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Separating the impact of gradual lockdown measures on air pollutants from seasonal variability

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ARTICLE INFO

Keywords:
Air pollution
Meteorological model
Lockdown measures
Traffic emission
COVID-19

ABSTRACT

Analysis of near-surface measurements at several measuring points in Graz, Austria, reveals the impact of restrictive measures during the COVID-19 pandemic on the emission of atmospheric pollutants. We quantify the effects at traffic hotspots, industrial and residential areas. Using historical data collected over several years, we are able to account for meteorological and seasonal confounders. Our analysis is based on daily means as well as intraday pollution level curves. Nitrogen dioxide (NO2) has decreased drastically while the levels of particulate matter PM10 and carbon monoxide (CO) mostly exhibit little change. Traffic data shows that the decrease in traffic frequency is parallel to the decline in the levels of NO2 and NO.

1. Introduction

The coronavirus disease COVID-19 has spread around the world since the end of 2019. In an effort to halt this infectious disease, many countries imposed restrictions on public gatherings, travel, free movement of their citizens and public life in general. The Chinese government introduced the first measures to drastically shut down public life when Wuhan, the capital of Hubei Province, was locked down from January 23 to March 27, 2020. Following this precedent, countries around the world soon followed in implementing restrictions. The Austrian government ordered schools, shops and restaurants to be closed starting from March 17, 2020, effectively imposing a limited shutdown of public life.

With the decline in economic activities, a decrease in air pollution was observed in the major industrial centers of developed and emerging economies worldwide. Because of the wide availability of environmental surveillance both on the ground and from space, this unprecedented development sparked intensive research in the field.

In this paper, we focus on the impact of the lockdown in Graz, the second largest city in Austria, where pollution data has been diligently recorded for a long time. We can build upon a long expertise in pollution level monitoring and forecasting. Our aim is to investigate how the economic shutdown in Graz affected the levels of local near-surface pollution with nitrogen dioxide (NO2), nitric oxide (NO), particulate matter (PM10) and carbon monoxide (CO) across different types of stations (traffic, industrial, residential).

Similar studies have been carried out in different geographical regions. Bauwens et al. (2020) show that tropospheric NO2 levels fell by 40% over Chinese cities and by 20–38% in Europe and North America. Kanniah et al. (2020) found a drop of around 30% over urban areas in Malaysia. The effect was even stronger for near-surface levels of NO2. Lee et al. (2020) found reductions of 42% in urban areas in the UK, Baldasano (2020) found reductions of 50–62% in Spain, Kanniah et al. (2020) found reductions of 63–64% in Malaysia. In contrast, the reduction of particulate matter PM10 was less pronounced and amounted to 26–31%. (Kanniah et al., 2020).

When pollution levels are strongly impacted by a seasonal trend or meteorological variables (as is the case in Graz), we need to account for these effects and can assess changes in the concentration only after eliminating these influences by means of a statistical model of some kind. The above mentioned papers do not take meteorological effects into account. In contrast, Bao and Zhang (2020) analyzed data of near-surface measurements from 44 Chinese cities during the lockdown period, taking local weather conditions into account. They found that under lockdown, the levels of NO2, PM10, and CO were reduced by 25%, 14%, and 5%, respectively. Using the CHIMERE multi-scale model, Menut et al. (2020) carried out simulations for the month of March 2020. A reference scenario with emissions as usual was compared to a scenario that took into account the reduction of pollutant emissions due to lockdown measures. This reduction in emissions was estimated for

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Peer review under responsibility of Turkish National Committee for Air Pollution Research and Control.

https://doi.org/10.1016/j.apr.2020.10.011
Received 19 July 2020; Received in revised form 13 October 2020; Accepted 13 October 2020
Available online 2 November 2020
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different sectors in each country. For example, they found a reduction in surface concentration of 37% for NO\textsubscript{2} and 10% for particulate matter PM\textsubscript{2.5} in Austria.

