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A Double-Edged Sword: Impact of Covid-19 on Environment

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IMPACT OF COVID-19 ON ENVIRONMENT

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Abstract

In this paper, we study the causal effect of COVID-19 related reduction in mobility and economic activity on environment. First using spatial and temporal variation in curfews in a difference-in-differences setup and second using a regression discontinuity design, we show that ambient air quality improved following travel restrictions, public place closures and business shutdowns. Our results confirm that economic activity induces substantial negative consequences on environment and public health and highlight the need for formulating environmentally oriented strategies that harmonize economic, public health and environmental interests.

Keywords: Covid-19, environment, air quality

JEL Classifications: Q5

ملخص

في هذه الدراسة نبحث التأثير السببي الناتج عن جائحة فيروس كورونا (كوفيد-19) على خفض الحراك والنشاط الاقتصادي. أولًا، باستخدام التباين المكاني والزماني في حالات الحظر فى سياق اختلاف الاختلافات، وثانيًا، باستخدام تصميم انحدار الإنقطاع (RDD)، اتضح تحسن نوعية الهواء المحيط بعد فرض قيود السفر، وإغلاق الأماكن العامة، وإغلاق الأعمال. وتؤكد نتائج البحث ما يتسبب به النشاط الاقتصادي من عواقب سلبية وخيمة على البيئة والصحة العامة، كما أنه يسلط الضوء على الحاجة إلى صياغة استراتيجيات مراعية للبيئة توائم بين مصالح الاقتصاد والصحة العامة والبيئة.

1. Introduction

There is now a consensus that the COVID-19 pandemic represents one of the largest economic shocks to world economies in recent decades. Negative effects of the epidemic have been documented on a wide array of outcomes ranging from income losses, rising unemployment, declining consumption to mental health deprivations and increased domestic violence (see Baker et al. 2020; Coibon et al. 2020; Horvat et al. 2020; Altindag et al., 2020; Erten et al., 2021). Despite all the economic, social and health related negative consequences, COVID-19 offers an opportunity to causally identify and quantify the effect of economic activity on environment. In particular, due the lockdowns, it might be expected to see improvements in the level of greenhouse gas emissions, air quality and surface water quality. Although, the impacts would be temporary and are expected to return to initial levels once the mobility restrictions are revoked, these unanticipated changes in the economic activity induced by the pandemic provide a quasi-experimental setup to examine the effects of the human-induced environmental changes. Studying the environmental consequences of the decline in economic activity and civilian mobility is invaluable for economic, public health and environmental policy makers in formulating environmentally oriented strategies that harmonize economic, public health and environmental interests. In this study we causally examine the effect of the reduced mobility and economic activity on environment.

Quantifying the causal association between economic activity and air quality has a particular importance for the countries in the MENA region. This region has the second highest air pollution levels in the world and according to the World Health Organization (WHO) air pollution levels are by 4-5 times in most of the MENA cities (WorldBank, 2020), and yet air pollution in the region is currently understudied (Barkley et al., 2017). The economic costs of the health effects from air pollution include premature deaths and people suffering from respiratory and cardiovascular diseases, among many others and reduced labor productivity. Therefore, it is of academic and policy concern to examine the effects of economic activity on air pollution levels and incentivize inclusion of green and sustainable practices in post-COVID-19 era.

The existing evidence on the effect of lockdowns on air quality is not conclusive yet. He et al. (2020), Brodeur et al. (2020) show improvements in air quality in China and US, respectively, whereas Almond et al. (2020) shows that COVID-19 had ambiguous impacts and might even decrease air quality in China. In addition to these country specific studies, Lenzen et al. (2020), Venter et al. (2020), Dang and Trinh (2021) provide global estimates of improvements in air quality. Our results contribute to this growing literature by particularly providing evidence from MENA region.

Due to high population growth rates and rapid urbanization, water demand has been increasing rapidly in the MENA region; and overexploitation of surface and ground water, uncontrolled discharge of domestic and industrial wastewater, pesticides and fertilizer-derived plant nutrients into the water resources contributes to water pollution exacerbate the already alarming water stress in the region. Future development scenarios are expected to further aggravate these challenges, especially given that MENA is one of the regions that is most vulnerable to the impacts of climate change (IPCC, 2013). As such, it is crucial to study the effects of human induced changes in pollutants on water pollution and the COVID-19 slowdown provides an unintended controlled experiment to do so. The current evidence on the subject is sparse. Yunus et al. (2020) using satellite data and Cherif et al. (2020) using water surface temperature data, document improvements in surface water quality and coastal water quality. Our study add to this literature by providing evidence on water quality using complete set of real time water quality measures including dissolved oxygen level, pH, temperature, concentrations of BOD, Cd, Hg, Fe and Mn, chloride, particulate matter (turbidity), hardness etc.

As a populous and emerging market, Turkey is among the countries that are hit hardest economically by the pandemic and among the one with the highest case numbers. As of December 2020, Turkey has the 9th highest case number with over 2.9 million cases; 1,6 million recoveries and 29.696 deaths.[3,4] Turkey provides a unique setting to study the effect of COVID 19 pandemic on environment, as it is one of the fastest countries to impose measures and tight restrictions against the epidemic. After the first official COVID-19 case on March 10, 2020 and first death on March 15, 2020 are reported, on March 16, 2020, the Turkish government closed schools until further notice. Starting on March 15, 2020, public places such as malls, bars, restaurants, cafes, theatres, cinemas, and hairdressers were gradually closed. Operating times and capacities of supermarkets and groceries were regulated. Moreover, partial curfews were imposed for population over age of 65 on March 22nd, and for population under age of 20 on April 4th. Since these precautions did not provide the desired decline in case numbers general curfews are imposed in 31 provinces on weekends between April 11th and May 3rd, in 23 provinces between May 9th and May 10th, in 15 provinces between May 16th and May 19th, in 81 provinces between May 23rd and May 26th and finally in 15 provinces between 30 and 31st May. This spatial and temporal variation in curfews provide quasi-experimental setup for studying the effect of epidemic and related restrictions on air and surface water quality.

