 doi:10.20944/preprints202008.0171.v1

Article

The Effect of Air Quality and Weather on the Chinese Stock Market: Evidence from Shenzhen Stock Exchange

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Abstract: We investigate the impact of air quality and weather on the stock market returns of the Shenzhen Exchange. To capture the air quality and weather effects, we apply dummy variables generated by applying a moving average and moving standard deviation. Our study provides several interesting results. First, in the whole sample period (2005–2019), we find that high air pollution and extremely high temperature have significant and negative effects on the Shenzhen stock returns. In the sub-period I (2005–2012), the 11-day model and 31-day model show that high air pollution have significant and negative effects on the Shenzhen stock returns. Second, the results of the quantile regression show that high air pollution have significant and negative effects during bullish market phase, and extremely high temperature have significant and negative effects during bearish market phase. This implies that the air quality and weather effects are asymmetric. Third, the more the Shenzhen stock returns drop, the greater the effect of the abnormal temperature is. Whereas, the more the Shenzhen stock returns increase, the greater the effect of the abnormal air quality is. Fourth, the least squares method underestimates the air quality and weather effects compared to the quantile regression method, suggesting that the quantile regression method is more suitable in analysing these effects in a very volatile emerging market such as the Shenzhen stock market.

Keywords: Air quality; Extreme weather; MA-MSD method; Investor sentiment; Behavioural finance

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1. Introduction

Recently, Chinese residents' material and cultural living standards are increasing day by day, and people are increasingly concerned about and sensitive to the air quality problems that depend on them. The air quality and its changes will trigger and affect people's psychology and behaviour in an in-depth and comprehensive manner [14]. Regarding behavioural finance, Chinese stock markets are interested in examining weather effect on stock returns. In case of domestic investors, investment decisions can be affected by local weather conditions in China and, thus, the effect of weather conditions may be existed in Chinese stock markets.

Some weather variables, such as sunlight, humidity, daylight, and temperature, are regarded as mood proxies for large groups of investors and are found to be significantly correlated with movement of stock returns. For example, by using the percentage cloud cover in New York City as the measure of trader mood, Saunders [22] found that the amount of sunshine (or cloud cover) is significantly related to the returns of three global indices of the US stock market. Hirshleifer and Shumway [10] subsequently extended the research to 26 countries and regions, and obtained similar evidence. Chang et al. [2] further discovered a significant negative relationship between cloud cover and investor behaviour.

Yoon and Kang [28] investigated whether a relationship exists between stock returns and the weather variables of temperature, humidity, and cloud cover in the Korean stock market. They attempted to determine these relationships using a moving average and moving standard deviation (MA-MSD) method and found that market structural changes resulting from the October 1997 Asian financial crisis eliminated the existence of a weather effect. Jiang et al. [11] investigated the impact of extreme weather conditions on the stock market returns of the Hong Kong Stock Exchange and Shenzhen Exchange. For the weather conditions, the study incorporated dummy variables generated by applying a MA-MSD method. The study found that extreme weather conditions have a significant impact on the stock returns of the Shenzhen Exchange, indicating that the Shenzhen market is inefficient. The study also found that, during the pre-QFII period, extreme weather conditions have a strong impact on the returns of the Shenzhen stock market, but the impact is significantly weaker in the period after QFII. This means that the efficiency of the Shenzhen stock market has significantly increased since the QFII program due to the market openness to foreign institutional investors.

Some studies show interest in the effect of cognitive awareness of environmental problems on stock market. For instance, Li and Peng [18] use China as a natural experiment to explore the effect on stock returns of depressed moods induced by air pollution. Daily air-pollution data from 2005 to 2014 are analysed and the results obtained from the empirical research show that a contemporaneous negative and a two-day lagged positive relationship exists between air pollution levels and stock returns. The relationship is mediated by the influence of air pollution on investment decisions. The results also indicate that the effect is weakened for companies that protect air quality, but no stronger effect is detected for polluting companies. The findings imply that air pollution is a behavioural factor with some connection to stock returns in China.

This study aims to examine the effect of air quality and weather conditions on stock returns of Shenzhen stock market indices, Shenzhen Component Index (SZI), which is a representative index of the Shenzhen Stock Exchange. For this purpose, we consider the daily index of air quality (AQI), and the weather variable (temperature, humidity, and sunshine period) from January 2005 to June 2019 (except 2013).

The contributions of our study are as follows. First, although, in the mainland stock markets, the Shanghai stock market is well known as the market representing the Chinese stock market, the Shenzhen stock market has its own multi-tier capital market characteristics, but is less known stock market. In light of this situation, we will explain the structure and operation of the Shenzhen stock market in detail, and, based on this, we will look at the impact of investment sentiment on the movement of Shenzhen stock price. Second, unlike previous studies, we identify the variables of air quality and weather conditions using a MA-MSD approach of Yoon and Kang [28]. We conduct empirical analysis in three categories: 11-day/21-day/31-day moving average models. Third, most of previous studies use the least squares estimation method, whereas we use the quantile regression method to consider the volatile fluctuation of Shenzhen stock price. The quantile regression method can capture the nonlinearity and asymmetry of the impact of air quality and weather conditions on the movement of the Shenzhen stock price. Fourth, we analyse the volatility effect in addition to the price effect of air quality and weather conditions. The impact of air quality and weather conditions on volatility is important because the Shenzhen stock market is very volatile and displays boom and crash frequently. Fifth, most of previous studies focus only one of the weather effect and air quality effect in their analysis. However, we will incorporate these two effects simultaneously in the analysis.

The main findings of our study are as follows. First, in the whole sample period (2005–2019), we find that apH (extremely high air pollution) and tmH (extremely high temperature) have significant and negative effects on the Shenzhen stock returns. In the sub-period I (2005–2012), the 11-day model and 31-day model show that apH has have significant and negative effects on the Shenzhen stock returns. Second, the results of the quantile regression show that apH has have significant and negative effects in the bull market, and tmH has have significant and negative effects in the bear market. This implies that the air quality and weather effects are asymmetric. Third, the more the Shenzhen stock returns drop, the greater the effect of the abnormal temperature is. Whereas, the more the Shenzhen stock returns increase, the greater the effect of the abnormal air quality is. Fourth, the least squares method underestimates the air quality and weather effects compared to the quantile regression method, suggesting that the quantile regression method is more suitable in analysing these effects in very volatile emerging market such as the Shenzhen stock market.

The rest of the paper is organized as follows. Section 2 discusses previous research on the impact of weather (air quality) on the stock market. Section 3 presents detailed description Chinese stock markets and statistical characteristics of the markets. Section 4 describes the measurement method of the air quality and weather variables based on 11 (21, 31)-days moving averages and standard deviations. Section 5 examines the results of the relationship between weather (air quality) and Shenzhen stock returns. Finally, Section 6 provides some conclusions.

2. Literature Review

In financial studies, environmental stimuli such as sunshine, temperature, and daylight are often used as proxies for people's collective mood/sentiment swings to test their effects on the stock market. Saunders [22] and Hirshleifer and Shumway [10] reported that cloud cover negatively affects daily stock returns. Recently, some studies consider more various weather conditions.

There are several empirical studies on weather and air quality effects in the Chinese stock market. For example, Yi and Wang [27] provided evidence of the weather effects (humidity and wind) on the Shanghai Composite Index. Han and Wang [8] and Han [6,7] found significant impacts of weather on the Shanghai and Shenzhen stock markets. Kang et al. [12] considered the market openness effect of Shanghai B-stock market to domestic investors and compared the weather effect between before and after the stock market openness. They found a strong evidence of weather effect on the B-share returns only during the period after the opening, possibly indicating that the weather effect seems to be caused by the participation of domestic investors.

Lepori [14] analysed data from 1980 to 2006 in Italy, the U.S., Spain, and Germany, and showed that air pollution negatively affects stock returns. Levy and Yagil [16] studied the relationship between daily stock returns and air quality index (AQI) levels in the U.S. from 1997 to 2007. They found that air pollution is negatively related to stock returns. Levy and Yagil [17] extended their previous research and found a similar negative relationship in Canada, the Netherlands, Hong Kong, and Australia.

