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Nexus between Air Pollution and NCOV-2019 in China: Application of Negative Binomial Regression Analysis

Abstract

On a global scale, the epidemic of the novel coronavirus (NCOV-2019) has become a major issue that seriously harming human health and impairing the environment's quality. The current study examines the association among air pollution and NCOV-2019 in China, where cases of NCOV-2019 are correlated with deaths in public databases with data on air pollution tracked at multiple locations in different provinces of China. A negative binomial regression (NBR) model was applied to examine the difference between the number of people infected with NCOV-2019 and the number of deaths in China. The findings show that, after population density regulation, there is a positive connection between air pollutants concentration (particularly nitrogen dioxide) and the number of NCOV-2019 cases and deaths. Furthermore, $PM_{2.5}$ is the key cause of NCOV-2019 cases and deaths in China. The results indicate that a 1% increase in the average of $PM_{2.5}$ was correlated with an increase of 11.67% in NCOV-2019 cases and a rise of 18% in NCOV-2019 deaths. We concluded that a slight rise in air pollution has caused the number of NCOV-2019 cases and deaths to increase dramatically. This research provides a basis for future policies affected by this pandemic in terms of health and pollution.

Keywords: COVID-19, Air pollution; PM2.5; SO2; PM10; NO2; O3; Negative binomial regression

Graphical Abstract

1. Introduction

The 2009 H1N1 in Mexico, the 2014 Ebola in West Africa, the 2014 Polio in the Middle East, and the 2016 Zika virus in Brazil are some of the recently faced pandemics. Along with uncountable deaths and illnesses, trillions of dollars are lost worldwide as a result of such pandemics (Coccia, 2021a). Overtaking the world at the end of 2019, NCOV-2019 is another pandemic, initially born in Wuhan China. Regardless of a lockdown policy initially implemented in Wuhan on 23 January (Tadano et al., 2021) and later on, applied to another 95 cities (Sanchez-Lorenzo et al., 2021), the pandemic managed to spread to the other provinces, eventually covering more or less, all the regions in China, with the first confirmed case reported in Wuhan in late December 2019. WHO declared NCOV-2019 as a global pandemic on 30 January 2020 with its fast spread across the regions of Asia, Africa, America, and Europe, despite the countless effort by the Chinese government to isolate Wuhan City from the rest of China (Tung et al., 2021). Affecting both advanced and emerging economies, NCOV-2019 is now recorded in 216 countries (Yuan et al., 2021). Due to a lack of disease-resistant medicines and vaccines, some countries are, to this date, observing an increasing trend.

A recent research elaborates on the pandemic's epidemiology and clinical features explaining how the first line of defence of the upper respiratory tract, called cilia is damaged by the $PM_{2.5}$ with a diameter of $\leq 2.5\mu m$ (Sarmadi et al., 2020). With higher death rates in areas where air quality continues to deteriorate, SARS is an epidemic caused in the past by a virus inherently identical to COVID-19. $PM_{2.5}$ distributed in 120 cities and NCOV-2019 infection have a concrete relationship (Mehmood et al., 2020). A study conducted by (Zhang et al., 2020) investigates that a significant increase in the daily count of confirmed NCOV-2019 positive cases is evident as a result of the 10μgm-3 increase in the pollution concentration. Fattorini and Regoli (2020) suggests a 15% rise in the number of NCOV-2019 deaths as a result of 1μgm-3 increase in $PM_{2.5}$. A higher chance of increasing chronic respiratory diseases, beneficial to infectious agents, are highly possible in people exposed to high concentrations of PM2.5 particles (Bashir et al., 2020). With more impact on children and unhealthy populations, Long-term exposure to $PM_{2.5}$ results in chronic inflammation. Since particulate pollution can damage the human respiratory tract, a viral infection is possible as a result of continued exposure to $PM_{2.5}$, which causes increased susceptibility to infection (Coccia, 2021b). The human body loses its strength to fight a viral disease, when exposed to $PM_{2.5}$ pollutants (Tang et al., 2014). White blood cells, lung parenchyma, serum and macrophages are recorded to have excessive amounts of TGF-β1 (transforming growth factor), interleukin 4 (IL-4) and TNF-α (tumor necrosis factor) in an investigation conducted on a small group of mice exposed to $PM_{2.5}$ for three months (Fattorini and Regoli, 2020). According to another test, done on a group of mice exposed to $PM_{2.5}$, heart function is likely impaired as a result of large systemic inflammation (Chen et al., 2017). Humans are also susceptible to this phenomena as systemic inflammation in healthy, non-smokers and young people is caused by $PM_{2.5}$ (Ficetola and Rubolini, 2021).

A higher NCOV-2019 mortality rate is observed as a result of both long-term and short-term exposure to $PM_{2.5}$. China is recorded as the first affected country, according to the official data from the World Health Organization on NCOV-2019 (Han et al., 2021). The second wave of the infection is said to be more prominent according to the senior medical adviser from the Chinese government. In order to calculate the impact of $PM_{2.5}$ on the exposed populations in every country, epidemiological and experimental studies should be conducted immediately. In policy formulation to decrease the effect of COVID-19, it is importance for the governments and researchers from different countries to study the areas with high levels of air pollution for $PM_{2.5}$ and other air pollutants' (e.g. PM_{10}, SO_2, NO_2 and O_3) exposure.