We conduct our empirical analysis using two datasets. First, air quality data comes from the Turkish Ministry of Environment and Urbanization Air Quality Monitoring Stations. Our second data source is on water quality data from Water Quality Stations. Using these datasets, we identify and quantify the environmental effects of declining mobility and economy activity first by employing a difference-in-differences design, where we utilize the temporal and provincial variation in curfews and the length of curfews. Second, we carry out a Regression Discontinuity (RD) design and observe the immediate impact of the spread of the pandemic and policy measures passed to contain it.

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[3] Johns Hopkins Coronavirus Resource Center (CRC)
[4] Turkish Ministry of Health

Our results demonstrate that ambient air quality has improved following the announcement of first COVID-19 case and related precautions announced against it in Turkey. In particular, a reduction in mobility and economic activity due to in-city and intercity travel restrictions, curfews, school and business (both private sector and public sector) closures, public place closures (malls, bars, restaurants, cafes, theatres, cinemas, hairdressers, and etc.) is the direct mechanism explaining the improvements in air pollutant concentrations in Turkey. We also provide some suggestive evidence on the improvements of water quality indicators during this reduced mobility period. Our results quantify the human induced environmental pollution and magnify the need for designing policy alternatives that harmonizes sustainable growth objectives with public health and environmental concerns.

The rest of the paper proceeds as follows. The next section describes data sources and summarizes the data. Section 3 explains empirical framework. Section 4 lays out the results and Section 5 concludes.

2. Data

In this study we employ two sets of data source. First, we use air quality data from the Turkish Ministry of Environment and Urbanization Air Quality Monitoring Stations. This data provides several air quality measures including $PM_{2.5}$ and PM_{10}, inhalable particles with diameters that are generally 2.5 and 10 micrometers, respectively and NO_2 which primarily gets in the air from emissions from cars, trucks and buses, power plants, and off-road equipment. We also examine the concentration of SO_2, CO and O_3.[5] Additionally, from these seven pollutants we also create an aggregate air quality index using principal component analysis. Second data is from Water Quality Stations and include water quality measures such as dissolved oxygen level (DO), pH, temperature, concentrations of BOD, Cd, Hg, Fe and Mn, chloride, particulate matter (turbidity), and hardness.

We have air quality indicators from 314 stations in 81 provinces in Turkey between 01.01.2018 and 27.07.2021. Table 1 provides summary statistics of daily concentrations of air pollutants in 314 stations. It reveals that there is too much daily variation which can be attributed both to seasonality characteristic of the air pollution and also province specific differences such as urbanization, industry, population, weather etc. This variation is especially substantial for $PM_{2.5}$ and CO concentrations. Therefore, in our estimation framework, we have incorporated controls for seasonality and time-invariant city characteristics to account for such potential differences.

Table 2 provides city level descriptive statistics for years 2018, 2019 and 2020, respectively. It is hard to deduct a single trend across years- while for some pollutants there is an improvement between 2018 and 2020, for others concentrations display an increasing trend. According to WHO's guidelines for air pollution, interim targets for PM_{10} and $PM_{2.5}$ annual concentrations are

[5] Definition and principal sources of outdoor air pollutants are given in Appendix.

20 μg/m^3 and 10 μg/m^3, respectively. According to Table 2, both pollutants are above the target concentrations. The WHO estimates that reducing annual average $PM_{2.5}$ concentrations from levels of 35 μg/m^3, common in many developing cities, to the WHO guideline level of 10 μg/m^3 can reduce air pollution-related deaths by around 15%. For NO_2 WHO's interim annual target is 40 μg/m^3; in average through 2018-2020, NO_2 concentrations in Turkey satisfies this limit.

Figures 1 (a)-(f) plot the time series graphs of the daily air pollutant concentrations to have a general overview of the effect of COVID-19 pandemic on pollution patterns in Turkey. Figures reveal the expected seasonal characteristics of air pollutants -displaying elevated levels in winter months and low levels in summer months. An exception in this case is ozone, which is found in higher concentrations in longer days and higher air temperatures (Jez, 2009). Higher levels of air pollution in winter months are associated with higher energy use (biomass burning) and increased atmospheric stability and slow air movement which trap pollutants and lead them to remain in air for much longer and be breathed in at a higher rate.

Figures 3 further displays the time series graphs of the average water quality indicators and suggest a similar improvement in water pollution levels.[6] Based on the monthly averages total organic carbon, FE, Mn concentrations and water turbidity there is a temporary improvement during the lockdown period between March and June of 2020.

