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SHORT COMMUNICATION

Effects of $PM_{2.5}$ and Meteorological Parameters on the Incidence Rates of Chronic Obstructive Pulmonary Disease (COPD) in the Upper Northern Region of Thailand

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Abstract

The research aimed to study the effect of ambient $PM_{2.5}$ and meteorological parameters on the incidence rates of COPD. The study, using the panel model, lasted for 7 years and covered eight provinces in the upper northern region of Thailand (January 2014–December 2020). The feasible general least squares (FGLS) for the heteroscedasticity were used to estimate all the parameters in the model. The study result showed that all $PM_{2.5}$ and meteorological parameters contributed to an increase in COPD cases. Chronic obstructive pulmonary disease, or COPD, refers to a group of diseases that cause airflow blockage and breathing-related problems, including emphysema and chronic bronchitis (Mannino et al. 2002). We found that the average increase of $PM_{2.5}$ by 1%, would add an increased risk of COPD cases by 0.25% at a significance level of 0.10. Our study results also revealed that the average increase of temperature, humidity and hot spots by 1% would lead to the increased risk of new COPD cases by 0.42% at a significance level of 0.05. Moreover, a rise in the average of the lowest temperature in the provinces under the study by 1%, would increase the number of new cases of COPD by 0.92% at a significance level at 0.01. There were some challenges involved in investigating health impacts of $PM_{2.5}$. This study demonstrated that evidence from the econometric panel data model provided valuable information for future efforts to prevent incidence of $PM_{2.5}$ disease. It is recommended that a more comprehensive program is needed to reduce the exacerbation rate of COPD.

Keywords Chronic obstructive pulmonary disease · $PM_{2.5}$ · Climatic change · Panel data model

1 Introduction

Chronic obstructive pulmonary disease (COPD), a significant public health problem worldwide, is characterized by irreversible and progressive airflow limitation associated with chronic and aberrant pulmonary inflammation and pulmonary remodeling induced by the abnormal pulmonary response to inhaled noxious particles and gases or air pollution (Vestbo et al. 2013). In recent years, COPD has been a significant cause of global morbidity and mortality. It is predicted that it will become the third leading cause of death and the fifth global burden worldwide by 2020 (Barnes 2007). For decades, the most important causal factor for COPD has been cigarette smoking, yet only a few smokers (15–20%) eventually develop COPD (Lamprecht et al. 2011). Moreover, approximately 25% of COPD patients are non-smokers (Salvi and Barnes 2009). A multitude of epidemiological studies have shown that ambient fine particulate matter (diameter < 2.5 um; $PM_{2.5}$) was associated with increased morbidity and mortality of COPD (Zhao et al. 2019). Thus, it suggests that there are several factors that contribute to COPD development and progression. In recent decades, substantial epidemiological evidence has indicated that ambient particulate air pollution, including $PM_{2.5}$, is becoming a crucial detrimental risk factor for COPD (Song et al. 2017).

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On average, each year there are 6.5–7 million premature deaths due to air pollution, among which 1.7 are children (Landrigan et al. 2017). USA is in the 7th rank of the world's highest death toll from air pollution (Global Alliance of Health and Pollution 2019). According to reports of the Energy Policy Research Institute of the University of Chicago, USA, in 2018, China and India had the highest rate of death from air pollution, 1 million and more than 600,000, respectively, whereas the number of deaths in Thailand was 50,000. Moreover, nearly 90% of people who died from air pollution were in low-to-middle-income countries, especially in Southeast Asia and the Western Pacific, including China, with higher concentrations of particulate matter and being of the world's most polluted cities in Asia (Chongsuvivatwong et al. 2011). Numerous studies have been conducted over the past few decades in several cities of Thailand focusing on chemical characterization of air pollutants (Choochuay et al. 2020a, b, c; Pongpiachan 2014, 2016; Pongpiachan and Iijima 2016; Pongpiachan and Paowa 2015; Pongpiachan et al. 2013, 2015a, b, 2017, 2018, 2021). Thailand spent approximately 2000–3000 million Baht on healthcare costs in medical treatment, masks, and air purifiers (Chairattanawan and Patthirasinsiri 2020). However, the expenses on air pollutant-related diseases were relatively small compared to obesity, Type 2 diabetes, and neurodegenerative diseases (Health et al. 2018; Pholthaweechai and Pengnoo 2021).

