HIGH VOLUME TRANSPORT APPLIED RESEARCH

Bangladesh University of Engineering and Technology

UNIVERSITY OF LEEDS


# FINAL REPORT: Modelling the links between transport, air quality and COVID-19 spread using naturalistic data from Dhaka and Bangladesh

## COVID-19 Response & Recovery Transport Research Fund

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| Author(s) | Zia Wadud, Sheikh Mokhlesur Rahman, Annesha Enam |
| Lead contact | Zia Wadud |
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Abstract

Transport clearly has a large role in spreading contagious diseases such as COVID-19. Standard response to fighting COVID-19 in most countries was to impose a lockdown – including on the transport sector – to slow down the spread. Often various such measures were taken at different times, but their relative impacts are not well quantified, especially in low-income countries. This motivates this study to assess the interactions between policy interventions, and transport, air quality and COVID-19 impacts in Bangladesh. Using aggregate time-series models relative contribution of different policies on mobility outcome and disease spread are estimated. It is observed that, policy interventions played a significant role in controlling the COVID-19 spread in Bangladesh. In most cases, the policy interventions had the desired effect on COVID-19 infection as well as changes in people's mobility patterns, although there were a few which were not as effective. Mobility changes were also highly correlated with COVID-19 spread. There is a lag of approximately ten days between the introduction of an intervention and changes in mobility and corresponding changes in daily infections. Although the policy interventions resulted in a reduction in accidents and related fatalities, when normalised against reduced mobility, accidents and fatalities increased nationally. Air quality improved noticeably in areas with large construction and transport activities, however such improvements were not statistically significant in other areas in Dhaka. The outcomes of the project are especially useful in understanding the differential impacts of different policy measures on transport, air quality and COVID-19 spread, and can help evidence-based decision making to combat next waves of COVID-19 or similar pandemics.

| | |
|---|---|
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# ACRONYMS

| | |
|---|---|
| ARI | Accident Research Institute |
| BARC | Bangladesh Agriculture Research Centre |
| BMD | Bangladesh Meteorological department |
| BUET | Bangladesh University of Engineering and Technology |
| CAMS | Continuous Air Quality Monitoring Stations |
| COVID-19 | Coronavirus Disease 2019 |
| DFID | Department for International Development |
| DoE | Department of Environment, Bangladesh |
| FIR | First Information Record |
| FCDO | Foreign, Commonwealth and Development Office |
| GoB | Government of Bangladesh |
| HVT | High Volume Transport |
| IEDCR | Institute of Epidemiology, Disease Control and Research |
| IMC | IMC Worldwide Ltd |
| LIC | Low-income country |
| MERS | Middle East Respiratory Syndrome |
| NHTSA | National Highway and Traffic Safety Administration |
| NOAA | National Oceanic and Atmospheric Administration |
| NPI | Non-pharmaceutical Interventions |
| $PM_{2.5}$ | Particulate Matter with an aerodynamic diameter less than 2.5 microns |
| $PM_{10}$ | Particulate Matter with an aerodynamic diameter less than 10 microns |
| SARS | Severe Acute Respiratory Syndrome |
| WP | Work Package |

# EXECUTIVE SUMMARY

The aim of the project is to investigate the effects of Coronavirus disease 2019 (COVID-19) related policy interventions on the transport outcome and correlating these with potential changes in air quality, traffic fatality and spread of the disease in Bangladesh. Transport clearly has a large role in spreading contagious diseases such as COVID-19. On the one hand, this project aims to understand the differential contribution of various COVID-19 related policies – most of which also substantially affected mobility – to the spread of the disease. On the other hand, the project investigates the impacts of these policies on various transport related outcome such as traffic/ mobility, accidents and air quality.

In order to meet the project objectives, data on mobility, accidents, air quality and the spread of the disease have been collected from various sources, both public and private. Data on COVID-19 infection, traffic and mobility parameters, and accidents were collected for both national level and Dhaka city. Additionally, air quality data were collected for Dhaka City only. As in many low-income countries, the quality of data was a cause of concern – especially some of the regional COVID-19 infections related data were a clear suspect. As such only national level data on daily new infections were used to represent infections. Data visualisation, statistical and time-series econometric regression modelling techniques were then applied to arrive at the relevant conclusions, which are described below:

## Effects of COVID-19 related policies on the spread of the pandemic

Regression analysis of daily new positive COVID-19 cases reveals that many of the policies had the desired effects in terms of reducing the spread of the pandemic. Although some of the restrictions were combined at the beginning, the main interest is on the relative impacts of individual measures. The largest beneficial impact was derived from the full closure of offices and public transport. Since these two happened at the same time, their effects could not be estimated separately. The closure of shops at the beginning had similar beneficial effects, but effect of this was around 65% of the joint effects of full office closure and public transport closure. Statistically, the operation of public transport system and offices at half capacity did not have any impact on the spread – this is possibly a result of lax implementation. Opening of garment factories earlier than other offices did not have a statistically significant adverse effect. Somewhat surprisingly, the compulsory mask use regulation did not have any statistically significant effect. This is possibly because of the already declining phase of the pandemic, the lax use of masks, and the increased mobility and interactions resulting from a sense of safety due to the mask regulation. Stricter implementations and effective messaging could have had a significant effect in the desired direction. The Eid-ul-Fitr increased the spread, which is expected due to increased social interactions during the festivities. It appears the policy effects can be observed at around ten days after the implementation, which is shorter than what is observed in some developed countries, potentially hinting at a quicker transmissions due to the higher population density in Bangladesh.

## Effects of COVID-19 related policies and interventions on mobility

Daily activities and – as such mobility – at different types of locations in Bangladesh had reduced dramatically during the COVID-19 related disruption. After an initial rapid reduction, mobility started to recover gradually, and returned to near-normal just before September. Regression analysis shows that most of the policy measures affected mobility in the expected direction, with some differences in the magnitude of these effects in different locations. Closure of education institutes, offices, public transport, and shopping malls all reduced mobility at most locations. The closure of garment factories reduced mobility for work and at transit stations only. Office opening at half capacity had a significant effect on office travel, but not at other locations. As mobility at other locations fell, home stays increased substantially. After mask use was made mandatory, mobility was increased at all places (except in residences) and suggests why this important policy did not reduce the spread of COVID-19 significantly. This potentially hints at risk-compensating behaviour.

## Effects of mobility on COVID-19 spread

Many of the policy interventions designed to curb the spread of COVID-19 acted through reducing mobility. As such, changes in mobility at different locations directly affected the spread of COVID-19 infection in Bangladesh. The COVID-19 daily cases showed positive association with grocery, transit and retail related mobility indicating an increase in mobility led to an increase in the COVID-19 infection. As expected, COVID-19

infection decreased when more people stayed at home. Any change in mobility took about ten days to manifest its effects on COVID-19 infection.

### Effects of COVID-19 related policies on road accidents

Road accidents and related fatalities appeared to have fallen in Bangladesh during a 5-month travel disruption period (April 2020 – August 2020), but compared to a longer 19-month normal period (January 2019 – December 2020, barring the disruption), statistically, accidents and fatalities in Bangladesh did not fall. This is because of large variability in monthly accidents. More importantly, once the effects of the reduction in mobility was considered, normalised accidents and fatalities increased in Bangladesh in a statistically significant way during the travel disruptions. Increases in speed resulting from reduced traffic on the road is the likely cause of this increase. However, in Dhaka normalised accidents and fatalities fell and roads became safer during the disruptions. This was likely driven by a lower degree of exposure due to fewer numbers of pedestrians and vulnerable road users in Dhaka during the disruption period as well as the absence of unhealthy and aggressive competition among fragmented bus companies. This result suggests – a) road safety impacts are location specific; b) there should be adequate policy attention on road safety even during the reduced mobility periods, especially outside of Dhaka; c) safer travel options for vulnerable road users have a large role to play in improving road safety; and d) not controlling for reduced mobility presents a misleading picture during data analysis.

### Effects of COVID-19 related policies on improvement of air quality

Improvement of air quality due to reduction of traffic as a result of COVID-19 related policy interventions are location specific. Statistically, air quality improved at Farmgate, Dhaka – this was likely due to the large contribution of construction pollution at that location as well as possible reduction of congregation of buses at this major transport hub. At Baridhara, Dhaka, air quality improved immediately in the first month, but over the five months of traffic disruptions, it did not. Air quality did not improve at Darussalam Road in Dhaka either in the first month or during the longer five months of traffic disruptions. All these results controlled for the differences in weather elements over the year, which was very important. Results indicate – a) air quality impacts and associated health benefits are location specific – even within the same city and for the same policy, impacts vary; b) traffic may not be as large a source of air pollution in Dhaka now (as large reductions in traffic did not improve air quality as much); and c) not controlling for weather results in faulty conclusions.

The outcomes of the project are especially useful in understanding the differential impacts of different policy measures on transport, air quality and COVID-19 spread. The relative effectiveness of different policies on spread of COVID-19, mobility at different locations, accident, and air quality can be used for future intervention design. Thus, project outcomes may help the policy makers in future to take evidence-based decisions for intervention measures. However, it should be noted that the results are dependent on the quality of the underlying data. Also, the effect of a particular policy largely depends on how well that policy is implemented or enforced as well as the awareness among the population and results could vary in other countries.

# 1. Introduction

## 1.1 Project aims and objectives

The aim of this 'research' project is to investigate the effects of Coronavirus disease (COVID-19) related policy interventions on transport activity and correlate these with potential changes in air quality, traffic accidents and spread of the disease.

Given the background above, the specific research questions that this project aims to address are:

- What are the differential impacts of policy and business decisions on the spread of the disease?
- What are the differential impacts of specific policy and business decisions on various transport outcome such as traffic, speed or delay?
- What are the impacts of mobility outcomes (arising from policy interventions) on the spread of the disease?
- What are the road accident impact of these policies?
- What are the air quality impacts of these policies?

## 1.2 Transport challenge being addressed during/ post-COVID-19

The increasingly interconnected transport system has a large role in spreading contagious diseases like the current pandemic of COVID-19, and previously regional epidemics such as Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS). The standard response to COVID-19 in most developing countries has been to impose a complete lockdown or severe restrictions on mobility and the transport sector – along with the rest of the economy – to reduce population exposure and slow down the spread of the virus. On the other hand, having a safe and functioning transport system is necessary to opening up the economy; transport activities itself can also act as a marker for the economic activities. As such, transport has a delicate role in the current COVID-19 pandemic.

Little is known about how the various lockdown measures in the economy and transport sector or its easement affect various transport and non-transport indicators such as traffic, air quality and accidents in developing countries. Even less is known about the correlation between transport activities and its effects on the spread of the virus among population – especially so in low-income countries (LICs). Given the absence of any prior evidence base on these relationships, often decisions are taken on a trial and error or ad-hoc basis, sometimes skewed by vested interests. This could often lead to wrong or conflicting policy choices and potentially adverse outcomes. Developing an evidence base for these relationships is vitally important – this can help other countries which are further down the virus spread curve to make rational decisions in terms of lockdown and the easing of it. It can also guide the countries prepare for subsequent waves of virus spread, which has been observed in many countries already. This project aims to address this challenge using a case-study approach with Bangladesh and its capital Dhaka, as the focus.

## 1.3 Alignment with the HVT research themes, priorities and programme objectives

The project falls within the theme of low carbon transport with cross-cutting links to road safety covered under the HVT theme for gender, inclusion and vulnerable groups. The research also has strong policy implications for COVID-19 mitigation in LICs.

## 1.4 Alignment with FCDO priorities

From Foreign, Commonwealth and Development Office (FCDO) perspective, this project aligns with their priority for 'evidence based thought pieces and insights'.

# 2. Methodology

## 2.1 Summary of approach

The transport and COVID-19 challenge addressed in this project is the development of an evidence based on the relationships between COVID-19 related decisions and transport metrics (traffic, speed, flow, accidents), air quality and COVID-19 spread. This required two distinct set of activities:

**Activity 1: data collection.** The following data were collected for the project: i) traffic descriptive parameters (speed, flow, activity changes from a baseline), ii) road accidents, iii) air quality, and iv) COVID-19 infections. Details of the data collection and cleaning process is presented in Section 4.

**Activity 2: data analysis.** This involved visual data presentation, econometric modelling of the relationships of interest and where detailed econometric modelling is not possible, calculating descriptive statistics. The key relationships the project explored, and the methods applied are presented below in Table 1.

Table 1: Data and analysis methods to address the research questions

| RQ | Relationship of interest | Data | Analysis Method |
|---|---|---|---|
| 1 | Specific policies and COVID-19 spread | Timing of policies, daily number of infections, daily positivity rate | Data visualisation and econometric modelling |
| 2 | Specific policies and mobility | Timing of policies, daily changes in activities from a baseline, daily traffic speed, daily traffic flow | Data visualisation and econometric modelling |
| 3 | Mobility and COVID-19 | Daily changes in activities from a baseline, daily number of infections | Econometric modelling |
| 4 | COVID-19 disruptions and air quality | Hourly $PM_{2.5}$ (Particulate matter smaller than 2.5 microns) concentration (converted to daily means), weather (daily rainfall), mobility disruption period | Data visualisation and econometric modelling |
| 5 | COVID-19 disruptions and road accidents | Monthly road accidents, mobility disruption period, daily changes in activities from a baseline | Data visualisation and comparative statistics |

Another significant component of the project was the dissemination of the findings. For this purpose, a non-technical summary of the findings and an infographic were prepared. A video is also under preparation for wider dissemination. An opinion piece was published in the most-circulated newspaper in Bangladesh.

## 2.2 Innovation

The key innovation of this project is the use of aggregate time-series data to understand the relative contribution of various COVID-19 related policies on different COVID-19 and transport outcome. While sophisticated disease spread models (1,2) have been used in developed countries, there is a serious lack of data in most LICs, making such detailed models less useful. Using aggregate time-series model and timeline of various interventions allowed us to determine the relative contribution of different policies on mobility outcome and disease spread. The project also utilises advanced econometric methods for data analysis, unlike the mostly descriptive works found so far in academic literature (3–5). Thorough literature review was conducted to summarise the existing literature on COVID-19 and related policy, mobility, accident, and air quality effects to guide the modelling exercise.

## 2.3 Research activities undertaken

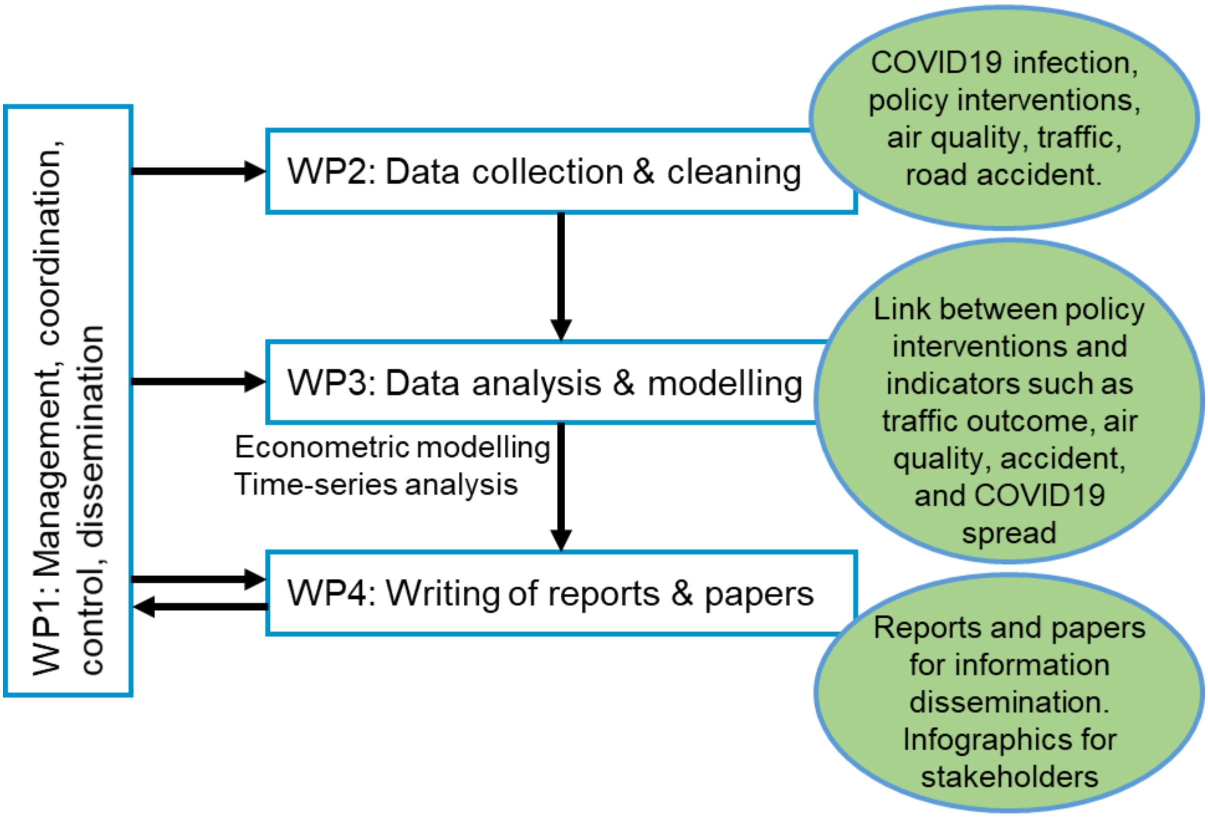
The list of activities conducted are provided below:

- Literature review
- Data collection

- Data cleaning and processing
- Data analysis and visualisation
- Modelling
- Preparation of communication material (policymakers' brief, infographics, animation)

The project activities have been divided into several work packages (WP), as described in Figure 1.

Figure 1: Methodology and work plan of the study




## 2.4 Intellectual property

As part of the project, confidential data on vehicle traffic through a toll booth were collected. These were normalised to remove actual vehicle numbers. Our partners also supplied vehicle speed data in Dhaka, based on confidential vehicle GPS tracking data. However, data processing was carried out by a partner, so we did not have access to the raw individual vehicle tracks.

# 3. Implementation

## 3.1 Activities conducted

### 3.1.1 Data collection

This work package involved the collection of various types of data relevant to the project ideas. These included the timeline for different external interventions, COVID-19 data, air quality data, traffic data, road accident data and weather data.

External policy drivers include various government level decision on transport usage, educational institutions closing, shopping closure (and opening), intercity travel restrictions, local lockdowns etc. At least one decision made by the business leaders were thought to have contributed to worsening the pandemic, too – the announcement of opening of the garment factories defying government instructions. These information were collected from newspaper articles and local sources from both government agencies as well as business entities.

COVID-19 infection data of Bangladesh and Dhaka district were collected from the Institute of Epidemiology, Disease Control and Research (IEDCR), Government of Bangladesh (6), and Johns Hopkins University (7,8). COVID-19 infection data of Bangladesh consist of daily new cases, daily deaths, and daily number of tests between April 2020 and October 2020. For Dhaka district number of daily cases between 15 April 2020 and 31 December 2020 were also collected by mining the web for daily press briefings by Ministry of Health and Family Welfare, Bangladesh.

Traffic data for Dhaka were collected from Dingi Technologies, which had fine-grained location and time stamps of a set of vehicles running in Dhaka. The location and time stamps of the vehicles were processed to obtain speeds at different road corridors by time of day. After processing georeferenced data traffic flow and delay data were generated. Traffic speed data were collected for two major road corridors in Dhaka. However, there were missing data during April-May (2020) due to very few vehicles on the road due to the COVID-19 disruptions. Detail description of these data is available in Section 4.3. Consequently, we collected people's out-of-home and in-home activity engagement data from Google Community Mobility Reports (9). Though the Google mobility report does not report traffic count, it provides the percentage change in the mobility pertaining to different sectors (e.g., retail, grocery, park, transit, work, and residential) with respect to a baseline (3 January to 15 February 2020) from mid-February to end of October 2020. This report uses Google mobility data as a proxy for traffic count. Additional details about the speed variation and changes in the mobility due to COVID-19 disruption are reported in Section 4. It can be noted that Google mobility report best captures the trends for regional mobility. To capture the variation in long-distance traffic we collected data from a private toll collection operator on the Meghna-Gomoti bridge system – the system consists of two bridges on the most important highway in Bangladesh, connecting the capital Dhaka with the port city Chattogram. Further details about the long-distance traffic fluctuation are reported in Section 4.5.

Monthly accident data for the period of January 2019 to December 2020 were collected from the First Information Record (FIR) of Bangladesh Police. This data contains the aggregate statistics in terms of accidents, fatalities, injuries by major police range office and metropolitan areas. This report also contains the number of accidents by some major vehicle categories such as buses, trucks, motorcycle etc. Additionally, accident data was also collected from the Accident Research Institute (ARI) of Bangladesh University of Engineering and Technology (BUET). This was done to cross-check the accuracy of the FIR data. Like the FIR data, ARI data also contain accidents, fatalities and injuries data at monthly frequencies, but ARI collects this information from newspaper articles. Section 4.6 reports further detail about the collected accident information.

Air quality data were collected from various sources including the US embassy in Dhaka (10), and the Continuous Air Quality Monitoring Stations (CAMS) of the Department of Environment (DoE), Bangladesh. Data from airnow.gov contains daily and hourly $PM_{2.5}$ concentrations from January 2016 to October 2020 recorded at the US embassy in Dhaka. Concentrations of criteria air pollutants such as CO, $O_3$, $SO_x$, $NO_x$, $PM_{2.5}$, and $PM_{10}$ (Particulate matter smaller than 10 microns) are recorded in CAMS stations across the country. Daily concentrations of these pollutants were collected for 2 stations in Dhaka for January 2012 to November 2020.

Meteorological data including rainfall and temperature, wind speed and direction, and humidity were collected from National Oceanic and Atmospheric Administration (11) and Bangladesh Meteorology Department for the period between January 2012 to November 2020.

Nearly all the data required cleaning and checked against alternative sources wherever possible, given the often poor nature of data in developing countries. Some of the fine-grained data were processed further to convert to a daily index. Some commercially sensitive data were normalised to remove the raw numbers. Detail description of the data is provided in Section 4.

### 3.1.2 Data analysis and modelling

Several modelling and analysis activities were performed to address the research questions.

- Modelling the effects of policy and external interventions on COVID-19 spread: We developed models using advanced time-series econometrics to correlate external interventions and events with COVID-19 infection directly. Various time lags were used to model the effects of these external interventions, acknowledging the lag in the effects being visible in the infections data. Details of modelling approach and outcome are explained in Section 5.2.
- Modelling the effects of COVID-19 related policy and external interventions on traffic outcome: Using advanced time-series econometric tools we modelled and quantified the impact of the discrete external events related to COVID-19 on mobility in Dhaka. Section 5.3 describes the model framework and outcome.
- Modelling the effects of the traffic mobility on COVID-19 spread: The traffic flow and/or mobility were directly related to movement of people at various sectors of life and hereby affect the spread of COVID-19. We developed a model to decipher whether (and how, what share of) the external factors affected the spread primarily through transportation system. The model framework and outcome are explained in Section 5.4.
- Analysis of COVID-19 related factors on accident outcome: Monthly statistics of accident is used to test the overall impact of COVID-19 related policies on road accidents, injuries and fatalities. Given the lack of finer resolution data, this task is limited to visual presentation and descriptive statistics. Statistical inference tests are conducted to find the significance of the impacts on accident. The details are available Section 5.5.
- Modelling the effect of COVID-19 related factors on air quality outcome: Using advanced time-series statistical methods similar to above but with additional control from meteorological data, we correlate the external factors to air quality. Section 5.6 contains the model framework and outcome.

### 3.1.3 Dissemination of outcomes

This report and upcoming journal articles are the primary modes that are used to disseminate the outcomes of the analysis and modelling results. A short summary was also prepared for policymakers and already uploaded to HVT website and disseminated via official and personal channels to some of the decision makers in Bangladesh. Furthermore, infographics and animation are being prepared for wider dissemination of the outcome of the project. A webinar was already held on May 4, 2021 hosted by partners Bangladesh University of Engineering and Technology. An opinion piece was published in the leading newspaper in Bangladesh on 29 April.

## 3.2 Project findings

From the study it is observed that, policy interventions played a significant role in controlling the first wave of COVID-19 spread in Bangladesh. In most cases, the policy interventions had a desired effect on COVID-19 infection as well as changes in people’s mobility pattern. Furthermore, mobility changes also affected the COVID-19 spread. While longer stays in residential places reduced the spread, increases in retail, grocery, and transit related mobility increased COVID-19 spread in Bangladesh. Reduced traffic due to policy interventions resulted in reduced number of accidents and related fatalities. However, when normalised against the reduced mobility, number of accidents and fatalities increased nationally. Effect on air quality was location specific. While in Farmgate area in capital Dhaka improvement of air quality was observed during the COVID-19 disrupted period, in Darussalam Road and the US embassy the improvement in air quality was not statistically significant. Data quality and availability was a significant challenge, and the national level COVID-

19 data appeared more plausible compared to regional data due to various limitations with regional data. More detailed description of the project findings is provided in Section 5.

## 3.3 LIC beneficiaries

The project was conducted with the data from Bangladesh, which is the primary beneficiary of the study. The research provided:

- a general understanding and created an evidence base of potential impacts of lockdown policy related to COVID-19 – on transport, air quality and road accidents
- a unique understanding of the impacts of different local and national level decisions on the spread of COVID-19. It showed which policies had impacts on COVID-19 spread and their relative impacts, which can guide policies during the ease of lockdown or re-lockdown, or even during the next such pandemic.

The findings about the relative impacts of different policy measures or events on COVID-19 or impacts of mobility on COVID-19 can be useful to guide policies in other LICs too.

## 3.4 Limitations of the innovation/ approach/ design/ system

Data availability and data quality is possibly the most important limitation in this research. A significant share of data collected had to be discarded due to questionable quality (accuracy) or missing data during important phases (e.g. vehicle speed data was missing exactly during the COVID-19 disruption period, which was the period of interest). In some cases, the official data differed from data from other sources (e.g. accidents), official data was used in these cases, with the caveat that the quality of official data is not guaranteed. The quality of some of the COVID-19 infection data were also suspect.

# 4. Description of data

Data on policy interventions, COVID-19 infections, traffic accidents, mobility changes, air quality, and meteorology were collected for the project. This chapter highlights and describes the collected data.

## 4.1 Policy and other interventions

In response to the first wave of the COVID-19 pandemic in early 2020, the Government of Bangladesh has adopted several policy measures to mitigate the spread of the virus. Various measures from business entities also followed the government decisions. Several key policy interventions taken in Bangladesh are listed in Table 2. Table 2 also includes other events that could have affected COVID-19 spread or disrupted normal travel patterns, e.g. the two Eid festivities. The COVID-19 response measures encompass all aspects of day-to-day life. At the early onset of COVID-19 infection, the interventions began with the closings of educational institutions, all government and private offices, shopping malls except pharmacies and grocery stores, and factories including garments factories. After initial period, gradually activities resumed one by one. Resumption of office activities and public transport were made gradually. As initially they are resumed at reduced capacity and after observing the situation the government allowed resumption of offices and public transport in full capacity. All these policy interventions would result in changes in human mobility and subsequently would have impacts on COVID-19 infection. Additionally, movement of people during the religious festivals Eid-ul-Fitr and Eid-ul-Adha may also contributed to the spread of the COVID-19 infection. Mandatory mask wearing in public spaces was prescribed after COVID-19 infection had started to fall already.

**Table 2: COVID-19 related interventions and events in Bangladesh**

| Event ID | Date | Policy Decisions and Other Events |
|---|---|---|
| a | 18 March 2020 | Educational institutions closing |
| b | 26 March 2020 | Closing of offices, garments, shopping malls, public transportations including air travel, ride sharing services |
| c | 5 April 2020 | Indecision regarding garments opening† |
| d | 26 April 2020 | Garments opening |
| e | 10 May 2020 | Shopping mall opening |
| f | 25 May 2020 | Eid-ul-Fitr |
| g | 31 May 2020 | Office opening (limited scale) |
| h | 1 June 2020 | Public transport resumption (limited capacity) |
| i | 28 June 2020 | End of free tests in Government facilities‡ |
| j | 22 July 2020 | Beginning of mandatory mask wearing |
| k | 1 August 2020 | Eid-ul-Adha |
| l | 7 August 2020 | Office opening (full capacity) |
| m | 1 September 2020 | Public transport resumption at full capacity |

Note:

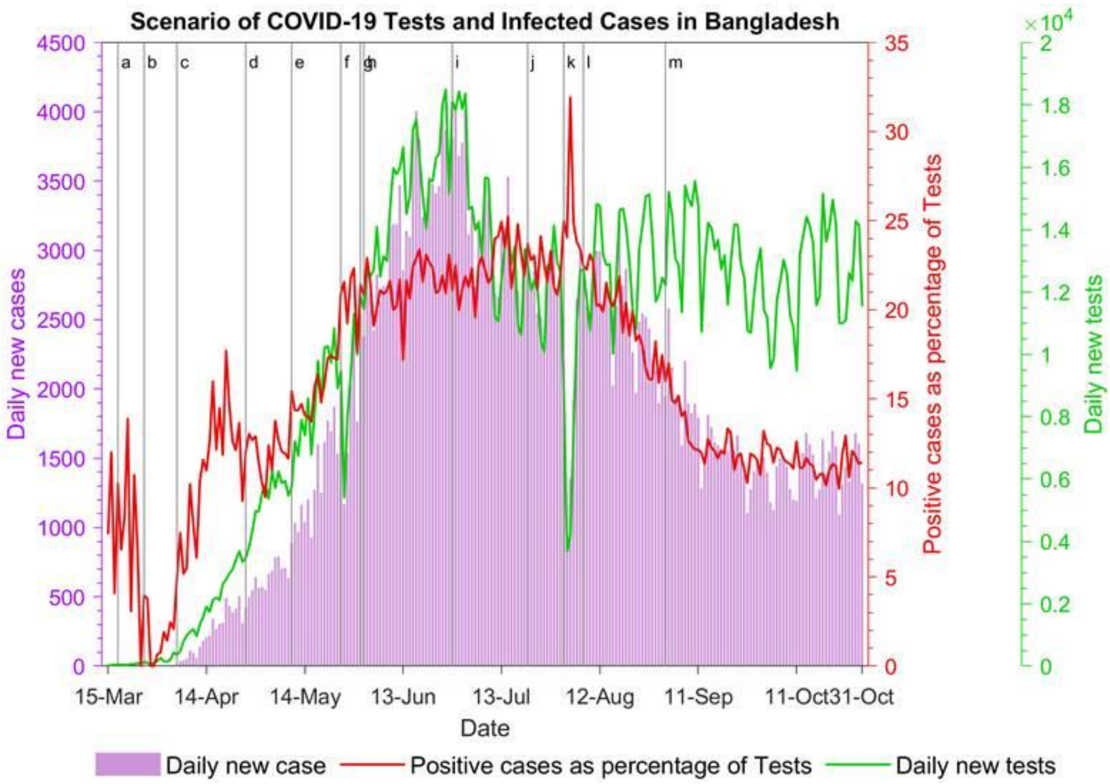
† The garment factories were initially closed until 4 April 2020. Although the public transport and other offices remained closed on 5 April, initially the industry leaders announced the opening of their factories on the 5 April, leading a substantial mobilisation of their workers from rural areas to large cities. However, eventually the decision was overturned, leading another round of return journey for the workers. This dilemma, and associated movement of people, may have had impacted the spread of COVID-19.

‡ COVID-19 testing in Government facilities were conducted free of cost initially. Starting from 28 June 2020, a small fee was imposed for testing at government facilities (though a significant portion of the cost was still subsidised by the government). Costs of testing at private facilities were always borne by the patients.

## 4.2 COVID-19 infection

COVID-19 infection data were collected from publicly available sources. Daily number of new COVID-19 cases and tests conducted in Bangladesh are collected from databases made available by IEDCR, Government of Bangladesh (6), Johns Hopkins University (7), and our world in data (12) . However, finer resolution data at different geographies were not available as a database. We collected the number of cases and tests for Dhaka by mining the web for daily press briefings by Ministry of Health and Family Welfare, and IEDCR. Daily positivity rate of COVID-19 infection was calculated by taking the daily new cases as percentage of tests conducted daily. Figure 2 presents the evolution of COVID-19 in Bangladesh for the period between 15 March 2020 to 31 October 2020, along with the interventions (from Table 2) shown as vertical lines. Daily new cases kept on increasing up to 2 July 2020 beyond which it started to decrease. A slight increasing trend is observed again starting from 1 October 2020. On the other hand, positivity rate increases over time until reaching the peak at around 4 August 2020. However, positivity rate also shows a decreasing trend at the very early stage of the pandemic (15 March 2020 to 2 April 2020), which was most likely due to increased availability of tests.

