high (low) weather conditions. ***, **, * indicate statistical significance at 1%, 5% and 10%. Bold indicates statistical significance.

Extreme weather impacts on stock turnover are minimal. High temperature ($TEMP^{75}$) raises stock turnover in Shanghai, while low pressure ($PRES^{25}$) lowers it. Meanwhile, the high temperature ($TEMP^{75}$) raises the stock turnover in Hong Kong. The variables FW, JAN, and SAD are significant for Shanghai, while MON and interest rate differences (ΔINT) are significant for Hong Kong. The GJR-GARCH variance components show patterns similar to those of the entire sample. The alphas are close to one and statistically significant, indicating that variance volatility responds to new information. Meanwhile, the betas are small in magnitude, and the Hong Kong beta is not statistically significant. The gammas are negative and statistically significant for both markets, indicating that investors react negatively to bad news. Lastly, variance volatility exhibits overall long-run persistence, but it is lower than that of stock returns.

This is the first instance of extreme weather impacting Hong Kong more than Shanghai. Higher temperatures (TEM^{75}) decrease volatility in the Shanghai market, while higher pressure ($PRES^{75}$) raises volatility. However, higher humidity (HUM^{75}) and lower pressure levels ($PRES^{25}$) lower stock volatility in Hong Kong, while high $PRES^{75}$ raises volatility. Only one control variable, SAD, influences the Shanghai Stock Market, whereas no control variables affect the Hong Kong market. The variance components differ from the results of the entire dataset. The beta is close to one, with a small alpha for Shanghai. Both are statistically significant. However, Hong Kong shows a small but statistically significant alpha and a beta close to zero. Lastly, the gamma parameters are statistically significant for both stock markets. Chinese investors tend to react negatively to negative news, whereas Hong Kong investors respond positively to positive news.

The findings suggest that the weather has less influence on investors in bull markets. However, Hong Kong exhibited stock volatility with more statistically significant weather variables than Shanghai. Nevertheless, the results support the hypothesis that weather has a greater impact on the Shanghai stock market due to different investor composition.

4.3. Weather's Impact During Bear Markets

Table 7 summarizes the results for bear markets during the COVID-19 pandemic, which affected both the Hong Kong and Shanghai stock markets. The Hong Kong bear market began on August 9, 2021, while Shanghai's started on March 26, 2021; both bear markets lasted until December 31, 2023.

Both markets have statistically significant low humidity (HUM^{25}). It raises Shanghai's returns but lowers those in Hong Kong. Furthermore, the interest rate difference (ΔINT) is significant for Shanghai, while the Monday Effect (MON) is significant for Hong Kong. The variance parameters are similar, with near-zero alphas and betas close to one. Both markets' positive and statistically significant gammas indicate that investors respond to positive news during a bear market. Lastly, both GJR-GARCH models exhibit overall persistence.

The stock turnover measure shows differences between the markets. Low pressure ($PRES^{25}$) increases stock turnover, while high sunshine hours (SUN^{75}) decrease it. Meanwhile, Hong Kong has only one significant upper-temperature effect ($TEMP^{75}$), which lowers stock turnover. The interest rate difference (ΔINT) is significant for Shanghai, while the January (JAN) effect and seasonal affective disorder (SAD) are significant for Hong Kong. Both markets display significant long-run persistence in variance volatility. Alphas and betas are statistically significant, with alphas having larger magnitudes than betas, indicating that investors respond to new information. Lastly, both gammas are negative and statistically significant, indicating that investors respond to bad news.

Table 7. GARCH Estimations for the bear markets.

Variables	Mainland China						Hong Kong					
	Returns		Turnover		Stock Volatility		Returns		Turnover		Stock Volatility	
	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.	Coef.	t-Stat.
$\hat{\mu}$	-0.2302	-0.1788	**7.9901**	**42.4368**	**11.5245*** **	**14.9640**	-0.1332	-0.0861	**228.1352*** **	**33.4355**	**17.4244*** **	**20.5980**
TEM^{25th}	0.1550	0.1430	0.1533	0.8197	-1.0562	-1.6114	1.7974	1.0004	5.1620	0.6279	-0.7629	-0.7963
TEM^{75t}	0.6009	0.6224	-0.1766	-1.0165	-0.8792	-1.4802	-1.9631	-1.1398	**-12.9495***	**-1.6833**	0.3340	0.3817
HUM^{25th}	**1.3588***	**1.9215**	-0.0198	-0.1916	0.0125	0.0295	**-2.5582***	**-1.7112**	-8.9380	-1.3085	0.2005	0.2516
HUM^{75th}	-0.1424	-0.1744	0.1109	1.0370	0.7333	1.5512	-0.3711	-0.2021	-0.6303	-0.0877	0.7363	0.8598
PRES^{25th}	-1.1775	-1.2574	**0.4122*** **	**2.7851**	0.6048	1.1082	1.2454	0.7243	5.8518	0.8220	**-1.3194***	**-1.7306**
PRES^{75th}	-0.8139	-0.7285	-0.0273	-0.1763	**1.0464***	**1.9209**	-1.4327	-0.9701	8.4556	0.9963	1.1882	1.2031
SUN^{25th}	-0.5437	-0.7414	0.0303	0.3203	**-0.7785***	**-1.7329**	-2.1488	-1.2969	-4.6031	-0.7065	-0.2848	-0.3790
SUN^{75th}	0.2371	0.3279	**-0.1861***	**-1.7789**	-0.4573	-1.0439	-0.9023	-0.5954	-3.5185	-0.5479	-0.2581	-0.3575
FW	-1.8773	-1.5181	-0.6425	-1.2794	0.2485	0.5369	0.3836	0.2218	-5.2832	-0.6269	-0.2481	-0.2599
MON	0.7371	0.9379	0.1526	1.6334	0.7211	1.5150	**-2.5635***	**-1.6907**	2.2859	0.3965	0.1571	0.2273
JAN	0.4690	0.3321	0.1265	0.3254	0.6119	0.7593	3.9612	1.6156	**34.1409*** **	**2.9227**	1.9058	1.5854
SAD	-1.0980	-1.3116	0.2967	0.7864	**1.1422** **	**2.3314**	-0.9615	-0.5395	**27.1334** **	**2.1513**	**2.5702** **	**2.3165**
ΔINT	**73.3516*** **	**3.8989**	**7.5048*** **	**3.0871**	-6.2376	-0.5927	-0.6471	-0.0333	-143.1312	-1.5863	-14.0946	-1.5316
$\hat{\omega}$	**0.0000*** **	**29.4670**	**0.0000***	**1.8332**	**0.0000*** **	**89434.8667**	0.0000	0.3846	**0.0014*** **	**4.7004**	**0.0000*** **	**6.3170**
$\hat{\alpha}$	0.0000	0.0000	**0.6970*** **	**7.2503**	**0.2200*** **	**4.5214**	0.0000	0.0000	**0.4455*** **	**4.2699**	**0.0952*** **	**5.8591**
$\hat{\beta}$	**0.8829*** **	**63.8878**	**0.2899*** **	**7.6270**	**0.4042*** **	**9.1326**	**0.9303*** **	**16.0770**	**0.3306*** **	**3.2908**	**0.8781*** **	**70.1860**
$\hat{\gamma}$	**0.1290*** **	**3.7402**	**-0.1723***	**-1.7473**	**-0.4694*** **	**-4.9880**	**0.1375*** **	**4.9612**	**-0.2577** **	**-2.1403**	**-0.0472*** **	**-2.7078**
Persistence	0.9474		0.9008		0.3896		0.9990		0.6472		0.9497	
OBS	673		673		673		591		591		591	