This study is focused on assessing the relationship between NCOV-2019 cases and deaths with the provincial air pollution exposure in China. The contribution of this research to the existing literature is given as follow: (1) The impact of air pollution (such as $PM_{2.5}$, SO_2, PM_{10}, NO_2 and O_3) on spreading the coronavirus in China are identified and elaborated through the detailed framework proposed by this study. Previous studies fall short on the analysis of controversial findings and are focused specifically on the effects of the atmospheric conditions. Second, the regional analysis should be more reliable and accurate in assessing the effects of air pollution compared to the provincial analysis, taking into account the scale of China's provinces and their apparent climate variations. This is more likely to be the first interactive analysis focusing on how the spread of NCOV-2019 is affected by air pollution, making this research more practically significant. Similarly, the risk of NCOV-2019 can be minimised, along with the intensity of future pandemics by identifying key and variable environmental factors. Moreover, a comprehensive analysis of the relationship between air pollution and NCOV-2019 can be achieved by implementing disease management policies and public health procedures in clinical practice.

The rest of the paper includes: Section 2 represents the description. Section 3 discusses the methodology. Section 4 elaborates on the research results and discussion and the last section of this paper represents the concluding remarks, including policy implications, and study limitations.

3. Methods and Martial

3.1 Econometric Model Specification

The variation among the number of people infected with NCOV-2019 and the number of deaths in China is assessed with the help of the negative binomial regression model. Data prediction based on counts (Wang et al., 2019) is supported perfectly by the Poisson-Gamma mixed distribution (Hilbe, 2011), which the negative binomial regression is based on. Due to the variance of the dependent variable, which is more than the average and the dependent variables (the number of deaths and the number of NCOV-2019 cases) with only non-negative integer values, this method functions precisely. A positive skewness and kurtosis (skewness = 6.002, kurtosis = 43.308) is evident from the dependent variable. According to (Joe and Zhu, 2005), this data set cannot support standard linear regression techniques, pertaining to the abnormal, highly skewed and discontinuous nature of the dependent variable (Miaou, 1994). The preferred modelling technique is given as follows:

$$P(Y_i = y_i) = \frac{\mu_i^{y_i}(-\mu_i)}{y_i^!} \quad (1)$$

where the probability of number of cases (Y_i) found in the i^{th} province of China for a specified time period is represented by $P(Y_i = y_i)$. The anticipated cases of NCOV-2019 cases in the province are represented by μ_i, whereas values of 0,1,2,.... are signified by y_i. The expected frequency of NCOV-2019 cases is measured as a function of the X_i vector of the exploration variable, according to the Poisson regression model. Therefore:

$$ln(\mu_i) = X_i^t \beta \qquad (2)$$

where the estimated coefficient vector of the survey variables, including population density, $PM_{2.5}$, PM_{10}, NO_2, O_3 and SO_2 is represented as β. By the maximization of the logarithm of likelihood function given below, it is easy to assess the coefficient vector (β).

$$\ln L\,(\beta) = \sum_i \left[-exp(X_i^t \beta) + (X_i^t \beta) y_i - lny_i^{!}\right] \qquad (3)$$

Considered as one of the key attributes for the Poisson distribution, the μ_i parameter is equal to the variance and mean (Wong et al., 2007). The assumption regarding mean and variance to be the same is not satisfied by the data used in this study.

The greater the variance to mean ratio, the greater the dispersion, typically due to the variability between observations. Hence, the problem regarding excessive dispersion is solved by applying negative binomial regression. In order to relax the Poisson regression assumption, other randomness is included and error term of the gamma distribution is included in equation (2).

$$ln(\mu_i) = X_i^t \beta + \varepsilon_i \qquad (4)$$

With a mean μ_i, $\mu_i + \alpha\mu_i^2$ represents the variance of negative binomial regression distribution (Miaou, 1994). In the given situation, the measure of dispersion used in this case is the over-dispersion parameter, represented as α. The following model is considered for investigating changes in the dependent variables:

$$\mathrm{NCOV} - 2019_{\,Cases} = \beta_0 + \beta_1(PM2.5) + \beta_2(PM10) + \beta_3(NO2) + \beta_4(SO2) + \beta_5(O3) + \beta_6(Popdensity) \qquad (5)$$

$$\mathrm{NCOV} - 2019_{\,deaths} = \beta_0 + \beta_1(PM2.5) + \beta_2(PM10) + \beta_3(NO2) + \beta_4(SO2) + \beta_5(O3) + \beta_6(Popdensity) \qquad (6)$$

3.2 Data and variable selection

Tab. 1 shows the publicly available data from 30 provinces of China, for the initial analysis of this study. Between 24 January and 30 November, 2020, this study assesses 29 provinces from mainland China. In order to avoid the extreme values effects and domestic influence, the Hubei province is not considered. The new confirmed cases and the number of deaths on a daily basis form the dependent variables for this study. The data consisting of concentrations of five air pollutants, including $PM_{2.5}$, NO_2, O_3, PM_{10}, and SO_2, recorded on a daily basis is used in this study. The daily mean data of air pollutants from 24 January 2020 to 30 November 2020 is acquired from the database of "National Meteorological Information Centre" (http://data.cma.cn), whereas the National Health Commission is used to acquire data for the number of NCOV-2019 new cases and deaths (http://www.nhc.gov.cn/). A daily pattern of air Pollutants emissions is shown in Fig. 2.