A lot of scholars in behaviour finance have applied the findings from medicine and psychology in research on the association between environmental stimuli and stock market. Some of them look at actual air quality, and found that in some developed countries, poor air quality induces negative emotional reactions and then negatively affects stock returns. For example, Levy and Yagil [16] found that air pollution induces negative moods and risk-aversion behaviours among investors, leading to a negative relationship between air pollution and stock returns. This finding indicates that in the U.S., air pollution near the areas where stock exchanges are located negatively correlates with market index returns. However, Lepori [15] confirmed that this negative effect only exists when stock exchange facilities use trading floor technology.

Recently, Chinese scholars have actively conducted the research on this issue, and reported several results. For example, Guo and Zhang [5] found that air quality may affect stock market participants and ultimately affect stock market through the channels of emotion, policy and expect. This study empirically analysed how whether and air quality affects stock market by using the data of Shanghai air quality index and Shanghai stock index from 2006 to 2013 and the multivariate progressive methods. They found that the air quality has influences on the stock market returns, turnover rate and volatility, suggesting that the emotion and other channels of the air quality's effect on stock market exist.

Wu et al. [26] explored the relationship between air pollution and stock prices of locally headquartered firms using firm-level data in China. They found that severe air pollution results in low returns, turnover, volatility, and low liquidity. They also found that the relationship between air pollution and local firms' performance is insignificant, implying that the air pollution effects can be attributed to investor mood bias rather than to economic effects. He and Liu [9] considered the effects of public awareness of environment on stock market in China. They showed that enhanced public environmental awareness negatively influences trading activities in stock market. All these studies suggest that both actual air quality and awareness of environmental problems can influence investor behaviour and stock market.

As shown above, all previous studies focus only one of the weather effect and air quality effect in their analysis. However, we will incorporate these two effects simultaneously in the analysis. And most previous studies use least squares method, whereas we use the quantile regression method to capture the nonlinearity and asymmetry in the relationship of very volatile market.

3. Overviews of Chinese Stock Markets

3.1. Overviews of Hong Kong and Mainland Stock Markets

Table 1 briefly summarizes the key statistics of Hong Kong and mainland stock markets. The Hong Kong Exchange is one of international financial centres, and its exchanges and clearing houses provide a wide range of financial service to private companies, investors, and financial intermediaries. After 29 years of rapid development, the two mainland exchanges (Shanghai and Shenzhen) has grown into a comprehensive, open and service-oriented exchange. The Shanghai and Shenzhen stock markets have grown rapidly both in its size and the number of investors, making the exchanges one of the most representative emerging capital markets.

Table 1. Overview of the Hong Kong and mainland market exchanges

	Hong Kong Exchange		Shanghai Stock Exchange		Shenzhen Stock Exchange	
	Main Board	GEM	A-Share	B-Share	A-Share	B-Share
No. of listed companies	2,071	378	1,495	50	2,195	47
No. of listed H-shares	262	22	n.a.	n.a.	n.a.	n.a.
No. of listed red-chips stocks	168	5	n.a.	n.a.	n.a.	n.a.
No. of listed securities	12,416	379	n.a.	n.a.	n.a.	n.a.
Market capitalization (Billion)	HK$38,058	HK$107	RMB 34,609	RMB 79	RMB 23,689	RMB 52.4
Total negotiable capitalization (Billion)	n.a.	n.a.	RMB 29,918	RMB 79	RMB 18,169	RMB 51.6
Average P/E ratio (Times)	13.28	22.04	14.28	9.03	26.25	10.17
Total turnover (Million shares)	80,247	351	21,609	21	28,248	18
Total turnover (Million)	HK$48,434	HK$86	RMB 220,143	RMB 137	RMB 307,635	RMB 66

Source: Website of Hong Kong Exchange (http://www.hkex.com.hk).
Note: These are the statistics for December 2019.

Chinese companies can be listed on H-Shares in the Hong Kong market and on A-Shares in the mainland market through IPOs. Hong Kong is the gateway to mainland China and has close business relationships with other Asian economies. Therefore, the Hong Kong stock market is strategically positioned as a regional financial centre to finance many Asian and multinational corporations. The Shenzhen-Hong Kong Stock Connect, Qualified Foreign Institutional Investor (QFII) and Renminbi Qualified Foreign Institutional Investor (RQFII) programs are channels through which international investors can invest in the Chinese capital market. Although they share many similarities, these three channels have differences as well.[1]

3.2. Overview of Shenzhen Stock Markets

This study considers the Shenzhen stock market. As shown in Table 1, the Shenzhen Stock Exchange (SZSE) has two major sub-markets: the A-share2 and the B-share3. As of 31 December 2019, the SZSE has 2,195 listed companies with a combined market capitalization of RMB 23,689 billion in A-share market.

The SZSE is established for developing China's multi-tiered capital market system, serving national economic development and transformation, and supporting the national strategy of independent innovation. The SME Board was launched in May 2004. The ChiNext market was inaugurated in October 2009. Thus, the SZSE has basically put in place a framework of multi-tiered capital market comprising the Main Board, SME Board, and the ChiNext market. Table 2 summarises the listed securities in the SZSE. The subsidiary markets of SZSE are as follows.

Main Board: The Main Board dates to 1986. It evolved and grew along with the shareholding system reform in state-owned-enterprises (SOEs) and in response to SOE development. The SZSE Main Board market has raised RMB 881 billion (USD 139.8 billion) and become a vital financing channel for major enterprises.

SME Board: The Small and Medium Enterprise (SME) Board, which is found in June, 2004, offers services for small and medium enterprises listing. It is an important component of Shenzhen multi-tier capital market system. The SME Board highlights its role in supporting independent innovation.

ChiNext: The ChiNext market was launched in the SZSE on 23 October 2009. It offers a new capital platform tailor – made for the needs of enterprises engaged in independent innovation and other growing venture enterprises. It is an important component of Chinas multi-tier capital market [23]. The ChiNext market promotes allocation of social funds to innovative businesses and emerging industries.

B-shares: The B-shares refer to the RMB-denominated special shares with their par values marked in RMB in their circulation and to be subscribed and traded in Hong Kong Dollars. The trading of B-shares was launched in 1992, giving foreign investors the access to Chinese equity market. Now, domestic investors can also invest in B-shares using foreign currencies.

Table 2. Listed securities in the Shenzhen stock market

Stocks	**No. of listed securities**	**Total issued capital (Shs.)**	**Total negotiable capital** (Shs.)	**Total market capitalization** (RMB Yuan)	**Negotiable market capitalization** (RMB Yuan)
Main Board A shares	461	797,185,123,699	696,114,461,407	7,686,204,108,110	6,779,766,998,846

[1] For more details on the difference among the three channels, see the below webpage. http://www.szse.cn/enSzhk/introduction/cscqr/index.html

[2] A-shares, or RMB-denominated common shares, refer to ordinary shares issued by companies which are incorporated and listed in mainland Chinese stock market, and subscribed and traded in RMB.

[3] B-shares refer to RMB-denominated special shares subscribed and traded in foreign currencies. B-shares are foreign investment shares listed and traded in mainland Chinese exchanges, i.e. Shanghai Stock Exchange and Shenzhen Stock Exchange. They are issued by companies incorporated and listed in mainland China.

SME Board	943	932,212,187,067	716,627,455,305	9,868,131,938,227	7,366,129,440,415
ChiNext	791	409,711,487,697	306,186,903,232	6,134,761,852,701	4,023,173,660,498
Main Board B shares	47	12,941,222,935	12,811,181,406	52,388,606,609	51,603,614,196

Source: Shenzhen Market Monthly Report 2019.12 [24].
Note: These are the statistics for December 2019.