Note: Using a skewed normal distribution, the maximum likelihood function estimates the GJR-GARCH(1,1). The parameter estimates are scaled by 1×10^3 except for the variance parameter estimates because stock returns vary to the thousandths. WEATHER$^{75th(25th)}$ denotes extreme high (low) weather conditions. ***, **, and * indicate statistical significance at 1%, 5%, and 10%. Bold denotes statistical significance.

The weather affects stock volatility differently in both stock markets. The Shanghai stock market has significant upper pressure ($PRES^{75}$) and lower sunshine hours (SUN^{25}), while low pressure ($PRES^{25}$) is significant for Hong Kong. The SAD control variable is statistically significant for both stock exchanges. All variance parameter estimates with betas exceeding alphas are statistically significant, indicating long-run variance volatility persistence. Lastly, investors respond to bad news, and the overall long-run persistence is high, indicating volatility clustering.

These findings suggest that weather conditions influence investor behavior, with a more pronounced effect in the Shanghai market compared to Hong Kong. Therefore, the findings support the hypothesis that it holds during bear markets, albeit with less effect.

5. CONCLUSION

This study investigates the impact of extreme weather on the Hong Kong and Shanghai Stock Exchanges. The Hong Kong Stock Exchange is less susceptible to weather-related effects due to the presence of institutional and international investors. These investors have access to more resources, adopt long-term investment strategies, and are less likely to engage in speculative trading. Nevertheless, the Shanghai Stock Exchange primarily comprises individual retail investors who engage in short-term, frequent, and often speculative trading. These investors are also more susceptible to herding behavior.

The hypothesis guiding this study posits that institutional investors would insulate the Hong Kong market against the influence of weather, whereas local investors dominating the Shanghai market would be more vulnerable to weather conditions. This hypothesis is also tested to determine whether it holds during bull and bear markets, as investors' outlooks and economic conditions differ. Lastly, the weather variables should accurately reflect China's vast and diverse meteorological conditions, as Chinese investors may reside far from the Shanghai stock market.

The empirical findings support the hypothesis that extreme weather has a stronger influence on the Shanghai Stock Exchange than on the Hong Kong Stock Exchange. Stock turnover is affected the most, while stock returns are the least responsive. Notably, extreme weather exerts a modest effect on the Hong Kong market, although investors located far from Hong Kong are unlikely to be influenced by its meteorological conditions.

The empirical findings indicate that weather still has a greater impact on the Shanghai market than on the Hong Kong market, regardless of the market state, albeit with less pronounced effects. Bull (bear) markets are characterized by overconfidence (low confidence) and exuberance (pessimism). Extreme weather still influences investors during these emotionally charged times, albeit with fewer statistically significant weather variables. The weather has the greatest impact on stock turnover and the least impact on stock returns. Interestingly, the Hong Kong Stock Exchange exhibited a higher sensitivity of stock volatility to weather conditions than the Shanghai market during a bull market, suggesting that even institutional investors are not entirely immune to the effects of weather conditions. Thus, extreme weather has a strong influence on investors, regardless of the market state.

Future research could explore the effect of long-term climate change on investment behavior. As atmospheric greenhouse gases rise, surface temperatures increase, which alters the climate. The frequency and intensity of extreme weather events are likely to increase, which would affect investment behavior.

Funding: This study is supported by the Ministry of Higher Education Malaysia through the Fundamental Research Grant Scheme (FRGS) (Project number: FRGS/1/2020/SS01/XMU/02/1), and by the Xiamen University Malaysia Research Fund (Grant No: XMUMRF/2024-C13/ISEM/0047).
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: Upon a reasonable request, the supporting data of this study can be provided by the corresponding author.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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