The Effect of Air Pollution on Cognitive Performance of Children
Evidence from Bengaluru, India

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Disclaimer:

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List of Acronyms

AQI	Air Quality Index
BoY	Beginning of Year
CPCB	Central Pollution Control Board
ECE	Early Childhood Education
EoY	End of Year
HEI	Health Effects Institute
ISS	Institute of Social Studies
KEF	Key Education Foundation
MOEF	Ministry of Environment, Forest and Climate Change
NAMP	National Air Quality Monitoring Programme
NGO	Non-Governmental Organization
OLS	Ordinary Least Squares
UNEP	United Nations Environment Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNICEF	United Nations Children's Fund
USEPA	United States Environmental Protection Agency

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Abstract

Air pollution has been found to have negative effects on various aspects of human life. However, the burden of these effects are disproportionately shared by certain groups, including children. Research on effect of air pollution on cognitive performance started to surface post the first decade of the 21st century, however most of them are set in context of a developed country. There were also very few research that studied these effects for children in the age group of 4-6yrs. This study contributes to the literature on both these fronts. Using test scores of 539 children in the age-group of 4-6yrs, the relationship between air pollution and cognitive performance is studied. The OLS estimates provide mixed results of $PM_{2.5}$, CO and O_3 being positive and statistically significant, indicating a marginal (less than 1 more correct answer in all three cases) increase in number of correct answers given by a child with a unit increase in these pollutants. However, a unit increase in NH_3 decreases the number of correct answers given by a child by almost 2 answers (-1.66). Although, the study cannot provide any conclusive direction for the effect of air pollution on cognitive performance, it provides a direction for exploration of the effects of the NH_3, a resultant pollutant from poorly managed waste (including human and animal waste) on individuals forced to live in close proximality to it, especially in urban cities like Bengaluru.

Relevance to Development Studies

Performance on tests in schools/universities has a large influence on the life outcomes of an individual. Air pollution is found to be negatively (and disproportionately) affecting individuals, and having an impact not just on health but aspects of their cognitive abilities as well. The disproportionate exposure to such pollutants has the potential to increase the existing social gaps by burdening the poor. Attention of researchers, policy makers, school authorities, parents and individuals to taken actions towards minimising pollution and providing environment justice to all thus becomes important.

Keywords
Air pollution, cognitive performance, India, Bengaluru, children

Chapter 1
Introduction

As per a story published on the website of the World Bank, in 2017 "more than 90% of the world population was exposed to unhealthy air" (Pirlea *et al.*, 2019). The State of Global Air Report by HEI (2019) ranked air pollution to be the 5th cause of mortality across the globe in 2017. Like all other global problems, "the burden of air pollution is not evenly shared" (American Lung Association, 2021). The poor, people from some racial and ethnic groups, the elderly and children are more impacted by air pollution than the rest (American Lung Association, 2021; UNEP, 2021). Developing countries too are more severely affected than developed countries (UNEP, 2019).

If we go by rankings, "India continues to dominate annual $PM_{2.5}$ rankings by city - 22 of the top 30 most polluted cities are located in India" (IQAir, 2021a, p.22). As per the 2011 Census data, more than 8 million children in India are living in slums[1] (Ministry of Housing and Poverty Alleviation, p.32, 2015). The intersectionality of these two facts exposes a large group of children in India to the harmful effects of air pollution. This motivated this thesis to be focused on the effects of air pollution on children in India.

There is an abundance of research done on the health effects of air pollution, however, the literature on the effect of air pollution on cognitive performance is relatively new. Additionally, as per my knowledge, there are only two such studies based in the context of a developing country, Bedi *et al.* (2021) and Balakrishnan *et al.* (2021). All of these factors contributed to channelling this research towards exploring the effect of air pollution on a child's cognitive performance in India. The study is set in the context of a metropolitan city in the southern state of Karnataka in India and uses data on air quality and test scores of 539 children to analyse the problem at hand.

This study is an attempt to draw attention towards the menace caused by air pollution especially to those who have possibly done nothing to cause it, i.e. the children. There is an urgent need to attend to this issue and this study can be seen as a means that could pave the way for more research and action in this area, especially in India.

The rest of the thesis is organised as follows: Chapter 2 presents a background to the study. Chapter 3 reviews the literature on air pollution and cognitive performance. Chapter 4 informs about the research methodology of the study – the data used for analysis and the descriptive statistics. Chapter 5 includes the hypotheses and the empirical strategy to test them. Chapter 6 presents the results followed by a discussion in Chapter 7 and a conclusion in Chapter 8.

[1] Slums are densely populated areas in urban cities with poor living conditions.

Chapter 2
Background

This section provides a brief background on air pollution. It motivates the choice of children as the focus group for this study. The mechanism through which air pollution could affect cognitive skills is explained in this chapter. This section also provides an insight into the problem of air pollution in India, with a focus on Bengaluru.

2.1 Air Pollution

Any form of harmful substance added to the environment can lead it to be termed 'polluted'. Pollution can be observed in various forms, however, the three most broadly categorized types of pollution are air, water, and land. In this study, the focus is on air pollution mainly due to the severity and scale at which it has been affecting people. With each passing day, we are learning more about the challenges caused by air pollution. It has been tagged as "one of the world's biggest health hazards" (IQAir, 2021a, p.4). Being responsible for 7 million premature deaths annually, 600,000 of them being children, (IQAir, 2021a, p.4) the problem demands attention.

Although air pollution can be caused by natural activities like volcanic eruptions, sea spray and lightning, the main contributor to it is human activities (UNEP, 2021). Industrial activities, non-environmentally friendly methods of cooking, poor management of waste, and toxins released from vehicles are some of the most prominent contributors to toxins in the air. Each of these activities may release different kind(s) of toxins which may have severe harmful effects.

There is a difference between outdoor air and indoor air. The USEPA (2021a) highlights that indoor air quality may be worse than outdoor air and this is a matter of serious concern for individuals who spend a large chunk of their time indoors. Poor ventilation, high temperature, and humidity levels can all aggravate the problem (USEPA, 2021a). In addition to the entry of pollutants from the outdoors, the indoor air pollutants could be from sources like the burning of oil, kerosene, coal, wood, tobacco products, and material used for the construction of the building. (USEPA, 2021a).

For this study, we have access to information regarding outdoor air pollution. Due to logistical constraints posed by COVID-19, it was difficult to gather real-time data from test centres and hence we rely on data provided by stations monitoring outdoor pollution levels for the area within 5kms air radius from the test location.

2.1.1 The Pollutants

There are five recognized pollutants by the USEPA namely, ground-level ozone, particle pollution (or particulate matter $PM_{2.5}$ and PM_{10} , carbon monoxide CO, sulphur dioxide SO_2 and nitrogen dioxide NO_2 (AirNow, 2021). The pollution board of India, CPCB identifies 12 pollutants however for making AQI dynamically available, CPCB relies on the five pollutants recognized by the USEPA plus Ammonia NH_3, and Ozone O_3 This study captures information about these seven pollutants for the test dates. The next few paragraphs explains the source and effects of each of these pollutants.

Particulate Matter (PM) is a combination of solid and liquid particles present in the air (USEPA, 2021b). Some of them are like dust, dirt, smoke which are visible to the naked eye while others are very small and can be observed only under a microscope (USEPA, 2021b). The two particulate matters that are categorised as pollutants are $PM_{2.5}$ and PM_{10}, one with a diameter of 2.5 micrometres and the other with 10 micrometre or smaller. For reference, the diameter of a single strand of human hair is 70 micrometre. PM is both directly emitted in the air from sources like construction sites, fields, unpaved roads or fires and formed in the atmosphere as a result of chemical reactions between chemicals like sulphur dioxide and nitrogen oxides emitted from vehicles, industries and power plants (USEPA, 2021b). $PM_{2.5}$ and PM_{10} pose great risks to individuals since they are small enough to be inhaled and get deep into the lungs and sometimes even get into the bloodstreams (USEPA, 2021c). These particles can pose serious harm to health by targeting the lungs and the heart and the most vulnerable group are children, older adults and individuals with pre-existing heart or lung diseases (USEPA, 2021c). The effects can range from irritation of the airways, coughing or difficulty in breathing, aggravated asthma and sometimes even premature deaths (USEPA, 2021c).