Cameletti (2020) used an interrupted time series approach to assess the lockdown effect on NO\textsubscript{2} and PM\textsubscript{10} for five different measuring stations in the city of Brescia (Italy). In this approach, the initiation of the lockdown in Lombardy on March 8, 2020 was taken as the point of intervention for the model, allowing for an evaluation of the change in level and trend before and after the lockdown. As a result, they found a significant reduction only for NO\textsubscript{2} at one of the above mentioned stations, which is located in a heavy traffic zone.

A survey by Myllyvirta and Thieriot (2020) assessed the meteorology-corrected reduction of air pollutants in Europe during the time of the lockdown and found population-weighted average decreases of 17–58% for NO\textsubscript{2} and up to 55% for PM\textsubscript{10}, depending on the country. Two countries even showed a slight increase in PM\textsubscript{10} levels. Ordóñez et al. (2020) investigated 1-h daily maximum NO\textsubscript{2} levels as well as maximum daily 8-h average ozone levels (O\textsubscript{3}). Taking meteorological effects into account, they fit generalized additive models for 1331 rural and urban sites in Europe to obtain a model for the “business-as-usual” circumstances. They then compare model predictions and true observations in the period from mid-March to the end of April and find an average decrease in 1-h maximum daily NO\textsubscript{2} of approximately 34.4% in urban Austrian sites and a decrease of 27.6% in rural Austrian sites.

A machine-learning approach to assessing the effect of lockdown on NO\textsubscript{2} levels in different parts of Spain was taken by Petetin et al. (2020). Using the data from 2017 to 2019 as a training set, they trained a Gradient Boosting Machine to predict the NO\textsubscript{2} concentration for each day based on a set of meteorological predictors. In a second step, they compared the predictions of this “business-as-usual”-model to the actual observations in 2020. Their results show a decrease of 56–57% with respect to the predicted NO\textsubscript{2} levels at the traffic-intensive measuring stations in Madrid and Barcelona, but only 40–43% for the respective urban background stations.

Our approach is a statistical one, and we intend to quantify the impact of the lockdown based on measured pollution concentrations. We use pollutant measurements and meteorological data from several ground-based measuring sites within the city borders for our analysis. While Bao and Zhang (2020) restricted their analysis to data sampled in 2020, we include historic data going back to 2015 for building our statistical models. A unique feature of our data is their 30 min resolution, which means that we have access to 48 half-hourly mean values for each day. This allows us to capture intraday effects. The dataset is part of a long-going campaign to measure atmospheric pollution in Graz in a major effort to meet EU pollution standards. Graz has struggled with increased PM\textsubscript{10} levels for decades, but has seen the pollutant levels steadily decreasing in recent years (Stadlober and Burger-Ringer, 2019). The dataset has been subject to intensive and continuous research with a particular focus on the forecasting of PM\textsubscript{10} levels (Stadlober et al., 2008).

In addition, we also compare our findings on the pollution levels with the traffic count data that is available in Graz for the lockdown period.

2. Data and methods

2.1. Shutdown measures

Beginning on March 15, 2020, the Austrian government issued a series of decrees that instated the shutdown. Essential and public gatherings were banned. Starting from March 17, with the exception of essential services such as supermarkets, pharmacies, post offices etc., all commercial shops, restaurants, bars, cinemas and public entertainment venues were closed. Schools and universities shut down. With encouragement from the government, many companies had their employees working from home. The initial response of the population was positive and the adherence to the reduction of movement and social activities was consistently high.

After a shutdown period, shops were reopened in two steps on April 14 and May 2. On May 15, a limited reopening of bars and restaurants took place. Schools were reopened in a stepwise scheme.

The establishment and abandonment of these measures divides the investigation time frame into four different periods that we will analyse: Phase 0 (Feb 1-Mar 15), Phase 1 (Mar 16-Apr 14), Phase 2 (Apr 15-May 18), Phase 3 (May 19-June 14). In 2020, each of these periods constitutes a different amount of restrictions and starts with the first working day in the corresponding week.

2.2. Data sources

Graz is the capital of the Austrian Province of Styria. It has close to 300k residents and is situated on the South side of the Alps in a basin at 350m above sea level. The data we use stem from the permanent pollutant monitoring network of the city. These data are publicly available (Land Steiermark, 2020). The pollutants are measured at five sites, two of which are situated in areas with heavy traffic (TR1, TR2), two in commercial and industrial areas (IN1, IN2) and one in a residential area (RE). The location of these measuring stations permits investigation of local effects in different areas of the city (see Fig. 1).