3. Empirical framework

In this section, we provide a detailed description of our estimation framework. For the causal identification of the potential pollution effects of the pandemic, we explore the length of curfews as an exogenous shock to air quality and employ a difference-indifferences design. In this effect, we exploit the temporal and provincial variation in the implementation and the length of the curfews to causally quantify the environmental effects of declining mobility and economic activity. Our difference-in-differences analysis assumes that the COVID-19 had disproportionately larger impact on air quality in provinces with curfews and longer curfews than provinces without the curfews. Moreover, the validity of the difference-in-differences estimation relies on the parallel trend assumption which suggests that the change in concentration of the pollutants over time would have been similar in all provinces if there had not been pandemic related curfews. Later, we test the robustness of our main difference-in-differences specification by relaxing this parallel trend assumption through allowing for provinces to differ in terms of time trends (Angrist and Pischke, 2015). More specifically, we estimate the following differences-in differences equation for province *p* in day *t*:

$$Y_{pt} = \alpha + \beta\ Curfew\ City * Curfew\ Days_{pt} + \theta_t + \vartheta_p + \delta \mathrm{s} + \delta X_{pt} + \varepsilon_{pt}$$

[6] Since the number of observations in water quality station data is not enough for empirical analysis yet, only descriptive analysis performed on water quality for this version of the paper.

where Y_{pt} denotes the environmental quality measures of province p at day t. We measure the air quality using several indicators including $PM_{2.5}$ and PM_{10}, inhalable particles, with diameters that are generally 2.5 and 10 micrometers, respectively, and NO_2 which primarily gets in the air from emissions from cars, trucks and buses, power plants, and off-road equipment. We also examine the concentration of SO_2, CO and O_3. Finally, we use a combined measure of air quality index (AQI) to incorporate all different types of air quality measures in one indicator. Curfew city is an indicator which takes a value of 1 if a province was under the mandated curfew and 0 for cities which were not affected by the curfews. Curfew Days is a dummy variable taking a value of 1 on the curfew days and 0 otherwise. ϑ_p is province fixed effects, controlling for the fact that provinces might be systematically different from each other. θ_t is day fixed effects and δ_s is station fixed effects. X_{pt} is a vector of time-varying province-level control variables that might be correlated with pollution such as daily temperature and rainfall. Following Bertrand, Duflo and Mullainathan (2004), the standard errors are clustered by province to account for correlations in outcomes between individuals residing in the same province over time. Finally, β is the main coefficient of interest in this difference-in-differences framework.

In addition to the difference-in-differences analysis, we further supplement our analysis with a Regression Continuity (RD) Design through exploring the clear cut-off day in the implementation of the curfews. Particularly, we estimate the following basic sharp RD specification:

$$Y_i = \alpha + \beta t_i + f(x_i) + \varepsilon_i \qquad (1)$$
$$\forall x_i \in (c - h, c + h)$$

where Y_i is the air quality indicator for province i. As postulated in Cattaneo et al. (2019), we correct for the bias and variance in the reported RD specification. More specifically, we exploit the exact dates in the implementation of the curfew rules in the RD design, with data points after COVID-19 reached to Turkey (16 March 2020) being assigned to the treatment group. x_i is the running variable (days in our setting), and h is the bandwidth around the cut-off point c (i.e., March 16th). We follow the bandwidth selection procedures provided by Cattaneo et al. (2019) to obtain the data-driven bandwidths for our RD analysis. In particular, we employ the MSE-optimal and CER-optimal bandwidths by allowing for common and different bandwidths in each side of the cut-off. The use of various bandwidth selection procedures enables us to test the robustness of our results and ensure that our results are not sensitive to the chosen bandwidth. The control function $f(x_i)$ is a continuous n-order polynomial function of the running variable on each side of the cut-off c. Following Gelman and Imbens (2017) and Imbens and Lemieux (2008), we use local linear regressions in our main specification to avoid the problem of over fitting. We further test the robustness of our results with the quadratic polynomial of the running variable. Finally, we use the triangular kernel function in our estimations as suggested in Cattaneo et al. (2019).

4. Empirical results

Difference-in-Differences Estimation

We begin by estimating difference-in-differences analysis through exploring spatial and temporal variation in curfews. Results summarized in Table 3 demonstrate that a reduction in mobility through curfews led to an improvement in air quality, with provinces with longer curfews experiencing the largest decline in air quality. We further test the robustness of our results through employing different specifications including combining station, province, date, day and month controls. Only, exception to our finding is surface level ozone concentration and SO_2.

Identifying assumption in this difference-in-differences setup is that in the absence of COVID-19 related reduction in mobility and economic activity, changes in ambient air quality would have been the same in curfew cities and others. However, this assumption might fail if province-by-time variation in curfew restrictions is related to other province-specific changes that are related to air pollutant concentrations. We test our identifying assumption with two different specification checks. First, following Angrist and Pischke (2015), we include province specific time trends and relax the parallel trend assumption in order to flexibly deal with possible differences across provinces during the time period analyzed. Table 4 shows the results for this specification. The results continue to show that on curfew dates in curfew cities, in which human mobility and economic activity was further restricted, air pollutant concentrations are statistically significantly lower and ambient air quality is significantly higher.

In addition, we perform a placebo experiment using the time period before COVID-19 and its restrictions. Particularly, we replicate the analysis in Table 3, but only include the data before June 1, 2019, i.e., the period long before the first of official case of COVID-19 is reported in Wuhan, China on December 31, 2019. We use the province curfew identifiers in 2020, and assign same curfew days to provinces in 2019. For example, a province that had a curfew on April, 11, 2020 receives a placebo curfew at April, 11, 2019. Here, the idea is that since there was not an actual curfew or official mobility restrictions or individual mobility hesitancy during that time period, coefficient of interest in difference-in-differences estimation should be statistically insignificant. Table 5 reports these results. For all of the air pollutants, the coefficient of placebo curfews are insignificant indicating that placebo curfews did not have disproportionately larger impact on provinces with placebo curfews and the change in the concentration of the pollutants over time was the same in all provinces. This exercise bolsters the conclusions derived from Table 3 and shows that underlying province specific differences or equal-trend assumption do not drive our results.