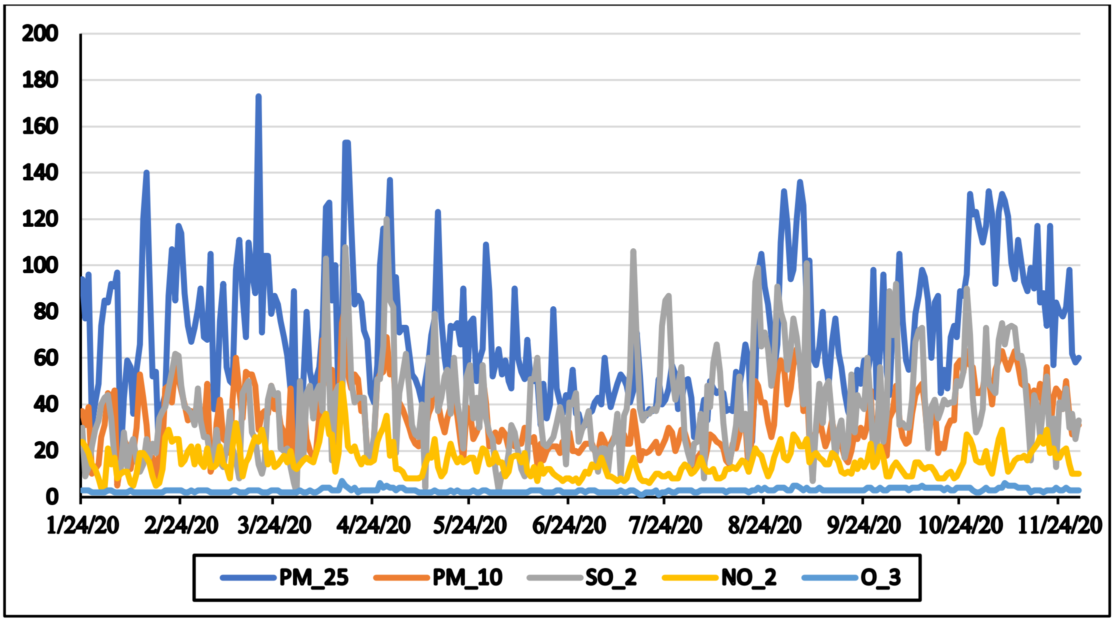

Figure 2 Average daily concentration of air pollutants

Table 1. Descriptive statistics of selected variables

	Mean	Std	Minimum	Maximum
Pop_density	484.00	726.33	8	3829
cases	523.55	411.45	17	1620
deaths	4.31	4.40	1	21
PM_{25}	91.24	23.81	8	128
PM_{10}	42.90	11.22	8	64
SO_2	38.55	14.71	2	52
NO_2	21.55	10.32	8	49

O_3	9.52	11.97	1	45

4. Results and Discussion

4.1. Air Pollutants and NCOV-2019 Nexus

This study considers the five major air pollutant concentrations for the time period between 24 January, 2020 to 30 November, 2020, to find out the associations between NCOV-2019 cases and the number of deaths, calculated on a daily basis. Focusing on the most consistent aggregation type reported for all air pollutants as explained through the analysis, the mean values of daily measurements are exclusively considered by the data, pertaining to the variation observed in the available data for each air pollutant. The spatial distribution for the number of NCOV-2019 cases observed on a daily basis, number of deaths and air pollutants are represented in Fig. 3. Considering the highest recorded deaths in Henan and Heilongjiang, following the Hubei province, the spatial pattern for number of deaths due to NCOV-2019 are aligned with the number of new cases on the basis of geographical distribution. Particulate matters and nitrogen dioxides concentration is recorded at a highest annual average value in the two given areas. On the basis of the ozone (O_3) concentration in the free troposphere, the transport emission, latitude and altitude are recorded to have affected the ground-level ozone concentrations in the past. This study assessed the relationship between the increase in the number of NCOV-2019 infections and the spatial changes in air pollutants (especially PM2.5, NO2 and O3) levels and the concentration of ground ozone in China.