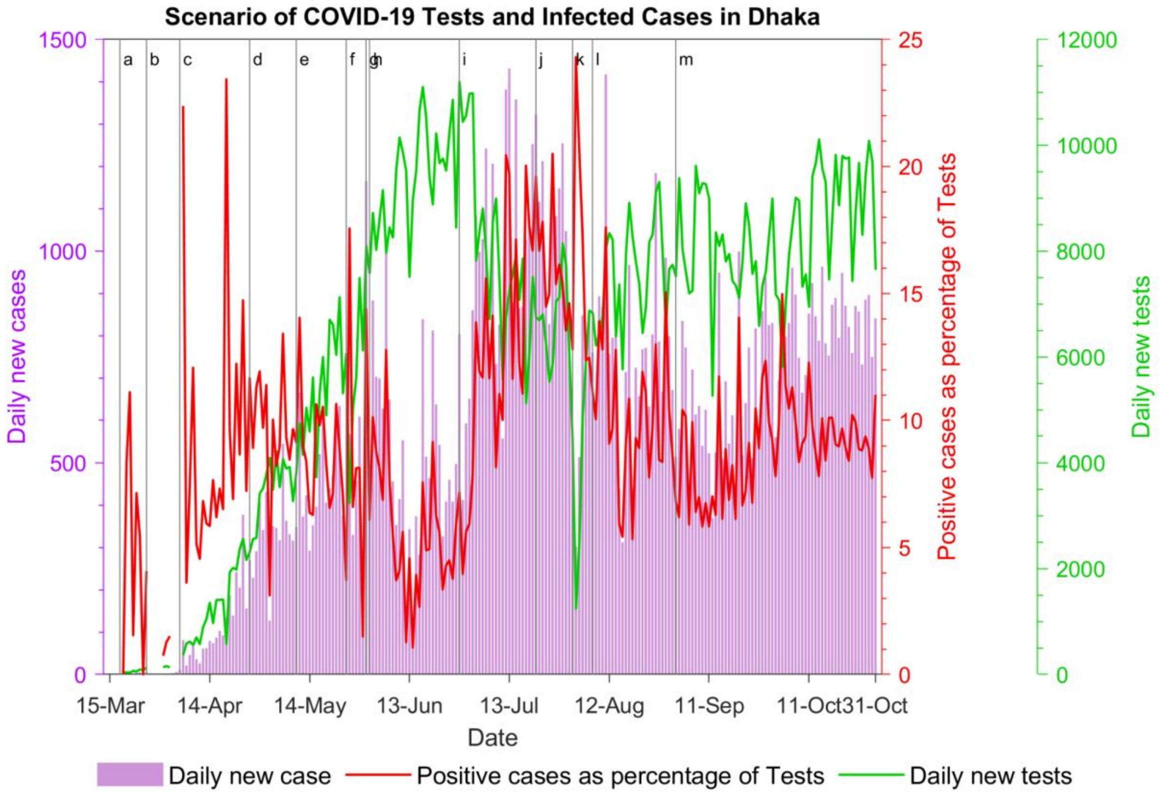
Figure 2: Daily new COVID-19 cases, daily tests and positivity rate, March to October 2020, Bangladesh




Data source: IEDCR, GoB, and Johns Hopkins University

Figure 3 shows the COVID-19 disease spread in capital Dhaka, along with the interventions (from Table 2) shown as vertical lines. After the initial increases in daily cases in Dhaka, it started to decrease in early June 2020 then again started increasing at later stages of June. This profile did not match the national profile. Also, daily fluctuation of positivity rate appears more erratic for Dhaka than for the whole country. This raises concern about the accuracy of the Dhaka specific data. Especially, the key focus of the government data collection was on getting a national level infection data, and the region-wise data most likely went through a less rigorous checking. Positive case reports were prioritised over the number of tests conducted, as such it is also possible that some of the regional detail data may have arrived centrally at different dates and could lead to mistakes in logging. There were also reports, especially initially that people were hesitant to share their addresses. These limitations possibly affected local data more than the national data. Hence for further analysis we used the national data. It was judged that the daily new cases nationally were the most reliable data, and the rest of the COVID-19 spread analysis will be based on this data.

**Figure 3: Daily new COVID-19 cases, daily tests and positivity rate, March to October 2020, Dhaka**




Data source: IEDCR, GoB

## 4.3 Traffic data

Vehicle tracking data were collected from Dingi Technologies, who had fine-grained location and time stamps of a set of vehicles running in Dhaka. From those GPS tracking information speed in a particular corridor at a particular time could be obtained. Two major road corridors in Dhaka were selected to study traffic speed: Mirpur Cantonment to Motijheel and Abdullahpur to Gulistan (Figure 4). Speed was selected as a proxy measure for traffic in Dhaka, since no official or unofficial statistics on daily traffic flow is available for any Dhaka roads. From the GPS tracks, traffic speed data were calculated for the period between January 2019 and October 2020. Traffic speeds for both directions of the two roads were collected. Several time-periods (8:30 AM – 10:00 AM, 10:00 AM – 11:00 AM, 8:30 AM – 11:00 AM, 11:00 AM to 12:00 PM, 5:30 PM – 6:30 PM, 6:30 PM – 8:00 PM, 8:00 PM – 9:00 PM, 6:00 – 9:00 PM) within a day were selected to identify variations in traffic flow in peak (both morning and evening) and off-peak hours. Figure 5 presents the daily time-series of the average speed in Abdullahpur to Gulistan road corridor for a selected few time slots. Unfortunately, there were missing data for the most important periods, either due to data loss from the server (January – February 2020) or due to very few numbers of tracked vehicles on the road during the COVID-19 disruption period (April – May 2020). Similar situation was observed for the traffic data of other road corridors (Appendix A). As such, despite the best laid plans and an innovative approach to collect daily traffic related data, the collected tracking data were not useful to carry out any statistically meaningful analysis. As such, Google's Community Mobility Report (9) was used instead, as described later.

Figure 4: Location of two road corridors for speed data

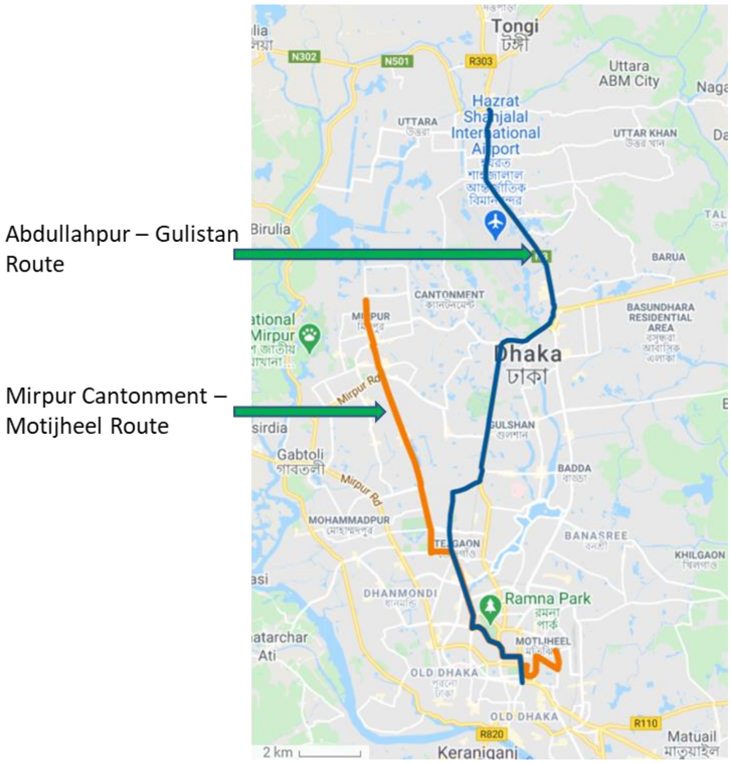
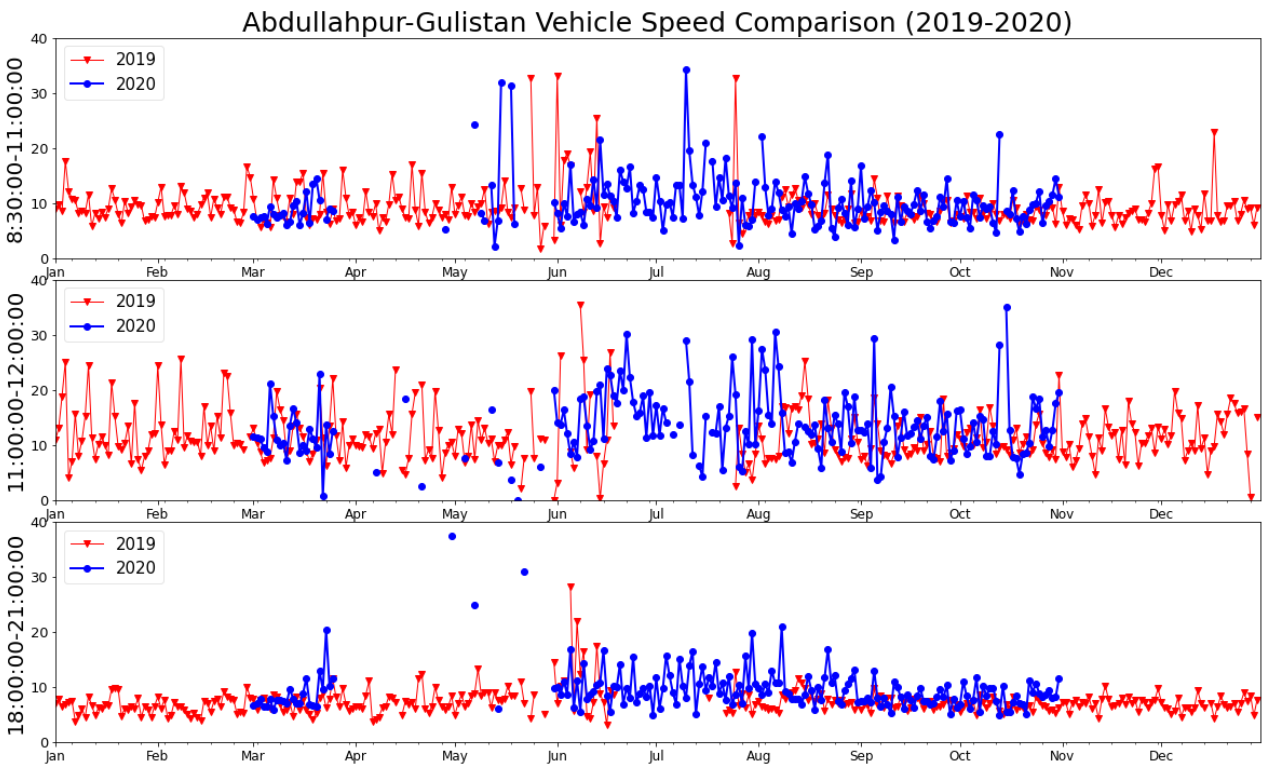


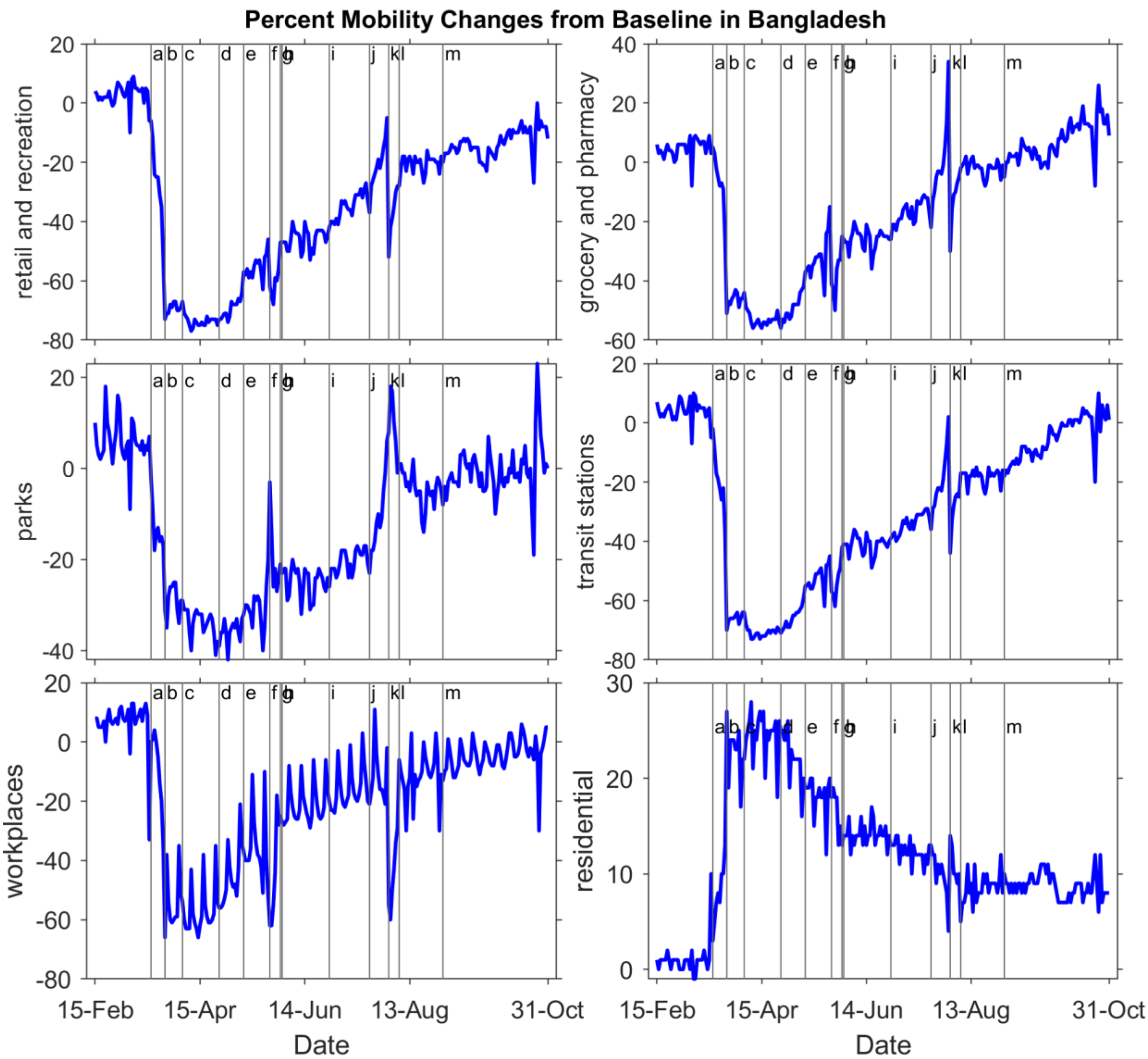

Figure 5: Daily traffic speeds at Abdullahpur – Gulistan road corridor




## 4.4 Mobility data

Daily mobility activity data were collected from the publicly available Google Community Mobility Reports (9). For Bangladesh, only the nationwide changes in mobility were available. Figure 6 presents the activity trend from February 15 to October 31 in different sectors including retail and recreation, grocery and pharmacy, parks, transit stations, work, and residences. The mobility changes were calculated as the percent differences in the number of visitors compared to the baseline for all sectors except for residents. The residential values are calculated as the percentage changes in the number of hours spent at home. Retail and recreational mobility captures the changes in visitors at restaurants, cafes, shopping centres, theme parks, museums, libraries, and cinemas. Grocery and pharmacy capture the trend in supermarkets, food warehouses, farmers markets, speciality food shops, and pharmacies. While these mobility data do not translate into traffic directly, they are representative of the mobility around those activity locations. The baseline in the Google mobility data are median values, for the corresponding days of the week from 3 January 2020 – 6 February 2020. The vertical lines in Figure 6 are superimposed to indicate the dates of specific policy interventions and each event is denoted by a letter. Little variation around the baseline was noted from mid-February till mid-March which was followed by a sudden drop due to the closure of educational institutions, shopping malls, offices, and transit operation. We also notice a rise in the time spent in residences during this period. After that, as the restrictions on operations were removed or relaxed gradually mobility started to increase and the trends approached the pre-COVID-19 state.

Figure 6: Percentage changes in mobility from baseline, Bangladesh




Source: Community Mobility Reports (https://www.google.com/COVID-19/mobility/)

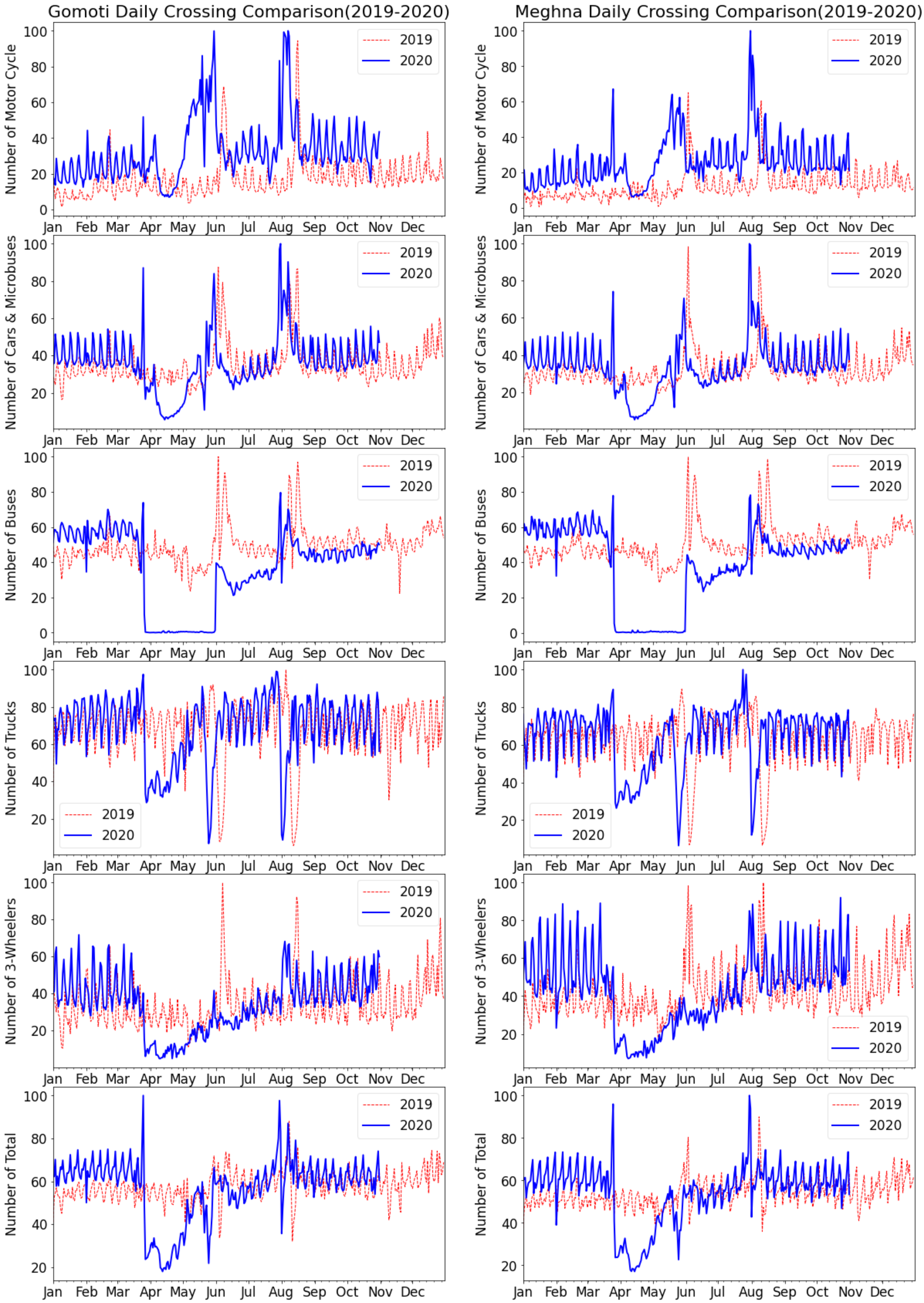
## 4.5 Intercity traffic data

Although it is not clearly stated in the documentation, given the high density of population in urban areas, the Google Community Mobility Report likely covers urban and regional mobility more (except, possibly for parks and recreation). However, long-distance transport is also a useful metric to understand. Daily, monthly, or weekly traffic flow or count data on national highways were not available from government sources. As a proxy, the project collected data from a private toll collection operator on the Meghna-Gomoti bridge system. These are a set of two bridges on the most important highway in Bangladesh, connecting the capital Dhaka (the largest city) with the port city Chattogram (the second largest city). Daily number of vehicles, disaggregated by vehicle types, were collected from January 2019 to October 2020.

Figure 7 presents the monthly counts over the bridge in two directions. The 2019- and 2020- series of each vehicle category are normalised through dividing by the observed maximum count of the same category and then multiplied by 100. This was necessary to protect the confidentiality of the commercially sensitive raw count data. There was a rapid fall in all types of vehicle count in April 2020, immediately after the lockdown on March 27. However, the traffic rebounded very quickly to normal levels, mostly, in May 2020. Flow of motorcycles rebounded back to normal quicker than other types of vehicles. Numbers of trucks also rebounded quickly to the level prior to lockdown. Bus traffic took the most time to return to the pre-pandemic level.  Since trucks are used for the inter-regional transport of essential goods such as food, their operations started earlier than other types of vehicles. This may have led to the early recovery of the truck count. Intercity public transportation was banned between 26 March and 1 June – this period is represented by zero bus count in the figure. During this period, trucks also appeared to have carried some long distance passengers on top of freight.

Between June and September public transportation was allowed to operate at 50% capacity. The limited bus capacity and the COVID-19 related concern might have led people to rely on personalised vehicles such as motorcycles. This might have caused the higher motorcycle count in 2020 than in 2019; visually motorcycle counts appear to be higher during the disrupted periods. Both the motorcycle and the car counts show two distinctive peaks during late May and early August – around the time of two major religious festivals, namely, Eid-ul-Fitr and Eid-ul-Adha. The truck count shows a drop during the same period – since public holidays are observed during these two festivals. Other than that, all traffic showed a spike just before the strict measures (e.g., closure of offices, garments, shopping malls, public transportations, and ride sharing services) were undertaken by the government on March 26 to curb the spread of COVID-19. The March 26 shutdown of different sectors was announced as a public holiday on March 23. Consequently, many people left their workplaces to join their family which led to the spike of private vehicles just before the steep drop in the traffic count on March 26; this shows the importance of ‘announcement’ effect of the impacts of interventions. The total traffic count shows a significant drop during the period of strict measures such as banning of public transportation, but they reverted to the 2019 level rather quickly, especially after the restrictions on public transportation are relaxed.

**Figure 7: Normalised vehicle count at two toll plazas on Dhaka-Chittagong highway**



## 4.6 Number of accidents in Dhaka and in Bangladesh

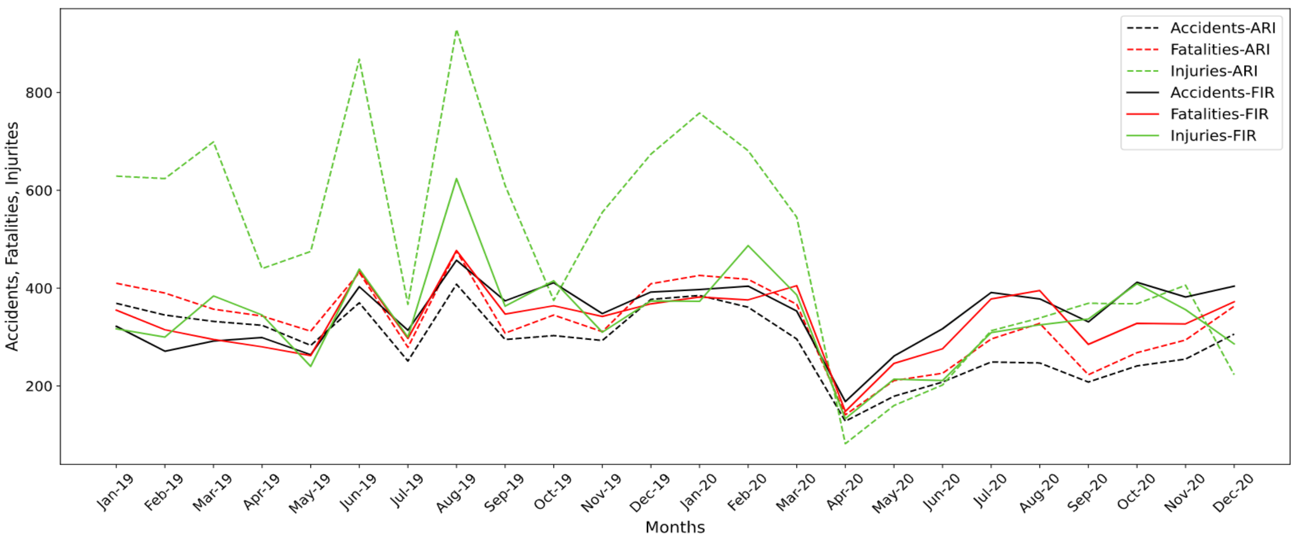
Each year thousands of people are killed and injured on the roads of Bangladesh. Though officially there are around 2,500 fatalities and 3,000 injuries on Bangladesh roads each year, the actual magnitude of this problem is possibly larger. A recent report estimates the annual road traffic fatalities in Bangladesh to be around 10,000 (13). The fatality rate, ranging from 60 to 150 fatalities per 10,000 motor vehicles in Bangladesh, is high as per international standards (14). According to official government statistics, the capital Dhaka accounts for about 20% of all reported crashes with 15-20% of the country's road traffic crash fatalities and injuries (15).

Despite its limitations, the only official source for recent crash statistics in Bangladesh is the police reported First Information Record (FIR). This data contains the aggregate statistics in terms of accidents, fatalities, injuries by major police range offices and metropolitan areas. This report also contains the number of accidents by some major vehicle categories such as buses, trucks, motorcycle etc. While there is another database containing detailed information about accidents (e.g. date, time, and type of accident) that dataset lags by several years (2015 being the most recent available year). As such no useful daily accident data were available for the country, or for Dhaka. While aggregated annual road traffic accident statistics are available from Bangladesh Bureau of Statistics (informed by Bangladesh Police) for Bangladesh, there are some crucial discrepancies in this dataset. This discrepancy, combined with only 1 year of COVID-19 disrupted data, means typical time-series analysis of accident data cannot be reliable.

Given the above limitations, the primary road accident data source in this study is Bangladesh Police's FIR information. These data are readily available in monthly frequency for the whole country only from October 2018, and data from January 2019 to December 2020 were utilised in the visualisation and analysis later. Monthly crashes, fatalities and injuries were collected from this source.

In addition to the FIR data, accident data were also collected from the Accident Research Institute (ARI) of Bangladesh University of Engineering and Technology (BUET). This was done to cross-check the validity of the FIR data. Like the FIR data, ARI data also contain accidents, fatalities, and injuries data at monthly frequencies, but ARI collects this information from newspaper articles. As Figure 8 below shows, there are some agreements in the pattern among these two sources; however, the numbers do not precisely match. Especially, there is little agreement in the injuries data. As such, injuries data will not be included further for analysis.

**Figure 8: Accidents, fatalities, and injuries per month, Bangladesh**

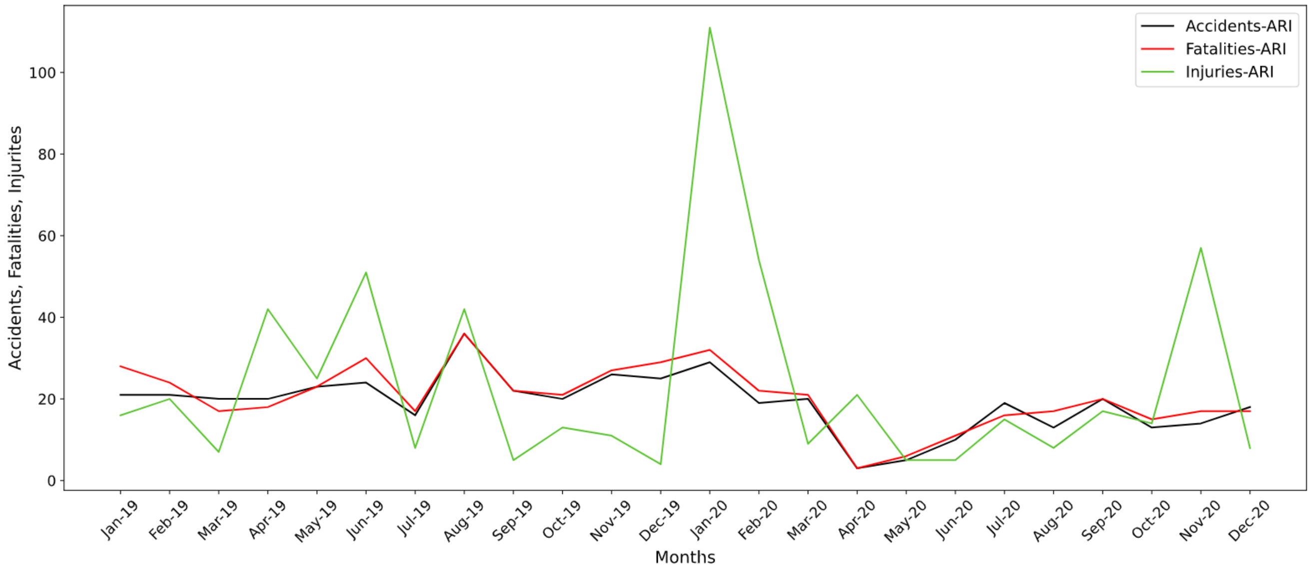



Source: FIR, ARI

While some monthly data for Dhaka (as a Metropolitan region) are collected by Bangladesh Police, a continuous time series for 2 years was not available to the project team (recent, COVID-19 period data were not ready). As such, monthly data on accidents, fatalities and injuries for Dhaka district are from ARI's newspaper derived data. These are presented in Figure 9.

Both the accidents and fatalities data for Dhaka and Bangladesh show a clear dip in April, certainly a result of the nationwide closure of offices from 27th March. As traffic increased over time due to relaxation of the lockdown and other intervention measures (see Section 4.1), both accidents and fatalities started to increase again. Section 5.5 provides further statistical analysis on accident data.

**Figure 9: Accidents, fatalities, and injuries per month, Dhaka**




Source: ARI

## 4.7 Air quality in Dhaka

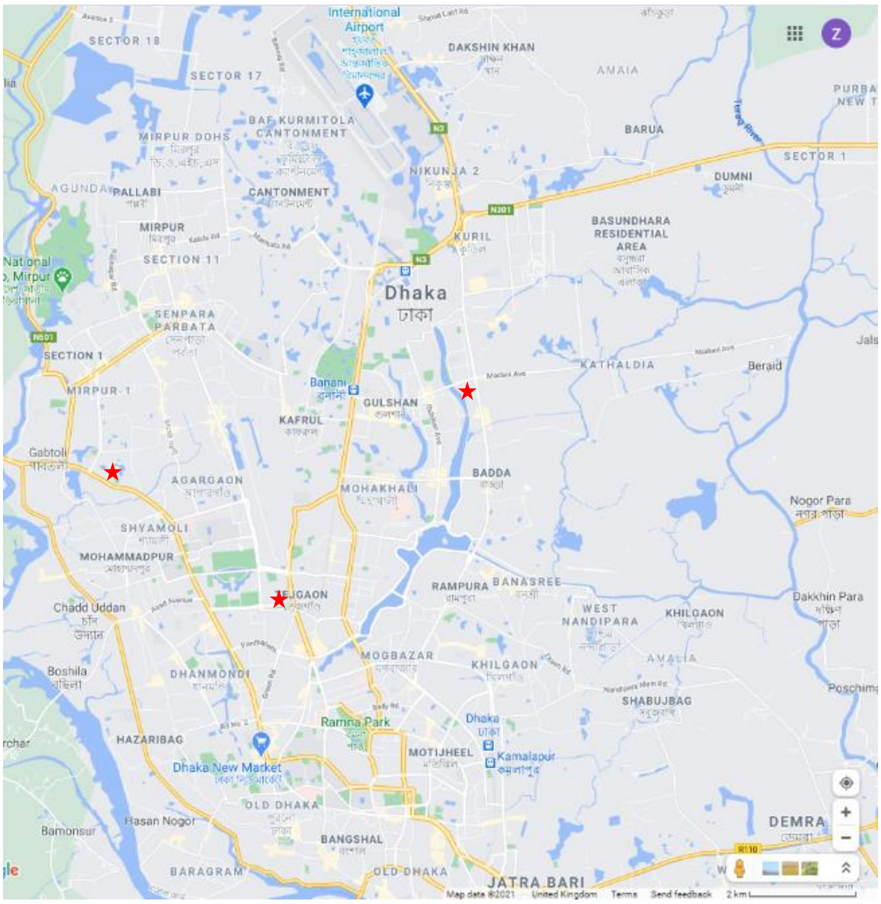
Air quality data were collected from two sources: Department of Environment (DoE) of the Government of Bangladesh, and the Embassy of the United States of America. DoE data were from its two Continuous Ambient Monitoring System (CAMS) located at Bangladesh Agriculture Research Centre (BARC) at Farmgate, one of the busiest transport hubs at the centre of the city, and at Darussalam Road near Kalyanpur, another major thoroughfare. Data were collected from January 1, 2015 for both these stations. Air quality indicators were 3-hourly $PM_{2.5}$, 3-hourly $PM_{10}$, daily CO, daily $SO_2$, daily $NO_2$, daily $NO_x$, 3 hourly Ozone and 8-hour Ozone. The US Embassy monitor is located at the Baridhara diplomatic enclave region of the city. This monitor collects data on daily $PM_{2.5}$ only. The monitor locations are indicated using red stars in Figure 10.

A continuous, uninterrupted time series of observations was not available for any of the above pollutants. While $PM_{2.5}$ and $NO_x$ are possibly the most important pollutants in the context of transport induced air pollution and its adverse health effects, $NO_x$ data were missing for extended periods (41% data were missing at BARC and 23% data were missing at Darussalam station), making any robust analysis difficult. As such, this report focused on $PM_{2.5}$, for which a decent time-series could be constructed (16% data were missing at BARC, 8% data were missing at Darussalam station, and 8% data were missing at US embassy). Figure 11 presents the daily mean $PM_{2.5}$ from 1 January 2015 until 30 November 2020, except for the monitor at US embassy where data collection started on 1 January 2016.

