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The Effect of Corona Virus Lockdown on Air Pollution: Evidence from the City of Brescia in Lombardia Region (Italy)
Michela Cameletti

**HIGHLIGHTS**

- Po Valley in Italy is one of the most polluted areas in Europe.
- Italy has taken extraordinary measures to prevent the spread of the Corona virus.
- Interrupted time series models are used to analyse PM and NO\textsubscript{2} concentration.
- The aim is to evaluate the effectiveness of the lockdown on air quality.

**ABSTRACT**

After the outbreak of Corona virus pandemic in Italy, the government has taken extraordinary measures, including a national lockdown, to prevent the spread of the infection. This extraordinary situation has led to a reduction in air pollution levels measured in the whole Po Valley, usually known as one of the most polluted areas in Europe in terms of particulate matter (PM) and nitrogen dioxide (NO\textsubscript{2}) concentrations. The main aim of this paper is to evaluate the effectiveness of the lockdown on the air quality improvement. In particular, an interrupted time series modelling approach is employed to test if a significant change in the level and the trend of the pollutant time series has occurred after the lockdown measure. The case study regards the city of Brescia (Northern Italy) and focuses on the comparison of the period before (January 1st–March 7th, 2020) and after (March 8th–March 27th, 2020) the lockdown. By adjusting for meteorology and Sunday effect, the results show that a significant change in air quality occurring in the post intervention period was observed only for a single NO\textsubscript{2} station located in a heavy traffic zone. In particular, the estimate of the time series slope, i.e. the expected change in the concentration associated with a time unit increase, decreases from -0.25 to -1.67 after the lockdown. For the remaining stations, no significant change was found in the concentration time series when comparing the two periods. This confirms the complexity of air pollutant concentration dynamics for the considered area, which is not merely related to emission sources but depends also on other factors as, for example, (micro and macro) meteorological conditions and the chemical and physical processes in the atmosphere, which are all independent of the lockdown measure.

1. **Introduction**

Po Valley in Northern Italy is known as one of the most polluted areas in Europe in terms of particulate matter (PM) and nitrogen dioxide (NO\textsubscript{2}) concentration (EEA, 2019). This is due to the peculiar geographical structure of the area and the exceptional meteorological conditions that do not favour the pollutant dispersion. At the same time the four regions of Po Valley (Lombardia, Emilia Romagna, Piemonte and Veneto, see Fig. 1) are densely populated (with about 23.8 millions inhabitants\textsuperscript{1} representing about 40% of the total Italian population), heavily industrialised and with a strongly developed agricultural sector. Due to these particular conditions, the air quality thresholds set for human protection are frequently exceeded: the European Environment Agency (EEA) estimates for 2016 that 3.3% of the Po Valley population live in areas where standard levels for three different pollutant were not respected (i.e. PM\textsubscript{10} daily limit value, ozone target value and NO\textsubscript{2} annual limit value) (EEA, 2019). This has a consequent impact on human health in terms of premature mortality and morbidity, mainly related to respiratory and cardiovascular diseases. For this reason, air pollution represents the single largest environmental risk in Europe today (Lim et al., 2012) and different statistical approaches can be used for measuring the effects of air pollution exposure on health outcomes.

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\textsuperscript{1} Last available data from http://demo.istat.it/ referred to January 1st 2019.

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The earliest cases of Corona virus (COVID-19) occurred in Italy on 31st January 2020, followed by a rapid spread of the pandemic starting from the end of February which has led to about 120 thousand cases on 03/04/2020. Lombardia has represented the main hotspot being the region with the highest number of infected and dead people with about 47.5 thousand total cases on 03/04/2020. In order to control the COVID-19 spread and the resulting pressure on the healthcare system, on March 8th 2020 the Italian Prime Minister decided the lockdown for the entire Lombardia region, extended to all Italy on the following day. The lockdown decree provides for the closure of schools and universities, for the stop of the non-essential work activities and for ban on people gatherings. Stronger restrictions have been introduced later with subsequent decrees of the Italian government (see the link in footnote 2 for a timeline of the measures taken to manage the Corona virus pandemic).

The lockdown has proved to have a positive effect on air quality in Europe and in the Po Valley in particular. From the analysis of air pollutant concentrations from the 3000 monitoring stations across European countries, the EEA found evidence of a large decrease in air pollutant concentrations. Two recent reports by the Copernicus Atmosphere Monitoring Service and the Sistema nazionale di protezione ambientale, based on the analysis of satellite data, ground observations and numerical modelling outputs, confirm a reduction in the surface concentration of NO$_2$, in the main European cities and all over the Po Valley. All these reports provide a simple descriptive analysis of an unprecedented situation of low air pollution, without however considering the possible effect of meteorology. For this reason, a statistically robust analysis of the decreasing trend in pollutant concentrations is still missing.