The data we consider is for the pollutants NO\textsubscript{2}, NO\textsubscript{x}, CO and PM\textsubscript{10}. All raw measurements of the pollutants and the meteorological variables are available as half-hourly mean values. The pollutant data is collected at all five measuring sites we consider, except for CO which is not collected at the sites IN2 and RE.

The meteorological data is provided by the same measuring network. An additional measuring station (ME1) substitutes meteorological measurements whenever unavailable at the locations. The data on precipitation is provided by the station RE for all the analyses. Finally, we use additional temperature data from Kalkleiten (ME2), which provides temperatures from a higher altitude (710m). This is an important variable to quantify diffusion conditions.

![Fig. 1. The location of the measuring sites.](image-url)
While the monitoring history reaches back even further into the past, we use only data starting from the year 2015 in our statistical model. This serves to avoid a bias due to the significant reduction in the pollution levels during the last decades. For each of these years, we use data from February 1 to June 14. This allows us to compare Phases 0–3 using the characteristics of 5 years of training data. It also provides enough data for the statistical models to be fit on a variety of meteorological conditions, thus improving accuracy and stability.

2.3. General method

Our first step is to provide statistical models for pollution levels taking into account mainly meteorological variables. We consider regression models for the daily averages and intraday pollution level curves, the latter being entirely novel. The models are fitted using observations of the years 2015–2019 (training set). Then we analyse the out-of-sample prediction errors for 2020.

Because we model the status quo ante, any potential effect which is not described by the variables in our model (like lower traffic intensities) will show in systematic anomalies of the prediction error. For example, if the lockdown invokes changes which have a significant positive impact on specific pollution levels, then we expect a systematic increase in pollution levels in the city (Stadlober et al., 2008). That is, we construct dummy variables that have proven to be useful in previous analyses of pollution levels in the city (Stadlober et al., 2008). While the monitoring history reaches back even further into the past, we include a more extensive timespan for the year 2020 to investigate different phases of the lockdown measures. In doing so, we may ascertain if and how the relaxation of some measures causes pollution levels to return to the status quo. The model we use is very transparent in the set-up and can be expected to produce stable and valid predictions. It could also be a useful template for related questions. For example, if one wants to quantify the effect of certain environmental policies, e.g. speed limitations or other traffic restrictions.

2.4. Input variables

We process the meteorological data before using them as input for the regression model. The air temperature (temp), relative humidity (hum) and wind speed (wisp) are summarized into daily mean values.

The wind gust speed (gust) is obtained from the half-hourly data by taking the maximum value of each day. The precipitation is aggregated over the course of the day (prec). Additionally, we calculate the temperature difference (td) between the air temperature at the station of interest and station ME2 as an indicator of atmospheric temperature inversion.

From these daily data, we further derive categorical meteorological variables that have proven to be useful in previous analyses of pollution levels in the city (Stadlober et al., 2008). That is, we construct dummy variables to indicate frost days, when temp is below zero; inversion days, when td is below zero (note that this definition is particular to our paper); wind days, when wisp is above 0.6 m/s; precipitation days, when prec is above 0.1 l/m². These dummy variables are dependent solely on the daily average of the meteorological covariates. While helping to keep the models simple and parsimonious, the dummy variables are only able to provide a rough separation of different meteorological situations.

Lastly, we also included control variables that are independent of the meteorology. This includes a 3-level factor indicating working days, Saturdays and Sundays/holidays, and a continuous variable indicating the year. This is necessary to represent the general trend of declining pollutant levels in previous years.

A small portion of the meteorological data is missing. In these cases, we imputed the meteorological data via a multiple linear regression model, using the data from other stations in the city as predictors. This only concerns 0% (RE) to 2% (IN1) of each sample.

Furthermore, we also removed some pollutant measurements which we deemed implausible and excluded known events of Saharan dust reaching the region of Graz from the analysis of the particulate matter.