Regression Discontinuity Design

As described in the estimation framework section, we exploit the discrete and abrupt change in the mobility restrictions dictated by the pandemic to provide causal evidence on the effect of economic activity on air pollution. As it is customary for the RD analysis, we first begin with the graphical illustration of the RD design in Figure 2 (a)-(f). Our cut-of date is March 16, 2020, date at which the nationwide restrictions and lockdowns were first imposed. These pollutant-specific figures are generated using the data-driven optimal number of bins procedures provided by Cattaneo et al. (2019). We also use polynomial of degree 1 for the running variable in these RD figures. These figures visually demonstrate the significant and negative impact of COVID-19 related slowdowns on air pollutant concentrations.

As discussed in detail in the identification strategy section, we present the robust RD estimates which are corrected for the bias and variance, as suggested in Cattaneo et al. (2019). We allow for both linear and quadratic polynomials in running variable for the possibility of the pre-trends and non-linearity in our data. We further present the RD results with two data-driven bandwidth selection procedures summarized in Cattaneo et al. (2019), to ensure that our results are not driven by the choice of the bandwidth, or polynomial degree of the running variable. We find that the RD estimates are robust to a different bandwidth selection procedures and polynomial choice for the running variable.

Panel A of Table 6 presents the RD estimates with MSE-optimal bandwidth selection, whereas Panel B summarizes the RD results with CER-optimal bandwidth with the associated bandwidths used in each regression. Similar to the difference in differences estimations, the RD framework also shows that air pollutant concentrations significantly declined following the mobility restrictions, except for SO_2 and O_3 concentrations.

Having shown that pandemic improved ambient air quality, we further provide additional evidence on the robustness of our main results and formally test their validity. In this pursuit, we performed a battery of validity checks as suggested in Cattaneo et al. (2019) to ensure that our data exhibits no other jumps before and after the restrictions took place, and that our findings are not sensitive to observations near the cut-off. Our results are robust to varying degrees of polynomial of the running variable, as shown in Table 6 Columns 7-12 in each panel. We conclude therefore that our results are not sensitive to the selection of the bandwidth procedures or a degree of polynomials of the running variable.

We further perform a placebo experiment, similar to the placebo experiment in difference in differences setup, in which we set the cut-off point to March 16, 2019, exactly a year prior to the actual curfew. In table 7, none of the point estimates in these alternative cut-offs are statistically significant bolstering our confidence that the estimated effects are indeed due to COVID-19 pandemic and subsequent mobility restrictions rather than other confounding factors, jumps or non-linearity in the data.

5. Conclusion

Better understanding of the impact of economic activities on environment and climate change is a stepping stone to promote green alternatives that minimizes risk to human health and the environment without sacrificing economic efficiency. In such, the results of this study provide policy makers with invaluable information to develop environmentally sustainable economic development strategies.

Our results show that ambient air quality was improved during COVID-19 related lockdowns and decreased economic activity. Particulate matter, CO, NO_2, NOX concentrations statistically significantly declined, while O_3 and SO_2 concentrations remain unchanged. We also provide some suggestive evidence that surface water quality was also improved possibly due to mobility restrictions, air quality improvements and reduced industrial activity.

In this regard, our results stress the human induced environmental impact and its indirect effect on human health and provide further empirical evidence supporting the need for governments to design sustainable economic policies that acknowledges the public health and environmental concerns.

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Table 1. Daily Concentration of Air Pollutants

	Number of Obs	Mean	Std. Dev.	Min	Max
PM10 (µg/m³)	241,571	45.55	38.07	0	1591.74
PM25µgm3	101,126	619,45	124708	.02	3.40e+07
SO_2 (µg/m³)	233,218	12,60	30.91	.03	3658.12
CO (µg/m³)	111,540	1015.93	33334.51	.09	8695796
NO_2 (µg/m³)	184,693	31.55	25.79	0	594.76
NOX (µg/m³)	180,814	58.97	77.96	.01	4396.95
O_3 (µg/m³)	130,820	45.015	30.67	.42	1002.74

Notes: Table summarizes daily pollutant levels from 314 stations between 01 January 2018 and 27 July 2021.

Table 2. Annual Average Concentration of Air Pollutants in Cities

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: 2018					
PM10 ($\mu g/m^3$)	77	50.38	18.66	18.22	129.38
PM2.5 ($\mu g/m^3$)	43	24.28	11.96	11.78	86.46
SO_2 ($\mu g/m^3$)	79	13.46	9.47	4.623	51.61
CO ($\mu g/m^3$)	42	1027.02	840.16	416.98	3954.34
NO_2 ($\mu g/m^3$)	52	28.99	12.56	6.72	68.02
NOX ($\mu g/m^3$)	52	51.33	41.29	6.95	289.15
O3 ($\mu g/m^3$)	49	43.51	15.41	14.87	78.89
Panel A: 2019					
Variable	Obs	Mean	Std. Dev.	Min	Max
PM10 ($\mu g/m^3$)	77	46.77	17.06	13.24	136.38
PM2.5 ($\mu g/m^3$)	46	22.39	8.25	6.12	53.55
SO_2 ($\mu g/m^3$)	78	12.88	8.94	3.35	57.99
CO ($\mu g/m^3$)	44	735.07	240.43	282.89	1229.41
NO_2 ($\mu g/m^3$)	57	33.55	18.29	6.94	122.46
NOX ($\mu g/m^3$)	57	53.37	28.64	13.19	184.42
O3 ($\mu g/m^3$)	56	42.80	19.04	14.50	118.17
Panel B: 2020					
Variable	Obs	Mean	Std. Dev.	Min	Max
PM10 ($\mu g/m^3$)	79	46.98	15.06	15.30	109.31
PM2.5 ($\mu g/m^3$)	54	23.61	11.82	7.81	85.81
SO_2 ($\mu g/m^3$)	79	14.96	20.32	3.44	175.48
CO ($\mu g/m^3$)	51	916.74	938.43	329.83	7034.91
NO_2 ($\mu g/m^3$)	62	33.50	14.00	8.93	66.73
NOX ($\mu g/m^3$)	62	58.98	30.28	17.34	163.49
O3 ($\mu g/m^3$)	61	39.87	15.15	9.54	69.26

Notes: Table summarizes annual pollutant averages by city.