Converting daily time series to a monthly data provides an aggregated summary of the air pollution level in different years. Figure 12 presents the boxplot of monthly $PM_{2.5}$ recorded in all three monitoring stations. From the figure, monthly variation of $PM_{2.5}$ recorded in 2020 can be compared with that observed in the same months during 2015-2019 (2016-2019 for the US embassy). To check the significance of the observation, a one-tail t-test analysis was conducted assuming the alternative hypothesis as the monthly average of $PM_{2.5}$ concentration was higher in 2015-2019 (2016-2019 for station at US embassy) period than that of 2020. The results of t-test are summarised in

.

**Figure 10: Location of three air quality monitoring stations, Dhaka**



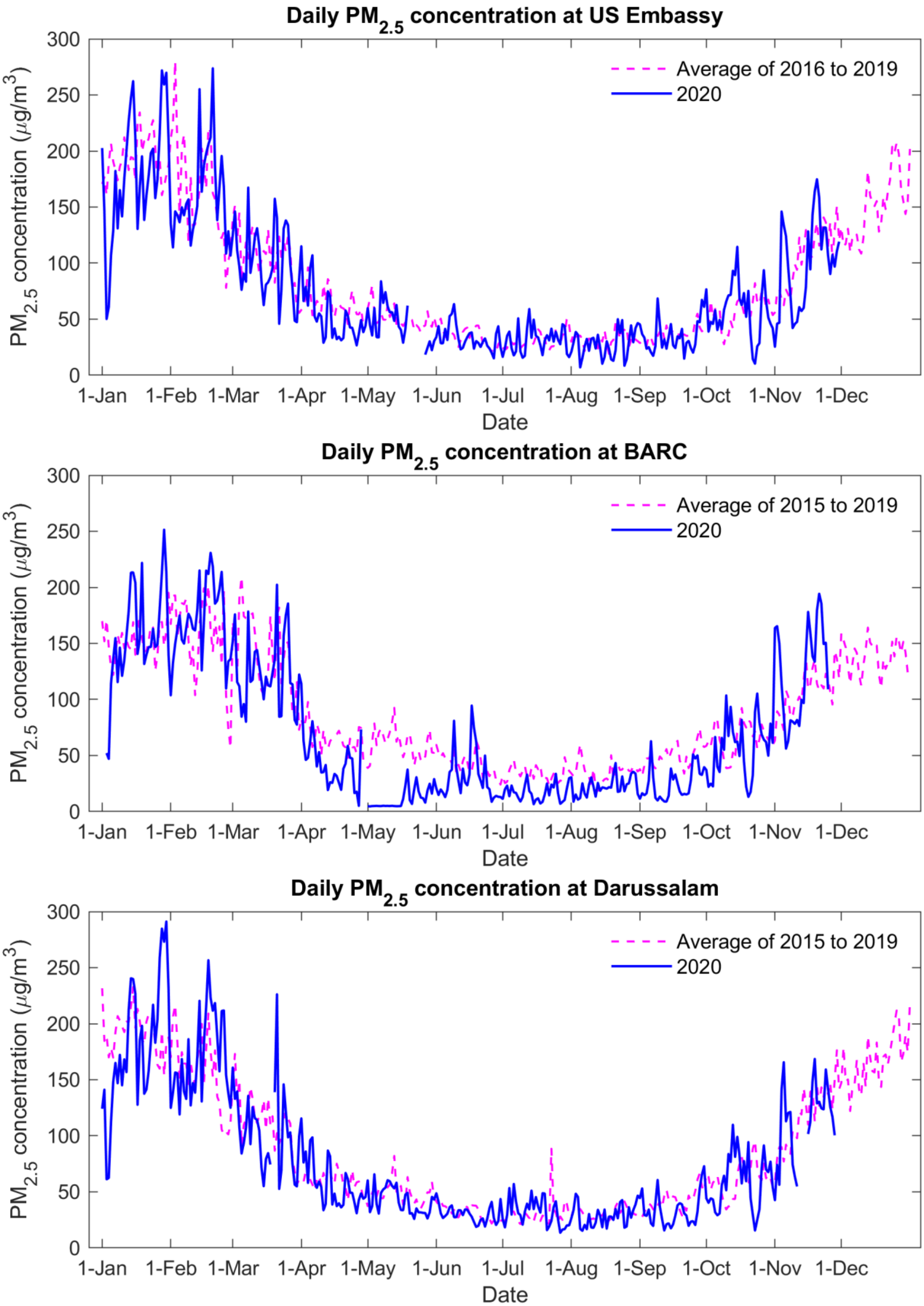

At the CAMS station at BARC in Farmgate, monthly average $PM_{2.5}$ concentrations were significantly lower in 2020 for the months of April to October than that of corresponding months from 2015 to 2019. At US embassy, $PM_{2.5}$ concentrations were lower in April and August of 2020 than that of corresponding months of the period 2016 to 2019. Lower $PM_{2.5}$ concentrations were observed in May and September of 2020 than during the same months from 2015 to 2019 at the Darussalam CAMS station. Though concentrations were lower in January 2020 than that of the same period of prior years at US embassy and Darussalam CAMS stations, it was not affected by the COVID-19 related policy measures, indicating the limitations of such simple averages. Not considering the differences in weather pattern between the same months in different years is another weakness. In Section 5.6, these limitations will be addressed using a regression analysis.

**Table 3: t-statistics to compare monthly average $PM_{2.5}$ concentrations in 2020 vs 2015-2019**

| Month | US embassy | BARC CAMS | Darussalam CAMS |
|---|---|---|---|
| January | 1.411* | -0.37 | 1.375* |
| February | 0.672 | -0.598 | -1.09 |
| March | 0.893 | 1.077 | 0.964 |
| April | 2.115** | 4.065*** | 0.477 |
| May | 1.088 | 12.502*** | 1.946** |
| June | 0.391 | 2.599*** | 0.717 |
| July | -0.331 | 4.427*** | -0.266 |
| August | 1.701** | 3.449*** | 0.851 |
| September | 0.761 | 6.334*** | 2.305** |
| October | -0.238 | 1.447* | 0.25 |
| November | 0.705 | -2.012 | 0.457 |

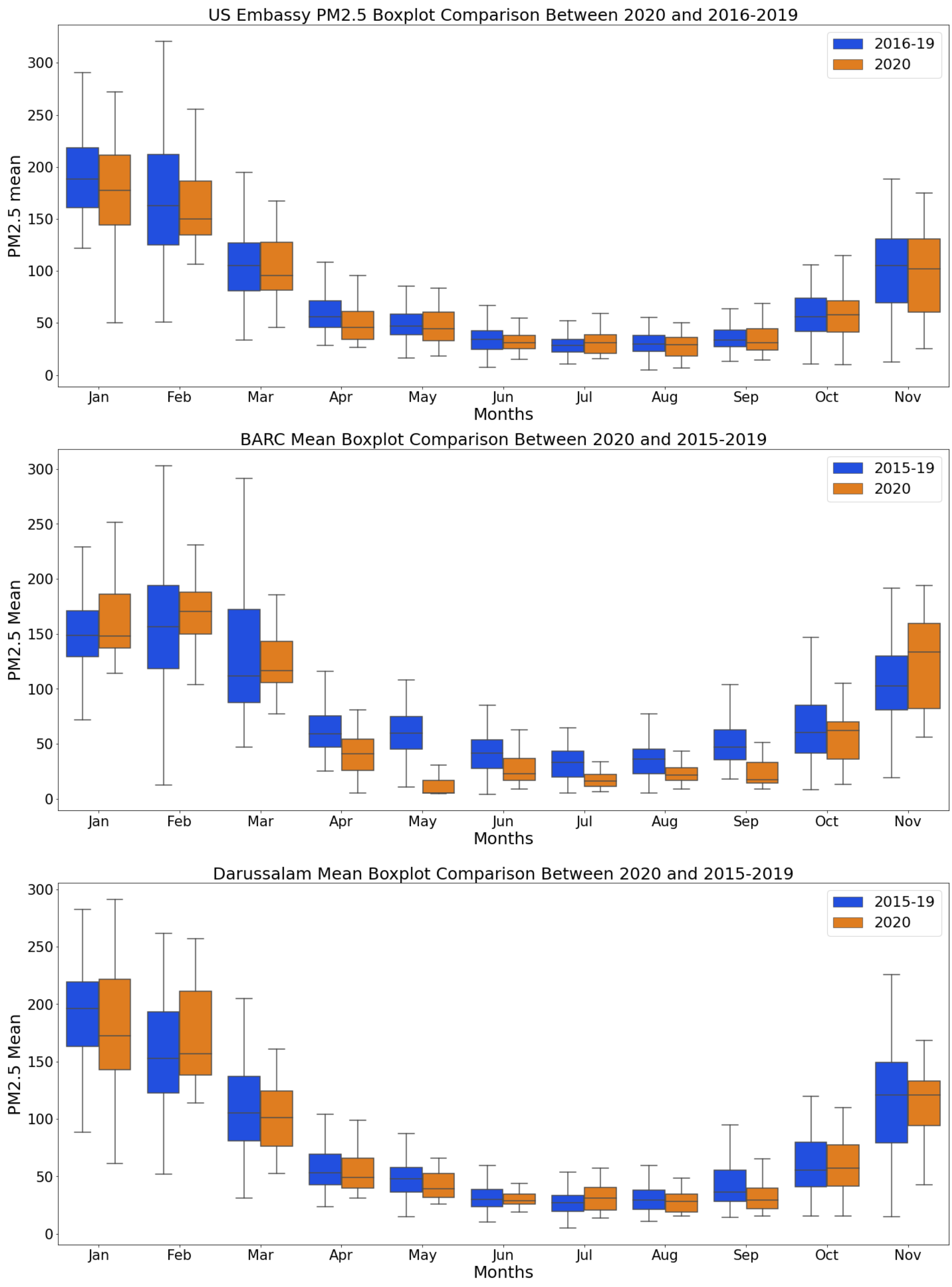
Notes: *** statistically significant at 99% confidence, ** statistically significant at 95% confidence, * statistically significant at 90% confidence for one-tailed t-test

Figure 11: Daily average $PM_{2.5}$ concentrations



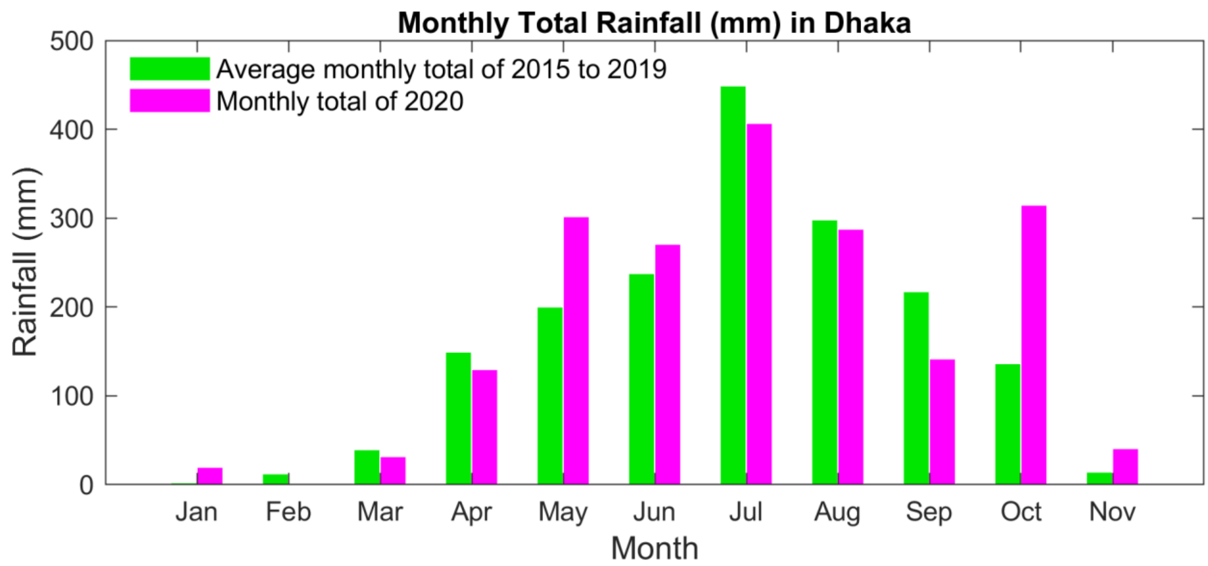

Source: DoE, US Embassy

Figure 12: Boxplot of daily average $PM_{2.5}$ concentrations (µg/m³)



More importantly, the air quality in Dhaka shows a strong seasonal pattern, as can be seen above. This is related to two factors: seasonality in emissions, especially the operation of brick kilns during the dry seasons (which are often inundated during the monsoon), and meteorological conditions, especially the heavy monsoon season (June-August) and the heavy rainfall during the North-westerly Kalboishakhi storms (April) clearing the ambient pollution. As such meteorological data on rainfall, temperature and humidity were collected from National Oceanic and Atmospheric Administration (NOAA) and Bangladesh Meteorological Department (BMD) for the same period. Where hourly or 3-hourly data were reported, they were converted to daily data by making appropriate adjustments (e.g. for hourly temperature, averaging over 24 hours, for rainfall, summing over 24 hours). NOAA data is used as the baseline data - where data were missing, BMD data were used to fill the gaps. Figure 13 presents the comparison of average monthly rainfall in Dhaka between the period 2015 to 2020 and monthly rainfall in 2020. Total rainfall in May, June, October, and November of 2020 are higher than the average monthly rainfall of previous five years. Daily rainfall data will be later used for regression analysis in Section 5.6.

**Figure 13: Average monthly total rainfall, Dhaka**




Source: NOAA, BMD

# 5. Impacts of COVID-19-related policy interventions

## 5.1 Indicator variables for policy interventions

Before the econometric modelling and data analysis were undertaken, it was necessary to represent the policy interventions in the model. The dummy variables that represented various policy decisions and events in modelling framework are shown in Table 4. The dummy variables would represent the average effect of the intervention on the variable of interest. Although there were some interventions on international and domestic flights, these interventions were frequently changing (e.g. country lists changing), making it difficult to introduce them in our models.

Table 4: Dummy variables for COVID-19 related policy interventions, Bangladesh

| Indicator variables | Description | Policy duration | Variable definition |
|---|---|---|---|
| education_institution_close | Closing of educational institute | 18 March 2020 - Ongoing | 0: open<br>1: closed |
| shopping_mall_close | Closing of shopping mall | 26 March 2020 – 9 May 2020 | 0: open<br>1: closed |
| Garments_close | Closing of garments | 26 March 2020 – 25 April 2020 | 0: open<br>1: closed |
| Public_Transport_close | Closing of public transports | 26 March 2020 – 31 May 2020 | 0: open<br>1: closed |
| Office_close | Closing of all offices | 26 March 2020 – 30 May 2020 | 0: open or running at half capacity<br>1: closed |
| Office_half | Offices were closed until 31 May 2020;<br>Offices were open with reduced capacity until 7 August 2020 | Reduced Capacity: 31 May 2020 – 6 August 2020 | 0: fully open or fully closed<br>1: open at half capacity |
| Public_Transport_half | Public transports were closed until 1st June 2020<br>Public transports were operating at reduced capacity until 30 August 2020 | Reduced Capacity: 1 June 2020 – 30 August 2020 | 0: fully open or fully closed<br>1: operating at half capacity |
| Garments_open_dilemma | Indecision related to garments opening lead to movement of people to and from their workplace | 5 April 2020 | 0: inactive;<br>1: active |
| Eid_ul_Fitr_day | Day of Eid-ul-Fitr (religious festival) | 26 May 2020 | 0: other days<br>1: day of the Eid-ul-Fitr |
| Eid_ul_Adha_day | Day of Eid-ul-Adha (religious festival) | 1 August 2020 | 0: other days<br>1: day of the Eid-ul-Adha |
| Eid_ul_Fitr | Holidays due to religious festival, Eid-ul-Fitr | 24 – 28 May 2020 | 0: other days<br>1: holidays (5-day) due to Eid-ul-Fitr |

| Indicator variables | Description | Policy duration | Variable definition |
|---|---|---|---|
| Eid_ul_Adha | Holidays due to religious festival, Eid-ul-Adha | 29 September – 3 August 2020 | 0: other days<br>1: holidays (5-day) due to Eid-ul-Adha |
| Eid-ul-Fitr_before | Holidays due to religious festival "Eid-ul-Fitr" | 24 May 2020 – 25 May 2020 | 0: other days<br>1: 24 & 25 May 2020 |
| Eid-ul-Fitr_after | Holidays due to religious festival "Eid-ul-Fitr" | 27 May 2020 – 28 May 2020 | 0: other days<br>1: 27 & 28 May 2020 |
| Eid-ul-Adha_before | Holidays due to religious festival "Eid-ul-Adha" | 30 July 2020 – 31 July 2020 | 0: other days<br>1: 30 & 31 July 2020 |
| Eid-ul-Adha_after | Holidays due to religious festival "Eid-ul-Adha" | 2 August 2020 – 3 August 2020 | 0: other days<br>1: 2 & 3 August 2020 |
| Eid_outlier | Outliers around Eid-ul-Adha when number of cases were exceptionally low compared to the surrounding days | 2-4 August 2020 | 0: other days<br>1: 2-4 August 2020 |
| Mandatory_mask | Order for mandatory mask wearing at public places | 22 July 2020 – ongoing | 0: inactive<br>1: active |
| Free_test_stopped | End of free tests in Government facilities | 28 June 2020 – ongoing | 0: inactive<br>1: active |

## 5.2 Policy interventions and COVID-19 infection

Policy and other non-pharmaceutical interventions had large impacts in reducing the spread of COVID-19 infections all over the world (16–18). In some cases the timing of adopting those interventions was found to be crucial in curbing the spread (19). In Appendix B, a summary table of literature on COVID-19, policy interventions, and traffic mobility is presented. In this section the impact of policy interventions on COVID-19 infections is explored. This section explores the relative contribution of the various policy interventions on daily new cases in Bangladesh.

Dummy variables presented in Table 4 were used to represent the policy interventions, the estimated coefficients of which will quantify the effects of those interventions on COVID-19 infection. Given there is a natural growth and decay in the number of affected persons in any such pandemic, time-trend variables were included to investigate the presence of any remaining trend that were not captured by the policy intervention dummies. The dependent variable used in the model was the daily new COVID-19 cases as they were reported for the whole country. This was due to the lack of reliable regional or city-level data as identified in Section 4.2. We note that logistic growth curves are often adopted by the epidemiologists (20,21) to capture the spread of infectious diseases like COVID-19 across various regions. Such models are helpful for comparing the spread of the disease across multiple regions; however, they are seldom useful for quantifying association with external factors such as non-pharmaceutical interventions we are interested in. Hence, in this section we adopted autoregressive time-series models where the spread of the disease temporally is captured through the dependency of the reported COVID-19 cases across successive days and time-trend variables. The approach is similar to the segmented multiple regression technique (22) or interrupted time-series approach (23).

Eq. 5.1 presents the generic structure of the econometric model estimated here:

$$C_t = \alpha + \varphi C_{t-1} + \sum_{d=1}^{D} \beta_d I_{d,t-l} + \rho E_t + \delta F_t + \gamma_1 T_{1,t} + \gamma_2 T_{2,t} I_{T2,t} + \gamma_3 T_{3,t} I_{T3,t} \quad (5.1)$$

Where,
$C$ = daily new COVID-19 cases
$I_d$ = policy intervention dummies presented in Table 4
$l$ = days lagged between policy interventions and COVID-19 new cases.
$E$ = Eid-ul-Adha outlier dummy
$F$ = Friday dummy, 1 if Friday and zero otherwise
$T_1, T_2, T_3$ = Trend parameters
$T_1$ = linear time trend with 1 representing 1 April 2020 and chronologically increasing till 31 October 2020
$T_2 = T_1 - 93$; linear time trend, representing trend from 2 July 2020 (= T1- 2 Jul 2020)
$T_3 = T_2 - 90$; linear time trend representing trend from 30 September 2020 ($= T_2 - 30\ September\ 2020$)
$I_{T2} = 1$ if t $> 2$ July 2020 and zero otherwise
$I_{T3} = 1$ for t $> 30$ September 2020 and zero otherwise

The constant, $\alpha$, autoregressive parameters, $\varphi$, the dummy variable parameters, $\beta$, Eid parameter ($\rho$), Friday dummy parameter ($\delta$), and the time trend parameters ($\gamma$) are estimated for the model with daily new cases as dependent variable. The final model is chosen based on model fit (adjusted $R^2$, AIC, BIC). Robust standard errors were used to tackle potential residual autocorrelation among errors.

The summary results of the model estimated with daily new cases as dependent variables ($C_t$) are presented in Table 5. The best significant model was observed when the lag between policy implementation and their impacts on COVID-19 is considered as 8 (eight) days (at larger and smaller lags model fit is slightly worse). The best models for impacts of mobility on COVID-19 were obtained with 10-day lag. Usually, the policy implementation would influence the mobility, which eventually affect the COVID-19 spread. Hence, it can be presumed that, lag between policy interventions and COVID-19 spread should be at least equal to the lag between the mobility changes and COVID-19 spread. On this note, the model with 10-day lag was considered for further discussion. However, model parameters and goodness-of-fit of the 10-day lag model are very similar to the best model which was obtained with 8-day lag.

The coefficients of variables or policy interventions that are significant demonstrated intuitive results, which indicate that many of the policies had the desired effect on reducing the spread of COVID-19 infection. Closure of shopping malls, offices, and public transportation are associated with reductions in daily new cases. The largest beneficial impact was observed due to the full closure of offices and public transport. Although our intention was to identify separately the impacts of different interventions, since these two interventions occurred exactly at the same time, the effects of public transport closure could not be separated from the effects of closure of offices. Closure of shopping malls also led to a reduction in COVID-19 cases, but the effect was around 65% of the joint effects of full closure of offices and public transport. The relatively large impact was possibly due to increased shopping activities prior to the Eid-ul-Fitr, when the restriction was lifted. Statistically, the operation of public transport system and offices at half capacity did not have any impact on the spread – this is possibly a result of lax implementation. Opening of garment factories earlier than other offices did not have a statistically significant adverse effect, but the large mobilisation of people during the indecision of opening garment factories by the business leaders did.

Somewhat surprisingly, the regulation on mandatory mask use did not have any statistically significant effect, although there is a hint of potential increase in spread. Deciphering the effects of mask use can be complex. While, physiological studies show that masks can reduce the spread substantially, is the implementation of the policy was fairly lax in the country. Even when worn, the masks were not of good quality, or were worn in incorrect ways. It is also not impossible that people were already using the masks (however inappropriately) before the policy was implemented, which would make the incremental effects of policy small. More importantly, risk compensating behaviour possibly had an important role in this finding. It is possible that mobility and interactions among people had increased since the mask regulation as the policy may have generated a sense of security that travelling was safe. Indeed, we shall see later in Section 5.3 that mobility went up since the introduction of the mandatory mask use policy. Stricter implementation and effective messaging are therefore necessary to circumvent such unintended effects of a well-meaning policy.

Eid-ul-Fitr had increased the spread, likely due to the increased social interactions during the festivities. We did not get statistically significant effects for Eid-ul-Adha, possibly because mobility was already increasing due to the compulsory mask mandate, just before the Eid-u-Adha. However, there were a few days around Eid-ul-Adha where new cases were drastically decreased. This is probably due to smaller number of tests conducted on those days and these days were treated as outliers in the model.

**Table 5: Model estimation results for association between COVID-19 infection and external interventions**

| Lag of Independent variable → | 8-day Lag | | 10-day Lag | |
|---|---|---|---|---|
| Parameters ↓ | Coef. | Std. Err. | Coef. | Std. Err. |
| Daily_new_case – Lag 1 | 0.19** | 0.08 | 0.2** | 0.08 |
| Garments_close | 118.71 | 80.51 | 117.01 | 88.13 |
| Garments_open_dilemma | 107.45** | 45.79 | 138.78*** | 53.56 |
| Shopping_mall_close | -326.41*** | 101.03 | -362.1*** | 116.77 |
| Office_close | -430.58* | 245.3 | -541.31** | 253.39 |
| Office_half | -39.74 | 147.83 | -168.93 | 148.75 |
| Public_transport_half | 166.39 | 106.42 | 74.07 | 103.36 |
| Mandatory_mask | 179.12 | 145.95 | 202.35 | 154.47 |
| Eid_ul_Fitr | 371.11** | 148.43 | 291.25* | 153.84 |
| Eid_ul_Adha | 99.74 | 142.04 | 222.39 | 152.92 |
| Eid_outlier | -1142.62*** | 366.88 | -1098.17*** | 375.7 |
| Free_test_stopped – Lag 3 | -555.03*** | 124.71 | -515.52*** | 123.86 |
| Friday | 8.04 | 43.78 | -0.89 | 41.21 |
| Trend 1 (April 1 to October 31, 2020) | 29.9*** | 4.98 | 30.95*** | 4.99 |
| Trend 2 (July 3 to October 31, 2020) | -48.02*** | 7.21 | -52.44*** | 7.27 |
| Trend 3 (October 1 to October 31, 2020) | 22.82*** | 5.81 | 27.14*** | 5.75 |
| Intercept | -216.64 | 430.01 | -121.18 | 457.02 |
| **Model Statistics** | | | | |
| Observations | 204 | | 204 | |
| Adjusted $R^2$ | 0.9386 | | 0.9376 | |
| AIC | 2840.51 | | 2843.92 | |

Notes: Dependent variable: daily new cases in Bangladesh. *** statistically significant at 99% confidence, ** statistically significant at 95% confidence, * statistically significant at 90% confidence

Imposing of a small fee for testing at Government facilities starting from 28 June 2020 led to a decrease in daily new cases (indicated by the highly significant negative coefficient value) at 3-day lag. Though a significant portion of the cost was subsidised by the Government, people with low income were likely discouraged in going to the testing facilities due to the imposition of test fees. Usually, a smaller number of tests are conducted on Fridays compared to tests conducted on other days. To control for that a dummy for Friday was added in the model. However, the effect of that on the daily new case was found to be statistically insignificant.

The three trends considered in the model were all found to be statistically significant. The trends indicate that initial increasing trend was observed up to 2 July 2020. After that, a decreasing trend of daily new cases is started which continued till 30 September 2020. Starting from 1 October 2020 another increasing trend was observed for daily new cases till the end of the analysis period, i.e., 31 October 2020.

The observation in this study is similar to the findings in studies focusing on other countries (24). In a study where measures from around 175 countries were evaluated, it was estimated that closers of educational institutes and workplaces significantly reduced COVID-19 infections. In cases where public transports were closed with or after the closing of other public gathering events, effect of public transport closure was not that much evident in reducing infection (17).

## 5.3 Policy interventions and mobility

The year 2020 had seen unparalleled interventions by governments in different countries to curb the spread of COVID-19. This has spurred a substantial body of studies to analyse the effect of policy interventions on mobility. The studies can be grouped into two categories. The first type of research involved before-after comparison of different mobility indicators. They did not quantify the impact of policies on the changes in mobility (25–27). The second type of studies attempted to identify the association between various policy interventions and mobility reduction. For example, in one study an aggregate variable, "aggressiveness", is developed to capture the intensity of government policies in 75 Canadian and American cities and conducted regression analysis to decipher its impact on mobility (28). Another study identified the most effective policies for the mobility changes resulting from regular activity participation, transit ride and stay-at-home duration in different states of the USA, using Google mobility data (29). Researchers also applied time-series analysis to identify the most effective duration of different policy interventions using Google mobility data from 135 countries (30). This section presents a similar approach using Google mobility data to identify the relative contribution of various policy measures for reducing mobility in different sectors such as retail, grocery, park, transit, and work for Bangladesh. The analysis also explored the changes in stay-at-home duration. Since the analysis was conducted for one country it was also possible to decipher the effects of local special events (e.g., religious festivals) from the COVID-19 related policy measures.

Specifically, this section explores the relative contribution of the various policy interventions on 6 mobility trends, as presented in Table 6. Auto-regressive time-series models (31) were adopted to capture the correlation between successive days' mobility trend. Dummy variables presented in Table 4 corresponding school, shopping mall, garments, office, public transportation closure and capacity reduction were used to quantify the effect of policy interventions. We also included weekend indicator to capture the inherent difference in mobility pattern across weekdays and weekends. We created three indicator variables to quantify the impact of each of the two major special events during the modelling period, i.e., Eid-ul-Fitr and Eid-ul-Adha. Two indicator variables captured the effect of the two days before and after the festival, whereas the third variable captured the effect of the festival day. Additionally, mandatory mask mandate was included in the model to test the potential risk-compensation effects. Six separate models were estimated to capture the mobility trend in the retail and recreation, grocery, park, transit, work, and residential sectors. Eq. 5.2 presents the generic model formulation.

$$M_t = \alpha + \varphi_{t-1} M_{t-1} + \sum_{d=1}^{D} \beta_d I_{dt} + \delta W_t \quad (5.2)$$

Where,

M = one of the six mobility trends i.e. retail, grocery, park, transit, work or resident
$I_d$ = policy intervention dummies presented in Table 2
$W$ = Weekend dummy 1 if Friday or Saturday and zero otherwise

The constant $\alpha$, auto-regressive parameters, $\varphi$, the dummy variable parameters, $\beta$, and the weekend parameter, $\delta$ are estimated separately for each of the six mobility models. Table 6 presents the model estimation result. All the mobility models show strong correlation between successive day's mobility as evident from the very strong auto-regressive coefficient.

Among various COVID-19 related policy interventions, education had the largest impact on retail mobility reduction followed by the office and public transport closure. Shopping mall and garments shut down also were found to have significant influence on the changes in the retail activity. Half capacity reduction of the public transportation resulted in significant reduction in the retail and recreation related mobility. However, similar reduction in the government office capacity was not found to have any significant influence. Mandatory mask mandate caused a significant increase in the retail sector mobility. The retail mobility plummeted during the weekend – since the mobility data are already normalised with respect to the days of the week, the negative coefficient on weekends might indicate comparatively larger reduction of retail mobility during the weekends than during the weekdays. Substantial reduction in the retail mobility was noted on the days of Eid-ul-Fitr and Eid-ul-Adha as well as on the days following the festival. However, an increase was noted in the days prior to the festivals as people increased their visits to the shopping malls to prepare for the festivals.

**Table 6: Model estimations results for the association between interventions and events with mobility**

| Dependent variable → | Retail and recreation | | Grocery and pharmacy | | Parks | | Transit stations | | Workplaces | | Residential | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Parameters ↓ | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| Lag 1 of independent variable | 0.68*** | 0.04 | 0.64*** | 0.05 | 0.57*** | 0.05 | 0.63*** | 0.04 | 0.11** | 0.06 | 0.11* | 0.06 |
| Education_institution_close | -12.47*** | 1.65 | -6.6*** | 1.33 | -9.5*** | 1.48 | -10.43*** | 1.49 | -12.98*** | 2.26 | 7.84*** | 0.78 |
| Shopping_mall_close | -4.56*** | 1.45 | -6.28*** | 1.61 | -2.15 | 1.44 | -5.18*** | 1.49 | -10.73*** | 2.57 | 4.23*** | 0.72 |
| Garments_close | -1.86 | 1.19 | -1.68 | 1.31 | 0.95 | 1.27 | -2.39* | 1.23 | -9.88*** | 2.26 | 1.63*** | 0.59 |
| Office_close | -5.16*** | 1.98 | -6.19*** | 2.04 | -6.18*** | 1.6 | -9.58*** | 2.12 | -22.5*** | 2.95 | 6.69*** | 0.84 |
| Office_half | 1.05 | 1.22 | 0.44 | 1.32 | -1.06 | 1.23 | -0.12 | 1.24 | -3.66* | 2.14 | 2.62*** | 0.6 |
| Public_transport_half | -2.09** | 0.9 | -3.32*** | 1 | -1.86** | 0.9 | -4.74*** | 1.02 | -5.89*** | 1.61 | 0.09 | 0.42 |
| Mandatory_mask | 7.56*** | 1.03 | 7.63*** | 1.15 | 6.79*** | 1.13 | 7.42*** | 1.07 | 2.99* | 1.71 | -1.25*** | 0.46 |
| Weekend | -0.25 | 0.52 | 0.77 | 0.56 | 1.06* | 0.56 | 1.3** | 0.53 | 10.48*** | 1.03 | -1.25*** | 0.26 |
| Eid_ul_Fitr_before | 3.69 | 2.79 | 6.92** | 3.1 | 7.25** | 2.9 | 2.21 | 2.87 | -15.41*** | 5.18 | 2.54* | 1.38 |
| Eid_ul_Fitr_after | -6.24** | 2.79 | -8.43*** | 3.06 | -1.68 | 3.07 | -4.66 | 2.87 | -18.89*** | 5.31 | 0.57 | 1.37 |
| Eid_ul_Adha_before | 6.05** | 2.86 | 17.97*** | 3.16 | 7.12** | 2.92 | 10.12*** | 2.94 | 2.09 | 5.13 | -4.92*** | 1.38 |
| Eid_ul_Adha_after | -3.19 | 2.86 | 1.53 | 3.09 | 13.59*** | 3.08 | 0.73 | 2.9 | -31.84*** | 5.54 | -0.63 | 1.37 |
| Eid-ul-Fitr_day | -13.69*** | 3.85 | -20.1*** | 4.3 | 21.83*** | 4.02 | -9.54** | 3.95 | -23.53*** | 7.11 | -0.1 | 1.88 |
| Eid-ul-Adha_day | -43.13*** | 3.99 | -52*** | 4.66 | 6.99* | 4.1 | -39.59*** | 4.14 | -48.65*** | 7.11 | 4.22** | 1.94 |
| Intercept | 0.74 | 0.69 | 1.44* | 0.78 | 2.19*** | 0.78 | 0.9 | 0.73 | 2.95** | 1.3 | 1.27*** | 0.34 |
| **Model Statistics** | | | | | | | | | | | | |
| Observations | 259 | | 259 | | 259 | | 259 | | 259 | | 259 | |
| Adjusted $R^2$ | 0.9778 | | 0.9661 | | 0.9357 | | 0.9776 | | 0.8992 | | 0.9313 | |
| AIC | 1427.66 | | 1475.69 | | 1451.57 | | 1443.29 | | 1747.38 | | 1061.97 | |

Notes: Dependent variable: Per cent changes in daily mobility compared to a baseline. *** statistically significant at 99% confidence, ** statistically significant at 95% confidence, * statistically significant at 90% confidence

Office closure, shopping closure and school shut down had similar impact on the reduction of grocery mobility. Garment factory closure did not have any significant influence on grocery mobility. Like retail, grocery mobility was not impacted by the capacity reduction in the government offices; however, the public transport capacity reduction impacted the mobility considerably. Grocery mobility was comparatively higher during the weekends than on the weekdays which is intuitive – unlike the retail this might indicate a lower reduction of grocery related activities during the weekend than during the weekdays. Mandatory mask wearing had strong positive influence on increasing grocery activity. Like retail, we notice substantial drop in the grocery mobility on and after the days of the festival. However, the days prior to the festival exhibited noticeable increase as people prepared for the festival.