Table 3 shows the composition of investors in the Shenzhen stock market. As shown in this table, during 2011 to 2018, number of individual investors increased 2.7 times, while number of institutional investors increased 1.9 times. As of 2018, individual investors are 430 times larger than institutional investors. Local individual investors dominate more than 80% of the market [20]. The number of foreign investors is relatively very small, although it has been increased after the launch of the QFII program in 2003.

Chinese stock market is known to be speculative. The stock market was established in 1991. In the beginning, there were only individual investors. The individual investors did not care about the quality of the business, but only concerned about the rise and fall of the stock price. They speculated specifically, which caused big speculation in the stock market. In Table 3, we can see that there are many individual investors in China, and the rate of increase is also speedy. In contrast, there are few institutional investors. Since 1998, the market has learned from foreign experiences and introduced investment funds. The result is that many funds not only speculate but also operate to manipulate the market price of stocks [19].

Table 3. Composition of investors in the Shenzhen market (Year-end, 10,000 people)

Year	No. of personal investors	No. of institutional investors	Total
2011	10,091.18	33.4	10,124.57
2012	10,537.82	35.48	10,573.30
2013	11,047.50	38.05	11,085.56
2014	11,995.29	41.58	12,036.87
2015	16,839.70	49.22	16,888.92
2016	20,841.00	56.12	20,897.13
2017	24,482.57	62.51	24,545.08
2018	27,621.26	64.06	27,685.32

Source: Shenzhen Stock Exchange [23].

For example, as is well known, the formation of the NYSE stock price is mainly based on market maker quotations. Given the concentration of the world's top financial institutions and investors in the Manhattan area of New York, the office locations of these market makers are also concentrated near Lower Manhattan. Therefore, it is easy to understand how the bidding behaviour of the market makers is affected by the weather in Manhattan. For another stock price formation mechanism, the order-driven trading system, there is still a lack of research on the relationship between weather and stock trading. The establishment of a stock exchange in the mainland of China is relatively late. Since its establishment, it has fully adopted an electronic order-driven trading system. There are no market makers, and investors enter all trading quotes through brokers into the matching system of the exchange.

Due to the regional nature of air quality, the direct effect of air quality on investor sentiment is mainly limited to local investors, especially individual investors. Of course, air pollution may also affect the stock market by influencing the mood/sentiment of stock traders.

At present, the two major stock exchanges in mainland China adopt the order-driven system rather than the quote-driven system (or market-maker system). All are buying and selling quotations are entered into the matching system of the exchange by investors through agent brokers. As a trader of an order trading system operator, when his emotions are affected by local air pollution, he may also reduce his due rational judgment and choice ability to make irrational trading behaviours and cause fluctuations in stock prices [21].

Table 4 shows the trading volume ranking of cities where the securities are traded. As shown in this table, the top 8 cities are Shanghai 30,224 Billion yuan, accounting for 14.99% of total trading volume; Shenzhen 23,309 Billion Yuan, accounting for 11.56% of the transactions; Beijing 16,275 Billion yuan, accounting for 8.07%; Guangdong 9,328 Billion yuan, accounting for 4.62%; Guangzhou 8,111 Billion yuan, accounting for 4.02%. Also, foreign investors accounted for 2.36%. Shenzhen, Guangdong, and Guangzhou account for 20% of the transactions, which provides a basis for us to study whether the weather and air quality index impact the order-driven stock trading behaviour. Since the proportion of local individual investors in the Shenzhen stock market is high, the market is expected to be sensitive to local air quality and weather conditions.

Table 4. Trading value and shares by region (RMB, Billion)

Area (province)	**Total trading** (RMB)	**Weight** (%)	**Share trading**
Shanghai	30,224	14.99	18,993
Shenzhen	23,309	11.56	13,332
Zhejiang	19,460	9.65	17,051
Jiangsu	16,865	8.36	12,692
Beijing	16,275	8.07	10,268
Fujian	9,916	4.92	7,037
Guangdong	9,328	4.62	7,450
Guangzhou	8,111	4.02	5,464
Foreign	4,769	2.36	4,769

Source: Shenzhen Stock Exchange [24].

3.3. Descriptive Statistics of Stock Returns

For the empirical analysis, we use the daily stock returns of Shenzhen stock exchanges. The stock market indices employed are the Shenzhen Component Index (SZI), which are the most often-used market indices to represent the performance of the Shenzhen exchanges. The SZI data is obtained from Infomax database. Daily returns were calculated as $r_t = \ln(P_t/P_{t-1}) \times 100$, where P_t is the current index and P_{t-1} is the previous day's index.

Figure 1 displays the dynamics of daily price and return series of SZI. The return series show volatility clustering. And Table 5 summarizes the descriptive statistics of stock returns. As shown in the table, the results of the Jarque-Bera test to check normality show that the sample returns is not normally distributed.

Table 5. Descriptive statistics of sample returns

Variables	Obs.	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	Jarque-Bera

 doi:10.20944/preprints202008.0171.v1

SZI	3,647	0.036	11.63	−9.75	1.86	−0.41	6.35	1817.8 ***

Notes: The Std. Dev., Skew., and Kurt. denote the standard deviation, skewness, and kurtosis of sample returns, respectively. The Jarque-Bera test statistics are to check the normality of sample returns. *** indicates the rejection of the null hypothesis of normality at the 1% significance level.

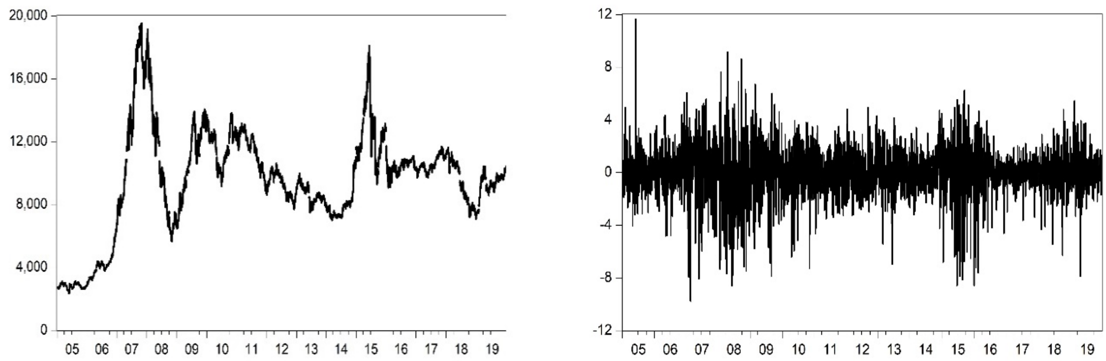

Figure 1. Dynamics of SZI: daily price (left) and daily returns (right)

The 30 years of economic prosperity have brought severe environmental degradation to China, most notably poor air quality. There are two reasons for this result. First, air-pollution awareness has soared in China since 2009, as evidenced by postings on Twitter by the U.S. Embassy during 2009. Around the middle of 2009, the Embassy started to monitor the level of PM2.5 in Beijing and Shanghai, and posted the automated air-quality measurements on Twitter every day [18]. The second reason is that in February 2012, the State Council of China first requested local governments to publish PM2.5 level, and issued "Ambient Air Quality Standards (GB3095-2012)" which formally includes PM2.5 level in regular air quality assessment. After that, the terms of haze and PM2.5 have frequently emerged on various media, and air pollution has attracted a major concern. This greatly enhanced public concern about air pollution and participation in environmental protection [25]. Daily air pollution data were collected from the CSMAR DB, and covers the period from 1 January 2005 to 31 December 2019. During this period, the public awareness of environmental protection is believed to have been gradually increasing.

The air quality index (AQI) provides information on local air quality and focuses on health effects that people may experience after exposure unhealthy air. The larger the AQI value, the higher air pollution level and the greater the threat to health. It is noted that since 2013, the AQI has been widely adopted in China instead of the original air pollution index API. For convenience of discussion, we refer to both the AQI and the API as the AQI in the following sections. We divide the whole sample period (2005–2019) into two sub-periods in the analysis: sub-period I (2005–2012) and sub-period II (2014–2019).

