

Climate indicators and COVID-19 recovery: A case of Wuhan city during the lockdown

Zhai Shuai

School of Business Huzhou University, Huzhou, Zhejiang, China

Zeeshan Fareed (✉ zeeshanfareed@hotmail.com)

School of Business Huzhou University, Huzhou, Zhejiang, China

Najaf Iqbal

School of Finance Anhui University of Finance and Economics, Bengbu, China

Farrukh Shahzad

School of Economics and Management, Guangdong University of Petrochemical Technology, Guangdong, China <https://orcid.org/0000-0003-1971-8867>

Yong Yan

School of Business Huzhou University, Huzhou, Zhejiang, China

Research Article

Keywords: COVID-19 recovery, Wuhan, Environment, Pollution, Quantile on Quantile Regression

Posted Date: August 31st, 2020

DOI: <https://doi.org/10.21203/rs.3.rs-68229/v1>

License:  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Version of Record: A version of this preprint was published at Environment, Development and Sustainability on September 23rd, 2021. See the published version at <https://doi.org/10.1007/s10668-021-01794-2>.

Climate indicators and COVID-19 recovery: A case of Wuhan city during the lockdown

Abstract

The world needs to get out of the COVID-19 pandemic smoothly through a thorough socio-economic recovery. The first and the foremost step towards this process is the recovery of the people affected medically (COVID-19 patients). This is probably the first empirical study discussing the recovery from COVID-19 disease, and specifically aiming at exploring the environmental impact on COVID-19 recovered patients. The sample data is taken during the lockdown period in Wuhan from 23rd January 2020 to 8th April 2020. The novel econometric technique of Quantile-on-Quantile regression, recently proposed by Shin and Zhu (2016), is employed to capture the asymmetric association between environmental factors (TEMP, HUM, PM_{2.5}, PM₁₀, CO, SO₂, NO₂, and O₃) and number of recovered patients from COVID-19 disease. We observe the heterogeneity among the variables across different quantiles of both independent and dependent variables. The findings suggest that TEMP, PM_{2.5}, PM₁₀, CO, NO₂, and O₃ are negatively related to the COVID-19 recovery, while HUM and SO₂ show a positive association at most of the quantiles. The study recommends that maintaining a safe and comfortable environment for the patients may increase the number of recovered cases from COVID-19. The success story of Wuhan, the initial epicenter of the novel coronavirus in China can serve as an important case study for other countries to bring the outbreak under control. The current study could be conducive for the policymakers of those countries where the COVID-19 pandemic is still unrestrained.

Keywords: COVID-19 recovery, Wuhan, Environment, Pollution, Quantile on Quantile Regression.

Introduction

The recent outbreak of COVID-19 disease throughout the world has created unprecedented uncertainty in each and every sector of the economy, politics, and public health. The total number of infections has reached 7.15 million, while 407,326 patients are dead and 3.32 million have come out as triumphant (recovered) as of June 9, 2020 (Center for Science & Systems Engineering, Johns Hopkins University). The situation varies greatly across the countries as some have seen the peak (Europe) while others are still at the beginning stages (South American and South Asia). As COVID-19 pandemic is slowing down in many countries of the world recently, the efforts to develop a vaccine or cure are also entering a crucial stage of success. The socio-economic disorder brought to the world by this disease can only be dealt with a step-wise approach. While there is a fierce debate in the world about creating a balance between the public health and economic recovery in case of any policy formulation including lockdowns, we believe that the health/medical recovery of the COVID-19 patients must be considered as the most critical step forward in this long process. There is no price/alternative of even a single human life and there would be no economy without a healthy public.

The city of Wuhan where it all started has ended the 76-days-long lockdown, and life is returning to almost normal there while other countries are still struggling. Wuhan's case is important for the rest of the world and can serve as a guide for understanding different aspects of the COVID-19 pandemic. Figure 1 demonstrates the current scenario of the COVID-19 situation on the map of China. Until a reliable cure is discovered or a vaccine developed, there is no sign of herd immunity as the WHO reports no evidence of patients' immunity after recovery from this disease. A study and retest on five medical personnel in Wuhan who were infected and already recovered from COVID-19 showed that they caught the virus again, though remained asymptomatic later (Lan et al., 2020). Similar results have been reported in other related studies also (Xing et al., 2020). As vaccines can take as long as 12-15 months to develop, even following a fast track, the need of the hour points a finger towards the other forms of prevention and a better understanding of COVID-19 interaction with the environment and beyond can be helpful to prevent the harmful impact of environmental pollution in aggravating the situation. Figure 2 shows the time trend of daily new recovered patients from COVID-19 during the lockdown in Wuhan.

[INSERT FIGURE 1 HERE]

[INSERT FIGURE 2 HERE]

An enormous amount of research is being conducted on the interaction of COVID-19 outbreak and other factors related to health care, public policy, social distancing measures, lockdown, and atmosphere, etc. Some of these research articles studied the interaction of climate indicators (temperature, humidity, air quality index) and COVID-19 infections and mortality, specifically for Wuhan city (Iqbal et al., 2020; Ma et al., 2020). Most of these studies are using daily new COVID-19 infections in the research process, and little attention has been given to the recovered cases until now. Table 1 describes the detailed list of the literature review on the relationship between environmental factors and COVID-19 cases.

[INSERT TABLE 1 HERE]

Recovered cases are equally important for studying as they reveal the process of desired outcomes after a huge number of infections. As Wuhan has completed its cycle of susceptible, exposed, infected, and recovered (SEIR), it is hugely beneficial to know the interaction of recovered cases with the climate indicators there (Zhang et al., 2020). Figure 3 illustrates the time trend of different climatological indicators during the lockdown period in Wuhan. So, we attempt to check the non-linear association between climate indicators and recovered cases in Wuhan city using quantile on quantile (QQ) regression-based analysis. The outcome of this study can be beneficial for the rest of the world to expedite recovery by better understanding the environmental interaction with this disease where the COVID-19 pandemic is still spreading the havoc. The quantile on quantile (QQ) based regression approach is especially useful where the relationship between the variables of interest is expected to be non-linear and asymmetric. It has recently been used in the COVID-19 related studies in the city of Wuhan (Shahzad et al., 2020).

[INSERT FIGURE 3 HERE]

A group of medical science researchers conducted an experiment on the difference of features associated with the dead and the recovered patients from COVID-19 in Wuhan. They found that patients with pre-existing medical conditions, older in age, having a large count of white blood cells, low count of lymphocytes, acute lung disease, and acute cardiac injury were abundant in the dead group (Deng et al., 2020). Many of these diseases may get worsened after exposure to bad environmental conditions.

Exposure to air pollution can have a devastating impact on pneumonia patients also, and this

disease is the second largest to have shortened the human lives on earth (Jary et al., 2015). Millions of people die each year because of health complications arising from exposure to air pollution. Children are more vulnerable as pneumonia and air pollution seem to be correlated for their age group (Jary et al., 2017). Air pollution is a major source of complicating respiratory issues in humans. Since patients with preexisting lung infections are more vulnerable in the case of being infected with COVID-19, it seems very important to provide them and others with a cleaner atmosphere for a smooth recovery.

In spite of an expected critical role of air pollution in COVID-19 related recoveries, no one has studied the relationship between these two variables (climate indicators and COVID-19 recoveries) up to the best of our knowledge till now. So, we attempt to fill this research gap by checking the impact of all contributing factors of air quality index (PM_{2.5}, PM₁₀, CO, SO₂, and NO₂) and weather (temperature and humidity) on the COVID-19 related recoveries in the city of Wuhan, China.

Data and Research Methodology

Data

To investigate the asymmetric impact of the air quality factors and weather on COVID-19 recovered cases, the present study has selected the lockdown period from 23rd January 2020 to 8th April 2020 in Wuhan, China as the research sample. The daily data of air quality factors were manually obtained from the online platform (<https://www.aqistudy.cn>). These six factors include (1) Particles with diameters $\leq 10 \mu\text{m}$ (PM₁₀), (2) Particles with diameters $\leq 2.5 \mu\text{m}$ (PM_{2.5}), (3) Carbon monoxide (CO), (4) Ozone (O₃), (5) Sulfur dioxide (SO₂) and (6) Nitrogen dioxide (NO₂). The variables such as temperature and humidity are calculated by averaging the hourly observations collected from another online platform (<https://www.wunderground.com>). The daily data of COVID-19 recovered cases were manually extracted from the official website of the Chinese National Health Commission (CNHC, <http://www.nhc.gov.cn/>).

Research Methodology

In this portion, we briefly explain the dynamic features of the Quantile-on-Quantile (QQ) regression recently proposed by Sim & Zhou, (2015) and its model description to determine the asymmetric nexus between environmental factors and COVID-19 recovered patients. The QQ is a more generalized form of basic quantile regression approach. This novel QQ approach enables us to analyze how quantiles of one variable affect the conditional quantiles of another variable. This

technique theoretically considers the mixture of basic quantile regression and nonparametric estimations. Firstly, the quantile regression was developed by (Koenker & Bassett, 1978) to investigate how quantiles of independent variables affect the conditional means of the dependent variable. Secondly, quantile regression is the extended version of the classical linear regression method (CLRM). In contrast to the ordinary least square regression, the quantile regression identifies the impact of explanatory variables on dependent variable at top, medium and lower quantiles' distributions, thus aiding us to evaluate the comprehensive association between the variables at different periods of time. Thirdly, Stone (1977) and Cleveland (1979) proposed a local linear regression model that is used to determine the local impact of the specific quantile of the explanatory variable on the fitted values of dependent variables. This approach is added to develop the final methodology of QQ regression.

Moreover, the local linear regression approach deals well with the problem of “curse of dimensionality,” which is not tackled by non-parametric estimations. The main motivation behind using the local linear regression model is to fit linear regression estimation locally around the nearest region of each point of data in the given sample by assigning more weights to the nearer data points. Thus, the amalgamation of these two methods enable us to assess the association between quantiles of both independent and dependent variables and delivers deeper information as compared to the conventional methods such as quantile regression or ordinary least squares.