Closure of the educational institutions had the strongest bearing on reducing park activities, followed by the office shut down. Although the public transport capacity reduction decreased the park mobility substantially, the impact of office capacity reduction was only marginal. The mandatory mask mandate caused a significant increase in the park traffic. Though the mandatory mask mandate was not strictly imposed by the government, the policy might have created a sense of safety among the public, ultimately increasing the leisure activity participation like visiting parks. As expected, weekend dummy showed positive magnitude – indicating lower reduction of park mobility during weekends than during the weekdays. Unlike retail and grocery, substantial increase in the park mobility was observed on the days of the Eid-ul-Fitr and Eid-ul-Adha as well as on the days prior to the festival. In case of Eid-ul-Adha, the increase in mobility continues even after the festival day, whereas no considerable impact was noticed on the days after the Eid-ul-Fitr.

Office and school closure had similar impact on transit mobility reduction followed by the shopping mall and garment shut down. The half capacity reduction of public transportation was influential in reducing transit mobility; however, the similar reduction of the office capacity was not found to have any considerable impact. Like previous mobility, mandatory mask mandate increased the transit mobility substantially. Transit mobility decreased substantially on the days of two religious festivals. Transit mobility increased considerably before Eid-ul-Adha – but no such trend was noticed before Eid-ul-Fitr. This is because a substantial part of public transit was still closed during the Eid-ul-Fitr.

As expected, office closure had the strongest impact on work related mobility reduction followed by the closure of the educational institutions and shopping malls. Unlike, previous mobility trends, work activities reduced significantly due to the garments shut down. The capacity reduction of both the public transportation and the government offices reduced the work mobility significantly, although office capacity reduction was less effective for changing mobility in other sectors such as retail and grocery. Mandatory mask regulation increased the mobility at workplaces; however, the contribution is not as strong as in the previous mobility models. This is possibly because work travel is a necessity and had recovered already to its near-full level. As expected, work mobility reduced before, and on the day of Eid-ul-Fitr and Eid-ul-Adha which are observed as public holidays in the country.

In contrast to the last five activity trends, residential activity measured the amount of time people stays at home – hence, this trend showed a mirror image of the previous mobility variables (Figure 6). All the policy intervention dummies have positive and significant impact on residential mobility except the public transportation policy dummy. School shut down had the strongest positive bearing on residential mobility followed by the shopping mall and office closure. Office capacity reduction had significant effect in increasing residential mobility, but the public transport capacity reduction did not. The model shows an increase in the stay-at-home duration before Eid-ul-Fitr, whereas a decrease was noticed before the day of Eid-ul-Adha. As expected, mandatory mask mandate reduced the stay-at-home duration as reflected in the negative parameter estimate. As discussed before, mandatory mask rule might have created a sense of safety among the public which might have led to spending more time outside of homes.

In summary, office and school shut down were identified as the most effective policies for controlling mobility. Shopping mall closure had significant influence on all but park mobility. On the other hand, garment factory closure had considerable influence only on transit, work mobility, and stay-at-home duration (residential activity). Since the public transportation closure overlapped with the office closure the office closure dummy captured the combined effect of these two policy interventions – hence we could not ascertain the marginal impact of public transportation closure through this model. Though the impact of public transportation capacity reduction was significant in almost all cases, the same was not true for the office capacity reduction – it only had observable impact on work mobility reduction. Another compelling observation can be made regarding the mandatory mask policy – this policy showed statistically significant positive influence on mobility for all sectors i.e., the mobility in all sectors increased after the mandatory mask mandate (stay-at-home decreased). However, no significant effect of mandatory mask policy was noticed on the spread of COVID-19 in Section 5.2. Hence, if such precautionary policies are not strictly enforced by the government, it could potentially lead to unintended consequences such as no reductions in COVID-19 infections, or even an increase in extreme cases.

## 5.4 Effects of mobility on COVID-19 infection

The spread of COVID-19 has produced a considerable amount of research on the topic – while many researchers explored the impact of non-pharmaceutical interventions (NPI) on COVID-19 (32); the direct association between mobility change and COVID-19 spread has also generated lots of interest. A study reported that mobility reduction has led to lower transmission rate in majority of the 52 countries (33). Similarly, time-lagged regression using data form Italy reveals that mobility habit of people can affect the COVID-19 spread (34). A reduction in mobility led to decreased COVID-19 deaths in the UK (35). China (3) has also observed strong positive correlation between domestic and international air traffic and COVID-19 case reporting. Human movement from one place to another was also observed to be a key factor in spreading COVID-19 in Bangladesh early on (36). In this section we extend the model presented in Section 5.2 to investigate the direct association between COVID-19 cases and mobility.

In Section 4, we explored data from multiple sources to understand the mobility change during the analysis period. However, the vehicle tracking data (Section 4.3) was missing during April and May – two critical months from the perspective of COVID-19 spread. Similarly, though the information collected from toll plaza (Section 4.5) is an important proxy for inter-city travel it is not a good proxy for intra-city travel. Therefore, we used Google mobility data as proxy for the traffic in this section.

Specifically, we developed a model with daily new case presented in Figure 2 as the dependent variable and six mobility trends presented in Figure 6 as the exogenous variable for this section. Since, the explanatory mobility variables are highly correlated among themselves we developed separate models for each mobility trend. Furthermore, we conducted a systematic search to identify the most significant lag of the mobility to impact the COVID-19 infection. Like the previous section, we applied autoregressive time-series formulation to model COVID-19 daily cases. In addition to the intercept, we estimated three time-trend parameters to capture the time-varying trends of COVID-19 spread. The generic equation used to model the COVID-19 infection as function of mobility is presented in Eq. 5.3.

$$C_t = \alpha + \varphi_1 C_{t-1} + \varphi_2 C_{t-2} + \beta M_{t-l} + \rho E_t + \delta W_t + \gamma_1 T_{1,t} + \gamma_2 T_{2,t} I_{T2,t} + \gamma_3 T_{3,t} I_{T3,t} \qquad (5.3)$$

Where,

$C$ = daily new COVID-19 cases
$l$ = days lagged between mobility measure and COVID-19 new cases
$M$ = one of the six mobility trends i.e. retail, grocery, park, transit, work or resident
$E$ = dummy for outliers around Eid-ul-Adha, 1 on and 2 days after the day of Eid-ul-Adha (where COVID-19 cases are comparatively different than surrounding days) and zero otherwise
$W$ = weekend dummy, 1 if Friday or Saturday and zero otherwise
$T_1, T_2, T_3$ = Trend parameters
$T_1$ = linear time trend with 1 representing 1 April 2020 and chronologically increasing till 31 October 2020
$T_2 = T_1 - 93$; linear time trend, representing trend from 2 July 2020 (= T1- 2 Jul 2020)
$T_3 = T_2 - 90$; linear time trend representing trend from 30 September 2020 ($= T_2 - 30\ September\ 2020$)
$I_{T2} = 1$ if t $>$ 2 July 2020 and zero otherwise
$I_{T3} = 1$ for t $>$ 30 September 2020 and zero otherwise

$\alpha$ is the intercept, $\varphi$ is the autoregressive coefficient, $\beta$ is the coefficient to the mobility trend, $\rho$ is the coefficient for Eid-ul-Adha outliers, $\delta$ is the coefficient for weekend, and $\gamma$ is the time trend parameter.

Table 7 presents the model estimation results. We have presented the results for retail and recreation, grocery, parks, transit, work and residences. As can be noted the lag 1 autoregressive parameter was statistically significant and positive revealing a strong positive association of COVID-19 cases across successive days. The first time trend coefficient is always significant and positive. The second time-trend parameter is negative indicating a decreasing rate in case reporting between July and September. However, the trend started to increase after September 30 as captured through the third time-trend variable. The negative weekend dummies indicate lower case reporting during weekend throughout the analysis period – this might have captured the reduced testing capacity during the weekends. A similar impact is noticed on and after the day of Eid-ul-Adha.

The COVID-19 daily cases show positive association with retail and recreation, grocery, parks, and transit mobility indicating an increase in mobility led to an increase in the COVID-19 infection. Moreover, the significance of the tenth lag of the mobility trends indicates that a rise in the mobility took around ten days to manifest in rising COVID-19 infection. As expected, the residential activity was negatively correlated with COVID-19 infection meaning that the higher people stayed at home the lesser was the spread of COVID-19. Though the work mobility showed a hint of positive association with COVID-19 infection, the association was not statistically significant. Work mobility had returned closer to baseline earlier than other mobility sectors. Prevalence of distinct weekly pattern in work-related mobility along with its quick recovery may have led to this statistically inconclusive finding for the effect of work mobility on COVID-19 spread. Again, there is a lag of ten days between the time people start staying at home and the evidence of a reduction in COVID-19 infection.

The observed lag of around ten days between the mobility changes and COVID-19 spread in Bangladesh is considerably lower than the lags reported in Italy (21 days) (34) and in the UK (18 days) (35); but is comparable with the lags reported in the context of China (16) and the USA (37). The UK lag was measured to relate the COVID-19 death with mobility and not with COVID-19 cases. Hence, the UK lag is expected to be higher than what we observed. Additionally, the mobility measures used by the above countries are different – Italy used the number of people who made at least one trip to calculate the mobility during the analysis period. Whereas the UK used the driving, walking and transit trips reported by Apple as a proxy for mobility. It can be noted that, the medical journals have reported an incubation period of two to fourteen days with five days being the mean (38) and median (39). Given the potential delay in taking the tests and in getting the test done, ten day lag between the changes in mobility and the changes in COVID-19 cases as in this analysis are comparable to other studies. Additionally, the population density in Bangladesh might have played a crucial role in shortening the lag compared to other developed countries where the population density is much lower. The population density in Bangladesh is 1,260 people per thousand km which is 5 to 6 folds higher than that in Italy (206 per square km) and the UK (275 per square km). This may have resulted in a relatively higher viral load for the exposed population, shortening the time required for the disease to transmitted and detected after an event. Clearly, the analysis presented in this section suggests the presence of a direct association between mobility and COVID-19 spread in the context of Bangladesh.

Table 7: Model estimation results for the association between mobility and COVID-19 infection

| Mobility type as Independent variable → | Retail and recreation | | Grocery and pharmacy | | Parks | | Transit stations | | Workplaces | | Residential | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Parameters ↓ | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| Daily new cases – Lag 1 | 0.43*** | 0.07 | 0.41*** | 0.07 | 0.32*** | 0.07 | 0.39*** | 0.07 | 0.46*** | 0.07 | 0.41*** | 0.07 |
| Mobility – Lag 10 | 7.73** | 3.71 | 9.32*** | 2.88 | 14.36*** | 3.89 | 14.3*** | 4.51 | 0.86 | 1.98 | -35.73*** | 8.03 |
| Eid_outlier | -864.54** | 389.58 | -878.81** | 375.22 | -906.23*** | 349.62 | -902.13** | 367.77 | -786.9** | 396.83 | -845.51** | 372.85 |
| Weekend | -160.55*** | 36.5 | -146.2*** | 36.18 | -157.87*** | 34.01 | -152.77*** | 35.92 | -158.79*** | 37.88 | -138.68*** | 36.44 |
| Free_test_stopped – Lag 3 | -429.38*** | 99.92 | -427.33*** | 96.21 | -492.25*** | 98.93 | -411.19*** | 94.33 | -378.59*** | 93.52 | -406.71*** | 93.03 |
| Trend 1 (Apr 1 to Oct 31, 2020) | 27.04*** | 3.42 | 27.17*** | 3.37 | 33.7*** | 3.69 | 25.59*** | 3.3 | 28.1*** | 4.08 | 25.35*** | 3.26 |
| Trend 2 (Jul 3 to Oct 31, 2020) | -41.61*** | 4.99 | -42.47*** | 4.91 | -52.14*** | 5.64 | -43.54*** | 5 | -39.81*** | 5.36 | -39.86*** | 4.59 |
| Trend 3 (Oct 1 to Oct 31, 2020) | 14.85*** | 3.16 | 13.93*** | 2.96 | 22.03*** | 3.54 | 13.26*** | 2.92 | 12.54*** | 3.04 | 15.71*** | 2.85 |
| Intercept | -275.92 | 311.76 | -362.19* | 195.86 | -591.9*** | 157.22 | 228.75 | 354.12 | -846.68*** | 228.56 | 87.97 | 234.64 |
| **Model Statistics** | | | | | | | | | | | | |
| Observations | 204 | | 204 | | 204 | | 204 | | 204 | | 204 | |
| Adjusted $R^2$ | 0.9362 | | 0.9380 | | 0.9409 | | 0.9392 | | 0.9345 | | 0.9395 | |
| AIC | 2840.65 | | 2834.93 | | 2825.23 | | 2831.09 | | 2846.08 | | 2829.82 | |

Notes: Dependent variable: Daily new cases in Bangladesh. *** statistically significant at 99% confidence, ** statistically significant at 95% confidence, * statistically significant at 90% confidence

## 5.5 Effects on road traffic accidents

It is only natural that road accidents and resulting fatalities fell during the COVID-19 related lockdown, as can be seen from the figures in Section 4.6 earlier. However, the accident data required further analysis. As the traffic data earlier shows, the 5 months period between April and August could be taken as the period of substantially perturbed mobility and traffic flow. The average monthly accidents in Bangladesh during the 5 months perturbed period was 303, which was substantially smaller than the average during the rest of 2019-2020, which was 359.8. Similarly, average monthly *fatalities* were 288.6 and 348 during the disrupted and normal periods of traffic, respectively. However, despite the seemingly large reductions during the COVID-19 period, the average reductions were not statistically significant (t-stat for accidents 1.319 and for fatalities 1.264, p-value > 0.1 for both cases), due to the large variability in monthly accidents and fatalities.

The simple average accident or fatality data – while useful – are not the only interesting metric for transport safety analysis. The vehicle speed increased during the disruption period (Section 4.3). This raises an interesting research question whether accident and fatality *rates* – after controlling for the reduction in traffic – had increased during this period. National Highway and Traffic Safety Administration (NHTSA 2021) reported that the fatality rates and risky driving behaviour had increased in the US during the COVID-19 period (40). On the other hand, road accidents and fatalities had reduced more than the traffic in the UK (41) and Spain (5). No such evidence exists on such comparisons either in Bangladesh or in other low-income countries.

Accidents or fatality 'rates' are often normalised with respect to vehicle miles travelled. However, such information is not available in Dhaka or Bangladesh. As such the absolute monthly accidents and fatalities were normalised in the following ways. Firstly, the monthly accident and fatality data were normalised to 30-day months to even out monthly differences in the number of days. Secondly, Google Community Mobility report data were used to infer average monthly reductions in traffic, as before. Given Google Mobility report does not exactly measure traffic count or flow, three separate metrics from this report were used to normalise accident to ensure a robust finding. These three normalising variables are the activities in work, retail and recreation, and transit stations (activities = 100 + reduction in activities, as in the Google Mobility Report). These three normalising traffic metrics were assumed to have a value of 100 as the baseline traffic for all months before February 2020, as no Google Mobility was available for that period. While this neglects the potential variations in vehicle miles or traffic at a monthly level, this was necessary to overcome the limitations in data availability. Figure 14 presents the FIR accident and fatality rates for Bangladesh with respect to various traffic reduction metrics.

**Figure 14: Accident rates and fatality rates, Bangladesh, normalised using traffic metrics**

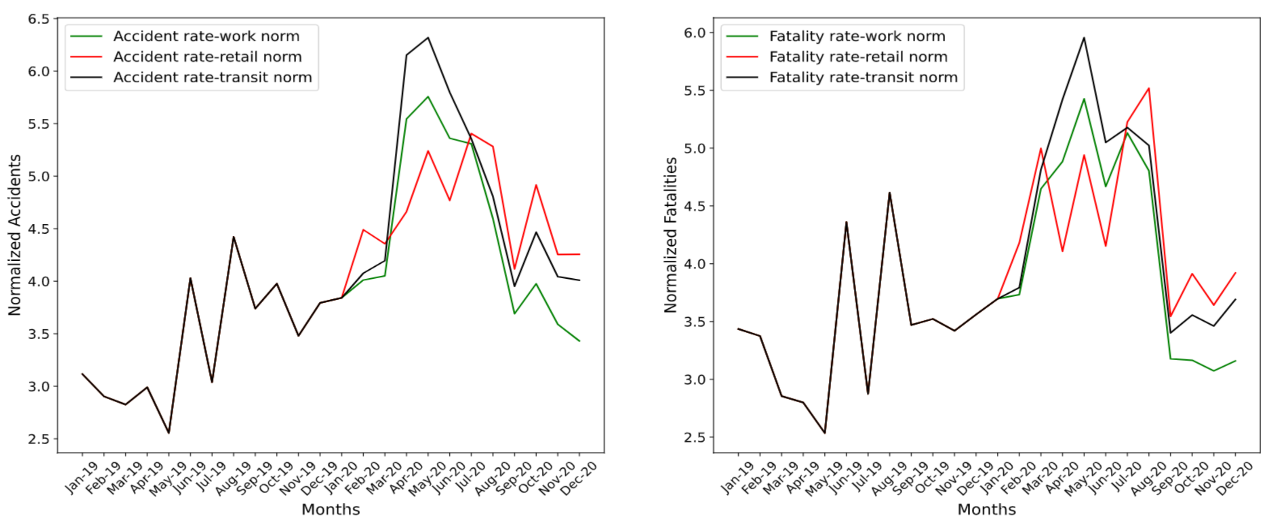



Table 8 presents the two-sample t-test with unequal variance for accident and fatality rates during and outside COVID-19 disruption periods. These results are for both FIR and newspaper data for Bangladesh and Dhaka. Accident and fatality rates in Bangladesh have increased during the COVID-19 disruption in a statistically significant way – this finding is robust for all three normalising traffic measures and using both FIR and ARI data. This tends to support the hypothesis that higher speed (and possibly COVID-19 related driving stress) during COVID-19 made road travel less safe than before, as seen in the US. This finding suggests that traffic safety authorities need to take additional measures during such reduced traffic episodes, whether induced by a pandemic or other event.

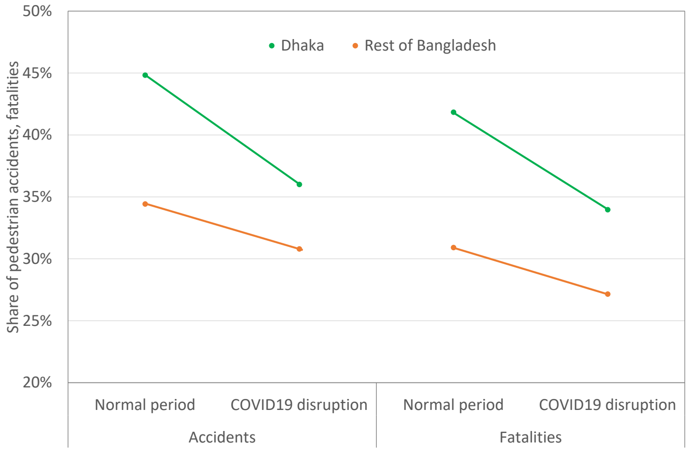
**Table 8: t-test results for accident and fatalities during COVID-19 disruption and normal periods**

| Normalising factor | | FIR Data | | | | | | ARI (newspaper) data | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Accident rate | | | Fatality rate | | | Accident rate | | | Fatality rate | | |
| | | Work | Retail | Transit | Work | Retail | Transit | Work | Retail | Transit | Work | Retail | Transit |
| Bangladesh | Normal period | 3.742 | 3.656 | 3.551 | 3.617 | 3.539 | 3.446 | 3.259 | 3.196 | 3.123 | 3.660 | 3.587 | 3.504 |
| | Disrupted period | 5.072 | 5.687 | 5.313 | 4.789 | 5.326 | 4.983 | 3.434 | 3.876 | 3.615 | 4.045 | 4.527 | 4.227 |
| | t-stat | 1.761 | 1.943 | 1.895 | 1.943 | 1.833 | 1.771 | 1.734 | 2.015 | 1.895 | 1.833 | 1.895 | 1.796 |
| | p (one tail) | <0.001 | <0.001 | <0.001 | 0.005 | <0.001 | <0.001 | 0.108 | 0.038 | 0.044 | 0.073 | 0.007 | 0.005 |
| Dhaka | Normal period | -- | -- | -- | -- | -- | -- | 0.221 | 0.217 | 0.212 | 0.236 | 0.232 | 0.228 |
| | Disrupted period | -- | -- | -- | -- | -- | -- | 0.156 | 0.168 | 0.159 | 0.166 | 0.178 | 0.168 |
| | t-stat | -- | -- | -- | -- | -- | -- | 2.015 | 1.943 | 1.943 | 2.015 | 1.895 | 1.895 |
| | p (one tail) | -- | -- | -- | -- | -- | -- | 0.056 | 0.071 | 0.066 | 0.038 | 0.034 | 0.030 |

Interestingly, a reverse pattern is observed in Dhaka using the ARI data: both accident and fatality rates were statistically lower during the COVID-19 disruption. This finding is robust for normalised fatalities for all three normalising traffic metrics, and slightly less robust for accident rates. There are several potential explanations for this intriguing finding in Dhaka. Firstly, motorcycle ride-hailing services, which form a larger share of motorcycles in the capital than in the rest of the country and which had increased rapidly in number in Dhaka (42), were banned for an extended period – affecting their operations in Dhaka substantially more than in the rest of the country. At the same time, motorcycles became quite popular for intercity travel during the disrupted period, as long-distance buses were either banned or operated at a reduced capacity. Secondly, the mobility of vulnerable (children, women) pedestrians was likely reduced substantially more in the capital compared to other places (e.g. women work in garment factories in large numbers in Dhaka, while women's participation in the formal economy in the rest of the country is far less). Thirdly, footpaths in Dhaka are often encroached by street vendors, forcing pedestrians to walk on roads, which is very risky. The footpaths were substantially free from any such encroachment during the disruption period, making pedestrian travel safer. Fourthly, given the original hyper-congested situation in Dhaka, increase in speed during the whole of disrupted period was possibly not enough to increase accident and fatality risks substantially. Visually, it appears that the shares of pedestrians in both accidents and fatalities have fallen more in Dhaka during the COVID-19 disruptions compared to that in the rest of the country (Figure 15). Data also showed that the motorcycle share of accidents in the rest of the country increased marginally (from 21% to 23%) but remained the same in Dhaka (21%).

On the other hand, it is not impossible that traffic reduction in the rest of the country was less compared to Dhaka (i.e. the COVID-19 related regulations were observed less strictly), as such using the same normalisation metrics for Dhaka and Bangladesh may have adversely penalised the accident and fatality statistics for Bangladesh. However, unless these differences are large, it is reasonable to conclude that roads became safer in Dhaka than the rest of the country during the COVID-19 induced disruptions.

**Figure 15: Pedestrian accidents and fatalities, Dhaka and Bangladesh during normal and COVID-19 disruption periods**




Source: ARI

## 5.6 Effects on air quality

There is now a large body of literature, which shows that the air quality has improved in many cities or regions of the world as a result of COVID-19 related lockdown and disruptions. In some areas, the improvement was remarkably visible through simple data plots (43,44), in others more sophisticated statistical methods were applied (45,46). Consensus is that $PM_{2.5}$, $PM_{10}$, $NO_x$ reduced as a result of COVID-19 related lockdown, but ozone increased (see Appendix C for a summary table of literature). It is interesting to note that a significant share of this peer-reviewed academic literature simply compared before-after pollutant concentrations, without controlling for changes in weather during the before-after periods, which could present a misleading picture.

The simple data visualisations and descriptive statistics in Section 0 earlier, however, do not reveal any substantial improvement in air quality (i.e. reduction in ambient air pollutant concentration). Given a substantial period of the COVID-19 related disruptions took place during the North-Western *Kalboishakhi* storm and peak monsoon seasons, when ambient $PM_{2.5}$ is naturally low, it was difficult to visually separate the effects of COVID-19 from simple data plots. A direct comparison of before-after lockdown periods is also incorrect due to the seasonal variations. As such statistical regression techniques were applied to investigate the impacts in further detail.

As before, the segmented multiple regression technique (22) or interrupted time-series approach (23) is followed here to determine the effects of COVID-19 related disruptions on air quality. In this method a dummy variable for the disrupted period was introduced in the regression, which captured the differential impacts during that period. The dependent variable was daily mean $PM_{2.5}$ concentration, explanatory factors are dummy variables for seven days of the week to capture daily variations in traffic and other activities (especially weekends), twelve months in order to capture the seasonality of emissions (e.g. emissions from brick kilns) and general weather pattern, holidays to capture changes in emissions pattern, and COVID-19 disruption period; and continuous variables for daily rainfall to capture the direct effects of weather and a time trend to capture general increases or reductions in air pollution. Since, there is a strong correlation between today's air pollution with yesterday's the lagged dependent variable was also included as an explanatory factor. The continuous variables $PM_{2.5}$ and rainfall are converted to logarithm for better results. Eq. 5.4 below presents the model.

$$lnP_t = \tau + \sum \beta_i D_{it} + \sum \gamma_j M_{jt} + \delta T_t + \mu H_t + \theta lnR_t + \alpha C_t \qquad (5.4)$$

Where,

P = daily $PM_{2.5}$ concentration
$D_i$ = dummy variable for weekday i (i= 1…6)
$M_j$ = dummy variable for month j (j= 1.. 11)
T = time trend
H = dummy variable for national holidays (except COVID-19 closures)

R = daily rainfall
C = dummy representing COVID-19 disruption period (March 27 to August 31)

Greek letters = parameters to be estimatedTable 9 presents the parameter estimates for $PM_{2.5}$ concentrations at three locations. As can be seen, the monthly dummy variables confirm seasonality in ambient $PM_{2.5}$ concentrations in all three locations. Air pollution was high during the dry months of December, January, February and March, while it was significantly lower during the monsoon season of July and August (largest negative parameter estimates, negative was relative to January concentration). It is important to note the large drop between March and April (e.g. from -0.24 to -0.44 at the US embassy). The brick kilns – one of the largest sources of particulate emissions –close and the North-Westerly *Kalboishakhi* storm cause large rainfall around April, causing this large improvement in air quality in April. This indicates that even if there were no COVID-19 related disruptions, $PM_{2.5}$ concentration would have fallen by that amount between March and April.

Fridays – which are weekends in Bangladesh – showed a statistically significant improvement in air quality in all three locations (although only marginally significant at 90% confidence at BARC), suggesting a weekly pattern in $PM_{2.5}$ pollution. While there was a hint that air pollution improved during holidays (negative parameter estimate), the effect was statistically not significant. As can be expected, rainfall had a statistically significant impact on reducing $PM_{2.5}$ concentrations at all three locations. No long-term increasing or

**Table 9: Estimation results for association between daily mean $PM_{2.5}$ and disruptions at three locations**

| Dependent variable → | log ($PM_{2.5}$) at BARC | | log ($PM_{2.5}$) at Darussalam Road | | log ($PM_{2.5}$) at US Embassy | |
|---|---|---|---|---|---|---|
| Parameters ↓ | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| Lag 1 of dependent variable | 0.705*** | 0.017 | 0.642** | 0.018 | 0.593*** | 0.020 |
| Lag 7 of dependent variable | 0.061*** | 0.017 | -- | -- | -- | -- |
| (D) Monday | -0.013 | 0.032 | 0.008 | 0.026 | 0.011 | 0.029 |
| (D) Tuesday | 0.034 | 0.032 | -0.003 | 0.026 | -0.003 | 0.029 |
| (D) Wednesday | 0.005 | 0.032 | -0.011 | 0.026 | 0.014 | 0.029 |
| (D) Thursday | -0.024 | 0.033 | -0.035 | 0.026 | -0.030 | 0.029 |
| (D) Friday | -0.057* | 0.033 | -0.066** | 0.026 | -0.083*** | 0.030 |
| (D) Saturday | 0.033 | 0.033 | -0.009 | 0.026 | -0.002 | 0.030 |
| (M) February | -0.044 | 0.043 | -0.087** | 0.036 | -0.083** | 0.042 |
| (M) March | -0.070* | 0.043 | -0.218*** | 0.034 | -0.245*** | 0.040 |
| (M) April | -0.225*** | 0.046 | -0.417*** | 0.040 | -0.441*** | 0.046 |
| (M) May | -0.254*** | 0.050 | -0.481*** | 0.042 | -0.481*** | 0.048 |
| (M) June | -0.320*** | 0.051 | -0.618*** | 0.046 | -0.661*** | 0.052 |
| (M) July | -0.337*** | 0.056 | -0.607*** | 0.049 | -0.661*** | 0.054 |
| (M) August | -0.325*** | 0.055 | -0.595*** | 0.048 | -0.671*** | 0.054 |
| (M) September | -0.298*** | 0.053 | -0.519*** | 0.044 | -0.621*** | 0.053 |
| (M) October | -0.229*** | 0.047 | -0.411*** | 0.040 | -0.479*** | 0.048 |
| (M) November | -0.086** | 0.044 | -0.184*** | 0.036 | -0.260*** | 0.042 |
| (M) December | -0.037 | 0.044 | -0.052 | 0.035 | -0.094** | 0.041 |
| (T) Trend | 0.00003** | 0.00002 | 0.00001 | 0.00001 | 0.000003 | 0.00001 |
| (R) log (Rainfall) | -0.009*** | 0.003 | -0.018*** | 0.003 | -0.020*** | 0.003 |
| (H) Holiday | -0.049 | 0.038 | -0.008 | 0.029 | -0.041 | 0.034 |
| (C) COVID-19 disruption | -0.185*** | 0.040 | -0.008 | 0.030 | -0.025 | 0.033 |
| Constant | 1.117*** | 0.107 | 1.807*** | 0.096 | 2.044*** | 0.110 |

Note: *** statistically significant at 99% confidence, ** statistically significant at 95% confidence * statistically significant at 90% confidence decreasing trend was observed in US Embassy or Darussalam, but an increasing trend was observed in Farmgate. This is possibly driven by the presence of a large construction yard near the site, which was being used for the construction of the elevated mass rail transit system in Dhaka nearby, which had increased air pollution in that area.

The parameter estimate for the variable C, which represents the transport and economic disruptions due to COVID-19 related policies, is statistically significant and negative for BARC location. This indicates that $PM_{2.5}$ concentration was smaller than was expected during the disrupted period, so air quality had indeed improved. However, at the Darussalam Road and US Embassy locations, the relevant model parameters are negative, but statistically insignificant. This indicates that air quality in these two locations did not show a sustained improvement over the disrupted period to be differentiated from the noise in the data. Using different disruption periods (shorter than the five months in the main model) shows that the air quality at US embassy marginally improved for only a month immediately after the disruptions (that too at a liberal 90% significance level). Darussalam location did not register any statistically significant improvement even within the first one month of closures. The results thus show that there were clearly differential air quality impacts of the lockdown in different parts of the city.

The contradictory findings are intriguing and require further explanation. The BARC location is not only a traffic hotspot, but also very close to a large construction yard, which serves the ongoing construction of the elevated mass rapid transit system nearby. This means construction related pollution (primarily dust due to yard activities and escape during transport of construction materials) was a major part of the ambient $PM_{2.5}$ concentration at that location. The closure of economic activities did not only reduce traffic on road, but also stopped (or slowed down) the construction activities, resulting in a large enough fall in $PM_{2.5}$ concentration during the disrupted period at BARC location. No such large construction activities were observed at the two other locations and any reductions at these locations would have been a likely result of reductions in traffic.

That the large drop in traffic activities due to COVID-19 (Section 4.3 and 4.4) did not improve air quality in a significant way in two locations is also in contradiction to the findings in many locations around the world. This suggests that traffic related emissions may not be a large a contributor to ambient $PM_{2.5}$ in Dhaka. Given a large share of Dhaka's vehicles run on CNG (47), which emits very few particles, such results are plausible. Indeed, earlier source apportionment studies showed that the share of motor vehicle related emissions in ambient $PM_{2.5}$ in Dhaka was reduced from 43% in 2001-2002 to only 10% in 2011-12 (48), lending support to the findings here. Further source apportionment studies using samples collected during the COVID-19 disruptions could shed more light on this subject.

Taken together, the results are also important for policymaking. Firstly, the results show a decreasing importance of motor vehicles' combustion emissions to air quality in Dhaka. As such, a comprehensive air quality management strategy is required for the city, covering other emission sources such as construction activities and brick kilns. Secondly, given air pollution aggravates the COVID-19 infections, the double dividend of lockdown (reduction in spread of disease through reduced travel and reduction in the severity of infection through better air quality) may not have been realised in Dhaka. Thirdly, it is important to be very cautious about previous findings of large improvements in air quality in Dhaka during COVID-19 restrictions (49) as these studies did not control for the natural seasonality and the effects of weather (especially rainfall) in $PM_{2.5}$ concentrations.

