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## Article

# Does environmental issue matter? Effect of air pollution on the stock market performance

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## FINANCIAL ECONOMICS | LETTER

# Does environmental issue matter? Effect of air pollution on the stock market performance

Kelvin Yong Ming Lee<sup>1</sup>, Pick-Soon Ling<sup>2,3\*</sup> and Chiang-Ching Tan<sup>2,3</sup>

**Abstract:** Air pollution is one of the most serious environmental issues. In Malaysia, the emission of air pollutants has increased in recent years. This study aimed to examine the impact of air pollution on sectoral indices in Malaysian stock market. The dependent variables used in this study were the daily return of 13 sectoral indices, while the independent variables were as follows: (i) the lagged daily return of sectoral indices; (ii) the lagged standard deviation of sectoral indices; and (iii) the Air Quality Index (AQI). The sample period of this study covered from 5 July 2019 to 8 April 2022. The findings showed that the lagged daily return only significantly affected the daily return of few sectors. Meanwhile, the lagged standard deviation significantly affected the daily return of all the sectoral indices, but not under all the market conditions. The lagged AQI and AQI also significantly affected the daily return of eight sectors, which included finance, property, construction, healthcare, technology, energy, utilities, and consumer sectors. Hence, investors need to observe the changes in the air pollution level and market conditions when making investment decision. These findings could help investors in identifying the environmental factors that need to be considered before investing in the stocks of particular sectors.

**Subjects:** Environmental Economics; Finance; Investment & Securities

**Keywords:** air pollution; air quality index; sectoral index; stock market performance; Malaysia

## 1. Introduction

According to the World Health Organisation (WHO), almost everyone on the planet is exposed to levels of air pollution that put them at risk for diseases, such as heart disease, stroke, and cancer. In 2019, Fine Particulate Matter (PM 2.5) pollution has caused 6.4 million of premature deaths. The global cost of health problems related with air pollution is estimated to be USD8.1 trillion, or 6.1% of global GDP (World Bank, 2022). PM 2.5 was the driver of health impacts in air pollution, which consists of a complex mixture of potentially dangerous components. Both short-term and long-term exposures to PM 2.5 also had an adverse impact to people's health. Long-term exposure to air pollution increases the probability of morbidity and mortality in the population (Dominski et al., 2021). On the other hand, Liu et al. (2021) revealed the effects of short-term exposure to PM 2.5 on total mortality and mortality from cardiovascular and respiratory disorders. An increase of 10 µg/m<sup>3</sup> in the 2-day moving average of PM 2.5 concentration was linked to an increase in daily all-cause mortality by 0.68%, cardiovascular mortality by 0.55%, and respiratory mortality by 0.74% (Liu et al., 2021). Practically, Air Quality Index (AQI) was used to measure the air pollution and it comprised six different pollutants, namely ground-level ozone (O<sub>3</sub>), carbon monoxide (CO), nitrogen dioxide (NO<sub>2</sub>), sulphur dioxide (SO<sub>2</sub>), particulate matter which is less than 10 microns (PM 10) and less than 2.5 microns (PM 2.5).

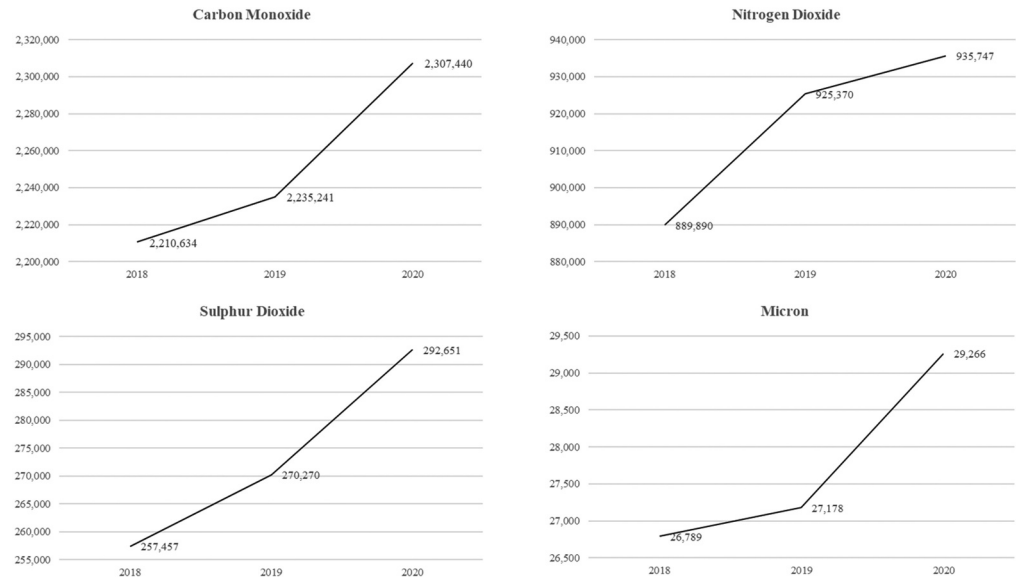
Additionally, rapid industrialisation and urbanisation have also resulted in a significant increase in urban population, motorised vehicles, and energy consumption (Teng & He, 2020). Meanwhile, the industrialisation also led to severe pollution, such as air pollution, in developing countries. Although environmental issues are getting more attention nowadays, yet the relationship between the environmental issues and economic activity is complex. Therefore, policy-makers or researchers must properly comprehend the two's reciprocal influence (Li et al., 2021). Air pollution is also one of the most serious environmental issues as it reduces physical activity levels or prevents people from participating in physical activity during periods of high pollution (Tainio et al., 2021). Air pollution also increases the rate of hospitalisations among older adults and migrants (Giaccherini et al., 2021). Moreover, a person's emotions and health could have an immediate and detrimental effect caused by the poor air quality (Liu et al., 2022). In short, air pollution had significant psychological, economic, and social impacts (Kiihamäki et al., 2021). Furthermore, Liu et al. (2022) further remarked that consumer's consumption decision-making behaviour, like investment behaviour, could be influenced by air pollution. large amount of mental effort. Yet, air pollution appears to have a negative influence on the investor's decisions that involved mental effort (Huang et al., 2020). Investors who were exposed to air pollution would feel anxious and moody, causing them to make wrong judgments in stock trading (Lu et al., 2018). Air pollution also reduces investors' cognitive function, causing them to rely on heuristics and exhibit behavioural biases in their decision-making (Ding et al., 2021). Under such circumstances, investors tend to be risk averse and reduce their holdings in risky asset, which would lead to a decrease in stock returns (Guo et al., 2022). In short, air pollution also posed some significant effect on the investors' behaviours and stock market performance (Li et al., 2021). In addition, recent studies also discovered that air pollution tends to negatively impact stock returns (Ding et al., 2021; 2021; Huang et al., 2020; Jiang et al., 2021; Xu et al., 2021). Although stock-trading decisions are usually seen as cognitively taxing and can have significant financial consequences for households, the impact of air pollution on investor outcomes has received little attention (Huang et al., 2020).