The current research agenda aims to apply Quantile-on-Quantile (QQ) approach to capture (a) the quantiles' impact of climatological factors (TEMP, HUM, PM_{2.5}, PM₁₀, SO₂, NO₂, CO, O₃) on the quantiles of COVID-19 recovered cases. For this purpose, the following nonparametric quantile regression models are proposed.

$$COV19_REC_t = \beta^\varphi(CLMF_t) + \mu_t^\varphi \quad (1)$$

Where $COV19_REC_t$ denotes the daily coronavirus recovered patients while $CLMF_t$ shows the climatological factors ($TEMP_t, HUM_t, PM_{2.5_t}, PM_{10_t}, SO_{2_t}, NO_{2_t}, CO_t$ and O_{3_t}). φ is the φ th quantile of uncertain distributions of $CLMF_t$, and μ_t^φ is the residual term with zero φ -quantile. $\beta^\varphi(.)$ is

an unknown function because we do not have prior evidence about the relationship between $CLMF_t$ and $COV19_REC_t$.

The quantile regressions help to evaluate the impact of $CLMF_t$ across different quantiles of $COV19_REC_t$. This regression method is flexible because it captures the functional dependency relationship between $CLMF_t$ and $COV19_REC_t$. Flexibility is the main benefit of this method because no prior hypothesis exists about the functional dependency between $CLMF_t$ and $COV19_REC_t$. However, quantile regression overlooks the nature of dependency between the variables which is the constraint of this method. In this way, quantile regression does not count the behavior of positive and negative shocks of $CLMF_t$ that could also influence the association between $CLMF_t$ and $COV19_REC_t$. For example, the association between $CLMF_t$ and $COV19_REC_t$ might be different in different periods of economic cycles. Hence, Sim and Zhou (2015) provide a comprehensive QQ approach that can capture the dependency association between $CLMF_t$ and $COV19_REC_t$. Then, in order to find the linkage between φ th quantile of $CLMF_t$ and τ th quantile of $COV19_REC_t$, the local linear regressions are estimated for equation (1) in the neighborhood of $CLMF_t$. The regression function can be extended due to the unknown function of $\beta^\varphi(\cdot)$ with the help of first-order Taylor expansion around a quantile of $CLMF_t$ as under;

$$\beta^\varphi(CLMF_t) \approx \beta^\varphi(CLMF^\tau) + \beta^{\varphi'}(CLMF^\tau)(CLMF_t - CLMF^\tau) \quad (2)$$

Where $\beta^{\varphi'}$ denotes the partial derivative of $\beta^\varphi(CLMF_t)$ for climatological factors in equation (2), unfolding marginal effect. Yet, it provides the same explanation to the slope of the coefficients in the linear regression framework. Moreover, following Sim and Zhou (2015), $\beta^\varphi(CLMF^\tau)$ can be renamed as $\beta_0(\varphi, \tau)$. Accordingly, we can reformulate the equations (2) as under;

$$\beta^\varphi(CLMF_t) \approx \beta_0(\varphi, \tau) + \beta_1(\varphi, \tau)(CLMF_t - CLMF^\tau) \quad (3)$$

By subtracting equation (3) from equation (1), we can get Eq. (4).

$$COV19_REC_t = \underbrace{\beta_0(\varphi, \tau) + \beta_1(\varphi, \tau)(CLMF_t - CLMF^\tau)}_* + \mu_t^\varphi \quad (4)$$

In described equation (4), the (*) shows the φ th conditional quantile function of $COV19_REC_t$. Due to the dual index of β_0 & β_1 in φ and τ , the standard quantile function conditionally reflects the true association between φ th quantile of $COV19_REC_t$ and τ th quantile of $CLMF_t$ in the given formula of equation (4). These parameters may produce different outputs based on φ th quantile of $COV19_REC_t$ and τ th quantile of $CLMF_t$. Moreover, there is no linear relationship anticipated at any point in time, hence, equation (4) measures the overall dependence relationship between $CLMF_t$ and $COV19_REC_t$ through their distribution. Finally, we provide estimated coefficients of climatological factors, as represented by b_0 and b_1 , in equation (5) by applying local linear regression contingent upon minimization problem. Moreover, \widehat{CLMF}_t and \widehat{CLMF}^τ are the estimated values of $CLMF_t$ and $CLMF^\tau$ in equation 2.

$$\min_{b_0, b_1} \sum_{i=1}^n \rho_\varphi \left[COV19_REC_{2t} - b_0 - b_1(\widehat{CLMF}_t - \widehat{CLMF}^\tau) \right] K \left(\frac{F_n(\widehat{CLMF}_t) - \tau}{h} \right) \quad (5)$$

Where $\rho_\varphi(\cdot)$ shows quantile loss function and $K(\cdot)$, the Gaussian kernel function in both the minimization problems as minimal weighting criterion to improve the estimation efficiency. The selection of bandwidth, h , in this non-parametric QQR approach is very crucial as it determines the smoothness of the estimated coefficients. Following Sim and Zhou (2015) and Arain et al., (2019), we have selected 5 percent ($h=0.05$) bandwidth of density function for optimal parameters of quantiles-on-quantiles approach.

Results and discussion

[INSERT TABLE 2 HERE]

Table 2 reports the descriptive statistics and the results of unit-root tests such as Dickey and Fuller, (1979) and Zivot and Andrews, (2002). The mean value of daily new COVID-19 recovered patients is 601.532 in Wuhan which is very high, indicating the success story against the COVID-19. The average temperature is 11.34°C which shows that Wuhan was a little colder during the epidemic. The average humidity is 70.60% which was moderate. The average daily concentrations of PM_{2.5}, PM₁₀, NO₂, CO, O₃, and SO₂ were 16.53 µg/m³, 70.60 µg/m³, 38.24 µg/m³, 8.11 µg/m³, 0.903 µg/m³ and 51.70 µg/m³, respectively. The Jarque-Berra (JB) test shows the normality of the data distribution. The JB findings are statistically significant for all the variables except CO. Therefore, the non-normality of the variables shows asymmetric behavior which confirms that quantile on quantile regression is an appropriate approach to estimation here. The

results of ADF and ZA unit root tests show that all variables are significant at the first difference-1(1) and suggest that we can proceed further for QQR estimations.

[INSERT FIGURE 4 HERE]

Figure 4 shows the results of the correlation analysis of our variables of interest. The colored vertical bar on the right side shows the scale while the colored boxes inside the huge square show the magnitude and strength of the association. All variables show a negative association with COVID-19 recoveries, represented mainly by different shades of red color except CO, SO₂, and humidity (HUM), which show positive, neutral, and extremely weak positive associations, respectively.

[INSERT FIGURE 5 HERE]

Figure 5(a-h) presents the findings from Quantile-on-Quantile regression analysis. The slope of the coefficients $\beta_1(\varphi, \tau)$ are estimated, indicating the impact of τ^{th} quantiles of TEMP, HUM, PM_{2.5}, PM₁₀, CO, NO₂, O₃ and SO₂ on θ^{th} quantiles of COVID-19 recovered patients. We have observed significant heterogeneity between metrological factors and COVID-19 recovered cases.

Figure 5(a) shows the QQ result of the relationship between temperature and COVID-19 recoveries, which is almost dominantly negative, implying that an increase in temperature leads to a decrease in COVID-19 recoveries. Lower quartiles of temperature and COVID-19 recoveries are strongly and negatively related while interestingly the upper quartiles of COVID-19 recoveries weakly negatively related to lower quartiles of temperature. The overall scenario suggests a weak positive to the negative association between temperature and COVID-19 recoveries in Wuhan. The mixed result is consistent with the earlier studies related to the role of temperature in COVID-19 infections in Wuhan (Iqbal et al., 2020; Jahangiri et al., 2020; Shi et al., 2020).

Figure 5(b) displays the impact of humidity on COVID-19 recoveries which is negative with a prominent, blue-colored, and downward spike at lower quartiles of humidity and lower-middle quartiles of COVID-19 recoveries. The middle quartiles of humidity and COVID-19 recoveries are representing neutral to positive association mostly. The upper quartiles of both the variables are flat, suggesting an insignificant relationship. Earlier studies show a negative association between an increase in humidity and daily additional COVID-19 infections (Qi et al., 2020). The QQ results of this study show that an increase in humidity does play a significant role in increasing

COVID-19 recoveries, consistent with the findings of the earlier studies.

Figure 5(c) shows the results from the QQ regression of COVID-19 recoveries on $PM_{2.5}$, revealing a negative association between these two variables. Dark, light and sky-blue colors scattered throughout the graph show that an increase in pollution ($PM_{2.5}$) caused a slow-down in COVID-19 recoveries. The upper quartiles of COVID-19 recoveries show a mild negative association with almost all the quartiles of $PM_{2.5}$ while a strong negative association represented by the dark red color is observable in the 50th to 70th quartiles of COVID-19 recoveries with 10th to 30th and 70th to 95th quartiles of $PM_{2.5}$, respectively. The previous research observed a positive relationship between $PM_{2.5}$ and COVID-19 daily new confirmed cases (Zhu et al., 2020). However, we have taken daily new recovered cases, which are negatively related to $PM_{2.5}$. Hence, we can say that the overall scenario of this portion of the results is similar to the previous research.

The impact of another environmental pollutant, PM_{10} , on the COVID-19 recoveries is given dominantly by the red-colored graph in Figure 5(d). This result shows that the level of PM_{10} in the air is positively linked with COVID-19 recoveries. Almost all quartiles of PM_{10} have a positive impact on all the quartiles of COVID-19 recoveries except the 20th quartile of PM_{10} on the 50th quartile of COVID-19 recoveries which is blue in color representing a strong negative association. Although it is counter-intuitive but similar results have been reported in other related studies recently, with the COVID-19 daily new cases (Zhu et al., 2020). The overall findings signify the asymmetric relationship between COVID-19 recoveries and PM_{10} through different quartiles' patterns.