The main aim of this short communication is to evaluate the effectiveness of the lockdown measure (in force since March 8th 2020) on the improvement of air quality. As a particular case study the city of Brescia is considered: it is the second most populated city of the region after Milano, located in the eastern side of Lombardia region (see Fig. 1). Air quality has always been an issue for Brescia who registered in 2018 the unpleasant record of the highest number of exceedances: 47 days of PM$_{10}$ levels over 50 μg/m$^3$ (24-hour mean) and 103 days of ozone concentration over 120 μg/m$^3$ (daily maximum 8-hour mean).

The PM$_{10}$ and NO$_2$ concentrations recorded from January 1st 2020 to March 27th 2020 by the monitoring stations located in the municipality of Brescia are analysed in order to understand if a significant reduction in air pollution occurred thanks to the lockdown intervention. In this regard, an interrupted time series (ITS, or segmented regression) model is employed (Wagner et al., 2002). This kind of modelling approach is widely used for the evaluation of the longitudinal impact of public interventions or important population related actions. For example, Grundy et al. (2009) quantify the effect of the introduction of 20 mph traffic speed zones on road collisions, injuries, and fatalities in London; Bernal et al. (2016) analyse the effect of the late 2000s financial crisis on suicides in Spain; similarly, Lopez Bernal et al. (2013) study the effects of the Italian smoking ban in public places on hospital admissions for acute coronary events. In the considered case study, the change in the level and/or the trend of PM$_{10}$ and NO$_2$ concentrations is modelled by including in a linear regression model a dummy variable and an interaction term. Moreover, to adjust for seasonality and autocorrelation in the response variable, meteorological variables are included in the model and an Autoregressive Moving Average (ARMA) structure for the error term is assumed. In the time series literature this kind of model is also known as ARMAX model (Hyndman and Athanasopoulos, 2019). The analysis is implemented using the forecast package of the R software (R Core Team, 2020).

2. Data

We consider data from January 1st 2020 to March 27th 2020 measured by five air pollutant and weather monitoring stations located in the city of Brescia (see Fig. 2 and Table 1). The data are provided by the Regional Agency for Environmental Protection (ARPA Lombardia). Sensors for measuring concentrations of NO$_2$ and PM$_{10}$ are installed in three and two stations, respectively. In particular, station no. 1 and 3 in Fig. 2 are traffic stations located close to the city centre, while station no. 2 is classified as of background type. We include in the analysis meteorological information (temperature, precipitation and wind speed) measured in two stations (number 4 and 5 in Fig. 2). For all the considered variables the daily mean is considered with the exception of precipitation for which the total daily amount is used. Moreover, as the two available temperature time series (from station no. 4 and 5) are strongly and positively correlated (Pearson correlation index = 0.95), the average daily values are computed.

3. Methodology

To evaluate if the lockdown in force from March 8th 2020 reduced significantly the PM$_{10}$ and NO$_2$ concentrations in the city of Brescia, an interrupted time series regression has been employed for the comparison of the period before (January 1st–March 7th, 2020) and after (March 8th–March 27th, 2020) the containment measure.

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2 https://en.wikipedia.org/wiki/2020_coronavirus_pandemic_in_Italy.
3 This is the most updated information at the time of writing; for more updated official data from the Italian Ministry of Health, visit http://opendatadpc.maps.arcgis.com/apps/opsdashboard/index.html#/b0c68bce2c2ce478eac82fe38d4138bb1.
4 https://www.eea.europa.eu/highlights/air-pollution-goes-down-as.
5 https://atmosphere.copernicus.eu/air-quality-information-confirms-reduced-activity-levels-due-lockdown-italy.
6 https://www.snambiente.it/2020/03/23/pianura-padana-biossido-di-azoto-no2-graduale-riduzione-della-concentrazione-nelle-ultime-settimane/.
7 The last days of March are excluded due to an extraordinary event of dust observed on March 28th and 29th which gave rise to an increase in pollutant concentration independent of the lockdown effects.
represents the lockdown (L) dummy variable which is equal to 0 for all
the time points before the lockdown and 1 afterwards (i.e. from March
8th 2020 to March 27th 2020). The variable \( T = 1, \ldots, n \) represents
the time elapsed (in days) starting from January 1st 2020 which is the
first considered time point in the analysis (\( n = 87 \) is the total number
of days). The \( 1 \times p \) vector \( X_t \) contains the values of the considered
regressors referred to day \( t \) given by temperature, precipitation, wind
speed and a dummy variable introduced to capture the Sunday effect
(the variable is equal to 1 if day \( r \) occurred on Sunday, and 0 otherwise).
The choice of including a variable for Sunday, instead of one for the
weekend effect (Saturday–Sunday), is based on a visual inspection of
the time series seasonality.