Compared to other countries, Thailand's effort to solve air pollution problems, especially in Northern Thailand, is still very low and at a critical level (Sutthichaimethee and Ariyasajjakorn 2018). There is a lot of forest burning and burning of biomass for agricultural land that causes air pollution (Pongpiachan et al. 2015a, b). Exposure to ambient particles is found to be a risk factor that causes an acute exacerbation of chronic obstructive pulmonary disease (AECOPD) (Pipatvech 2021). It was found that, in 2016, 75% of the Thai population lived in areas surrounded by air pollution exceeding an acceptable level (Department of Health 2020). One of the reasons behind this is that the Thai government has set air quality index (AQI) values higher than that set by WHO and as such the official acceptable healthy AQI level in Thailand is higher than that accepted. (Clean Air Network Thailand 2019). However, when analyzed at the local level, the data showed that the worst area in the country was Chiang Rai, with a record of life expectancy reduced by 3.9 years on average, whereas in Bangkok by 2.4 years (Attavanich 2019). Hence, the apparent problem of Thailand's air pollution is that the Thai government emphasizes the importance of economic growth over environmental degradation and its impact on public health. In summary, this study aimed at investigating effects of a $PM_{2.5}$ and meteorological parameters on incidence rates of COPD in the upper northern region of Thailand through the use of an econometric panel data model to design a practical guideline. In addition, data were also obtained from Moderate Resolution Imaging Spectroradiometer (MODIS), The National Aeronautics and Space Administration (NASA), Institute of Emergency Medicine, National Health Security Office, Cancer Institute, National Statistical Office, and the Pollution Control Department of Thailand. Overall, to answer the main research question of this study, we needed to assess the impact of $PM_{2.5}$ and meteorological parameters on COPD prevalence rates. Based on our air quality impact assessment in Thailand, it was found that the biomass burning contributed 72% to air pollution in Thailand. Especially in the Northern Thailand, the impact of biomass burning is very significant with a contribution of 94% to air pollution (Vongruang and Pimonsree, 2020). Provinces in the northern region where many people suffer from repeated smog problems are Chiang Mai, Chiang Rai, Mae Hong Son, Lamphun, Lampang, Phrae, Nan and Phayao. In spite of the fact that the upper northern region of Thailand has been experiencing adverse health impacts from air quality problems for decades, the haze episode began to catch public attention in 2014 (Wichit and Udom 2016).

2 Research Methodology

2.1 Objectives

To study the effect of ambient $PM_{2.5}$ and meteorological parameters on incidence rates of COPD.

2.2 Research Hypothesis

Ambient $PM_{2.5}$ and meteorological parameters increase incidence rates of COPD.

2.3 Overview of the Data

This study employed a quantitative research method to analyze the correlation between $PM_{2.5}$ and meteorological parameters and the incidence rates of COPD using statistical panel data between 2014 and 2020 in the eight provinces: Chiang Mai, Nan, Chiang Rai, Lampang, Phrae, Phayao, Lamphun, and Mae Hong Son provinces.

The meteorological parameters data (weather information, average rainfall, average temperature, average-highest and lowest temperature, average relative humidity (%) and average visibility (km)) were collected from the Thai Meteorological Department (2020) and the MODIS satellite heat point factors (GISTDA 2020). The $PM_{2.5}$ data source came from the monthly average of pollution (Pollution Control Department 2020). And the disease data source of COPD were collected from the Control Department and the Health Data Center (HDC) system. To support the advance service system policy and drive the country's public health reform (Ministry of Health 2020).

2.4 Panel Data Analysis

Several empirical studies have used the information panel data to examine the degree and association of non-communicable diseases (NCD_s) correlation effects on illness (Marthias et al. 2021). Different steps were taken to analyze the data to find the relationship between meteorological parameters and incidence rates of COPD. There is also an econometric approach that uses real data from the past to analyze statistical processes. This economic approach has been widely used internationally, such as the studies by (McCarl et al. 2008; Cabas et al. 2010). However, this model still has limitations: the number of new cases of COPD that occur may not be the result of climate change but may be due to other environmental factors. Furthermore, this economic approach cannot identify the impact of change. This approach starts with checking the stability of the economic approach. Its first step is to check the stability of the information using the test of stability introduced by the Augmented Dickey-Fuller Unit Root Test. In addition to this step, once the data is stable, the next step is to proceed. Nevertheless, if the data are unstable (non-stationary), the adjustment will be made to stabilize the initial data either by different methods or adding a logarithm. The next step is to test the linear relationship using multicollinearity, of which the variables relate to others in typical linearity. Panel data are a group of data collected from the same collecting data at different interval changes (Baltagi 1995). So the panel data are cross-sectional. Together with time series data (cross section and time series data), the panel data will enable the study of change in the explanatory variable of each cross-sectional unit over the changing times; and units were studied in the same period (Baum 2006).

Fixed and random effects of equation model were tested by the method, 'Hausman's Specification Test' (Mandel 2010). Coefficient of each input variable analysis of this kind of data therefore vary as follows.