Empirically, several studies have been carried out to investigate the connection of air pollution towards the financial markets and performance. For instance, the negative impact of the air pollution towards the stock returns has been documented in numerous developed markets, such as the United States (Levy & Yagil, 2011), China (Guo et al., 2022), Turkey (Demir & Ersan, 2016), and the like. However, the impact of air pollution on the stock market in an emerging market like Malaysia is relatively scarce. In finance, a developed market tends to be more efficient than emerging market, and, thus, different outcomes may be perceived in emerging market, as compared to plenty of evidence on developed markets. In this study, Malaysia is the focused as the statistics showed that the emission loading for all the pollutants increased from 2018 to 2020, as shown in Figure 1. This trend signified that the air pollution in Malaysia was currently in a worrying situation. Table 1 further provides the details on the different sources of air pollutants in 2020 and shows that the motor vehicle was the highest contributor to the emission of CO (2,210,695 metric tonnes), and power station was the greatest contributor to the NO<sub>2</sub> (584,889 metric tonnes), SO<sub>2</sub> (182,950 metric tonnes), and PM (11,415 metric tonnes). Interestingly, the Malaysian stock market movements are also in line with the emission loadings of air pollutants over the years from 2018 to 2020. Figure 2 shows that the Kuala Lumpur Composite Index (KLCI) grew from only -5.167% in 2018 to 1.542% in 2020. Indeed, the trend for both the air pollutants and KLCI contradicted the recent findings presented by Ding et al. (2021), Huang et al. (2020), Jiang et al. (2021), and Xu et al. (2021). Thus, Malaysia could be an interesting study sample on the relationship between air pollution and stock market movements.

Moreover, previous studies were conducted in different research contexts. For example, some of the studies were conducted using a composite stock index, such as S&P 500, DJIA, NASDAQ, AMEX, PHLX (Levy & Yagil, 2011), Shanghai Composite Index (Xu et al., 2021), Shenzhen Component Index (Jiang et al., 2021), and others, while some other studies utilised the firm-level data in their studies, such as Ding et al. (2021) and Wu et al. (2020). However, the evidence from the different sectors was limited, although different stock behaviours may be postulated in different sectors.

**Figure 1. Emission loading of air pollutant in Malaysia from year 2018 to 2020.**

Sources: Environmental Quality Report 2020, Department of Environment (DOE)



Hence, examining the impact of air pollution on the sectoral stock indices would comprehensively examine the different impact of air pollution on the sectoral indices, which was limitedly addressed in previous studies.

Therefore, this study addresses the knowledge gap by including all the sectoral indices in Malaysia as the sample of study. The main aim of this study is to examine how air pollution affected the performance of sectoral indices in the Malaysian stock market. This is crucial in developing an investment environment that is more sustainable, not only on the ecological but also for the investors' mentality health. With evidence from this study, policy-makers or regulators could formulate some policies or strategies to encourage a healthier and sustainable investment environment. The outcomes of this study are expected to contribute to the existing literature in several ways. Firstly, by identifying the sectors that are affected the most by the air pollution issue. Secondly, by identifying the impact of air pollution issues on the daily return of sectoral indices in different market conditions. These findings shall be referred to as useful guidance for the stakeholders, such as policy-makers and market regulators, in formulating their policies and strategies. The remainder of this study is organised as follows. Section 2 discusses the related research and the relationship between air pollution and stock market. The data and methodology shall be

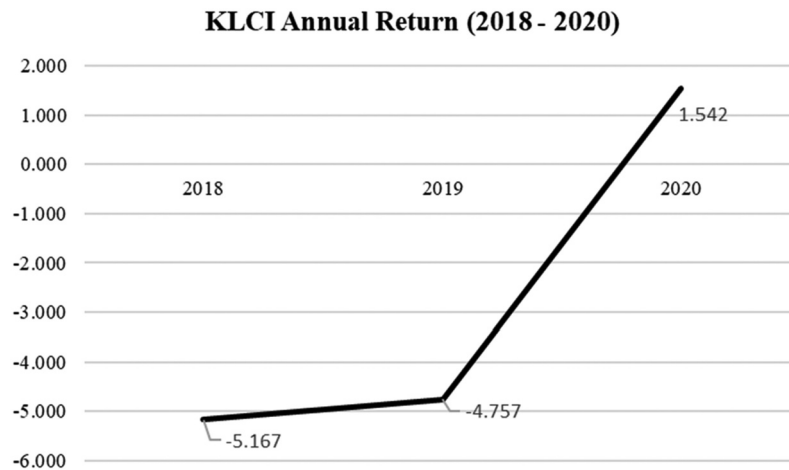
**Table 1. Sources of air pollutant in Malaysia in year 2020**

	CO	NO <sub>2</sub>	SO <sub>2</sub>	PM
	Metric Tonnes	Metric Tonnes	Metric Tonnes	Metric Tonnes
Motor Vehicle	2,210,695 (95.81%)	225,369 (24%)	14,652 (5%)	3,645 (12%)
Power Station	76,234 (3.30%)	584,889 (62%)	182,950 (63%)	11,415 (39%)
Industry	12,176 (0.53%)	80,480 (9%)	18,376 (6%)	8,441 (29%)
Others	8,326 (0.36%)	45,010 (5%)	76,673 (26%)	5,764 (20%)

Sources: Environmental Quality Report 2020, Department of Environment (DOE)

**Figure 2. Kuala Lumpur Composite Index (KLCI) annual return from year 2018 to 2020.**

Sources: Investing.Com



discussed in Section 3. In Section 4, this study presents the empirical results. Section 5 provides a brief conclusion, limitations, and recommendations for future researchers.

## 2. Literature review

Today, air pollution appears to be a long way from the stock market, but in the near future, it will have a closer relationship, as responsible investors are more concerned with long-term returns on their investments (Fang et al., 2021). As a result, discovering the relationship between air pollution and the financial market is becoming more popular over time (Banga, 2018). As the importance of air pollution has grown, the public awareness on environmental protection has also increased. As a result, scholars have begun to pay more attention to the link between air pollution and stock markets (Liu et al., 2021). Air pollution can influence the stock market trading behaviour through two different ways. Firstly, polluted air may impair investors' cognitive abilities and influence behavioural biases in financial markets (Li et al., 2021). Secondly, air pollution affects investors' moods and their investment decisions. The exposure to air pollution could lead to the problem of sleep loss, judgment errors, loss of attention, and inefficient information processing capacity (Heyes & Zhu, 2019). Air pollution makes investors depressed and risk averse, making them less eager to buy equities and causing a detrimental impact on stock returns (Wu et al., 2018).

