https://doi.org/10.59865/abacj.2024.18

A MULTIVARIATE MEDIATION ANALYSIS OF $PM_{2.5}$ POLLUTION AND STOCK MARKET RETURNS

Anya Khanthavit[1]

Abstract

Particulate matter 2.5 ($PM_{2.5}$) is considered the most dangerous air-polluting particle, causing premature death and inducing severe mental and physical diseases worldwide. $PM_{2.5}$ affects stock market returns directly via the fundamental channel and indirectly via the behavioral channel. This study examines the effects of Bangkok's $PM_{2.5}$ pollution on the return on the Market for Alternative Investment index portfolio using a multivariate mediation analysis. Attention, awareness, mood, sentiment, and stress, the mediating variables known to influence investors' behavior, were considered jointly and explicitly in the model. This study is the first to introduce stress as a behavioral mediator. The roles and effects of the behavioral mediators were identified, measured, and compared. Using daily data from August 1, 2016, to November 30, 2023, this study found that the total, direct, and indirect effects were not significant. Stress was the only behavioral mediator that significantly and positively contributed to the indirect effects. This result remains unchanged for different estimation techniques, sample periods, representative stock returns, and $PM_{2.5}$ occurrence times.

Keywords: Air Quality, Behavioral Finance, Good Health and Well-Being, Stress

1. INTRODUCTION

The World Health Organization (2023) considers air pollution to be a significant environmental threat. It is a leading cause of death worldwide. The United Nations Environment Programme (2023) estimated that each year, pollution causes approximately 7 million premature deaths worldwide; particulate matter 2.5 ($PM_{2.5}$) has been identified as the most dangerous air pollution particle. In China, there are 156,588 premature deaths and more than 6 million individuals suffer from air pollution-related diseases annually. This has caused a loss of 3,026.62 million Chinese yuan in labor losses and medical expenditure (Chen et al., 2019). For the United States, Deryugina et al. (2019) reported that an increase in $PM_{2.5}$ of 1 microgram per cubic foot led to a loss of 2.99 life years per 1 million beneficiaries over three days, amounting to a loss of 299,000 dollars.

Airborne $PM_{2.5}$ is a pollutant mixture of many chemical species with a diameter less than 2.5 microns. Its structure is a complex mixture of solids and aerosols, composed of small droplets of liquid, dry solid fragments, and solid cores with a liquid coating (California Air Resources Board, 2023). $PM_{2.5}$ chemical species that contribute to premature death and poor health include ammonium, black carbon, chromium, iron, manganese, nickel, nitrate, sulfate, and zinc (Ahmad et al., 2022).

$PM_{2.5}$ pollution affects all individual and economic sectors, including investors and stock markets. Its effects on investors and stock markets occur through fundamental and behavioral channels. The effects of the fundamental channel are direct, and its direction on

[1] Dr. Anya Khanthavit is a Distinguished Professor of Finance and Banking at the Faculty of Commerce and Accountancy, Thammasat University, Bangkok, Thailand. He holds a Ph. D. in International Business and Finance from New York University's Leonard N. Stern School of Business. Email: akhantha@tu.ac.th.

stock returns can be positive or negative. $PM_{2.5}$ raises public awareness of pollution, leads to strict environmental regulations, high political costs, limited investment opportunities (An et al., 2018; Luo, 2017), demand shifts from old to emerging industries (Xu & Chen, 2022), productivity losses (Fu, Viard, & Zhang, 2021), shortages of general and skilled labor (Huang, 2023; Zhao & Yuan, 2020), improved corporate governance (Liu & Wu, 2024), and high cash holding levels (Tan, Tan, & Chan, 2021).

Behavioral channels convey the indirect effects of pollution on stock returns. The behavioral mediators included attention, awareness, mood, sentiment, and stress. Zhang and Tao (2019) explained that pollution attracts investor attention through direct physical and psychological experiences, pollution-related news, and government regulations. Increasing attention to pollution and pollution-induced activities lowers stock market activities. Thus, returns decrease (Smales, 2021). Relying on the attention hypothesis, Wu and Lu (2020) and Zhang and Tao (2019) reported that pollution has a negative relationship with stock returns in the Chinese market.

Awareness influences stock market returns because it affects the perceived severity of pollution. This perception, in turn, leads to investors changing their trading behaviors, and stock prices will be discrepant (Teng & He, 2020). Teng and He (2020) and Xu, Wang, and Tu (2021) studied the link between $PM_{2.5}$ and stock returns in China. In these studies, awareness was related to two variables. However, the results were inconsistent. Although Teng and He (2020) reported a positive relationship, Xu et al. (2021) reported a negative relationship.

Most previous studies referred to the mood explanation for the relationship between $PM_{2.5}$ and stock returns—this includes Li and Peng (2016) and Zhang, Jiang, and Guo (2017) for China, Lepori (2016) for Italy, Murger (2022) for Romania, Ming (2023) for Singapore, Lin (2021) for Thailand and Indonesia, Levy and Yagil (2011) for the United States, and Bảo and Văn (2023) for Vietnam. For international markets, Kiihamäkil, Korhonen, and Jaakkola (2021) studied the relationships among 47 cities worldwide.

$PM_{2.5}$, which causes a bad mood, leads to investors' pessimism, depression, and rising consumption. Consequently, stock prices fall (Li & Peng, 2016). A negative relationship was reported by Levy and Yagil (2011) for U.S. returns and by Zhang et al. (2017) for Chinese returns. For Thailand, the relationship with stock returns is negative for lagged $PM_{2.5}$ but not for its current level, whereas the relationship is non-significant for Indonesia (Lin, 2021). The significant results can be trading system or sample period-dependent. Lepori (2016) found that in Italy, the relationship was negative for the floor trading system but non-significant for the electronic trading system. For Vietnam, Bảo and Văn (2023) reported positive and negative relationships for the pre-COVID-19 and COVID-19 periods, respectively. Ming (2023) did not report on the direction of this relationship in Singapore. However, for the same market, Hao (2020) found a non-significant relationship.