Missing or implausible pollutant data were then replaced by an interpolation based on the local polynomial regression model LOESS if the timespan of interest was below 8 h. Otherwise, the data of the day

Table 1

| Pollutant | Unit | Site        | 02/01–03/15 | 03/16–04/13 | 04/14–05/17 | 05/18–06/14 |
|-----------|------|-------------|-------------|-------------|-------------|-------------|
| NO₂       | [µg/m³] | TR1 | 51.76 | 23.27 | 43.48 | 22.32 | 36.10 | 19.21 | 32.87 | 15.75 |
|           |      | TR2 | 37.72 | 18.72 | 29.09 | 16.69 | 23.34 | 13.51 | 20.64 | 11.35 |
|           |      | IN1 | 39.41 | 21.28 | 30.36 | 20.48 | 21.59 | 15.96 | 18.59 | 12.38 |
|           |      | IN2 | 34.74 | 20.26 | 25.93 | 18.00 | 18.34 | 13.84 | 15.52 | 10.48 |
|           |      | RE  | 29.90 | 18.03 | 20.07 | 14.13 | 23.83 | 22.23 | 18.15 | 22.15 |
| NO        | [µg/m³] | TR1 | 56.94 | 62.70 | 34.23 | 42.09 | 23.83 | 32.23 | 18.15 | 22.15 |
|           |      | TR2 | 18.93 | 33.76 | 7.30  | 13.95 | 5.23  | 9.91  | 4.10  | 6.60  |
|           |      | IN1 | 33.09 | 51.06 | 14.50 | 27.69 | 7.58  | 16.13 | 5.24  | 9.30  |
|           |      | IN2 | 17.65 | 29.94 | 6.04  | 14.54 | 3.63  | 9.62  | 2.48  | 5.84  |
|           |      | RE  | 8.89  | 21.65 | 3.44  | 8.89  | 2.04  | 5.70  | 1.68  | 3.74  |
| CO        | [mg/m³] | TR1 | 0.51  | 0.25  | 0.35  | 0.13  | 0.27  | 0.09  | 0.23  | 0.08  |
|           |      | TR2 | 0.46  | 0.23  | 0.29  | 0.11  | 0.22  | 0.08  | 0.19  | 0.07  |
|           |      | IN1 | 0.51  | 0.28  | 0.33  | 0.15  | 0.24  | 0.09  | 0.20  | 0.06  |
| PM₁₀      | [µg/m³] | TR1 | 36.04 | 22.64 | 27.63 | 15.46 | 21.07 | 11.97 | 20.64 | 10.14 |
|           |      | TR2 | 30.59 | 21.29 | 23.18 | 13.34 | 16.34 | 9.40  | 15.76 | 8.10  |
|           |      | IN1 | 35.64 | 23.36 | 27.92 | 17.69 | 21.88 | 11.71 | 17.92 | 9.52  |
|           |      | IN2 | 29.48 | 20.76 | 23.71 | 13.93 | 17.37 | 10.33 | 17.26 | 9.07  |
|           |      | RE  | 26.46 | 18.92 | 22.96 | 14.10 | 16.61 | 12.27 | 16.16 | 9.55  |
was discarded and not included in the fitting and evaluation of the model.

Some details on average pollution levels at the different sites can be seen in Table 1.

2.5. Model setup

We analyse the data on two levels. In a first step, we investigate the effect of the lockdown measures on the daily mean values of the pollutants. Secondly, we take a closer look to determine the intraday effect of the lockdown measures on the daily mean values of the pollutants.

Following on from this, we fit two regression models for each station and pollutant: one multiple linear regression model for the daily means and one scalar-on-function regression model for the daily curves (i.e. 48 half-hourly measurements per day). In both regression approaches, we use the variables mentioned in Section 2.4 as predictors. In addition to the meteorological variables from the same day, we also include lag-1 differences of the meteorological variables. Furthermore, we use two-way interactions and quadratic effects.

To account for skewness, heavy tails and heterogeneous variances, it is common to apply a log-transform to pollutants. We use a logarithmic transformation for NO and CO. However, we noted that a square-root transformation is better suited for NO$_2$ and PM$_{10}$. This has a better stabilizing influence on the residual variances and conforms with previous work on pollution data regarding particulate matter in Graz (Stadlober et al., 2008).