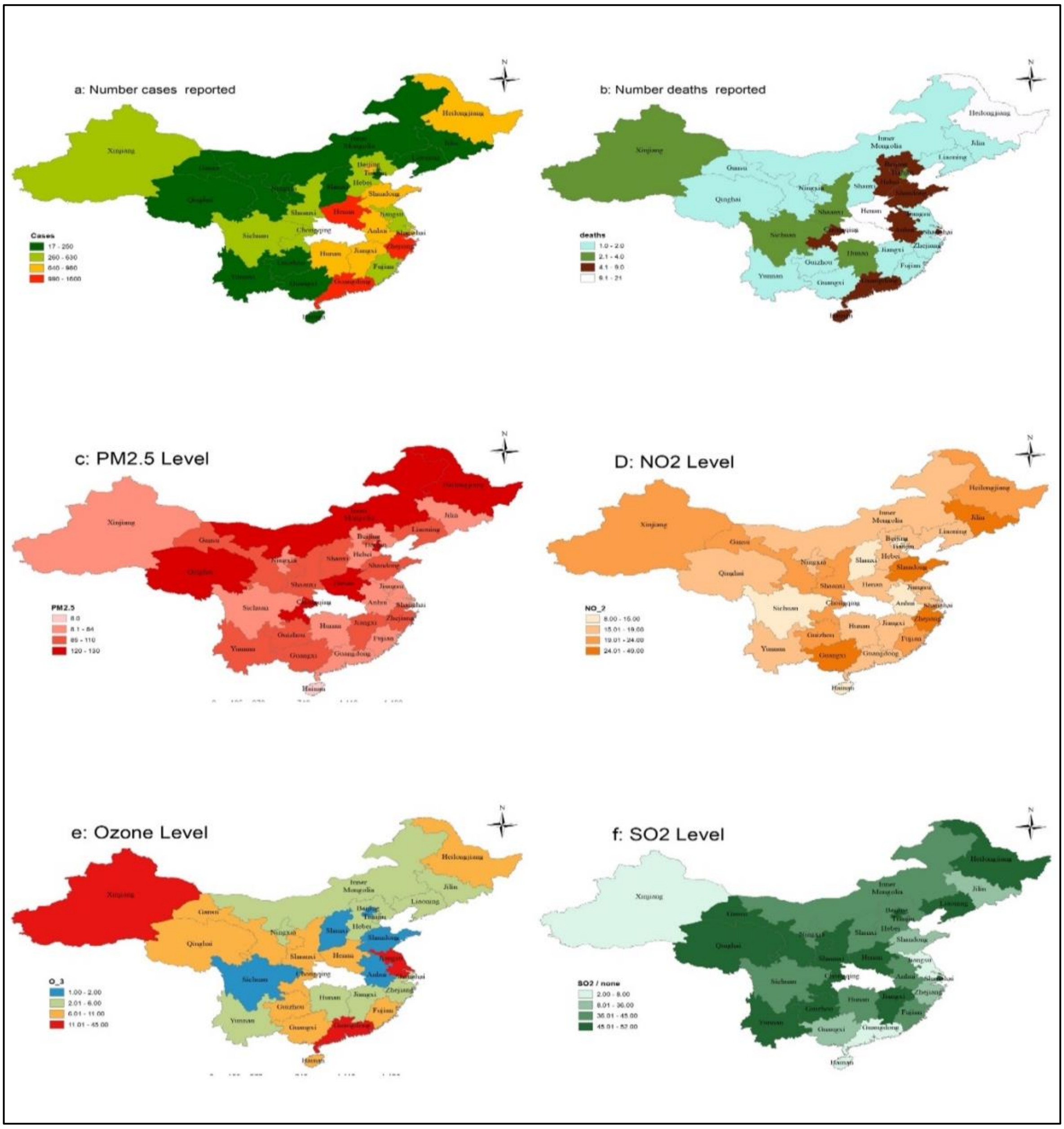

Figure 3. Provincial heat map of number of NCOV-2019 case, deaths and air pollutants

4.2. Analysis of Correlation Tests

The newly confirmed cases, number of deaths and air pollution variables on a provincial level are assessed with the help of Spearman and Kendall correlation tests as the variables are not distributed normally. Population density is said to affect the spread of COVID-19, indicated by the average population density (rs=0.42, rs=0.32) positively correlated to the number of accumulated cases and deaths at 1% significant level through the Kendall and Spearman correlation test, as shown in Tab. 2. NCOV-2019 cases and deaths have a positive correlation with the air pollution variables $PM_{2.5}$ (rs=0.16, rs=0.08), whereas a negative relationship is observed between PM_{10} and SO_2 . Moreover, valid slump effects of air pollution variables on transmission of NCOV-2019 are indicated by the positive correlation between NO_2 (rs=0.17, rs=0.08) and the considerable number of recently confirmed cases and number of deaths at 5% or higher. Tosepu et al., (2020) performed a similar study, which took Jakarta for the application of climate-related factors, whereas this study considers the stated factors with a focus on NCOV-2019 cases in China on a provincial level. Fig.4 reflects a moderate to weak relationship between population density and air pollution. Considering it's frequency in various provinces of China, significant information is gathered by the association between air pollutants and NCOV-2019 cases. Wasim et. al,(2020) proposed an increased risk of mortality in regard to its connection with the increase in $PM_{2.5}$ level in relation to the respiratory and cardiovascular diseases in thirty Asian countries,.