In the last step, panel data have the variable time invariant: a_i, which is a variable that is always constant no matter how much time has changed. It cannot be measured because it is hidden outside the equation addition. There may be a return from many risks from this. Therefore, a_i becomes an unobserved individual specific effect that is embedded in an equation creating a serial problem: correlation and heteroskedasticity problems. Based on the above problem, panel analysis presents a method for manipulating time invariant variable: a_i which can be done in two ways:

1. Random effect model is an analysis that allows a_i to come in effects on variables in equations using Methods Feasible generalizing the least squares, (FGLS). To solve the serial correlation problem, the Random Effect Model is used to combine a_i with the correlation value. Error U_{it} becomes New Tolerance $V_{it;}$; such analysis will have important assumptions. That is a_i must not be related to any independent variables. In the equation, the mean point is zero and there is a variance equal to $Q^2{}_a$, changing the shape of the variable with FGLS method.
2. Fixed effect model is an analysis that controls a_i by eliminating its influence. Once a_i is taken out of the equation, it can no longer interfere with the demean analysis method, where the key assumption is a_i. a_i must be related to the independent variables in the equation and must not be related to each other $\mathrm{Cov}(a_i, a_j) = 0$; $i \neq j$. The demean extracts the variable a_i from the V_{it} error first, becoming $a_i + U_{it}$ afterwards. It then takes the sample variable value minus the mean of the sample variable and adds the time and sample. All Fixed Effect methods provide results that mean sample has constant behavior over time. No matter how outside influences affect it, it does not change behavior.

Fixed effects model and random-effects model is shown as follows:

Fixed effects model:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} \beta_k x_{\mathrm{kit}} + u_{\mathrm{it}} \quad i = 1, \ldots, N, \quad t = 1, \ldots, T \tag{1}$$

Random effects model

$$y_{it} = \sum_{k=1}^{K} \beta_k x_{kit} (\alpha_i + u_{it}) \quad i = 1, \ldots, N, \quad t = 1, \ldots, T \tag{2}$$

According to Index i, the differentiation between the subjects and ranges was one to N, in which N represents the number of subjects. Furthermore, each subject was observed T time, and the index t differentiated the observation times from one to T. In addition, K is the number of the explanatory (independent) variables.

2.5 Statistical data

In this study, using a database consisting of the panel data set, K represented the monthly data (N) obtained from eight provinces in the 2014–2020 terms (T), in a total of 7 years due to some constraints of data collection. The dataset is a balanced panel and has $(N) \times T \times K = (8 \times 12) \times 7 \times 9 = 6{,}048$ observations. Each variable has $(N) \times T = (8 \times 12) \times 7 = 672$ observations.

There are two parts of the analysis as follows:

1. Descriptive statistical analysis, mean, maximum, maximum and standard deviation.
2. Econometric model, to analyze the impact factors affecting on COPD in the Upper North Region of Thailand in the panel data collected during 2014–2020 by the panel data model. The dependent variable and the descriptive variable in the model are defined as follows.

The dependence variable is $COPD_{it}$ the (COPD: ppl); where $MINT_{it}$ is the average minimum temperature (degrees Celsius), $MAXT_{it}$ is the average maximum temperature (degrees Celsius), $TRAI_{it}$ is Total rainfall (mm), RHM_{it} is relative humidity average (%), $VISIT_{it}$ is visibility (kilometers), $PM_{2.5it}$ is an ambient fine particulate matter (ug m^{-3}), $HOTS_{it}$ it is the hotspot heat point dot, and $TIME_{it}$ is a time trend variable. If the province effects are uncorrelated with the regression, they are known as random effects. This is because in the random-effect model, there is no correlation between the province-specific effects and the regressions. Once the province effects correlate with the regressions, they are known as fixed effects. In addition to this, a theoretical model to analyze the factors affecting the climate factors showed that, (Sinnarong et al. 2019). Applying the concept of modeling in econometrics for panel data had advantages in taking into account the impact of differences in space and temporal differences. The model for data estimation is shown as follows:

$$COPD_{it} = \propto_1 + \beta_{11}MINT_{it} + \beta_{12}MAXT_{it} + \beta_{13}TRAI_{it} + \beta_{14}RHM_{it} + \beta_{15}VISIT_{it} + \beta_{16}PM_{2.5it} + \beta_{17}HOTS_{it} + \beta_{18}TIME_{it} + \mu_{it} \quad (3)$$

$COPD_{it}$ to respiratory syndrome (ppl), $MINT_{it}$ to the average minimum temperature (℃), $MAXT_{it}$ to the average maximum temperature (℃), $TRAI_{it}$ to Total rainfall (mm), RHM_{it} to the relative humidity average (%), $VISIT_{it}$ to visibility (km), $PM_{2.5it}$ to ambient fine particulate matter (ug m^{-3}), $HOTS_{it}$ to hotspot heat point dot, $TIME_{it}$ to a time-trend variable, μ_{it} to an error that cannot be observed, β to a casual regression coefficient, α to a casual constant.