As evident from figure 5(e), the association between SO_2 and COVID-19 recoveries is dominantly mixed in nature as shown by the blue, light green, red, light blue and light-yellow colors scattered throughout the graph, in different quartiles-combinations. 20th to 40th quartiles of SO_2 affect 50th and 70th to 80th quartiles of COVID-19 recoveries positively but weakly. Lower to middle quartiles of SO_2 affect lower (up to 20th) quartiles of COVID-19 recoveries strongly positively. The upper quartiles of SO_2 are indicating a weak relationship (positive and negative) with middle and upper quartiles of COVID-19 recoveries. Overall results of this graph show a mixed and non-deterministic relationship between SO_2 and COVID-19 recoveries and these results are also

consistent with the recent literature (Pansini & Fornacca, 2020; Zhu & Xie, 2020b).

Figure 5(f) shows the coefficients resulting from the QQ regression between NO₂ and COVID-19 recoveries. It is notably a negative association represented by the scattered bluish colors throughout the graph with very few red spots. The upper quartiles (60th to 100th) of NO₂ show a very strong and negative impact on the lower quartiles of COVID-19 recoveries represented by a dark blue colored downward spike. These findings support the results of yet another recent study (Ogen, 2020).

From Figure 5(g), the impact of CO on COVID-19 recoveries is also negative predominantly like other pollution factors, with only a few exceptions. Almost all the quartiles of CO affect the lower quartiles (up to 20th) of COVID-19 recoveries positively. The lower and lower-middle quartiles of CO show a strong negative association with the upper (90th) quartile of COVID-19 recoveries. The findings are parallel to the outcomes of a recent study (Zhu et al., 2020). The lower to middle quartiles of CO affect 50th to 60th quartiles of COVID-19 recoveries negatively while 60th to 100th quartiles of CO affect the same i.e. 50th to 60th quartiles of COVID-19 recoveries positively. The heterogeneous relationship confirms the non-linear/asymmetric association between CO and COVID-19 recovered patients.

Overall, O₃ has a weak and negative association with COVID-19 recoveries with a few areas of strong positive and strong negative relationships in figure 5(h). The quartiles 10th to 30th of O₃ show a strong negative association with lower i.e. up to 20th quartiles of COVID-19 recoveries as represented by the dark blue color. The results support the previous research (Zhu et al., 2020). Some red areas can be found at the intersection of lower and upper quartiles of O₃ with the middle quartiles of COVID-19 recoveries showing a positive association.

Conclusion

The most critical step forward in the process of any socio-economic recovery from the current COVID-19 pandemic must prioritize the public health. This paper examined the impact of temperature, humidity, and different components of air quality index on COVID-19 recoveries in the Wuhan city, using quantile on quantile (QQ) regression approach. This method helps to extract non-linear associations between different quartiles of the independent and dependent variables.

Temperature and humidity played a negative and positive role in COVID-19 recoveries, respectively. These results are consistent with recent literature on the interaction between weather and COVID-19 at various places around the world (Iqbal et al., 2020; Shahzad et al., 2020). Bad air quality affected COVID-19 recoveries negatively as indicated by the majority of the factors of air quality index, including CO, PM_{2.5}, PM₁₀, O₃, and NO₂. An exception is SO₂ which shows a positive association with COVID-19 recoveries. Another study related to COVID-19 and SO₂ found similar results, so the reason behind this phenomenon needs further investigation. Future research can be conducted to check the reverse impact of COVID-19 recovered cases on the metrological factors due to lockdown in different regions of the world.

Declarations

Declaration of Interest

The authors declare that they have no known competing for financial interests or personal relationship that could have appeared to influence the work reported in this paper. No funding was received for this research work. The dataset used during the current study are available from the website and are available on request.

ORCID

Zeeshan Fareed <https://orcid.org/0000-0003-1971-8867>

Farrukh Shahzad <https://orcid.org/0000-0002-1095-7207>

References

- Arain, H., Han, L., Sharif, A., & Meo, M. S. (2019). Investigating the effect of inbound tourism on FDI: The importance of quantile estimations. *Tourism Economics*. <https://doi.org/10.1177/1354816619859695>
- Bashir, M. F., Ma, B., Komal, B., Bashir, M. A., Tan, D., & Bashir, M. (2020). Correlation between climate indicators and COVID-19 pandemic in New York, USA. *Science of The Total Environment*, 138835.
- Briz-Redón, Á., & Serrano-Aroca, Á. (2020). A spatio-temporal analysis for exploring the effect of temperature on COVID-19 early evolution in Spain. *Science of The Total Environment*, 138811.
- Cleveland, W. S. (1979). Robust locally weighted regression and smoothing scatterplots. *Journal of the American Statistical Association*, 74(368), 829–836.
- Dantas, G., Siciliano, B., França, B. B., da Silva, C. M., & Arbilla, G. (2020). The impact of COVID-19 partial lockdown on the air quality of the city of Rio de Janeiro, Brazil. *Science of the Total Environment*, 729, 139085.
- Deng Y, Liu W, Liu K, Fang Y-Y, Shang J, Wang K, et al. Clinical characteristics of fatal and recovered cases of coronavirus disease 2019 (COVID-19) in Wuhan, China: a retrospective study. *Chinese medical journal* 2020.
- Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a), 427–431.
- Fareed, Z., Iqbal, N., Shahzad, F., Shah, S. G. M., Zulfiqar, B., Shahzad, K., ... Shahzad, U. (2020). Co-variance nexus between COVID-19 mortality, humidity, and air quality index in Wuhan, China: New insights from partial and multiple wavelet coherence. *Air Quality, Atmosphere & Health*. <https://doi.org/10.1007/s11869-020-00847-1>
- Iqbal, N., Fareed, Z., Shahzad, F., He, X., Shahzad, U., & Lina, M. (2020). Nexus between COVID-19, temperature and exchange rate in Wuhan City: New findings from Partial and Multiple Wavelet Coherence. *Science of The Total Environment*, 138916.
- Jahangiri, M., Jahangiri, M., & Najafgholipour, M. (2020). The sensitivity and specificity analyses of ambient

- temperature and population size on the transmission rate of the novel coronavirus (COVID-19) in different provinces of Iran. *Science of The Total Environment*, 138872.
- Jary H, Mallewa J, Nyirenda M, Faragher B, Heyderman R, Peterson I, et al. Study protocol: the effects of air pollution exposure and chronic respiratory disease on pneumonia risk in urban Malawian adults-the Acute Infection of the Respiratory Tract Study (The AIR Study). *BMC pulmonary medicine* 2015; 15: 96.
- Jary HR, Aston S, Ho A, Giorgi E, Kalata N, Nyirenda M, et al. Household air pollution, chronic respiratory disease and pneumonia in Malawian adults: a case-control study. *Wellcome open research* 2017; 2.
- Koenker, R., & Bassett, G. (1978). Regression Quantiles. *Econometrica*, 46(1), 33. <https://doi.org/10.2307/1913643>
- Lan L, Xu D, Ye G, Xia C, Wang S, Li Y, et al. Positive RT-PCR test results in patients recovered from COVID-19. *Jama* 2020; 323: 1502-1503.
- Ma Y, Zhao Y, Liu J, He X, Wang B, Fu S, et al. Effects of temperature variation and humidity on the death of COVID-19 in Wuhan, China. *Science of The Total Environment* 2020: 138226.
- Muhammad, S., Long, X., & Salman, M. (2020). COVID-19 pandemic and environmental pollution: A blessing in disguise? *Science of The Total Environment*, 138820.
- Ogen, Y. (2020). Assessing nitrogen dioxide (NO₂) levels as a contributing factor to coronavirus (COVID-19) fatality. *Science of the Total Environment*, 726, 138605. <https://doi.org/10.1016/j.scitotenv.2020.138605>
- Otmani, A., Benchrif, A., Tahri, M., Bounakhla, M., El Bouch, M., & Krombi, M. (2020). Impact of Covid-19 lockdown on PM₁₀, SO₂ and NO₂ concentrations in Salé City (Morocco). *Science of The Total Environment*, 139541.
- Pansini, R., & Fornacca, D. (2020). COVID-19 higher induced mortality in Chinese regions with lower air quality.
- Pirouz, B., Shaffiee Haghshenas, S., Pirouz, B., Shaffiee Haghshenas, S., & Piro, P. (2020). Development of an assessment method for investigating the impact of climate and urban parameters in confirmed cases of covid-19: a new challenge in sustainable development. *International Journal of Environmental Research and Public Health*, 17(8), 2801.
- Prata, D. N., Rodrigues, W., & Bermejo, P. H. (2020). Temperature significantly changes COVID-19 transmission in (sub) tropical cities of Brazil. *Science of the Total Environment*, 138862.
- Qi, H., Xiao, S., Shi, R., Ward, M. P., Chen, Y., Tu, W., ... Zhang, Z. (2020). COVID-19 transmission in Mainland China is associated with temperature and humidity: A time-series analysis. *Science of the Total Environment*, 138778.
- Şahin, M. (2020). Impact of weather on COVID-19 pandemic in Turkey. *Science of The Total Environment*, 138810.
- Shahzad, F., Shahzad, U., Fareed, Z., Iqbal, N., Hashmi, S. H., & Ahmad, F. (2020). Asymmetric nexus between temperature and COVID-19 in the top ten affected provinces of China: A current application of quantile-on-quantile approach. *Science of The Total Environment*, 139115.
- Shi, P., Dong, Y., Yan, H., Zhao, C., Li, X., Liu, W., ... Xi, S. (2020). Impact of temperature on the dynamics of the COVID-19 outbreak in China. *Science of The Total Environment*, 138890.
- Sim, N., & Zhou, H. (2015). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking and Finance*, 55, 1–8. <https://doi.org/10.1016/j.jbankfin.2015.01.013>
- Stone, C. J. (1977). Consistent nonparametric regression. *The Annals of Statistics*, 595–620.
- Tobías, A. (2020). Evaluation of the lockdowns for the SARS-CoV-2 epidemic in Italy and Spain after one month follow up. *Science of the Total Environment*, 138539.
- Tosepu, R., Gunawan, J., Effendy, D. S., Ahmad, L. O. A. I., Lestari, H., Bahar, H., & Asfian, P. (2020). Correlation between weather and Covid-19 pandemic in Jakarta, Indonesia. *Science of The Total Environment*, 138436. <https://doi.org/10.1016/j.scitotenv.2020.138436>
- Xing Y, Mo P, Xiao Y, Zhao O, Zhang Y, Wang F. Post-discharge surveillance and positive virus detection in two medical staff recovered from coronavirus disease 2019 (COVID-19), China, January to February 2020. *Eurosurveillance* 2020; 25: 2000191.
- Zhang Y, Yu X, Sun H, Tick GR, Wei W, Jin B. COVID-19 infection and recovery in various countries: Modeling the dynamics and evaluating the non-pharmaceutical mitigation scenarios. *arXiv preprint arXiv:2003.13901* 2020.
- Zhu, Y., & Xie, J. (2020a). Association between ambient temperature and COVID-19 infection in 122 cities from China. *Science of The Total Environment*, 724, 138201. <https://doi.org/10.1016/j.scitotenv.2020.138201>
- Zhu, Y., & Xie, J. (2020b). Association between ambient temperature and COVID-19 infection in 122 cities from China. *Science of The Total Environment*, 138201. <https://doi.org/10.1016/j.scitotenv.2020.138201>
- Zhu, Y., Xie, J., Huang, F., & Cao, L. (2020). Association between short-term exposure to air pollution and COVID-19

infection: Evidence from China. *Science of the Total Environment*, 727(December 2019), 138704. <https://doi.org/10.1016/j.scitotenv.2020.138704>

Zivot, E., & Andrews, D. W. K. (2002). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business & Economic Statistics*, 20(1), 25–44.