# 6. Research uptake and next steps

## 6.1 Research uptake/ dissemination activities

A webinar to disseminate the findings of the research project was held on 4 May 2021 primarily focusing on a Bangladeshi audience, with support from BUET. However, the links were shared with international colleagues via Facebook, LinkedIn and Twitter. The webinar was attended by 56 participants (with some international participation) and the webcast on Facebook was viewed around a thousand times. At least two journal papers are under preparation for submission to transport and public health related journals. The findings will also be presented in an international workshop hosted by the PI for his GCRF COVID19 Agile Response Fund research project later this year. The paper will also be submitted for peer reviewed-presentation at the Annual Meeting of the Transportation Research Board in August 2021. A non-technical summary was published on HVT website and disseminated among the relevant decision makers in Bangladesh. An opinion piece in the leading national daily was authored by the investigators as well.

## 6.2 Planned next steps and upscale in low-income countries

Preparation and publication of journal articles with the findings of the project is the immediate future step. The methodology adopted in this project can be replicated in other countries including LICs. As such the project team will actively seek opportunities to apply the methods applied here in the context of other LICs. However, no concrete proposal has been made or activities being undertaken at the moment.

## 6.3 Project outputs

Outputs of the project is listed below:

- Final report (this report), available on HVT website research hub;
- Journal article (under preparation);
- Conference presentation (under preparation);
- Non-technical summary for policymakers, available at on HVT website research hub at this link;
- Infographics on research findings, will be available on HVT website research hub;
- Video of research findings, will be available at HVT YouTube channel; and
- Newspaper opinion piece (in Bengali), available at this link.

# 7. Conclusions

The aim of the project was to investigate the effects of COVID-19 related policy interventions on the transport outcome and correlating these with potential changes in air quality, traffic fatality and spread of the disease in Bangladesh. A separate 'summary findings' document was published earlier to present the highlights from the project. We present below the key findings and some implications arising from our five research questions mentioned in the introduction.

**1) What are the differential impacts of policy and business decisions on the spread of the disease?**

(a) Many of the interventions had the desired effect in curbing the spread of COVID-19 in Bangladesh, although there were some unexpected effects too.

(b) Around ten days of lag was observed between an intervention and its effects to be realised on the infections data in Bangladesh. This was smaller than in some developed countries, suggesting high population density in Bangladesh could result in a higher viral load reducing the time lag.

(c) The largest beneficial impact was derived from the full closure of offices and transport system. The opening of shops a few weeks before Eid-ul-Fitr increased the spread. Keeping the offices and public transport operational at half capacity did not have any discernible beneficial effect in curbing the spread of the disease (compared to full opening). Clearly full closure measures should be prioritised over the ineffective half-closure measures, where possible.

(d) The movements and social interactions around Eid-ul-Fitr had increased the spread of the virus. Although Eid-ul-Adha did not show any statistically discernible worsening of the spread, this was possibly due to the already declining phase of the virus and confounding with other measures around that time. With the upcoming Eid-ul-Fitr, this is a matter of immediate concern during the ongoing second wave.

(e) Somewhat surprisingly, mandatory mask-use policy did not have a statistically beneficial impact in curbing the spread. This is due to risk compensating behaviour and potentially lax monitoring and implementation, and inappropriate use of masks. This is an example where a good and well-known intervention did not have the potentially beneficial impact in Bangladesh due to lax implementation, and failure of communication and messaging.

(f) Above findings suggest that educating and communicating with the public and monitoring and enforcement are both essential for the interventions to work in the desired directions. Some of the failures were not because the interventions were bad, but because their implementation was ineffective.

(g) The relative effectiveness of different interventions can be used to guide interventions for the next wave of COVID-19 infections and other such pandemics.

(h) Data quality on infections is a major weakness. Good, transparent data is essential for appropriate evidence-based decision-making and developing a system to gather such information will be very useful for mitigating future such pandemics.

**2) What are the differential impacts of specific policy and business decisions on various transport outcome such as traffic, speed or delay?**

a) Daily activities and – as such mobility – at different types of locations in Bangladesh had reduced dramatically during the COVID-19 related interventions. This is expected, as the objective of many of the interventions was to disrupt mobility and interaction among people.

b) Closure of education institutes, offices, public transport, and shopping malls have all reduced mobility at most locations. The closure of garment factories reduced mobility for work and at transit stations only. Office opening at half capacity had a significant effect on office travel, but not at other locations. As mobility at other locations fell, home stays have increased substantially.

c) Surprisingly, a non-mobility related policy – mandatory use of masks – increased mobility at all non-residential venues. This supports the hypothesis of risk-compensating behaviour in Bangladesh, whereby people started to become more mobile due the feeling of safety afforded by the use of masks, thus countering the beneficial effects of the mask. Educating the members of the public is crucial to mitigate against such unintended effects.

d) Intercity mobility recovered quicker than intracity travel in Bangladesh – especially for trucks and motorcycles. Motorcycle travel increased during the disruption (as buses were either operating at half capacity or banned from plying), which has implications for safety and carbon emissions.

**3) What are the impacts of mobility on the spread of the disease?**

(a) Changes in mobility at different locations due to COVID-19 related policy interventions correlate well with the spread of COVID-19 infection in Bangladesh. The COVID-19 daily cases show positive association with activities at grocery, transit and retail, although a statistically significant association with work activities could not be ascertained. As can be expected, COVID-19 infection decreased when higher number of people stayed at home. Around ten days of lag observed between mobility changes and changes in daily infection.

**4) What are the road accident impact of these policies?**

(a) Road accidents and related fatalities appear to have fallen in Bangladesh during the 5-month travel disruption period however, statistically, accidents and fatalities did not fall. More importantly, once the effects of the reduction in mobility is considered, normalised accidents and fatalities increased in Bangladesh during the travel disruptions. Increased travel speed and higher use of motorcycles may have been the main reason for this increase.

(b) In Dhaka normalised accidents and fatalities fell and roads became safer during the disruptions. Reduction in the number of vulnerable users (pedestrians), motorcycles and increased safety due to the use of footpaths (which were no longer encroached by street vendors) may have resulted in this improvement.

(c) As such, accident impacts are location specific and may need targeted intervention. At the same time, results indicate that common sense approaches (keeping vulnerable users safe, lower speed) are effective means to reduce accidents and fatalities.

(d) The increase in motorcycle travel during the disrupted period for long distance travel is a cause of concern due to their safety risks and requires attention from road safety stakeholders.

(e) Normalisation of accident data with respect to travel reduction is important to decipher the nuances, simply comparisons of monthly accident and fatality data can be misleading. Detail investigation of different types of accidents and how they have changed during the disruptions can be useful in revealing these nuances further.

**5) What are the air quality impacts of these policies?**

(a) Any improvement of air quality due to reduction of traffic as a result of COVID-19 related interventions were location specific, with some unexpected results.

(b) Within Dhaka, air quality appears to have improved in places where there large construction activities. In areas where brick kilns likely govern the ambient particulates, no improvements in air quality was observed. In areas where traffic possibly dominates the ambient pollution air quality improved immediately after the disruption, but over the longer disruption period the improvement was insignificant.

(c) This suggests that the traffic's contribution to air pollution in Dhaka may not be as high as some other cities in the world, which showed a rapid reduction in air pollution in cities. Previous source apportionment studies appear to support our conclusion, but further source apportionment research using more recent data can confirm or refute the hypothesis.

(d) Controlling for weather is very important in understanding air quality impacts of the disruptions and a simple before-after study can be misleading.

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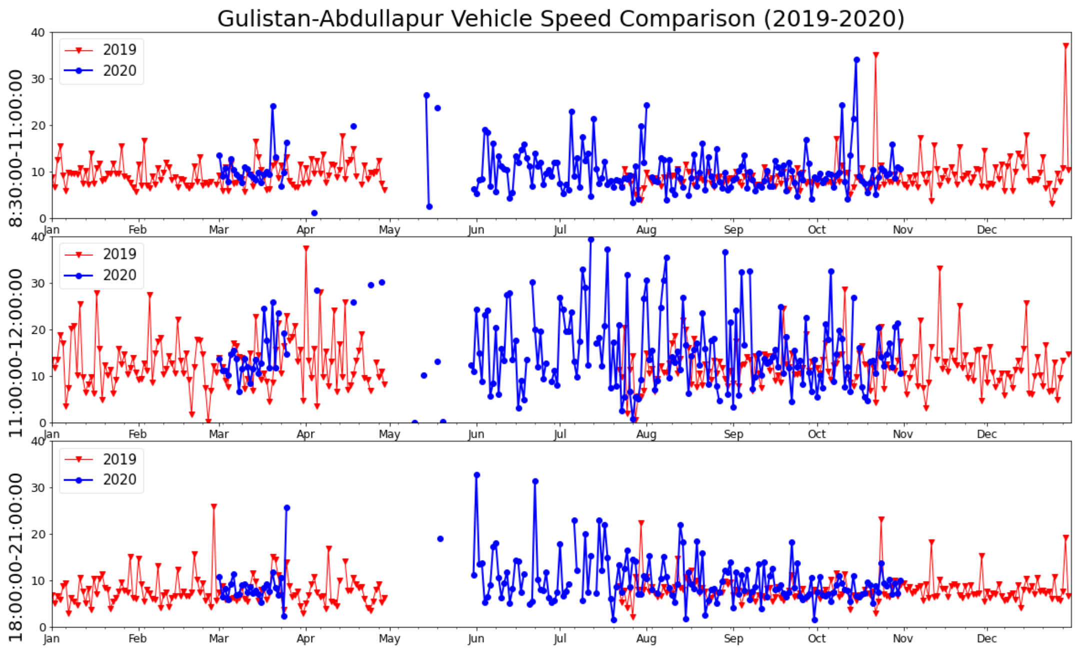
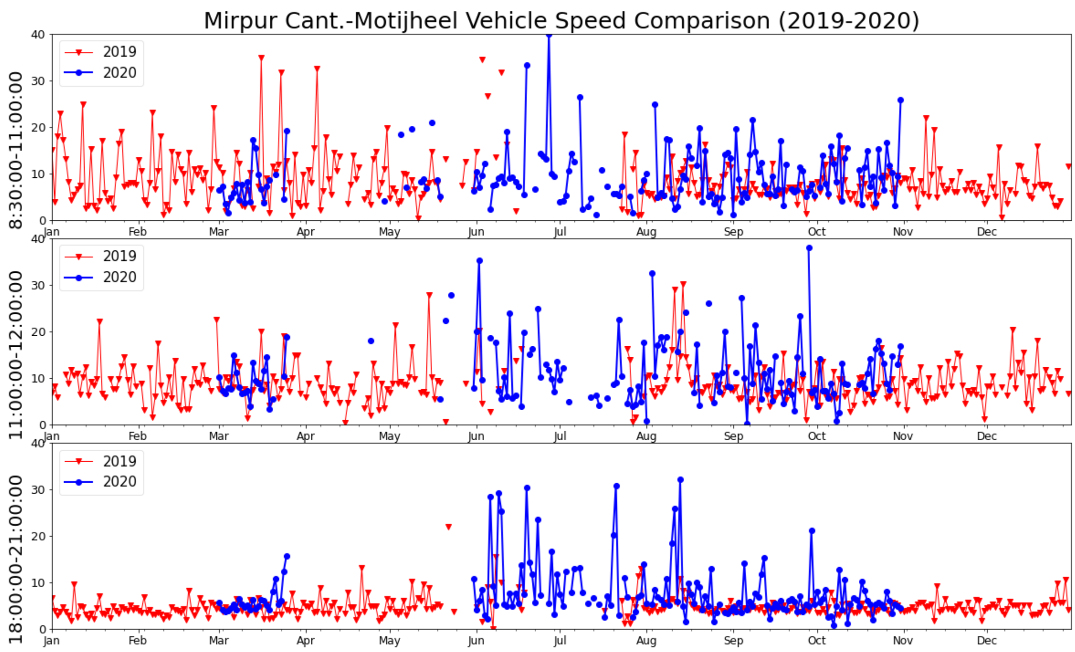
# APPENDIX A: TRAFFIC SPEED ALONG ROAD CORRIDORS IN DHAKA

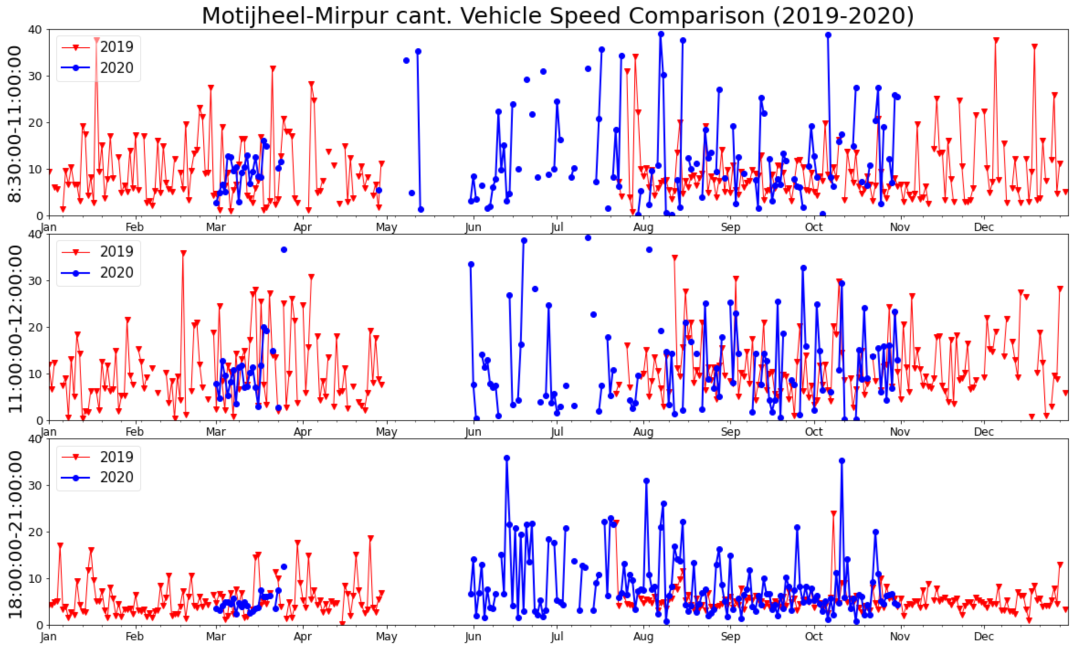
The following figure shows daily traffic speeds at different time-period for the period of 1 January 2019 to 31 October 2020 in Gulistan - Abdullahpur road corridor. Missing data interferes with the comparison across the two years. In general the speed was higher in 2020 than in 2019.




The following figure shows the daily traffic speeds at different time-period for the period of 1 January 2019 to 31 October 2020 in Mirpur Cantonment - Motijheel road corridor. Missing data interferes with the comparison across the two years. In general the speed was higher in 2020 than in 2019.



This following figure shows the daily traffic speeds at different time-period for the period of 1 January 2019 to 31 October 2020 in Motijheel - Mirpur Cantonment road corridor. Missing data interferes with the comparison across the two years. In general the speed was higher in 2020 than in 2019.



# APPENDIX B: LITERATURE SUMMARY ON COVID-19, POLICY INTERVENTION AND MOBILITY RESEARCH

***Note for Category: (a) Comparison between the pre and post lockdown situations, (b) Comparison with respect to previous years' data, (c) Comparison using machine learning models***