3 Results

This section discusses results of a study on the effects of $PM_{2.5}$ and meteorological parameters on COPD incidence rates in the upper northern region of Thailand, 2014–2020. The average number of new cases of COPD value was 32.72 cases per month. Here, in addition, the average of $PM_{2.5}$ was 144.71 (ug m^{-3}) with the standard deviation of 29.51 (ug m^{-3}), while the minimum, maximum values appeared to be 61 (ug m^{-3}) 258 (ug m^{-3}), respectively. In terms of the hot spot heat, the average result was 233.07 points with the standard deviation of 2.10 points, while the minimum and maximum were equal to 2 and 2703 points, respectively. The minimum and maximum values are 0 and 464 cases, respectively. Regarding temperature, the average was 35.71 ℃, while the minimum and maximum were 26.65 ℃ and 43.65 ℃, respectively, with the standard deviation of 3.15 ℃. The total rainfall was at an average of 48.24 mm with a standard deviation of 187.52 mm, in which the minimum and maximum total rainfall were 0.00 mm and 1061.8 mm, respectively. Regarding the humidity, the average was 73.63 % with a maximum value of 86%, and the minimum was 45%, whereas the standard deviation was 9.49. The average visibility was 7.46 km with a standard deviation of 2.08 km, in which the minimum and maximum values were 1.50 km and 12.50 km, respectively (Table 1).

Data's suitability (Pre-estimation Specification Test) was tested for the monthly COPD in the Upper Northern Region of Thailand, panel data (2014–2020). Regarding the regression analysis with panel data analysis in case of variance problem (Heteroscedasticity), it is necessary to test the suitability of the data first. In addition, the use of a stability test of balance panel data was employed to avoid spurious correlation. The test consisted of two methods. One method was Levin, Lin and Chu (LLC) (Baltagi 1995). And the other, Im, Pesaran and Shin (PIS) (Baum 2006). The test results showed that the monthly COPD, maximum temperature, minimum temperature, total rainfall, relative humidity average, visibility, $PM_{2.5}$ (ug m^{-3}), and hotspot heat were at a stationary level. Hence, it is not necessary to determine the difference of the data before performing the regression analysis. In addition, we have also tested the problem of the variance of inconstant error. To find the

Table 1 Descriptive statistics of $PM_{2.5}$ and meteorological parameters related to on COPD

Variables	Aver	SD	Min	Max
COPD (ppl)	32.72	36.99	0.00	464.00
$PM_{2.5}$ (ug m^{-3})	144.71	29.51	61.00	258.00
Hot spot heat (point dot)	233.07	2.10	2.00	2703.00
Maximum temperature (℃)	35.71	3.15	26.65	43.65
Minimum temperature (℃)	16.66	4.55	5.70	26.50
Total rainfall (mm)	48.24	187.52	0.00	1061.80
Relative humidity average (%)	73.63	9.49	45.00	86.00
Visibility (km)	7.46	2.08	1.50	12.50

Source: From the calculation of the Individual Sample (monthly from 2014–2020) relationship, the variance describes the error in the form of experiments of the long-term variability and the error in the meteorological parameter model with the monthly COPD. The Breusch–Pagan–Godfrey test was used to determine the relationship between the square error and the explanatory variable and the auto regressive method. Conditional heteroscedasticity (ARCH) from determining the relative square of values error with the lag from the test results of both methods revealed that there was a problem of the variance of the error which was not constant. Hence, (FGLS) was conducted, which was appropriate for the analysis of the meteorological parameters with the monthly COPD (Torres-Reyna 2007). The form of the equation in a double-log format and consider the P value from the estimation of the coefficients of the Fixed Effect Model and Random Effect Model functions. The resulting value is 0.000 which is a small value. Then the level of statistical significance at the 99% confidence level means that the fixed effect model is more suitable than the random effect model. This study, therefore used the fixed effect model coefficient estimation of the mean function; it was more suitable by comparison. The regression equation had an unstable variance problem. Heteroscedasticity was used to investigate the problem of the variance of the inconsistency with the Wald test method and to solve the problem of the variance of the inconsistency of the error with the instability the most common least squares estimation possible (a feasible generalized the least squares, FGLS). Problem test results heteroscedasticity test of the Wald Test method of Fixed Effect Model COPD showed that the calculated Chi-Square statistic was higher than the critical value (Prob.< α) at the significant level of 0.01 (Prob. = 0.000) rejecting the main assumption, but indicating that the regression equation had an invariant variance problem. The fixed effect model estimation of heteroscedasticity to solve the problem of the variance of the error was therefore not constant, with the most common least squares estimation possible (a feasible generalized least squares, FGLS), as shown in Table 2 below.

