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$PM_{2.5}$ POLLUTION, RETAIL TRADING, AND STOCK MARKET RETURNS

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Abstract

$PM_{2.5}$ is a dangerous airborne pollutant. Its induced health and economic losses affect investors and stock markets worldwide. This study applies mediation analyses to examine the relationship of Bangkok's $PM_{2.5}$ pollution with Thai stock market returns, where retail trading serves as a mediator. Investors are unaware of the actual $PM_{2.5}$ level, therefore, the $PM_{2.5}$ level is a perceived level, not an actual level. Perception is measured by Google's relative search volume index on "PM 2.5". It is decomposed into correct perception (actual $PM_{2.5}$ level) and misperception (regression residual of the full perception on the correct perception). Using a daily sample from August 1, 2016, to December 28, 2023, the generalized method of moments regression uncovered a negative and significant relationship. The main contributor was found to be the mediating effect of retail net buying volume induced by misperception. Further investigation suggests that this relationship is consistent with the noise-trader-risk explanation.

Keywords: Air quality, Perception, Noise trader risk, Pollution, Thai stocks

1. INTRODUCTION

Particulate matter 2.5 ($PM_{2.5}$) refers to tiny airborne pollutant particles or droplets with a diameter of ≤ 2.5 microns. The pollution causes poor physical (Sharma, Chandra, & Kota, 2020) and psychological health (King, Zhang, & Cohen, 2022) as well as premature death (World Health Organization, 2023). The World Health Organization (2023) considers air pollution a significant environmental threat, whereas the United Nations Environment Programme (2023) has identified $PM_{2.5}$ as the most dangerous air pollutant. The World Bank Group (2022) estimated the global health cost of mortality and morbidity from exposure to $PM_{2.5}$ pollution to be 8.1 trillion dollars or 6.1% of global gross domestic product. Moreover, pollution increased work absences worldwide by 1.8 billion days, equal to an annual economic loss of 101 billion dollars in 2018 (Farrow, Miller, & Myllyvirta, 2020). Therefore, $PM_{2.5}$ inevitably affects investors and stock markets.

$PM_{2.5}$'s effects originate from fundamental and behavioral channels. These fundamental effects are direct. $PM_{2.5}$ has multiple impacts on society, including raising public awareness, generating strict environmental regulations, high political costs, limited investment opportunities (An et al., 2018), 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), cash flow (Li *et al*., 2024) and environmental and social (Han, Park, & Park, 2024) risks, and high cash holding levels (Tan, Tan, & Chan, 2021).

The behavioral effects are explained by the fact that $PM_{2.5}$ affects investors' psychological health (King et al., 2022)—their trading behavior changes, leading to rising or

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falling stock returns. $PM_{2.5}$-induced psychological factors include attention (Zhang & Tao, 2019), awareness (Teng & He, 2020; Xu, Wang, & Tu, 2021), mood (Levy & Yagil, 2011; Zhang, Jiang, & Guo, 2017), sentiment (An et al., 2018), and stress (Khanthavit, 2024).

Most empirical studies have focused on the mediating roles of psychological factors in the relationship between $PM_{2.5}$ and returns. Tests are based on the regression results for the return on the actual $PM_{2.5}$ level; a significant slope serves as evidence of a significant relationship and supports the motivating psychological factor. This relationship was negative (Levy & Yagil, 2011; Zhang & Tao, 2019). Only a few studies have reported a positive (Teng & He, 2020) or non-significant relationship (Lepori, 2016; Hao, 2020).

When psychological factors were not incorporated into the regression model, a significant relationship did not necessarily imply that the motivating psychological factor was a mediator. Alternative factors may also explain these results. To ensure the significant mediating roles of the psychological factors, Khanthavit (2024), Li and Peng (2016), Xu et al. (2021), and Zhang et al. (2017) applied mediation models to their analyses.

Investors find it difficult to determine the exact level of $PM_{2.5}$. Instead, investors' perceptions influence their changing behavior (Chen et al., 2020) and stock returns (Hu, Li, & Lin, 2014). Only a few studies (Wu, Chou, & Lu, 2020; Wu & Lu, 2020) used the perceived $PM_{2.5}$, rather than its actual level, in their analyses.