Some of the half-hourly measurements regularly drop to zero on days with low pollution levels, therefore we included an intercept $a$ in the transformation $f(Y_t) = \log(a + Y_t)$, where $Y_t$ is the pollutant concentration. This problem is not present in daily data because the peak at rush hours usually suffices to pull the daily mean up and far enough away from zero. The regression models take the form

$$f(Y_t) = \sum_{i=1}^{p} X_{it} \beta_i + \epsilon_t,$$

where $Y_t$ is the pollutant concentration, $f$ is a transformation function, $X_{it}$ are the predictors and $\epsilon_t$ is a random noise that represents the unexplained fluctuations and the deviation from the linear model.

The models of the daily means are multiple linear regression models (lm) that we fit using the function stepAIC from the R-package MASS (Venables and Ripley, 2002). All computations in this paper were carried out using R 4.0.0 (R Core Team, 2020). We use the Bayesian Information Criterion (BIC) for model selection, because we prefer parsimonious models. Compared to models that result from cross-validation, we found our method to have a similar predictive performance while including significantly fewer predictors. The models for the daily means reach coefficients of determination ($R^2$) of 0.76–0.92 for NO$_2$, NO and CO, and 0.53–0.70 for PM$_{10}$. Due to the transformations used, the model diagnostics regarding homoscedasticity and normality of the residuals are inconspicuous.

The analysis of the intraday effects is a problem of scalar-on-function regression. For a review of methods for this kind of problems, we refer to Reiss et al. (2017). Because of the underlying mechanisms and the inertia of air pollutant levels, we can treat the problem as essentially low dimensional and reduce the data to a small number of principal components (Jolliffe, 2002; Härdle and Simar, 2015). We chose a number of principal components that cover a large portion of the variability of the data and can be explained well by the covariates. We came to the conclusion that using 4 principal components is a good compromise across all measuring sites and pollutants. This explains 81–92% of the variability. The first principal component can generally be explained very well by the covariates, reaching an $R^2$ between 0.5 and 0.9, while $R^2$ for the subsequent principal components declines moderately fast. We select predictors by using the univariate procedure stepAIC for each principal component separately and then verify the significance of the predictors on the fitted multivariate model (mlm) using Pillai’s test statistic. As before, we compared different model selection procedures and found that our method is on a par with cross-validation while producing simpler models.

2.6. Analysis of the prediction errors

The models that we fitted in Section 2.5 are used to predict the pollution levels for the year 2020. Assuming that there has been no significant change in the model, the residuals for 2020 shall fluctuate unsystematically around zero. Any additional effect will cause a shift in the mean of the residuals.

In order to formally compare the deviation of the daily means from the meteorological model in the different phases of the lockdown, we
use a linear model with a four-level factor variable. After the initial variance stabilizing transformation we confirmed by Levene’s test that the variances within the four groups did not show any notable violation of homogeneity. The significance of the mean-shift is then assessed using two-sided Wald-type tests on the contrasts, taking the pre-lockdown period (Phase 0 of 2020) as control group. These tests are done for each site and pollutant separately.

For the half-hourly measurements, we perform tests on the 4-dimensional principal component score-vectors, again using the Phase 0 of 2020 as control group. Since the variance/covariance matrices $\Sigma_i$ of the score-vectors for Phase $i = 0, \ldots, 3$, are expected to be non-homogenous, we have estimated these matrices from the in-sample-residuals of the years 2015–2019 for the respective phases. We standardize the 2020 residuals by $\Sigma_i^{-1/2}$, from the appropriate Phase $i$. Then we apply the regression model approach mentioned above to the standardized score vectors, testing the contrasts using Pillai’s test statistic.

3. Results

3.1. Daily averages

Recall from Section 2.5 that we modelled the transformed pollution data and therefore are dealing with two different scales: the original scale and the transformed scale. While on the transformed scale the model assumptions hold, the original scale is more accessible for direct interpretation. Boxplots for the residual deviations (on the original,
untransformed scale) with respect to the different phases, stations and pollutants are given in Fig. 2. Most notable effects for the daily means are in the lockdown period (Phase 1) on NO$_2$ and NO levels. We see, for example, that NO$_2$ and NO were about 20 μg/m$^3$ below the expected level during Phase 1 in some stations. This needs to be compared to average concentrations of 43.5 μg/m$^3$ and 34.2 μg/m$^3$, respectively, in the years 2015–2019.