Table 3. Effect of Curfews on Air Pollutants: Difference-in-Differences Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	AQI	PM10	SO2	CO	NO2	NOX	O3	AQI	PM10	SO2	CO	NO2	NOX	O3
Curfew City x	-0.226	2.259	-0.041	91.647	-7.610***	-22.091***	6.561**	-0.155**	-4.207**	-3.160	18.075	-9.638***	-16.330***	5.018**
Curfew Days	(0.138)	(2.164)	(2.317)	(143.270)	(2.572)	(6.363)	(2.993)	(0.065)	(1.642)	(5.860)	(75.043)	(1.697)	(4.858)	(2.188)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No
Station FE	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day X Month FE	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,824	81,242	77,848	38,207	59,012	59,137	45,571	10,824	81,242	77,848	38,207	59,012	59,137	45,571
R-squared	0.323	0.385	0.347	0.104	0.373	0.278	0.331	0.570	0.478	0.632	0.158	0.655	0.574	0.542

Notes: Regressions include province fixed effects, population and number of motor vehicles per 1000 population. Additionally, Columns 1-7 control for date fixed effects, Columns 8-14 control for station fixed effects, day, month and day x month fixed effects. AQI is the aggregate air quality index calculated by principal component analysis using 6 pollutants Robust standard errors clustered at the province level are in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Effect of Curfews on Air Pollutants: Difference in Difference Estimates -Without parallel trend assumption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	AQI	PM10	SO2	CO	NO2	NOX	O3
Curfew City * Curfew Days	-0.680***	-15.669***	-10.489	-378.270***	-15.444***	-46.711***	15.631***
	(0.196)	(2.033)	(6.304)	(44.641)	(2.076)	(6.951)	(1.741)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,824	81,242	77,848	38,207	59,012	59,137	45,571
R-squared	0.480	0.281	0.631	0.214	0.568	0.457	0.472

Notes: Regressions include province fixed effects, date fixed effects, station fixed effects, province specific time trends, population and number of motor vehicles per 1000 population. AQI is the aggregate air quality index calculated by principal component analysis using 6 pollutants. Robust standard errors clustered at the province level are in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5. Effect of Curfews on Air Pollutants: Placebo Experiment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	AQI	PM10	SO2	CO	NO2	NOX	O3	AQI	PM10	SO2	CO	NO2	NOX	O3
Placebo Curfew	-0.092	-2.035	-0.148	-34.968	-0.682	-3.383	-1.733	-0.067	-1.502	-0.130	-39.217	-0.335	-2.786	-1.293
	(0.073)	(1.322)	(0.918)	(28.943)	(1.111)	(3.107)	(1.570)	(0.063)	(1.466)	(0.883)	(31.787)	(0.864)	(2.802)	(1.426)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No
Day and Month FE	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,562	11,814	11,280	5,216	9,058	9,041	6,348	1,562	11,814	11,280	5,216	9,058	9,041	6,348
R-squared	0.429	0.356	0.421	0.439	0.375	0.322	0.552	0.790	0.554	0.512	0.636	0.833	0.753	0.819

Notes: Placebo curfew days creating by taking actual curfew dates one year back at 2019. Regressions include province fixed effects, population and number of motor vehicles per 1000 population. Additionally, Columns 1-6 control for date fixed effects, Columns 7-12 control for station fixed effects, day, month and day x month fixed effects. AQI is the aggregate air quality index calculated by principal component analysis using 6 pollutants Robust standard errors clustered at the province level are in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6. Effect of COVID-19 Restrictions on Air Pollution: Regression Discontinuity Design