Carbon Monoxide (CO), is a colourless and odourless gas, with vehicles and machines that burn fossil fuels being its greatest source outdoors (USEPA, 2021d). However, very high levels of CO are often found only in indoor spaces or closed environments and can cause dizziness, confusion, unconsciousness, impaired vision and coordination and even death at high levels of concentration (USEPA, 2021d; USEPA, 2021e). When an individual inhales air with high concentrations of CO, there is a reduction in the amount of oxygen that can reach the blood stream in the heart and the brain (USEPA, 2021d). The sources of indoor CO are unvented kerosene and gas heaters, gas stoves and leaking chimneys and furnaces (USEPA, 2021d).

Ozone O_3, found at ground-level is said to be a harmful pollutant. Unlike some pollutants, it is a resultant of chemical reactions between oxides of nitrogen and volatile organic compounds, i.e., when pollutants from vehicles, industries and other sources react while there is sunlight (USEPA 2021f). The people most at risk to be affected by ozone are people who spend a lot of time outdoors and people with asthma (USEPA, 2021g). It poses a great risk to children since their lungs are still developing, they are more likely to be playing outdoors, and they are more susceptible to asthma than adults (USEPA, 2021g).

Sulphur dioxide (SO_2) is another pollutant emitted in the atmosphere by burning of fossil fuels in power plants and industries (USEPA, 2021h). They affect our respiratory systems and cause difficulty in breathing especially for children with asthma (USEPA, 2021h). Another mechanism through which (SO_2) affects us is when it chemically reacts with other pollutants in the atmosphere to generate particulate matter (USEPA, 2021h).

Burning of fossil fuel generates another hazardous pollutant called Nitrogen Dioxide (NO_2). Its main source of formation is emissions from trucks, buses and cars (USEPA, 2021i). With children and asthma patients facing the brunt of its effect the most. Short term exposure to NO_2 can lead to coughing, wheezing or difficulty in breathing while a long-term exposure can exacerbate asthma and respiratory infections (USEAP, 2021i).

Ammonia NH_3, is another pollutant which is corrosive, colourless and has a distinct, pungent odour. It is both an air pollutant by itself and is formed in the atmosphere when it chemically reacts with nitric acid and the sulphates present in the air to add to atmospheric particulate matter by 5-20% (IQAir, 2021c). The main sources of NH_3 are decaying organic matter, and human and animal waste (natural sources), and fertilizers, industries, and waste disposal sites (manmade sources) and its long term effects include cardiovascular and respiratory effects, asthma aggravation and premature deaths (IQAir, 2021c).

2.2 Air Pollution and Cognitive Abilities

Various studies have highlighted that exposure to toxic elements in the air has detrimental health effects on both children and adults. The length of the exposure also plays a role in determining the severity of health effects. Longer the exposure, the graver the severity. Miller *et al.* (2013, p.4) provides an extensive review of literature highlighting acute and chronic health effects, particularly for children.

However, the effects are not limited to health. There has been a growing body of work that has been finding associations between air pollution and cognitive performance. The early associations started to be drawn between air pollution and absenteeism (Gillilan, *et al.,* 2001, and Currie *et al.* 2009), and pollution and productivity (Zivin et al., 2012; Chang et al., 2016). This inspired researchers like Zweig *et al.* (2009), Mohai *et al.* (2011) and Miller *et al.* (2013) to start looking for the relationship between air pollution and academic performance, and Lavy *et al.* (2014) to study the relationship between pollution and cognitive performance. They all echoed a similar argument in their papers, i.e. air pollution has negative effects on humans beyond health.

Cognitive performance have been defined in a range of ways in the existing literature - university test scores (Roth, 2016), matriculation certificate examination (Lavy *et al.,* 2014; Ebenstein *et al.,* 2016), cognitive tests in the form of mathematics and word recognition tests (Zhang *et al.,* 2018); cognitive tests checking for simple and complex attention, arithmetic processing speed, fluid reasoning and working memory (Bedi *et al.* 2021) and academic performance in math and reading tests (Stafford, 2015; Balakrishnan *et al.,* 2021)

The study by Marcotte (2017) and Shier *et al.* (2019) is based on child outcomes from Early Childhood Longitudinal Surveys of children in kindergarten. The survey includes information about the child's cognitive, health and developmental outcomes, and their family, teacher and school backgrounds. Both studies uses math and reading test scores to assess children's cognitive outcomes.

In the current study, data is available from tests conducted by Key Education Foundation, an NGO in India, Bengaluru, to assess a child's school readiness twice in the academic year 2019-20. The test includes 37 questions assessing for a range of skills including self-awareness, fine motor skills, gross motor skills, cognitive development, numeracy, language development and social and emotional learning as mentioned by the organization. All these skills are highly interrelated and have overlaps and interactions. The National Research Council (2015, pp. 85-86), indicates that these domains are "not easily separable". Hence, in this study, these test scores are used as an indicator of children's cognitive performance.

2.2.1 Mechanism

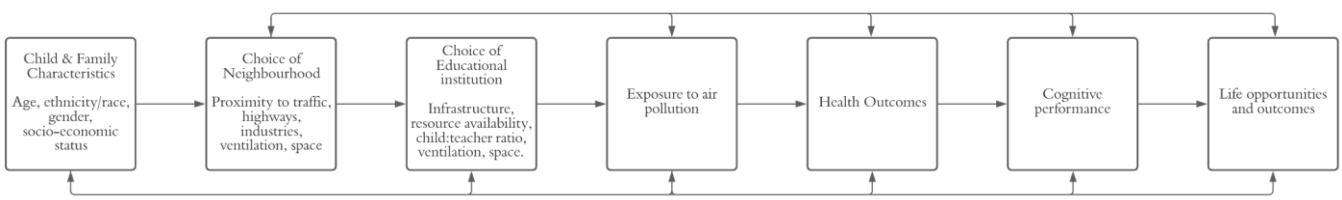
The health effects of the key pollutants are well known and established as discussed in section 2.1.1, however, the mechanism by which pollutants affect cognitive performance or other related outcomes is still unknown (Bedi *et al.,* 2021, p.3*;* Balakrishnan *et al.,* 2021, p.12).

Researchers have speculated a range of possibilities. Zweig *et al.* (2009) postulate four possible pathways - (i) school absenteeism due to health issues caused by pollution, (ii) inattentiveness in school due to health issues caused by pollution, (iii) fatigue while studying at home due to health issues caused by pollution, and (iv) pollution negatively affecting brain development. Marcotte (2017), Bedi *et al.* (2021), and Balakrishnan *et al.* (2021) echo similar thoughts. The latter goes on to add, teacher absenteeism and avoidance behaviour from parents where they choose not to send children on highly polluted days as another set of potential mechanisms that could lead to lower cognitive performance with increasing pollution. Shier *et al.* (2019) also provide a similar framework. In the framework, child and family characteristics are said to have an effect on the neighbourhood choices made by families, and both, directly and indirectly, increase exposure to air pollution. From there on, the pathway discussed are similar to the previous literature.

The mechanism proposed in this paper is aligned with the literature discussed above along with the proposal of two additions. First, the child and family characteristics and neighbourhood choices both define the school the child is enrolled in (Denessen *et al.,* 2007; Bhattacharya *et al.,* 2015). Based on the information collected from the NGO, it is found that the children are enrolled in schools closer to their homes (within 5-10km radius). Family characteristics like number of children, education level of parents, their economic status, etc. also influences the choice of school for children. This acts as an additional factor in the level of air pollution exposure of the child since children spend a significant amount of time of their day at school (9A.M – 3P.M for children in this study). Second, the health and test outcomes determine the life outcomes of the child. That would have an influence on the next generation thereby creating an endless loop.

Adapted from Shier *et al.* (2019, p. 349), Fig.1 depicts the pathways through which exposure to air pollution could increase and subsequently affect the health, cognitive, and life outcomes of an individual and their upcoming generations.

Figure 1: Conceptual Framework



Source: Adapted from Shier *et al*. 2019, p.349

2.3 Air Pollution and Children

UNEP (2018) states that 17 million babies around the world are exposed to toxic air and unborn and new-born babies, and children are one of the most vulnerable groups to the negative effects of air pollution. Exposure to polluted air in the early (and developmental) stages of life "can hinder lung growth, inhibit brain development and increase the risk of conditions such as asthma" (UNEP, 2018).

A report by WHO (2018, p.4), also highlights children's heights and breathing pace as reasons for their increased susceptibility to the harmful effects of air pollution. Due to their short height, children are closer to the emissions made by vehicular exhaust pipes and exposed to more air pollution than adults while walking on a busy road. They also "live closer to the ground" (WHO, 2018, p.4) which is where some pollutants attain their peak concentrations. Children also breathe faster increasing the amount of air and thereby pollutants they inhale (WHO, 2018, p.4).