Huang (2017) applied the emotion recognition theory to relate investors' $PM_{2.5}$-induced emotions to investor sentiment, which eventually led to negative stock returns. Huang (2017) found that for China, the effects were negative for heavily polluting firms. Environmentally friendly firms exhibited a positive relationship. Jiang et al. (2021) found similar results for highly polluting Chinese firms. However, these effects were not significant for low-polluting firms. An et al. (2018) constructed a national air quality index, relating it to individual stock returns in China. The relationship discovered was negative and significant. A negative effect has been reported for the Korean market (Kim & Yoo, 2020), whereas the results have been mixed for the U.S. market (Muntifering, 2022)

$PM_{2.5}$ pollution can affect stock returns through stress. Pollution with $PM_{2.5}$ directly causes mental diseases through the induction of systemic or brain-based oxidative stress and inflammation (Power et al., 2015), as well as dysfunctional breathing and heart performance (Yohannes et al., 2010). Indirectly, certain $PM_{2.5}$-induced diseases, such as respiratory or cardiovascular diseases, lower work efficiency, and labor productivity, result in work stress, fear of unemployment, and poor mental health (Goldberstein, 2015). Li et al. (2021) reported mental stress due to concerns or fear of $PM_{2.5}$-induced diseases. Khanthavit and Khanthavit (2024) found that $PM_{2.5}$ pollution was related to the mental stress of Bangkok residents.

Stress affects decision-making (Starcke & Brand, 2012). This can change an individual's risk preferences and induce attitude misattribution. Stress can be acute or chronic (Gatersleben & Griffin, 2017). Acute and chronic stresses lead to different responses in decision-making (Starcke & Brand, 2012). Kandasamy et al. (2014) reported that acute stress on Days 0 and 1 of cortisol administration did not affect participants' risk preference, whereas chronic stress on Days 2 to 7 increased the level of risk aversion and pessimism. However, Ceccato, Kudielka, and Schwieren (2015) reported that chronic stress leads to increased risk-taking. Increased risk aversion is associated with falling stock returns, whereas increased risk-taking leads to rising stock returns (Lee et al., 2015). Imisiker et al. (2019) found that traffic-induced stress was associated with falling stock returns in the U.S. and U.K. markets. Khanthavit (2021) reported similar results for the Thai market. In the literature, stress has never been studied for its mediating role in the relationship between $PM_{2.5}$ pollution and stock returns.

In previous studies, behavioral mediators theoretically motivated and explained the links between $PM_{2.5}$ and stock returns. Nevertheless, these mediators have appeared in empirical models in few studies. Li and Peng (2016), Xu et al. (2021), and Zhang et al. (2017) incorporated behavioral mediators as explanatory variables in addition to $PM_{2.5}$. In contrast, Teng and He (2020) added the product of $PM_{2.5}$ and behavioral mediators as explanatory variables.

In the empirical models without behavioral mediators, the significance of relationships between $PM_{2.5}$ and stock returns were insufficient to conclude that the referenced mediator is the mediating factor. Alternative mediators or fundamental factors could explain the relationship. Adding a behavioral mediator or a product of $PM_{2.5}$ and a mediator as an explanatory variable in the model does not help. The explanatory mediator serves as the control variable, whereas the explanatory product variable reveals how the relationship varies at different mediator levels.

This study employs a multivariate mediation analysis to examine the total, direct, and indirect relationships between $PM_{2.5}$ pollution and stock market returns in Thailand. The total relationship is the sum of the direct and indirect relationships. In this model, a direct relationship is explained by fundamental factors. Behavioral mediators—attention, awareness, mood, sentiment, and stress–determine these indirect relationships. Hence, this study will identify, measure, and compare, the mediating roles of behavioral mediators.

In this study, the $PM_{2.5}$ level is that of Bangkok, and the stock return is the return on the Market for Alternative Investment (mai) index portfolio. Bangkok, Thailand's capital, with 1,569 square kilometers in size and more than 14 million residents, was chosen as the sample city as it is one of the most $PM_{2.5}$-polluted cities. On April 15, 2023, Bangkok was among the top 10 worst cities in the world, ranking in seventh place (Bangkok joins Chiang Mai, 2023). At the time of writing this study (January 1, 2024), it ranked 33rd among 110 cities (IQAir, 2024).

For investors living in the country, Kirk-Reeve et al. (2021) recommended that the national $PM_{2.5}$ pollution level be used. It is more representative than regional or city levels. However, local investors in Thailand are concentrated in the Bangkok metropolitan area. In 2015, 88% of investors lived in Bangkok (SET, together with brokers, 2015). According to a recent study (Phringphred, 2023), the percentage is still high at 63%. Therefore, Bangkok's $PM_{2.5}$ is deemed to be representative in this study, as Bangkok's pollution affects the majority of local investors.

The Thai market is a leading market among emerging economies. According to an assessment in October 2023 by the World Federation of Exchanges (2023), Thailand ranks 10th among the markets in the Asia-Pacific region and is the 23rd largest market in the world. The country has two stock exchanges— (1) the Stock Exchange of Thailand (SET) and (2) the mai. The SET is much larger than the mai in terms of market capitalization, the number of listed companies, investor accounts, and trading turnover. However, this study chooses the mai returns over SET returns, as almost all the trading volume of mai stocks come from local investors. From August 1, 2016, to November 30, 2023, the average trading shares of local investors in the mai and SET were 92.44% and 60.00%, respectively. Local investors are exposed to the country's $PM_{2.5}$ pollution, while foreign investors are not.

This study makes four main contributions to the literature. First, the multivariate mediation analysis reveals the role and significance of behavioral mediators and fundamental factors via indirect and direct effects on stock returns. Second, this study incorporated all behavioral mediators in the multivariate analysis. The importance of behavioral mediators was also compared. Third, previous studies have not examined stress as a behavioral mediator. To the best of our knowledge, this is the first study to analyze this variable. Fourth, most studies on the relationship between $PM_{2.5}$ and stock returns are based on Chinese markets. Studies for other countries are few. Only one study has been conducted in Thailand (Lin, 2021). This study addresses the Thai market in the literature on markets outside China.