However, an earlier study by He and Liu (2018) found that air pollution does not pose a significant impact on the Chinese stock market in the long term. The sample period of this study has also been split according to four important events hosted in China. They revealed that air pollution carried a significant negative impact on the stock market after all these events. The establishment of the environmental protection system and regulatory measures also contributed to the reduction of public concern about air pollution. Thus, the emotional shift caused by the air pollution scenario gets reduced, resulting in different impacts caused by air pollution in the recent event. On the other hand, Wu et al. (2018) found that air pollution does not bring significant impact on the firms' performance; however, it affects the investors' mood. Stocks with characteristics of fast growth, distress, and higher volatility had higher sensitivity to air pollution. The researchers also highlighted that the air pollution levels from different cities in China were not synced to each other due to the large spatial distance. Thus, the selection of cities shall be a factor in affecting the results of this kind of study.

Huang et al. (2020) also conducted a study to investigate the impact of air pollution level on the investors' trading behaviours. By analysing the transaction data from more than 80,000 traders, they revealed that there was a negative relationship between air pollution and trading performance. Their findings indicated that air pollution made the investors more vulnerable to the

disposition effect and attention-driven buying behaviour. In addition, Ding et al. (2021) reported that higher level of air pollution shall lead to the lower stock returns. They highlighted that the impact of air pollution was stronger for the firms with the characteristics of younger firm age and lower institutional ownership. Jiang et al. (2021) also discovered that the air pollution only had a significant and negative impact on the stock returns during bullish period. Meanwhile, Xu et al. (2021) revealed that worsening air condition in few consecutive days or air pollution in a bigger area tends to cause an adverse effect to the stock returns. Teng and He (2020) reported that rising pollution awareness influenced the investors cognitive abilities and losing their desire to trade. On the other hand, Wu et al. (2018) conducted a study to explore the impact of fund manager's mood on the stock returns. Similar to previous studies, air pollution tends to cause fund managers to feel depressed, and results in lower stock returns and turnover.

Recently, governments around the world followed the Kyoto Protocol and enforced stricter environmental policies to overcome the air pollution issues (Nerger et al., 2021). However, the former United States (US) president, Donald Trump, rolled back some environmental policies that were implemented before. Nerger et al. (2021) also carried out a study to investigate the impact of Trump's environmental policies towards the stock returns of 49 different sectors from the United States. The researchers revealed that only coal industry benefited from the Trump's environmental policies, while the other industries experienced mixed impacts or negative impacts. The researchers also concluded that the reduction in environmental policies did not have any major impact on US industries.

Based on the review of related literature, air pollution undeniably affected the stock market performance. However, existing studies only investigated the impact of air pollution on the major indices of a particular developed country. The existing major indices only capture the stock price movements of several listed companies. Investors who decide based solely on the movements of existing stock indices may not understand the movements of other sectors in a particular stock market. Although a recent study has found that environmental policies pose some significance to specific sector, however, there is a lack of consensus on the impact of air pollution towards the performance of specific sectors. Thus, this study aims to fill the knowledge gap by including all the sectors from Malaysian stock market. The relationship between the air pollution level and the performance of sectoral indices is then tested under different market conditions. The methodology applied in this study is further discussed in Section 3.

### 3. Data and methodology

This section starts with a discussion of the data and methodology used in this study. To examine the impact of air pollution on the stock market, this study used the recent daily data of 13 sectoral indices, as provided in Table 2 and AQI. The sample period was covered from 5 July 2019 to 8 April 2022. The dependent variables used were sectoral indices from the Malaysian stock market. Data on sectoral indices were collected from Investing.com. Meanwhile, the independent variables used were lagged daily return, lagged standard deviation, and AQI. Daily AQI was collected from the Air Pollutant Index Management System, Malaysia Department of Environment (DOE). Generally, the lower the AQI, the better is the air pollution level. Table 3 provides the description for the different AQI levels.

The raw daily sectoral indices have been transformed into daily return data. Equation 1 was used to calculate the daily return of the sectoral index:

$$R_{i,t} = \ln(\text{Sectorial index at day } t / \text{Sectorial index at day } t - 1) \quad (1)$$

Besides that, the standard deviation of the daily returns was also calculated as one of the independent variables used to represent the volatility of the stock. The standard deviation of the daily returns was calculated using Equation 2:



**Table 2. List of sectors in Malaysian stock market**

No	Sector
1	Finance
2	Property
3	Construction
4	Healthcare
5	Real Estate Investment Trust (REIT)
6	Technology
7	Industrial Production
8	Transportation
9	Energy
10	Telecommunication
11	Utilities
12	Consumer
13	Plantation

$$SD_{i,t} = \sqrt{\sum_{t=1}^n \frac{(R_t - \bar{R})^2}{n-1}}, \text{ where the } n = 5 \quad (2)$$

Before performing further econometric analysis, both the Augmented Dickey Fuller (ADF) and Phillips–Perron (PP) tests were performed to check whether the series of daily returns of sectoral indices and AQI has a unit root. The null hypothesis for both tests stated that the time series was nonstationary. Rejection of the null hypothesis indicated that the time series was stationary and therefore could be used for further analysis.

This study applied the quantile regression analysis proposed by Koenker and Hallock (2001) to determine the dependency structure of the variables under various market conditions. The quantile regression analysis is widely used in financial studies due to its capacity to find the asymmetric relationships between financial variables (Dawar et al., 2021; Kannadhasan & Das, 2020). Quantile regression analysis is a statistical technique for calculating and inferring conditional quantile functions. This analysis is appropriate when the conditional distributions do not have a standard shape, such as asymmetric and fat-tailed distribution (Koutsomanoli-filippaki & Mamatzakis, 2010).

The quantile regression analysis also has two main advantages as compared to the ordinary least square (OLS) regression analysis. Firstly, quantile regression analysis is able to explain the entire picture of the conditional distribution, instead of conditional expectations of the explained variable.

**Table 3. Air pollution level**

Air Quality Index	Air Pollution Level
0–50	Good
51–100	Moderate
101–150	Unhealthy for Sensitive Groups
151–200	Unhealthy
201–300	Very Unhealthy
300 +	Hazardous

Sources: <https://aqicn.org/city/malaysia/>



The regression coefficients are varied according to different quantiles. For instance, the impact of AQI on stock return may vary according to the different market conditions. Secondly, the quantile regression analysis does not need the random error terms and fulfills econometric assumptions such as zero mean and homoscedasticity. The estimated values of the parameters in quantile regression are more resilient for non-normally distributed variables (Harding & Lamarche, 2018).

The quantile regression model is as below:

$$Q(R_t) = \mu_0 + \mu_{1q}R_{t-1} + \mu_{2q}SD_{t-1} + \mu_{3q}AQI_{t-1} + \mu_{4q}AQI_t + \epsilon_t \quad (3)$$

Where,  $\mu_{iq}$  ( $i = 1, 2, 3, 4$ ) represents the parameters that need to be estimated and  $q$  represents the quantile points. The quantile points ranged from 0.1 to 0.9. The quantile points of 0.1 to 0.4 refer to bearish market condition, whereas the quantile points of 0.5 and above refer to bullish market condition.