Zoran, M. A., Savastru, R. S., Savastru, D. M., & Tautan, M. N. (2020). Assessing the relationship between surface levels of PM2.5 and PM10 particulate matter impact on COVID-19 in Milan, Italy. *Science of The Total Environment*, 139825.

Figure 1 Map showing the latest epidemic situation in China

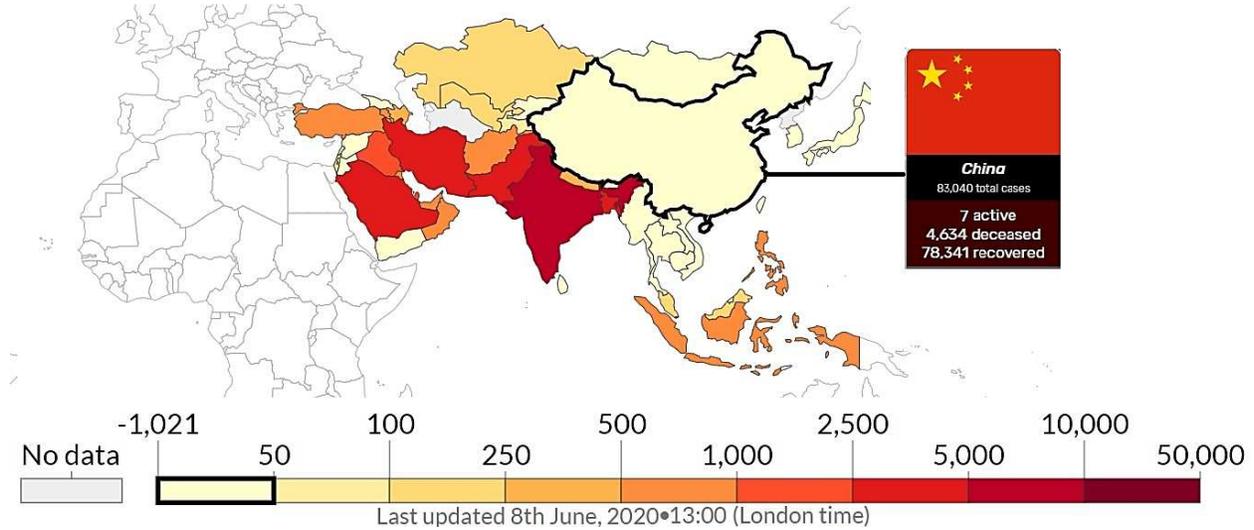


Figure 2 Daily new recovered patients from COVID-19 during the lockdown in Wuhan



Figure 3 Daily time trend of metrological factors during the lockdown period in Wuhan