The mediating role of psychological factors in the PM2.5-return relationship confirms the changes in investors' trading behavior. However, the mediating role of investor trade has not been studied, and the mediating investor group has never been identified.

This study tested the mediating role of retail trading in the relationship between Bangkok's $PM_{2.5}$ pollution and Thai stock returns. Retail investors' net buying volume was the mediating variable in the mediation model, which ensures that the mediation net buying volume is the variable that links $PM_{2.5}$ pollution and return.

The pollution level was determined as the perceived $PM_{2.5}$ level. This study acknowledges that full perception can be decomposed into correct perception (actual $PM_{2.5}$ level) and misperception (Chen et al., 2020). This study followed Khanthavit and Khanthavit (2025) in decomposing the full perception into correct perception and misperception. Decomposition helps in gaining insight into whether and in what way the three different perceptions affect returns.

Bangkok, Thailand's capital, was selected as the sample city because it is one of the most $PM_{2.5}$-polluted cities. On April 15, 2023, Bangkok was among the top 10 worst polluted cities in the world. It is ranked seventh (Bangkok joins Chiang Mai, 2023). On February 14, 2024, the $PM_{2.5}$ level was high at 75 micrograms per cubic meter. The severe pollution level prompted the Bangkok Metropolitan Administration to advise state agencies and private organizations to allow their staff to work from home and schools to manage their staff and students' activities to avoid exposure to $PM_{2.5}$ on February 15 and 16, 2024 (Wancharoen, 2024).

Local investors live and trade in the country's cities, suggesting that the national pollution level, not Bangkok's, should be considered (Kirk-Reeve et al., 2021). However, most local investors are concentrated in Bangkok's metropolitan area. In 2015, 88% of investors lived in Bangkok (SET, together with brokers, 2015). While this percentage is falling but is remians high at 63% (Phringphred, 2023). Thus, Bangkok's pollution affects most local investors.

The Stock Exchange of Thailand (SET) was selected as the sample market for this study, as it is one of the world's most important markets. An assessment in March 2024 by the World Federation of Exchanges (2024) ranked Thailand as the 11th largest market in the Asia-Pacific region and 26th largest in the world. Return refers to the log return on the SET index portfolio, whereas the retail net buying volume represents mediational investor behavior. The SET index return has served as the representative return of SET in previous studies (Zhong &

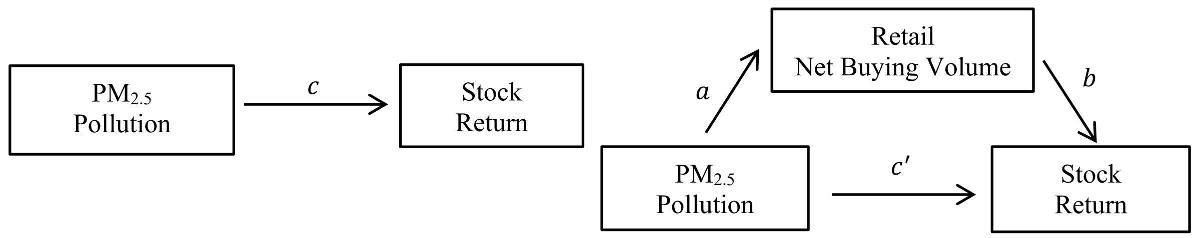
Liu, 2021). Retail investors contribute a much larger share of the trading volume in the market than institutional investors. From August 1, 2016, to December 28, 2023, their average shares were 39.55 and 20.34%, respectively.

2. METHODOLOGY

2.1 The Mediation Model

This study employs mediation analysis (Baron & Kenny, 1986) to examine the direct and mediational effects of Bangkok's $PM_{2.5}$ on Thai stock returns. In the left panel of Figure 1, $PM_{2.5}$ is the determining variable, while stock return is the outcome. The total effect on stock returns is c, which is the sum of the direct and mediation effects. In the right panel, the net retail buying volume is the mediator. The direct effect is denoted by c'. Thus, the mediation effect is $c - c' = ab$.