Table 2. Spearman and Kendall rank correlation tests results

	Spearman correlation coefficient		**Kendall correlation coefficient**	
	(Cases)	**(No. of Deaths)**	**(No. of cases)**	**(No. of Deaths)**
Pop_density	0.42***	0.32***	0.58***	0.41***
PM_25	0.16***	0.08***	0.19***	0.11***
PM_10	-0.14*	-0.03*	-0.17*	-0.02*
SO2	-0.14	-0.15	-0.20	-0.21
NO_2	0.17***	0.04***	0.25**	0.01***
O_3	-0.13***	0.03***	-0.21***	0.00***

Note: ***p-value<0.001 means 1% significance level; **p-value<0.01 means 5% significance level; * p-value<0.05 means 10% significance level.

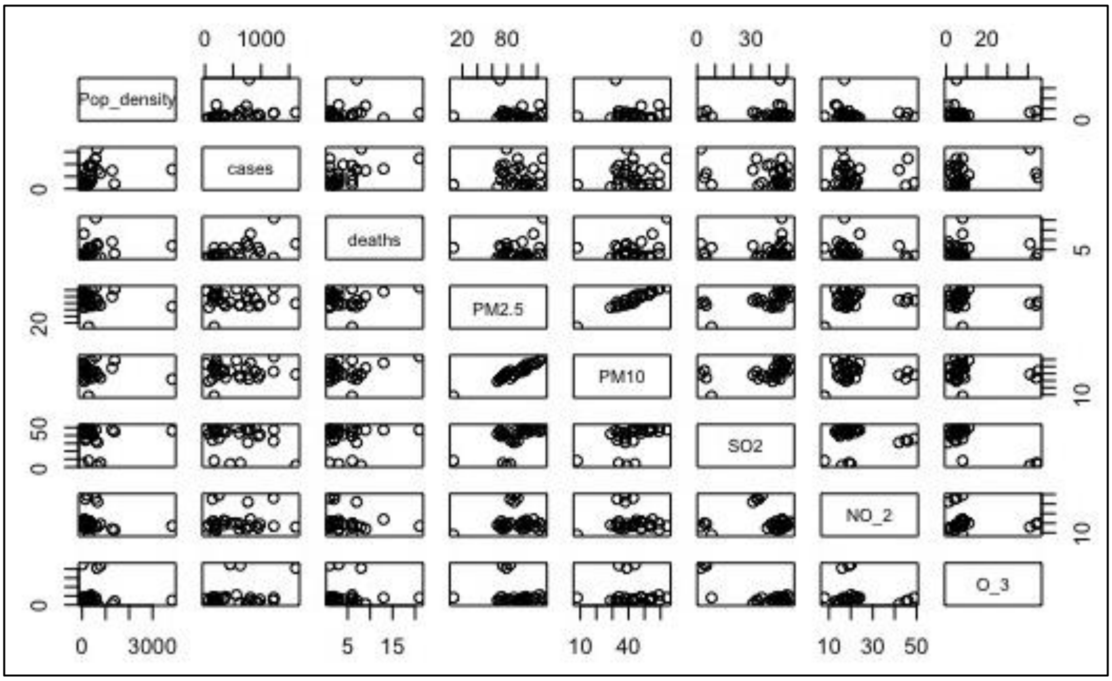

Figure 4. Correlation analysis between Air Pollutants and analysis daily NCOV-2019 confirmed cases and deaths

4.2. Estimation Results of Negative Binomial Regression

The association between air pollutant (MP2.5, PM10, NO2, SO2, O3) and the collective number of NCOV-2019 cases and deaths at provincial and regional levels for China is calculated with the help of a negative binomial regression model. Factors, such as data type, log likelihood and AIC scores are considered the top choices for this model. To validate the number of inhabitants throughout the provinces, population density is added to the model as an independent variable. The impact of air pollutants on NCOV-2019 cases in China on a provincial level is represented in Tab.3. According to the results, two significant predictors for NCOV-2019 cases ($p < 0.01$) include levels of particular matter (PM2.5), and nitrogen dioxide (NO2), regardless of the population density. At the significance level of 1% [0.1167332***; 95% CI: 0.00074,0.2247], $PM_{2.5}$ is positively related to the number of NCOV-2019 cases, depicting a significant 11.67% increase in the number of new cases for NCOV-2019 as a result of 1% increase in $PM_{2.5}$. Travaglio et al.(2021) validates the effect of $PM_{2.5}$ on the number of coronavirus cases, which is consistent with our findings. At 5% significance level [-0.047***;

95% CI: -0.10389-0.0098], the number of NCOV-2019 is correlated with the PM_{10} negatively. According to the results, at 1% significance level [0.0161756***; 95% CI: -0.00163-0.04992], NO_2 showed positive association with number of people infected with NCOV-2019. Moreover, SO_2 and O_3 also showed negative correlation with the case of NCOV-2019 at a substantial 5 percent level, suggesting that the decrease in air pollution is can prevent the invasion and spread of coronavirus (Zhang et al., 2021). A nonlinear dose-response relationship between the spread of coronavirus and air pollution is eminent through the results. SARS patients were said to die from pneumonia more than twice as likely according to a research carried out by researchers from the UCLA School of Public Health amidst the SARS outbreak in China. NCOV-2019 is also said to be highly affected by pollution, the same way as the previous diseases.