Of the deaths attributable to air pollution in 2016, 8% were children under the age of 5 as compared to 1% between the age of 5-15 (UNEP, 2018). It is also recognized that the problem of air pollution is exacerbated in urban areas (UNICEF, 2016, p.22; UNEP, 2018). All these factors together motivated this study which focuses on kindergarten children, primarily between the age of 4-6. These children are also from low-income families, which increases their risk of being exposed to polluted air (UNICEF, 2016, p.38). Additionally, these are children who attend a school within their neighbourhood and often walk to school through highly congested areas in terms of traffic, compounding the existing list of risk factors for them (UNICEF UK, 2019, p.10).

2.4 Air Pollution and India

If we go by rankings, India dominates the list of the most polluted cities globally, with 22 of the top 30 cities situated in India (IQAir, 2021a, p.22). Although the AQI has been improving post 2018, the pollution level in the country is still dangerously high (IQAir, 2021a, p. 22). As per the AQLI (2021a), an average Indian's life expectancy would increase by 5.9 years if the WHO guidelines on PM2.5 were met, and 3 years if India met its own national standards. The situation is extremely severe in the states in the Indo-Gangetic planes like Uttar Pradesh and Delhi where people stand to lose more than 7 years of life if the pollution levels from 2019 continue to exist (AQLI, 2021a).

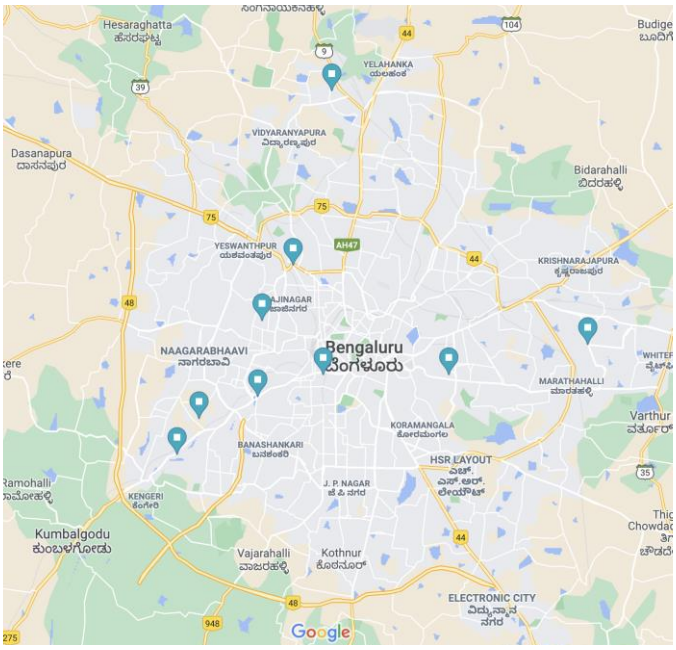
The north of India has taken the brunt of air pollution when compared to the rest of country due to reasons including high population density implying higher levels of pollution from vehicular, residential and agricultural sources (AQLI, 2021b). However, when compared to the developed countries in the world like the US, even south Indian cities like Bengaluru, fare worse than the most polluted cities in the US (Anien, 2020).

2.4.1 Bengaluru, India

Bengaluru is the capital of the southern state of Karnataka. With a boom in the IT sector, the city is recognized as the 'Silicon valley of India'. The population in the city has grown exponentially in the last few decades and industrialisation has been attributed to abnormal and unplanned growth (Puttaswamy in Sastry, 2020). This has led to an increase in various kinds of pollutants, poor management of garbage and sewage, and brought about various infrastructural issues as well (Puttaswamy in Sastry, 2020). The city has become susceptible to increased vehicular traffic and excessive construction activities. These are the key factors contributing to the air pollution in the city as well (Anien, 2020).

There are various ongoing initiatives by the government of India to tackle the problem of air pollution. National Air Quality Monitoring Programme (NAMP) is one of them. At present, the programme has a network of "703 manual operating stations covering 307 cities/towns in 29 states and 6 Union Territories of the country" (MOEF, 2019, p.10). One of the actions taken under NAMP is the regular monitoring of four pollutants, $PM_{2.5}$, PM_{10}, SO_2 and NO_2. Bengaluru is one of the cities where regular monitoring is conducted. The monitoring data available for Bengaluru is available from 2013 onwards. There were 8 monitoring stations[2] (See Figure 2) under NAMP in Bengaluru until 2016 and a 9th one was added in 2017. Data on PM_{10}, SO_2 and NO_2 is available from 2013-2019. Tracking of $PM_{2.5}$ started from 2015 in one station and was eventually scaled to other stations. Graph 1 shows the averages of the 4 pollutants in the city between 2013-2019.

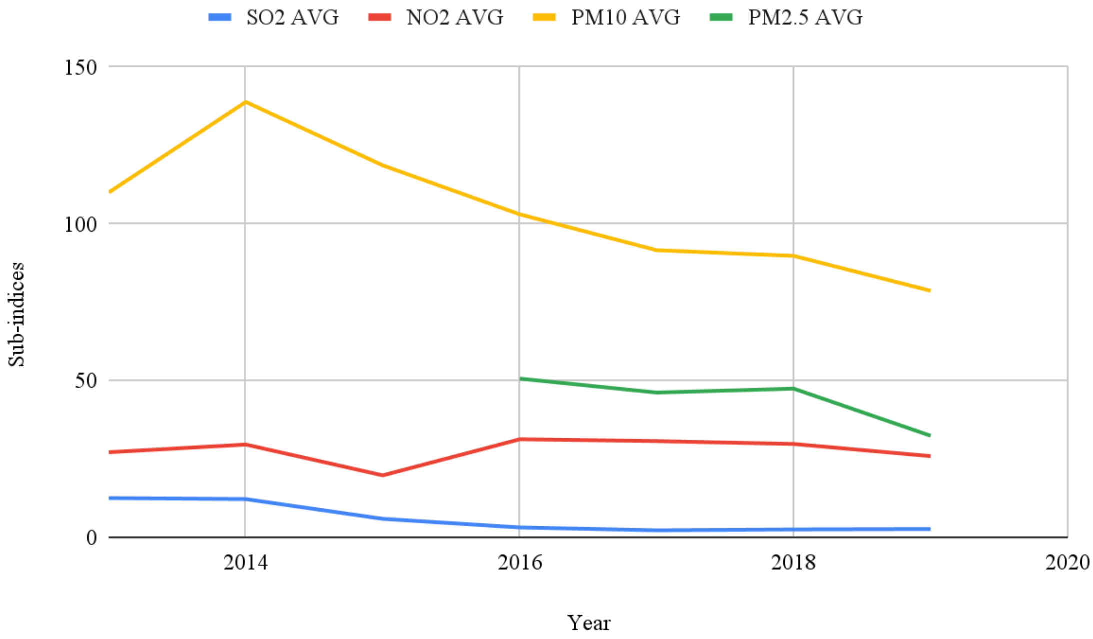
Figure 2: NAMP Monitoring Stations in Bengaluru



Source: CPCB, 2021d

[2] (1) Graphite India, White Field Road, (2) Yeshwanthpura police station, (3) Peenya Industrial Area, (4) KHB Industrial Area, Yelahanka, (5) AMCO Batteries, Mysore Road, (6) Jnanabharathi, Bangalore University, (7) TERI office, Vital Medi healthcare Pvt Ltd, (8) Victoria hospital, were the 8 monitoring stations under NAMP until 2016. In 2017, another monitoring station was added at (9) RV College of Engineering, Mysore Road.

Graph 1: Pollution Trends in Bengaluru between 2013-2019 as per NAMP Monitoring Stations



Source: CPCB, 2021d

Aligning with the national trend, the pollution in Bengaluru too seems to be on the path of improvement. However, Bengaluru continues to be in the list of non-attainment, cities categorized by NAMP, indicating that Bengaluru is still violating the national standards set for air quality.

One of the objectives of the NAMP programme is to identify the cities where the national air quality standards are violated and thereby identify them as non-attainment cities (MOEF, 2019, p.10). Bengaluru, the city of interest in this study is one of the 102 cities that fall under the list of non-attainment cities (MOEF, 2019, pp.16-18). This indicates that air quality standards are being violated in the city of Bengaluru and its residents, especially children, are vulnerable to the negative effects of air pollution.