The ITS ARMA model is defined by the two equations: the first
includes the intercept, the linear effect of time and of the regressors
together with the dummy for the lockdown, which is included also in the
interaction term with time. The second equation instead defines the
temporal structure of the regression errors. Thus, the model is specified
as follows:

\[
y_t = \alpha_0 + \alpha_1 T + \alpha_2 T L_t + \alpha_3 (T L_t) + X_t \beta + \eta_t
\]

\[
\eta_t = \phi_1 \eta_{t-1} + \ldots + \phi_p \eta_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \ldots + \theta_q \epsilon_{t-q}
\]

In particular, the regression error term \( \eta_t \) follows an ARMA process
with coefficients \( \phi_1, \ldots, \phi_p, \theta_1, \ldots, \theta_q \), whereas the innovation error term
\( \epsilon_t \) is assumed to be a Normally distributed white-noise process with
zero-mean and variance \( \sigma^2 \).

In this model \( \beta \) is the \( p \times 1 \) vector of coefficients for the regressors.
Moreover, \( \alpha_0 + X_t \beta \) represents the baseline level of the response variable
when \( L_t = 0 \) (before the lockdown), whereas \( \alpha_1 \) is the baseline trend
trend, i.e. the expected change in \( y_t \) that occurs with each day before the
intervention. When the lockdown takes effect, the level and the trend
slope become equal to \( \alpha_0 + \alpha_2 + X_t \beta \) and \( \alpha_1 + \alpha_3 \), respectively. Thus,
\( \alpha_2 \) (\( \alpha_3 \)) represents the post-intervention level (trend slope) change.
The final vector of parameters is given by \( (\alpha, \beta, \phi_1, \ldots, \phi_p, \theta_1, \ldots, \theta_q, \sigma^2) \),
with \( \alpha = (\alpha_0, \alpha_1, \alpha_2, \alpha_3) \), and the maximum likelihood approach is used
for estimation (Hyndman and Athanasopoulos, 2019). In particular, a
backward stepwise approach is adopted by starting from the full model
and by removing the non significant regressors (among temperature,
precipitation, wind speed and Sunday dummy variable) according to
the value of the \( p \)-value (the considered threshold is \( \alpha = 0.05 \)).
The ARMA coefficients are kept in the model even if not significant because
they improve the model fit. Also the \( \alpha \) parameters are not removed
from the model in order to discuss the effectiveness of the lockdown
intervention in changing the level and trend slope of the time series.
The best ARMA structure for the error term is chosen by using the
Akaike Information Criterion (AIC) and a residual analysis was carried
out in order to assess that the ARMA errors \( \epsilon_t \) resemble a white-noise
series.

4. Results

Figs. 3 and 4 display the distribution of PM_{10} and NO_{2} concentrations
by sensor and year, separately for the two considered periods: January 1st–March 7th and March 8th–March 27th. It can be observed
that for the considered years (2017–2020) the second period is always
characterised by lower level of concentrations. This is due to the fact
that March is usually the winter month with the most favourable air
quality conditions also thanks to the effect of the meteorology. When
comparing 2020 with the previous years, no noteworthy differences
occur for PM_{10}. Instead, all the NO_{2} sensors show for 2020 a more
evident difference between the distributions in the two considered time
intervals, that could be ascribed to the effect of the lockdown. To assess
any significant change in the level and in the trend of the NO_{2} and
PM_{10} time series for 2020, five ITS ARMA models are implemented as
described in Section 3. All the models include meteorology in order
in Table 1 where the details about the stations and sensors are
reported.