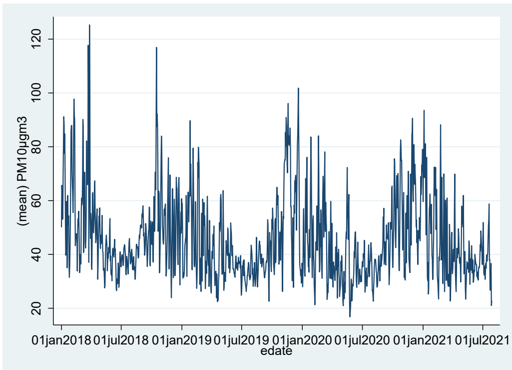
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	AQI	PM10	PM2.5	SO2	CO	NO2	NOX	O3	AQI	PM10	PM2.5	SO2	CO	NO2	NOX	O3
PANEL A: Bandwidth Selector: MSERD																
Treatment	-0.326***	-22.400***	-7.813**	-1.980**	-277.751***	-9.700***	-36.186***	2.714	-0.232*	-25.784***	-8.713**	-1.703	-265.957***	-7.038*	-29.317**	2.478
	(0.124)	(5.749)	(3.061)	(0.941)	(61.621)	(3.157)	(10.739)	(2.514)	(0.139)	(6.902)	(3.644)	(1.290)	(76.438)	(3.748)	(11.859)	(3.344)
Bandwidth Selector	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD
Polynomial	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2
Observations	18,048	153,023	60,346	149,928	68,974	114,201	114,675	81,460	18,048	153,023	60,346	149,928	68,974	114,201	114,675	81,460
PANEL B: Bandwidth Selector: CERRD																
	AQI	PM10	PM2.5	SO2	CO	NO2	NOX	O3	AQI	PM10	PM2.5	SO2	CO	NO2	NOX	O3
Treatment	-0.225*	-22.494***	-6.564**	-1.234	-278.481***	-8.470**	-31.402***	2.506	-0.117	-23.178***	-6.918*	-0.568	-232.516***	-5.968	-23.429*	2.437
	(0.134)	(6.148)	(3.323)	(1.030)	(66.271)	(3.400)	(11.622)	(2.770)	(0.151)	(7.580)	(3.955)	(1.374)	(83.941)	(4.167)	(13.023)	(3.745)
Bandwidth Selector	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD
Polynomial	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2
	18,048	153,023	60,346	149,928	68,974	114,201	114,675	81,460	18,048	153,023	60,346	149,928	68,974	114,201	114,675	81,460

Table 7. Regression Discontinuity Design – Placebo Exercise (2018-2019)

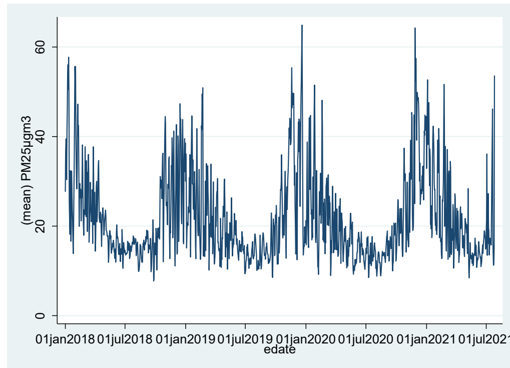
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	AQI	PM10	PM2.5	SO2	CO	NO2	NOX	O3	AQI	PM10	PM2.5	SO2	CO	NO2	NOX	O3
	PANEL B: Bandwidth Selector: MSERD															
Treatment	0.134	0.456	3.748	0.262	-16.199	1.736	9.117	1.304	0.220	3.943	5.001	2.172	47.774	2.205	10.211	-0.761
	(0.241)	(6.885)	(4.167)	(1.513)	(78.735)	(5.561)	(15.699)	(3.220)	(0.261)	(8.070)	(4.626)	(1.665)	(94.460)	(5.905)	(16.709)	(3.915)
Bandwidth Selector	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD	MSERD
Polynomial	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2
Observations	8,705	83,730	28,213	83,940	35,278	62,968	63,178	42,648	8,705	83,730	28,213	83,940	35,278	62,968	63,178	42,648
	PANEL B: Bandwidth Selector: CERRD															
	AQI	PM10	PM2.5	SO2	CO	NO2	NOX	O3	AQI	PM10	PM2.5	SO2	CO	NO2	NOX	O3
Treatment	0.201	0.587	2.650	0.157	2.610	4.421	10.659	-0.032	0.357	2.623	5.799	2.411	85.929	6.553	19.031	-2.447
	(0.225)	(6.133)	(3.811)	(1.379)	(71.360)	(5.146)	(14.667)	(2.881)	(0.252)	(8.755)	(4.333)	(1.682)	(96.038)	(5.687)	(15.774)	(4.076)
Bandwidth Selector	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD	CERRD
Polynomial	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2
Observations	8,705	83,730	28,213	83,940	35,278	62,968	63,178	42,648	8,705	83,730	28,213	83,940	35,278	62,968	63,178	42,648