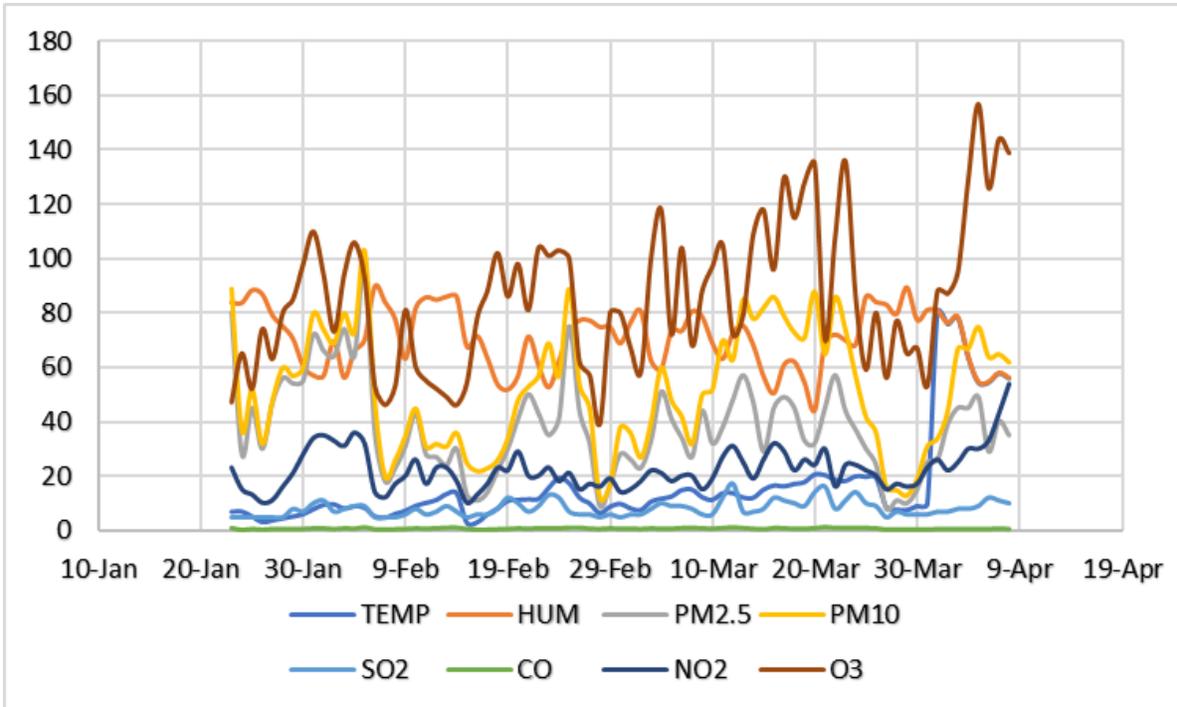


Figure 4 Correlation plot between variables

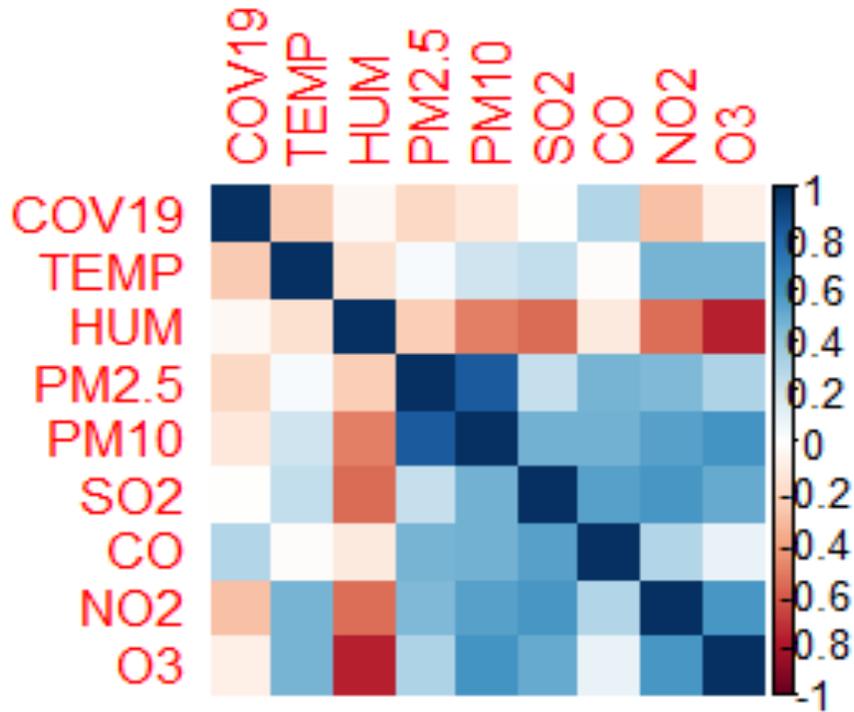
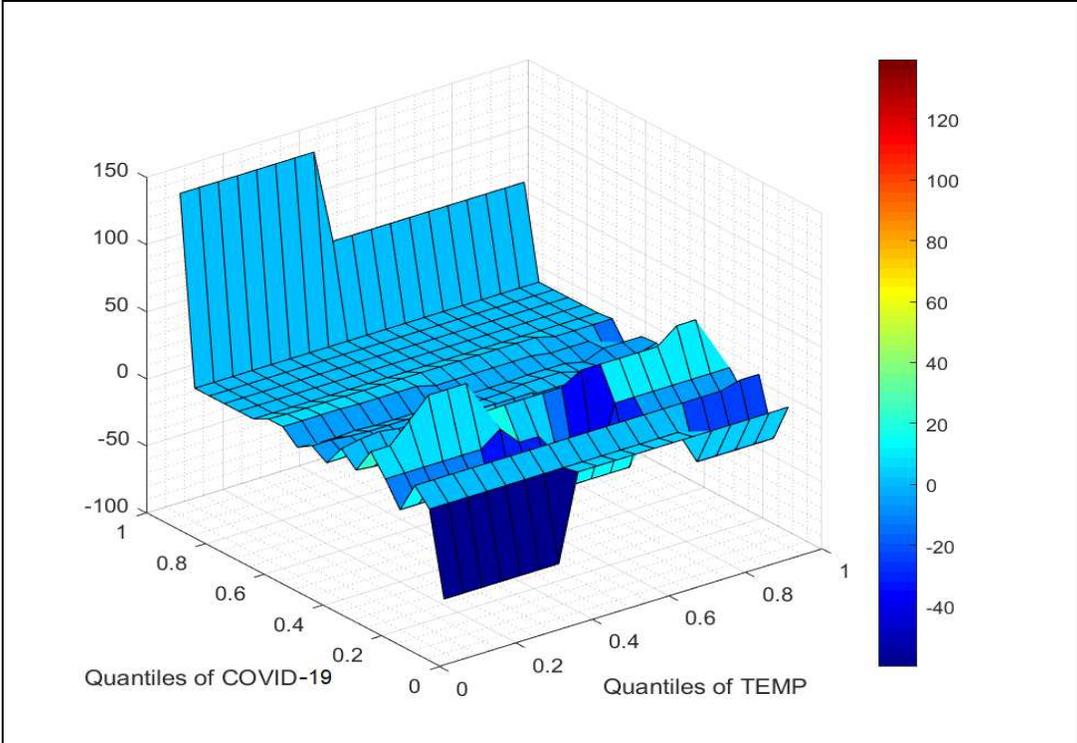
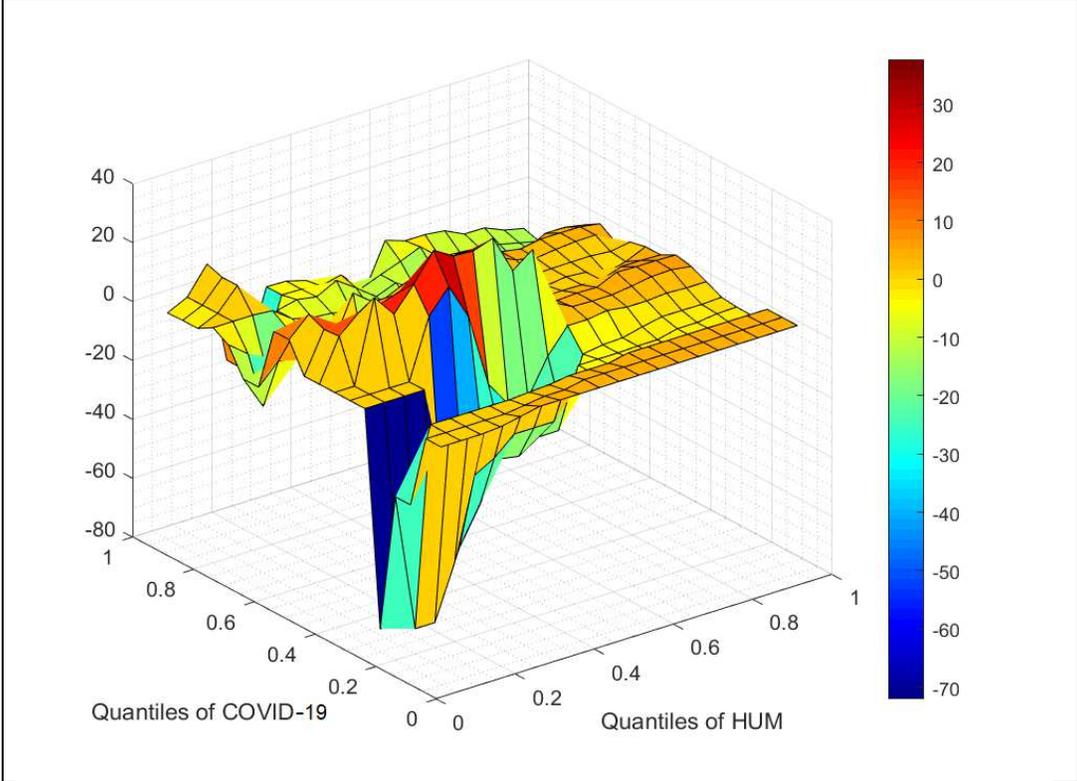


Figure 5. Quantile on Quantile regression estimates slope of the coefficients, $\hat{\beta}_1 = \theta\tau$