Table 2. Regression results of air pollutants on NCOV-2019 cases in China at the provincial level.

	Estimate	St. Error	Z_Value	Confidence Interval	Pr(>|z|)
Pop_density	0.0004***	0.00019	2.062	(0.00006,0.0008)	0.0003
PM2.5	0.1167***	0.0619	1.885	(0.00074,0.2247)	0.0005
PM10	-0.04705**	0.0309	-1.52	(-0.10389,0.0098)	0.0012
SO2	-0.0207**	0.0245	-0.843	(-0.0067,0.02627)	0.0033
NO2	0.0161***	0.01801	0.898	(-0.00163,0.04992)	0.0004
O3	-0.0086**	0.02494	-0.347	(-0.0057,0.03928)	0.0072
Intercept	5.7996***	0.8781	6.127	(3.95131,7.8539)	0.0000
Theta:	1.847	0.452			
log-likelihood:	-410.96				
AIC:	426.96				

Note: AIC: Stands for Akaike information criteria, ***p-value<0.001 means 1% significance level; **p-value<0.01 means 5% significance level; * p-value<0.05 means 10% significance level.

Tab. 4 represents a relationship between air pollutants ($PM_{2.5}$, PM_{10}, NO_2, SO_2 and O_3) levels and the number of NCOV-2019 deaths. In addition to population density, NCOV-2019 deaths are directly affected by the $PM_{2.5}$, nitrogen dioxide and ozone levels. At 1% significance level [0.1167: 95% CI: 0.00074,0.2247], $PM_{2.5}$ is related with the number of COVID_19 deaths positively, according to Tab. 3. Following the population density account, deaths caused by NCOV-2019 are predicted by NO_2 and O_3, a 1% significant level [0.0071***; 95% CI: -0.0250, 0.0393] is positively correlated with NO_2 , whereas deaths caused by NCOV-2019 are negatively associated with O_3 [-0.0480; 95% CI: -0.0891, -0.0075]. The relationship between the variation of air pollution in China on a provincial level and NCOV-2019 cases and the number of death is provided by this study for the first time. The two main contributors for an increased number in NCOV-2019 deaths, include $PM_{2.5}$, and NO_2 . Pollutants, such as PM_{10}, and SO_2 are not validated for affecting the number of NCOV-2019 deaths in China in any way. The first association between air pollution and NCOV-2019 deaths in the US is found by a Harvard study. The relationship between air pollution and death rates is supported by various recently conducted studies on NCOV-2019 in many countries.

Table 4. Regression results of air pollutants on NCOV-2019 deaths in China at the provincial level.

	Estimate	Std. Error	Z_Value	Confidence Interval	P_Value
Pop_density	0.0004***	0.0002	2.42	(0.0001, 0.0007)	0.0001
$PM_{2.5}$ level	0.1840***	0.0635	2.896	(0.07992, 0.2921)	0.0037
PM_{10} level	-0.0657	0.0312	-2.105	(-0.1198, -0.0130)	0.3528
SO_2 level	-0.0457	0.0232	-1.969	(-0.0860, -0.0062)	0.4898
NO_2 level	0.7123***	0.0176	0.405	(0.0250, 0.993)	0.0006
O_3 level	-0.0480***	0.0235	-2.035	(-0.0891, -0.0075)	0.00041
Intercept	1.2654***	0.8781	1.441	(-0.1554, 2.6982)	0.0001
Theta	4.29	2.16			
log-likelihood:	-130.128				
AIC:	146.13				

Note: AIC: Stands for Akaike information criteria, ***p-value<0.001 means 1% significance level; **p-value<0.01 means 5% significance level; * p-value<0.05 means 10% significance level.

According to Fig. 5, provinces with higher population density have a higher number of NCOV-2019 cases, evident through the moderate relationship between population density and the number of NCOV-2019 cases, depicted by the R square value (0.5118). It can be concluded from current research and study that NCOV-2019 cases are affected by many variables (i.e., economic conditions, genetic factors, changes in population disorders, geographical climate, health care systems, number of tests, and variations in age). The various possible dependencies cannot be calculated, pertaining to the lack of a basic direct and explicit method. Therefore, more research needs to be conducted in order to solve the problems mentions above.