Figure 1 Path Diagram for Mediation Analysis



Source: Author

To estimate the parameters a, b, c, and c', and the direct (c') and mediational ($c - c' = ab$) effects, this study runs three linear regressions. Equation (1) links stock return R_t with perception P_t. The intercept and slope coefficient are α_{R1} and c, respectively. The variable $\varepsilon_{R1,t}$ is the regression error.

$$R_t = \alpha_{R1} + cP_t + \varepsilon_{R,t}. \tag{1}$$

In Equation (2), the study regresses retail investors' net buying volume B_t on the perception variable P_t.

$$B_t = \alpha_B + aP_t + \varepsilon_{B,t}, \tag{2}$$

where α_B and a are the intercept and slope coefficient, respectively. The regression error is the term $\varepsilon_{B,t}$. Parameter a measures the effect of $PM_{2.5}$ on retail trading.

The third regression in Equation (3) regresses stock returns R_t on $PM_{2.5}$ perception P_t and mediational retail net buying volume B_t.

$$R_t = \alpha_{R2} + c'P_t + bB_t + \varepsilon_{R2,t}. \tag{3}$$

The slope coefficient c' is the direct effect of $PM_{2.5}$ on return after controlling for the mediating retail-trading variable. Meanwhile, the slope coefficient b measures the impact of the mediating retail trading variable on returns after controlling for the determination of $PM_{2.5}$ pollution. The parameter α_{R2} is the intercept, whereas the variable $\varepsilon_{R2,t}$ is the regression error.

Regarding perception, this study considers the effects of full, correct, and misperceptions. A mediation model was estimated for the three different perceptions.

2.2 Estimation and Test

2.2.1 Decomposition of Full Perception

This study follows Khanthavit and Khanthavit (2025) in decomposing the full perception of P_t^F into correct perception (actual $PM_{2.5}$ level) P_t^A and misperception P_t^M components. That is, $P_t^F = P_t^A + P_t^M$. If the perception is correct, the level must be the actual $PM_{2.5}$ level. This study set the correct perception of P_t^A to equal the $PM_{2.5}$ level as reported by the Bangkok Air-Quality Monitoring Station. Misperception is the deviation of full perception from the correct perception. The residual from the regression of full perception P_t^F estimates the value based on correct perception P_t^A.

2.2.2 Model Estimation

Equations (1)–(3) suffer from endogeneity problems due to errors in the variables and omitted variables. The error-in-variable problem results from the fact that perception cannot be observed. It must be estimated. The estimate is the correct level, plus the error.

In these equations, the explanatory variables are limited to perception or perception and retail trading. More variables than those in the equations explain the dependent variables. For example, in Equation (1), the return R_t can be explained by fundamental factors, such as world market returns, interest rates, and unemployment, as well as behavioral factors, such as gambling attention and weather-related mood. When endogeneity problems are present, ordinary least squares regressions for Equations (1)–(3) provide biased and inconsistent estimates. This problem is resolved using instrumental-variable (IV) regression (Greene, 2018).

In this study Hansen's (1982) generalized method of moments (GMM) regression was chosen to estimate the model. 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.

2.2.3 Empirical Tests

The mediation effect, $c - c' = ab$ was tested by Sobel's (1982) approach. The total (c) and direct (c') effects were tested using a traditional *t* test. The standard deviations were taken from the heteroskedasticity and autocorrelation-consistent (HAC) covariance matrix (Newey & West, 1987).

3. DATA

Daily data were used, beginning on August 1, 2016, and ending on December 28, 2023 (1,807 observations). Returns were the logged returns on the SET index portfolio obtained from the SET database. This study measured retail trading using the ratio of retail net buying volume to market trading volume. Net retail buying and market trading volumes were also downloaded from the SET database.

The correct perception was measured using Bangkok's $PM_{2.5}$ level. The $PM_{2.5}$ series was recorded by the Pollution Control Department of Thailand's Ministry of Natural Resources and Environment and downloaded from https://aqicn.org/data-platform/register/.