2. METHODOLOGY

2.1 The Model

In this study, a multivariate mediation analysis (MacKinnon, 2000) was applied to examine the effects of Bangkok's $PM_{2.5}$ pollution on Thai stock returns. In the left panel of Figure 1, $PM_{2.5}$ is the determining variable, and stock returns are the outcome. The total effect on stock returns is c, which is the sum of the direct and indirect effects. In the right panel, the direct effect is denoted by c'. Thus, the indirect effect is $c - c'$. The behavioral mediators of attention, awareness, mood, sentiment, and stress contribute $a_1 b_1$, $a_2 b_2$, $a_3 b_3$, $a_4 b_4$, and $a_5 b_5$, respectively, to the indirect effect $c - c'$. That is, $c - c' = a_1 b_1 + a_2 b_2 + a_3 b_3 + a_4 b_4 + a_5 b_5$.

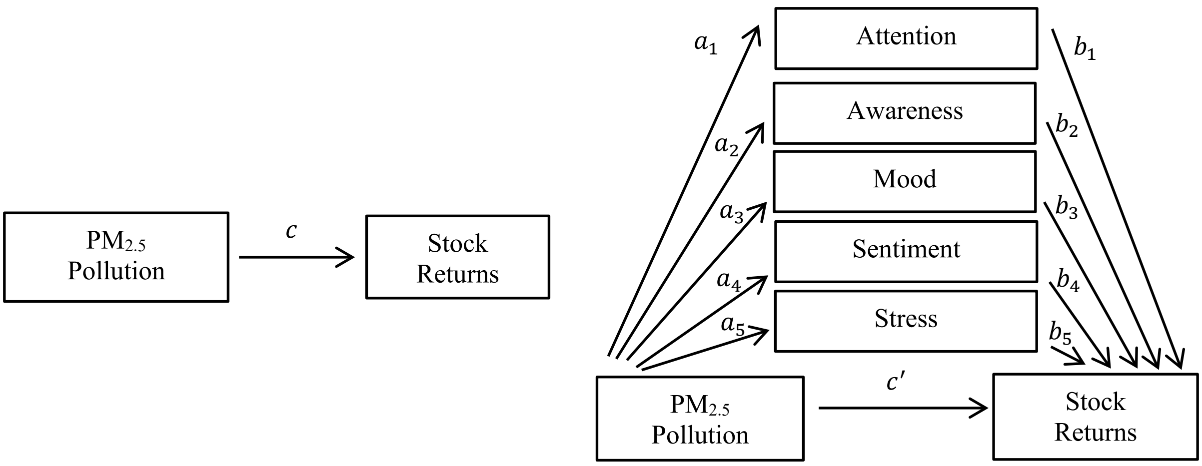

Figure 1 Path Diagram for the Multivariate Mediation Analysis

This study conducted three linear regressions for parameter estimation. The first regression conducted using Equation (1) runs the stock return variable (R_t) on the $PM_{2.5}$-pollution variable (P_t) to estimate coefficient c to measure the total effect.

$$R_t = \alpha_{R1} + cP_t + \varepsilon_{R1,t}. \quad (1)$$

The second regression involved Equations (2.1) to (2.5), considering the PM2.5 variable (P_t) with attention (A_t^t), awareness (A_t^w), mood (M_t^o), sentiment (S_t^e), and stress (S_t^t), as mediators to estimate the coefficients a_1 to a_5.

$$A_t^t = \alpha_{A^t} + a_1 P_t + \varepsilon_{A^t,t}. \quad (2.1)$$

$$A_t^w = \alpha_{A^w} + a_2 P_t + \varepsilon_{A^w,t}. \quad (2.2)$$

$$M_t^o = \alpha_{M^o} + a_3 P_t + \varepsilon_{M^o,t}. \quad (2.3)$$

$$S_t^e = \alpha_{S^e} + a_4 P_t + \varepsilon_{S^e,t}. \quad (2.4)$$

$$S_t^t = \alpha_{S^t} + a_5 P_t + \varepsilon_{S^t,t}. \quad (2.5)$$

The third regression conducted using Equation (3) regressed the stock-return variable (R_t) on the PM2.5 variable (P_t) and the five behavioral-mediation variables. The coefficients b_1 to b_5 from this regression indicate the effects of the behavioral mediators A_t^t, A_t^w, M_t^o, S_t^e, and S_t^t, which also serve as the regression control variables on stock returns. The coefficient c' measures the direct effect of PM2.5 after controlling for the behavioral mediators.

$$R_t = \alpha_{R2} + c'P_t + b_1 A_t^t + b_2 A_t^w + b_3 M_t^o + b_4 S_t^e + b_5 S_t^t + \varepsilon_{R2,t}. \quad (3)$$

In all equations, the constant α_k and variable $\varepsilon_{k,t}$ are the intercepts and regression errors, respectively. Subscript $k = R1, A^t, A^w, M^o, S^e, S^t, R2$.

2.2 Estimation and Test

This study follows Li and Peng (2016) and Wu and Lu (2020) in estimating all equations using ordinary least squares (OLS) regressions. This technique has been used in most studies in this subject area. Statistical tests are performed based on Newey and West's (1987) heteroscedasticity and autocorrelation-consistent (HAC) standard deviations. The standard deviations for the individual and aggregate indirect effects were computed using MacKinnon's (2000) method.

3. DATA

The data consisted of daily data beginning on August 1, 2016, and ending on November 30, 2023 (1,789 observations). The stock return is the logged return on the mai index portfolio, while the PM2.5 level is Bangkok's level. The study is well aware that the behavioral mediators are unobserved. They must be proxied. Except for the sentiment mediator, the proxies for the four remaining mediators were constructed based on Google's relative search volume index (SVI) for Bangkok.