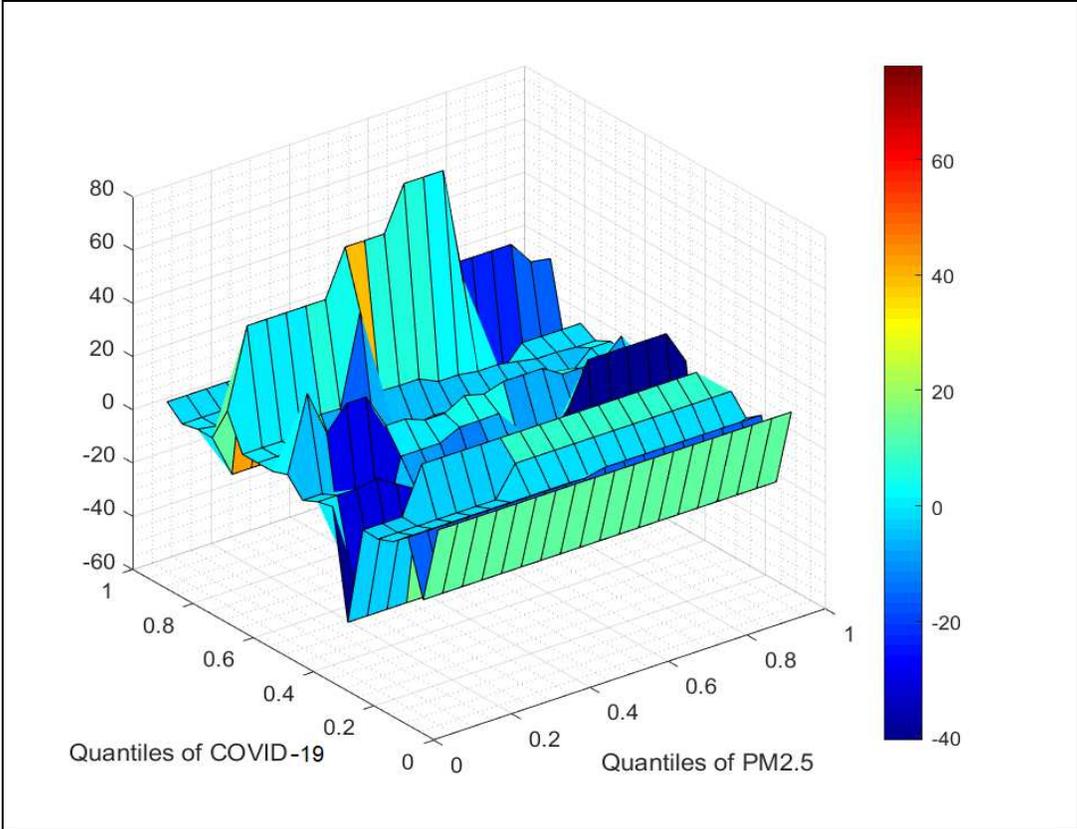
a) The impact of TEMP on COVID-19



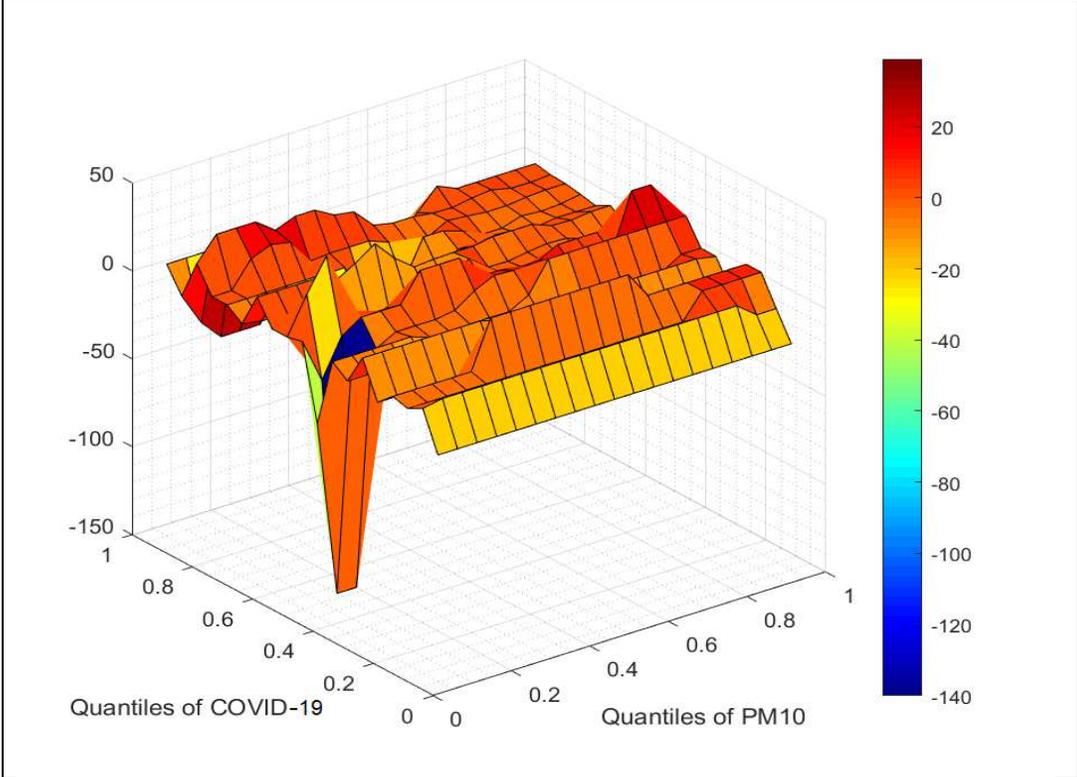
b) The impact of HUM on COVID-19



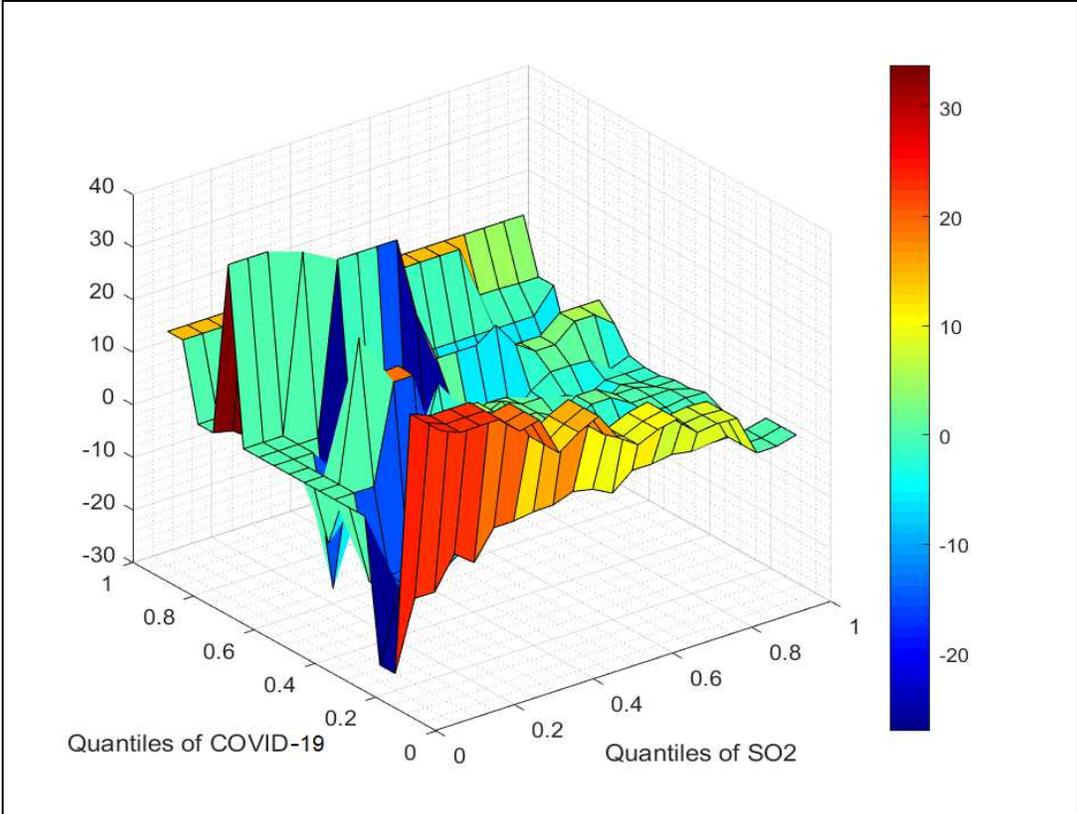
c) The impact of PM_{2.5} on COVID-19



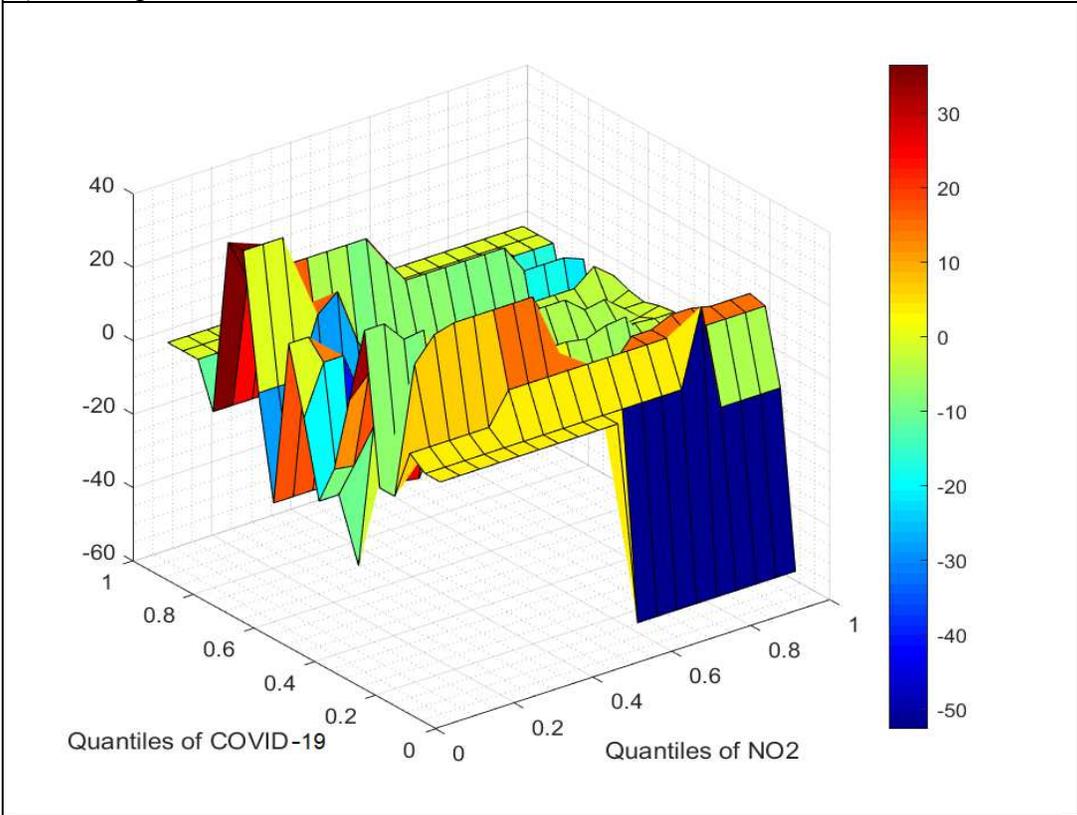
d) The impact of PM₁₀ on COVID-19



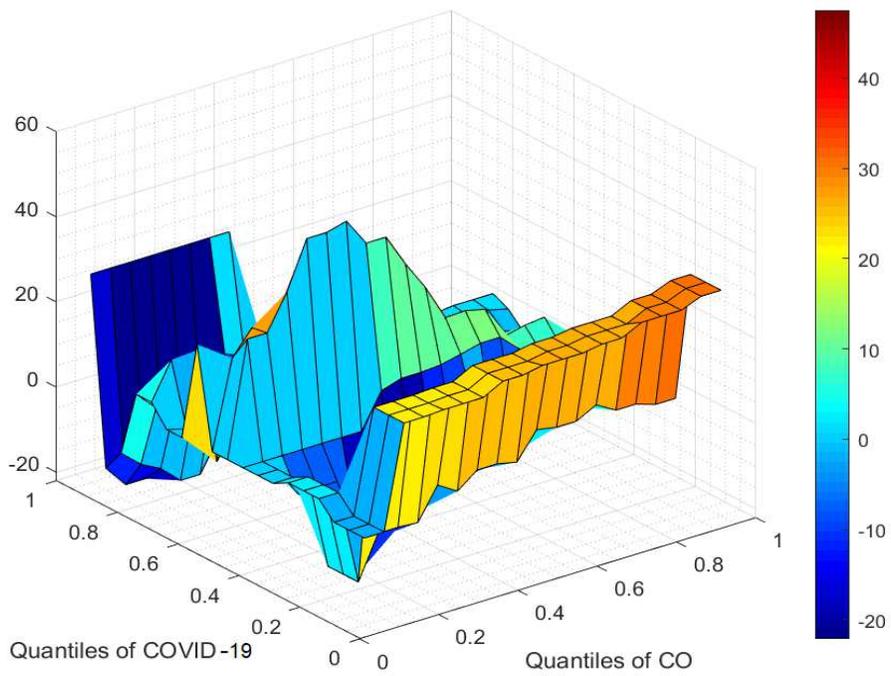
e) The impact of SO₂ on COVID-19



f) The impact of NO₂ on COVID-19



g) The impact of CO on COVID-19



h) The impact of O₃ on COVID-19

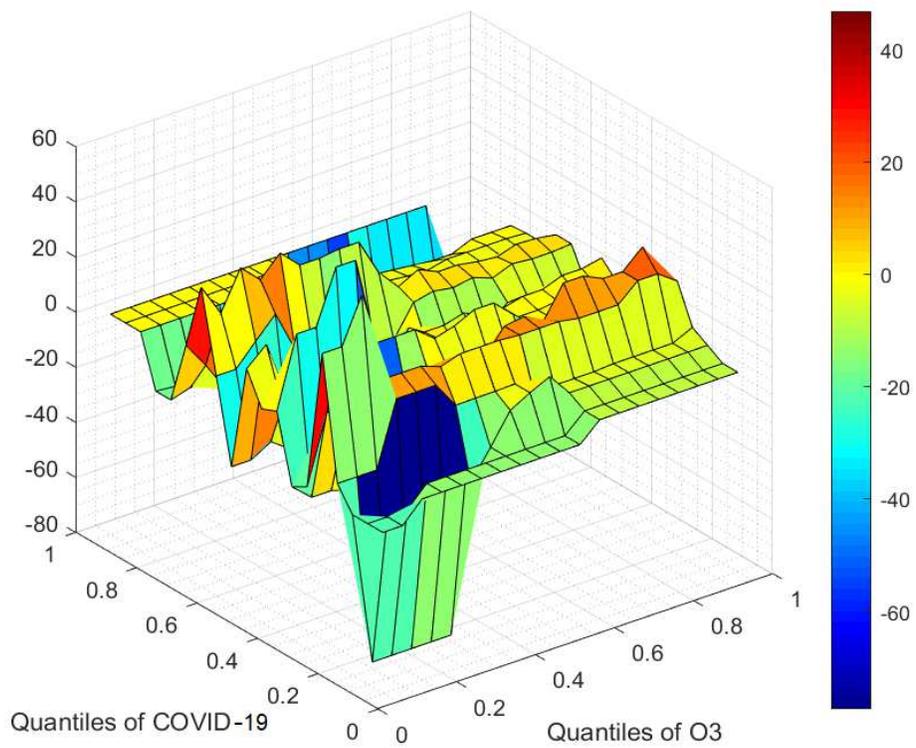


Table 1. A summary of a recent literature review (Environment & COVID-19)