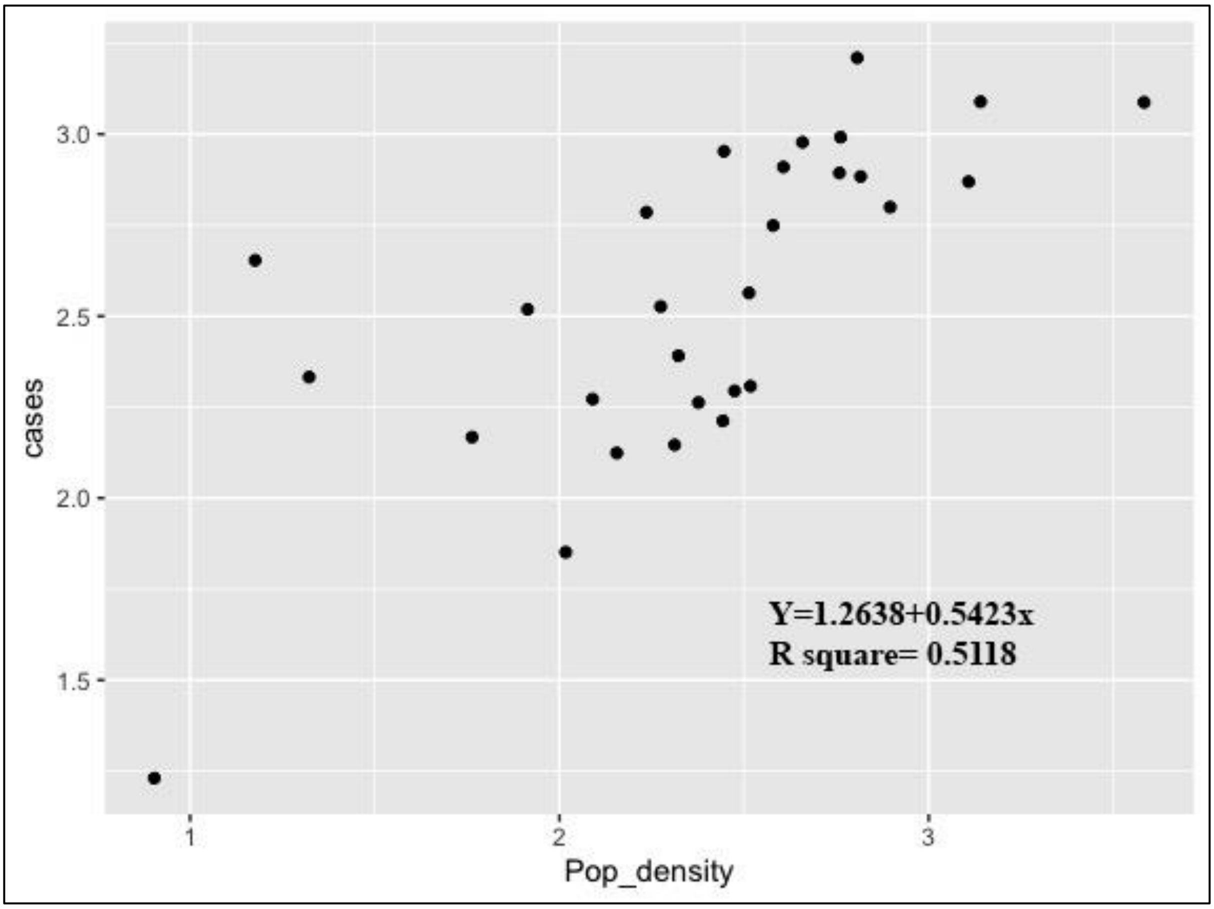

Figure 5. Relationship between population density and NCOV-2019 cases

4.3 Discussion and Comparison

The ability of our body to defend itself against infections becomes limited as it experiences chronic respiratory stress and therefore, a polluted environment means a polluted body. People are more susceptible to contracting NCOV-2019 due to the harmful exposure of pollutants (e.g., $PM_{2.5}$ and NO2) causing serious damage to health, particularly causing respiratory and lung diseases. The effects of air pollution on the recently confirmed cases and number of deaths in China due to NCOV-2019 are calculated by a negative binomial regression model, depicting a significant correlation between air pollutants and number of NCOV-2019 cases and deaths. The findings of the study represents that 11.67% (95% CI: 0.074%, 22.47%) increase in the NCOV-2019 new case and an 18% (95% CI: 7.992%, 29.21%) in the number of deaths occurs with 1% increase in long-term exposure to $PM_{2.5}$. The significant association between NCOV-2019 cases and deaths with long-term exposure to $PM_{2.5}$ is evident by our study. By adjusting various demographic and health-related confounders, Our findings are similar to other studies conducted in China, France, the United States, and the United Kingdom . These studies evaluated the long-term effects of $PM_{2.5}$ on NCOV-2019 cases and deaths, our findings are consistent with the observations made by studies done in the US and Northern Europe (Konstantinoudis et al., 2020). A recent study by Wang et al.(2020) has shown a significant reduction of $PM_{2.5}$ emissions in China during the lockdown. Another study in United States also assessed the impact of PM2.5 on COVID-19 mortality. Their exposure model has been verified, and the annual estimate $R^2 = 0.89$. The evidence of $PM_{2.5}$ is very weak, that is to say, every increase of 3.4μg/m3 in $PM_{2.5}$ concentration after adjustment will increase by 10.8% (95%CI: -1.1%, 24.1%) (each increase of about 3.2%) 1μg/ m3). The strict and stringent steps to control the worldwide spread of NCOV-2019 had an exceptional environmental impact by significantly reducing pollutant emissions, particularly $PM_{2.5}$ concentrations.