This study uses the price-to-book ratio to measure sentiment mediators. A shock in investor sentiment affects investors' beliefs and stock trading. Limited arbitrage creates demand pressure that causes mispricing. For this reason, Baker and Wurgler (2007) suggested the price-to-book ratio as a proxy for sentiment.

SVIs offer deep insights into individual behavior. Individuals actively relay information about their identities, thoughts, and behaviors, when searching Google (Eysenbach, 2011); they search Google only for information they prefer (Da, Engelberg, & Gao, 2011).

Zhang and Tao (2019) measured pollution attention levels in China using East Money's Investor Attention Index. The index is constructed from the total number of posts containing the topic of attention. However, this index was not available for Thailand. Therefore, this study focuses on $PM_{2.5}$ level. The SVI based on the "PM 2.5" query should proxy the attention level as well.

Xu et al. (2021) proposed a proxy for awareness. This is the first principal component of a group of four pollution-related SVIs. This study applied the approach where the pollution-related SVIs include "PM 2.5", "ไอ" (*Xị*, meaning cough in the Thai language), "โรคทางเดินหายใจ" (*Rokh thāng dein h̄āycı*, meaning respiratory disease), and "เครื่องฟอกอากาศ" (*Kherụ̄̀xng fxk xākāṣ̄*, meaning air purifier).

In previous studies (e.g., Dowling & Lucey, 2008), weather variables were a popular choice for mood variables. Weather variables were not considered, as this variable could not be caused by $PM_{2.5}$. Choi (2016) proposed that the suicide rate could represent the degree of negative social mood; the suicide rate was found to be negatively associated with U.S. stock returns. In this study, the SVI for "ฆ่าตัวตาย" (*K̄h̀ā tạw tāy*, meaning suicide) proxied investors' mood (Kristoufek, Moat, & Preis, 2016)

Finally, the stress mediator was proxied by the SVI for "เครียด" (*Kherīyd*, meaning stress). The stress query was used in previous studies by Brodeur et al. (2021), Khanthavit and Khanthavit (2023), and Khanthavit and Khanthavit (2024).

This study retrieved stock market data from the Stock Exchange of Thailand's database. Bangkok's $PM_{2.5}$ level was measured by the Pollution Control Department of Thailand's Ministry of Natural Resources and Environment. The series was downloaded from https://aqicn.org/data-platform/register/. Meanwhile, the SVIs were available from https://trends.google.co.th/trends/.

All variables were tested for non-stationarity. The price-to-book ratio was found to be non-stationary; its first difference was used in the analysis. The $PM_{2.5}$ level and SVIs exhibited trends and seasonal patterns (Mavragani, Ochoa, & Tsagarakis, 2018; Zhao et al., 2018). For this reason, the $PM_{2.5}$ and SVI variables were de-trended and de-seasonalized using the logged time trend and day-of-week and month-of-year dummy variables. In the final step, the variables, except for stock returns, were standardized by their averages and standard deviations so that the sizes of the effects could be compared.

Table 1 presents the descriptive statistics for the variables. The Jarque-Bera statistic indicated that all variables, except for $PM_{2.5}$ and stress, were not distributed normally. The first-order autocorrelation coefficients were positive and significant. The autocorrelation property supports the use of the HAC variances and covariances. The augmented Dickey-Fuller statistic was used to ensure that all variables were stationary and, therefore, usable for statistical analyses.

Table 1 Descriptive Statistics

Statistics	$PM_{2.5}$ Pollution	mai Return	Behavioral Mediator				
			Attention	**Awareness**	**Mood**	**Sentiment**	**Stress**
Average	0.0000	-2.25E-04	0.0000	0.0000	0.0000	0.0000	0.0000
Standard Deviation	1.0000	0.0108	1.0000	1.0000	1.0000	1.0000	1.0000
Skewness	0.5311	-0.8155	8.2654	8.3442	6.6011	-4.9245	0.5135
Excess Kurtosis	0.3417	6.8767	97.6034	103.8888	108.0581	101.5864	0.6400
First-Order Autocorrelation	0.7448^{***}	0.1373^{***}	0.7986^{***}	0.8150^{***}	0.3364^{***}	0.0891^{***}	0.4477^{***}

Table 1 (Continued)

Statistics	$PM_{2.5}$ Pollution	mai Return	Behavioral Mediator				
			Attention	Awareness	Mood	Sentiment	Stress
Jarque-Bera Statistic	0.4090	3.91E+02***	8.09E+06***	9.34E+06***	6.32E+06***	3.11E+06***	1.3418
Augmented Dickey-Fuller Statistic	-16.2140***	-26.0679***	-9.3006***	-9.1679***	-15.3150***	-38.6479***	-3.9778***
Number of Observations	1789	1789	1789	1789	1789	1789	1789

Note. *** denotes significance at the 99% confidence level.

4. EMPIRICAL RESULTS

4.1 Full Sample Period

Column 2 of Table 2 reports the effects of Bangkok $PM_{2.5}$ pollution on mai returns for the full sample period (August 1, 2016, to November 30, 2023). (Parameter estimates are not shown. These data are available from the author upon request.) However, the overall effect was not statistically significant. This non-significant result is consistent with Lin's (2021) result for the current $PM_{2.5}$ on the Thai stock returns. The total effect was the sum of the direct and indirect effects. Neither the direct nor indirect effects were significant. The non-significant direct effect could be explained by the fact that the listed firms in the mai index portfolio are from various industrial sectors. Firms in different sectors are fundamentally affected by $PM_{2.5}$ in positive or negative ways, depending, for example, on induced demand shifts (Xu & Chen, 2022) and regulations and controls (Liu & Wu, 2024). The positive and negative effects cancel each other out, resulting in a non-significant direct effect.