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| (Praharaj et al. 2020) | Sydney, New South Wales;<br><br>London, England;<br><br>Phoenix, Arizona;<br><br>Pune, Maharashtra | • Daily percentage change in movements between 13th January and 12th July 2020.<br>• The data was divided into three phases:<br><br>Phase I: the pre-lockdown period<br>Phase II: the lockdown<br>Phase III: the period after the lockdown was removed<br>Three travel modes: driving, transit, walking | • A two-standard deviation (2-SDs) band statistical analysis performed to measure the degree of changes in mobility between lockdown phases<br>• Nonoverlap of all pair (NAP) analysis/ the Mann-Whitney U-test to examine whether mobility changes among the pairs of phases were statistically significant | • Trip requests declined before restrictions were issued<br>• While Phoenix and Sydney saw a gradual decline in people's movements, Pune shows a radical plunge a week before the lockdown<br>• Trip requests in Sydney and Phoenix increased after the lifting of lockdown interventions, but upward changes in mobility in London and Pune in Phase III were not significant<br>• Phase I and Phase II were found to be statistically significant for four cities ($p<.05$), with a substantial decrease in mobility during the lockdown<br>• Mobility recovered significantly in Phase III relative to Phase II for the four cities | • Mobility drop began in a similar period, but the four cities responded to policy differently<br><br>• Lifting lockdown did not reverse the falling trip requests in all cities<br><br>• Significant variations Phoenix across the four cities on the immediate response by people to the lockdown | a |
| (Zhu et al. 2020) | 120 cities from China | • Daily confirmed cases, air quality data, human mobility data, and meteorological variables between 23rd January 2020 and 29th February 2020<br>• Meteorological data: mean temperature, relative humidity, atmospheric pressure, and wind speed | • Generalised additive model to investigate the relationship between human mobility index and COVID-19 confirmed cases,<br>• The model was also used for assessing the mediating effects of the air quality index and each pollutant<br>• Mediation analysis to test the hypothesis that air quality could partially | • $PM_{2.5}$, $PM_{10}$, $NO_2$ mediated significant proportions of the relationship between human mobility and COVID-19 infection<br>• No mediating effects of $SO_2$ and CO<br>• Human mobility was negatively associated but positively related to COVID-19 infection for $O_3$ | **Limitations**:<br>• The human mobility index from Baidu does not represent the actual number of people going outside<br>• Subgroup analysis by age group or gender to explore the sensitive population could not be conducted due to the lack of related information<br>• Findings are not globally representative | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| | | | mediate the association of human mobility with COVID-19 infection | | • Human mobility restrictions help control the epidemic but could increase $O_3$ pollution<br>• Air quality and decreasing social contact both impact COVID infections | |
| (Cartenì, Di Francesco, and Martino 2020) | Italy | • Daily reports on COVID-19 positive cases (21 February – 5 May 2020)<br>• Italian national census data (2019)<br>• 1200 car traffic count automatic sensors data (January 2020-May 2020)<br>• PM pollutant measures (2020)<br>• Average daily temperature (January-May 2020) Italian mobility rates (2020) | Multiple linear regression model linking the number of daily new positive cases to socioeconomic, environmental, territorial, health care, and mobility habits variables | • Higher population densities indicating a higher probability of contagion<br>• The proximity effect was most significant within the first days and then "decayed" in its incidence with the passing of the time (new contagion by the local mobility in the region)<br>• A positive correlation between daily cases and PM pollution indicating people with long-term exposure to air pollution are more likely to become infected<br>• Warmer areas contributed to contain the virus contagion. | • Trips of 21 days before best reproduced current COVID infection trend<br>• Lockdown measures set in 14 days were underestimated and may slowdown implementing restrictive action | c |
| (Yabe et al. 2020) | Tokyo, Japan | • Mobility data collected at large-scale from more than 200K mobile phones across four months: Mobile phone location data<br>• To characterise human mobility patterns three indexes were used: Radius of Gyration (RG), total travel distance (TTD), and stay-at-home rates<br>• Socioeconomic data (23 wards of Tokyo): The | • Spatio-temporal interpolation of the GPS location observations was performed to overcome data sparsity<br>• Social contact analysis was performed to observe the temporal transitions in the relative average social contact index<br>• Correlation between mobility behaviour changes and effective reproduction number R(t) was analysed | • Decline in human mobility behaviour (~ 50%) by 15th April (1 week into the state of emergency), resulting in reduced of social contacts (70%) in Tokyo, showing strong relationships with non-compulsory measures<br>• Strong negative correlation (R = −0.696) between income per household and contact index, indicating homes in higher-income regions reduced social contacts and risk of COVID-19 transmission was more in lower-income regions<br>• The reduction in data-driven human mobility metrics showed a correlation | **Limitations**:<br>• Sanitising hands more often or higher rates of wearing face masks could affect the reduction in cases that weren't considered. Because of such factors, the relationship between mobility reductions and transmissibility could change after lifting the state of emergency.<br>• It is crucial to analyse the mobility of the more vulnerable and elderly population due to the high mortality rate of COVID-19. | |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| | | number of households and total taxable income collected from the residents was available through the Portal Site<br>• Social contact index: the relative value of mean social contacts concerning typical mobility patterns, observed before the pandemic<br>• Effective reproduction number R(t): average number of secondary cases generated by a single infectious case | | with the decrease in the estimated effective reproduction number of COVID-19 | | |
| (Hadjidemetriou et al. 2020) | United Kingdom | • Government's measures in response to the COVID-19 pandemic<br>• Driving, walking, and transit data provided by Apple mobility trends report<br>• The input parameters of the logistic function consist of the 7-day moving average number of deaths, the limiting value of the number of deaths, the midpoint where the epidemic starts to slow down, and the growth rate determining how many | • The human mobility trends data was compared to a baseline volume of the previous year (2019)<br>• A generalised logistic model was used to investigate the correlation between human mobility and the number of COVID-19 related deaths<br>• The 7-day moving average of deaths was selected over a daily number of deaths to reduce statistical error and inconsistency in reporting deaths.<br>• The predicted and actual number of deaths related | • A notable drop in people driving and using public transport was observed from 8th March 2020, indicating direct impact of the government's press release on this date<br>• Continuous reduction in human mobility until 23rd March 2020 and no further significant fluctuation until May 2020<br>• Reduction in driving, transit, and walking (60%, 80%, 60%, respectively) compared to the same period of the previous year (2019)<br>• Human mobility decreased with stricter government measures and stabilised at around 80% after imposing lockdown while also reducing COVID-19 deaths | • Some levels of travel restrictions and social-distancing measures may need to continue to reduce the risk of a resurgence in COVID-19 transmission<br>• A larger dataset, model validation, and comparison with other performance metrics are necessary to generalise the presented methodology<br>• No human mobility reduction would lead to a much higher number of deaths | b, c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| | | people each person infects. | to COVID-19 were compared for period 1 (until 25th March) and period 2 (until 10th April) | • Initial control measured aimed at human mobility reductions had a direct impact on the number of COVID-19 related deaths. | | |
| (Kuo and Fu 2021) | United States (3219 counties) | County-level demographic, environmental, and mobility data for the state-wide lockdown period | • Eight types of ML models were used: (1) elastic net (EN), (2) principal components regression (PCR), (3) partial least squares regression (PLSR), (4) k-nearest neighbours regression (KNN), (5) regression tree (RT), (6) random forest (RF), (7) gradient boosted tree (GBM), and (8) 2-layer artificial neural network (ANN) <br>• For each learner, 10-fold cross-validation was conducted, and data of 1st June was used for testing <br>• The modelling performance is assessed by R-square, root mean square error (RMSE), and mean absolute error (MAE) | • Mobility dramatically decreased in mid-March due to strict policies and remained an increasing trend with a weekly pattern, <br>• Substantial increase in incidence rate from late March until late April and early May. <br>• Mobility had peaks on the weekend, and the incidence rate had peaks on Thursday or Friday. <br>• The incubation period for COVID-19 was found to be 4–5 days from exposure <br>• Compared with Phase-I reopen, a 1-week and 2-week lockdown could reduce 4-29% and 15-55% infections in the future week <br>• 2-week Phase-III reopening could increase 16-80% infections | • After early May, increasing mobility but decreasing pandemic indicated that increased public awareness (social distancing/ mask-wearing) decreased transmission of COVID-19 <br><br>Strengths: <br>• Assuming no linear relationship between variables and response, <br>• Selecting important variables and discard noise variables during modelling <br>• GLM hybrid technique combined all modelling results and enhanced the performance of hybrid results. | c |
| (Lau et al. 2020) | China | • Chinese international air traffic data (2011-2016) <br>• Number of Chinese international routes (2011-2016) <br>• Data on confirmed COVID-19 cases | • Linear Regression Analysis to evaluate correlations <br>• P-value <0.05 was considered statistically significant | • Strong linear correlation (linear regression) between: <br>• Domestic COVID-19 cases and domestic passenger volume, and international COVID-19 cases and passenger volume <br>• Total number of passenger throughput and the total amount of annual domestic passenger from 2013 to 2018 | • The total number of COVID-19 cases showed a correlation with the current passenger volume <br>• The global distribution of COVID-19 cases occurred in Asia, where most flight routes were destined to. | |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| | | • Total annual international passenger numbers (2011-2016) | | • The number of passenger throughput and the total annual domestic passenger in each economic region in China from 2013 to 2018 | • The number of flight routes and total passenger volume were the risk factors for the spread of the current COVID-19.<br>• Asian, North American, and European regions were at serious risk of constant exposure to COVID-19 from China<br>• The risk for COVID-19 exposure remained low in South America and Africa. | |
| (Loske 2020) | Germany (two depots of a large full-range food retailing company) | • Traffic volume data (n=15,715 routes) from 23.03.2020 to 30.04.2020<br>• COVID-19 cases and related deaths per day from 31.12.2019 to 30.04.2020 for 208 countries | • Correlation matrix and linear regression analysis to investigate the relationship between the cause (COVID-19 outbreak) and the effect (freight market dynamics)<br>• To ensure the data is suitable for a further investigation several statistical tests were conducted: (a) residuals versus fitted plot (to detect non-linearity, unequal error variances, outliers), (b) normal Q-Q (compares the shapes of distributions, how properties such as location, scale, and skewness are similar or different in the two distributions), (c) scale location, and (d) residuals versus leverage | • Increasing freight volume (dry products) in retail logistics did not depend on the duration of the COVID-19 epidemic but the strength quantified through the total number of new infections per day<br>• For (a), the residuals bounce randomly around the 0-line, and so a linear relationship is reasonable.<br>• For (b), the points form a roughly straight line, indicating a normal distribution | **Limitations**:<br>• Real-life data restrictions due to limited access to transport volume for different countries<br>• All results address a specific location and time combination and are primarily not transferable | |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| (Pawar et al. 2020) | India | • An online questionnaire survey (1542 commuters) to capture travel behaviour information of commuters before and during the transition period of the COVID-19 outbreak<br>• Responses corresponded to a period of 15th March to 24th March 2020<br>• The commuters' decision to choose the preferred mode of transport (public or private) was the dependent variable and, the independent variables include socioeconomic and travel characteristics and the safety shift: the difference between the health-related safety perception of private and public modes. | • Change in commuter behaviour from the beginning of March 2020 was observed<br>• A decision tree approach (5-fold cross-validation method and tree depth=5) to investigate the modal preference (public or private modes) of commuters considering socioeconomic and travel characteristics and safety perceptions regarding public and private modes during the lockdown. | • Around 41% of the commuters stopped traveling during the transition to lockdown phase<br>• 51.3% was using the same mode of transport<br>• 5.3% shifted from public to private mode<br>• 18.3% continued using public transport during this period<br>• Health-related safety perception of the commuters did not play a significant role in their mode choice behaviour during the transition phase<br>• Travel time was observed to be the most important feature considered by the commuters to decide their work-related travel mode | **Limitations**:<br>• As the survey was conducted online, commuters not compatible with technology might have been left out during the data collection process<br>• Online questionnaires are susceptible to have a non-responder bias<br>• Limited user characteristics were enquired about for rapid collection of data<br>• The study is only focused on work-related travel behaviour<br>• The variation in the usage of ridesharing services was not examined<br>• The influence of social media was not addressed | a |
| (Aleta et al. 2020) | China (31 regions) | • Resident population<br>• Infected individuals and their distribution across regions on 5th February 2020<br>• Number of people leaving each region each day for 2019 (no travel restrictions) and 2020 | • A stochastic SEIR-metapopulation model was used to simulate the spread of the epidemic across mainland China<br>• The outbreak is simulated by introducing 40 exposed individuals on 1st | • Travel restrictions, if applied very early, might be an effective measure in the short term,<br>• Reducing the travel was ineffective in the long term if not accompanied by other measures to eliminate the disease<br>• The model was able to predict the basic dynamics of the epidemic better than | **Limitations**:<br>• The geographic resolution allowed by the mobility data here was low<br>• It was assumed that the transmissibility did not change for the whole simulation period<br>• Improvement is required in the use of the disease parameters | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| | | (implemented travel restrictions)<br>• In both cases, the day of the Spring Festival was considered as "Day 0" (25.01.2020 and 05.02.2019), and the simulation run to 13 days after the festival to eliminate the exogenous effects (05.02.2020 and 16.02.2019) | December 2019 (12th December 2018 for 2019)<br>• The simulation was run for 66 days, and the cumulative number of infected cases in each region was collected as a function of time<br>• Correlation between the real and simulated values of infected cases (2020) was analysed<br>• Sensitivity analysis was performed to gauge the effect of chosen parameterisation of the model | its random counterpart, as indicated by the Pearson correlation of 0.80 | | |
| (Anwar, Nasrullah, and Hosen 2020) | Bangladesh | • COVID-19 scenario and mitigation measures corresponding to March 2020 | • Briefly articulated the current scenario of Bangladesh COVID-19 in Bangladesh<br>• Provided some recommendations on how the country can combat this pandemic | **Challenges:**<br>• Maintaining social distancing protocol<br>• Inadequacy of COVID-19 testing facilities<br>• Scarcity of personal protective equipment (PPE)<br>• Providing sanitisation facilities to the slum dwellers and Rohingya refugees<br>• Coping with mental stress due to COVID-19 | **Recommended mitigation measures:**<br>• Continuing the lockdown with more strict maintenance<br>• Imposing home office laws whenever possible<br>• Expanding testing and healthcare facilities<br>• Providing mobile sanitisation facilities and temporary quarantine sites<br>• Ensuring a constant supply of PPE for healthcare workers<br>• To train students at life science departments in universities to carry out COVID-19 case diagnosis | |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| | | | | | • Supplying free sanitiser and mobile washrooms to the marginal people<br>• Cancelling all non-essential surgeries and hospital admissions<br>• Seeking international help | |
| (Barnes et al. n.d.) | Louisiana, USA | • Traffic crash data including information on the crash, vehicle, and people involved from 26th January to 5th May 2020<br>• Stay-at-Home order implemented from 16th March 2020<br>• Google Mobility data including information on visits to and lengths of stay in specific place (baseline period: 3rd January to 6th February 2020) | • A regression discontinuity (RD) design to study the effect of the COVID-19 lockdown on mobility and traffic accidents | • Large decrease in traffic accidents (-47%) involving injury (-46%), distracted drivers (-43%), and ambulances (-41%)<br>• Change in the accident composition<br>• More incidents involved individuals aged 25 to 64, male, and non-white drivers<br>• No impact on ambulance response time, despite lower traffic<br>• A reduction in car accident externalities by $21 billion nationally and $289.6 million in Louisiana alone<br>• A large decrease in mobility and a large increase in time spent in residential location | • The results have important policy implications for traffic management policies in urban areas.<br>• A severe decrease in accidents resulted from decreased traffic on roads.<br>• Removing cars on the road could significantly reduce accidents and other traffic externalities | c |
| (Basu and Campbell 2020) | United States:<br>(i) New York City, New York,<br>(ii) Cook, Illinois,<br>(iii) Fulton, Georgia,<br>(iv) King, Washington, and | • Time-series data of COVID-19 confirmed cases, deaths, and recovered cases over the period from 22nd January to 11th May for the purpose of training, validation, and testing of the model. | • A Long Short Term Memory (LSTM) based model was proposed to understand the dynamics of COVID-19 disease<br>• The model was trained on over three months of cumulative COVID-19 cases and deaths<br>• The data is separately trained on three different train and validation splits, and hyper parameters with | • Mitigation measures New York City, New York, and King, Washington had worked well in terms of lowering the rate of infections as well as deaths.<br>• Mitigation measures in Cook, Illinois, were working in terms of infections even though deaths show an increasing trend, so prolonged mitigation measures may be needed.<br>• Mitigation measures were also yet to work in Fulton, Georgia, and based on the increasing trend of infections. | • Despite the declining rates, as in the case of New York City, New York, and Cook, Illinois, the variations in cases were still high, which indicates that careful reopening measures might need to be taken as the infection rates have still not stabilised well.<br>• Additional measures might be required like rapid testing, contact tracing, and phased reopening depending on the situation in | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| | (v) Los Angeles, California | | minimum validation root mean squared error (RMSE)<br>• A quantitative comparison of mitigation measures was also performed. | • Mitigation measures were yet to work in Los Angeles, California, in terms of both infections and deaths | various places before the entire nation resumes a normal lifestyle. | |
| (Calderon-Anyosa and Kaufman 2021) | Peru | • Data on deceased adults (18 years old or older) from 1st January 2017 until 26th September 2020<br>• Mobile-phone mobility data to have a measure of the degree of compliance with lockdown and an approximation to the use of motor vehicle<br>• Lockdown period: 16th March 2020-end of June 2020. | • An interrupted time-series analysis was performed to assess the immediate impact and change in the trend of lockdown on external causes of death<br>• A linear regression model fitted to the external death rates to evaluate a change in the slope of the outcome trend after lockdown.<br>• A stratified analysis was performed for women and men.<br>• Autocorrelation of the time series was assessed through a correlogram and seasonality through visual inspection of the plots. | • A sudden drop in all forms of deaths examined was observed after the lockdown.<br>• The biggest drop was related to traffic accidents (12.22 deaths/million men/month and 3.55 deaths/million women/month)<br>• Homicide and suicide patterns showed a similar decline in women, whereas the reduction in homicide was 2.5 times the suicide reduction size in men.<br>• Increase in the slope in homicide in men during the lockdown period (6.66 deaths/million men/year). | • Reduction in traffic accidents can be explained by the falls in mobility.<br>• Suicide and homicide patterns are less intuitive and reveal important characteristics of these events.<br>• There is an urgency for implementing a comprehensive response service for mental health during the pandemic. | b |
| (Dandekar, Rackauckas, and Barbastathis 2020) | Top 70 affected countries from Europe, North America, South America, Asia | • Data for the infected and recovered case count<br>• Recovered count = recovered healthy + deceased | • SIR epidemiological model to study the quarantine control globally<br>• Modified SIR model or QSIR model in which the SIR model is augmented by introducing a time-varying quarantine strength rate term Q(t) and a quarantine | • A strong correlation between the strengthening of quarantine controls and actions taken by the regions' respective governments<br>• Quarantine efficiency higher in western Europe (e.g., Spain, Italy, Germany, France) than in eastern Europe (e.g., Switzerland, Turkey) | • Globally applicable, independent and interpretable quarantine model<br>• Diagnosed quarantine policy mimics the real-time, on-ground situation | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| | | | population T(t), which is prevented from any further contact with the susceptible population<br>• Q(t) denotes the rate at which infected persons are effectively quarantined and isolated from the remaining population and gives composite information about (1) the effective testing rate of the infected population as the disease progressed and (2) the intensity of the enforced quarantine as a function of time<br>• Gaussian Process Residue Model was used to validate the robustness of the model | • Significantly lower recovery rate in North America compared to Europe<br>• In the USA, the north-eastern and western states were much more responsive in implanting rapid quarantine measures compared to the southern and the central states<br>• No significant difference in recovery rates observed among the Asian countries<br>• Quarantine efficiency higher in China and South Korea compared to India<br>• Low quarantine efficiency and the low recovery rate in Peru<br>• For Brazil and Chile, infected and recovered counts remained close to each other | | |
| (De Vos 2020) | | • Potential effects of social distancing on travel behaviour<br>• Potential implications for health and well-being<br>• Policy recommendations | | • Potential changes:<br>• Less car traffic, and less congestion during peak hours, and reduced public transport ridership<br>• Fewer shopping trips<br>• Avoiding public transport<br>• Traveling during off-peak hours to avoid crowded buses and trains<br>• People with access to a car be inclined to drive more<br>• Increase in walking and cycling in case of short trips<br>• Potential implications: | Recommendations:<br>• Allocating less used street space to cyclists and pedestrians<br>• Restricting cars from certain local streets, placing additional cycling parking, and reducing waiting time for pedestrians to crossroads<br>• Making public transport a safer way of traveling during the social-distancing period<br>• The government could temporarily provide financial support to public transport | |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| | | | | • Negatively affecting subjective well-being due to reduced activity participation<br>• Inaccessibility to the reduced public transport services for those without a car<br>• More recreational travel resulting in a certain level of subjective well-being<br>• Significant reduction in traffic accidents and safer walking and cycling conditions<br>• Reduced air pollution | operators to maintain a certain level of service<br>• Reorganising the interior of buses and trains (e.g., making more separate compartments) to prevent social contact<br>• To create and open more public green spaces in cities | |
| (Oguzoglu 2020) | Turkey | • Monthly data on all accidents, injuries, and fatalities (from 2013) for the whole country<br>• Monthly city-level traffic accident reports from December 2018 to April 2020<br>• Apple mobility data trends<br>• A quarantine was imposed only on 31 cities in April | • Percentage change in all traffic accidents (including those involving injury or death) compared to the previous year<br>• Models that describe the city level and country level accident outcomes were estimated using Poisson's models and coefficients.<br>• Deaths (reports included those occurred at the scene of accident) and injuries were adjusted to account for the individuals who were admitted to hospitals with traffic injuries die within 30 days | • Decrease in driving and walking in Istanbul (one of the quarantined cities) was more than the decline for the whole country<br>• Decrease in accidents involving death or injury by 35% (death by 72%; injuries by 19%)<br>• Decline in traffic accidents (~ 60%), deaths (43%), and injuries (64%) compared to April of last year<br>• Approximately 21,000 accidents, 17,600 injuries, and 200 deaths avoided in only one and a half months of lockdown compared to the statistics of March and April 2019. | • The Lockdown effect has been more pronounced the more the city was congested | b, c |
| (Qureshi et al. 2020) | Missouri, USA | • 2292 road traffic accidents data from 1st January 2020 through 15th May 2020 | • Primary analysis based on the mean daily number difference of accidents<br>• Two-sample t-test to identify the differences before and during the | • Significant reduction in accidents resulting in minor/no injuries (mean 14.5 vs. 10.8, $p < 0.0001$; from ITS: parameter estimate -5.9, $p = 0.0028$), but not in accidents resulting in | • The mandatory societal lockdown policies led to a reduction in non-serious road accidents involving no injuries but no reduction in those resulting in serious/fatal injuries. | a |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| | | • First day of mandated societal lockdown: 23rd March 2020<br>• First day of reopening: 3rd May 2020 | lockdown regarding road traffic accidents<br>• Interrupted time series (ITS) to identify trends in and effect of lockdown on road traffic accidents. | serious/fatal injuries (mean 3.4 vs. 3.7, p = 0.42) after the lockdown.<br>• Increase in accidents resulting in minor/no injuries after reopening (mean 10.8 vs. 13.7, p = 0.04) | • Increased speeding due to less traffic congestion might cause serious or fatal accidents | |
| (Saladié, Bustamante, and Gutiérrez 2020) | Tarragona Province, Spain | • Data on traffic accidents, including information about the date, municipality, road code, street name, injured or trapped victims, and UTM coordinates<br>• Before the lockdown period: 3 February -15 March 2020<br>• Lockdown period: 16 March – 26 April 2020<br>• Historical data for comparison for the equivalent period of 5 February – 29 April 2018, and 4 February – 28 April 2019 | • Compared the number of accidents and daily averages both before and after the lockdown (2020) with those that occurred during the equivalent period in 2018-2019<br>• The severity of accidents and their occurrences on weekends/holidays, on urban or interurban roads, the typology of the roads on which they occurred were also analysed similarly<br>• A chi-squared test was used to analyse the statistical significance | • Reduction in the number of accidents: -74.3% compared to those on February 14-20 (reference week) and -76% compared to the equivalent period in 2018-2019<br>• Reduction in accidents (74.3%) higher than the decrease in mobility (62.9%) during the same reference period<br>• More intense reduction at weekends/holidays: -85% compared to weekdays of 2020 and -89% when compared to the equivalent period in 2018-2019 | • A multiplicative positive effect of the reduction of traffic on road safety<br><br>**Limitations**:<br>• No information about the exact time of each accident, the speed at which it occurred, the typologies of the vehicles involved, or the number of people involved, among other relevant factors<br>• Lack of access to new data after the lockdown. | b |
| (Şensöz, Wagner, and Platzer n.d.) | Mediterranean countries | • Effects of the epidemic on transportation<br>• Detailed observations from Tunisia and Turkey<br>• Potentials discovered | • Comprehensive transport responsive model against Covid-19<br>• Avoid-Shift-Improve Approach:<br>• 1. Reduction of (motorised) transport demand (Avoid),<br>• 2. Promotion of public transport and active mobility (Shift), | • Potentials discovered:<br>• Bicycle and Pedestrian Friendly Streets<br>• Green Recovery on Transportation to create more sustainable, resilient, and inclusive societies<br>• Reviewing the regional limitations to develop more feasible and localised policies | • Recommendations:<br>• Promotion of compact resource and space-saving, human-centred accessible, barrier-free, mixed-use oriented cities<br>• Promotion of remote working and learning<br>• Promotion of safe, reliable, affordable, accessible, and high-quality public transport, cycling, and walking | |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
|---|---|---|---|---|---|---|
| | | | • 3. Improving the quality of transport (Improve) | | • Provision of "mobility bonus" instead of "car bonus | |
| (Yadav, Perumal, and Srinivas 2020) | Mainland China,<br>US,<br>Italy,<br>South Korea,<br>India | • Dataset containing total number of COVID-19 positive cases and the number of recoveries and deaths for different countries from 22.01.2020 to 24.04.2020<br>• Weather data (temperature, humidity, and wind speed) for New York (US) and Milan (Italy) city only | Five tasks as follows:<br>1. Predicting the spread of coronavirus across regions using Support Vector Regression (SVR) model<br>2. Analysing the growth rates to evaluate the effectiveness of mitigation measures across countries<br>3. Predicting how the epidemic will end<br>4. Analysing the transmission rate of the virus<br>5. Correlating the coronavirus and weather conditions using Pearson's correlation<br><br>Besides, the SVR models were evaluated and compared with other well-known regression models on the standard available dataset | 1. 98.31% (India) to 99.75% (Italy) accuracy of the SVR model in predicting the total number of positive cases<br>2. 96.76% (South Korea) to 99.6% (India) accuracy of the SVR model in predicting the growth rate<br>3. 86.39% (India) to 99.47% (Mainland China) accuracy in predicting the total number of recoveries<br>4. 37.9% (Mainland China) to 92.1% (US) accuracy in predicting the total number of newly found cases per day<br>5. Positive cases decreased with increasing temperature (r=0.38) and increased with increasing humidity (r=0.36) in NYC, whereas positive cases are mostly affected by humidity in Milan (r=0.29) | • SVR models gave better classification accuracy than simple regression and polynomial regression models in almost all the cases according to the comparisons presented in this study. | c |
| (Ferguson et al. 2020) | Great Britain, United States | • Population density data (to define individuals residing in areas)<br>• Census data (age and household distribution size) | • Individual-based transmission model to explore COVID-19 scenarios in GB.<br>• Analyses of data from China and of those | • Population-wide social distancing was found to have the largest impact as a whole or in combination with other interventions<br>• Relatively short-term (3-month) mitigation policy might minimise deaths | • Mitigation may not be feasible unless emergency surge capacity limits of the US and UK healthcare systems are exceeded many times | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| | | • Average class sizes and staff-student ratios data (to generate a synthetic population of schools)<br>• Workplace size distribution data. | returning on repatriation flights<br>• Five different non-pharmaceutical interventions (NPI) were implemented individually and in combination | observed in the epidemic by up to 50% and peak healthcare demand by 67%.<br>• The most effective policy combination was found to be consisting of case isolation, household quarantine, and social distancing of those at higher risk of severe outcomes<br>• Deaths in the order of 250,000 in GB and 1.1-1.2 million in the US were predicted even if it were possible to treat all the patients | • At the current stage, suppression of the epidemic is the only feasible strategy | |
| (Gatto et al. 2020) | Italy | • COVID-19 epidemiological data<br>• Mobility data at municipality scale<br>• Population census data<br>• 21st February 2020 (first case confirmed in Italy) – 25th March 2020 | • SEIR like transmission model, termed as SEPIA (Susceptible-Exposed-Pre-symptomatic-Infected with heavy symptoms-Asymptomatic/mildly symptomatic) to explore different scenarios of different containment interventions and their impacts<br>• A generalised effective reproduction number (R0 = 3.60 [3.49 to 3.84]) was estimated to measure the potential spread in the absence of the interventions | • Reduction in the transmission by 45% (42%-49%) resulting from the restrictions posed to mobility and human-to-human interactions<br>• The results showed much larger estimates of the total number of contagions than those obtained from the datasets<br>• The expected number of averted hospitalisations was estimated to be a total of 200,000 cases for the whole country (up to 25th March 2020) | **Limitations**:<br>• The granularity of available data in time, spatial resolution, and individual information was limited<br>• Unavailability of anonymised individual information from hospitals and laboratories<br>• The effect of age structure in terms of differential mobility, social contact patterns, case fatality ratio, and vulnerability was not included in the model | c |
| (Kraemer et al. 2020) | Wuhan, China | • Epidemiological data including (basic demographics, travel histories, and key dates)<br>• Real-time mobility data | • Three different Generalised Linear Models (GLM) were fitted to province-level data:<br>• A Poisson GLM and a negative binomial GLM to | • The correlation between COVID-19 cases and human mobility dropped after the implementation of the control measures (including travel restrictions), and the growth rates became negative in most of the locations. | • Travel restrictions may become less effective once the outbreak is more widespread, and it is only useful at the early stage when the infection is confined to a certain area acting as a major source. | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| | | • Detailed case data, including travel history | estimate daily case counts and a log-linear regression to estimate daily cumulative cases<br>• Full-time series analysis was performed for the optimal lag structure for province-level cases and mobility data<br>• Elastic-net regression and n-fold cross-validation were used to validate the models.<br>• Mixed-effects Poisson GLM to estimate the epidemic doubling time across each province | | | |
| (Pak et al. 2020) | Wuhan, China | • Data on clinically confirmed cases with symptoms from 2 sources (30th March 2020) | • A generalised odds-rate class of regression models (including the log-logistic proportional odds model and the Weibull proportional hazards model in special cases) was applied to model the incubation period of COVID-19.<br>• Sensitivity analyses to check for the robustness of the estimates. | • The effect of gender was not statistically significant in the model<br>• Mean incubation periods (95% CI) of 6.6 (5.4–7.8) days for the younger patients and 8.8 (7.2–10.3) days for the older patients during the outbreak period<br>• About seven-day differences between the two age groups (≤ 42 years and > 42 years) at the 97.5th quantile, although the difference became obvious after the 25th quartile<br>• The risk of infection before the onset of the symptoms (8.4% and 17.1% for the younger and older patients, respectively) was estimated to be reduced (2.2% and 5.8% for the younger and older patients, respectively) | • The older age group had a longer incubation period than that of the younger age group (17.4 days and 13.1 days, respectively, for 90% of symptoms manifestation)<br>• An age-specific quarantine policy might prove to be more efficient than a unified policy in confining COVID-19 | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| (Nikolaos Askitas, Tatsiramo, and Verheyden 2021) | 175 countries worldwide | • Publicly available data on several NPIs (timing and intensity of the policies)<br>• Data on daily confirmed COVID-19 cases<br>• Mobility data<br>• Baseline period: 3 January – 6 February 2020 | • A multiple-event model was developed to study the causal effect of 8 lockdown policies on the daily COVID-19 cases and on human mobility patterns | • Cancellation of public events, restrictions on private gatherings, and closing schools and workplaces had the most significant effects on reducing COVID-19 incidences<br>• No significant effect of restrictions on internal movement and public transport<br>• Short-lived effect of restrictions on internal movement and public transport, due to early implementation of other effective policies | • Each policy is targeted to deliver its effect on reducing the contagion by changing people's whereabouts.<br>• The effective policies prevent people's exposure to numerous and dense locations, increase their time spent at home and reduce various types of commuting | c |
| (Nikos Askitas, Tatsiramo, and Verheyden 2021) | 135 countries worldwide | • Data on the non-pharmaceutical interventions implemented by governments<br>• Data on the daily number of infections<br>• Data on the evolution of population's mobility patterns<br>• Data on various country characteristics (e.g., GDP per capita, population, population density, and urbanisation rates) | • A multiple-events model to study the dynamic effects of the timing, type, and level of intensity of various public policies on the daily COVID-19 incidences and on the mobility patterns between and within the country | • Cancelling public events and restrictions on private gatherings and subsequent closure of schools had the most significant effects quantitatively.<br>• Workplace closures and stay-at-home requirements did not have a much-pronounced level of effects as well as statistical significance<br>• No significant effect of public transport closures, international travel controls, and restrictions on movements within the country | | c |
| (Bönisch et al. 2020) | Germany | • Unique mobility data that including an individual person's characteristics (through the online panel)<br>• Daily new cases data<br>• Reproduction number (R) estimated by the government | • Interrupted time-series analysis of mobility (median daily distance travelled before and after restrictions) by three age groups, gender, and previous (13th January and 8th March 2020) average mobility | • A rapid decline in mobility in the mid-March after the implementation of mobility restrictions followed by the strongest decline in the last week of March, while mobility increased slightly again by the advent of April<br>• An increase in mobility became noticeable from mid-April onwards, | **Limitations**:<br>• Restricted length of the time-series<br>• Possible selection bias during online data collection<br>• The sample could not be considered as representative<br>• Weather effects were not accounted for. | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| | | • Study period: 13th January until 17th May 2020<br>• Three age groups: 16 - 29, 30 - 59, ≥60 years<br>• Three mobility groups: <20km per day, 20–50km per day, >50km per day | • SARIMA model was used for time-series analysis. | however not resulting in an increasing number of cases<br>• Relative reductions in mobility differ insignificantly among age groups, gender, and groups with different mobility before the pandemic | • Reduced mobility was not any causal prove for reduced transmission of the virus | |
| (Bryant and Elofsson 2020) | 11 European countries | • Observational mobility data<br>• Data on NPIs, populations, and weighted fatality of the countries | • Markov-Chain Monte-Carlo (MCMC) model to estimate the spread of the infection<br>• Bayesian model to estimate the number of deaths on a given day<br>• 3-week epidemic forecasts were predicted using real-time observations of changes in the mobility patterns<br>• The basic reproductive number, R0, was estimated using the SIR model<br>• Correlation analysis to evaluate the relation between the daily deaths and the mobility changes, and between the deaths/ day and the different mobility parameters | • Considerable overlap between the mobility changes and the introduction of governmental NPIs<br>• High correlations between mobility shifts in all categories and the death rates one month later<br>• A decline in the basic reproduction number, R0, was mostly due to the mobility reduction within the grocery and pharmacy sector. | • The impact of NPIs in Denmark and Sweden was overestimated, and that in France and Belgium was underestimated<br>• Small errors had an extensive effect on the predictions due to the exponential nature of the models | c |
| (Hu et al. 2021) | United States | • The daily average number of trips/ person<br>• Daily average person-miles travelled<br>• Daily percentage of residents staying home | • The effects of stay-at-home orders and reopening guidelines on human mobility were analysed using a set of generalised | • Only a contribution of 3.5%- 7.9% decrease in human mobility from stay-at-home orders<br>• 1.6%-5.2% mobility increase resulted from reopening guidelines | • The non-pharmaceutical interventions play a limited, region-specific, and time-decreasing role in influencing human movement | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| | | | additive mixed models (GAMM)<br>• Akaike Information Criterion (AIC) and Conditional R2 were used for model selection | • Reasonable spatial heterogeneity among the counties where the major roles were played by confirmed COVID-19 cases, income levels, industrial structure, age, and racial distribution | | |
| (Jiang and Luo 2020) | Hubei, China (16 prefecture-level cities) | • City-level data on confirmed COVID-19 cases<br>• Data on the lag of proportion of the population shifting from Wuhan to each of the prefecture-level cities in Hubei province<br>• Date of lockdown in the cities<br>• Control variables: economic development (Per capita GDP in 2018), health resources richness (no. of beds in medical and health institutions and healthcare workers / thousand persons in 2017), population density, and distance to Wuhan<br>• Study period: 6th January to 6th February 2020 | • Descriptive analysis to visualise the time series of confirmed cases within the study period<br>• Random effects model to estimate the effect of human mobility on the COVID-19 transmission ($p<0.05$ considered to be statistically significant) | • The infection was more likely to be confirmed within 11-12 days of contact<br>• Obvious declines in the daily confirmed cases and daily increase in incidence after 9–12 days from the adaptation of city lockdown in cities | • Population mobility was found to act as a driver in rapid COVID-19 transmission<br>• The city lockdown policy was effective in mitigating the epidemic in the study area.<br>• Policies including social distancing, travel restrictions, and quarantine of at least 12 days should be encouraged to mitigate the epidemic. | c |
| (Lai et al. 2020) | China (340 prefecture-level cities) | • Epidemiological data on COVID-19 (numbers of susceptible, exposed, infectious, and recovered/removed | • A daily travel network-based, stochastic SEIR (susceptible–exposed–infectious–removed) modelling framework to | • 114,325 cases of COVID-19 (IR: 76,776–164,576) in total were estimated for mainland China where 85% were in Hubei province (as of 29th February 2020) | • The country should continue at least the parts of NPIs even after travel and work have begun to resume to ensure that the | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| | | individuals/day from 1st December 2019)<br>• Anonymised data on human mobility<br>• Travel restrictions lifted from 17th February 2020 | simulate the different COVID-19 outbreak and intervention scenarios across the counties<br>• The risk of spreading of the coronavirus since the lifting of travel restrictions was also assessed | • Without the NPIs, the number of cases was predicted to be 67-fold higher (IR: 44–94-fold) by 29th February 2020<br>• Improved detection and isolation of cases and social distancing had a greater effect on preventing infections compared to travel restriction<br>• A limited extent (e.g., an average of 25% contact reduction between individuals) until late April would help to control for the epidemic even after the lifting of traffic restrictions | outbreak is sustainably controlled for its first wave.<br>**Limitations:**<br>• The parameters might not account for asymptomatic and mild infections; thus underestimated total number of infections<br>• Other factors that varied during the outbreak might confound the findings.<br>• The estimates of the efficacy might be biased if the parameters (based on data when no NPI imposed) of transmission in other cities differed from the estimates<br>• Probable biases in population coverage<br>• Only three main groups of NPIs were examined; thus ignoring the contributions of other NPIs during the outbreak | |
| (Nouvellet et al. 2021) | 52 countries worldwide | • Country-level data on deaths due to COVID-19<br>• Mobility data | • Correlation between mobility and transmissibility was assessed for the countries using the renewal equation.<br>• Transmissibility, R, was estimated using mobility data<br>• Two models fitted to the country-specific time-series of deaths were used to evaluate the correlation | • Significantly decrease in transmission with the initial mobility reduction in 73% of the countries<br>• For 80% of countries, decoupling of transmission and mobility was evident following the relaxation of strict control measures<br>• Mobility was found to be associated with lower rates of transmission after the relaxation of control measures in countries with a clear relationship between mobility and transmission | • A strong link between mobility and transmissibility, supporting the efficacy of population-wide social distancing interventions to control the epidemic<br>• Substantial beneficial effects of ongoing social distancing measures | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| | | | between mobility and transmissibility | during both pre-and post-relaxation of the control measures. | | |
| (Pei, Kandula, and Shaman 2020) | United States (3142 counties) | • County-level data on daily confirmed cases and deaths<br>• Inter-county movement data from US census survey before 15th March 2020<br>• Estimates of the reduction of inter-county visitors<br>• Real-time mobility data from 1st March - 7th June 2020<br>• Study period: 15th March to 3rd May 2020 | • A metapopulation susceptible-exposed-infectious-recovered (SEIR) model was used to simulate the transmission among the counties<br>• Two counterfactual simulations were performed for the inference of the sequence of transmission and ascertainment rates for 1 or 2 weeks earlier than the study period (21st February to 8 or 1 March 2020)<br>• Effects of response time on rebound outbreaks were quantified through further simulations | • Social distancing and other control measures were associated with a marked, asynchronous (for counties with ≥400 cases) decrease in the basic reproductive number (Re) throughout the country<br>• If the control measures were adopted 1 or 2 weeks earlier, a marked reduction in confirmed cases (601,667 and 1,041,261, respectively) and deaths (32,335, 59,351, respectively) would have been observed.<br>• Relaxation of control measures in counties with Re < 1 did not lead to increased no. of cases, while in counties with Re close to 1, reopening resulted in case growth | • Aggressive, early response to the pandemic was recommended to reduce morbidity and mortality.<br>• This study underscored the importance of maintaining control measures until sound public health targets are achieved so that benefits gained from the control measures would be sustained. | c |
| (Soucy et al. 2020) | 40 global cities | • Daily city-level Mobility Index<br>• Data on regional and national-level cumulative COVID-19 cases time series used for estimating growth rates<br>• COVID-19 instantaneous reproductive number estimated using the EpiEstim package in R (for the corresponding weeks of 23rd March, 30th March and 6th April) | • Multilevel linear regression was used for the estimation of the association between the:<br>• i) Mean daily growth rate and mean mobility index in prior weeks; ii) Instantaneous reproductive number and mean mobility index in prior weeks | • A 10% reduction in mobility was associated with a decrease of 14.6% in the average daily growth rate and a decrease of 0·061 in the instantaneous reproductive number 2 weeks later. | **Limitations:**<br>• The availability of the predicted metric is limited only to a handful of cities mainly located in Europe and North America.<br>• The study did not account for imported cases due to the unavailability of the data. | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| | | • Daily incidence data from 8th March to 12th April | | | | |
| (Summan and Nandi 2020) | 130 countries | • Data on the daily number of COVID-19 cases<br>• Global, country-level data on NPIs (national lockdown, global travel ban, and national school closure) and their implementation dates<br>• Google's mobility data<br>• Baseline period: 3rd January to 6th February 2020 | • Fractional logit regression To estimate the association between country characteristics and delay in policy implementation after first case detection and two additional models (fractional probit model and beta regression model) for sensitivity analysis<br>• A probit model to regress the binary indicator of whether a country implemented NPI on a set of covariates including region, income level, the date of arrival of the first case, and number of cases/ 100,000 people, etc. two weeks after first case detection | • Greater delays in implementation in countries with larger populations, higher income, and better health preparedness<br>• Implementations of NPIs more likely in countries with greater population density, more democratic political system, later arrival of the first case, and lower case detection capacity<br>• Further reduction in mobility resulted from lockdowns enforced with curfews or fines, or strictly defined lockdowns<br>• No significant effect of national school closure | • Stricter lockdowns could result in a greater sustained reduction in mobility.<br>• The international community should implement NPIs in a timely manner<br>**Limitations:**<br>• There might be data censoring issues to consider, e.g., outliers resulting from a lack of control variable data<br>• There might be data quality issues, e.g., measurement error caused by lack of testing capabilities and pandemic preparedness<br>• Google mobility data did not provide perfect measures of mobility<br>• Due to data collection challenges, countries that implemented sub-national NPIs were excluded from the analysis<br>• There were challenges in categorising different types of NPIs across the countries | c |
| (Aloi et al. 2020) | Santander (Spain) | • Basic mobility data before (2018) quarantine (mode share, trip reason, trips per hour, mode choice) | • Origin-Destination trip matrices were re-estimated to obtain an initial diagnostic of how daily mobility has been reduced and how the modal distribution and | • An overall decline in mobility (76%) is less important in the case of the private car<br>• Public transport users decreased (up to 93%)<br>• $NO_2$ emissions were reduced (up to 60%) | • There is a real risk of a decline in the sustainability of mobility in urban areas.<br>• Users' willingness to take over collective and shared transport systems will be an important issue to be assessed. | b |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| | | • Urban mobility patterns resulting from the quarantine<br>• Public transport GPS positioning data<br>• Pedestrian flows data<br>• Restrictions on mobility introduced on 15th March 2020 | journey purposes have changed | • Reduction in traffic accidents (up to 67%) in relative terms | • New strategies in both public and private sector operators are required to make public transport systems attractive again | |
| (Bo et al. 2021) | 415 sites from 190 countries | • Daily number of confirmed COVID-19 cases from 23 January - 13 April 2020<br>• Demographic and socioeconomic status data<br>• Four categories of non-pharmaceutical interventions (NPI): Mandatory face mask in public, isolation/ quarantine, social distancing, and traffic restrictions<br>• Time-varying effective reproduction number (Rt): the average number of secondary infected cases generated by a primary infected individual at time t, to estimate the changes in COVID-19 transmissibility | • Generalised Linear Mixed Model (GLMM) to assess and compare among the effectiveness of the different NPIs on the transmission of COVID-19<br>• Stratified analysis to investigate whether the associations were modified by WHO regions, population density, and Global Health Security Index<br>• Three sensitivity analyses to check for the robustness of the associations and lag effects | • The NPIs of the mandatory mask, quarantine, distancing traffic were associated with changes of -15.14%, -11.40%, -42.94%, and -9.26%, respectively, in the Rt of COVID-19 compared to those without the implementations of the corresponding NPIs.<br>• The NPI of distancing and simultaneous implementation of two or more NPI types were associated with a greater decrease in transmissibility | • Implementation of any kind of NPI was significantly associated with lower transmissibility of COVID-19<br>• Distancing and simultaneous implementation of two or more NPIs should be the strategic priorities | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| (Bucsky 2020) | Budapest | • Daily transport volumes by mode of transport for the month of March 2020 (lockdown being started from 16th March)<br>• Daily user number calculated based on passenger counting, and it was apportioned by day<br>• Number of cyclists, bike-sharing system users, car users, public transport users, pedestrians, and car-sharing system users<br>• Traffic data from 2017 was used as baseline data | • The daily usage data was compared with yearly modal split surveys and/or previous years measurement data<br>• Three scenarios were used to model the impact of transport restructuring in the second half of March 2020 (week12 and 13) | • Mobility was severely reduced (51% to 64%)<br>• Number of daily trips dropped from 10.1 to 4.3 million in the most likely scenario<br>• The greatest reduction in public transport demand (80%)<br>• Lowest decrease in cycling and bike-sharing (23% and 2%, respectively)<br>• The unprecedented growth of car usage in the modal share (43% to 65%)<br>• The modal share of cycling increased from 2% (2018) to 4% (March 2020)<br>• Share of public transport decreased from 43% to 18% | • The presumably higher penetration of home offices will reduce the demand for urban mobility.<br>• Cities require new ways of making public transport attractive again and overcome the fear of contamination<br>• Consumers can expect growing competition and, therefore, low pricing for mobility | b |
| (Chen et al. 2021) | Wuhan main urban districts, China<br><br>Central wards of Tokyo, Japan<br><br>Centre of Rome, Italy<br><br>New Delhi, India<br><br>New York City main urban districts, USA | • Traffic data: high temporal Planet multispectral images (from November 2019 to September 2020) to detect traffic density<br>• Road network data<br>• COVID-19 data<br>• Government Response Stringency Index (GRSI) | • Firstly, radiometrically corrected images and road mask need to be prepared for the detection framework<br>• Secondly, a morphological-based vehicle detection method is conducted to capture vehicle pixels<br>• Thirdly, traffic flow intensity index is calculated to capture traffic density for each temporal scene | • The proposed vehicle detection method was achieved a detection level at an accuracy of 68.26% in most of the image<br>• The trend of traffic density negatively correlated with the GRSI, Pearson correlation coefficients for the cities Rome, New York, and New Delhi, Wuhan and Tokyo were −0.48, −0.75 and −0.87, −0.33, and −0.18, respectively<br>• Correlation between traffic density and the newly confirmed cases was still showing as negative but less strong than GRSI | • A comparative analysis of how satellite-based and other approaches (mobile phone data, traffic counter data) should be conducted in the future to assess how they perform differently<br>• The relatively low resolution may produce outliers in vehicle detection<br>• The method yielded a relatively coarse traffic measure in order to understand extreme events | c |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| (Doucette et al. 2021) | Connecticut, USA | • Daily motor vehicle traffic counts (MVC)<br>• Detailed information related to the severity of crashes and other variables to understand MVC circumstance<br>• Total vehicle miles travelled, i.e., VMT (estimated)<br>• Weather data (average daily precipitation, average daily maximum temperature<br>• Data collected for each day between 1st January and 30th April in 2017, 2018, 2019 and 2020 | • Descriptive analysis within 2020 by comparing the mean daily counts and total counts for all MVC outcome models for the pre and post- stay-at-home periods<br>• An interrupted time-series design using a segmented Poisson regression analysis to compare daily VMT and MVCs before and during the COVID-19 stay-at-home order | • Significant decrease in the mean daily VMT 43% in the post-stay- at-home period (2020)<br>• Compared to the average of previous years,<br>• Single vehicle fatal crash rates were found to be 2.35 times (2.29 times compared to the pre-stay-at-home period, 2020) greater than expected during the post-stay- at-home period;<br>• All types of crash rates lowered except fatal crashes | • Despite a decrease in the total counts and mean daily counts of crashes during the post-stay-at-home period, fatal crashes and the crash rate of single vehicles increased significantly after accounting for reductions in VMT as well as weather conditions.<br>• The use of Street Light Insight data to estimate VMT is relatively new and so it might be a potential source of bias. | a, b |
| (Katrakazas et al. 2020) | Greece, Kingdom of Saudi Arabia | • Driving behaviour data from smartphone sensors (GPS, accelerometer data, and gyroscope data) both during COVID-19 pandemic and normal operations<br>• Traffic data<br>• COVID-19 data regarding cases and casualties as well as national countermeasures<br>• Accident data (only for Greece) | • Cross-country exploratory analysis of driving behaviour and road safety before and during COVID-19 lockdown period (2020) | • Slight increase in speeds (6%-11%) due to the reduced volume of traffic during lockdown<br>• Increased harsh acceleration and harsh braking events (increased up to 12%)<br>• Increased mobile phone use (up to 42%)<br>• Reduction in accidents (-41%) and early morning hour (00:00-05:00) driving (-81%) in Greece during the first month of the COVID-19 induced measures | • New speed limits should be established<br>• Larger spaces should be ensured for cycling and pedestrians to enlarge distances between users<br>• The effect of road type on driving behaviour could not be analysed as explicit geolocation data (e.g., road type) was missing from the dataset<br>• Confounding factors (e.g., gender, age, educational level, and mental health state) were not taken into consideration due to the anonymous data collection procedure | a |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| (Lee et al. 2020) | South Korea | • Traffic data based on vehicle detection systems (VDS) that use both in-ground and above-ground sensors to measure the number of traffic passing over specific points<br>• Public data on confirmed COVID-19 cases<br>• Data were collected for the first three months of 2019 and 2020 | • Compared traffic volumes between 2019 and 2020<br>• Trends in nationwide traffic (non-linear regression) and in COVID-19 cases (single linear regression) were analysed (2020)<br>• Correlation between traffic and the number of daily confirmed cases were evaluated using regression coefficient, t-ratio, and p-value | • Decrease in nationwide traffic by 9.7% (compared to the same period in 2019)<br>• A positive but insignificant linear relationship between the increasing number of newly confirmed cases and increasing traffic ($p=0.056$, $\beta=43\ 146$) | • The government should come up with suitable policies, such as total social distancing. | b |
| (Li et al. 2020) | Hubei Province, China | • COVID-19 confirmed cases data<br>• Migration data<br>• The policy of traffic blockage executed from 23rd January 2020 | • Flow-SEIR model to simulate the number of infections and then intuitively understand the efficacy of the traffic blockage and quarantine | • A significant decrease in the peak number of cases (by 89.68%) will occur if the masses take protective measures<br>• Peak is predicted to increase by 20.40% if self-isolation is completely ignored<br>• 21.06% - 22.38% of the peak number of infections can be alleviated by provincial-level traffic blockage | • more reliable and sufficient source of data can improve the accuracy of the model<br>• The age distribution was not districted in the model<br>• The quarantine is much more effective than traffic blockage control in general | c |
| (Muley et al. 2021) | State of Qatar | • Preventive measures and implementation timeframe<br>• Traffic demand data<br>• Traffic safety data (Number of crashes and violations)<br>• Data collected for the time interval of January to June for 2019 and 2020 | Quantified the traffic impacts of travel restrictions using the following comparisons:<br>• Traffic entering and exiting the City of Doha before and after implementing a series of preventive actions were compared.<br>• Traffic before and after the start of the pandemic was compared. | • Preventive measures did not affect the daily traffic demand distribution over the course of the day.<br>• Overall demand reduction of in baseline traffic (30%) when all preventive measures were active<br>• Traffic violations and the total crashes dropped by 73% and 37%, respectively.<br>• The highest reduction in peak traffic demand was associated with measure 2 (closure of all commercial establishments) and measure 3 (limited number of employees at the workplace | • These finding can be found beneficial in planning Temporary Traffic Management (TTM) measures during special/ mega-events | a, b |

| Study author (year) | Location | Data | Model type/ Methodology | Findings | Comments | Category |
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| | | | • Monthly crashes and violations were compared with those of 2019. | to 20% and promoting remote working, banning all non-essential travels) | | |