In Fig. 3, we present the in-sample model residuals for 2015–2019 as well as the out-of-sample residuals for 2020 for the two pollutants NO and NO$_2$. Again, for better interpretability, we plotted the data on the original and not the transformed scale. Furthermore we included the weekly averages of the prediction errors in 2020 (red curve). This notably depicts the influence of the lockdown phases. For NO$_2$ the effect is visible across all stations, differing only in intensity, with a stronger reduction in traffic and industrial areas. For NO, a systematic reduction is clearly visible only at sites TR1 and IN1.

A summary of the prediction errors in 2020 on the transformed scale along with a standard deviation and color code for the p-values can be found in Table 2. The statistical testing procedure described in Section 2.6 reveals that there has been a highly significant difference between Phase 0 and Phase 1 in all five sites for the pollutants NO$_2$ and NO. For NO$_2$ this deviation is still present in Phase 2 for all stations, while for NO the site IN2 no longer shows a significant deviation from Phase 0. In Phase 3, we see a mixed picture, but with a trend back to normal levels.

The pollutants CO and PM$_{10}$ show a different structure. While for CO we can detect significant differences across the phases in IN1, for the two remaining stations we see less effect in the lockdown period (Phase 1) but a significant effect in the Phases 2 and 3. PM$_{10}$ shows a quite surprising behavior. There is no significant effect for the industrial and traffic sites, but we observe a positive shift in the means at the residential site. This negative effect could potentially be explained by an increase in domestic fuel use, while people were staying at home. To a certain extent, this phenomenon is also due to the fact that we had unusually low PM$_{10}$ values in the control group (Phase 0 of 2020).

### Table 2

| Pollutant | Ph. 0 (02/01–03/15) | Ph. 1 (03/16–04/13) | Ph. 2 (04/14–05/17) | Ph. 3 (05/18–06/14) |
|-----------|---------------------|---------------------|---------------------|---------------------|
| **NO$_2$** |                     |                     |                     |                     |
| TR1       | -0.33               | -1.48               | -1.03               | -1.72               |
|           | 0.47                | 0.34                | 0.36                | 0.39                |
| TR2       | 0.07                | -1.09               | -0.96               | -0.72               |
|           | 0.41                | 0.29                | 0.30                | 0.39                |
| IN1       | -0.18               | -1.27               | -0.98               | -0.72               |
|           | 0.45                | 0.30                | 0.32                | 0.39                |
| IN2       | -0.14               | -1.02               | -0.65               | -0.72               |
|           | 0.46                | 0.31                | 0.28                | 0.39                |
| RE        | -0.25               | -0.98               | -0.72               | -0.55               |
|           | 0.40                | 0.45                | 0.39                | 0.28                |
| **NO**    |                     |                     |                     |                     |
| TR1       | 0.00                | -0.71               | -0.29               | 0.03                |
|           | 0.26                | 0.18                | 0.27                | 0.22                |
| TR2       | -0.17               | -1.45               | -0.64               | -0.20               |
|           | 0.39                | 0.67                | 0.42                | 0.28                |
| IN1       | -0.12               | -0.9                | -0.53               | -0.18               |
|           | 0.42                | 0.37                | 0.37                | 0.32                |
| IN2       | 0.04                | -0.97               | 0.11                | 0.62                |
|           | 0.61                | 0.74                | 0.67                | 0.45                |
| RE        | 0.04                | -0.6                | -0.22               | 0.03                |
|           | 0.62                | 0.58                | 0.48                | 0.53                |
| **CO**    |                     |                     |                     |                     |
| TR1       | -0.10               | -0.14               | -0.15               | -0.16               |
|           | 0.11                | 0.13                | 0.10                | 0.09                |
| TR2       | 0.01                | -0.03               | -0.14               | -0.21               |
|           | 0.14                | 0.14                | 0.13                | 0.14                |
| IN1       | -0.02               | -0.17               | -0.16               | -0.12               |
|           | 0.12                | 0.10                | 0.12                | 0.09                |
| **PM$_{10}$** |                 |                     |                     |                     |
| TR1       | 0.02                | -0.12               | 0.14                | -0.23               |
|           | 0.69                | 0.59                | 0.44                | 0.45                |
| TR2       | -0.35               | -0.02               | -0.14               | -0.37               |
|           | 0.66                | 0.66                | 0.54                | 0.25                |
| IN1       | -0.41               | -0.21               | -0.29               | -0.38               |
|           | 0.72                | 0.61                | 0.51                | 0.38                |
| IN2       | -0.33               | 0.00                | -0.29               | -0.6                |
|           | 0.54                | 0.58                | 0.51                | 0.49                |
| RE        | -0.47               | 0.40                | 0.09                | 0.18                |
|           | 0.50                | 0.67                | 0.50                | 0.49                |