Table 2 Unit root test of variables used for panel data analysis (2014–2020)

Variables	LLC test	IPS test
COPD (ppl)	94.7405**	210.021**
$PM_{2.5}$ (ug m^{-3})	196.165**	93.1704**
Hot spot heat (point dot)	213.082**	189.1841**
Maximum temperature (℃)	151.368**	85.1101**
Minimum temperature (℃)	163.888**	97.7393**
Total rainfall (mm)	124.026**	144.305**
Relative humidity average (%)	173.912**	86.9104**
Visibility (km)	193.170**	127.205**
COPD test results	Chi-square	Probability
Hausman's Specification Test	49.48**	(0.000)
Heteroscedasticity in fixed effect regression model	34.10*	(0.000)

Source: researcher own estimated using panel data (2014–2020)

* and **indicate that the significant at the 0.10 and 0.01, respectively

Table 3 Estimation from climate change model to the monthly COPD

Variable	Panel least square	FGLS
ln $MAXT_{it}$	0.604151* (0.0854)	0.420052** (0.0428)
ln $MINT_{it}$	0.953027*** (0.0005)	0.923923*** (0.0000)
ln $TRAI_{it}$	0.071944* (0.0697)	0.006262 (0.7974)
ln RHM_{it}	− 0.020536** (0.0100)	0.425054** (0.0208)
ln $VISIT_{it}$	0.231764 (0.2434)	− 0.232925 (0.2031)
ln $PM_{2.5it}$	0.241168*** (0.0073)	0.256456* (0.0898)
ln $HOTS_{it}$	0.115116* (0.0854)	0.049328** (0.0119)
ln TT_{it}	0.296496 (0.2492)	0.022844 (0.8989)
Constant	30.31845 (0.5082)	3.811666 (0.0000)
R-squared	0.589322	0.608333
Adjusted R-squared	0.579814	0.559418
SE of regression	0.664969	0.662105
Prob (F-statistic)	19.70729	21.33047

Source: researcher own estimated using panel data (2014–2020).

*, **, and *** indicate that the significant at the 0.10, 0.05 and 0.01, respectively

4 Estimation of Meteorological Parameter Model of COPD

In this study, the *FGLS* procedure was used to estimate coefficient the parameters of the higher equation. The results of the fixed effect from panel data, least squares (*PLS*) had a linear relationship, according to the concept (Di 2006, 2009). Because R-squared the *FGLS* had higher equation and SE of regression, adjusted R-squared had lower equation the coefficient was more efficient (Sinnarong et al. 2018). The panel with the least squares (PLS) are illustrated in Table 3 for the monthly information of the effects of time trend (T) on COPD. Hence, with that $PM_{2.5}$ meteorological parameters had a negative impact on COPD. We found that 1% increase of $PM_{2.5}$ led to increase of the number of new cases of COPD by 0.25% at a significant level of 0.10. The result was congruent with the study of (Zhao et al. 2019). With a rise of the average high-temperature, humidity and hot spot by 1%, the positive risk of the number of new cases of COPD increased by 0.42% at a significant level of 0.05. This was consistent with the results of the study by Li (2015). Zanobetti et al. (2013) also found the largest effect of $PM_{2.5}$ on respiratory mortality during high temperatures. Their studies showed that for a 1% increase in the concentration of $PM_{2.5}$ at 10 (ug m^{-3}), there was an increase of 1.70% of RR of respiratory mortality. It has been pointed out that high relative humidity often occurs at high temperatures, the air feels humid and stuffy (Ehlig and LeMert 1973). Conversely, low relative humidity occurs at low temperatures, the air feels dry leading to uncomfortable itchy and cracked skins (Sunwooet al. 2006). People affected with COPD are more susceptible to temperature extremes (Hanselet al. 2016). Moreover, rises in the average lowest-temperature by 1% would increase the number of new cases of COPD by 0.92% at significant level at 0.01. Some challenges were involved in investigating the health impacts, particularly the negative impact on COPD, of $PM_{2.5}$ and meteorological parameters.

5 Conclusion

Several attempts have been made to obtain information related to COPD, a preventable and treatable lung disease. There has been a substantial increase of COPD cases worldwide (Vestbo et al. 2013) and numerous epidemiological studies have revealed the associations between particulate pollution exposure, including $PM_{2.5}$, with the increased morbidity from COPD, in both developed as well as developing countries (Guan et al. 2016). However, it remains poorly understood about the underlying effects and the associated mechanisms by which $PM_{2.5}$ exposure triggers and causes COPD. In this study, we demonstrated that $PM_{2.5}$ and meteorological parameters had a negative impact on COPD. Most importantly, prolonged exposure to $PM_{2.5}$ can significantly have adverse effects on COPD. Previous studies showed a significant relationship between $PM_{2.5}$ and COPD; an increase in ambient $PM_{2.5}$ concentrations of 10 ug m^{-3} correlated with a 2.5% increase in COPD-related mortality, and an increase of COPD hospitalizations by 3.1% (Li et al. 2016). However, such correlations vary in different geographic locations (Samet et al. 2000). Our study showed that there was a significant correlation between $PM_{2.5}$ and meteorological parameters and incidence rates of COPD in the upper north of Thailand. Our study results showed that average $PM_{2.5}$, maximum temperature, humidity, hot spots and lower temperatures significantly increased the incidence rates of new COPD cases.

