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COVID-19 Outbreak and Air Pollution in Iran: A Panel VAR Analysis

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Abstract

The new Coronavirus pandemic has extensive negative socioeconomic impacts. However, its effects on climate change and in particular air pollution, at least at the beginning of the outbreak, is not clear. Fear of getting the Coronavirus in crowded public spaces increased the use of personal cars, while prevention policies that seek to decrease population movement reduced their usage. This paper investigates the relationship between the outbreak of COVID-19, measured by the number of infected cases, and air pollution, measured by PM2.5, in 31 Iranian provinces over the 19 February 2020 to 11 March 2020 period. We employ a panel vector autoregressive (PVAR) approach along with impulse response functions (IRFs), variance decomposition, and Granger causality tests. The analysis shows negative responses of the PM pollution to positive shock in COVID-19 cases in Iran.

Keyword: COVID-19, Iran, panel vector autoregressive model, air pollution.

JEL Classifications: I18, Q53

1. Introduction

Iran is one of the countries that has affected the most from the COVID-19 pandemic. Right after the first confirmed cases of COVID-19 in Iran on February 19, 2020, many communal events and public places were closed to diminish its spread. The closure of many businesses and the need for a severe decline in social communication have led to a sharp decline in production in various sectors of the economy. Therefore, apart from significant influence on public health, the COVID-19 pandemic has widespread socioeconomic consequences that are difficult to capture due to the lack of up-to-date data. For instance, GDP data are published at long intervals in seasonal frequency.

However, the associated variables such as environmental pollution indices, and especially particulate matters (PM), can be used to estimate the GDP reduction. (Sarkar et al., 2019; Salahuddin & Gow, 2019; Balsalobre-Lorente et al., 2018; Lægreid & Povitkina, 2018; Farzanegan & Markwardt, 2018; Chaabouni & Saidi, 2017; and Rafindadi, 2016). Results of Asadikia et al. (2009) and Fotros (2012) maintain that the air quality, in terms of CO_2 emissions, gets worse as the economy grows in Iran as well. In the absence of real-time data with daily frequency for GDP, the relationship between economic activities and air pollution gives us the chance to analyze how a positive shock in the outbreak of COVID-19 can influence economic activities which are manifested in the development of PM pollutants. According to World Health Organization, PM is a common proxy indicator for air pollution. It affects more people than any other pollutant. The major components of PM are sulfate, nitrates, ammonia, sodium chloride, black carbon, mineral dust and water[1]. The main sources of PM are human made (e.g., road vehicles, industrial emissions).

There is also a substantial collection of literature devoted to evidence that air pollution is a principal determinant of epidemic diseases like influenza[2] and the coronavirus pandemics, as increased contamination can increase people's respiratory tract vulnerability. Air pollution can also cause diabetes and respiratory diseases which are associated with higher mortality rates for COVID-19[3]. That is why the European Public Health Alliance warned that people living in contaminated cities are more at risk from COVID-19[4].

However, the COVID-19 outbreak has mixed effects of air quality as well. On the one hand, fear of getting the Coronavirus in crowded public spaces has changed the style of inner-city travel and increased the use of personal cars. On the other hand, prevention policies that seek to reduce population movement and serious advice to people on voluntary quarantine, staying at home and avoiding unnecessary intra-urban and inter-city travel reduced the use of personal vehicles.

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[1] https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health

[2] Xu et al. (2013) found a significant association between children influenza in Australia and PM10 and O3. Liang et al. (2014) demonstrated the positive effects of PM2.5 on influenza transmission in Beijing. Su et al. (2019) illustrated that the risk of influenza-like illness (ILI) can intensify with an increase in PM2.5, PM10, CO and SO2 in Jinan. Liu et al. (2019) confirmed that clinical ILI had a significant association with PM10 and PM2.5 and no relation with SO2 and NO2. Chen et al. (2018) noticed that PM2.5 has an influence on adult/elderly populations in southwest Taiwan. Chen et al. (2017) documented PM2.5 as an increasing factor of influenza in china with a stronger effect in cooler days.