Investors' full perception of $PM_{2.5}$ pollution cannot be observed. This study proxies the perception by utilizing Google's relative search volume index (SVI) for Bangkok on the query

"PM 2.5". When searching Google, investors relay information about their identities, thoughts, and behaviors (Eysenbach, 2011). The "PM 2.5" SVI was obtained from https://trends.google.co.th/trends/.

The $PM_{2.5}$ level and "PM 2.5" SVI have trends and show seasonal patterns (Mavragani, Ochoa, & Tsagarakis, 2018; Zhao et al., 2018). In this study, the two series are detrended by logged time and deseasonalized by day-of-the-week and month-of-the-year dummies. The detrended and deseasonalized "PM 2.5" SVI was then regressed on the detrended and deseasonalized $PM_{2.5}$ level. The resulting residual is the level of misperception. From the regression, correct perception at 2.65% explains the full perception. Misperception explains 97.35% of its movement.

All variables are standardized by means and standard deviations so that the effects can be compared based on the sizes of the estimates.

Table 1 presents the descriptive statistics for the variables. The augmented Dickey-Fuller test rejects the nonstationarity hypothesis for all variables. Therefore, this data can be employed for statistical analyses. The Jarque-Bera statistic rejects the normality hypothesis for all variables except correct perception. Full and correct perceptions and retail trading are serially correlated in the first order, whereas SET index returns and misperceptions show no autocorrelation. The evidence on non-normality and serial correlation supports the use of GMM regression for the estimation and HAC standard deviations for the hypothesis tests.

Table 1 Descriptive Statistics

Statistic	Return	Full Perception	Component		Retail Net Buying Volume
			Correct Perception (Actual Level)	Misperception	
Average	-4.08E-05	0.0000	0.0000	0.0000	0.0015
Standard Deviation	0.0095	1.0000	1.0000	1.0000	6.44E-04
Skewness	-1.8313	8.1417	0.5262	7.9602	1.3051
Excess Kurtosis	2.73E+01	9.54E+01	0.3348	9.41E+01	2.1965
First-Order Autocorrelation	-0.0352	0.7953***	0.7445***	0.8018	0.8329***
Jarque-Bera Statistic	3.15E+04***	7.56E+06***	0.3894	7.05E+06***	1.03E+02***
Augmented Dickey-Fuller Statistic	-10.9523***	-9.3964***	-16.3083***	-9.0584***	-4.0037***
Number of Observations	1,807	1,807	1,807	1,807	1,807

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

4. EMPIRICAL RESULTS

Column 2 of Table 2 reports the results (Parameter estimates can be obtained from the author upon request). The regressions of the return on perceptions reveal that the explanatory power is low, at 0.1962, 0.0422, and 0.1723% for full and correct perceptions and misperceptions, respectively.

For full perception, the total effect is negative and significant. The significant result comes from the mediating effect of retail trading. Correct perception affects returns only directly and negatively. This negative direct effect is consistent with the correct perception at the actual $PM_{2.5}$ level. Thus, the variable is a fundamental factor with direct effects due to, for example, public awareness, strict environmental regulations, high political costs, limited investment opportunities (An et al., 2018), and productivity losses (Fu et al., 2021). However, the mediating effect canceled out the direct effect; the total impact of correct perception on returns was negative but non-significant.

The total effect for misperception is -0.0513 and is significant. The size was approximately the same as the full perception of -0.0576. Mediational retail trading can explain the total effect of misperceptions. The findings conclude that retail investors' net buying drives the negative effect of $PM_{2.5}$ pollution, whereas $PM_{2.5}$ misperception induces net buying.