As per a newspaper article, between 2015-2020 the city has witnessed a rise of 80% in respiratory illnesses alone (Anien, 2020). Undoubtedly, there are other parts of the country, like Delhi and the areas around it, where both the level of air pollution and the issues associated are perhaps more challenging, however, attention is needed towards cities like Bengaluru, where pollution may not be as high as in the most polluted cities in the country but violations in national air quality standards are observed. Resources allocated to these areas, in terms of research and fund allocations could ensure early action and prevention from irreversible damages that severely polluted air is likely to cause.

Chapter 3
Literature Review

The health effects of air pollution have been widely studied. Associations between air pollution and mortality started to surface from the early 1930s (Pope *et al.,* 1995, p.2). From then on, our understanding has only improved. In a review study conducted by Pope *et al.* (1995, pp.13-14), it is highlighted that various studies report associations between human health issues like increased cardiopulmonary mortality, hospitalization due to respiratory issues, increase in cases of asthma, and decline in lung function due to acute and/or chronic exposure to air pollution. Today, as per the UNEP (2021), air pollution contributes to 43% of deaths from chronic obstructive pulmonary disease, 24% deaths from ischemic heart disease, 25% from stroke and 29% from lung cancer.

While there is an abundance of literature that highlights the negative health effects of air pollution on individuals, more recently, a little longer than the last decade, researchers have started to explore the effects of poor quality air on various aspects other than health. In this research, the key area of interest is the effect of poor quality air on children's cognitive performance. This section provides a review of the existing literature focusing primarily on the relationship between air pollution and cognitive performance.

Literature around this subject is still fairly new and limited to examples and evidence from developed countries. To the best of my knowledge, there is only one paper, Balakrishnan *et al.* (2021), which provides evidence from India, the country of interest in this study.

This section is further divided into two parts. In the first half, the focus is on relevant literature available from the developed world while the second half focuses on the literature that is set in the context of the developing world. The review of literature is organized mostly in chronological order, with an attempt to trace the origins of the idea of exploring the relationship between exposure to air pollution and cognitive performance and find inspiration and incentive for this study. Towards the end, the relevance of this study is also discussed.

3.1 Air Pollution and Cognitive Performance

Post the first decade of the 21^{st} century, studies highlighting the impact of air pollution beyond health started to surface. A number of researchers examined the association between air pollution and worker productivity (Zivin *et al.*, 2012; Chang *et al.,* 2016). These studies inspired Lavy *et al.* (2014) to recognize that cognitive performance is closely linked to productivity and by transitive properties, could be linked to air pollution.

The work by Lavy *et al.* (2014) examined the relationship between short-term exposure to air pollution and cognitive performance based on the Bagrut examination (matriculation certificate) in Israel conducted for grades 10-12 students (aged 16-18 yrs.)for enrolment in university. Based on test data from almost a decade ago (2000-2002) and the air quality information corresponding to those test dates, , the results highlighted by the authors are of great significance. With particulate matter $PM_{2.5}$ and Carbon Monoxide CO as the main pollutants studied, the results show a statistically significant negative relationship between these two pollutants and test scores. While the magnitude of the result changes based on the specifications, the sign remains the same. Based on OLS estimations, a unit increase in $PM_{2.5}$ reduces test scores by 0.055 points with no controls, while with controls like various individual and family characteristics of the students, the effect increases slightly to 0.065.

Since panel data is available, Lavy *et al.* (2014) specify and estimate three fixed-effects models - that is, city, school and student fixed-effects. Based on the student fixed effects model Lavy *et al.'s (2014),* preferred specification, a unit increase in $PM_{2.5}$, leads to a decline in test results by 0.046. This result indicates that on a day with average pollution of 59.74 AQI, the test scores declines by 0.10sd relative to a test taken on a day with minimum pollution of AQI 10.1. The results for CO mirror the results for $PM_{2.5}$.

Ebenstein *et al.* (2016) add information about the level of education, annual earnings and employment duration in 2010 for the same set of individuals in 2000-2002 dataset to conduct a study on the long-run economic consequences of high-stake exams. In this study, it is proposed that cognitive abilities can be affected by many short term factors like sleep deprivation, noise and transitory air pollution and hence, using such high-stakes exams for determining student performance is unfair. The research is conducted using data about transitory air pollution, with the focus on $PM_{2.5}$ and it is found that transitory exposure to $PM_{2.5}$ reduces student performance in the short-run (the same results as in Lavy *et al. (*2014)) It is also found that enrolment rates in higher education decline by 3 percentage points and schooling declines by 0.15 years due to an increase of exposure by 10 units of $PM_{2.5}$ thereby indicating towards long term effects of taking exams on highly polluted days.

Inspired by studies conducted to understand association between classroom ventilation and reaction time on tasks (Wargocki *et al.*, 2007; Bakó-Biró, 2012), Stafford (2015) studied the impact of indoor air quality and academic performance in Texas school district. Due to passing of a bond[3] focused on improving water intrusion issues and ventilation systems in the state, the schools in the district were allocated with budgets for renovations. Stafford (2015) capitalized on this change and tried to study the effect of improved ventilation on student scores. The study does not include measurement of air pollution in the conventional way, but uses the occurrence and timing of renovations as proxy for indoor air quality. The study is conducted for students in 65 schools and a panel fixed effects approach is undertaken to estimate the relationship. The results from the study show that the average ventilation improvement project increased test scores by 0.14-0.15 standard deviations and improved pass rates by 3-4%.

Research conducted by Braniš *et al.* (2005) provides evidence of a highly significant and positive relationship between outdoor and indoor air pollutant particles. However, Roth (2016) ventures into the effects of indoor air quality by mentioning that previous studies have only focused on ambient pollution, thereby distancing from the study by Braniš *et al.* (2005). The study by Roth (2016) is based on students in a university in the Greater London Urban Area. The indoor air quality data is self-collected by the author and includes information about PM_{10} , CO_2 , and temperature in Celsius. The study has a sample set of 2,418 students. As in the case of the previously mentioned literatures, this study as well uses the panel structure of the available data and estimates models with student and subject fixed effects. The study compliments the existing literature and finds that a unit increase in PM_{10} reduces test score by 0.3 percent of sd.

[3] In 2001, a $49.3 bond was passed by the school board in Texas, USA, to fund renovations in numerous damaged schools in the district.

A paper of prime importance to this study is the one where Marcotte (2017) has provided evidence on the relationship between poor air quality and cognitive performance of children in the age group of 5-8 years old from 20 counties of the United States of America. There are two elements that have been focused on in this paper. One is exposure to poor quality air in early childhood and academic achievement and another is the lifetime exposure and school readiness. To develop this paper, the authors relied on data on math and reading scores available from kindergarten, first grade and second grade for the same set of children. This is the basis that allows the researchers to adopt a panel fixed effects approach for their analysis. However, a major drawback of this paper is the unavailability of the exact date on which the tests were conducted. The researchers rely on period of the exams. For the second focus of the paper as well, where Marcotte (2017) tries to explore the lifetime exposure and school readiness, data on child's residence before kindergarten is unavailable and it is assumed that they did not relocate. These two limitations are concerning. Irrespective, the author conducts the analysis and finds that on days when PM2.5 or pollen levels are high, students math and reading score declines by 1-2 percent. Ozone has a much larger impact on students with a history of asthma. When tested on days with high ozone, asthmatic students score 10 percent less on math and reading as compared to days when they are tested on days with low levels of ozone. Lifetime exposure to pollen is also found to have substantial negative effect on math and reading scores at the beginning of kindergarten for these children.

Similar to the approach of Marcotte (2017), Zhang *et al.* (2018) focuses on both the transitory and cumulative effects of poor air quality on cognitive performance. However, unlike most of the papers discussed above (Lavy *et al.,* 2004; Ebenstein *et al.,* 2016; Roth, 2016; and Marcotte, 2017) that focuses on the younger age group, this paper focuses on a larger range of age for the analysis, from 10 years to more than 65 years in China for a span of 3 years. The main finding of the research is that the negative effects of poor air quality become more pronounced with age. They find that with one unit increase in $PM_{2.5}$, there is a 4 percent decline in verbal scores and 1.5 percent decline in math scores of older adults.

There are studies (Austin *et al.* 2019; Heissel *et al.,* 2019; and Gilraine, 2020) that have imposed a different strategy than the studies highlighted previously. Instead of finding evidence for exposure of poor air quality on cognitive performance, these studies make use of a change that has been made in the environment of the group under study, to directly or indirectly change their exposure to pollution and then evaluate if their cognitive performance has improved as a result of the change.