Daily data of weather condition were used: Sunshine (SUNSH), temperature (TEMP), and humidity (HUMI). The data series were obtained from the Hong Kong Observatory.[4] Sunshine is measured in terms of the number of hours of sunshine duration; temperature in terms of Celsius degrees; humidity in terms of relative humidity (the percentage of moisture contained in the air). Table 6 summarizes the descriptive statistics of the AQI and weather condition variables. The empirical analysis of this study is divided into three cases by the length for moving average. For that reason, there are three data sets should be measured.

[4] http://www.weather.gov.hk/. The weather conditions in Hong Kong and Shenzhen are very similar, because the two regions are in fact the same area. In this region, the weather is very hot, humid, and rainy in summer, while relative mild and humid in winter.

 doi:10.20944/preprints202008.0171.v1

Table 6. Descriptive statistics of weather variables for Hong Kong and Shenzhen

Variables	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	Jarque-Bera
Panel A: Data from the 11-day MA-MSD model							
AQI	53.32	289.00	15.00	22.55	1.35	8.34	5040.5***
TEMP	23.70	31.80	7.40	5.14	-0.53	2.25	236.6***
HUMI	78.49	99.00	29.00	10.23	-1.00	4.90	1067.4***
SUNSH	4.99	12.40	0.00	3.88	0.08	1.52	312.7***
Panel B: Data from the 21-day MA-MSD model							
AQI	53.29	289.00	15.00	22.51	1.35	8.40	5130.1***
TEMP	23.70	32.40	8.40	5.14	-0.52	2.22	235.1***
HUMI	78.48	99.00	31.00	10.16	-0.97	4.84	1006.4***
SUNSH	5.02	12.40	0.00	3.89	0.06	1.52	312.3***
Panel C: Data from the 31-day MA-MSD model							
AQI	53.26	289.00	15.00	22.50	1.36	8.42	5168.7***
TEMP	23.71	32.40	8.40	5.14	-0.52	2.23	234.9***
HUMI	78.49	99.00	31.00	10.16	-0.97	4.84	1008.7***
SUNSH	5.02	12.40	0.00	3.89	0.07	1.52	311.9***

4. Methodology

4.1. Weather Variables

To examine the effect of air quality and weather on the Shenzhen stock market, the air quality and three weather variables used in this study were converted into dummy variables because they are subject to seasonal factors. For example, in Shenzhen, 15°C in winter is relatively warm, but the same weather in summer is felt relatively cold. Thus, directly using raw weather data may result in seasonal bias in the measurement of the effect of weather on stock market returns. For this reason, following Yoon and Kang [28], we recalculated weather variables using moving averages (MA) and moving standard deviations (MSD). Specifically, we used the following 11-day (21-day; 31-day) MA and MSD method:[5]

$$MA_t = \frac{1}{11}\sum_{i=-5}^{5} V_{t+i} \tag{1}$$

$$MSD_t = \sqrt{\frac{1}{10}\sum_{i=-5}^{5} \{V_{t+i} - MA_t\}^2} \tag{2}$$

$$MA_t = \frac{1}{21}\sum_{i=-10}^{10} V_{t+i} \tag{3}$$

$$MSD_t = \sqrt{\frac{1}{20}\sum_{i=-10}^{10} \{V_{t+i} - MA_t\}^2} \tag{4}$$

[5] See Yoon and Kang [28] for the case of 21-day method, and Kang et al. [12] for the case of 31-day method. See Jiang et al. [11] for the case of 11-day method. Our study uses all of these three methods.

$$MA_t = \frac{1}{31}\sum_{i=-15}^{15} V_{t+i} \tag{5}$$

$$MSD_t = \sqrt{\frac{1}{30}\sum_{i=-15}^{15} \{V_{t+i} - MA_t\}^2} \tag{6}$$

where V_t is the daily values of air quality and three weather variables—AQI, SUNSH, TEMP, and HUMI—at day t. Since extreme weather (or air quality) conditions are expected to be more likely to substantially augment the weather (or air quality) effects on stock returns than normal conditions, two dummy variables using each raw variable were generated as follows:

$$\begin{gathered} \text{If } V_t < (MA_t - MSD_t)\text{, then } VL = 1\text{; otherwise, } VL = 0, \\ \text{If } V_t > (MA_t - MSD_t)\text{, then } VH = 1\text{; otherwise, } VH = 0, \end{gathered} \tag{7}$$

where VL represents a dummy variable for extremely below-average weather (or air quality) and VH is a dummy variable for extremely above-average weather (or air quality). The air quality and weather dummies used in the study are summarized in Table 7.

Table 7. Description of extreme air quality and weather condition dummies

Air quality and weather condition dummies	Description
apH	Extremely high air pollution (low air quality)
apL	Extremely low air pollution (high air quality)
tmH	Extremely high temperature
tmL	Extremely low temperature
snH	Extremely long sunshine duration
snL	Extremely short sunshine duration
hmH	Extremely high humidity
hmL	Extremely low humidity

4.2. Empirical Model

Using the air quality and weather dummy variables generated in the above section, we estimated the following model for analysing the effect of air quality and weather conditions on stock returns:

$$\begin{aligned} R_t = \mu_0 + \mu_1 apL + \mu_2 apH + \mu_3 tmL + \mu_4 tmH + \mu_5 hmL + \mu_6 hmH + \mu_7 snL + \mu_8 snH \\ + \theta January + \varphi Monday + \varepsilon_t \end{aligned} \tag{8}$$

In this equation, R_t denotes the daily returns of the Shenzhen stock market; μ_i denotes the coefficients of air quality and weather dummies; $January$ and $Monday$ denote the dummies for January and Monday effects, respectively. Additionally, we considered the nonlinear problem of time varying heteroskedasticity in the error of the above model using the following GARCH(1,1) model:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1},\ \varepsilon_t = z_t\sigma_t,\ z_t \sim N(0,1), \tag{9}$$

where ε_t denote an independent time series with a zero mean and an unconditional variance, σ_t^2, and h_t denotes the conditional variance. All parameters (ω, α, and β) are expected to be positive for non-negativity of variance, and the sum of $(\alpha + \beta)$ indicates the persistence of shocks to volatility. The GARCH(1,1) model can capture the feature of volatility clustering in the return dynamics of Shenzhen stock market.

 doi:10.20944/preprints202008.0171.v1

Since first introduced by Koenker and Bassett [13], the quantile regression analysis has been continuously developed as a very important research topic in applied economics as well as in econometrics, due to its advantages of providing detailed information about the conditional distribution of dependent variable and nonlinearity and asymmetry in the relationship.

For quantile regression, Eq. (8) is transformed into the following form:

$$\begin{aligned} Q_\tau(R_t) = \mu_0 + \mu_{1\tau} apL + \mu_{2\tau} apH + \mu_{3\tau} tmL + \mu_{4\tau} tmH + \mu_{5\tau} hmL + \mu_{6\tau} hmH + \mu_{7\tau} snL \\ + \mu_{8\tau} snH + \theta_\tau Jan + \varphi_\tau Mon + \varepsilon_t \end{aligned} \tag{10}$$

where $\mu_{i\tau}$ $(i = 1, 2, \cdots, 8)$ represents the parameters that needs to be estimated, τ represents the quantile point, and Q represents the quantile regression estimate. High quantile implies bull market, while low quantile implies bear market. We will compare the results between the high and low quantiles.

5. Empirical Results

5.1. Effects of Air Quality and Weather on Shenzhen Stock Returns

Table 8 shows the effects of air quality and weather on the returns of the SZI using 11-day MA-MSD method. As shown in the table, the estimated values of parameters (ω, α and β) in the GARCH model are positive and $(\alpha + \beta) < 1$. These results indicate that the non-negativity constraint and stationarity in the conditional variances are satisfied, respectively. Additionally, the estimates of January effect ($January$) and Monday effect ($Monday$) is not significant, indicating the absence of a market anomaly, such as calendar effects, in the Shenzhen markets.