Moreover, the studies evaluated the long-term effects of NO_2 on NCOV-2019 cases and deaths, our findings are consistent with the observations made by studies done in the US and Northern Europe (Konstantinoudis et al., 2020). A 2% (95% CI: -0.00163,0.04992) and 7.2%(95% CI: 0.0250%, 0.993%) increase in the number of NCOV-2019 cases and deaths is evident by the increase in long-term exposure of NO_2 to 1%. Our findings are in line with a study conducted in 335 cities in the Netherlands showed that the average exposure level during the period 2015-2019 and the COVID-19 death report on June 5, 2020 showed that for every increase of 1 μg/m3 in NO_2, the number of COVID-19 deaths will be increase by 0.35 (95% CI: 0.04, 0.66). Similarly, the discontinuation of industrial activities in this period has minimized harmful wastes that stem from the recovery of the environment and, most notably, reduced $PM_{2.5}$, NO_2 and O_3 concentrations to a certain extent (Ataguba, 2020). Studies have revealed that NCOV-2019 is transmitted from China to other parts of the world through the medium of air, and air pollution is considered a carrier of coronavirus (Sciomer et al., 2020) and (Bashir et al., 2020). In such situations, there is a clear scope to provoke appropriate public health intrusions and robust policies that reassess our lives and have a marginal effect on the environment and individual lives.

In addition, there is a negative correlation between the levels of O_3 and the number of new cases of COVID-19, and deaths can be due to decreased conversion of nitrogen oxide to ozone in urban areas, a phenomenon previously recorded in highly trafficked areas. A nonlinear relationship between nitrogen oxides and ozone is found, regardless of the gasses constituting the key ozone precursors. Scavenging close to where its emitted and consistent with an increase in nitric oxide, an inverse relationship between ozone levels and NCOV-2019 is seen due to the highly reactive nature of ozone. A substantial relationship is not found between the number of NCOV-2019 deaths and the other pollutants, such as PM_{10}, SO2. (Tang et al., 2014) validates these findings and are consistent with the studies conducted during the previous SARS outbreak on how long-term exposure to pollutants has caused harmful effects to the patients suffering from SARS in China the past.

5. Conclusions and Policy Implications

Both coronavirus and air pollution can cause or exacerbate respiratory health problems. The latest research argue that long-term exposure to air pollution will not only affect the severity and vulnerability of COVID-19, but also adversely affect the respiratory system and increase the risk of death. This study examines the air pollution impact on the transmission of NCOV-2019 in China, using data from 24 January to 30 November 2020 on newly reported cases from 29 provinces (excluding Hubei province to remove the effects of endogenous control and extreme values). The study uses the NBR (negative binomial regression) model to evaluate air contaminants' (MP2.5, PM10, NO2, SO2, O3) correlation with the number of cases of both NCOV-2019 and deaths at Chinese provincial and regional levels. The model is selected according to the data format, AIC and log likelihood score. As an independent variable to account for variations in the number of inhabitants across the provinces, population density (a confusing factor) was applied to this model. Empirical outcomes of the negative binomial regression model analysis show that:

- $PM_{2.5}$ emissions are significantly positively correlated with the number of NCOV-2019 cases and deaths. A 1% increase in PM2.5 resulted in a 11.67% increase in new NCOV-2019 cases and an 18% increase in NCOV-2019 deaths.
- The number of NCOV-2019 cases and deaths rose by 2.00 percent and 7.2 percent, respectively, with a 1 percent rise in long-term exposure to NO2.
- There is a negative correlation between O_3 and the number of new NCOV-2019 cases and fatalities.
- There was no substantial relation between the number of deaths from NCOV-2019 and other contaminants, including PM_{10} and SO_2.

Environmental pollution, which leads to environmental destruction, is a product of human actions. Because of the NCOV-2019 pandemic, public perception of environmental issues is expected to increase. There are some practical effects of the results of this study. In the process of preventing and predicting the spread of the coronavirus, air pollutant indicators are crucial and indispensable. To avoid the coronavirus pandemic, colder regions of the world should adopt stricter measures. Air pollution has a significant and credible impact on the spread of coronavirus and is of great significance for mitigation policies needed to avoid and predict the spread of other new epidemics. China should step up its efforts to transform the energy system from coal to clean energy, especially in power generation and house heating. In addition to industrial production and transportation, this is also the main source of air pollution. Similarly, if the new coronavirus coexists with humans for a long time, all countries should adopt anti-epidemic policies. On a global scale, immediate measures must be taken to reverse climate deterioration, change habitats, and decentralize international cooperation and monitoring of sustainable development.

Furthermore, the research results conclude that the current NCOV-2019 epidemic and epidemics similar to NCOV-2019 can not only be solved through medical research and practice, but also interdisciplinary scientific research must be conducted on the basis of environmental and sustainable science. There are some challenges in conducting such research on the factors that determine the infectious spread of the virus. In order to develop appropriate sustainable policies to reduce infections, more detailed studies on the spread of NCOV-2019 are needed, which requires a complex relationship between environmental and atmospheric factors. Air pollution and indirect interaction with viral vectors may have a negative impact on the country's public health.

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