Our study findings reveal effects of ambient $PM_{2.5}$ and meteorological parameters on the incidence rates of COPD in eight provinces using econometric panel data models (FGLS). Evidence from econometric data models provides useful information for future efforts to maintain sustainable health. In short, our data suggest that when $PM_{2.5}$ and meteorological parameters occur, Highest temperatures, humidity, hot spots and lower temperatures All variables will increase the positive risk of COPD, Increase the number of new COPD cases. Further studies are required to extend these findings.

6 Recommendations

We recommend that a surveillance system monitoring the health impacts from $PM_{2.5}$ (during December–May) needs to be set up, for example, a respiratory disease surveillance that involves: (i) necessary medicines and medical supplies, such as generic home remedies, personal medications, and kits, and (ii) close observation of people susceptible to COPD. People displaying unusual or suspicious symptoms, such as shortness of breath, chest tightness, dizziness, or loss of consciousness, should be given first aid and immediately taken to the hospital. To solve the $PM_{2.5}$ problem and to come up with a sustainable solution, all parties must work together; our changes in lifestyle and agricultural or industrial productions that do not cause dust generation. Therefore, it is necessary to have a management system to reduce dust and smoke from all types of combustion. Such a management system should be based on scientific data and close cooperation with local communities and local government organizations in the Upper Northern Region of Thailand.

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Declarations

Conflict of Interest The corresponding author certifies that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

References

Attavanich W (2019) Social cost of air pollution in Thailand and solutions. PIER Discussion Paper **(forthcoming)**

Baltagi BH (1995) Econometric analysis of panel data. West Sussex

Barnes PJ (2007) Chronic obstructive pulmonary disease: a growing but neglected global epidemic. PLoS Med 4(5):e112

Baum CF (2006) An introduction to modern econometrics using stata. Texas USA

Cabas J, Weersink A, Olale E (2010) Crop yield response to economic, site and climatic variables. Clim Change 101:559–616

Chairattanawan K, Patthirasinsiri N (2020) Emission source impact and problem solving and management on $PM_{2.5}$ in the northern part of Thailand. J Assoc Res 25(1):432–446

Chongsuvivatwong V, Phua KH, Yap MT, Pocock NS, Hashim JH, Chhem R, Wilopo SA, Lopez AD (2011) Health and health-care systems in southeast Asia: diversity and transitions. Lancet 377(9763):429–437

ChooChuay C, Pongpiachan S, Tipmanee D, Suttinun O, Deelaman W, Wang Q, Cao J (2020a) Impacts of PM2.5 sources on variations in particulate chemical compounds in ambient air of Bangkok Thailand. Atmos Pollut Res 11(9):1657–1667

ChooChuay C, Pongpiachan S, Tipmanee D, Deelaman W, Suttinun O, Wang Q, Cao J (2020b) Long-range transboundary atmospheric transport of polycyclic aromatic hydrocarbons, carbonaceous compositions, and water-soluble ionic species in southern Thailand. Aerosol Air Qual Res 20(7):1591–1606

ChooChuay C, Pongpiachan S, Tipmanee D, Deelaman W, Iadtem N, Suttinun O, Cao J (2020c) Effects of agricultural waste burning on $PM_{2.5}$-bound polycyclic aromatic hydrocarbons, carbonaceous compositions, and water-soluble ionic species in the ambient air of Chiang-Mai, Thailand. Polycycl Aromat Compd. https://doi.org/10.1080/10406638.2020.1750436

Clean Air Network Thailand (2019) "Clean white-collar, clean air" (clean air white paper). http://www.tei.or.th/file/library/2019-clean-air-white-paper_26.pdf

Department of Health (2020) Health Data Center Announcement of the Department of Health on the cost of monitoring the health impact of small dust in the atmosphere in Thailand

Di Falco S, Chavas JP (2006) Crop genetic diversity, farm productivity and the management of environmental risk in rainfed agriculture. Eur Rev Agric Econ 3(33):289–314

Di Falco S, Chavas JP (2009) On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia. Am J Agr Econ 3(91):599–611

Ehlig CF, LeMert RD (1973) Effects of fruit load, temperature, and relative humidity on boll retention of cotton 1. Crop Sci 13(2):168–171