As shown in this table, for the whole sample period, we find can the estimated coefficient of the apH variable is negative and significant. We also find that the estimate of the apH is even more significant (with greater coefficient and t-value) in case of the sub-period I (2005–2012). These results imply that stock returns decrease when air pollution increases, consistent with the notion that investors who suffer from air pollution have less demand on stock markets and, hence, depress current Shenzhen stock prices and returns. However, an insignificant relationship between air quality and returns is presented during the second sub-period II (2014–2019).

Table 8. Effects of air quality and weather on returns using 11-day MA-MSD method

	SZI					
	Whole period (2005–2019)		**Sub-period I (2005–2012)**		**Sub-period II (2014–2019)**	
	Coeff.	**t-value**	**Coeff.**	**t-value**	**Coeff.**	**t-value**
μ	0.080	1.906	0.078	1.248	0.084	1.438
apH	**-0.174**	-2.223**	**-0.322**	-2.686***	-0.072	-0.659
apL	-0.066	-0.865	-0.141	-1.088	-0.037	-0.393
tmH	-0.113	-1.414	-0.219	-1.785	-0.013	-0.120
tmL	0.048	0.627	0.075	0.635	0.025	0.241
snH	-0.019	-0.255	-0.001	-0.009	-0.055	-0.534
snL	0.012	0.136	-0.020	-0.150	0.050	0.434
hmH	0.008	0.092	0.207	1.630	-0.156	-1.330
hmL	-0.036	-0.468	0.147	1.276	-0.177	-1.704
$January$	-0.078	-0.947	0.009	0.077	-0.221	-1.767
$Monday$	0.055	0.997	0.049	0.552	0.075	1.021
ω	0.028	6.43***	0.067	4.85***	0.016	4.22***
α	0.059	13.82***	0.064	9.11***	0.048	8.84***
β	0.934	212.37***	0.920	106.46***	0.946	183.90***
Log$L$	-6525.760		-3937.94		-2572.62	
AIC	3.869		4.086		3.577	

Notes: log$L$ and AIC denote the calculated values of log-likelihood and Akaike information criterion, respectively. *** and ** indicate significance at the 1% and 5% levels, respectively.

Table 9 (Table 10) shows the effects of air quality and weather on the stock returns of the SZI using 21-day (31-day) MA-MSD method. As shown in these table, the estimated values of parameters (ω, α and β) in the GARCH model are positive and $(\alpha + \beta) < 1$. Thus we can confirm that the non-negativity constraint and stationarity in the conditional variances are satisfied. As well, we cannot find any calendar effects, $January$ and $Monday$, in both models.

As shown in Table 9, the weather variable of extremely high temperature (tmH) is statistically significant in the whole sample period case, providing evidence for the existence of weather effect on the SZI returns. Although, the temperature and humidity are very high in Shenzhen, extremely high temperature can make investors feel unpleasant and their sentiment negatively. Thus, extremely high temperature leads to negative impacts on Shenzhen stock returns, as expected. And as shown in the Table 10, the test results using 31-day MA-MSD method are similar to the results using 11-day MA-MSD method. The high air pollution has significantly negative influence on the stock returns in sub-period I.

Table 9. Effects of air quality and weather on returns using 21-day MA-MSD method

	SZI					
	Whole period (2005–2019)		**Sub-period I (2005–2012)**		**Sub-period II (2014–2019)**	
	Coeff.	**t-value**	**Coeff.**	**t-value**	**Coeff.**	**t-value**
μ	0.054	1.284	0.078	1.246	0.040	0.696
apH	-0.074	-0.964	-0.182	-1.617	0.011	0.103
apL	-0.053	-0.677	0.019	0.141	-0.166	-1.702
tmH	**-0.163**	-2.055***	-0.164	-1.449	-0.163	-1.402
tmL	0.059	0.846	0.061	0.524	0.041	0.453
snH	0.072	1.004	0.038	0.344	0.100	1.036
snL	-0.074	-0.962	-0.030	-0.240	-0.097	-0.986
hmH	0.052	0.625	0.003	0.026	0.090	0.792
hmL	-0.009	-0.127	0.029	0.241	-0.036	-0.385
$January$	-0.022	-0.269	0.040	0.335	-0.099	-0.873
$Monday$	0.052	0.929	0.041	0.460	0.069	0.931
ω	0.025	6.33***	0.064	4.66***	0.015	4.56***
α	0.057	13.91***	0.062	9.15***	0.048	9.20***
β	0.937	223.35***	0.922	108.97***	0.946	196.41***
Log$L$	-6521.030		-3940.74		-2570.57	
AIC	3.871		4.096		3.577	

Notes: log$L$ and AIC denote the calculated values of log-likelihood and Akaike information criterion, respectively. *** and ** indicate significance at the 1% and 5% levels, respectively.

Table 10. Effects of air quality and weather on returns using 31-day MA-MSD method.\

	SZI					
	Whole period (2005–2019)		**Sub-period I (2005–2012)**		**Sub-period II (2014–2019)**	
	Coeff.	**t-value**	**Coeff.**	**t-value**	**Coeff.**	**t-value**
μ	0.065	1.547	0.078	1.241	0.051	0.874
apH	-0.104	-1.364	**-0.226**	-1.975**	0.005	0.045
apL	-0.057	-0.713	0.029	0.218	-0.161	-1.562

tmH	-0.103	-1.347	-0.094	-0.832	-0.110	-1.013
tmH	-0.055	-0.780	-0.048	-0.429	-0.064	-0.688
snH	0.048	0.690	0.038	0.371	0.062	0.630
snL	-0.056	-0.708	-0.100	-0.809	-0.027	-0.257
hmH	0.062	0.720	0.067	0.502	0.063	0.551
hmL	0.004	0.049	0.124	1.062	-0.072	-0.752
$January$	-0.020	-0.224	0.063	0.471	-0.091	-0.791
$Monday$	0.055	0.975	0.038	0.432	0.082	1.100
ω	0.022	5.87***	0.054	4.26***	0.016	4.44***
α	0.054	13.88***	0.059	9.32***	0.048	9.05***
β	0.941	235.83***	0.928	117.57***	0.946	189.58***
Log$L$	-6513.630		-3933.75		-2571.64	
AIC	3.871		4.097		3.578	

Notes: log$L$ and AIC denote the calculated values of log-likelihood and Akaike information criterion, respectively. *** *** and ** indicate significance at the 1% and 5% levels, respectively.

The test results of Tables 8-10 are summarized in Table 11. As shown in this table, the estimate of apH is significantly negative in several cases; Whole period and sub-period I using 11-day MA-MSD method, and sub-period I using 31-day MA-MSD method. These results suggest evidence of air quality effect, implying high air pollution has negative impact on the stock returns of Shenzhen market. And the estimate of tmH is significantly negative in case of whole period, implying extremely high temperature has negative impact on the stock returns in the market. However, we cannot find these effects in the sub-period. Overall, from this table, we can conclude that there is air quality and weather effects in Shenzhen stock markets.

Table 11. Summary of significant dummy variables

	Dependent variable: SZI returns		
	Whole period (2005–2019)	**Sub-period I (2005–2012)**	**Sub-period II (2014–2019)**
11-day MA-MSD	apH, (-)	apH, (-)	
21-day MA-MSD	tmH, (-)		
31-day MA-MSD		apH, (-)	

These results show that domestic investors are affected in their investment decision by local air quality and temperature in a certain period. Investor sentiment is affected by various factors, such as air quality, weather conditions, and stock market ups and downs, etc. In a theoretical point of view, if the efficient market hypothesis of Fama [4] holds, these factors should not affect investors' decisions. However, as investors in China (Shenzhen) are mainly individual investors, these individual investors are more affected by sentiment than institutional investors. We think that the anomaly of air quality and weather effects is because of the trader composition of Shenzhen stock market.