Thereafter, the causal relationship of the daily returns for sectoral indices and AQI was further explored by using Granger Causality test. The Granger causality test was used to examine whether one time series could cause another series (Wang, 2016). The null hypothesis of Granger Causality test stated that the time series of one variable was not “Granger cause” another one series (Cincinelli et al., 2022). The independent variable was normally said to be “Granger-cause”-dependent variable if the past values of independent variable contain information that could cause the variation of the dependent variable beyond the information contained in past values of dependent variable alone (Granger, 1969).

#### 4. Result and discussion

This section discusses the results obtained by analysing all the 13 sectoral indices from the Malaysian stock market. Table 4 presents the descriptive statistics of the daily returns for the sectoral indices. The technology index had the highest average daily return of 14.89%, followed by healthcare index (9.37%) and industrial production (4.95%). In contrast, the REIT index had the lowest average daily return of -3.35%, followed by construction index (-3.29%) and

**Table 4. Descriptive statistics of daily return**

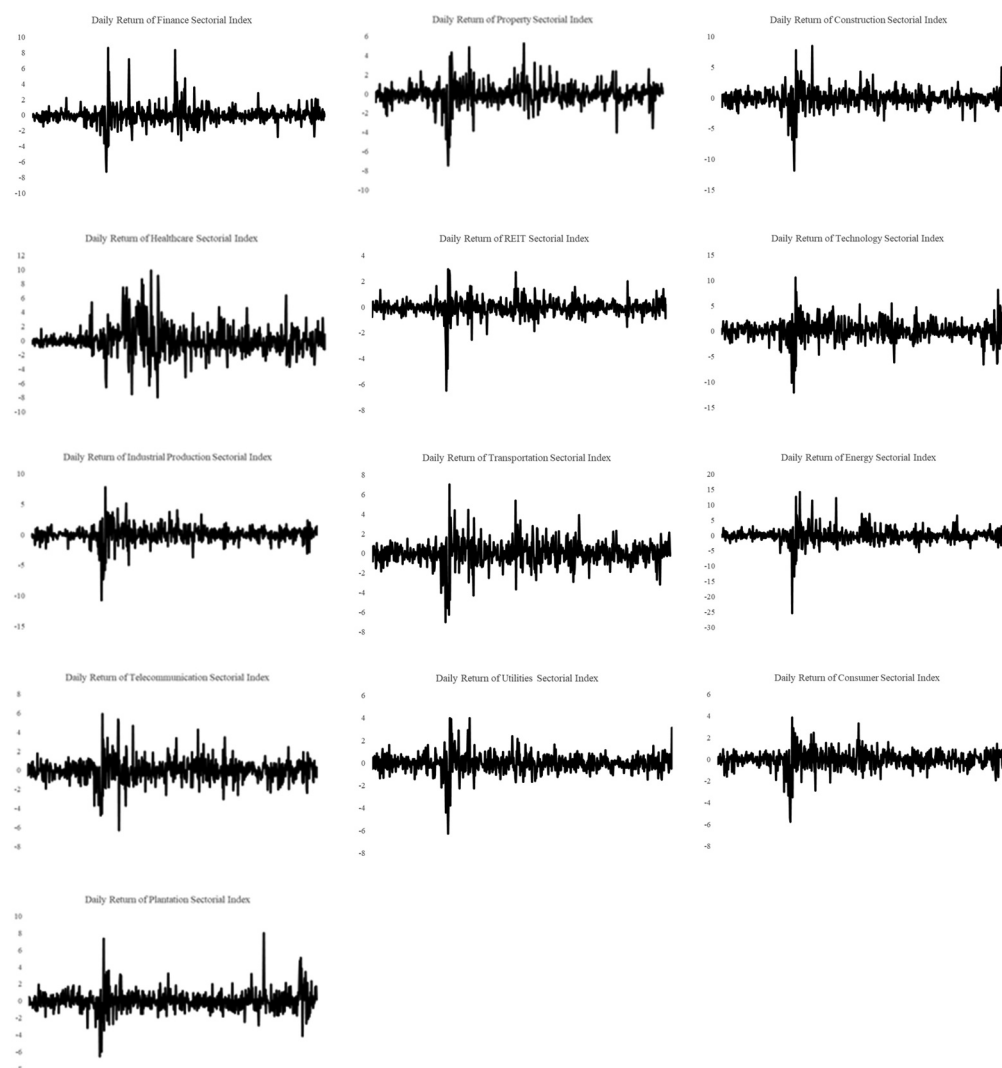
Sector	Mean	Std. Dev.	Max.	Min.
Finance	0.0054	1.1275	8.5992	-7.2300
Property	-0.0260	1.1137	5.2403	-7.4290
Construction	-0.0329	1.4372	8.5112	-11.8395
Healthcare	0.0937	1.9147	9.8475	-7.9797
REIT	-0.0335	0.6767	2.9507	-6.4731
Technology	0.1429	1.9367	10.5838	-12.0424
Industrial Production	0.0495	1.3036	7.8145	-10.7373
Transportation	0.0235	1.2203	7.0521	-7.0109
Energy	-0.0243	2.3890	14.2269	-25.3943
Telecommunication	-0.0090	1.1280	5.9313	-6.2904
Utilities	-0.0148	0.8382	3.9945	-6.2563
Consumer	-0.0186	0.8211	3.8626	-5.7519
Plantation	0.0338	1.1566	8.0102	-6.5189

property index (−2.60%). On the other hand, the energy index had the highest standard deviation of 2.3890, followed by technology index (1.9367) and healthcare index (1.9147). The REIT also had the lowest standard deviation of 0.6767, followed by consumer index (0.8211) and utilities index (0.8382). This indicated technology and healthcare indices were highly volatile during the sample periods, but it also matched with the higher average daily return. Both the consumer and utilities sector indices were relatively stable during the sample periods.

Figure 3 presents the dynamic of daily return for all the 13 sectors. Consistently, all the sectoral indices were highly volatile in the early stage of the sample period (COVID-19 outbreak). Among all the sectoral indices, the healthcare and transportation indices persist volatile for a longer period. The movements of utilities and consumer indices were also relatively stable throughout the sample period. Lately, plantation and technology indices also experienced high volatile movements.

Prior to the quantile regression analysis and Granger Causality analysis, both the ADF and PP tests have been applied to investigate the stationary properties of the related data series, including

**Figure 3. Dynamic of daily return series for 13 sectors.**



the return series of 13 sectoral indices and AQI. The results of both tests are provided in [Table 5](#) and show that the data series does not consist of unit root or stationary at the level (return series).