[3] https://www.theguardian.com/world/2020/mar/13/coronavirus-pandemic-visualising-the-global-crisis

[4] https://epha.org/coronavirus-threat-greater-for-polluted-cities/

In this paper, we use a panel vector autoregressive (PVAR) model and daily data to examine the relationship between the coronavirus outbreak and air pollution within the Iranian provinces. We simulate the response of PM2.5 pollution to a positive shock in COVID-19 outbreak in Iran. There are no prior empirical studies, to the best of our knowledge, to demonstrate the influence of epidemic infections on air quality[1].

Selection of PM2.5 as an air pollution indicator is justified based on its significant health impacts (besides its availability for Iranian provinces): because of its tiny size, PM2.5 can penetrate lungs at the alveolar level, translocate directly through the alveolar capillaries into the circulatory system. They can and leave toxic substances in the blood, causing cumulative damage to the body (Stanek et al., 2011). A long-term exposure to PM2.5 affects human development and life satisfaction (Ebenstein et al., 2016; Zhang et al., 2017).

The rest of the paper is organized as follows. Data and method are presented in the Section 2. Results are shown and discussed in Section 3. Section 4 concludes.

2. Data and Method

We use daily data on confirmed cases of Coronavirus across Iranian provinces from 19 Feb. 2020 to 11 March 2020. The Ministry of Health and Medical Education announces officially new confirmed cases of COVID-19 every day. It appears that the

[1] There are references in media which use Satellite videos and data and show a decreasing effect of COVID-19 outbreak on air pollution in Spain (Planelles, 2020), China (McMahon, 2020), and Italy (Mooney et al., 2020).

incidence of infection is higher in the central provinces, such as Semnan, Yazd, and Alborz, than the border regions, maybe because of the initial origin of the virus in the Qom city and Imam Khomeini International Airport.

PM is used extensively as a measure of air pollutant (see Ansari and Ehrampoush, 2019; Al-Hemoud et al., 2019; Gholipour and Farzanegan, 2018; Zhang et al., 2017; and Miri et al., 2016). The main sources of PM are combustion engines, solid-fuel combustion for energy production in households and industry, other industrial activities, erosion of the pavement by road traffic and abrasion of brakes and tires, chemical reactions of gaseous pollutants, and soil and dust re-suspension (World Health Organization, 2013).

The PM has two common variations: PM10 which refers to the mass concentration of particles with a diameter of <10 μm and PM2.5 which are particles with a diameter of <2.5 μm. The PM is a mixture of solid and liquid particles suspended in the air. The very small size and a lightness of PM2.5 particles allow them to stay in the air longer and enter the lungs and sometimes the blood system. To measure the quality of air pollution we use the average of PM2.5 at different stations of each province in Iran on a daily basis. The data is taken and calculated from the online portal of Air Pollution Monitoring System of Iran[1].

The summary statistics of the key variables, spanning the period from 19 Feb. 2020 to 11 March 2020, are presented in Table 1.

[1] https://aqms.doe.ir/

Table 1 Descriptive statistics

Variable		Mean	Std. Dev.	Min	Max	Obs.
COVID-19 confirmed cases	overall	13.22	37.43	0.00	468.00	N = 682
	between		20.66	0.50	107.73	n = 31
	within		31.42	-94.51	373.49	T = 22
Average of PM2.5	overall	63.91	69.31	0.00	1221.00	N = 682
	between		37.14	0.00	138.55	n = 31
	within		58.88	-41.50	1146.37	T = 22

To examine the dynamic relationship between COVID-19 outbreak and air pollution, we use the panel VAR (PVAR) methodology. Using the VAR methodology, we can treat our variables of interest as endogenous, enabling us to examine the response of air pollution to a positive shock in COVID-19 cases and vice versa. We exploit a PVAR generalized method of moments (GMM) estimator developed by Love and Zicchino (2006) to carry out the impulse response functions and variance decomposition analysis, using daily data of 31 provinces of Iran. Our panel VAR model can be written as follows:

$$Y_{it} = \Gamma_0 + \Gamma(L)Y_{it-1} + \mu_i + \theta_t + \varepsilon_{it} \qquad \text{i= 1, …, N \& t=1, …,T} \qquad (1)$$

where Y_{it} is a vector of two endogenous variables: COVID-19 cases, and PM2.5 pollution index; Γ_0 is a vector of constants; $\Gamma(L)$ is a matrix polynomial in the lag operator, μ_i denotes fixed effects, capturing unobservable time-invariant province specific factors (e.g., cultural and religious norms and attitudes or geographical, climate and ethnic conditions); θ_t refers to the forward mean-differencing; and ε_{it} is a vector of independently and identically distributed errors. N refers to number of provinces (31) and T refers to period of analysis (22 days).