Austin *et al.* (2019) exploits a diesel retrofit program implemented in the US to reduce the contributions of diesel buses towards air pollution exposure for school children from 3rd grade to 8th grade. The study was conducted between 2007 and 2015 in Georgia. The retrofits are found to have a positive and statically significant effect (0.09sd) on students English test scores. The results for math test scores are not statistically significant.

Heissel *et al.* (2019) exploits variations in wind patterns for schools equidistant from major highways to study the effect of traffic pollution on academic outcomes of middle and high school students. The study finds that students from schools placed downwind of a major highway have lower test scores by 0.04 standard deviation than students from schools that are not located downwind of major highways.

A huge gas leak in the US pushed offending gas companies to install air filters in classrooms only within five miles of the leak and Gilraine (2020) leveraged this situation. Air filters would have reduced the level of exposure children would have to polluted air and the negative effects it had on children. Gilraine (2020) provided evidence for exactly that. Air filters improved mathematics and English scores of children by 0.20sd.

It is appreciated that researchers undertook such studies and brought the conversation about air pollution on the table from a different yet relevant angle. It's effects on cognition is as serious as that on health and this information strengthens and provide incentive to policy makers and the public to work towards creating environments with cleaner air. However, the bulk of literature focuses on the developed world. It is not to say that air is not polluted there but to highlight that the results could be possibly skewed if not in direction, in magnitude since the problem of air pollution is extremely serious in the other side of the world. The next sub-section discusses this in further detail and highlights the results from literature based on the developing world.

3.2 Air Pollution, Cognitive Performance, and Developing Countries

In recent years, the studies focusing on air pollution and its impact beyond health has been getting traction. However, these studies are mostly from the developed world where both the grievousness and impact of air pollution may be much lesser than that in the developing world. As per the 2020 ranking list provided by IQAir (2021d), the top five polluted countries in the world are Bangladesh, Pakistan, India, Mongolia, and Afghanistan. Clubbed with serious pollution issues, these countries face various other socio-economic challenges. It is imperative then that such studies are conducted in these parts of the world to highlight the magnitude of the issue and swiftly work towards the solutions. (Un)surprisingly though, I have come across just two studies conducted in the context of a developing country. One is by Bedi *et al.* (2021) in which the region of study is Brazil and another by Balakrishnan *et al.* (2021) who conducted their work in India.

Bedi *et al.* (2021) conducted a study in Brazil to understand the impact of short-term exposure to $PM_{2.5}$ on the cognitive performance of university students. Data was collected for 464 students in 54 lab sessions conducted over a timespan of 3 years, 2014-16. Although the focus of this paper is still on cognitive performance, it does not use test scores like the literatures discussed above as an indicator of cognitive ability but a set of cognitive-domain-specific-tests. This adds to the uniqueness of the paper. The paper employs OLS estimation and finds that the performance on a cognitive test that evaluates "higher mental processes" declines when students are exposed to high levels of $PM_{2.5}$. It is also found that fluid reasoning scores is 17 percentage point lower on a 'poor' air quality day marked by $PM_{2.5} > 35\mu g/m^3$.

Balakrishnan *et al.* (2021) provide evidence from India for contemporaneous exposure to air pollution on the academic performance of children between 5-16 years of age in rural India. Data from the Annual Status of Education Report (ASER) from 2008-2014 is used to provide information about children's academic performance in terms of reading and math skills at 4 levels.[4] The data is a repeated cross-sectional data collected for a total of 3 million children. Due to unavailability of CPCB monitoring stations in rural areas, Aerosol Optical Depth (AOD)[5] is used as a proxy for air pollution. This does not provide air quality information in the conventional way where information about various pollutants are monitored however it is said to be a predictor of particulate matter (Chu et al. 2003; Gupta, Christopher, Wang, Gehrig, 2006; Kumar, Chu, Foster, 2007 in Balakrishnan *et al.*, 2021). IV estimates are used as an empirical strategy and a statistically significant negative relationship is found between AOD and academic outcomes. With a 0.01unit increase in yearly AOD, the probability of reading level 1 and level 2 text declines by 2.39 and 2.12 percentage points respectively indicating a 3.9 percent and 4.6 percent decline relative to the means of 2008. With a 0.01 unit increase in AOD, the math outcomes declined by 2.6 percent and 2.3 percent for 'counting 10-99' and 'subtraction' levels respectively.

Although the conclusions from the two studies discussed above are the same, i.e. poor air quality has an impact on the cognitive/academic performance of individuals, the magnitude of results in both these papers are vastly different. A comparison between them could be questionable too since the country, age group, variable for air quality and proxy for cognitive abilities are different. This highlights the need for more research from the developing world to contextualize and understand the severity of the problem of air pollution in varying age groups. Inspired by the literature, this paper aims to proceed in that direction.

Here, the aim is to explore the contemporaneous relationship between air pollution and test scores of 539 children from Bengaluru, India using scores from assessments created to test for language, cognitive, creative, physical, social, and emotional development skills of children between the age of 4-6 years. The data is in panel form since the same tests have been conducted for the same set of children twice, once in June/July 2019 and again in February/March 2020 as part of the beginning-of-year (BoY) and end-of-year (EoY) assessments conducted by a non-profit organization, Key Education Foundation (KEF). The dataset is from an urban setting but is for children from low-income households. Overall, the study is more localized and focused.

As compared to the existing literature, essentially Marcotte (2017), the paper focuses on children from a similar age group but offers some unique elements. First, it is set in a different context, i.e., of a developing country (India). Secondly, unlike some of the existing literature (Marcotte, 2017; Balakrishnan, 2021), this paper benefits from the availability of exact dates of exams conducted for children included in the study. Balakrishnan *et al.*'s (2021) work is also of prime importance to this study. However, it focuses on a different age group and offers a rural setting, unlike the urban setting of this paper.

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[4] Reading Levels: Letter, Word, Level 1 text, Level 2 text. Math Levels: Counting numbers 1-9, Counting numbers 10-99, Subtraction, Division.

[5] "Aerosol Optical Depth (AOD) indicates the level at which particles in the air (aerosols) prevent light from travelling through the atmosphere" (NASA Earthdata, 2021). AOD of <0.1 is categorized as "clean". As AOD increases, visibility decreases, indicating higher levels of particles in the air. The range of AOD <0.0 - >=5.0. Some of the sources of aerosols are, emissions from factories, dust, smog, smoke from fires. (NASA Earthdata, 2021).

Chapter 4
Research Methodology

A quantitative approach has been undertaken to explore the research question of identifying the relationship between air quality and test scores of children from Bengaluru, India. Secondary data has been collected from Key Education Foundation (KEF), that contains information regarding children in the age group of 4-6 years enrolled in affordable private schools. Data regarding air quality has been collected using the website of the Central Pollution Control Board (CPCB), Ministry of Environment, Forests and Climate Change, and weather-related data has been collected from a Norwegian company Time and Date AS. This section details the mechanism of data collection.

The attempt for data collection was to gather the most recent data available for test scores. In any other year, it would have been meaningful for that recent data to be from the academic year 2020-2021 but not this time. With the onset of the COVID-19 pandemic in the early months of 2020, there were drastic changes in the main variables of test scores and air quality understudy.

Among other aspects, education was heavily affected. The UN (2020) called it "the largest disruption of education in history." Schools in India were closed for more than 73 weeks (UNESCO, 2021) and even now, when the country is on the path of recovery, students in secondary and higher secondary schools are a priority. The children KEF works with are still unable to visit schools. It was fair to assume then that the intervention of KEF and the performance of students, would be sub-par due to COVID-19, and hence the decision was made to use the data from the academic year 2019-20.

The air quality data were also heavily affected. With lockdown imposed, various factories were shut, vehicular movements were negligible in comparison to pre-COVID-19 and only essential services were allowed to operate. This led to a major drop in concentration levels of PM_{10} $PM_{2.5}$, CO, NO_2, SO_2, and O_3 by as much as 33, 34, 21, 47, and 21% from before COVID-19 times, as per a study conducted by Verma et al (2020). With a slight change in magnitudes of result, another study conducted by Mahato et al. (2020) in Delhi, India, highlighted that PM_{10}, $PM_{2.5}$, (more than 50%) CO(30.35%), and NO_2 (52.68%) concentrations declined significantly. This implies that air quality data from the academic year 2020-21 would have been significantly different from other 'normal' years due to the effects of COVID-19 and hence would not allow meaningful conclusions to be derived from this study. One could argue that it provides an opportunity to check if the test scores improved, now that the air quality was better, however, at least for the group of children under this study it was not possible. KEF (and in fact many other organizations) had to change the delivery mechanism and their interventions during the peak of COVID-19. They were not able to actively collect data from the children they worked with. Therefore, it was in the best interest of the study to focus only on data for the academic year pre-COVID-19.