[Table 6](#) to [Table 18](#) present the results of quantile regression analysis for 13 different sectors. ( $q = 0.1$ ) to ( $q = 0.4$ ) refer to the bearish market condition, whereas ( $q = 0.5$ ) to ( $q = 0.9$ ) refer to the bullish market condition. The results showed that the lagged daily return contains predictive information about the daily return of property index ([Table 7](#)), healthcare index ([Table 9](#)), REIT index ([Table 10](#)), technology index ([Table 11](#)), and plantation index ([Table 18](#)). Specifically, the lagged daily contains predictive information about the daily return of property index and healthcare index during bullish market condition. In contrast, the lagged daily return contains predictive information about the daily return of property index and technology index during bearish market condition. The lagged daily return could be used to predict the daily return of plantation index in nearly all the market conditions. This indicated that investors must pay attention to the previous daily return for these four sectors. Based on [Table 6](#) to [Table 18](#), the lagged standard deviation could be used to predict the daily return for all the sectoral indices but not during all the market condition. This indicated that market volatility in the previous day may not be a good indicator for predicting the daily return under all the market condition.

[Table 6](#) shows the lagged AQI and the same-day AQI only have predictive power for the performance of finance sector during bullish market condition ( $q = 0.5, 0.6$ , and  $0.7$ ). On the other hand, [Table 7](#) shows that the lagged AQI has the predictive power for the performance of the property sector during both the bearish ( $q = 0.2$  and  $0.4$ ) and bullish market condition ( $q = 0.6, 0.7$ , and  $0.9$ ). Both the lagged AQI and the same-day AQI had a weak predictive power on the performance of four sectors, which included construction ([Table 8](#)), healthcare ([Table 9](#)), energy ([Table 14](#)), and consumer sectors ([Table 17](#)). Specifically, both the lagged AQI and the same-day AQI contain predictive information about the performance of construction sector ([Table 8](#)) during

**Table 5. Results of stationary test**

Variables	ADF	PP
Finance	-24.668	-24.938
Property	-21.639	-22.397
Construction	-23.264	-23.596
Healthcare	-21.820	-22.215
REIT	-23.015	-23.489
Technology	-26.031	-26.174
Industrial Production	-26.123	-26.377
Transportation	-25.395	-25.700
Energy	-26.541	-26.658
Telecommunication	-27.230	-27.262
Utilities	-23.928	-24.498
Consumer	-25.553	-26.089
Plantation	-26.823	-27.032
Air Quality Index	-7.417	-7.289

Notes: Critical value for Augmented Dickey Fuller and Phillips-Perron tests: -3.430 (1%), -2.860 (5%), and -2.570 (10%)

Table 6. Result of quantile regression analysis for finance sector

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.2056	0.0643	-0.0085	-0.0275	0.0109	0.0192	-0.0087	0.0448	0.0063
	-0.174	-0.088	-0.074	-0.092	-0.078	-0.055	-0.05	-0.084	-0.107
Standard Deviation <sub>t-1</sub>	-0.6333**	-0.3098**	-0.1957	-0.0331	0.0395	0.1941*	0.2821***	0.4114***	0.7402***
	-0.259	-0.13	-0.147	-0.104	-0.096	-0.108	-0.082	-0.143	-0.275
AQI <sub>t-1</sub>	0.0010	0.0048	-0.0019	-0.0044	-0.0057**	-0.008***	-0.008***	0.0006	0.0065
	-0.013	-0.007	-0.004	-0.004	-0.003	-0.002	-0.003	-0.007	-0.009
AQI	-0.0011	-0.0054	0.0034	0.0051	0.0054*	0.0073***	0.0062**	-0.0023	-0.0103
	-0.011	-0.006	-0.005	-0.004	-0.003	-0.003	-0.003	-0.007	-0.008
Constant	-0.4995	-0.3514	-0.2924*	-0.1463	-0.0167	0.0135	0.1728*	0.3230***	0.5971***
	-0.379	-0.31	-0.165	-0.089	-0.095	-0.121	-0.093	-0.117	-0.212

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ . Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.

Table 7. Result of quantile regression analysis for property sector

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.1822	0.1471	0.1208*	0.0756	0.0429	0.0495	0.0840*	0.1107**	0.1406
	-0.173	-0.095	-0.073	-0.072	-0.075	-0.065	-0.051	-0.044	-0.109
Standard Deviation <sub>t-1</sub>	-0.779***	-0.3451	-0.1831	-0.0615	0.0409	0.1083	0.3169*	0.4000***	0.4034***
	-0.237	-0.245	-0.142	-0.123	-0.118	-0.149	-0.184	-0.108	-0.137
AQI <sub>t-1</sub>	-0.0082	-0.0109*	-0.0050	-0.0069*	-0.0054	-0.0087**	-0.006***	-0.0046	-0.0162**
	-0.007	-0.006	-0.006	-0.004	-0.005	-0.004	-0.002	-0.003	-0.006
AQI	0.0098	0.0103*	0.0049	0.0070*	0.0047	0.0074	0.0047	0.0003	0.0093
	-0.007	-0.006	-0.005	-0.004	-0.005	-0.005	-0.003	-0.003	-0.006
Constant	-0.5923**	-0.3501	-0.2394	-0.1664	-0.0160	0.1510	0.2120	0.5773***	1.1625***
	-0.292	-0.271	-0.165	-0.157	-0.126	-0.181	-0.235	-0.167	-0.196

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ . Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.

Table 8. Result of quantile regression analysis for construction sector

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.1382	0.1250	0.0325	0.0396	0.0504	0.0342	0.0167	0.0709	0.0429
	-0.176	-0.082	-0.083	-0.053	-0.043	-0.024	-0.036	-0.056	-0.112
Standard Deviation <sub>t-1</sub>	-0.813***	-0.4871**	-0.1209	0.0388	0.1745*	0.1864*	0.2323**	0.3015**	0.4720***
	-0.262	-0.214	-0.226	-0.151	-0.096	-0.101	-0.092	-0.141	-0.176
AQI <sub>t-1</sub>	-0.0226**	-0.0127	-0.0084	-0.0067	-0.0113	-0.0060	-0.0095	-0.0149	-0.0079
	-0.01	-0.009	-0.009	-0.007	-0.007	-0.005	-0.007	-0.01	-0.007
AQI	0.0241**	0.0133	0.0079	0.0050	0.0094	0.0037	0.0069	0.0095	-0.0007
	-0.011	-0.008	-0.01	-0.006	-0.007	-0.005	-0.007	-0.011	-0.009
Constant	-0.679***	-0.4008*	-0.3554	-0.1864	-0.0724	0.1458	0.4096	0.8468***	1.3469***
	-0.262	-0.243	-0.34	-0.194	-0.182	-0.228	-0.26	-0.27	-0.285

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ . Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.