Figure 1. Daily Air Pollutant Concentrations

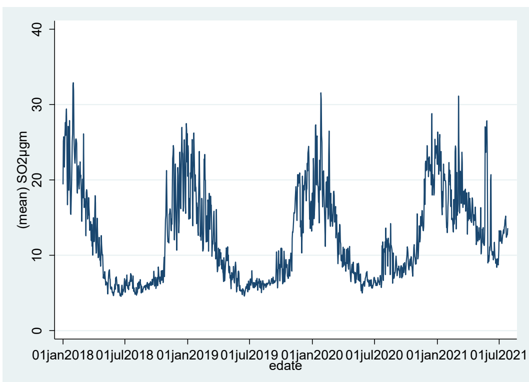
a) PM10



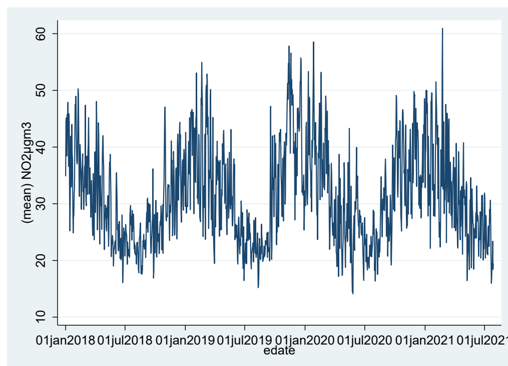
b) PM2.5



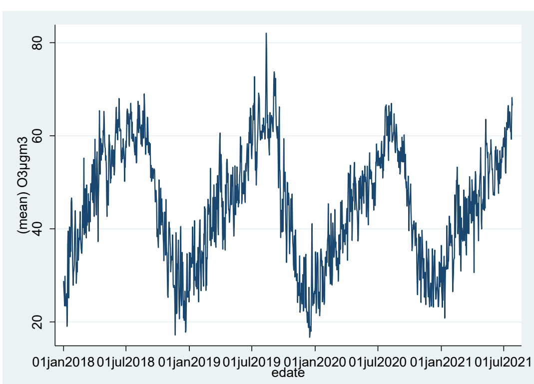
c) SO2



d) NO2



d) O3



e) NOX

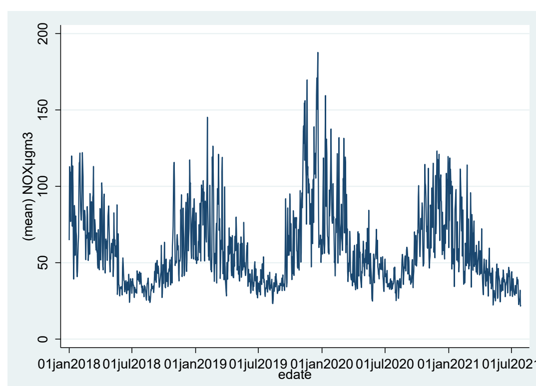
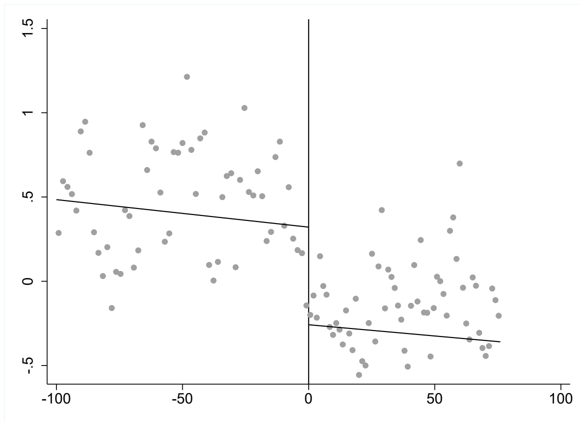
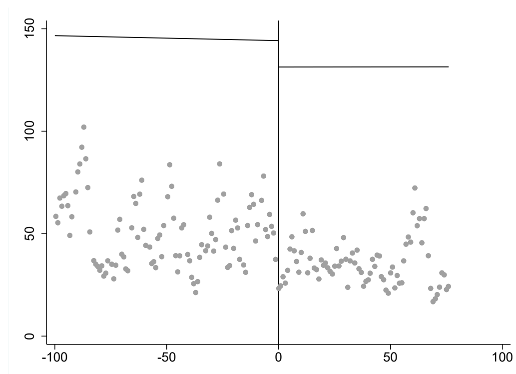


Figure 2. Regression Discontinuity Plots (Air Quality Indicators)