Table 2 Effects of $PM_{2.5}$ Pollution on Stock Market Returns

Effect	mai Return (OLS Regression)		Robustness Check (Full Sample)		mai Return (Lagged $PM_{2.5}$)
	Full Sample	COVID-19 Sub-sample	mai Return (Pal's IVs)	SET Return	
Total Effect (c)	-0.0189	0.0083	-0.0269	-0.0193	-0.0224
Direct Effect (c')	-0.0152	0.0124	-0.0107	-0.0213	-0.0154
Indirect Effect $(c - c' = a_1b_1 + a_2b_2 + a_2b_2 + a_2b_2)$	-0.0037	-0.0041	-0.0162	0.0020	-0.0070
(1) Attention (a_1b_1)	0.0023	0.0063	0.0160	-0.0020	0.0022
(2) Awareness (a_2b_2)	-0.0057	-0.0069	-0.0215	-0.0040	-0.0065
(3) Mood (a_3b_3)	-0.0001	0.0016	0.0003	0.0008	-0.0001
(4) Sentiment (a_4b_4)	-0.0064	-0.0112	-0.0172	0.0002	-0.0099
(5) Stress (a_5b_5)	0.0063***	0.0061*	0.0062**	0.0071**	0.0072**

Note. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Attention, awareness, mood, sentiments, and stress, were the mediating factors that jointly contributed to the indirect effect, which was found to be negative but not significant. For the five behavioral mediators, the first four were non-significant, whereas stress, the fifth mediator, was positive and significant at the 99% confidence level. The positive and significant effects of stress can be explained by the fact that $PM_{2.5}$-induced stress is chronic. This raises investors' risk-taking behavior and stock market returns (Ceccato et al., 2015; Lee et al., 2015). The indirect effect was the sum of the effects of the five behavioral mediators. Although the stress mediator was highly significant when summed with non-significant mediators, its significance was averaged. Therefore, the resulting indirect effects were not significant.

4.2 COVID-19 Sub-sample Period

Thailand suffered from the COVID-19 pandemic from April 3, 2020, to September 30, 2022 (Khanthavit & Khanthavit, 2023). During this period, quarantine was imposed to contain the disease, resulting in a significant improvement in air quality (Wetchayont, 2021). This study examined whether the effects changed owing to falling pollution levels during the COVID-19 pandemic. The results are reported in Column 3 of Table 2. This finding was similar to that of the full sample. The total, direct, and indirect effects are not statistically significant. The contribution of stress to the indirect effect was the same; it was positive and significant.

The positive effect of stress in this study contrasts with its negative effect during the COVID-19 period in Vietnam. Bảo and Văn (2023) explained Vietnam's negative effect by the public policies being more directed toward social factors such as air quality. In Thailand, however, during the COVID-19 period, the government focused on social protection and economic rehabilitation (Siranart, 2023).

5. DISCUSSION

5.1 Robustness Check

5.1.1 Instrumental-Variable Regression

Endogeneity problems are likely present in regression Equations (1), (2.1) to (2.5), and (3) due to errors in the variables and omitted variables. The OLS estimates are biased and inconsistent (Greene, 2018). Errors in the variables arise from the fact that the $PM_{2.5}$ level is Bangkok's level, while some investors live in other provinces. Moreover, behavioral mediators are unobserved. The variables used in the analysis are proxies, such that values were measured with errors.

This study considered a limited number of explanatory variables in the regression analysis. For example, in Equation (1), the study considered only the pollution variable, whereas other studies (e.g., Teng & He, 2020; Zhang & Tao, 2019) added certain control variables. Although a much larger set of explanatory variables was considered, it could not be a complete set. An omitted variable problem inevitably arises.

The endogeneity problem can be corrected using instrumental-variable (IV) regression (Greene, 2018). The robustness of the ordinary least squares (OLS) results were checked employing a generalized method of moments (GMM) regression (Hansen, 1982). GMM is an IV regression technique that returns consistent, asymptotically normal, and efficient estimates, even for non-normal variable specifications. The IVs were constructed using a two-step technique (Racicot & Théoret, 2010). Pal's IVs (1980) were used as the inputs for the first step. Statistical tests were performed based on the standard deviations of HAC.

Column 4 of Table 2 reports the results. These results are similar to those of OLS regression. This finding leads to the conclusion that the results are robust with respect to the estimation techniques.

5.1.2 Return on the Stock Exchange of Thailand Index Portfolio

In this study mai returns were chosen to represent returns on the Thai stock market, as local investors are exposed to $PM_{2.5}$ pollution, and contribute 92.44% of the mai trading volume. However, in terms of importance (market capitalization, trading volume, and number of listed stocks and investor accounts) to the country, the SET should represent the Thai market, despite the fact that local investors have only a 60% share of its trading volume. To ensure that the result is robust with respect to representative stock returns, the model was re-estimated by substituting the SET return for the mai return. The respective results are reported in Column 5 of Table 2, yielding a similar picture to the mai return in Column 2.

5.2 National *vs.* Bangkok Pollution

The local investors reside throughout the country. The national pollution level should be used in the estimation based on the work of Kirk-Reeve et al. (2021). Therefore, using Bangkok's pollution could result in incorrect estimates. It is agreed that the national pollution level is a better representation. However, Bangkok's pollution does not necessarily lead to incorrect estimates. Bangkok's pollution level can be considered the sum of the national pollution level and the error term. When this appears in the equations, an error-in-variables problem is present. In this study, the GMM regression was used to correct the problem in a robustness check. The results in Columns 4 and 2 are similar. The estimates and effects based on the Bangkok pollution variable were found to be correct.

5.3 $PM_{2.5}$ Occurrence Time

The effects of $PM_{2.5}$ pollution on behavioral mediators can be immediate or delayed (Li, Yang, & Li, 2021). This study examined whether the lagged $PM_{2.5}$ pollution has different effects on stock returns, by replacing the current $PM_{2.5}$ variable with its lagged variable. The model was then re-estimated. The results are reported in Column 6 of Table 2, where it can be seen that they remain unchanged.