![Fig. 2. Locations of the monitoring stations in Brescia. The numbers in the map refer to column ‘Station ID’ in Table 1 where the details about the stations and sensors are reported.](image1)

![Fig. 3. Distribution of PM_{10} concentration by sensor (see Table 1) and year, separately for the two considered periods: January 1st–March 7th and March 8th–March 27th. The white point represents the mean.](image2)
The parameter estimates for \( \alpha \) and \( \beta \) coefficients are reported in Tables 2 and 3. It can be noted that temperature has no significant effect on concentrations and for this reason it has been omitted from all the models, whereas precipitation has a significant negative effect only for the NO\(_{2}\) Sensor ID 6781. The most important meteorological variable is wind speed with a negative significant effect for all the models, whereas precipitation has a significant negative effect on the effect of the intervention on traffic reduction was weaker. These results are confirmed by the plots reported in Figs. 5–7, where the observed and fitted (using the estimated parameters reported in Tables 2 and 3) time series are represented together with the counterfactual time series (dashed red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The parameter estimates for \( \alpha \) and \( \beta \) coefficients are reported in Tables 2 and 3. It can be noted that temperature has no significant effect on concentrations and for this reason it has been omitted from all the models, whereas precipitation has a significant negative effect only for the NO\(_{2}\) Sensor ID 6781. The most important meteorological variable is wind speed with a negative significant effect for all the models ranging from -13.89 and -5.37. The dummy variable related to the Sunday effect is always significantly different from zero (with a reduction in concentrations) with the exception of the PM\(_{10}\) Sensor ID 6951 located in the city centre of Brescia in a 7 days limited traffic zone.

The parameter \( a_1 \), which measures the pre-intervention trend slope, is significantly negative for all the five models showing that a somehow decreasing trend was still happening for all the stations (after removing the effect of the other predictors). This is probably related to the spring approaching which favours the pollutant dispersion. The decreasing trend is also evident from the observed time series represented in Figs. 5–9 especially for NO\(_{2}\) concentrations. It is worth to note that a significant change in the level in the trend after the lockdown occurred only for the NO\(_{2}\) sensor 6781 (\( \hat{\alpha}_2=94.64 \) and \( \hat{\alpha}_1=-1.42 \), both with \( p\)-value < 0.001). This means that the estimate of the time series slope, i.e. the expected change in the concentration associated with a time unit increase, decreases from -0.25 to -1.67 after the lockdown. This sensor is installed in the station named “Via Turati” which is located next to a heavy-traffic ring road which surrounds the city centre. It is reasonable to suppose that the lockdown intervention has reduced significantly the road traffic along this main artery, which a consequent significant reduction in the NO\(_{2}\) concentrations. This is coherent with the road transport sector being the most significant contributor of NO\(_{2}\) emissions (EEA, 2019). For the other two NO\(_{2}\) stations this effect does not emerge so clearly (although for Sensor ID 6781 the \( p\)-values related to \( a_1 \) and \( a_2 \) are close to the significance level). This is probability due to the fact that they are located in low traffic areas where the effect of the intervention on traffic reduction was weaker. These results are confirmed by the plots reported in Figs. 5–7, where the observed and fitted (using the estimated parameters reported in Tables 2 and 3) time series are represented together with the counterfactual predictions. The latter represent the expected time series in the hypothetical scenario under which the lockdown had not taken place, i.e. with no intervention and assuming that the time series is stationary.

### Table 2

| Sensor ID | 6761 | 6781 | 30163 |
|-----------|------|------|-------|
| \( a_1 \) | 62.84 | 78.48 | 61.45 |
| \( \beta \) | -0.21 | 0.25 | -0.25 |
| \( a_1 \) | 54.47 | 94.64 | 43.52 |
| \( \beta \) | -0.83 | 1.42 | -0.68 |

| \( \beta_{\text{temperature}} \) | -6.91 | -6.66 | 0.018 |
| \( \beta_{\text{precipitation}} \) | -8.44 | -5.56 | -7.24 |

### Table 3

| Sensor ID | 6951 | 9961 |
|-----------|------|------|
| \( a_1 \) | 61.48 | 85.72 |
| \( \beta \) | -0.25 | -0.44 |
| \( a_1 \) | -77.40 | -41.17 |
| \( \beta \) | 0.96 | 0.65 |

| \( \beta_{\text{temperature}} \) | -6.97 | -13.89 |
| \( \beta_{\text{precipitation}} \) | -7.88 | -9.19 |

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![Fig. 4. Distribution of NO\(_{2}\) concentration by sensor (see Table 1) and year, separately for the two considered periods: January 1st–March 7th and March 8th–March 27th. The white point represents the mean.](image)