5.2. Effects of Air Quality and Weather on the Stock Returns Using Quantile Regression

The volatility of Chinese stock markets was extremely high from 2005 to 2009, as shown in Figure 1. Chinese stock market experienced the 'roller-coaster' effect during that period, which is affected by the very unstable investors' sentiment. This abnormal fluctuation is due to the composition of traders in the stock market. Individual investors dominate the Chinese stock market, and they usually do not have sufficient professional knowledge and analytical capabilities. At the same time, they have insufficient experience, so they are more likely to be affected by the decisions of other investors than institutional investors. The information they possess relies heavily on public opinion, and they blindly follow other investors' decision. Under these circumstances, the air quality and weather conditions can trigger some investors' sentiment favourable (unfavourable) to stock price movement. Once optimistic (pessimistic) sentiment is formed, many investors will rush for the stock market and buy (sell) stocks. If the irrational sentiment is serious, the movement of herding behaviour can be visible.

In the Shenzhen stock market, there are far more individual investors than institutional investors. The trader composition of individual investors is about 82% in the market [20]. Individual investors in China are not interested in the financial statements and business management of companies and are mainly interested in profit-taking. For this reason, the Chinese stock market has turned into a speculative market. Many listed companies do not have self-sustaining power, and such companies do not pay dividends properly. For this reason, individual investors are trying to profit from speculative trading [19]. In markets in this state, there is a probability of herding behaviour due to investors' sentiment.

As the price dynamics in Shenzhen stock market is very volatile, it is a good choice to analyse the relationship between air quality and weather and stock market returns using the quantile regression, because the quantile regression can capture the asymmetry and nonlinearity in the price dynamics, i.e. the difference of the relationship in the bull and bear markets. Tables 12-14 summarise the estimation results of quantile regression of the 11-day, 21-day and 31-day MA-MSD models.

In Table 12, the results of the quantile regression using the 11-day MA-MSD model, we can find that high air pollution has have significant and negative effects in the bull market $(\tau = 0.7)$, and extremely high temperature has have significant and negative effects in the bear market $(\tau = 0.3)$. This implies that the air quality and weather effects exist, but are asymmetric in the Shenzhen stock market.

In Table 13, the results of the quantile regression using the 21-day MA-MSD model, we can find we can find that high air pollution has have significant and negative effects in the bull market $(\tau = 0.7)$, and extremely high temperature has have significant and negative effects in the bear market $(\tau = 0.1$ and $\tau = 0.3)$. Interestingly, we can find that the more the Shenzhen stock returns drop, the greater the effect of the abnormal temperature is, if we compare the values of significant coefficient by quantile $(-0.63$ for $\tau = 0.1$ and -0.28 for $\tau = 0.3)$.

In Table 14, the results of the quantile regression using the 31-day MA-MSD model, we can find we can find that high air pollution has have significant and negative effects in the bull market $(\tau = 0.7, \tau = 0.8$ and $\tau = 0.9)$. Interestingly, we can find that the more the Shenzhen stock returns increase, the greater the effect of the air pollution is, if we compare the values of significant coefficient by quantile $(-0.21$ for $\tau = 0.7$, -0.32 for $\tau = 0.8$ and -0.44 for $\tau = 0.9)$.

If we put the above results together, the air pollution has negative influence on the SZI in the high quantile $(\tau \geq 0.7;$ bull market), whereas the extremely high temperature has negative influence on the SZI in the low quantile $(\tau \leq 0.3;$ bear market). This suggests that the air quality and weather have asymmetric effects in the Shenzhen stock market.6 Interestingly, in several cases, we can find that the Monday effect is significant, however the sign of the effect is also asymmetric.

Table 12. Quantile regression estimates for returns using the 11-day MA-MSD method

Variables	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Intercept	-1.87*	-1.03*	-0.54*	-0.20*	0.11*	0.39*	0.73*	1.17*	1.97*
apH	-0.12	-0.17	-0.15	-0.14	-0.12	-0.13	**-0.20***	-0.12	-0.17
apL	-0.23	-0.14	-0.12	-0.01	-0.01	-0.01	-0.04	-0.08	-0.23
tmH	-0.35	-0.21	**-0.25***	-0.16	-0.13	-0.14	-0.05	0.02	-0.12
tmL	-0.25	-0.04	-0.02	-0.01	-0.04	-0.03	-0.08	-0.07	0.11
snH	0.08	0.02	0.01	0.00	0.05	0.04	0.12	-0.02	-0.01

[6] Qualitatively similar conclusions in terms of asymmetric effects of air pollution on the Shenzhen stock returns were drawn based on the quantiles-based causality test of Chuang et al. [3]. Complete details of these results are available upon request from the authors.

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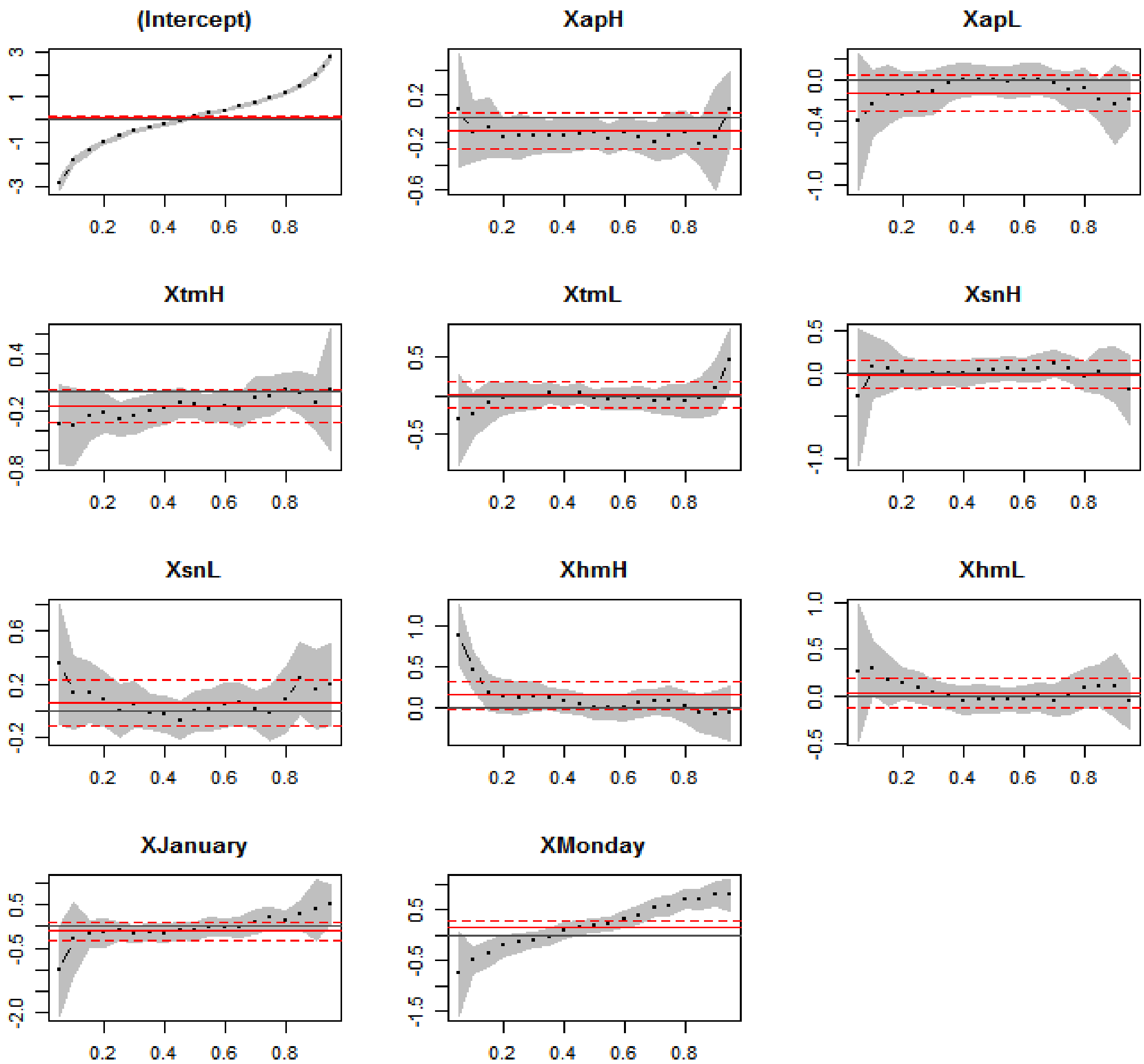
snL	0.13	0.09	0.04	-0.03	0.00	0.04	0.01	0.08	0.16
hmH	0.45	0.14	0.14	0.08	0.00	0.01	0.07	0.02	-0.08
hmL	0.31	0.14	0.04	-0.05	-0.03	-0.04	-0.05	0.09	0.11
January	-0.28	-0.14	-0.17	-0.16	-0.11	-0.02	0.10	0.14	0.38
Monday	-0.49*	-0.22	-0.10	0.10	0.18*	0.32*	0.56*	0.72*	0.81*

Note: * indicates significance at the 5% level.