6. CONCLUSION

$PM_{2.5}$ pollution affects stock market returns directly via the fundamental channel and indirectly via the behavioral channel. The literature suggests that attention, awareness, mood, sentiment, and stress, are potential mediating factors. This study used multivariate mediation analysis to examine the total, direct, and indirect effects. The five behavioral mediators were explicitly incorporated into the model to identify, measure, and compare their roles and effects. Using Bangkok's $PM_{2.5}$ pollution, Bangkok residents' behavioral variables, and Thai stock returns from August 1, 2016, to November 30, 2023, the total, direct, and indirect effects were found to be non-significant. The study found that stress was the only behavioral mediator that significantly and positively contributed to the indirect effect. This finding is consistent with the estimation techniques, sample periods, representative returns, and $PM_{2.5}$ occurrence times.

For investors, the $PM_{2.5}$ level can be actual or perceived. Actual and perceived $PM_{2.5}$ may have different mechanisms that influence investor behavior. Price reactions may not be the same. The question of how perceived and actual $PM_{2.5}$ affect stock market returns is interesting. This should be explored in future studies.

ACKNOWLEDGMENTS

The author thanks the Faculty of Commerce and Accountancy, Thammasat University, for the research grant, the Stock Exchange of Thailand for the stock market data, and Chanya Siriarayaphan for research assistance.

REFERENCES

Ahmad, M., Manjantrarat, T., Rattanawongsa, W., Muensri, P., Saenmuangchin, R., Klamchuen, A, Panyametheekul, S. (2022). Chemical composition, sources, and health risk assessment of $PM_{2.5}$ and PM_{10} in urban sites of Bangkok, Thailand. *International Journal of Environmental Research and Public Health*, *19*(21), 14281. https://doi.org/10.3390/ijerph192114281

An, N., Wang, B., Pan, P., Guo, K., & Sun, Y. (2018). Study on the influence mechanism of air quality on stock market yield and Volatility: Empirical test from China based on GARCH model. *Finance Research Letters*, *26*, 199–125. https://doi.org/10.1016/j.frl.2017.12.002

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, *21*(2), 129–151. https://doi.org/10.1257/jep.21.2.129

Bangkok joins Chiang Mai on list of 10 cities with worst air. (2023, April 15). *The Nation*. Retrieved from https://www.nationthailand.com/thailand/general/40026688

Bảo, N. K. Q., & Văn, L. (2023). The relation between stock return and air quality in Vietnam under impacts of COVID-19. *International Journal of Economic Policy in Emerging Economies*, *17*(2), 143–161. https://doi.org/10.1504/IJEPEE.2023.129781

Brodeur, A., Clark, A. E., Fleche, S., & Powdthavee, N. (2021). COVID-19, lockdowns and well-being: Evidence from Google Trends. *Journal of Public Economics*, *193*, 104346. https://doi.org/10.1016/j.jpubeco.2020.104346

California Air Resources Board. (2023). *Inhalable particulate matter and health ($PM_{2.5}$ and PM_{10})*. Retrieved from https://ww2.arb.ca.gov/resources/inhalable-particulate-matter-and-health

Ceccato, S., Kudielka, B. M., & Schwieren, C. (2015). Increased risk taking in relation to chronic stress in adults. *Frontier of Psychology*, *6*, 2036. https://doi.org/10.3389%2Ffpsyg.2015.02036

Chen, K., Wang, G., Wu, L., Chen, J., Yuan, S., Liu, Q., Liu, X. (2019). $PM_{2.5}$ pollution: Health and economic effect assessment based on a recursive dynamic computable general equilibrium model. *International Journal of Environmental Research and Public Health*, *16*(24), 5102. https://doi.org/10.3390/ijerph16245102

Choi, S. (2016). Stock market returns and suicide rates: Evidence from the United States. *Social Behavior and Personality: an international journal*, *44*(1), 89–102. https://doi.org/10.2224/sbp.2016.44.1.89

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *Journal of Finance*, *66*(5), 1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review*, *109*(12), 4178–4219. https://doi.org/10.1257/aer.20180279

Dowling, M., & Lucey, B. M. (2008). Robust global mood influences in equity pricing. *Journal of Multinational Financial Management*, *18*(2), 145–164. https://doi.org/10.1016/j.mulfin.2007.06.002

Eysenbach G. (2011). Infodemiology and infoveillance: Tracking online health information and cyberbehavior for public health. *American Journal of Preventive Medicine*. *40*(5), S154–S158. https://doi.org/10.1016/j.amepre.2011.02.006

Fu, S., Viard V. B., & Zhang, P. (2021). Air pollution and manufacturing firm productivity: Nationwide estimates for China. *Economic Journal*, *131*(640), 3241–3273. https://doi.org/10.1093/ej/ueab033

Gatersleben, B., & Griffin, I. (2017). Environmental stress. In G. Fleury-Bahi, E. Pol, & O. Navarro (Eds.), *Handbook of Environmental Psychology and Quality of Life Research* (pp. 469–485). Cham: Springer.

Goldberstein, E. (2015). The effects of income on mental health: Evidence from the social security notch. *Journal of Mental Health Policy and Economics*, *18*(1): 27–37. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4494112/

Greene, W. H. (2018). *Econometric Analysis* (8th ed.). London: Pearson.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, *50*(4), 1029–1054. https://doi.org/10.2307/1912775

Hao, L. X. (2020). Transboundary haze and stock market returns: Evidence from SGX. (Unpublished Bachelor's Thesis). National University of Singapore, Singapore. Retrieved from https://scholarbank.nus.edu.sg/handle/10635/170240

Huang, W. (2023). The impacts of PM2.5 on stock's earnings in China. *International Journal of Information Systems and Informatics*, *4*(1), 34–41. https://doi.org/10.47747/ijisi.v4i1.1099

Huang, X. (2017). PM2.5, investor sentiment, and stock returns. *DEStech Transactions on Engineering and Technology Research*. https:// 10.12783/dtetr/icaenm2017/7801

Imisiker, S., Tas, B. K. O., & Yildirim, M. A. (2019). Stuck on the road: Traffic congestion and stock returns. *SSRN Electronic Journal*. Retrieved from https://ssrn.com/abstract=2933561

IQAir. (2024). Live most polluted major city ranking. Available from https://www.iqair.com/th-en/world-air-quality-ranking