Table 2 Mediation Analyses of $PM_{2.5}$ Perception on Stock Market Returns

Effects	Retail Investor				Institutional Investor
	SET Return			mai Return	SET Return
	Full Sample, Pal's IVs	Full Sample, Durbin's IVs	COVID-19 Subsample, Pal's IVs	Full Sample, Pal's IVs	Full Sample, Pal's IVs
Full Perception					
Total	-0.0576**	-0.0714**	-0.0255	-0.0326	-0.0576*
Direct	0.0083	0.0014	0.0339	0.0105	-0.0457*
Mediational	-0.0659**	-0.0728**	-0.0594	-0.0431**	-0.0119
Correct Perception (Actual $PM_{2.5}$ Level)					
Total	-0.0260	-0.0328	-0.0211	-0.0319	-0.0260
Direct	-0.0372**	-0.0368**	0.0474	-0.0392	-0.0494***
Mediational	0.0112	0.0041	-0.0685	0.0073	0.0234
Misperception					
Total	-0.0513*	-0.0614*	0.0036	-0.0240	-0.0513*
Direct	0.0197	0.0190	-0.0036	0.0224	-0.0302
Mediational	-0.0710***	-0.0803**	0.0072	-0.0464**	-0.0210

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

5. DISCUSSION

5.1 Robustness Checks

5.1.1 Alternative Instrumental Variables

Durbin (1954) noted no single best IV set and recommended using an alternative IV set to check for robustness. In this study the model was re-estimated using Durbin's (1954) IV. The IV substitutes Pal's (1980) IV in the second construction step. Column 3 of Table 2 presents these results. The results in Columns 2 and 3 are similar. This finding is robust for the IV choice.

5.1.2 mai Return

Thailand has two stock exchanges: the SET and the Market for Alternative Investment (mai). The mai lists small and medium-sized stocks. The listing criteria are more relaxed than the SET criteria, while the mai's market capitalization is also much smaller. The average market capitalization from August 1, 2016, to December 28, 2023, was 2.04% of that of the SET. Despite its small size, the stock exchange was used in this study to check the robustness of the choice for return. The model was thus analyzed based on the mai returns and retail trades. In this study the mai return and net buying series were constructing using data from the SET database. Column 5 reports the results for the mai returns.

The result was consistent with the SET returns. The results were not very strong. However, the mai results show that retail net buying induced by misperception drives the negative relationship between $PM_{2.5}$ and stock returns.

5.2 COVID-19 Subsample

Quarantine was imposed to contain the disease during the COVID-19 period. Limited activities and mobility significantly improved air quality (Wetchayont, 2021). This study examines whether improved air quality lessen the effects of $PM_{2.5}$ on stock returns. The data for the COVID-19 subsample were collected for the period April 3, 2020, to September 30, 2022 (Khanthavit & Khanthavit, 2023), yielding results as presented in Column 4 of Table 2. The study found no relationship between $PM_{2.5}$ and stock returns during COVID-19. An explanation could be that $PM_{2.5}$ pollution was very low in that period (Wetchayont, Hayasaka, & Khatri, 2021), and was not an environmental threat or health risk. Alternatively, investors may have shifted their attention from $PM_{2.5}$ to the coronavirus during that period (Smales, 2021).

5.3 Mediational Role of Institutional Trading

Institutional investors breathe the same air as retail investors. For China, Wu et al. (2020) reported that the $PM_{2.5}$ perception of fund managers has a negative relationship with stock returns. This study examined the mediating role of institutional investors in SET. In the analysis, institutional investors' net buying volume was substituted for retail volume in Equations (2) and (3). Column 6 of Table 2 presents the results. Unlike Wu et al.'s (2020) results for the Chinese market, institutional investors do not appear to contribute to Bangkok's $PM_{2.5}$ effect on Thai stock returns. There are two possible explanations for this finding. First, the "PM 2.5" SVI is general and more representative of retail investors than institutional investors. Second, these institutional investors are informed traders, and their trading was unaffected by misperceptions.

5.4 Noise Trader Risk

Noise traders are uninformed investors who act on their sentiments and misperceptions regarding information (Baklaci, Olgun, & Can, 2011). In this study, retail investors are consistent with the noise traders defined by Baklaci et al. (2011). Their trading is based on the misperception of $PM_{2.5}$. Thus, the resulting negative return is consistent with noise trader risk in the overlapping generations model (De Long et al., 1990) and the agent-based artificial market model (Dai, Zhang, & Chang, 2023). In the models of De Long et al. (1990) and Dai et al. (2023), noise trader risk predicts rising return volatility and trading volumes.