**References of the articles included in Appendix B**


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# APPENDIX C: LITERATURE SUMMARY ON COVID-19 AND AIR QUALITY

***Note for Category: (a) Comparison between the pre and post lockdown situations, (b) Comparison with respect to previous years' data, (c) Comparison using machine learning models***

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| (Sicard et al. 2020) | 4 European and 1 Chinese city (Rome and Turin in Italy, Nice in France, Valencia in Spain, and Wuhan in China) | • Hourly Concentrations of the pollutants provided by the local and regional agencies in charge of air quality monitoring stations (from a total of 36 stations, 1st January 2020 - 18th April 2020)<br><br>• Three years (2017-2019) data to represent the baseline condition (DOY=1 to DOY=150) | NO, $NO_2$, $O_3$, $PM_{2.5}$, $PM_{10}$ | • To quantify the lockdown effect on the air pollutant levels along with the changes in the time series, the deviations of 24-H mean concentrations were computed for each day of the year before and during the lockdown (2020)<br><br>• The mean concentrations during the lockdown (2020) were compared to those during the weekdays and weekends of the three previous years (2017-2019) to estimate the reduction in activities compared to the decrease in activities due to typical weekends | • Substantial reduction in NOx concentrations in all cities during the lockdown (~56%)<br>• Reductions in PM were much higher in Wuhan (~42%) than in Europe (~8%)<br><br>• Higher $O_3$ concentrations during the lockdown in all cities (17% in Europe, 36% in Wuhan)<br><br>• The lockdown effect on $O_3$ production was higher than the weekend effect (10% higher in Europe, 38% higher in Wuhan)<br>• The change in the daily $O_3$ mean concentrations was associated with the decline in the mean $NO_2$ concentrations | • The leading causes of the higher $O_3$ concentrations were decreased NOx emissions from road traffic, lower PM emissions, higher solar radiation, and an increase in $O_3$ precursors' emissions from domestic activities.<br><br>• Reduction of secondary pollutants (i.e., $O_3$) will remain challenging even with effective policies for reducing primary pollutants | b | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | | | | • The non-parametric Kruskal-Wallis test and a subsequent post-hoc test using the criterion Fisher's Least Significant Difference and p adjusted with the Holm correction was used to test for statistical significances between groups | compared to baseline conditions | | | |
| (Siciliano et al. 2020) | Iraja and Bangu districts, Rio de Janeiro, Brazil | • Concentrations of the pollutants at 10-minute intervals collected from the automatic monitoring stations of the Municipal Department of the Environment<br>• Meteorological parameters (temperature, relative humidity, rainfall, solar radiation, wind speed, and direction) at 10-minute intervals and were used in the interpretation of air pollutant concentration data<br>• Data collected from 1st March 2020 to 16th | $NO_2$, NO, $O_3$, NMHC (Non-Methane Hydro-carbon) | • Quantitative comparisons using medians<br>• Locally weighted polynomial regression (LOESS) with a confidence interval of 95% for general trends analysis<br>• Backward dispersion model was used to simulate air masses arriving at 12:00 (local time, BRT) for two representative days with higher levels of $O_3$ and another two days representing lower levels of $O_3$ | • In both locations, NMHC/NOx ratios increased (up to 37.3%) during the partial lockdown, along with a subsequent increase in $O_3$ concentrations<br>• In both locations, an hourly average of NMHC and NOx reduced during the partial lockdown<br>• Higher NMHC/NOx ratios were due to a sharper decrease in NOx than NMHC | • Reduction of transportation by personal automobiles does not contribute much to the removal of $O_3$ concentrations despite reducing the concentrations of primary pollutants and greenhouse gases | a | |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | | April 2020 in 3 phases- before partial lockdown, partial lockdown, and relaxed lockdown periods | | | | | | |
| (Lian et al. 2020) | Wuhan and Hubei provinces, China | • Daily AQI data from 1st January 2016 to 23rd February 2020 provided by the Wuhan Ecology and Environment Bureau<br>• After the lockdown - 24th January 2020 to 23rd February 2020<br>• Before the lockdown - 24th December 2019 - 23rd January 2020<br>• Historical data for comparison- 24th January to 23rd February 2015-2020 | Standard Pollutants ($PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, CO, $O_3$) | • A spatial comparison of AQI before and after lockdown<br>• A linear regression model to determine the relationship between AQI improvement rate and population density<br>• Daily variation trend analysis of $PM_{2.5}$, $NO_2$, and $O_3$ concentrations before and after the lockdown | • After the lockdown, the AQI improvement rate increases with the population density in Wuhan<br>• After the lockdown, in Wuhan, the most influencing factor of AQI was $PM_{2.5}$ as it was the primary pollutant on 16 of the 18 pollution days<br>• $NO_2$ decreased the most in Wuhan, but $O_3$ increased significantly, and the Hubei province also showed a similar trend<br>• Concentrations of $PM_{2.5}$, $PM_{10}$, $SO_2$, and CO dropped to some extent | • Further exploration needed to combine the meteorological effect on the increase in $O_3$ concentrations<br>• The significant increase in $O_3$ concentrations might be associated with changes in $NO_2$, VOCs, and $PM_{2.5}$ | b | No |
| (Chauhan and Singh 2020) | • New York and Los Angeles, USA<br>• Delhi and Mumbai, India | • $PM_{2.5}$ data<br>• Rainfall data<br>• The period after the outbreak of COVID-19: December 2019 to March 2020 | $PM_{2.5}$ | • Changes in the average monthly $PM_{2.5}$ data from December 2019 to March 2020 and comparison among the average $PM_{2.5}$ values of | • A linear decline in $PM_{2.5}$ was observed in New York and Los Angeles in March 2020<br>• During the lockdown (March 2020), $PM_{2.5}$ | | b | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | • Beijing and Shanghai, China<br>• Dubai, UAE<br>• Rome, Italy<br>• Zaragoza, Spain | • Earlier years considered for comparing changes: 2017-2019 | | the cities around the world | declined in all the study areas | | | |
| (Sharma et al. 2020) | 22 cities of India<br>• Bhopal and Dewas in centre<br>• Jorapokhar, Patna, Gaya, Brajrajnagar and Kolkata in the east<br>• Faridabad, Jodhpur, Amritsar, Delhi, Agra, Kanpur, and Varanasi in the north<br>• Amravati, Bengaluru, Thiruvananthapuram, and Chennai in the south<br>• Ahmedabad, Nagpur, Mumbai, and | • Hourly concentrations of the pollutants for the period of 16th March to 14th April from 2017 to 2020<br>• Meteorological parameters including wind speed, wind direction, temperature, and relative humidity | $PM_{2.5}$, $PM_{10}$, $SO_2$, NOx, NO, $NO_2$, CO, $O_3$ | • Air Quality Index (AQI) computed, and correlations between AQI in cities of different regions analysed to understand the overall improvement in air quality<br>• Air Quality Dispersion Modelling (AERMOD) to investigate the effect of meteorology on the $PM_{2.5}$ concentrations in the National Capital Region (NCR) of Delhi<br>• Weather Research Forecasting model was used to simulate the required meteorological data | • $PM_{2.5}$ had a maximum reduction in most regions<br>• Four times reduction of the total Excess Risk (ER) due to PM (~52% reduction on an average in the country)<br>• Predictive $PM_{2.5}$ could increase only by 33% in unfavourable meteorology<br>• 17% increase in $O_3$ and negligible change in $SO_2$ during the lockdown<br>• 44, 33,29,15, and 32% reductions in AQI (overall 30%) in the north, south, east, central and western regions | • Even during unfavourable meteorology, air quality can be significantly improved if strict air quality control plans are implemented<br>• In addition to controlling the primary PM, attention is required to reduce the emission of precursors to secondary pollutants | b | Yes (using WRF-AERMOD model system) |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | Pune in the west | | | | | | | |
| (Mahato, Pal, and Ghosh 2020) | Delhi, India | • Daily or hourly concentrations of seven air pollutants from 34 stations<br>• Pre-lockdown phase - 3rd March to 23rd March 2020<br>• During lockdown phase – 24th March to 14th April 2020 | $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, CO, $O_3$, $NH_3$ | • Air quality assessment based on National Air Quality Index (NAQI) and concentrations of seven air pollutants during and pre-lockdown phase<br>• Trend analysis of 24-H average concentrations of $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, NH3, NAQI, and 8-h average daily maxima of CO, $O_3$<br>• Spatial patterns of NAQI and concentrations of the major pollutants during lockdown and pre-lockdown phase | • Maximum reduction in $PM_{2.5}$ (~60%) and $PM_{10}$ (~39%) concentrations during the lockdown (overall PM reduction >50%)<br>• Considerable decline in $NO_2$ (-52.68%) and CO (-30.35%) concentrations during lockdown<br>• Negligible increase in $O_3$ concentration with an insignificant rising trend (overall +0.78%)<br>• The daily average concentration of$PM_{10}$ strongly correlated with the daily average concentration of $SO_2$, $NO_2$, NH3, and 8-H concentration of CO<br>• Only on the 4th day of lockdown (27th March), PM concentrations dropped within the permissible limits, and NAQI reduced by 51% | • Temporary source control at suitable time interval may heal the environment by improving the air quality | a | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| (Kerimray et al. 2020) | Almaty, Kazakhstan | • The daily concentration of the pollutants<br>• Meteorological data (wind speed, wind direction, temperature, relative humidity, and precipitation)<br>• Before lockdown- 21st February to 18th March 2020<br>• During lockdown- March 19th to 14th April 2020<br>• Previous year (2018-2019 for PM, 2015-2019 for BTEX) data of the same period were also collected for comparison | $PM_{2.5}$, $SO_2$, $NO_2$, CO, $O_3$, BTEX (benzene, toluene, ethylbenzene and o-xylene) | • Daily concentrations of the pollutants were compared between the periods before and during the lockdown | • $PM_{2.5}$, CO, and $NO_2$ reduced by 21% (spatial variation of 6%-34%), 49%, and 39%, respectively, during the lockdown<br>• The averages of benzene and toluene were 3 and 2 times higher, whereas those of ethylbenzene and o-xylene were 4 and 2.7 times lower<br>• $O_3$ concentrations increased by 15%<br>• Meteorological conditions were in favour of air pollution reductions during the lockdown days compared to the preceding days | • The spatial variation in reduction of $PM_{2.5}$ during the lockdown could be attributed to the removal of traffic emissions with their varying contributions to the different locations | b | No |
| (Collivignarelli et al. 2020) | • Milan, Italy<br><br>Sub-areas (Remaining municipalities: SaA and SaB | • Daily averages of wind speed, rainfall, temperature, relative humidity, and solar irradiance<br>• Daily averages of the air pollutants for each area<br>• Reference period (CTRL)-February 7 to February 20, 2020 | $PM_{2.5}$, $PM_{10}$, BC, $C_6H_6$, $SO_2$, $NO_2$, NOx, CO, $O_3$, $NH_3$ | • Comparisons between the daily average concentrations of the pollutants in all three areas during the CTRL, PL, and TL periods | • Meteorological data were sorted into climatologically homogenous reference periods for the comparison of different scenarios<br>• Significant reduction in $PM_{2.5}$, $PM_{10}$, BC, $C_6H_6$, CO, and NOx | • The increase in $O_3$ was probably due to the reduction in NO concentrations during the lockdown | a | |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | | • Partial lockdown period (PL)-9th March to 22nd March 2020<br>• Total lockdown period (TL)-23rd March to 5th April 2020 | | | • $SO_2$ remained unchanged in the more peripheral areas | | | |
| (Otmani et al. 2020) | Salé City, Morocco | • Daily averages of the pollutants before (11th to 20th March 2020) and during (21st March to 2nd April 2020) the lockdown<br>• Three days backward, air trajectories arriving over the sampling point were computed as the variability of the air pollutants is closely related to the immediate history of the air masses before arriving at the sampling site | • $PM_{10}$, $SO_2$, $NO_2$ | • Three-dimensional backward air mass trajectory was calculated using the HYSPLIT model<br>• Evaluation of the relative variation (in%) and difference in the mean concentrations of the pollutants between both periods of sampling | • Dramatic decrease in the concentrations of $NO_2$ (-96%), $PM_{10}$ (-75%) and$SO_2$ (-49%) during the lockdown<br>• Significant difference among the rate reduction and temporal gradients in the concentrations of the three pollutants<br>• The benefits of $PM_{10}$ local emission reduction were overcome by the long-range transported aerosols contributions, as shown by the backward trajectories | • Reduction in the pollutant concentrations could be attributed to the limiting human movement and industrial activities<br>• The role of meteorological parameters is quite evident in this study, but they are not quantified. | a | No |
| (Berman and Ebisu 2020) | Continental US (122 counties from 37 states) | • County-level pollution concentrations<br>• COVID-19 period- 13th March to 21st April<br>• Pre COVID-19 period- 8th January to 12th March 2020 | $PM_{2.5}$, $NO_2$ | • Comparison between pollution concentrations during historical (2017-2019) versus current (2020) current periods using two-sided t-tests | • Significant decrease in the $NO_2$ (-25.5%) concentrations during the COVID-19 period compared to the historical data<br>• Absolute reduction of $NO_2$ in urban counties | • Decreases in $NO_2$ was likely associated with the decline in vehicular traffic and limited domestic travel<br>• This study potentially unaccounted for meteorological effects | b | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | • Historical data: matched pollution data from 2017 to 2019 | | paired by county (α=0.05). | was nearly 5-times greater than that of the rural counties<br>• Statistically significant reduction in $PM_{2.5}$ in the urban counties and counties from states instituting early business closure | | | |
| (Zheng et al. 2020) | Wuhan, China | • Hourly observations of $PM_{2.5}$ chemical compositions and sources for two periods (During lockdown: 1/23-2/22, 2020 and for the same period in 2019)<br>• In situ meteorological parameters including temperature, atmospheric pressure, wind speed, wind direction, and relative humidity | $PM_{2.5}$ | • Comparison between the mean and SDs of air pollutants, chemical compositions, and meteorological parameters for the two periods<br>• A Random Forest tree (RF) method was used to model the air pollutant concentrations<br>• Weather normalised technique was applied on the RF model to remove the influence of meteorology<br>• Positive Matrix Factorisation (PMF) model was used to apportion $PM_{2.5}$ sources<br>• Hourly backward air mass trajectories calculated using the | • Decreasing $PM_{2.5}$ (by 27 µg.m-3 on average compared to the 2019 data) and an enhancement of $O_3$ in most of the regions<br>• $PM_{2.5}$ reduction was predominantly caused by emission reduction (92%), retrieved from the RF approach<br>• All the main chemical species of $PM_{2.5}$ decreased significantly, ranging from 0.85 µg.m-3 (chloride) to 9.86 µg.m-3 (nitrate)<br>• Mass contribution of all seven $PM_{2.5}$ sources decreased as indicated by the PMF model (contribution % varying from -11% from industrial processes to | • The air quality improvement in Wuhan was dominated by emission reduction | c | Yes |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | | | HYSPLIT model was used to study the impacts of regional transport on the $PM_{2.5}$ concentrations<br>• ANOVA was used at a 95% confidence interval to test whether the differences of meteorological parameters, chemical compositions, and source contributions for the two periods were significant or not | 8.7% from secondary inorganic aerosols)<br>• Reduction in the source contribution from the potential geographic regions (mean values ranging from 0.22 µg.m-3 to 4.36 µg.m-3)<br>• Increased contributions to $PM_{2.5}$ from firework burning, secondary inorganic aerosol, road dust, and vehicle emissions from transboundary transport | | | |
| (Baldasano 2020) | Barcelona and Madrid, Spain | • Hourly concentrations of $NO_2$ from 24 (Madrid) and 9 (Barcelona) air quality monitoring stations during March 2020<br>• Meteorological data<br>• Previous years (2018-2019) data for the month of March were obtained for comparison | $NO_2$ | • Air quality data analysis for March 2020 was performed based on –<br>• (a) a situation dominated by meteorological conditions (first week, second week, second fortnight),<br>• (b) a situation of extreme emission reduction due to the lockdown measures (first two weeks, middle of the month when the lockdown was established) | • Reduction in $NO_2$ concentrations in Barcelona (50%) and Madrid (62%) during lockdown (March 2020)<br>• $NO_2$ reduction during the first two weeks (53% in Madrid, 34% in Barcelona) was due to windy weather conditions, and during the second fortnight (62% in Madrid, 50% in Barcelona), it was due to strong traffic reduction | • A substantial variation could occur in the hourly $NO_2$ data due to factors such as intensity of the local emissions, atmospheric chemistry, and meteorological conditions | b | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| (Selvam et al. 2020) | Four different zones of Gujrat, India:<br>Zone-1: Surat, Ankleshwar, Vadodra<br>Zone-2: Ahmedabad, Gandhinagar<br>Zone-3: Jamnagar, Rajkot<br>Zone-4: Bhuj, Palanpur | • Concentrations of the air pollutants obtained from the monitoring stations of CPCB (Central Pollution Control Board, 2020)<br>• Pre lockdown period- 1st January to 23rd March 2020<br>• During lockdown period- 24th March to 20th April 2020<br>• Previous year (2019) data for the same time interval were obtained for comparison | $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, CO, $O_3$ | • Comparison between the current (January to April 2020) and previous year (January to April 2019) air pollutants concentrations and AQI of the four zones to evaluate the effect of lockdown on the long-term changes in air quality | • Reduction in $NO_2$ (30%-84%, most significant), $PM_{2.5}$ (38%-78%), $PM_{10}$ (32%-80%), CO (3%-55%), and $SO_2$ (~40%) during the lockdown in western India<br>• Increase in 8-H daily maxima $O_3$ levels (16%-58%)<br>• Overall AQI improvement by 58%<br>• Higher air quality improvement in populated cities with more industrial activities (zone 2 and 3: 60-70% compared to zone 1 and 4: 34-39%) compared to the same interval of the previous year (2019) | • The increase in $O_3$ concentrations was mainly due to less NO emission and the usual increase of insolation and temperature during March-April<br>• Functioning of the power plants possibly caused the less reduction in CO<br>• Minimal shipping and fishing activities caused a reduction in $SO_2$<br>• Significant AQI improvement was due to the decrease in industrial activities and traffic flow | b | No |
| (Menut et al. 2020) | Western Europe | • A full set of hourly concentrations data of several pollutants for a large number of stations provided by the European Environment Agency (EEA) was obtained to compare with the modelling results for the month of March 2020 | $PM_{2.5}$, $PM_{10}$, $NO_2$, $O_3$ | • WRF and CHIMERE models were used to simulate hourly concentrations of numerous air pollutants without the biases of meteorological conditions over Western Europe for the whole month of March, with a spin-up 10-days | • Decrease in $NO_2$ concentrations (30%-50%) in all western European countries<br>• Increase in $O_3$ concentrations differently affected by the lockdown measures in urban areas throughout western Europe | • A less pronounced decrease in fine particles as in western European countries residential heating emissions and agricultural emissions are very substantial contributors to PM concentrations other than traffic<br>• A refinement in assumptions of emissions adjustment due to | c | Yes |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | | | period in February (20-29 February 2020)<br>• Two simulations are REF (Reference case), and CVD (with the lockdown scenario on the emissions)<br>• Daily average time-series (REF-CVD) compared to measurement stations<br>• The daily average percentage of changes in concentrations aggregated per countries<br>• Maps of differences | • A lower reduction in fine particles (5%-15%) | lockdown measures will be necessary to improve results robustness | | |
| (Adams 2020) | Ontario, Canada | • Hourly concentrations of air pollutants were obtained from the Ontario air monitoring network for 2020 (SOE weeks: 13-17, Pre-SOE weeks: 13-17) and five previous years (weeks 1 to 17)<br>• [SOE: State of Emergency] | $PM_{2.5}$, NOx, $NO_2$, $O_3$ | • Long-term trends (year-to-year) in air quality (mean concentration of each pollutant) for weeks 1 to 17 were assessed<br>• Seasonal trends (week to week) in air quality were assessed using local polynomial regression fit to the weekly mean values by year | • No reductions occurred for $PM_{2.5}$ that could be attributed to the SOE<br>• $O_3$ concentrations from12 of the 32 monitors were lower than the previous five years data<br>• Reduction in NOx and $NO_2$ across Ontario (12 of 29 stations displayed their lowest concentrations) | • Pollutants with source profiles dominated by transportation emissions showed strong reductions (i.e., NOx and $NO_2$) | b | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| (Pei et al. 2020) | Beijing, Wuhan, and Guangzhou representing the northern, central and southern China | • Remotely sensed TROPOMI products ($NO_2$, HCHO) were obtained to illustrate temporal-spatial distributions of those pollutants<br>• Daily and weekly average concentrations of atmospheric pollutants<br>• Data collected for 11/1/2020-14/2/2020 and 22/1/2019-25/2/2019 (the time intervals were further divided into five sub-periods) | Tropospheric: $NO_2$, HCHO<br><br>Atmospheric: $PM_{2.5}$, $SO_2$, $NO_2$, $O_3$ | • Trends of the three pollutants were studied using time-series<br>• To partially reduce the meteorological effects Chinese lunar calendar was used to align the two years of time-series data<br>• Spatial distribution of the remotely sensed concentrations | • A dramatic decrease in $NO_2$ concentrations (28%, 57%, 46% in Beijing, Wuhan, and Guangzhou, respectively) during the lockdown<br>• HCHO, as a proxy to VOC, kept steady in the major cities, though decreased in other regions<br>• $SO_2$ concentrations kept steady at low levels regardless of the cities<br>• $O_3$ concentrations decreased slightly but were still at high levels<br>• $PM_{2.5}$ concentrations increased in Beijing, decreased in Wuhan, and kept steady in Guangzhou | • The steady HCHO concentrations in urban areas provide sufficient fuels for generating atmospheric $O_3$, whereas there is not enough No to consume $O_3$ via the titration effect<br>• Reducing VOCs (Volatile Organic Compounds) in urban areas would be a critical mission for improving air quality | b | Yes (Partially) |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| (Chen et al. 2020) | United States (28 different cities from 23 different states) | • Daily concentrations of the pollutants from 28 National Core (NCore) sites<br>• Lockdown period: 15 March – 25 April 2020<br>• Pre-lockdown reference period: 25 January – 7 March 2020<br>• Historical baseline: 2017-2019 | $PM_{2.5}$, $PM_{10}$, $NO_2$, CO, $O_3$ | • The ratio of mean values of concentration during lockdown to pre-lockdown concentration was compared to the mean baseline concentration for each pollutant<br>• A bootstrapping procedure based on 12,000 resampling/recalculation of the data was carried out to estimate the confidence interval of the percentage of change | • Significant reduction in $NO_2$ (5%-49%) and CO (up to 37%) at two-third of the sites and tended to increase with local population density<br>• Significant PM reduction occurred where $NO_2$ declined the most (Northeast and California/Nevada metropolis)<br>• Changes in $O_3$ were mixed and relatively minor (generally within ±20%) | • The lockdown measures have non-uniformly impacted air pollution in the US. | b | No |
| (Wang et al. 2020) | Six megacities (Beijing, Chengdu, Shenzhen, Xi'an, Shanghai, and Wuhan), China | • Hourly observations of the ambient concentrations of the major pollutants<br>• Hourly meteorological data including wind speed, wind direction, ambient temperature, relative humidity, and atmospheric pressure<br>• Network-level traffic congestion index<br>• Hourly, link-level speed profiles | $PM_{2.5}$, $NO_2$, CO, $O_3$ | • Random Forest model to predict pollutant concentrations under the scenario without lockdown<br>• A second random forest (RF2) model was developed to quantify the trend in air quality for the municipality of Beijing and the urban area of Chengdu caused by changes in traffic emissions | • Reduction in ambient $NO_2$ by 36% to 53% during the most restrictive periods. This percentage dropped below 10% in late April when the "level-1 public health emergency response control actions" were lifted by several cities<br>• Significant increase in $O_3$ concentrations in Beijing, Xi'an, and Wuhan, though the enhancement was not | • Changes in air pollution levels reduced as the lockdown was gradually eased in various cities | c | Yes |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | | | • Dynamic traffic emission inventories were developed | as obvious in the other three cities<br>• Decreased $PM_{2.5}$ and CO concentrations during the lockdown, though relatively less significant as compared to $NO_2$ reduction<br>• Traffic emission changes acted as a major factor in the substantial $NO_2$ reduction and increased $O_3$ concentrations | | | |
| (He, Pan, and Tanaka 2020) | China | • City-level air pollution data aggregated from station-level data from 1600 stations<br>• Daily city-level weather data (temperature, precipitation, and snow)<br>• Local governments' lockdown information city by city<br>• socio-economic status (GDP, population, industrial output, number of firms, amount of traffic, and pollutant emission) | AQI, $PM_{2.5}$, $PM_{10}$, $SO_2$, $O_3$, $NO_2$, and CO | • Two sets of difference-in-differences (DiD) models to quantify the impact of city lockdown on air pollution | • AQI reduced by 19.84 points ($PM_{2.5}$ dropped by 14.07 μg m−3) in the lockdown cities compared to the control group<br>• AQI reduced by 6.34 points ($PM_{2.5}$ down by 7.05 μg m−3) in the lockdown cities relative to the previous years<br>• Larger lockdown effects in colder, richer, and more industrialised cities<br>• $PM_{2.5}$ remained four times higher than the | • Much further effort is needed to reduce $PM_{2.5}$ concentration<br>• Existing environmental policies are more suitable options to address environmental issues at a lower economic cost than city lockdown | b | Yes |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | | | | WHO recommendations | | | |
| (Ma et al. 2020) | China | • Annual average concentrations of the pollutants (2013-2019) | $PM_{10}$, $PM_{2.5}$, $SO_2$, CO, $NO_2$, $O_3$ | • Recapitulated the current knowledge gaps between air pollution controls and health impacts, including pathogen epidemic | • Annual average concentrations of $SO_2$ and $NO_2$ in 338 cities has been reduced by 72.5% and 38.6% in 2019 relative to 2013, respectively<br>• National annual mean $PM_{2.5}$ concentrations dropped from 72 in 2013 to 36 µg.m-3 in 2019 (higher than the WHO standard of 10 µg.m-3) | • Knowledge gaps to be addressed:<br>• health risks of PMs and adherent pollutants<br>• interplays between the spread of airborne pathogens and air pollution<br>• synergistic health effects of $O_3$ and other air pollutants | | No |
| (Rossi, Ceccato, and Gastaldi 2020) | Padova, Italy | • Average daily concentrations of $PM_{10}$ and hourly concentrations of NO, $NO_2$, NOx<br>• Traffic data (traffic counts, average speeds, and densities every 10 minutes, for both inbound and outbound traffic, of four classes of vehicles)<br>• Meteorological data (including temperature, wind direction, and speed, precipitation, | NO, $NO_2$, $NO_x$, $PM_{10}$ | • Statistical tests were applied to evaluate changes in average daily values of traffic flow<br>• Correlation analyses to evaluate the degree of association among pollutant concentrations, traffic flows, and the meteorological factors<br>• To assess the causal relationship between traffic flows and pollutants, multivariate linear regression | • Statistically significant reductions of vehicle flows (by 69–71%), NO (by 46–54%), $NO_2$ (by 34–40%), and NOx (36–44%)<br>• NO, $NO_2$ and NOx concentrations significantly affected by vehicle flows<br>• No evidence of a relationship between traffic and $PM_{10}$ | • Interventions to limit traffic flows seem to be effective in improving air quality only in terms of reducing nitrogen oxides | b | Yes |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | solar radiation, thermal inversion)<br>• Data collected for days in 2020 when the strictest policies and corresponding days in 2017, 2018 | | models were used, with traffic flows and meteorological parameters as independent variables. | | | | |
| (Xiang et al. 2020) | Seattle, Washington | • Hourly traffic/air pollutants/meteorological data were collected for five weeks before and ten weeks after Washington Stay Home Order (SHO), respectively (17th February – 31st May 2020)<br>• Pre-SHO (Weeks (−4) to 0) and post-SHO (Weeks 1 to 10) | Ultra-Fine Particles (UFPs), black carbon, $PM_{2.5}$, NO, $NO_2$, NOx, and CO | • Comparison between the pollutants between pre-and post-SHO periods and differences tested<br>• Multivariate autoregressive (MAR) models were used to analyse traffic-pollutant associations between road occupancy and each pollutant level | • Decrease in the median traffic volume (37%) and road occupancy (52%) during the post-SHO weeks<br>• Decreases showed in median black carbon, $PM_{2.5}$, NO, $NO_2$, NOx, and CO (25%, 33%, 33%, 29%, 30%, 17% respectively)<br>• The coefficient of determination (R2) for models ranges from 0.5 to 0.8, meaning 50–80% of data variances are explained by MAR (1) models.<br>• The regression coefficients of traffic indicators are significant for all pollutants indicating traffic contributed more to pollutant density | • The differences between pre-and post-SHO period differences are significant for traffic, pollutants except 11.5–115.5 nm particles, and meteorology variables except for precipitation<br>• Ignoring autocorrelation effects in the time-series observations resulted in much lower R2 and higher Akaike and Bayes information criteria<br>• COVID-19 impacts on traffic air pollutant levels can be different due to meteorology adjustment | a, c | Yes |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| (Yao et al. 2020) | Wuhan, China | • Data of confirmed cases and deaths on COVID-19<br>• Data on daily fine particulate matter $PM_{2.5}$ and inhalable particulate matter $PM_{10}$<br>• Meteorological data, including daily mean temperature and relative humidity<br>• 19th January to 15th March 2020 | $PM_{2.5}$, $PM_{10}$, $NO_2$, $O_3$, $SO_2$, and CO | • A time-series analysis to examine the association of $PM_{2.5}$ and $PM_{10}$ concentrations with the CFR of COVID-19 by using multivariate linear regression<br>• Adjustments were made for temperature, relative humidity, $SO_2$, $NO_2$, CO, and $O_3$.<br>• The lag effects of $PM_{2.5}$ and $PM_{10}$ on COVID -19 death rate was examined by analysing the association between the death rate and single-day daily average PM concentrations on the current day and up to 5 days before the date of infection | • $PM_{2.5}$ and $PM_{10}$ changed synchronously and were very similar.<br>• Two air pollutants and the daily death rate curves showed great similarity with a time lag that existed between them<br>• A higher death rate is seen with increasing $PM_{2.5}$ and $PM_{10}$ concentrations | **Limitations:**<br>• The time from infection to death is assumed to be constant for all, but in reality, it's different.<br>• Lack of detailed demographic/socio-economic data overlooks underlying explanations for the association between COVID-19 deaths and $PM_{2.5}$ and $PM_{10}$ concentrations.<br>• Data collected in a limited time span, so data variation was slight.<br>• Asymptomatic cases may lead to an underestimated COVID-19 rate | c | Yes |
| (Tanzer-Gruener et al. 2020) | Pittsburgh, Pennsylvania,<br><br>United States | • CO and $PM_{2.5}$ measured at 27 RAMP sites<br>• RAMP sites were grouped into four categories: High Traffic, Urban Residential, Suburban Residential, and Industrial<br>• $NO_2$ measurements from the ACHD | $PM_{2.5}$, CO, and $NO_2$ | • Comparison between the pre and post-COVID pollutant measurements for different traffic sites<br>• Two intra-day variations were defined, which focus on traffic and industrial-related | • $PM_{2.5}$ concentrations decreased during the COVID pandemic<br>• no significant change in industrial intra-day variability of $PM_{2.5}$ at the Industrial sites<br>• CO and $NO_2$ concentrations at the High Traffic sites | • A clear decrease in air pollution driven in large part by reductions in vehicle traffic<br>• One concern with low-cost pollutant sensors is uncertainty in the measurements<br>• The activity at the industrial sources continued after | b | No (same time period across different years to minimise the effects) |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | network includes two sites:<br>• High Traffic, Suburban Residential<br>• Traffic camera data to quantify the reduction in traffic<br>• Anonymous survey to determine activity changes<br>• Pre-COVID period: March 2019<br>• Post-COVID period: 14-31 March 2020 | | enhancements to determine the changes in source-related intra-day variability of pollutant concentrations | during the morning rush hour were reduced by 57% and 43%, respectively<br>• Reductions in restaurant activities (63%) and electricity-related emissions (8%) | social distancing was enacted as suggested by the industrial $PM_{2.5}$ enhancement | | |
| (IQAir 2020) | Ten major global cities (Delhi, London, Los Angeles, Milan, Mumbai, New York City, Rome, São Paulo, Seoul, and Wuhan) | • Hourly concentrations of $PM_{2.5}$<br>• A 3-week period for each city was considered during lockdown conditions (2020), and comparison with the same time span in 2019, 2018, 2017 and 2016<br>• The 3-week timeframe reflects the period of strictest lockdown measures to coincide with the 'peak' of daily reported COVID-19 cases | $PM_{2.5}$ | • Compared measurements of $PM_{2.5}$, prior to and during the pandemic | • 9 of 10 key global cities experienced $PM_{2.5}$ reductions (except Rome)<br>• Cities having historically higher levels of $PM_{2.5}$ pollution witnessed the most substantial drops, like Delhi (-60%), Seoul (-54%), and Wuhan (-44%)<br>• During Wuhan's 10-week lockdown, the city experienced its cleanest February and March air quality on record<br>• Delhi's worse rated hours plummeted from | • Increased reliance on residential heating systems, coupled with cool air inversions that trap particulate pollution, explains $PM_{2.5}$ gains in Rome as compared to 2019 | b | No (same time period across different years to minimise the effects) |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | | | | 68% in 2019 to 17% during the lockdown period<br>• Los Angeles experienced the longest stretch of clean air on record, meeting the WHO air quality guidelines | | | |
| (Pavel et al. 2020) | Dhaka, Bangladesh | • Air quality data of Dhaka (daily and monthly average concentrations, AQI)<br>• Data set for COVID-19<br>• Data on climate variables (average, relative humidity, wind speed, and rainfall)<br>• Data collection period: 8th March (First COVID case detected)-16th June 2020<br>• "Stay in Home Order" from 26th March 2020<br>• Previous year data: 2019 | $PM_{10}$, $PM_{2.5}$, $NO_2$ and $CO_2$ | • The Kendall and Spearman rank correlation tests were utilised to examine the correlation between variables and air quality parameters | • COVID-19 lockdown drastically reduced $PM_{2.5}$ and $PM_{10}$ concentrations up to 62%.<br>• During the lockdown, $NO_2$ emission abridged up to 80%, CO2 emission dropped by 2-4%.<br>• The comparison between April 13-27 in 2020 and April 15-29 in 2019 was also indicating a very drastic reduction of $NO_2$ concentration<br>• The curbing of lockdown on 30th May 2020 led to rising concentrations of the air quality parameters<br>• Climate variables revealed a strong positive correlation | • Despite good air quality during the lockdown, the mortality and morbidity were high because the COVID-19 patients may be experiencing bad air quality from the previous months (January, February, and March), impacting health.<br>• Knowledge from enormously improved air quality will be transmitted to the policy execution | b | No |