Jiang, Z., Gupta, R., Subramaniam, S., & Yoon, S. (2021). The effect of air quality and weather on the Chinese stock: Evidence from Shenzhen Stock Exchange. *Sustainability*, *13*, 2931. https://doi.org/10.3390/su13052931

Kandasamy, N., Hardy, B., Page, L., Schaffner, M., Graggaber, J., Powlson, A. S., … Coates, J. (2014). Cortisol shifts financial risk preferences. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3608–3613. https://doi.org/10.1073/pnas.1317908111

Khanthavit, A. (2021). Bangkok traffic congestion, stressed investors, and Thai stock-market returns. *ABAC Journal*, *41*(4), 2–23. https://doi.org/10.14456/abacj.2021.1

Khanthavit, A., & Khanthavit, S. (2023). ChatGPT and stress. *ABAC Journal*, *23*(3), 213–224. https://doi.org/10.59865/abacj.2023.39

Khanthavit, R., & Khanthavit, A. (2024). $PM_{2.5}$ pollution, perception, and mental stress. Working Paper. Chulabhorn Hospital, Bangkok, Thailand. Retrieved from https://www.dropbox.com/scl/fi/8pv9dwag0xv5tux05791p/PM2.5_Pollution__Perception__and_Mental_Stress.pdf?rlkey=z40kcglwpmnzbdvmvurwj2r5d&dl=0

Kiihamäkil, S., Korhonen, M., & Jaakkola1, J. J. K. (2021). Ambient particulate air pollution and daily stock market returns and volatility in 47 cities worldwide. *Scientific Reports*, *11*, 8628. https://doi.org/10.1038/s41598-021-88041-w

Kim, T., & Yoo, S. (2020). Air pollution, stock return, and volatility: Evidence from Korea stock markets. *Korean Journal of Financial Studies*, *49*(3), 375–413. https://doi.org/10.26845/KJFS.2020.06.49.3.375

Kirk-Reeve, S., Gehricke, S. A., Ruan, X., & Zhang, J. E. (2021). National air pollution and the cross-section of stock returns in China. *Journal of Behavioral and Experimental Finance*, *32*, 100572. https://doi.org/10.1016/j.jbef.2021.100572

Kristoufek, L, Moat, H. S., & Preis, T. (2016). Estimating suicide occurrence statistics using Google Trends. *EPJ Data Science*, *5*, 32. DOI 10.1140/epjds/s13688-016-0094-0

Lee, B., Rosenthal, L., Veld, C., & Veld-Merkoulova, Y. (2015). Stock market expectations and risk aversion of individual investors. *International Review of Financial Analysis*, *40*, 122–131. https://doi.org/10.1016/j.irfa.2015.05.011

Lepori, G. M. (2016). Air pollution and stock returns: Evidence from a natural experiment. *Journal of Empirical Finance*, *35*, 25–42. https://doi.org/10.1016/j.jempfin.2015.10.008

Levy, T., & Yagil, J. (2011). Air pollution and stock returns in the US. *Journal of Economic Psychology*, *32*(3), 374–383. https://doi.org/10.1016/j.joep.2011.01.004

Li, J., Huang, L., Han, B., van der Kuijp, T. J., Xia, Y., & Chen, K. (2021). Exposure and perception of $PM_{2.5}$ pollution on the mental stress of pregnant women. *Environment International*, *156*, 106686. https://doi.org/10.1016/j.envint.2021.106686

Li, Q., & Peng, C. H. (2016). The stock market effect of air pollution: Evidence from China. *Applied Economics*, *48*(36), 3442–3461. https://doi.org/10.1080/00036846.2016.1139679

Li, W., Yang, G., & Li, X. (2021). Correlation between PM2.5 pollution and its public concern in China: Evidence from Baidu Index. *Journal of Cleaner Production*, *293*, 126091. https://doi.org/10.1016/j.jclepro.2021.126091

Lin, F. (2021). The effect of air pollution on stock returns: Evidence from Thailand and Indonesia. (Unpublished Master's Thesis). Chulalongkorn University, Bangkok, Thailand. Retrieved from https://digital.car.chula.ac.th/chulaetd/7714/

Liu, X, & Wu D. (2024). Does $PM_{2.5}$ accelerate the firm evolution? Evidence from 800-mm isoline in China. *Energy Policy*, *184*, 113841. https://doi.org/10.1016/j.enpol.2023.113841

Luo, J. (2017). How does smog affect firms' investment behavior? A natural experiment based on a sudden surge in the PM2.5 index. *China Journal of Accounting Research*, *10*(4), 359–378. https://doi.org/10.1016/j.cjar.2017.09.001

Mavragani, A., Ochoa, G., & Tsagarakis, K. P. (2018). Assessing the methods, tools, and statistical approaches in Google Trends research: systematic review. *Journal of Medical Internet* Research, *20*(11), e270. https://doi.org/10.2196/jmir.9366

MacKinnon, D. P. (2000). Contrasts in Multiple Mediator Models: Multivariate Applications. In J. S. Rose, L. Chassin, C. C. Presson, & S. J. Sherman (Eds.), *Substance Use Research: New Methods for New Questions* (pp. 141–160). New York: Psychology Press.

Ming, K. L. Y. (2023). Testing the predictive power of machine learning algorithms for stock market movements based on air pollution data. In K. L. Y. Ming (Ed.), *Industry Forward and Technology Transformation in Business and Entrepreneurship* (pp. 151–160). Singapore: Springer Nature Singapore.

Muntifering, M. (2022). Air pollution, investor sentiment and excessive returns. In M. de Jong, & D. diBartolomeo (Eds.), *Risks Related to Environmental, Social and Governmental Issues (ESG)* (pp. 35–44). Cham: Palgrave Macmillan.