3.2. Half-hourly means

Intraday effects of functional out-of-sample residuals 2020 for the different pollutants are shown in Fig. 4 for the station TR1 (having the highest pollution levels) and in Fig. 5 for the residential station RE (having the lowest pollution levels). We essentially compare two pointwise boxplots without whiskers in Figs. 4 and 5 by plotting pointwise first and third quartiles for prediction errors of 2020 versus the corresponding pointwise quartiles of the model residuals for 2015–2019.

The typical intraday pattern is fundamentally different for working days and Saturdays, Sundays and holidays. We will therefore restrict this section to analysis of working days. When looking at these plots, it is important to take the scale into account. The levels of PM$_{10}$ and NO$_2$ exhibit changes of 20 μg/m$^3$ or more in the course of 6 h. Furthermore, we can only interpret the results in the context of what a typical intraday curve looks like.

Curves of NO$_2$ levels show two very distinct peaks and valleys each day, where the peaks coincide with morning and evening rush hours. The effect that we see under the lockdown is similar across all stations, but the exact shape differs. The traffic-intensive sites TR1 and TR2 and the residential area RE each show similar reductions in early morning and afternoon hours, whereas the industrial areas IN1 and IN2 show significantly stronger reductions in the early morning than in the early afternoon. This dichotomy can be seen in Phase 1, but is less pronounced in Phases 2 and 3. The strongest reduction at all sites is typically seen around 9pm.

The typical daily pattern of NO is dominated by a very high peak in the morning. Depending on the season, a secondary, very minor peak emerges in the evening. Accordingly, the reduction during Phase 1 is concentrated in the morning hours, where the peak is somewhat shaved off. Traffic-heavy stations TR1 and TR2 show clear reductions throughout the day. In Phase 2, the effect is still very visible in the morning hours. In Phase 3, it disappeared.

The most interesting picture is presented by PM$_{10}$. No clear patterns...
are discernible. In the pre-lockdown period, all sites showed lower values than predicted. In Phase 1 of the lockdown, the sites TR1, TR2 and IN1 showed decidedly low values in the morning hours. The residential area RE shows higher values than predicted. Only around noon is this deviation not present. In Phases 2 and 3, no clear effect is visible any longer.

Even before the lockdown, CO was lower than predicted by our model for the traffic-intensive sites TR1 and TR2. This mainly stems from relatively low values in the morning hours. The other stations show the same picture. On the start of the lockdown, a very pronounced drop emerges at morning rush hour. Additionally, there is a smaller deviation in the evening. This pattern remains faintly visible through Phase 2.

Investigating the daily curves of prediction errors on working days, the null hypothesis of no difference between the lockdown periods and the time period before the lockdown is rejected in all but four cases at a 5% significance level. It was revealed that NO at station RE during Phases 2 (0.07) and 3 (0.74), PM$_{10}$ during Phase 1 at station TR1 (0.06) and TR2 (0.17), and NO$_2$ during Phase 3 at station IN1 (0.06) are non-significant. Here the numbers in brackets are the corresponding $p$-values.

We conclude that the intraday analysis reveals further deviations in the shape of the pollution curves, which are not reflected in a daily average.