To address the possible correlation of fixed effects with regressors, the data were time demeaned and forward mean-differenced using the Helmert procedure and following Arellano and Bover (1995). Using GMM-style instruments (Holtz-Eakin et al., 1988), we estimate Model 1. We first present the results of PVAR estimations. Next, we carry out Granger causality Wald tests for each equation of the underlying PVAR model. We proceed with Impulse response functions (IRFs) using Monte Carlo (MC) simulations for the confidence intervals based as well as forecast-error variance decompositions (FEVDs) based on estimated PVAR. To transform our system in a recursive VAR for identification purposes, we follow Choleski decomposition of variance–covariance matrix residuals (Hamilton, 1994).

3. Results

To estimate the PVAR, we need first to check the optimum lags of endogenous variables. Model selection measures calculated for first-to-third-order panel VAR, using the first four lags of COVID-19 cases and PM as instruments, is shown in Table 2.

Table 2. Panel VAR lag order selection on estimation sample

lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.49	13.92	0.31	-61.28	-10.08	-30.13
2	0.51	10.09	0.26	-40.05	-5.91	-19.28
3	0.62	3.93	0.42	-21.14	-4.07	-10.75

No. of obs. = 527, No. of panels = 31, Ave. no. of T = 17

According to the three model selection criteria suggested by Andrews and Lu (2001), first-order panel VAR is the preferred model, since this has the smallest MBIC, MAIC and MQIC. As a result, we fit a first-order panel VAR model with the same specification of instruments as above using GMM estimation. Table 3 shows the results of PVAR (1) and GMM coefficients.

Table 3. PVAR (1) coefficient estimates

	Coef.	Std. Err.	z	P- value
Dependent variable: COVID-19 cases				
Independent variables				
COVID-19 cases (1)	0.94***	0.07	13.01	0.00
PM2.5 (1)	-0.02	0.02	-0.81	0.42
Dependent variable: PM2.5				
Independent variables				
COVID-19 cases (1)	-0.21***	0.06	-3.70	0.00
PM2.5 (1)	0.18	0.11	1.59	0.11

No. of obs. = 620, No. of panels = 31, Instruments: l(1/4). Robust standard errors are reported. *** denotes significance at the 1% level.

Although Granger causality for a first-order panel VAR may be inferred from the estimated results in Table 3, we still perform the test as an illustration. In Table 4, we report the chi-square Wald statistics for the null hypothesis that the PM pollution does not Granger cause COVID-19 and vice versa. Results of the Granger causality tests in Table 4 show that COVID-19 outbreak Granger-causes PM pollution at the usual confidence levels. There is a unidirectional causality.

Table 4. Granger causality tests

Equation \ Excluded	chi-square statistics	P- value
COVID-19 cases		
PM2.5	0.664	0.415
PM2.5		
COVID-19 cases	13.704***	0.000

The tests are based on the PVAR (1) model. The entries in the table are the chi-square statistics for the null hypothesis that the excluded variable does not Granger cause the equation variable vs. the alternative hypothesis that the excluded variable Granger causes the equation variable. *** denotes significance at the 1% level.

To examine the impulse response functions and variance decomposition analysis, we need to control the stability of estimated PVAR by checking whether all eigenvalues lie within the inner circle. The resulting Table 5 confirms that the estimate is stable and thus impulse responses are reliable.

Table 5. Eigenvalue stability condition

Eigenvalue		
Real	Imaginary	Modulus
.94	0	0.94
.17	0	0.17

All the eigenvalues lie inside the unit circle. PVAR satisfies stability condition

Using this Cholesky ordering (COVID-19, PM2.5), we calculate the implied IRF and the implied FEVD. To compute the IRF confidence intervals we use 200 Monte Carlo draws based on the estimated model. The IRF results are show in Figure 1. In IRF, we are interested to measure the response of one of variables to a positive shock in other variables. In Figure 1, we observe that the response of PM pollution to a positive shock in outbreak of COVID-19 cases is negative and statistically significant at 95% confidence intervals for about a week after the initial shock. The response of COVID-19 to a shock in quality of air is not statically significant.