Murger, A. (2022). Air pollution, mood and stock return in Romania. *Ovidius University Annals, Economic Sciences Series*, *22*(2), 943–952. Retrieved from https://stec.univ-ovidius.ro/html/anale/RO/2022-issue2/Section%205/18.pdf

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*(3), 703–708. https://doi.org/10.2307/1913610

Pal, M. (1980). Consistent moment estimators of regression coefficients in the presence of errors in variables. *Journal of Econometrics*, *14*(3), 349–364. https://doi.org/10.1016/0304-4076(80)90032-9

Phringphred, A. (2023). SEC applied big data for analyzing mutual-fund investment behavior for investors of different generations for capital-market improvement (ก.ล.ต. ใช้ Big Data เจาะพฤติกรรมการลงทุนกองทุนรวมของผู้ลงทุนแต่ละ generation ต่อยอดพัฒนาตลาดทุนไทย). Retrieved from https://secopendata.sec.or.th/PDF-Research/CMDC0900ST090201.pdf

Power, M. C., Kioumourtzoglou, M., Hart, J. E., Okereke, O. I., Laden, F., & Weisskopf, M.G. (2015). The relation between past exposure to fine particulate air pollution and prevalent anxiety: Observational cohort study. *BMJ*, *350*, h1111. https://doi.org/10.1136/bmj.h1111

Racicot, F. E., & Théoret, R. (2010). Optimal instrumental variables generators based on improved Hausman regression, with an application to hedge fund returns. *Journal of Wealth Management*, *13*(1), 103–123. https://doi.org/10.3905/JWM.2010.13.1.103

SET, together with brokers, the Thai Chamber of Commerce and Board of Trade of Thailand, and the Federation of Thai Industries initiated new frontier roadshow. Forty thousand, new investors were targeted (ตลท. จับมือโบรกฯ-หอการค้า-ส.อ.ท. เดินหน้าจัดโรดโชว์ ตั้งเป้าปีนี้มีผู้ลงทุนเพิ่ม 4 หมื่นราย). (2015, April 1). *Stock News Online*. Retrieved from https://www.dropbox.com/s/pzuecipcyl3yqxu/STOCK%20NEWS%20ONLINE.pdf?dl=0

Siranart, A. (2023). *Financing sustainable development amid crises, conflicts, and beyond: A case study from Thailand*. United Nations Development Programme. Retrieved from https://www.undp.org/thailand/blog/financing-sustainable-development-amid-crises-conflicts-and-beyond-case-study-thailand-1

Smales, L. A. (2021). Investor attention and global market returns during the COVID-19 crisis. *International Review of Financial Analysis*, *73*, 101616. https://doi.org/10.1016/j.irfa.2020.101616

Starcke, K., & Brand, M. (2012). Decision making under stress: A selective review. *Neuroscience and Biobehavioral Reviews*, *36*(4), 1228–1248. https://doi.org/10.1016/j.neubiorev.2012.02.003

Tan, J., Tan, Z., & Chan K. C. (2021). Does air pollution affect a firm’s cash holdings? *Pacific-Basin Finance Journal*, *67*, 100549. https://doi.org/10.1016/j.pacfin.2021.101549

Teng, M., & He, X. (2020). Air quality levels, environmental awareness and investor trading behavior: Evidence from stock market in China. *Journal of Cleaner Production*, *244*(20), 118663. https://doi.org/10.1016/j.jclepro.2019.118663

United Nations Environment Programme. (2023). *Pollution action note — Data you need to know*. Retrieved from https://www.unep.org/interactives/air-pollution-note/#:~:text=Pollution%20Action%20Note%20%E2%80%93%20Data%20you,million%20premature%20deaths%20every%20year

Wetchayont, P. (2021). Investigation on the impacts of COVID-19 lockdown and influencing factors on air quality in greater Bangkok, Thailand. *Advances in Meteorology*, *2021*, 6697707. https://doi.org/10.1155/2021/6697707

World Federation of Exchanges. (2023). Market Statistics—December 2023. Retrieved from https://focus.world-exchanges.org/issue/december-2023/market-statistics

World Health Organization. (2023). *Air pollution: The invisible health threat*, Retrieved from https://www.who.int/news-room/feature-stories/detail/air-pollution--the-invisible-health-threat

Wu, Q., & Lu, J. (2020). Air pollution, individual investors, and stock pricing in China. *International Review of Economics and Finance*, *67*, 267–287. https://doi.org/10.1016/j.iref.2020.02.001

Xu, H., & Chen Y. (2022). The impact of air pollution on the stock performance: Evidence from China new energy vehicle industry. *Energy Policy*, *184*, 113841. https://doi.org/10.1016/j.enpol.2023.113841

Xu, M., Wang, Y., & Tu, Y. (2021). Uncovering the invisible effect of air pollution on stock returns: A moderation and mediation analysis. *Finance Research Letters*, *39*, 101646. https://doi.org/10.1016/j.frl.2020.101646

Yohannes, A. M., Willgoss, T. G., Baldwin, R. C., & Connolly, M. J. (2010). Depression and anxiety in chronic heart failure and chronic obstructive pulmonary disease: Prevalence, relevance, clinical implications and management principles. *International Journal of Geriatric Psychiatry*, *25*(12), 1209–1221. https://doi.org/10.1002/gps.2463

Zhang, Y., Jiang, Y., & Guo, Y. (2017). The effects of haze pollution on stock performances: Evidence from China. *Applied Economics*, *49*(23), 2226–2237. https://doi.org/10.1080/00036846.2016.1234703

Zhang, Y., & Tao, L. (2019). Haze, investor attention and China's stock markets: Evidence from internet stock forum. *Finance Research Letters*, *31*, 363–368. https://doi.org/10.1016/j.frl.2018.12.001

Zhao, N., Liua, Y., Vanos, J. K., & Cao, G. (2018). Day-of-week and seasonal patterns of $PM_{2.5}$ concentrations over the United States: Time-series analyses using the Prophet procedure. *Atmospheric Environment*, *192*, 116–127. https://doi.org/10.1016/j.atmosenv.2018.08.050

Zhao, Q., & Yuan, C. (2020). Did haze pollution harm the quality of economic development?—An empirical study based on China's PM2.5 concentrations. *Sustainability*. *12*(4), 1607. https://doi.org/10.3390/su12041607