4.1 Data

4.1.1 Key Education Foundation[6]

To conduct this research, data was collected from a non-profit organization, Key Education Foundation (KEF), Bengaluru, India. KEF has been working towards providing early childhood education (ECE) to children enrolled in affordable private schools[7] and government schools in Karnataka, India since 2017 (KEF, 2021a). Their interventions within the School Readiness Program (SRP) includes equipping classrooms with learning materials, training teachers, and empowering parents. The aim of the program is to make sure all children are school-ready by the time they reach grade 1. They have impacted more than 100 schools and have had a reach of more than 8000 children, 300 teachers, and 8000 families in the Indian state of Karnataka (KEF, 2021a).

According to UNICEF (2021), ECE is the foundation of a child's learning journey upon which their following successes are dependent. However, more than 175 million children across the world do not have access to ECE and the situation is worse in low-income countries with 4 out of 5 children being deprived of it. (UNICEF, 2021). Places where ECE is available, "poorly trained educators, overcrowded and unstimulating environments, and unsuitable curricula" (UNICEF, 2021) are issues of concern. KEF is trying to work on these issues and make quality ECE accessible. With ECE's importance being linked to not just a particular child's life outcomes but also the country's human capital formation and economic growth, it makes both KEF's work and this research meaningful.

There are three main approaches adopted by KEF to work towards their goals. One is by providing children with "age-appropriate, safe and affordable teaching and learning material" (KEF, 2021b) by means of providing workbooks created by in-house curriculum design experts. Their second strategy is to provide training and coaching to educators working in affordable private schools and government schools they partner with. Parent engagement is the third strategy adopted by the organization to build awareness on improving their support for their children in the home environment. All these services are directed towards ensuring quality ECE for children in the age group of 4-6 years.

At the beginning of each academic year, the organization identifies the schools and students they would be working with and conducts a beginning of the year (BoY) assessment for a sample of students. The sample is selected based on the attendance of children on a

[6] A confidentiality agreement has been signed with KEF to ensure that the identity of the students and schools included in the study is kept confidential. Hence, both children and schools have been given identification codes and no original names have been used.

[7] Affordable Private Schools(APS) are education institutions which provide parents from low-income families a choice to enrol their children in schools they consider better than the public schools (Majumdar, 2018). These are schools with affordable fees, often not exceeding INR15,000 per annum.

The children in this study are all enrolled in APSs. Their average family of four have a total income of INR10,000-INR30,000 a month with mostly one of the parents employed in low-skilled jobs like domestic help. beautician, auto-truck drivers.

pre-decided test date by the organisation. The same set of children are assessed at the end of the year (EoY), post KEF interventions, to observe improvements in the child across their language, cognitive, creative, physical, and social, and emotional development skills. The attempt is to assess all the children who were sampled during BoY, however, due to reasons like dropouts or simply absence on the EoY testing dates for a given school, the data suffers from a loss of EoY test scores. The EoY data for the academic year 2019-20 also suffers some loss due reasons attributable to COVID-19, like school closures and lockdowns.

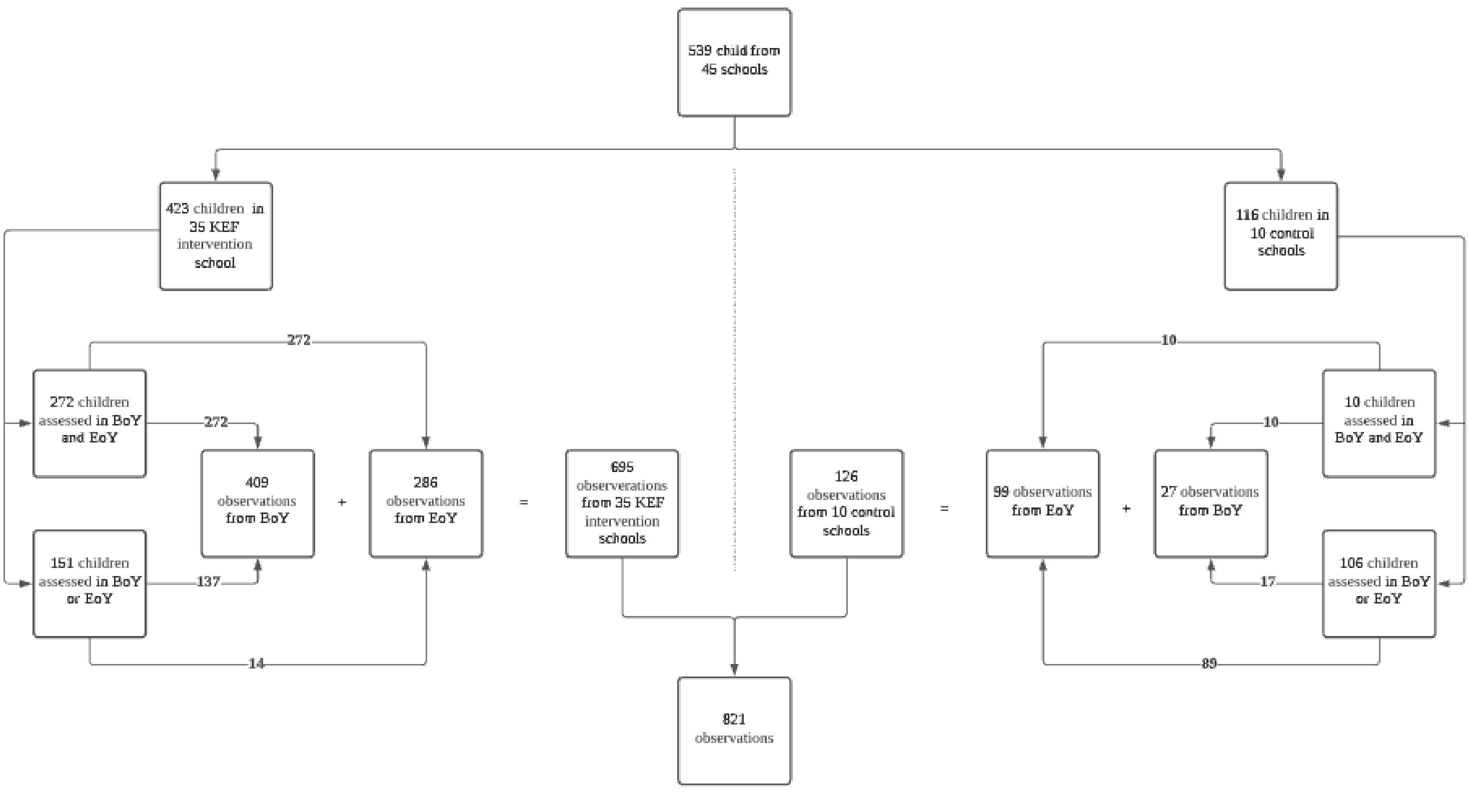
To check for the impact of KEF intervention, the organisation also collects data from control schools. For the year 2019-20, control schools were chosen in two ways. For BoY, data was mostly collected from any new school KEF had started working with in that academic year. For EoY, data was collected from any school KEF was going to partner with in the next academic year. This hampers the quality of control data in the study since in most cases, same students are not tested across the two periods in the control group.

For this study, the data is collected from 539 children across 45 schools. The split of these number based on KEF intervention and control schools, BoY and EoY, and the total number of observations are given in Figure 3.

Out of the 539 children, 423 are from 35 KEF intervention schools. Of them, 272 children were assessed at both BoY and EoY, and 151 were assessed in either of the two periods. This led to 409 observations at BoY and 286 at EoY. From the 35 intervention schools, the dataset has 695 observations.

Out of the 539 children, 116 are from 10 additional schools which acted as control schools. 10 of the 116 were assessed at both BoY and EoY, and 106 were assessed in either

Figure 3: KEF Data



of the two periods. This led to 27 observations from BoY and 99 observations from EoY. From the 10 control schools, the dataset has 126 observations.

In total, the study has 821 observations from 539 children, 45 schools and 2 periods.

Both the BoY and EoY tests include the same 37 questions and are conducted by trained evaluators, physically on the school premises. In the data set being used for this study, all the tests were conducted between 9 AM and 3 PM. The variable 'test scores' in this research are derived from grades obtained by students on these tests.