Author(s)	Variables	Sample/Region	Methodology	Findings
<i>COVID-19 and weather</i>				
Briz-Redón & Serrano-Aroca, (2020)	<ul style="list-style-type: none"> • Temperature • COVID-19 daily data • Number of travelers • Age • Number of firms • Population density 	Spain	Spatio-temporal modeling	Insignificant relationship between temperature and COVID-19 transmission.
Prata, Rodrigues, & Bermejo, (2020)	<ul style="list-style-type: none"> • Temperature • COVID-19 daily cases 	Brazil	<ul style="list-style-type: none"> • Polynomial (cubic) regression model • Generalized additive method 	Insignificant relationship between temperature and COVID-19 transmission.
Zhu & Xie, (2020a)	<ul style="list-style-type: none"> • Temperature • COVID-19 daily cases 	China	<ul style="list-style-type: none"> • Linear regression model • Generalized additive method 	Negative relationship between temperature and COVID-19 (When temp ranges 16.8°C-27.4°C).
Jahangiri, Jahangiri, & Najafgholipour, (2020)	<ul style="list-style-type: none"> • Ambient Temperature • COVID-19 transmission cases • Population size 	Iran	<ul style="list-style-type: none"> • Sensitivity and specificity analyses • Receiver operating characteristics (ROC) 	Negative relationship between ambient temperature and COVID-19
Shi et al., (2020)	<ul style="list-style-type: none"> • Temperature • COVID-19 daily cases 	China	<ul style="list-style-type: none"> • Random-effects meta-analysis • Locally weighted regression • Distributed lag nonlinear models • Smoothing scatterplot 	<ul style="list-style-type: none"> • Positive relationship between COVID-19 and temperature (< 3 °C). • Negative relationship between COVID-19 and temperature (8 °C-10 °C)
Shahzad et al., (2020)	<ul style="list-style-type: none"> • Temperature • COVID-19 daily new cases 	Chinese top 10 provinces affected by COVID-19	Quantile on Quantile (QQ) regression	Heterogeneous relationship between temperature and COVID-19 and vice versa.
Iqbal et al., (2020)	<ul style="list-style-type: none"> • Temperature • COVID-19 daily new cases • Exchange rate (USD/CNY) 	Wuhan, China	Partial and Multiple wavelet coherence techniques.	Insignificant association between temperature and COVID-19 cases.
Fareed et al., (2020)	<ul style="list-style-type: none"> • Humidity • COVID-19 daily new death • Air quality index 	Wuhan, China	Partial and Multiple wavelet coherence techniques.	<ul style="list-style-type: none"> • Humidity negatively related to COVID-19 deaths. • Air quality index positively related to COVID-19 deaths.
Tosepu et al., (2020)	<ul style="list-style-type: none"> • Temperature 	Jakarta, Indonesia	Spearman-rank	• Only temperature is

	<ul style="list-style-type: none"> • Humidity • COVID-19 cases 		correlation test	significantly correlated with COVID-19 cases.
Bashir et al., (2020)	<ul style="list-style-type: none"> • Temperature • Rainfall • Humidity • Wind speed • Air quality • COVID-19 daily cases 	New York, USA	Kendall and Spearman rank correlation tests	<ul style="list-style-type: none"> • Only temperature and air quality significantly correlated with COVID-19 cases.
Şahin, (2020)	<ul style="list-style-type: none"> • Temperature • Humidity • Dew points • Wind speed • Population • COVID-19 cases 	Nine cities of Turkey	Spearman's correlation coefficients	Only population, wind speed and temperature are significantly correlated with COVID-19 cases.
Pirouz, Shaffiee Haghshenas, Pirouz, Shaffiee Haghshenas, & Piro, (2020)	<ul style="list-style-type: none"> • Temperature • Wind speed • Humidity • Population density • COVID-19 cases 	Italy	Multivariate linear regression Trend analysis	Weather indicators affect the trend of daily COVID-19 cases.
<i>Air quality factors and COVID-19</i>				
Ogen, (2020)	<ul style="list-style-type: none"> • No2 • COVID-19 deaths 	France, Germany, Spain, Italy	Spatial analysis	Long term exposure increases COVID-19 fatalities.
Zhu, Xie, Huang, & Cao, (2020)	<ul style="list-style-type: none"> • PM_{2.5} • PM₁₀ • CO • O₃ • SO₂ • NO₂ 	China	<ul style="list-style-type: none"> • Generalized additive model • Spearman correlation coefficients 	<ul style="list-style-type: none"> • PM_{2.5}, PM₁₀, CO, O₃, NO₂ are positively related to COVID-19 cases. • SO₂ is negatively related to COVID-19 cases.
(Dantas, Siciliano, França, da Silva, & Arbilla, (2020)	<ul style="list-style-type: none"> • PM₁₀ • CO • O₃ • NO₂ • COVID-19 Partial lockdown 	Rio de Janeiro, Brazil	Standard methods by using R studio software.	<ul style="list-style-type: none"> • CO reduced during the lockdown. • NO₂ reduced during the lockdown • PM₁₀ decreases less during the lockdown • O₃ increased due to decrease in NO₂
Tobias, (2020)	<ul style="list-style-type: none"> • PM₁₀ • SO₂ • O₃ • NO₂ • BC • COVID-19 cases 	Barcelona, Spain	Data plotting by using google earth engine.	<ul style="list-style-type: none"> • NO₂ and Black Carbon reduced by 50% during the lockdown. • O₃ increased by 50% in the lockdown period. • PM₁₀ decreased in a

				lower amount in lockdown.
Muhammad, Long, & Salman, (2020)	<ul style="list-style-type: none"> • Air pollution before and after COVID-19 • COVID-19 cases 	China, France, Italy, Spain	• Comparison by graphs	<ul style="list-style-type: none"> • Air pollution decreased by 30% during the lockdown • Mobility decreased by 90%
Otmani et al., (2020)	<ul style="list-style-type: none"> • PM₁₀ • SO₂ • NO₂ • COVID-19 cases 	Sale, Morocco	HYSPLIT model	PM ₁₀ , SO ₂ , and NO ₂ are reduced by 50% during the lockdown
Zoran, Savastru, Savastru, & Tautan, (2020)	<ul style="list-style-type: none"> • PM₁₀ • PM_{2.5} • Air quality index • Temperature • Humidity • Wind speed • Air pressure • Planetary Boundary Layer-PBL height • COVID-19 daily new cases 	Melan, Italy	Correlation analysis	<ul style="list-style-type: none"> • PM and air quality index are positively related to daily new COVID-19 cases. • Dry air supports COVID-19 transmission. • Warm-season has no role to reduce COVID-19 cases.

Table 2. Summary Statistics and unit root tests

Variables	N	Mean	Std. Dev.	Min	Max	J-B Stats	ADF-1(1)	ZA-1(1)	Break Day
COVID-19	77	601.532	592.213	0	2498	12.56***	-10.771***	-6.639***	28feb2020
TEMP	77	11.341	4.808	2.731	20.579	162.8***	-8.736***	-6.053***	28mar2020
HUM	77	70.605	11.188	44.083	89.583	6.901*	-9.205***	-7.196***	28mar2020
PM _{2.5}	77	16.534	17.648	2.731	80.688	8.984***	-11.245***	-7.711***	06feb2020
PM ₁₀	77	70.605	11.188	44.083	89.583	7.07**	-11.013***	-11.095***	06feb2020
NO ₂	77	38.247	17.549	8	97	40.6***	-8.514***	-7.894***	02mar2020
SO ₂	77	51.701	22.298	12	103	15.35***	-9.521***	-8.117***	19feb2020
CO	77	8.117	2.748	5	17	1.908	-11.581***	-8.885***	05feb2020
O ₃	77	0.903	0.195	0.5	1.4	6.89*	-11.422***	-8.802***	28mar2020

Figures

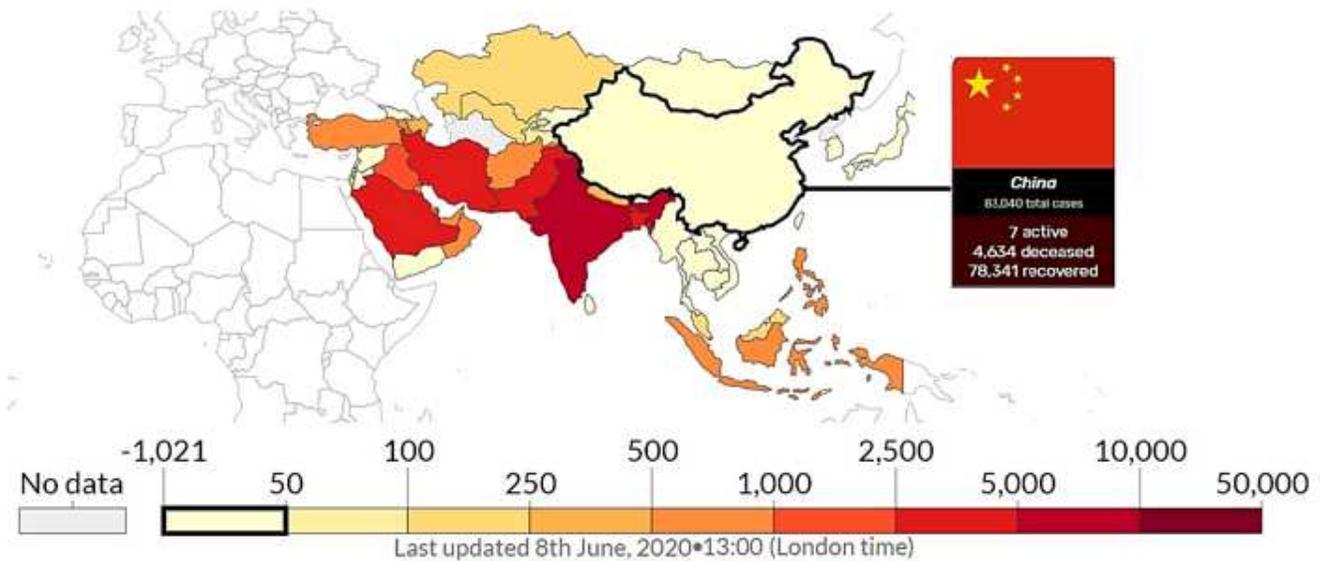


Figure 1

Map showing the latest epidemic situation in China. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.