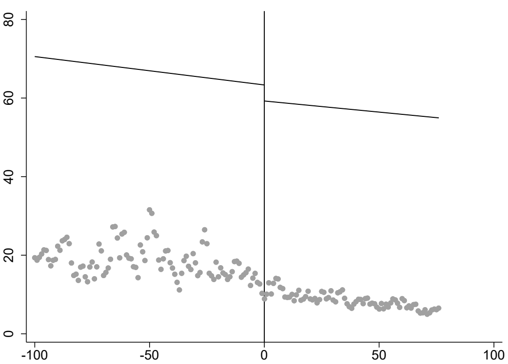
a) AQI



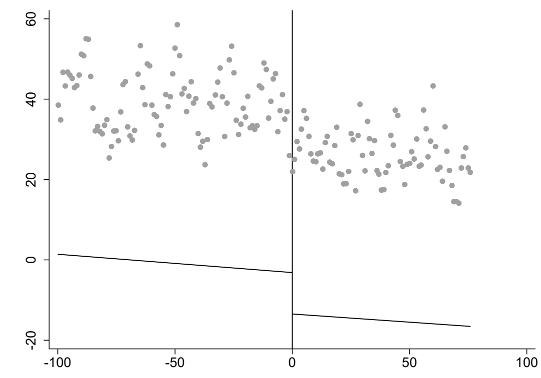
b)PM10



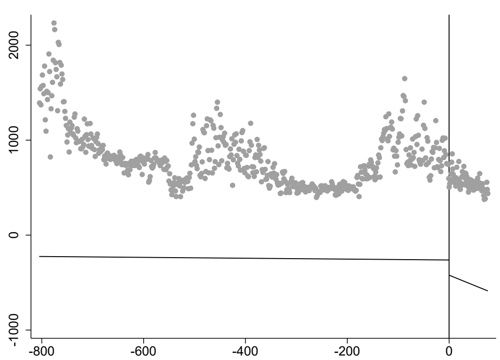
c) NO2



d) NOX



e) CO



f) PM2.5

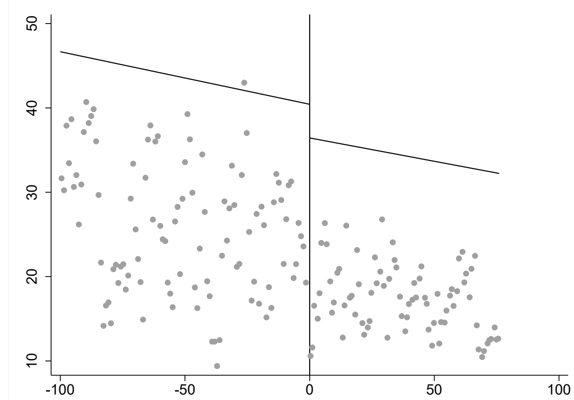
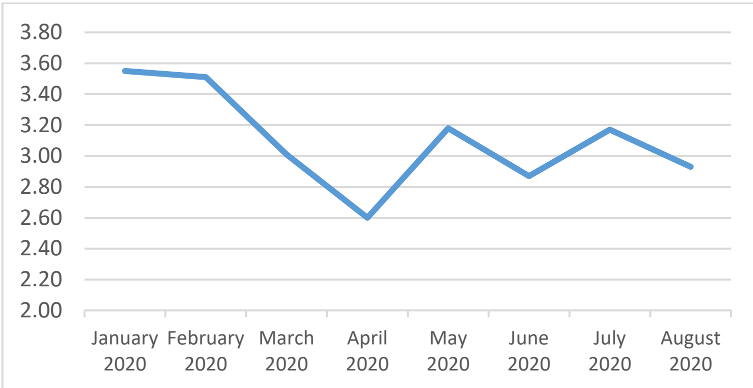
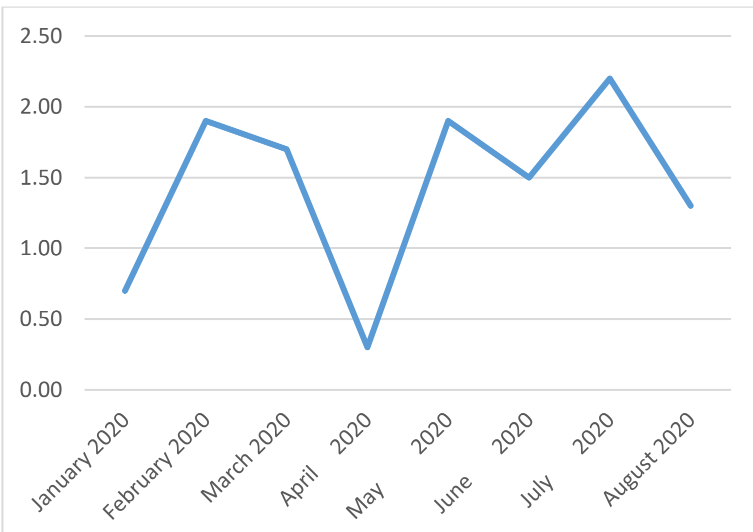


Figure 3. Water Quality Indicators

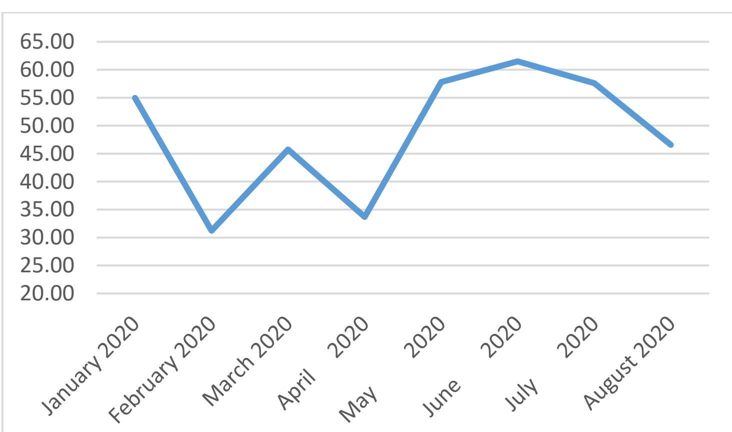
a) Total Organic Carbon



b) Turbidity



c) FE



Appendix

Primary and secondary air pollutants

Sulfur dioxide, oxides of nitrogen, carbon monoxide, volatile organic compounds, and carbonaceous and noncarbonaceous particles are defined as primary air pollutants and they are emitted from road transport, stationary combustion sources and other natural sources. Secondary pollutants, however, formed during chemical reactions of primary pollutants in the atmosphere and they include ozone, oxides of nitrogen and secondary particulate matter.

Particulate Matter

$PM_{2.5}$, PM_{10} are inhalable particles, with diameters that are generally 2.5 micrometers and 10 micrometers and smaller, respectively. These are either emitted directly from a source, such as construction sites, unpaved roads, fields, smokestacks or fire or formed in the atmosphere as a result of complex reactions of chemicals such as sulfur dioxide and nitrogen oxides.

Ozone

There are two types of ozone. Stratospheric ozone occurs naturally in the upper atmosphere and forms a protective layer against harmful ultraviolet rays. Tropospheric ozone (ground level ozone) is a harmful air pollutant and is the one analyzed in this paper. This is formed by chemical reactions between oxides of nitrogen (NOx) and volatile organic compounds (VOC) in the presence of sunlight.

Sulfur Dioxide

The main source of sulfur dioxide (SO2) is the combustion of fossil fuels containing sulfur. In developed countries much of the sulfur is removed from motor fuels in the refining process and from stack gases prior to emission, in less developed countries, however, burning of coal and the use of fuel oils and automotive diesel with a higher sulfur content are major sources of sulfur dioxide. (WHO, 2005).

Oxides of nitrogen

The main source of oxides of nitrogen (NO_2, NOX) is the combustion of fossil fuels. Coal is the most prevalent source in this context, as oil and gas contain much lower levels of nitrogen. In addition to this main source, oxides of nitrogen are also formed during high-temperature combustion from the reaction of atmospheric nitrogen and oxygen. Road traffic and electricity generation are the predominant sources of these gases.

Carbon monoxide

While carbon dioxide is formed during complete combustion, carbon monoxide is emitted through incomplete combustion of carbon-containing fuels. The major source of this emission is through the combustion of petrol in road vehicles.