This study examined rising volatility and trading volumes by estimating a model under the misperception specification. Return volatility was computed using Parkinson's (1980) extreme value method. Market trading volume is the aggregate trading volume divided by market capitalization. All variables were computed from data available in the SET database.

The results shown in the bottom row of Table 3 are consistent with predictions. The mediating effects of return volatility and trading volumes are positive. Thus, the effect on return volatility was significant. Although the effect on trading volume was not significant, its p-value was low at 0.1307, supporting the noise trader risk explanation for the negative relationship between Bangkok's $PM_{2.5}$ pollution in both Bangkok and Thai stock returns.

Table 3 Analyses of Noise Trader Risk

Misperception Effect	Dependent Variable	
	Return Volatility	Trading Volume
Total	0.1138***	-0.0371
Direct	0.0941**	-0.0451
Mediational	0.0198**	0.0080

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

5.5 $PM_{2.5}$ and Retail Net Buying Volume

The significant mediational effects of full perception and misperception (ab), equal to -0.0659 and -0.0710, were computed from the significant (a, b) values of (0.0938, -0.7029) and (0.1008, -0.0740), respectively. Negative b's were readily explained by noise trader risk, while the positive a's imply that retail investors buy more stocks when $PM_{2.5}$ perception and misperception increase. Investors spend more time indoors and are more tempted to trade (Huang, Xu, & Yu, 2020). Noise traders are likely to be net buyers, while investors buy stocks that attract their attention. However, they can only sell the limited number of stocks that they already own (Barber & Odean, 2008).

Investigating the $PM_{2.5}$-related psychological factors that drive retail investors to spend more time indoors and trade more stocks is interesting. In this study two $PM_{2.5}$-related psychological variables were constructed (attention and awareness) and regressed on misperception. The attention variable was the detrended and deseasonalized SVI for "ฝุ่น" (*Fǖn*, meaning dust in the Thai language) (Zhang & Tao, 2019). The study did not use the "PM 2.5" SVI, as did Zhang and Tao (2019). The "PM 2.5" SVI has been used to measure the full perception. Following Xu et al. (2021), this study constructs the awareness variable from the first principal component for four SVIs, namely "ฝุ่น", "ไอ" (*Xị*, meaning cough), "โรคทางเดินหายใจ" (*Rokh thāng dein h̄āycı*, meaning respiratory disease), and "เครื่องฟอกอากาศ" (*Kherụ̄xng fxk xākāṣ̄*, meaning air purifier). The SVIs were downloaded from https://trends.google.co.th/trends/. The slope coefficients of the attention and awareness variables were 0.7016 and 0.7222, respectively. These two analyses were statistically significant. Misperception convinces investors to pay more attention to $PM_{2.5}$ and raises awareness of $PM_{2.5}$-related health risks. Thus, investors stayed indoors to avoid exposure to $PM_{2.5}$ pollution.

6. CONCLUSION

The stock market reacts to $PM_{2.5}$ pollution. Most studies measure pollution objectively using actual $PM_{2.5}$ levels. However, investors are often not aware of the exact $PM_{2.5}$ level. Their perceived level should be the determining variable. In this study the perceived $PM_{2.5}$ level was considered, decomposing the full perception into correct perception and misperception components before applying mediation analyses to examine the total, direct, and mediational effects of full perception and its components on stock market returns. Retail investors' net buying volume served as the mediator. The misperception of retail investors was found to be negatively linked to Bangkok's $PM_{2.5}$ pollution and Thai stock returns via retail trading. This study provides evidence to support the noise-trader-risk explanation for this relationship, while institutional trading was found to make no significant contribution.

The authors of this study are aware that the proxy for full perception is more likely to represent retail investors than institutional investors. Therefore, a proxy that better represents institutional investor perceptions must be developed for future research.

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