The children are posed with a question or a task. The grader observes the answer or the action and determines the grade that should be given to the child. The grader has four options to choose from, which broadly falls in the category of 'a-correct', 'b-incorrect', 'c-does not know', and 'd-does not respond'. In this research, we have counted the number of questions marked as 'correct' or option 'a' for each child and obtained the key dependent variable, i.e., 'number of correct answers' or the 'percentage of correct answers' given by a child.

For this research, we have access to the assessment results for the academic year 2019-2020. An academic year in Karnataka begins in June and ends in March. Aligning with these months, the BoY data is from the months of June/July with a few exceptions of the tests being conducted in August. The EoY scores are from the months February/March with a few exceptions of the tests being conducted in January. This data is from the pre-COVID-19 time when children were going to school regularly.

The data set provided by KEF also has information about the location of the school, the date of birth of the child, the test date and time, and the gender of the child. Using the date of birth and the test date, the age of the child as on the date of the test is calculated. The information about gender is coded into 1 and 0 where 1 is 'male and 0 is 'female'. Additionally, the ethnicity of the child is also coded based on their names. Children have been split into two groups, Muslims are coded as 1 and non-Muslims are coded as 0.

Household information like the income level of the parents, the occupation, and education of parents, is unavailable. School attendance data on both the child and the teachers are also unavailable. This is a clear drawback. However, due to the COVID-19 pandemic, it was difficult to gather additional primary data. After unsuccessful attempts with more than 7 organizations/institutions, data from KEF came through and arguably provides a reasonably credible database to explore the relationship of interest.

4.1.2 Air Quality

The air quality data has been obtained from the CPCB, Ministry of Environment, Forest and Climate Change website. Originally constituted under the Water (Prevention and Control of Pollution) Act 1974, CPCB started operating under the Air (Prevention and Control of Pollution) Act, 1981 (CPCB, 2021a). One of its main functions is to "improve the quality of air to prevent, control or abate air pollution in the country" (CPCB, 2021a). This body is also responsible for collecting, compiling, and publishing technical and statistical data on air pollution (CPCB, 2021b). The work is decentralized by means of setting up the State Pollution

Control Board which functions at the state-level within the Indian states in collaboration with CPCB. (CPCB, 2021b).

The National Air Quality Index project was initiated by the CPCB to promote awareness and participation of the general public on issues relating to air quality and its associated health impacts by means of setting up systems to share air quality information. The objective of the project has been stated as: *"To adopt/develop an Air Quality Index (AQI) based on national air quality standards, health impacts and monitoring programme which represent perceivable air quality for general public in easy to understand terms and assist in data interpretation and decision making processes related to pollution mitigation measures."* (CPCB, 2015, p. 4).

The uniform AQI, along with the determinants used for its calculation, the method of calculation, the indicated health impacts, and qualitative descriptors all come under the scope of this project. (CPCB, 2015, p.4-5). Additionally, the web-based dissemination system, that has been used to collect data for this study as well, has been established under this project.

The computation of AQI, an easy number(s) to inform the general public about the quality of air, requires two basic steps: (i) computation of the sub-indices for the pollutants and (ii) aggregation of these indices to ascertain the AQI (CPCB, 2015, p. 7). As per CPCB (2015, p.7) the sub-index I_p (where *p* is the pollutant in discussion) for a pollutant concentration C_p is calculated using the following formula[8]:

$$I_p = \left[\frac{I_{HI} - I_{LO}}{B_{HI} - B_{Lo}}\left(C_p - B_{LO}\right)\right] + I_{LO}$$

where,

$B_{HI/LO}$ is the breakpoint concentration greater/less than or equal to C_p
$I_{HI/LO}$ is the AQI value associated with $B_{HI/LO}$
C_p is the pollutant concentration

This is done for all the pollutants in consideration and then aggregated to ascertain the overall AQI.

The breakpoint concentration has evolved over the years as and when limitations were identified for the existing index and newer indices were made to overcome them. Under the National Air Quality Index project, a uniform breakpoint was established using the information from historically and globally existing and recognized indices (CPCB, 2015, p.21-35). Figure 4 below informs us about the breakpoints for AQI Scale 0-500 in India.

[8] For example: Consider the concentration of PM_{10} in the air to be 95$\mu g/m^3$. The breakpoint values and index values associated with those breakpoint are taken from the Figure 4 ; B_{HI} = 100 and B_{LO} is 50; I_{HI} is 100 and I_{LO} is 50. Adding them to the equation (1) we get: I_p = {(100-50)/(100-50)}*(95-50)+50 = 95. This way, sub-indices can be calculated for each pollutant.

Figure 4: Breakpoints for AQI Scale 0-500 (Units: µg/m^3)

AQI Category (Range)	PM_{10} 24-hr	$PM_{2.5}$ 24-hr	NO_2 24-hr	O_3 8-hr	CO 8-hr (mg/m^3)	SO_2 24-hr	NH_3 24-hr	Pb 24-hr
Good (0-50)	0-50	0-30	0-40	0-50	0-1.0	0-40	0-200	0-0.5
Satisfactory (51-100)	51-100	31-60	41-80	51-100	1.1-2.0	41-80	201-400	0.6 –1.0
Moderate (101-200)	101-250	61-90	81-180	101-168	2.1- 10	81-380	401-800	1.1-2.0
Poor (201-300)	251-350	91-120	181-280	169-208	10.1-17	381-800	801-1200	2.1-3.0
Very poor (301-400)	351-430	121-250	281-400	209-748*	17.1-34	801-1600	1201-1800	3.1-3.5
Severe (401-500)	430 +	250+	400+	748+*	34+	1600+	1800+	3.5+

**One hourly monitoring (for mathematical calculation only)*

Source: CPCB, 2015, p.15

The aggregation of these sub-indices is generally a summation or multiplication operation or by using a maximum operator[9]. The index can suffer from challenges like ambiguity or eclipsing when additive or multiplicative operators are used (CPCB, 2015, p.14-15). Hence, the maximum operator approach is often used to ascertain the AQI. The data used in this research is arrived at using this approach. In this approach, the sub-indices of all the pollutants are identified and the maximum sub-index is reported as the overall AQI. Higher the AQI, poorer is the quality of air.

For the ease of the general public, the AQI range as described in Figure 4 also has health impacts corresponding to them. They are mentioned in Figure 5 below.

Figure 5: Health Impact Associated to AQI ranges

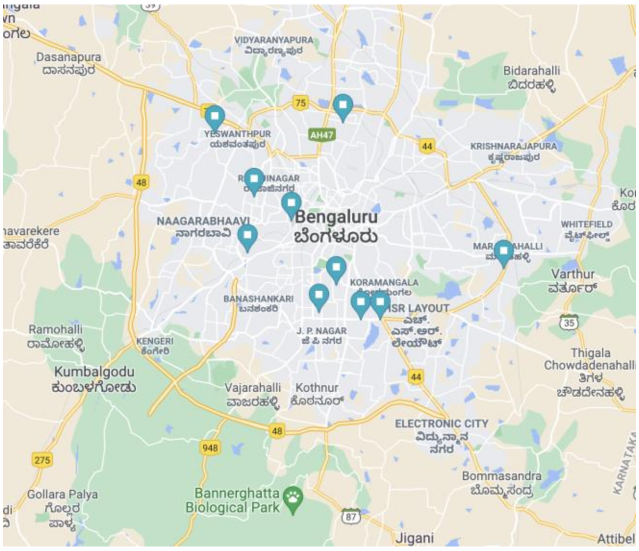
AQI	Associated Health Impacts
Good (0–50)	Minimal Impact
Satisfactory (51–100)	May cause minor breathing discomfort to sensitive people
Moderate (101–200)	May cause breathing discomfort to the people with lung disease such as asthma and discomfort to people with heart disease, children and older adults
Poor (201–300)	May cause breathing discomfort to people on prolonged exposure and discomfort to people with heart disease with short exposure
Very Poor (301–400)	May cause respiratory illness to the people on prolonged exposure. Effect may be more pronounced in people with lung and heart diseases
Severe (401-500)	May cause respiratory effects even on healthy people and serious health impacts on people with lung/heart diseases. The health impacts may be experienced even during light physical activity

Source: CPCB, 2015, p.36

[9] To ascertain the overall AQI, the maximum operator approach is used. Overall AQI = Max (I_i, where I = 1,2,3,…n). I_i is AQI sub-index for pollutant i. Say for instance, the sub-index value for $PM_{2.5}$ is 44, for PM_{10} is 72 and for CO is 70. Then, the Overall AQI = Max(44, 72, 70) = 72. For that time frame, it would be said that the AQI is 72 and the prominent pollutants is PM_{10}.