Figure 2

Daily new recovered patients from COVID-19 during the lockdown in Wuhan

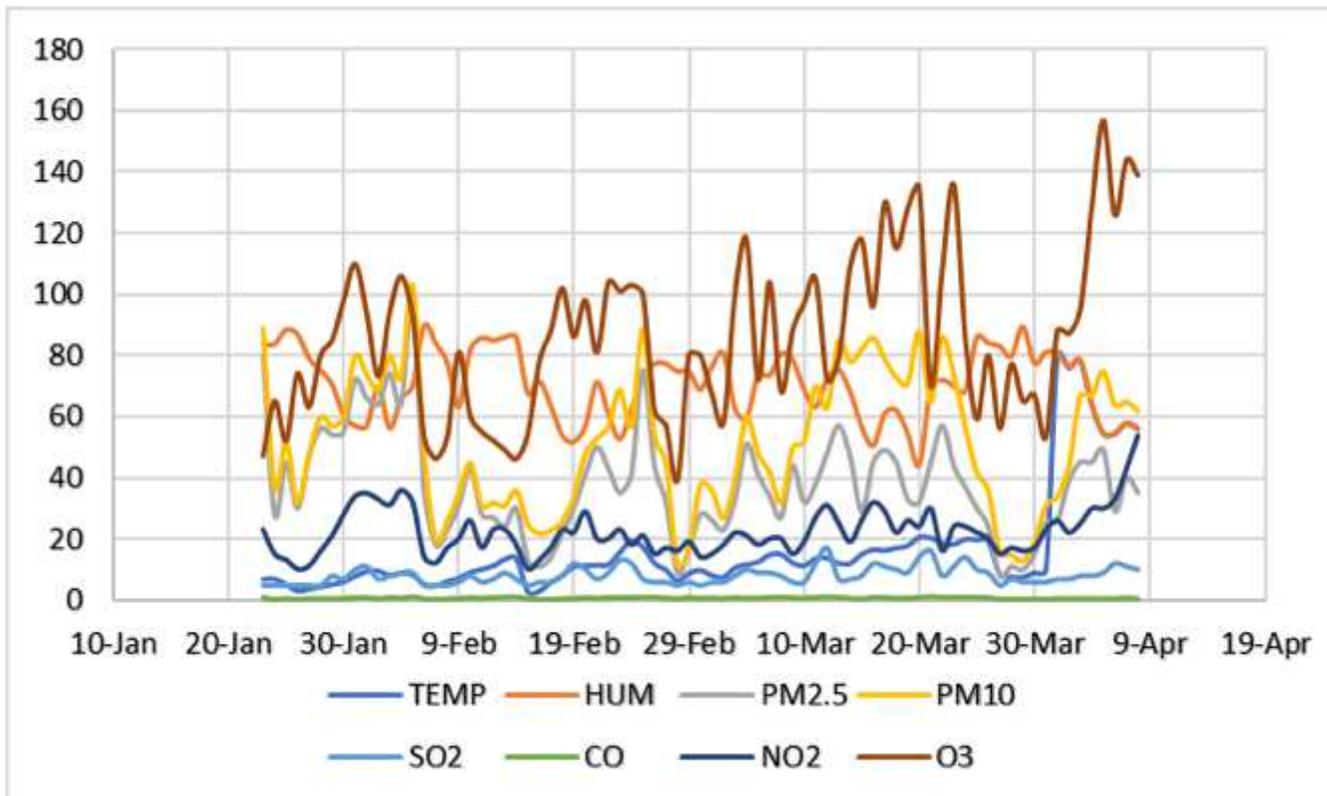


Figure 3

Daily time trend of metrological factors during the lockdown period in Wuhan

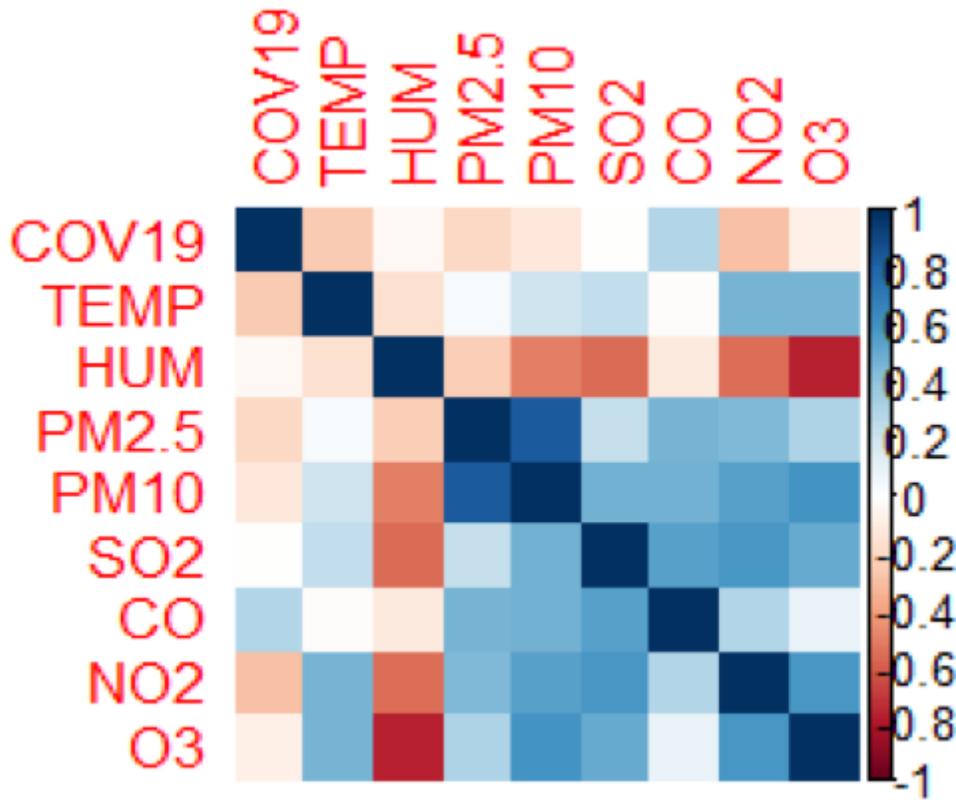


Figure 4

Correlation plot between variables

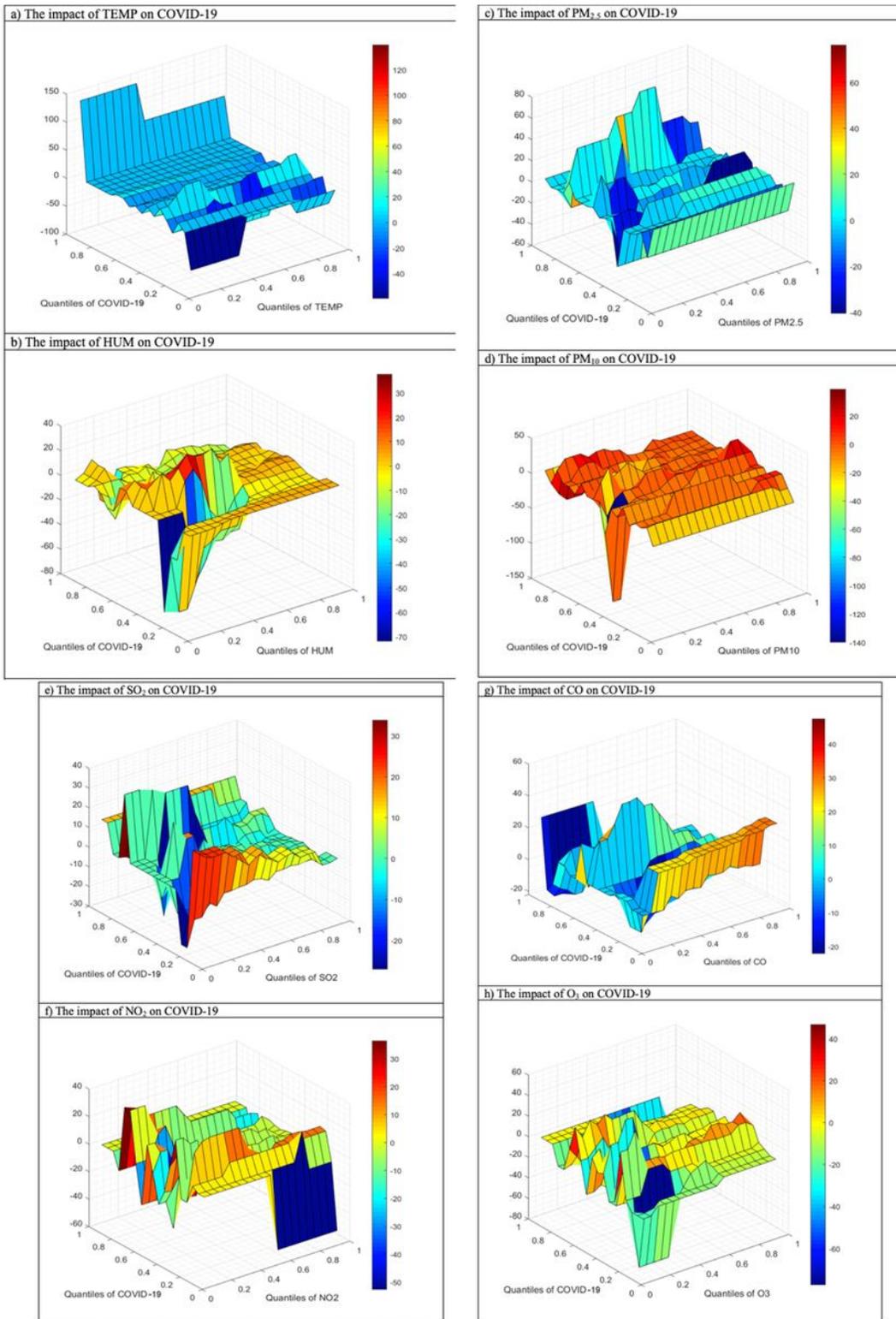


Figure 5

Quantile on Quantile regression estimates slop of the coefficients, $(\beta_1) \otimes = \theta\tau$