**Table 9. Result of quantile regression analysis for healthcare sector**

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.1886	0.0944	0.1060	0.1074	0.1215*	0.1662**	0.1760***	0.1610**	0.1213
	-0.115	-0.086	-0.074	-0.065	-0.062	-0.079	-0.055	-0.073	-0.119
Standard Deviation <sub>t-1</sub>	-0.556***	-0.367***	-0.2120*	-0.0825	0.0417	0.2087**	0.5151***	0.7117***	1.1057***
	-0.105	-0.073	-0.121	-0.117	-0.065	-0.1	-0.104	-0.166	-0.256
AQI <sub>t-1</sub>	-0.0118	-0.0077	-0.0131	-0.0101	-0.0042	-0.0045	-0.0090	-0.0083	0.0093
	-0.015	-0.007	-0.009	-0.009	-0.005	-0.005	-0.006	-0.011	-0.016
AQI	0.0176	0.0108**	0.0142*	0.0102	0.0062	0.0041	0.0076	0.0051	-0.0114
	-0.014	-0.005	-0.008	-0.008	-0.006	-0.005	-0.005	-0.011	-0.015
Constant	-1.237***	-0.725***	-0.4818*	-0.2429	-0.2451	0.0272	0.1294	0.3723	0.6463
	-0.256	-0.236	-0.275	-0.256	-0.244	-0.204	-0.184	-0.32	-0.398

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ ; Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.



Table 10. Result of quantile regression analysis for REIT sector

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.2319**	0.0784	-0.0311	-0.0272	-0.0011	-0.0090	0.0034	0.0724	0.0018
	-0.118	-0.088	-0.073	-0.053	-0.059	-0.066	-0.066	-0.071	-0.128
Standard Deviation <sub>t-1</sub>	-0.665***	-0.3117**	-0.0465	0.1141	0.1848	0.4288**	0.4482**	0.5473***	0.6866***
	-0.196	-0.136	-0.131	-0.161	-0.153	-0.171	-0.186	-0.161	-0.137
AQI <sub>t-1</sub>	0.0031	-0.0008	0.0032	0.0026	0.0023	0.0034	0.0008	0.0019	0.0020
	-0.007	-0.004	-0.004	-0.003	-0.002	-0.003	-0.003	-0.003	-0.005
AQI	-0.0018	0.0013	-0.0032	-0.0022	-0.0031	-0.0031	-0.0015	-0.0031	-0.0056
	-0.006	-0.004	-0.004	-0.002	-0.002	-0.003	-0.003	-0.002	-0.005
Constant	-0.459***	-0.3012**	-0.2209**	-0.2025**	-0.0624	-0.1195	0.0470	0.1589	0.4744***
	-0.127	-0.128	-0.089	-0.101	-0.11	-0.086	-0.122	-0.116	-0.15

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ ; Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.

**Table 11. Result of quantile regression analysis for technology sector**

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.3079***	0.1217	0.0153	0.0272	-0.0322	-0.0504	-0.0893	-0.1073	-0.0580
	-0.067	-0.109	-0.082	-0.065	-0.044	-0.054	-0.066	-0.094	-0.111
Standard Deviation <sub>t-1</sub>	-0.966***	-0.524***	-0.2461	-0.0389	0.0405	0.2006	0.4331***	0.5379***	0.8695***
	-0.208	-0.146	-0.177	-0.14	-0.119	-0.138	-0.104	-0.197	-0.145
AQI <sub>t-1</sub>	-0.0267	-0.0213**	-0.0179	-0.0170*	-0.0156**	-0.0173**	-0.0114**	-0.012***	-0.0091
	-0.017	-0.011	-0.012	-0.01	-0.007	-0.007	-0.006	-0.004	-0.01
AQI	0.0300*	0.0263**	0.0249**	0.0207**	0.0186***	0.0197***	0.0127*	0.0113**	0.0084
	-0.016	-0.01	-0.012	-0.01	-0.007	-0.007	-0.006	-0.005	-0.011
Constant	-0.8641	-0.6639**	-0.6239**	-0.3199	-0.0635	0.0872	0.3025	0.5950	0.9591***
	-0.551	-0.278	-0.291	-0.287	-0.234	-0.219	-0.202	-0.389	-0.318

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ . Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.

Table 12. Result of quantile regression analysis for industrial production sector

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.1269	-0.0548	-0.0864	-0.0154	-0.0293	-0.0462	-0.0246	-0.0745	-0.0417
	-0.114	-0.097	-0.068	-0.063	-0.065	-0.057	-0.057	-0.083	-0.106
Standard Deviation <sub>t-1</sub>	-0.911***	-0.375***	-0.2340**	-0.0883	0.0592	0.1862	0.3584***	0.5006***	0.6096***
	-0.2	-0.145	-0.117	-0.124	-0.138	-0.126	-0.093	-0.108	-0.167
AQI <sub>t-1</sub>	-0.0039	-0.0079	-0.0009	-0.0019	-0.0021	-0.0031	-0.0063	-0.0054	-0.0106
	-0.007	-0.008	-0.007	-0.005	-0.005	-0.006	-0.006	-0.006	-0.016
AQI	0.0070	0.0087	0.0031	0.0019	0.0002	-0.0004	0.0021	0.0045	0.0126
	-0.008	-0.006	-0.007	-0.005	-0.005	-0.007	-0.007	-0.005	-0.016
Constant	-0.5326*	-0.3763	-0.2693*	-0.0528	0.1473	0.3561	0.4459	0.4085	0.5968
	-0.285	-0.238	-0.152	-0.192	-0.227	-0.295	-0.287	-0.367	-0.408

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ ; Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.

**Table 13. Result of quantile regression analysis for transportation sector**

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.0495	0.0681	-0.0191	0.0041	-0.0131	-0.0117	0.0144	0.0331	0.0687
	-0.073	-0.092	-0.062	-0.05	-0.068	-0.07	-0.054	-0.036	-0.105
Standard Deviation <sub>t-1</sub>	-0.846***	-0.3740	-0.0994	-0.0180	0.0515	0.2072***	0.2882***	0.2838***	0.4864***
	-0.182	-0.309	-0.144	-0.108	-0.093	-0.07	-0.083	-0.104	-0.156
AQI <sub>t-1</sub>	-0.0059	-0.0051	-0.0077	0.0048	0.0017	0.0001	0.0046	-0.0034	0.0022
	-0.006	-0.007	-0.009	-0.006	-0.006	-0.005	-0.007	-0.007	-0.008
AQI	0.0089	0.0048	0.0077	-0.0024	-0.0007	-0.0001	-0.0052	-0.0007	-0.0083
	-0.008	-0.007	-0.01	-0.006	-0.005	-0.004	-0.005	-0.006	-0.008
Constant	-0.6665	-0.3882	-0.3249	-0.3178**	-0.0407	0.0891	0.3046**	0.7491***	1.1647***
	-0.41	-0.298	-0.245	-0.161	-0.146	-0.112	-0.124	-0.158	-0.25

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ ; Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.