For robustness check, we also re-estimate the PVAR by changing the ordering of variables (PM2.5, COVID-19). The IRF and other results remain unchanged.

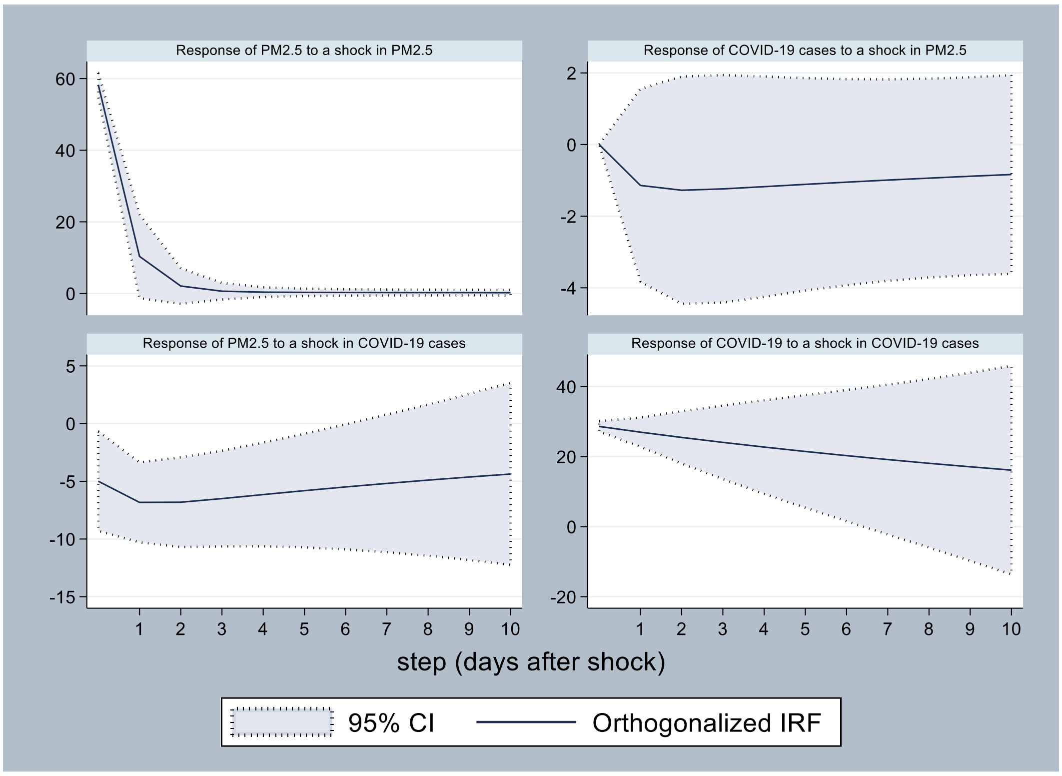

Figure 1. Impulse response functions

In addition to IRF, we carry out the forecast error variance decomposition (FEVD) analysis. Based on the FEVD estimates in Table 6, we see that as much as 8 percent of variation in PM pollution can be explained by COVID-19 outbreak shocks.

Table 6. Forecast-error variance decomposition

Response variable and forecast horizon (days after shock)		
	Impulse variable	
	COVID-19 cases	PM2.5
COVID-19 cases		
1	1.0000	0.0000
5	0.9982	0.0018
10	0.9979	0.0021
PM2.5		
1	0.0073	0.9927
5	0.0534	0.9466
10	0.0869	0.9131

On the other hand, almost all of fluctuations of COVID-19 cases are explained by its own past innovations and share of PM pollution in explanation of this variance is almost zero. This is in line with IRF findings.

4. Conclusion

In this study, we examine the impact of air pollution to a positive shock in outbreak of COVID-19, suing a panel data of 31 provinces in Iran from 19 Feb. 2020 to 11 March 2020 for which we have a complete data. Employing a panel VAR analysis and impulse response as well as variance decomposition tools, we show that a positive shock in COVID-19 cases is resulting in a negative (decreasing) response of air pollution in Iran. While COVID-19 has significant negative impact of economic activities and transportation, but on the side may dampen the pressure on environment. Our study provides the first empirical insights on such an effect for case stud of Iran.

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