4. Traffic data

Traffic data was collected with a resolution of 30 min at different counting stations throughout the city. This data spans two weeks from 2019, two weeks prior the lockdown in 2020 (one of which was in January and one right before the lockdown) as well as 13 weeks that span the entirety of Phases 1–3. The effect of the lockdown on overall urban traffic can be estimated by aggregating the data from three different traffic counting stations in the city. The first phase of lockdown saw working day vehicle numbers dwindle by 45% at morning peak hour, 45–55% during the day and 65–75% in the evening and night hours. In April and May, the traffic counts steadily rebounded and by June, they had returned to 5–10% below the pre-lockdown levels.

For our in-depth analysis, we will only use data from site TR1, where the pollutant measuring station and traffic counting point are in close vicinity. The co-movement of pollutant levels and traffic counts at this site can be seen in Fig. 6. The drop is sharpest for the traffic count, closely followed by NO and NO$_2$. The changes in the traffic seem to have no visible effect on CO and PM$_{10}$.

We would point out here that we have only limited traffic data from before the shutdown, which is why we did not include this as a separate variable in our regression models.

5. Summary and discussion

We have analyzed the effect of the lockdown measures on air pollution levels in the city of Graz, Austria. Using data from the preceding five years, we were able to provide well-founded models that account for meteorological influences on the pollution. The deviation from the meteorological models showed an abrupt change of NO$_2$ and NO, while we observed no significant effect on CO and no effect on PM$_{10}$.
that was consistent across all stations. In particular, we found daily mean NO\(_2\) levels reduced by 35–41%, depending on the measuring site, during the first phase of the lockdown in Graz. We can compare our findings to the results of Ordóñez et al. (2020) and Menut et al. (2020) on NO\(_2\) levels in Europe. Although the methods and time spans under analysis vary considerably, their results indicate reductions of 34.4% and 37.1%, respectively, in Austrian urban areas. This is remarkably close to our findings. Myllyvirta and Thieriot (2020) found population-weighted average reductions of 30% for NO\(_2\) and 1% for PM\(_{10}\) in Austria. Our results are also in line with the observed effect of lockdown measures on air pollution in other parts of the world, as estimated by Petetin et al. (2020), Baldasano (2020) and Kanniah et al. (2020), among others, but different environments and lockdown measures do not permit a quantitative comparison of the reduction effect.

While our statistical approach has the advantage that it doesn’t require complex geophysical models, it is less obvious how to attribute the decrease in emissions to the different sources. This problem, however, can be better understood with the intraday analysis which we have also performed. For example, it shows particularly strong reductions during morning and evening rush hours, which correlates with the corresponding strong reductions in traffic. Analysis of the half-hourly deviation curves also suggests that the increase of PM\(_{10}\) in the residential area stems from higher emissions in the hours from 10am to 8pm, which may potentially be explained by domestic fuel use. The intraday...
analysis is more sensitive and reveals significant differences in the shape of the pollution level curves, which remains undetected by comparing daily means.

The fact that reduced traffic was not reflected in lower PM$_{10}$ values in the industrial and traffic-intensive measuring sites might indicate that diverse actions taken to lower PM$_{10}$ in Graz over the past years have paid off. In this current situation, no linear relationship between traffic and PM$_{10}$ is evident anymore. While we cannot account for some important factors missing in the data (e.g. number of passenger cars versus the number of commercial vehicles), we may still infer from our findings that the plain traffic reduction does not result in a significant reduction in PM$_{10}$, even though this decrease in traffic is seen to correlate strongly with the reduction in NO$_2$. Air pollution in an urban environment is not a monocausal phenomenon and we think that the methodology presented here can help policymakers to make better founded decisions on how to reduce air pollution in order to ensure the protection of public health. This topic, however, requires further research.

Credit author statement

Siegfried Hormann: Conceptualization, Methodology, Supervision, Writing. Fatima Jammoul: Data curation, Formal analysis, Visualization, Writing. Thomas Kuenzer: Data curation, Formal analysis, Visualization, Writing. Ernst Stadlober: Conceptualization, Supervision.

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.

Acknowledgements

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors wish to thank the city of Graz for kindly providing the traffic count data.

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