GISTDA (2020) Department of environment and disasters office of geospatial applications and services geo-informatics and space technology development agency (public organization). GISTDA

Global Alliance on Health and Pollution (2019) Pollution and health metrics: global, regional, and country analysis

Guan W-J, Zheng X-Y, Chung KF, Zhong N-S (2016) Impact of air pollution on the burden of chronic respiratory diseases in China: time for urgent action. Lancet 388(10054):1939–1951

Hansel NN, McCormack MC, Kim V (2016) The effects of air pollution and temperature on COPD. COPD J Chron Obstr Pulm Dis 13(3):372–379

Health EPOP, Jeger M, Bragard C, Caffier D, Candresse T, Chatzivassiliou E, Dehnen-Schmutz K, Gilioli G, Grégoire JC, Jaques-Miret JA (2018) Evaluation of a paper by Guarnaccia et al. (2017) on the first report of *Phyllosticta citricarpa* in Europe. EFSA J 16(1):e05114

Lamprecht B, McBurnie MA, Vollmer WM, Gudmundsson G, Welte T, Nizankowska-Mogilnicka E, Studnicka M, Bateman E, Anto JM, Burney P (2011) COPD in never smokers: results from the population-based burden of obstructive lung disease study. Chest 139(4):752–763

Landrigan PJ et al. (2017) The lancet commission on pollution and health. https://doi.org/10.1016/S0140-6736(17)32345-0

Li Y et al (2015) Ambient temperature enhanced acute cardiovascular-respiratory mortality effects of PM2.5 in Beijing China. Int J Biometeorol 59(12):1761–1770

Li MH et al (2016) Short-term exposure to ambient fine particulate matter increases hospitalizations and mortality in COPD: a systematic review and meta-analysis. Chest 149(2):447–458

Mandel M (2010) Estimating disease progression using panel data. Biostatistics 11(2):304–316

Mannino DM, Homa DM, Akinbami LJ, Ford ES, Redd SC (2002) Chronic obstructive pulmonary disease surveillance-United States, 1971–2000

Marthias T, Anindya K, Ng N, McPake B, Atun R, Arfyanto H, Hulse ES, Zhao Y, Jusril H, Pan T (2021) Impact of non-communicable disease multimorbidity on health service use, catastrophic health expenditure and productivity loss in Indonesia: a population-based panel data analysis study. BMJ Open 11(2):e041870

McCarl BA, Villavicencio X, Wu X (2008) Climate change and future analysis: is stationarity dying? Am J Agric Econ 90(5):1241–1247

Meteorological Department (2020) Site: 4353 Sukhumvit Road, Bangna, Bangkok, Thailand

Ministry of Health (2020) From the HDC HIE system Website: https://hdcservice.moph.go.th/hdc/reports/page.php?cat_id=6a1fdf282fd28180eed7d1cfe0155e11

Phiphatthavej K (2561) Conflicting relationship with PM2.5 message and exacerbation of patients with celiac disease. COPD in Nan Hospital. J Health Sci Acad Conc 30(4):645–653

Pholthaweechai U, Pengnoo A (2021) Effect of nitrogen and *Bacillus subtilis* SM1 strain on white root rot disease (Rigidoporus microporus NK6 Strain) in laboratory. Songklanakarin J Plant Sci 8(1):44–49

Pipatvech K (2021) Relationship between PM2.5 dust exposure and exacerbation of chronic obstructive pulmonary disease patients in nan hospital, Thailand. J Health Sci Ministry Public Health. Thailand 30(4):645–653

Pollution Control Department Ministry of Natural Resources and Environment (2020) 92 PhahonYothin 7 Alley, Phaya Thai, Bangkok 10400. webmaster@pcd.go.th

Pongpiachan S (2014) FTIR spectra of organic functional group compositions in $PM_{2.5}$ collected at Chiang-Mai City, Thailand during the haze episode in March 2012. J Appl Sci 14(22):2967–2977

Pongpiachan S (2016) Incremental lifetime cancer risk of $PM_{2.5}$ bound polycyclic aromatic hydrocarbons (PAHs) before and after the wildland fire episode. Aerosol Air Qual Res 16(11):2907–2919

Pongpiachan S, Iijima A (2016) Assessment of selected metals in the ambient air PM_{10} in urban sites of Bangkok (Thailand). Environ Sci Pollut Res 23(3):2948–2961

Pongpiachan S, Paowa T (2015) Hospital out-and-in-patients as functions of trace gaseous species and other meteorological parameters in Chiang-Mai Thailand. Aerosol Air Qual Res 15(2):479–493

Pongpiachan S, Choochuay C, Chonchalar J, Kanchai P, Phonpiboon T, Wongsuesat S, Thamrongthanyawong S (2013) Chemical characterisation of organic functional group compositions in $PM_{2.5}$ collected at nine administrative provinces in Northern Thailand during the haze episode in 2013. Asian Pac J Cancer Prev 14(6):3653–3661