Figure 2 (for the 11-day model), Figure 3 (for the 21-day model), and Figure 4 (for the 31-day model) show the estimation results of quantile regression comparing the result of least squares estimation method. In these figures, the black dotted line shows the impact of influencing factors on stock returns at different quantiles. The shaded area represents 95% confidence interval for estimates of the quantile regression. The red straight line indicates the estimated coefficient of the least squares regression. The red dotted line represents the 95% confidence interval for estimates of the least squares regression. Looking at the these figures, we can find that the least squares method underestimates the air quality and weather effects compared to the quantile regression method, suggesting that the quantile regression method is more suitable in analysing these effects in a very volatile emerging market such as the Shenzhen stock market.



Notes: The black dotted line shows the impact of influencing factors on returns at different quantiles. The red straight line indicates the results of the least squares regression. The red dotted line represents the 95% confidence curve of the least squares regression. The shaded area represents 95% confidence interval for the quantile regression.

Figure 2. Quantile regression estimates using the 11-day MA-MSD method

Table 13. Quantile regression estimates for returns using the 21-day MA-MSD method.

Variables	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Intercept	-1.84*	-1.02*	-0.55*	-0.23*	0.12*	0.40*	0.75*	1.22*	2.02*
apH	-0.03	-0.07	-0.07	-0.07	-0.11	-0.11	**-0.18***	-0.15	-0.25
apL	-0.11	-0.09	-0.06	0.01	-0.04	0.01	-0.02	-0.10	-0.06
tmH	**-0.63***	-0.28	**-0.28***	-0.11	-0.13	-0.10	-0.10	-0.07	-0.00
tmL	-0.29	-0.04	0.02	0.02	0.00	0.02	-0.07	0.03	0.16
snH	0.20	0.11	0.07	0.02	0.00	0.00	0.07	-0.06	-0.16
snL	0.21	0.02	-0.09	-0.10	-0.09	-0.12	-0.08	-0.12	0.02
hmH	0.23	0.03	0.07	0.00	-0.03	-0.01	0.03	-0.11	-0.45*
hmL	0.06	0.07	0.04	0.04	-0.03	0.00	-0.01	0.06	0.18
January	0.00	-0.07	-0.07	-0.03	-0.08	0.01	0.06	0.09	0.35
Monday	-0.41*	-0.24	-0.06	0.12	0.16*	0.32*	0.56*	0.77*	0.86*

Note: * indicates significance at the 5% level.

Table 14. Quantile regression estimates for returns using the 31-day MA-MSD method

Variables	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Intercept	-1.91*	-1.03*	-0.59*	-0.24*	0.09*	0.39*	0.76*	1.21*	2.06*
apH	0.11	-0.03	-0.03	-0.06	-0.09	-0.11	**-0.21***	**-0.32***	**-0.44***
apL	-0.09	-0.05	-0.11	-0.03	-0.03	-0.06	-0.03	-0.12	-0.03
tmH	-0.27	-0.18	-0.06	-0.08	-0.11	-0.03	-0.07	0.01	-0.13
tmL	-0.37	-0.04	0.09	0.08	0.02	0.05	-0.09	-0.04	-0.12
snH	0.11	0.08	0.10	0.06	0.14	0.09	0.11	0.09	0.01
snL	0.19	-0.01	-0.11	-0.11	-0.12	-0.06	-0.06	0.02	-0.13
hmH	0.18	0.03	0.05	-0.01	0.00	-0.09	-0.05	-0.14	-0.16
hmL	0.05	0.03	0.04	0.05	-0.01	0.01	0.03	0.02	0.06
January	0.04	-0.13	-0.11	-0.07	-0.06	0.04	0.10	0.14	0.27
Monday	-0.36*	-0.23	-0.04	0.11	0.15	0.32*	0.53*	0.80*	0.83*

Note: * indicates significance at the 5% level.

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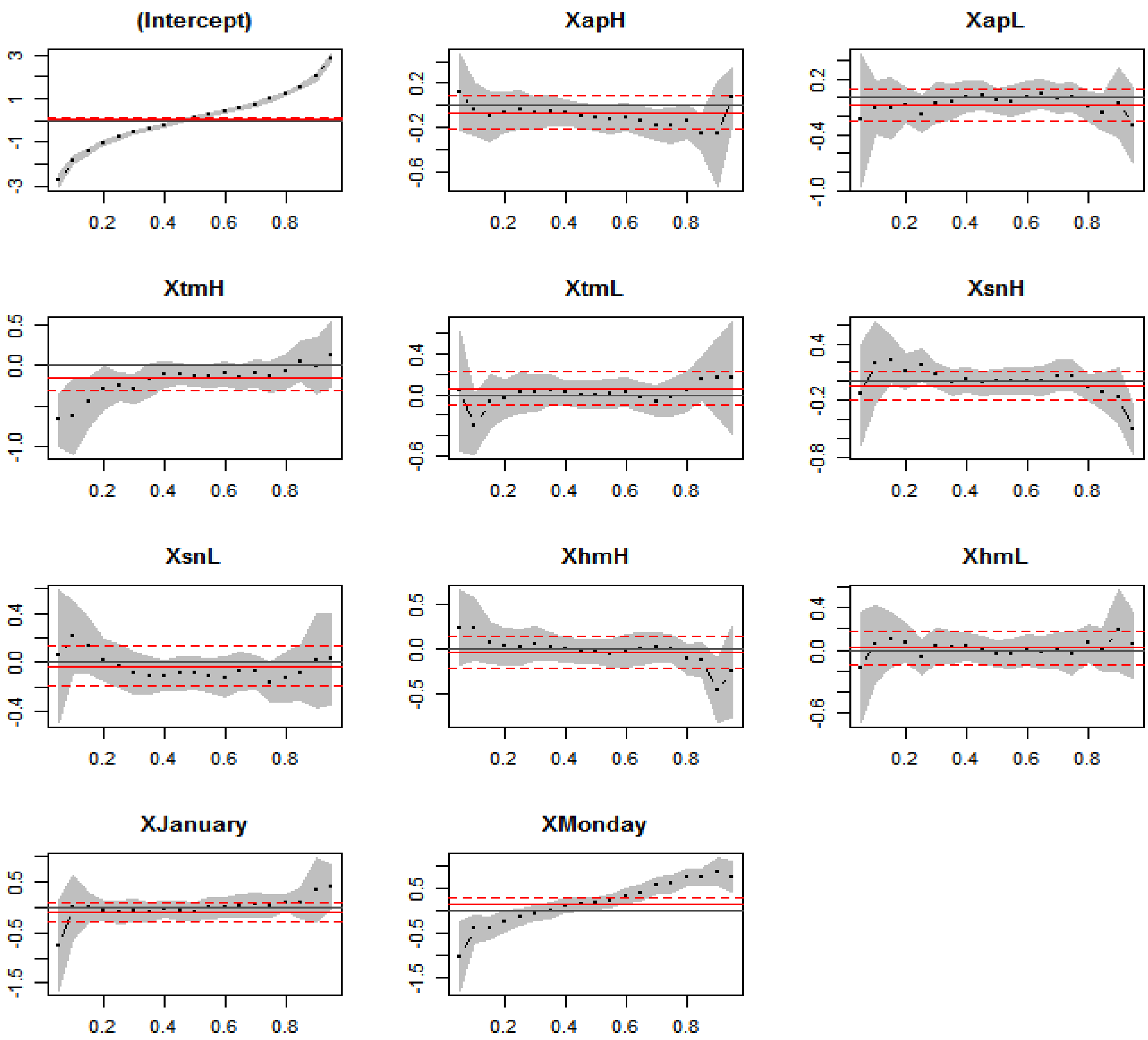

Notes: The black dotted line shows the impact of influencing factors on returns at different quantiles. The red straight line indicates the results of the least squares regression. The red dotted line represents the 95% confidence curve of the least squares regression. The shaded area represents 95% confidence interval for the quantile regression.