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| | | | | | with COVID-19 morbidity and mortality.<br>• Air quality index (AQI) has no positive, but a significant correlation (within 1.0%) with the number of COVID-19 confirmed cases and mortality | | | |
| (Bekbulat et al. 2021) | United States | • Daily averages of the air pollutants and meteorological parameters<br>• The data collection period (January 1-September 1, 2020) was divided into 3 phases: "before," "during," and "after" stay-at-home orders.<br>• Historical data: 2010-2019 (18 December -19 September) | $PM_{2.5}$, $PM_{10}$, $NO_2$, $O_3$, $SO_2$, and CO | • Temporal correction by robust differences was performed as air pollutant concentrations exhibit systematic long-term trends<br>• Actual year-2020 measurements were compared to the "expected" level for that week accounting for 10-year trends<br>• For sensitivity analyses, linear and spline first-order multivariate auto-regression was used to correct for temporal patterns and weather | • Noticeable $O_3$, $NO_2$, CO, and $PM_{10}$ declines started three weeks before stay-at-home orders.<br>• By six weeks after the stay-at-home orders, $O_3$ concentrations were not significantly different from their expected levels.<br>• Pollution levels modestly lower than expected for $NO_2$, CO<br>• $PM_{2.5}$, CO, and PM 10 were higher than expected<br>• For primary pollutants ($NO_2$, CO, $PM_{2.5}$), connections between changes in activity, emissions, and concentrations were relatively direct, and | • The effects on air quality of societal responses to COVID-19 may be lower in the US because:<br>• Comparatively cleaner air in the US due to lower vehicle emission<br>• Reducing emissions from one or a small number of source categories may or may not yield a large change in concentrations.<br>• Potential increase in emissions due to residential wood combustion, backyard BBQ cooking is possible.<br>• Emissions can be offset (workplace electricity consumption declines but household electricity consumption increases). | b | Yes |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | | | | for secondary pollutants ($O_3$, $PM_{2.5}$), these were more complicated<br>• The results from linear regression analysis mostly agreed with robust difference results | | | |
| (Lovrić et al. 2021) | Graz, Austria | • Target variables: Pollutant concentrations from five sites<br>• Predictive variables (X): Weather and environmental conditions, temporal variables with their lag-values (from the previous two days) to capture seasonal behaviour from industrial production and traffic flows<br>• Model training period: 3rd January 2014- 31st December 2019<br>• 2020 data separated into:<br>• External Validation set (VS): 3/1/2020-10/3/2020<br>• Lockdown set (LD): 10/3/2020-2/5/2020 | $PM_{10}$, $NO_2$, $O_3$, Ox (total oxidant) | • Swarm plots showing the distribution of median concentrations in the lockdown<br>• PCA to Investigate the existence of clusters among the pollutants<br>• Random forest regression (RF) optimised by means of Bayesian optimisation with 10x cross-validation (CV) and root mean square error (RMSE) as the cost function<br>• Comparison between the predicted (expected) and measured (true) values during the lockdown period | • Reduction in $NO_2$ (-36.9% to -41.6%) and $PM_{10}$ (-6.6% TO -14.2%) average concentrations during lockdown<br>• Increase in $O_3$ concentration (11.6% to 33.8%)<br>• Reduction in traffic flow (-51.6% to -43.9%) during the lockdown | • Reduction in the pollutant concentrations (especially $NO_2$) can be explained by a significant drop in traffic-flows during the lockdown<br>• A relatively modest reduction in $PM_{10}$ concentrations compared to $NO_2$ reduction indicated that there are more varied processes controlling PM concentrations in an urban atmosphere<br>• The selection of predictors was sufficient to explain changes in the pollutant concentrations as indicated by the good generalisation and performance of the model | c | Yes |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | | • Hard Lockdown set (HLD): 20/3/2020-14/4/2020 | | | | | | |
| (Jephcote et al. 2021) | United Kingdom | • Hourly measurements of the air pollutants (week 14-18 of 2017, 2018, 2019, 2020)<br>• Monthly-average daily traffic (MADT) counts on A-roads and motorways (January-May 2019 and 2020) | $NO_2$, NOx, $O_3$, $PM_{2.5}$ | • Daily concentrations of $NO_2$, $O_3$, and $PM_{2.5}$ of the lockdown period were compared with those over the same period during 2017-19<br>• Boosted Regression Trees (BRT) models were used to predict daily-average air pollution concentrations following a business as usual scenario (BAU)<br>• Comparisons were made with predicted concentrations for the 2020 period from business-as-usual (BAU) modelling, where the contributions of normal activities were estimated under observed meteorological conditions | • Reduction in traffic (-74%in light traffic, -35% in heavy vehicles, -69% overall) during lockdown<br>• From 129 stations, mean reductions identified for $NO_2$ and $PM_{2.5}$ were 38.3% and 16.9 %, respectively<br>• $O_3$ concentrations increased on average by 7.6%<br>• Comparable $NO_2$ reductions and $O_3$ gains were predicted by the BAU models<br>• Temporal variables explain 41-47% of the variation in $NO_2$ and PM concentrations, with meteorological factors explaining the remaining 53-58%.<br>• The BAU estimates showed meteorological conditions in April 2020 had a greater than average influence on air pollution | • Largest $O_3$ increase at the roadside sites due to the reduction in local emissions of NO<br>• In the BAU forecasts, identical meteorological conditions for each hour were assumed for each hour, leading to modelling uncertainty.<br>• There were periods of elevated concentrations of $PM_{2.5}$ and $O_3$ during the lockdown due to air stagnation under high pressure and Easterly winds drawing polluted air from Central and Eastern Europe<br>• Modest contribution of traffic to air quality was demonstrated by the results | b, c | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| (Cole, Elliott, and Liu 2020) | China (30 cities) | • City-level hourly concentrations of four pollutants between 18th January 2013 and 29th February 2020<br>• City-level hourly meteorological data (temperature, relative humidity, wind direction, wind speed, and air pressure) | $SO_2$, $NO_2$, CO, $PM_{10}$ | • ML (random forest and regression tree) to remove the confounding effects of weather conditions on pollution concentrations (weather normalisation), creating smoother data<br>• An augmented synthetic control method to estimate the impact of the lockdown on weather normalised pollution relative to a control group of cities where lockdown was not implemented<br>• The air pollution levels' trajectory in real Wuhan was reproduced, and the difference in the trajectories between the synthetic (experiencing the air pollution evolution without lockdown) and real Wuhan was the causal impact of the lockdown. | • Reduction in $NO_2$ concentrations by as much as 24 µg/m3 during the lockdown (-63%)<br>• Concentrations of $PM_{10}$ also dropped by over 20 µg/m3, although this reduction was short term<br>• No statistically significant impact on concentrations of $SO_2$ or CO<br>• The reduction of $NO_2$ concentrations could have prevented deaths (as many as 496 in Wuhan city, 3368 in Hubei province, and 10,822 across China as a whole). | • The country's reliance on coal-fired power plants and a need for domestic heating due to the relatively low temperature in Wuhan explained an insignificant reduction in $SO_2$ concentration | b, c | Yes |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | | | | • A number of selected estimates of the mortality effects associated with $NO_2$ concentrations was employed to compute the potential lives saved due to the cleaner air | | | | |
| (Anil and Alagha 2021) | Eastern Province, Saudi Arabia | • Air quality data (Hourly concentrations of the pollutants)<br>• Meteorological data (average wind speed)<br>• Three periods:<br>• (i) pre-lockdown (15 September 2019 – 22 March 2020),<br>• (ii) during-lockdown (23 March 2020 – 20 June 2020), and<br>• (iii) post-lockdown (21 June 2020 – 18 July 2020). | CO, $SO_2$, $NO_2$, $O_3$, $PM_{10}$ | • Descriptive statistics and outlier analysis methods were performed<br>• Box and whisker plots were depicted outliers of each pollutant observed at each station for the three periods<br>• Bivariate polar plots of concentrations were generated to determine the effect of wind velocity and wind direction data couple on each pollutant's concentration during the three periods | • $NO_2$ responded best to the lockdown measures (reductions ranged between 12–86% and 14–81% during- and post-lockdown periods, respectively)<br>• Significant concentration reductions at varying rates for $PM_{10}$ (21–70%), CO (5.8–55%), and $SO_2$ (8.7–30%), while $O_3$ concentrations increased (6.3 and 45%) compared to the pre-lockdown period | • It is quite challenging to control the ground-level $O_3$ formation is even by reducing the emissions of primary air pollutants significantly | a | No |
| (Rodríguez-Urrego and Rodríguez-Urrego 2020) | 50 most contaminated (2019) capitals of the world (12% of the | • Air quality data (AQI and $PM_{2.5}$) before and during the lockdown period | $PM_{2.5}$ | • Comparison of air quality with respect to $PM_{2.5}$ before and during the quarantine of each capital city. | • During the lockdown, Europe maintained a Good AQI level of less than 50 µg/m3, followed by America with a Moderate AQI | • Decrease in the $PM_{2.5}$ concentration during the confinement season, favourably restoring the air quality of most cities analysed | a | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | capitals did not apply any lockdown) | | | | level (57 µg/m3), Asia (82 µg/m3) and Africa (95 µg/m3)<br>• Highest $PM_{2.5}$ reduction in America (22%)<br>• 8 of the capitals (Bogotá, Kuwait City, Delhi, Tehran, Tashkent, Ulaanbaatar, Kabul, and Colombo) that maintain a moderate AQI level in typical days showed a decrease in $PM_{2.5}$ (20%-60%) during the lockdown period | | | |
| (Chen et al. 2021) | 49 cities from 4 provinces in China | • Daily AQI data<br>• Dates of policy changing<br>• Dates of suspensions of public transportation and the dates of reducing bus and subway shifts<br>• Meteorological data (precipitation, atmospheric pressure, relative humidity, temperature, and average wind speed) to control the time-varying change of | AQI ($PM_{10}$, $PM_{2.5}$, $SO_2$, $NO_2$, CO, $O_3$) | • Regression analysis of different types of private vehicle restrictions to find the most effective kinds of restriction policies to reduce air pollution<br>• Heterogeneity analysis for population size and economic development | • Restriction policy for fuel vehicles, local vehicles, and the restriction policy based on the last digit of license plate numbers mostly affects the reduction of air pollution (25.6%, 23.7%, and 22.2% reduction in AQI, respectively)<br>• Private vehicle restriction policy resulted in a reduction in $PM_{2.5}$ (32% in cities with GDP < 3.6X106 | • Effects of private vehicle restriction policy depended on the population size and economic development characteristics of the city | a | Yes |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | | meteorological conditions in every city<br>• Data collection period: 1st August 2019 and 7th February 2020 | | | million yuan, and 31.6% in the cities with a GDP growth rate < 7%)<br>• Effect of the policy varied with the suspension of public transport and the injunction of motor vehicle | | | |
| (Jiang, Zhao, and Fan 2021) | Hebei province, china | • Air quality (hourly concentrations of pollutants) and hourly meteorological data for the period of January to May 2019 and 2020 | $PM_{10}$, $PM_{2.5}$, $SO_2$, $NO_2$, CO, $O_3$ | • Decreasing ratio (DR) was calculated for each air pollutant.<br>• Probability Distribution Function (PDF) analysis of 2020 air quality data<br>• Significance of the difference of air pollutants between the two periods was tested with the two-sample t-test<br>• Occurrence frequency of clean, moderate, and pollution events during the study periods (2019 and 2020) | • Reduction in the concentrations of $SO_2$, $NO_2$, $PM_{10}$, $PM_{2.5}$, CO (by 39.2%, 38.2%, 42.1%, 39.8%, and 24.8% for lockdown period, and by 13.7%, 8.9%, 16.8%, 13.4%, and 10.6% for post-lockdown period)<br>• Increase in $O_3$ concentrations (by 8.0% and 5.5% for lockdown and post-lockdown periods) | • Meteorology had a dominant impact on the formation of pollution events. | b | No |
| (Nakada and Urban 2020) | São Paulo state, Brazil | • Daily concentration from February, March, and April of the years 2015, 2016, 2017, 2018, 2019, and 2020 used to calculate the | | • A five-year monthly trend was estimated (2015-2019) using the monthly mean concentrations | • Decrease in CO (up to 64.8%) concentrations (ppm) in city centre<br>• Decrease in NO (up to 77.3%) and $NO_2$ (upto54.3%) | • Though the partial lockdown contributed to air quality improvement, its negative impacts on the social impacts and economy should also be considered. | b | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | | monthly mean concentrations<br>• Before partial lockdown period (4 weeks): 25th February 2020 to 23rd March 2020<br>• During partial lockdown period (4 weeks): 24th March to 20th April, 2020 | | • Comparison between relative change (%) in the mean concentrations during the partial lockdown period and the 5-year monthly trend or to the four-week before partial lockdown | concentrations (µg.m-3) in urban road<br>• Increase in $O_3$ (~ 30%) concentrations (µg.m-3) | | | |
| (Qiu et al. 2021) | Nine major cities of Bangladesh (Dhaka, Rajshahi, Chattogram, Sylhet, Khulna, Barisal, Bhola, Mymensingh, and Rangpur) | • Terra and Aqua MODIS DTB monthly AOD (550 nm) data<br>• The vertical distribution of aerosol subtypes was investigated using the CALIPSO level 1 LIDAR images<br>• Hourly PM data from the CAMS<br>• Level 2 Sentinel-5P TROPOMI based tropospheric $NO_2$ and $O_3$ at 1-Orbit with a resolution of 7×3.5 km (5.5×3.5 km since 30th April 2018) product was obtained<br>• Strict lockdown: March-May 2020,<br>• Partial lockdown: June 2020 | aerosol optical depth (AOD), aerosol subtypes, $PM_{10}$, $PM_{2.5}$, $NO_2$, $O_3$ | • Monthly spatial distribution maps of $NO_2$, $O_3$, $PM_{2.5}$, and $PM_{10}$ generated from the daily observations from March to June 2019 and 2020<br>• Temporal analysis was performed for the cities based on the monthly MODIS AOD, CAMS (PM), and TROPOMI-5P ($NO_2$ and $O_3$) datasets | • Significant reduction in AOD (up to 47% during the strict lockdown, 26th March – 30 May 2020) in all major cities<br>• Significant reductions in $PM_{2.5}$ (37–77%) and $PM_{10}$ (33–70%) during the strict lockdown and partial lockdown<br>• Decrease in $NO_2$ levels (2020) by 3–25% in March (in Rajshahi, Chattogram, Sylhet, Khulna, Barisal, Mymensingh and increased in the rest), 3–43%in April (in Dhaka, Chattogram, Khulna, Barisal, Bhola, and Mymensingh), 12–42%in May ((in Rajshahi, Sylhet, | • Strict lockdown measures significantly improved the air quality conditions over Bangladesh. | b | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | | • Historical data obtained for 2019 | | | Mymensingh, and Rangpur) and 9–35% in June (Dhaka, Chattogram, Sylhet, Khulna, Barisal, and Rangpur) compared to the 2019 data<br>• Increase in $O_3$ levels throughout the country by 3–12% during the strict lockdown and only a slight reduction of 1–3% during the partial lockdown<br>• All types of aerosols decreased during the lockdown | | | |
| (Rahman et al. 2021) | Dhaka, Bangladesh | • Air quality (daily concentrations of the pollutants) and meteorological (Mean temperature (MT), relative humidity (RH), wind speed (WS), solar radiation, absolute humidity, air pressure, etc.) datasets obtained from the ground and satellite-based stations during March-May 2020.<br>• Daily concentrations of these criteria air | $PM_{2.5}$,<br>$NO_2$, $SO_2$, CO, and $O_3$ | • Generalised additive models (GAMs) framework to determine the effects of meteorological variables and adjust for probable static and time-varying relationships<br>• Three types of wavelet analysis, including Wavelet Transform Coherence (WTC), Partial Wavelet Coherence (PWC), and Multiple Wavelet | • No actual coherence between the COVID-19 infection rate (IR) and the air quality parameters (from wavelet coherence analysis), though IR had some coherences with the meteorological parameters (mean temperature and relative humidity)<br>• Significant coherence between the COVID-19 IR and the air quality | • A sudden reduction in air pollution was triggered by the lockdown policy in Dhaka city<br>• The highest pollution reduction effect was found during partial lockdown<br>• The containment policy did not have any crucial impact on modulating COVID-19 infection.<br>• The air quality parameters couldn't be explained as a COVID-19 transmission modulator. | c | Combined in the MWC analysis |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | | pollutants estimated with AQI conversion calculator<br>• Three time periods:<br>• before lockdown (8th March to 25th March), full lockdown<br>• (26th March to 10th April), and partial lockdown (11th April to 15th May). | | Coherence (MWC), were used to investigate the relationship between environmental parameters and the COVID-19 infection rate in Dhaka city<br>• Monte Carlo simulation method was used to test the significance of the outcomes of the coherence analyses<br>• RF (random forest) model to measure the importance degree of various contributing factors | parameters, when combined with mean temperature and relative humidity (from MWC analysis)<br>• A 1-unit increase in long-term exposure to $O_3$ and CO (lag1) was associated with a 2.9% (95% CI: -0.3%, 5.6%), and 53.9% (95% CI: 0.2%, -107.9%)] decreased risk of COVID-19 IR during the full lockdown period (from GAM analysis)<br>• MT and RH were found to be the most important parameter related to the COVID-19 cases, followed by $O_3$ and $PM_{2.5}$ (from the RF model's variable importance)<br>• 20.4%, 26%, 17.5%, 9.7% and 8.8% overall reduction in $NO_2$, PM 2.5, $SO_2$, $O_3$, and CO concentrations, respectively | | | |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| (Ropkins and Tate 2021) | United Kingdom | • 1-Hour resolution 1st January 2015 to 30th June 2020 air pollutant time-series from Automatic Urban-Rural Network (AURN) monitoring stations classified as 'Urban Traffic,' 'Urban Background' and 'Rural Background.'<br>• 2020 Automatic Traffic Count (ATC) data | NO, $NO_2$, $NO_x$, $O_3$, $PM_{10}$, $PM_{2.5}$ | • Break-point/segment methods were applied to air pollutant time-series from the first half of 2020 to yield an independent estimate of the timings of discrete changes in the pollutant time-series obtained from monitoring stations across the country | • NO, $NO_2$ and NOx concentrations reduced by (on average) 32% to 50% at roadsides during lockdown<br>• $O_3$ concentration increased by (on average) 20% on lockdown<br>• A gradual increase in the concentrations of Nitrogen oxides was observed after the initial abrupt reduction as vehicles returned to the road.<br>• Approx. 50–70%, of the air quality benefits observed during the lockdown had been offset by the return of the vehicle by the end of the study period (30th June 2020)<br>• Observed trends for both $PM_{10}$ and $PM_{2.5}$ were highly inconsistent with an air quality response to the lockdown | • Lockdown was not a major source of change for UK particulates as indicated by the change points | b | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| (Wu et al. 2021) | Shanghai, China | • Air quality data: Hourly ambient air pollutant (roadside and non-roadside) concentrations during the lockdown (1st January to 12th April) in 2020 and the same period averaged over the two previous years (2018–2019)<br>• Meteorological data: Hourly temperature, wind speed, wind direction, relative humidity, and pressure data in the same time span as for air quality data | $NO_2$, $PM_{2.5}$, $PM_{10}$, $SO_2$, CO, and $O_3$ | • Temporal variations in pollutants between the roadside and non-roadside stations during 2018–2019 and 2020 were assessed<br>• Pollutant variability in each station under different lockdown measures was assessed, and their values were compared to those from the same periods in previous years.<br>• Spearman's correlation analysis was used to evaluate the inter-relationships between the different air pollutants over the historical and current periods | • Reduction in the concentrations of $NO_2$, $PM_{2.5}$, $PM_{10}$, $SO_2$ by ~30–40% at each station during the COVID-19 pandemic compared to 2018–2019<br>• Moderate decline in CO concentrations (28.8% at roadside stations and 16.4% at non-roadside stations)<br>• Increase in $O_3$ concentrations by 30.2% at roadside stations and 5.7% at non-roadside stations<br>• The highest reduction of primary pollutants observed during the full-lockdown (by 34–48% in roadside stations and 18–50% in non-roadside stations)<br>• Most significant increase in the $O_3$ levels during full-lockdown (by 64% in roadside stations and 33% in non-roadside stations)<br>• Significant decrease in the Spearman's rank | • Increased $O_3$ concentrations could result from the declined NOx emissions from vehicles, which lowered $O_3$ titration. | b | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
|---|---|---|---|---|---|---|---|---|
| | | | | | correlation coefficients between $NO_2$ and other pollutants whereas increased values between $NO_2$ and $O_3$ at roadside stations | | | |
| (Dang and Trinh 2021) | 164 countries | • High-resolution global $NO_2$ data from monitoring satellites<br>• Station-based $PM_{2.5}$ data<br>• $PM_{10}$, $SO_2$, $O_3$ data for robustness checks<br>• Station-based AQI data<br>• Daily rainfall and temperature data at the sub-national level<br>• Global mobility data (for 132 countries)<br>• Data collection period: 1st October 2019 – 1st June 2020. | $PM_{2.5}$, $NO_2$ | • Regression Discontinuity Design approach to analyse the daily, sub-national and national level air quality data before and after the pandemic<br>• Discontinuity test to validate the RDD<br>• A set of placebo tests to check for the robustness<br>• For further robustness checks:<br>• Optimal bandwidth selection to minimise the mean squared error<br>• Additional covariates to control for the pre-pandemic country characteristics<br>• A weekly indicator to control for the substantial daily variation of the air pollutant data | • Using the optimal bandwidth selection, it was observed that the global concentrations of $PM_{2.5}$ and $NO_2$ decreased by 4% and 5%, respectively<br>• Mobility restrictions due to the lockdown were found to be a possible explanation of the air quality improvement. | • Cloud cover could bias the results of monitoring satellite by obscuring the sense of view of the lower atmosphere | c | |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | | | • A new index was created based on the PCA method for all the dimensions of the stringency index<br>• Heterogeneity analysis was performed to check if the lockdown impacts differ by country characteristics | | | | |
| (Ming et al. 2020) | China | • Real-time air quality data (aggregated into a daily-city panel consisting of 367 cities)<br>• Population travel data<br>• Sampling period: from 30 days before the Chinese New Year holiday to 45 days after, 2019 and 2020 | $PM_{2.5}$, $PM_{10}$ | • Comparison of the mean difference in air quality between the treatment group and control group before and after the Spring Festival<br>• A difference-in-differences (DID) model to investigate the impact of the pandemic on the air quality status of firms with the delayed resumption of production<br>• To check for further robustness, sample width was changed, and a placebo test was performed<br>• Heterogeneity analysis was performed to check if the intensity of | • Significant decrease in $PM_{2.5}$ and AQI levels by 7 µg.m-3 and 5 points, respectively, due to the delayed resumption of work during the lockdown period<br>• Coefficients for $PM_{10}$ became insignificant<br>• Besides the pandemic, both reductions in production intensity and population travel intensity served as pathways to air quality improvement.<br>• An increase in the GDP per capita by approximately US$103 as a result of air quality improvement was estimated | • Delayed reproduction of enterprises has indeed resulted in improved air quality<br>• The temporary effect of the COVID-19 pandemic on air quality improvement. | c | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | | | policy implementation differed by city characteristics | | | | |
| (Sahoo, Chauhan, et al. 2021) | Major cities of Punjab (Amritsar, Bathinda, Jalandhar, Ludhiana, and Patiala) and Chandigarh, India | • Concentrations of the air pollutants and meteorological data, including temperature, relative humidity, wind speed, and rainfall (1st March 2020 and 10th July 2020)<br>• AQI data<br>• Daily cases of new COVID-19 data (14 March 2020 and 10 July 2020)<br>• Pre-lockdown (PL: 1 March to 24 March 2020),<br>• Lockdown (phase 1.0: 25 March to 14 April 2020;<br>• phase 2.0: 15 April – 3 May 2020;<br>• phase 3.0: 4-17 May 2020;<br>• phase 4.0: 18-31 May 2020),<br>• Unlock periods (phase 1.0: 1-30 June 2020;<br>• phase 2.0: > 1 July 2020) | $NO_2$, $PM_{2.5}$, $PM_{10}$, CO, $SO_2$, $O_3$ | • Spearman rank correlation test to assess the association between air pollutants, meteorological parameters, and COVID-19 incidences<br>• p-values $< 0.01$ were considered to be statistically significant | • Maximum reduction in $PM_{2.5}$ and $PM_{10}$ concentrations (up to -52% and -53.5%, respectively) during lockdown 1.0, but the levels were increasing again during lockdown 4.0 and unlock phases, compared to the pre-lockdown phase<br>• Reduction in $NO_2$ during lockdown 1.0, but the levels remained variable among cities and different lockdown phases and unlock periods<br>• Overall increase in surface-level $O_3$ during the lockdown and unlock phases<br>• Positive correlation between ambient temperature and daily confirmed COVID-19 cases ($r<0.77$, $p<0.01$).<br>• Weak correlation between the | • The study area's hot tropical weather is not much effective in controlling the spread of COVID-19<br>• Particulate materials could lead to the spreading of the coronavirus | a | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | | | | meteorological parameters (relative humidity and wind speed) and COVID-19 incidences<br>• Positive correlation between PM and daily confirmed COVID-19 cases (r<0.55, p<0.01), especially in Jalandhar and Ludhiana. | | | |
| (Sahoo, Mangla, et al. 2021) | Maharashtra, the worst-hit state in India | • Daily average concentrations of the air pollutants<br>• Meteorological data including ambient temperature (AT), rainfall (RF), and wind speed (WS)<br>• Air quality and weather data were obtained for the pre-, during, and post-lockdown periods from 1 January - 3 July 2020<br>• Daily new cases of COVID-19 data between 14th March 2020 and 3rd July 2020 | NO, NOx, $NO_2$, $PM_{2.5}$, $PM_{10}$, CO, $SO_2$, $O_3$, toluene, benzene | • AQI was calculated<br>• Kendall rank correlation to estimate the ordinal association between variables, i.e., air pollutants, meteorological parameters, and COVID-19 incidences (p-value < 0.01 considered to be statistically significant)<br>• EDA plot and Shapiro-Wilk's (S-W) test used as a combination to check for the normality of the dataset<br>• Kruskal-Wallis test performed on the air quality and meteorological datasets to test the significance (p- | • Reduction in averaged $PM_{2.5}$ (up to 51%) and $PM_{10}$ (up to 47%) during the lockdown, and this continued up to 80% during the unlock periods<br>• Significant negative correlation between ambient temperature and air pollutants (r= – 0.35 to – 057)<br>• No improvement (increased in some cases) in $SO_2$ and $NO_2$ concentrations<br>• Strong positive correlation between the COVID-19 incidences and weather parameters [temperature(r<0.62) and dew point(r<0.73)] | • PM reduction due to reduced vehicular traffic and industrial closing resulted in a 'satisfactory' level of air quality index (AQI)<br>• An increase in temperature and dew point cannot minimise the transmission of coronavirus<br>• Population density played an important role in the spreading of the virus | a | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | | | value<0.05) of variation of the pollutants among the different time periods | • Negative correlation between COVID-19 incidences and air pollutants (r = −0.33 to− 0.74)<br>• PM and population density closely linked to morbidity and mortality | | | |
| (Sulaymon et al. 2021) | Wuhan, China | • Hourly concentrations of the air pollutants from 11 monitoring stations<br>• Meteorological data (temperature, wind speed, wind direction, and relative humidity)<br>• Three time spans: before (1-23 January 2020),<br>• during (24th January - 5th April 2020),<br>• after the COVID-19 lockdown (6th April - 20th June 2020) periods | $NO_2$, $PM_{2.5}$, $PM_{10}$, CO, $SO_2$, $O_3$ | • To investigate the impacts of the lockdown (LD) measures on air quality, the data for the three periods were compared using Kruskal-Wallis One Way ANOVA on Ranks test<br>• Comparisons of the 1-hr concentrations of the pollutants for the same time interval of the lockdown period for each of the last four years (2017–2020) using Kruskal-Wallis One Way ANOVA on Ranks and Dunn's tests<br>• Pearson correlation analysis to investigate the relationships between the six air pollutants and the three meteorological | • Decrease in the concentration of $NO_2$, $PM_{2.5}$, $PM_{10}$, CO by 50.6%, 41.2%, 33.1%, and 16.6%, respectively during the lockdown<br>• Increase in the $O_3$ levels by 149% during the lockdown<br>• An additional decrease in the concentration $PM_{2.5}$, CO, $SO_2$ by 19.6%, 15.6%, and 2.1%, respectively, after the lockdown<br>• Increase in the $NO_2$, $O_3$, and $PM_{10}$ levels by 55.5%, 25.3%, and 5.9%, respectively, after the lockdown compared to the lockdown period<br>• Negative correlation between wind speed | • Reduced NOx emissions had a strong influence on the increasing $O_3$ levels during the lockdown.<br>• Additional control strategies are required to continue to improve air quality. | a, b | No |

| Study author (year) | Location | Data | Pollutant type | Model type/ Methodology | Findings | Comments | Category | Meteorology control |
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| | | | | variables (temperature, wind speed, and relative humidity) during the three study periods<br>• Backward trajectory analysis to trace the sources and the transport pathways of air masses during the three study periods | and the other pollutants (except CO and $SO_2$) during the three period<br>• Relative humidity inversely related to all the pollutants<br>• Positive correlation between temperature and the pollutants during the lockdown | | | |
| (Zangari et al. 2020) | New York City, United States | • Daily concentrations of the pollutants from 15 central monitoring stations for the first 17 weeks (January to May) of 2015-2020 | $PM_{2.5}$, $NO_2$ | • A time-lagged linear regression model to test for significant differences between pollutants' concentrations by year.<br>• An ANCOVA was conducted using an F-test for Type III sums of squares on the model to test for homogeneity of the intercepts and slopes of each year and the results for the various intercepts. | • Reduction in $PM_{2.5}$ (36%) and $NO_2$ (51%) shortly after the shutdown was implemented<br>• No variation in air quality between 2020 and 2015-2019 according to linear time lag models | • It is important to consider the temporal variability and long-term trend of the pollutant concentrations when analysing short-term pollution changes. | b | No |

**References of the articles included in Appendix C**


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**University of Leeds**
Institute for Transport Studies
Leeds
LS2 9JT
United Kingdom
Tel: 0113 343 5325
Email: info@its.leeds.ac.uk
Web: www.leeds.ac.uk