Table 14. Result of quantile regression analysis for energy sector

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.0279	-0.0873	-0.0556	-0.0713*	-0.0538	-0.0549	-0.0285	0.0538	0.0286
	-0.105	-0.062	-0.05	-0.039	-0.04	-0.04	-0.041	-0.049	-0.107
Standard Deviation <sub>t-1</sub>	-0.674***	-0.459***	-0.2855**	-0.1265	0.0749	0.1220**	0.1490***	0.2512	0.6479***
	-0.198	-0.131	-0.142	-0.149	-0.092	-0.052	-0.053	-0.167	-0.213
AQI <sub>t-1</sub>	-0.0231	0.0025	-0.0053	-0.0060	-0.0050	0.0022	-0.0061	-0.0067	-0.0218*
	-0.016	-0.007	-0.007	-0.008	-0.009	-0.011	-0.009	-0.007	-0.012
AQI	0.0256*	0.0034	0.0103	0.0130	0.0077	0.0024	0.0129	0.0093	0.0184*
	-0.015	-0.01	-0.011	-0.011	-0.011	-0.013	-0.01	-0.006	-0.011
Constant	-1.1229**	-0.9279	-0.6477	-0.6451**	-0.3459	-0.1718	0.0849	0.6637*	1.3502***
	-0.541	-0.572	-0.474	-0.32	-0.333	-0.343	-0.321	-0.4	-0.502

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ . Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.

Table 15. Result of quantile regression analysis for telecommunication sector

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.0534	-0.0305	-0.0512	-0.0549	-0.0982	-0.0536	-0.0244	0.0041	-0.0491
	-0.142	-0.064	-0.049	-0.061	-0.069	-0.053	-0.055	-0.075	-0.118
Standard Deviation <sub>t-1</sub>	-0.5030**	-0.2183*	-0.1406*	-0.1166*	-0.0498	0.0723	0.1862	0.4127***	0.5434***
	-0.204	-0.121	-0.079	-0.06	-0.09	-0.137	-0.145	-0.128	-0.103
AQI <sub>t-1</sub>	0.0068	-0.0019	0.0010	0.0018	0.0021	-0.0028	0.0018	0.0003	-0.0073
	-0.008	-0.008	-0.008	-0.008	-0.005	-0.004	-0.005	-0.005	-0.009
AQI	-0.0096	-0.0003	-0.0002	-0.0014	-0.0036	0.0010	-0.0051	-0.0034	0.0039
	-0.01	-0.01	-0.009	-0.009	-0.007	-0.005	-0.005	-0.005	-0.008
Constant	-0.6417	-0.3889	-0.3573*	-0.1323	0.1480	0.2586	0.4750***	0.5145***	0.8570***
	-0.422	-0.371	-0.192	-0.185	-0.147	-0.17	-0.137	-0.196	-0.184

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ . Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.

Table 16. Result of quantile regression analysis for utilities sector

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.1142	0.0048	-0.0396	-0.0392	-0.0424	-0.0026	-0.0160	-0.0417	-0.0144
	-0.147	-0.079	-0.065	-0.048	-0.053	-0.053	-0.035	-0.046	-0.07
Standard Deviation <sub>t-1</sub>	-0.8078*	-0.1725	-0.1034	-0.0420	0.0295	0.1734	0.3803***	0.5715***	0.6899***
	-0.444	-0.287	-0.167	-0.147	-0.116	-0.144	-0.121	-0.21	-0.217
AQI <sub>t-1</sub>	-0.0090*	-0.0125**	-0.012***	-0.013***	-0.0085**	-0.008***	-0.0051**	-0.0051	-0.0031
	-0.005	-0.005	-0.004	-0.004	-0.003	-0.002	-0.002	-0.005	-0.008
AQI	0.0084	0.0123*	0.0110**	0.0114***	0.0100***	0.0086***	0.0043	0.0031	0.0046
	-0.006	-0.007	-0.004	-0.004	-0.003	-0.003	-0.003	-0.004	-0.008
Constant	-0.3596	-0.3810*	-0.2024	-0.0732	-0.1495	-0.0456	0.1109	0.2705	0.3372
	-0.315	-0.224	-0.158	-0.138	-0.133	-0.143	-0.124	-0.212	-0.227

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ . Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.



Table 17. Result of quantile regression analysis for consumer sector

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	0.1122	-0.0364	-0.0335	-0.0124	-0.0701	-0.0904	-0.0906	-0.0994	-0.0319
	-0.132	-0.078	-0.06	-0.068	-0.064	-0.055	-0.069	-0.071	-0.11
Standard Deviation <sub>t-1</sub>	-0.6945**	-0.3794	-0.1248	-0.0927	0.0617	0.2025	0.2965***	0.5482***	0.7776***
	-0.303	-0.246	-0.143	-0.131	-0.137	-0.131	-0.104	-0.144	-0.158
AQI <sub>t-1</sub>	0.0044	-0.0003	-0.0027	-0.0027	-0.0016	-0.0034	-0.0054**	-0.0049	-0.0044
	-0.01	-0.006	-0.006	-0.005	-0.003	-0.003	-0.002	-0.006	-0.006
AQI	-0.0022	-0.0004	0.0030	0.0020	0.0002	0.0022	0.0030	0.0033	0.0008
	-0.007	-0.006	-0.005	-0.005	-0.003	-0.003	-0.003	-0.006	-0.006
Constant	-0.5600**	-0.2756	-0.2270	-0.0457	0.0531	0.1006	0.2574**	0.3077**	0.5742***
	-0.227	-0.225	-0.195	-0.121	-0.098	-0.112	-0.111	-0.141	-0.156

Notes: \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.10$ . Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.

Table 18. Result of quantile regression analysis for plantation sector

Variables	q 0.1	q 0.2	q 0.3	q 0.4	q 0.5	q 0.6	q 0.7	q 0.8	q 0.9
Return <sub>t-1</sub>	-0.1521**	-0.220***	-0.1057**	-0.113***	-0.103***	-0.0731*	-0.0484	-0.0053	0.1031
	-0.073	-0.065	-0.042	-0.04	-0.037	-0.038	-0.047	-0.073	-0.076
Standard Deviation <sub>t-1</sub>	-0.478***	-0.2994	-0.0256	0.0501	0.2467***	0.3224***	0.2874***	0.3075***	0.4889***
	-0.131	-0.207	-0.091	-0.08	-0.085	-0.089	-0.079	-0.112	-0.156
AQI <sub>t-1</sub>	0.0119	-0.0007	-0.0026	-0.0011	-0.0042	-0.0022	-0.0022	-0.0079	-0.0102
	-0.009	-0.007	-0.005	-0.005	-0.005	-0.006	-0.007	-0.008	-0.006
AQI	-0.0122	0.0004	0.0013	-0.0003	0.0033	0.0012	0.0003	0.0035	0.0015
	-0.01	-0.008	-0.006	-0.006	-0.005	-0.005	-0.006	-0.008	-0.006
Constant	-0.704***	-0.4224	-0.2942	-0.1772	-0.1514	-0.0249	0.2756*	0.7056***	1.2653***
	-0.223	-0.322	-0.193	-0.116	-0.115	-0.148	-0.147	-0.126	-0.155

Notes: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ , Return<sub>t-1</sub> is daily return at day  $t-1$ ; Standard deviation<sub>t-1</sub> is standard deviation of daily return over the past five trading days; AQI<sub>t-1</sub> is the moving average of AQI over the  $n$  days; q 0.1 to q 0.9 were the quantile used in this study.