Figure 3. Quantile regression estimates using the 21-day MA-MSD method

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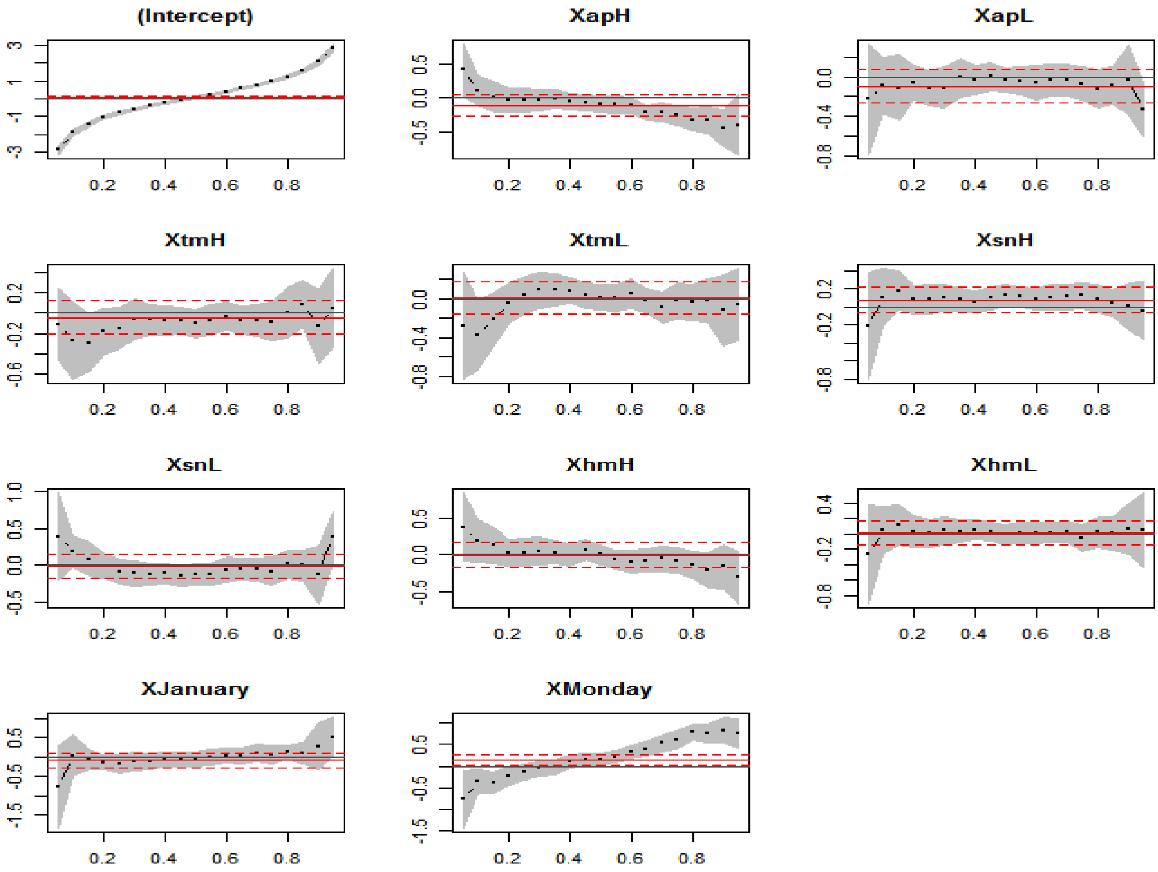

Notes: The black dotted line shows the impact of influencing factors on returns at different quantiles. The red straight line indicates the results of the least squares regression. The red dotted line represents the 95% confidence curve of the least squares regression. The shaded area represents 95% confidence interval for the quantile regression.

Figure 4. Quantile regression estimates using the 31-day MA-MSD method

6. Conclusions

The literature explains that air quality and weather can affect investors' sentiment or mood, and prevent them from making reasonable decisions. The influence of air quality and weather conditions on the investor's decision-making process can be reflected in the movement of stock returns. Especially, air pollution has increased considerably in recent years in China. Aggravating air pollution induces physical and mental health effects on individuals. As well as increased awareness of pollution promotes mood effects of air pollution and then impacts individual preference and decision making. Therefore, air pollution as well as weather condition may have remarkable effect on stock market returns.

In this paper, we examined the effect of air quality and weather conditions on stock returns using the Shenzhen Component Index (SZI) data, a representative stock market index of the Shenzhen Stock Exchange. For this purpose, we applied the 11-day (21-day and 31-day) MA-MSD method to the daily index of the variable (air quality, temperature, humidity and sunshine duration) from 1 January 2005 to 31 December 2019 (except 2013). We divided the whole sample period (2005–2019) into two sub-periods; sub-period I (2005–2012) and sub-period II (2014–2019).

The main results are as follows. First, in the whole sample period (2005–2019), we find that high air pollution and extremely high temperature have significant and negative effects on the Shenzhen stock returns. In the sub-period I (2005–2012), the 11-day model and 31-day model show that high air pollution has significant and negative effects on the Shenzhen stock returns. Second, the results of the quantile regression show that high air pollution has significant and negative effects in the bull market, and extremely high temperature has significant and negative effects in the bear market. This implies that the influence of air quality and weather conditions on the Shenzhen stock returns are asymmetric. Third, the more the Shenzhen stock returns drop, the greater the effect of the abnormal temperature is. Whereas, the more the Shenzhen stock returns increase, the greater the effect of the abnormal air quality is. Fourth, the least squares method underestimates the air quality and weather effects on the stock returns compared to the quantile regression method, suggesting that the quantile regression method is more suitable in analysing these effects in a very volatile emerging market such as the Shenzhen stock market.

The efficient market hypothesis (EMH) implies that stock prices are unpredictable. However, scholars in behaviour finance observe "market anomalies" that appear to be inconsistent with the EMH. This study contributes to the literature on market efficiency by uncovering that actual air quality and weather conditions play different roles in predicting the stock price movement. Investors need to know that they may make biased decisions due to poor air quality and weather problems rather than rational economic prospects. Our findings are helpful for investors in correcting biases in their investment behaviour.

As part of future research, it would be interesting to extend our analysis to check if air pollution tends to have higher-moment effects, for instance on volatility, which in turn is an important input in portfolio selection, the pricing of derivative securities and risk management.[7]

Author Contributions: All the authors contributed to the entire process of writing this paper. R.G. and S.-M.Y. conceived the idea and designed the structure of this paper. Z.J. collected and examined the data and devised the methodology. S.S. wrote the draft of Sections 1-2, Z.J. wrote the draft of Sections 3-4. R.G. and S.-M.Y. wrote Sections 5-6, and S.-M.Y. performed a final revision of the entire paper.

Funding: This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2017S1A5B8057488).

Conflicts of Interest: The authors declare no conflicts of interest.

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[7] Preliminary analysis based on the nonparametric *k*-th order causality-in-quantiles test of Balcilar et al. [1] does indeed confirm the impact of air pollution on not only returns, but also volatility (as captured by squared returns). Complete details of these results are available upon request from the authors.

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