Pongpiachan S, Tipmanee D, Khumsup C, Kittikoon I, Hirunyatrakul P (2015a) Assessing risks to adults and preschool children posed by PM2.5-bound polycyclic aromatic hydrocarbons (PAHs) during a biomass burning episode in Northern Thailand. Sci Total Environ 508:435–444

Pongpiachan S, Kositanont C, Palakun J, Liu S, Ho KF, Cao J (2015b) Effects of day-of-week trends and vehicle types on $PM_{2.5}$-bounded carbonaceous compositions. Sci Total Environ 532:484–494

Pongpiachan S, Liu S, Huang R, Zhao Z, Palakun J, Kositanont C, Cao J (2017) Variation in day-of-week and seasonal concentrations of atmospheric $PM_{2.5}$-bound metals and associated health risks in Bangkok, Thailand. Arch Environ Contam Toxicol 72(3):364–379

Pongpiachan S, Iijima A, Cao J (2018) Hazard quotients, hazard indexes, and cancer risks of toxic metals in PM_{10} during firework displays. Atmosphere 9(4):144

Pongpiachan S, Chetiyanukornkul T, Manassanitwong W (2021) Relationship between COVID-19-infected number and $PM_{2.5}$ level in ambient air of Bangkok, Thailand. Aerosol Sci Eng 1–10

Ruang PW, Sri SP (2018) Assessment of the impact of biomass burning on the level of particulate matter smaller than 10 microns (PM10) during the period of smog problem in Thailand using WRF model. CMAQ. Thai Sci Technol J 34–48

Salvi SS, Barnes PJ (2009) Chronic obstructive pulmonary disease in non-smokers. Lancet 374(9691):733–743

Samet JM, Dominici F, Curriero FC, Coursac I, Zeger SL (2000) Fine particulate air pollution and mortality in 20 US cities, 1987–1994. N Engl J Med 343(24):1742–1749

Sinnarong N, Pongcharoen K, Thaeye K, Phuntulee S, Ngampiboonwet W (2018) The association of weather variables with rice production and simulation of agro-adaptation measure for northeast Thailand: evidence from panel data model. Int J Glob Warm 14(3):330–355

Sinnarong N, Panyadee C, Aiikulolac OI (2019) The impact of climate change on agriculture and suitable agro-adaptation in Phufa Sub-District, Nan Province Thailand. J Community Dev Res (humanit Soc Sci) 12(3):47–60

Song C, He J, Wu L, Jin T, Chen X, Li R, Ren P, Zhang L, Mao H (2017) Health burden attributable to ambient $PM_{2.5}$ in China. Environ Pollut 223:575–586

Studenmund AH (2011) Using econometrics: a practical guide. Pearson Publishers, New York

Sunwoo Y, Chou C, Takeshita J, Murakami M, Tochihara Y (2006) Physiological and subjective responses to low relative humidity. J Physiol Anthropol 25(1):7–14

Sutthichaimethee P, Ariyasajjakorn D (2018) Forecast of carbon dioxide emissions from energy consumption in industry sectors in Thailand. Environ Clim Technol 22(1):107–117

Thai Meteorological Department (2020) Site: 4353 Sukhumvit Road, Bangna, Bangkok, Thailand

Torres-Reyna O (2007) Panel data analysis fixed and random effects using Stata (v. 4.2). Data & Statistical Services, Priceton University, 112

Vestbo J, Hurd SS, Agustí AG, Jones PW, Vogelmeier C, Anzueto A, Barnes PJ, Fabbri LM, Martinez FJ, Nishimura M (2013) Global strategy for the diagnosis, management, and prevention of chronic obstructive pulmonary disease: GOLD executive summary. Am J Respir Crit Care Med 187(4):347–365

Vongruang P, Pimonsree S (2020) Biomass burning sources and their contributions to PM10 concentrations over countries in mainland southeast asia during a smog episode. Atmos Environ 228:117414

Wichit AS, Udom TB (2016) Assessment project blue sky with no pollution, create economic community of natural resources, Lampang Province. and Environment Office, Lampang Province. J Humanit Soc Sci Rev 3(2)

Zanobetti A, O'Neill MS, Gronlund CJ, Schwartz JD (2013) Susceptibility to mortality in weather extremes: effect modification by personal and small area characteristics in a multi-city case-only analysis. Epidemiol (camb, Mass) 24(6):809

Zhao J, Li M, Wang Z, Chen J, Zhao J, Xu Y, Wei X, Wang J, Xie J (2019) Role of $PM_{2.5}$ in the development and progression of COPD and its mechanisms. Respir Res 20(1):1–13