**Table 19. Results of granger causality test**

<b>Sector</b>	<b>Null Hypothesis</b>	<b>p-value</b>
Finance	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.197
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.974
Property	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.445
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.899
Construction	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.374
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.820
Healthcare	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.886
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.059***
REIT	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.434
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.706
Technology	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.696
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.966
Industrial Production	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.865
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.755
Transportation	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.940
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.300
Energy	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.720
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.619
Telecommunication	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.845
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.777
Utilities	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.338
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.947
Consumer	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.439
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.707

(Continued)

**Table19. (Continued)**

Sector	Null Hypothesis	p-value
Plantation	<i>Stock Return</i> does not granger cause <i>AQI</i>	0.679
	<i>AQI</i> does not granger cause <i>Stock Return</i>	0.797

Notes: Critical value for Augmented Dickey Fuller and Phillips–Perron tests: −3.430 (1%), −2.860 (5%), and −2.570 (10%)

the worst market condition ( $q = 0.1$ ). The same-day AQI only contains predictive information about the performance of healthcare sector during bearish market condition ( $q = 0.2$  and  $0.3$ ). The lagged AQI only contains predictive information about the performance of energy and consumer sectors during bullish market condition ( $q = 0.9$  for energy sector and  $q = 0.7$  for consumer sector). The same-day AQI contains predictive information about the daily return of energy sector during the bearish ( $q = 0.1$ ) and bullish market condition ( $q = 0.9$ ).

Based on Table 11, both the lagged AQI and AQI had predictive power for the performance of technology sector in nearly all the market conditions. Based on Table 16, the lagged AQI had predictive power for the performance of utilities sector during nearly all the market condition ( $q = 0.1$  to  $0.7$ ). The same-day AQI had predictive power for the performance of utilities sector during both the bearish and bullish market condition ( $q = 0.2$  to  $0.6$ ). Lastly, the lagged AQI or AQI did not have any predictive power for the performance of five sectors, which included REIT (Table 10), industrial production (Table 12), transportation (Table 13), telecommunication (Table 15) and plantation (Table 18).

In summary, the lagged daily return only significantly affected the performance of the four sectors, which included property, healthcare, technology, and plantation sectors. Meanwhile, the lagged standard deviation had a significant relationship with the daily return for all the sectoral indices. This suggested that the lagged standard deviation shall be a useful indicator to predict the movements of all the sectoral indices, as compared to the lagged daily return. However, the lagged standard deviation did not show a significant impact on the daily return under all the market conditions.

Both the lagged AQI and AQI had a significant impact on the daily return of all the sectors, except for the REIT, industrial production, transportation, telecommunication, and plantation sectors. This suggested that air pollution level shall not affect the performance of these four sectors. Indirectly, these four sectors were the defensive sectors to invest regardless of the air pollution level. Generally, the lagged AQI was negatively related with the returns of nine sectors. This indicated that worsening air condition in the previous day affected the returns of sectoral indices the next day. This finding is consistent with Wu et al. (2018), Ding et al. (2021), and Xu et al. (2021). However, this study also found that the magnitude of the effect of air pollution was varying across different market conditions. This finding contradicts with those of Jiang et al. (2021) who revealed that the effect of air pollution was greater in bullish market condition. The discrepancy in this result may be due to the sample selection, whereas the focus of this study is an emerging market.

In addition, the Granger Causality test has been employed to examine the bidirectional causal relationship of the return of sectoral indices and AQI. As presented in Table 19, the results showed that all returns of sectoral indices and AQI did not have any causality relationship, except for return of healthcare indices. The healthcare sector found a unidirectional relationship running from AQI to healthcare sector in the short run.

## 5. Conclusion, limitation, and recommendation for future study

This study investigated the impact of air pollution on the performance of the different sectors in Malaysian stock market by using the recent daily data covering 5 July 2019 to 8 April 2022. This study also carried out a quantile regression analysis by including the daily return of 13 sectoral indices as the dependent variables. Meanwhile, lagged daily return, lagged standard deviation, and the proxy of air pollution—AQI—were used as the independent variables. The results of the quantile regression analysis revealed that lagged daily return only significantly affected the daily return of few sectors, whereas the lagged standard deviation significantly affected the daily return of all the sectoral indices, but not all the time. Interestingly, the lagged AQI and the same-day AQI significantly affected the daily return of eight sectors, which included finance, property, construction, healthcare, technology, energy, utilities, and consumer sectors. The impact of air pollution on the sectoral indices also varies across the sectors and market conditions. This study recommends that investors monitor the volatility (as measured by the standard deviation) in a particular sector and the air quality before making any investment decision. Moreover, the results of Granger Causality further showed that there was no causal relationship between the sectoral indices and AQI, except AQI that had a unidirectional relationship with healthcare sector. Thus, this study contributed to the existing finance literature by providing new evidence concerning the predictive power of AQI for the returns of different sectoral indices. Secondly, this study also provided evidence on the predictive power of AQI under different market conditions. Thirdly, the results of this study also would help the investors to figure out the potential factor to be considered for their investment decision.

However, this study faced several limitations. First, this study focuses only on the impact of AQI on the sectoral indices, without other macroeconomic variables, such as inflation and economic condition. Secondly, this study only included the sectoral indices as the sample. Each of these sectoral indices only consisted of five listed companies from the specific sector, which limits the generalisation of the findings to the other stocks from the same sector. Thirdly, this study only used the AQI from Kuala Lumpur city as the proxy of air pollution. Therefore, future research is recommended to include the macroeconomic variables in the analysis. Moreover, future studies should include other countries with high AQI or other individual stocks as the sample. Future studies should also consider the AQI from different cities in the same country.

The major practical implication of the findings is that an investor must consider the changes in the air pollution level before investing in a particular sector. This is due to the reason that higher air pollution level may adversely affect the investors' moods and lead to the decline in the stock market performance. The findings of this study also underscore the importance of monitoring not only the stock volatility but also the external factor—air pollution. Policy-makers and regulators should formulate some policies or strategies in order to encourage a healthier and sustainable investment environment, which attract investors to the stock market.

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