![Fig. 5. NO\(_{2}\) time series for Sensor ID 6761 from January 1 to March 27 2020: observed time series (blue solid line), fitted values (green solid lines) and counterfactual time series (dashed red line).](image)
after accounting for time-varying confounders. The counterfactual time series is obtained by computing the predicted values of $y_t$ using the parameter estimates obtained from the entire set of data (from January 1st to March 27th, see Tables 2–4) and assuming that the variable $L_t$ in Eq. (1) is equal to zero for all the time points, whereas the values of the other predictors are kept unchanged. We can observe a more pronounced distance between the observed and counterfactual time series for Sensor ID 6781, whereas for Sensor ID 6761 and 30163 there is no strong evidence of a reduction in NO$_2$ concentrations following the lockdown. A negligible effect of the intervention is observed also for PM$_{10}$ concentrations, with the counterfactual series being very close to the observed data as shown in Figs. 8–9. Also the parameters $\alpha_2$ and $\alpha_3$ cannot be considered significantly different from zero (see the corresponding estimates reported in Table 3). This could be related to the complexity of the process of PM$_{10}$ formation, given by the main sources of primary PM (domestic combustion in household heating, road traffic, industrial combustion, agriculture) but also by chemical reactions with other pollutants. It is very likely that the lockdown has reduced the road traffic but at the same time has led to a more intensive use of household heating due to the stay-at-home order.

In Table 4 the estimates of the ARMA coefficients are reported. Each time series is characterised by its own temporal dynamics: an AR(1)
structure is estimated for Sensor ID 6761, MA models of different order arise for Sensor ID 6781, 30163 and 9961, while an ARMA(2,1) is the best choice for Sensor ID 6951. These models give rise to different levels of lag-one autocorrelation: 0.463 for NO\textsubscript{2} Sensor ID 6761, 0.463 for NO\textsubscript{2} Sensor ID 6781, 0.677 for NO\textsubscript{2} Sensor ID 30163, 0.631 for PM\textsubscript{10} Sensor ID 6951 and 0.394 for PM\textsubscript{10} Sensor ID 9961. The correlation between predicted and observed values is quite high and ranging from 0.823 to 0.939. For all the time series the residuals analysis (results not shown here for the sake of brevity) leads to conclude that the ARMA errors are not significantly different from a Gaussian white-noise.

5. Conclusions

In this paper ITS ARMA models are employed to assess if the lockdown intervention (valid from March 8th 2020) has led to a significant reduction in NO\textsubscript{2} and PM\textsubscript{10} concentrations in the city of Brescia. After adjusting by meteorology and weekend effect, the results confirm that a significant change in the level and trend of the time series was observed only for a single NO\textsubscript{2} station located in a heavy traffic zone. The stay-at-home order has certainly lowered road traffic, thus reducing the main emission source connected to NO\textsubscript{2} concentrations. For the remaining NO\textsubscript{2} and PM\textsubscript{10} series of data, it is not possible to conclude that the intervention was helpful in improving air quality. This confirms the complexity of air pollution in the Po Valley, where a reduction in emissions does not automatically lead to a significant decrease in concentrations due to the contemporary existence of other important factors (at the local, regional an extra-regional level) such as weather conditions and chemical–physical reactions occurring in the atmosphere. This is particularly relevant if we consider that in the Po Valley, during the winter season, secondary aerosol is the main source for PM (followed by primary emissions from road transport and biomass burning) (Larsen et al., 2012). This explains why the lockdown, which in addition did not have a direct effect on the reduction of the emissions from the agricultural, livestock and residential sector, was not sufficient to reduce significantly and globally the PM concentrations. The same evidence was reported also in Tobías et al. (2020) for the city of Barcelona, in Otmani et al. (2020) for Salè City (Morocco) and in Li et al. (2020) for the Yangtze River Delta Region (China).

This analysis was conducted only for the city of Brescia. Future work will extend the analysis to all the regions in the Po Valley in order to understand the local differences and point out which are the relevant factors which concur in the dynamics of air pollution in the early months of 2020. In this regard also the methodological approach could be extended to include, for example, a more complex structure for the level, the slope and the seasonality as done in Maranzano et al. (2020) for assessing the impact of a new traffic policy in Milano, Italy. If the entire Po Valley is considered, a spatio-temporal modelling approach, similar to the one proposed in Cameletti et al. (2011), is also an option in order to take also into account the spatial correlation between time series.

CRediT authorship contribution statement

Michela Cameletti: Conceptualization, Methodology, Software, Data curation, Formal analysis, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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