For this research, the air quality data available on the CPCB website is used (CPCB, 2021c). The website has information segregated by state, city, station, date, and time. The data was collected for the city of Bengaluru in the Indian state of Karnataka. In collaboration with its state body (Karnataka Pollution Control Board, KPCB), CPCB has 10 online ambient AQI monitoring stations [10] in Bengaluru.

Figure 6: CPCB Monitoring Stations in Bengaluru



Source: CPCB, 2021c

The decision of the pollutants studied in the research is based on the availability of information on the CPCB website. Although CPCB identified 12 pollutants, namely particulate matter of less than 2.5 and 10-micron size ($PM_{2.5}$ and PM_{10}), Nitrogen Dioxide (NO_2), Ammonia (NH_3), Sulphur Dioxide (SO_2), Carbon Monoxide (CO), Ozone (O_3), Lead (Pb), Benzo(a)pyrene, Benzene, Arsenic, and Nickel, the initial eight have 1/8/24 hr standard and annual standard while the last four have only yearly standards. (CPCB, 2015, p. 17). Keeping the objective of AQI in mind, that is quickly making air quality information accessible to the general public, the AQI system of India focuses on $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, O_3, and Pb (CPCB, 2015, p.18). Information about Pb is also not available in real-time yet it is considered to be of importance since it is an important toxin. For the region of the study, information is available only about the first seven pollutants. The air quality data available here are the sub-indices of the pollutants and the overall AQI.

To collect the most accurate air quality for each test date, the ideal scenario would have been to gather air quality data from inside the classroom, however due to logistical constraints, it was not possible. It is hence assumed that air quality in the school is highly correlated with ambient air quality reading outdoor (Branis *et al.,* 2005 in Lavy *et al.*, 2014) and data is collected from monitoring stations within a 5km radius[11] of a school. Then the

[10] The 10 monitoring stations are: (1) Silk Board, Bengaluru - KSPCB, (2) BWSSB Kadabeesanahalli, Bengaluru - CPCB, (3) Saneguravahalli, (4) Peenya, Bengaluru - CPCB, (5) Bapujinagar, (6) Hebbal, (7) Hombegowda Nagar, (8) BTM Layout, (9)Jayanagar 5th Block, and (10) City Railway Station (See Figure 6).

[11] On average, schools in this study are within the 5kms air radius (~ 6km foot distance) from a monitoring station. This motivated the choice of obtaining data from a monitoring station within 5km air radius of the school. For more than 50% (25) of the schools in study air quality data could be collected from a monitoring station with 5kms radius.

data is noted down for 3 different times, 9 AM, 12 noon, and 3 PM. The data is available for each hour yet these three hours are chosen for two reasons. First, the tests are conducted between 9 AM and 3 PM on any given day, and hence to ascertain the contemporaneous effect of air quality on test scores, this specific time frame is focused on. Secondly, even if data is captured for each hour, there is not much daily variation. Once this information is gathered at these three points in time, the average is computed. This average is used as an indicator of air pollution on the specific test date.

While identifying the closest monitoring station within a 5km radius, one of the limitations faced was that the AQI for that day was not computed at that station possibly because the AQI was not captured for at least three parameters or one of the three figures captured was not $PM_{2.5}$ or PM_{10}. (CPCB, 2015, p. 40) In such instances, the AQI from the next closest station was recorded. Another challenge faced was when AQI data was available from the closest station for some of the test dates in a school but not for other dates. In such a scenario, the closest station within 5kms which had data available for all test dates for a school was chosen. It further happened that one station could only provide data for certain test date(s) and the next closest station could provide data only for the other test date(s). Then, data was captured from two different stations for those specific dates associated with a school. Such cases are applicable for 8 schools in the study out of which for 4 of them data is collected from different stations but both being within 5km air radius. For the other 4, data is collected from different stations and some of them are not withing the 5km radius.

A huge city like Bengaluru has only 10 monitoring stations. For 16 of the schools in the study there is no monitoring station within a 5km radius. In such cases, air quality data was captured from the closest monitoring station, at most being within a 15kms radius. A dummy variable is created to capture whether the AQI data is collected from a monitoring station within a 5kms radius of the school or not. In total, for 520 observations, the data was collected from a station within the 5kms radius while for 301 observations, it was collected from a station outside this radius.

The monitoring station within the 5km radius of a school was found with the help of a software that generates a circle on Google Maps using a point and a radius, made freely accessible by a private web platform called Map Developers. To create a circle, one needs to drop a point on Google Maps or type in the address and choose the desired radius of the circle (in this case, 5km) (Map Developers, 2021). Appendix 1. lists the schools, the monitoring station linked to them, and whether the station is within the 5km radius.

4.1.3 Weather Data

Weather conditions like temperature, humidity, and wind speed are used as control variables in this study since they are time-varying factors, which could be correlated with test scores and air quality. With the help of a website made available by a Norwegian company, Time and Date AS, the past weather data for Bengaluru is obtained. The website provides hourly information about temperature (in Celsius), wind (in kmph), and humidity (in %) (Time and Date AS, 2021). For this study, the minimum and the maximum values of the three parameters between 9 AM and 3 PM have been noted. The average is then computed. Weather data is available for all 74 test dates.

4.2 Descriptive Statistics

The dataset includes information about 539 children from 45 schools. The dataset contains 821 observations (See Figure 3). The tests were conducted on 74 unique dates and assessed by 25 assessors in total. The information about air quality is gathered from 10 monitoring stations.

Table 1. displays the summary statistics of the sample. The information about all pollutants is not available for all 821observations. This is due to the unavailability of the information on the CPCB website. The reason for the missing sub-indices of pollutants is not mentioned on the website. It is hence assumed that it could be a technical issue at the monitoring station that leads to values of some pollutants missing on certain days.

Table 1: Summary Statistics

Summary statistics			
Total Sample			
Variable	Total Observations	Mean	SD
Key outcome variable			
Number of correct answers	821	21.4592	6.8107
Child characteristics			
Age	821	4.8100	0.5826
Gender	821	0.5432	0.4984
Ethnicity	821	0.3508	0.4775
Pollutants			
$PM_{2.5}$	752	46.5971	21.0526
PM_{10}	660	69.5258	23.3192
NO_2	815	31.3203	18.1595
NH_3	587	2.7087	1.5049
SO_2	797	7.6286	4.7638
CO	821	38.7710	17.2721
O_3	727	37.7840	20.0830
Weather indicators			
Temperature	821	26.4324	1.2332
Windspeed	821	15.0372	6.8128
Humidity	821	61.7582	8.7383
Other variables			
Student_id	821	NA	NA
School_id	821	NA	NA
Intervention	821	0.8465	0.3607

Period	821	0.4686	0.4993
Station Within 5kms	821	0.6334	0.4822
Date of Test_id	821	NA	NA
Accessor_id	821	NA	NA
Station_id	821	NA	NA

Table 2 displays the summary statistics of the sample disaggregated by the two periods (0=BoY, 1=EoY) and Table 3. Displays the definition of these key variables and their unit of measurement,

From Table 2. It can be inferred that at large, the two groups are different from each other. The *p*-values indicating the difference-in-means between the two groups are displayed in the last column of the table. At the 5% level, equality of means can be rejected for almost all the variables except for gender, ethnicity, and station within 5 km.

The average number of correct answers increases by 34% by the EoY. The sub-indices of the pollutants also increase during EoY by at least more than 15%. In some cases, ($PM_{2.5}$ and SO_2), the increase is over 70%. This indicates that the toxicity of the pollutants and the performance of children are both increasing in the EoY. Both of these are expected. When children are tested at EoY, they are older, have spent the school year studying and perhaps most importantly, for those children enrolled under the KEF intervention, there is likely to be a positive impact of the intervention on their performance at the EoY. The pollutants are expected to increase during the winter months. This is attributed to factors including temperature and humidity. With a drop in temperature and humidity, the air quality is expected to worsen (AccuWeather, 2020). Lower wind speed also leads to a deterioration of air quality (The Economic Times, 2019). In this dataset, temperature wind speed, and humidity drop during EoY and could explain an increase in pollutants in the same period. For this reason, the specification (in Chapter 5) includes controls for intervention and weather indicators.

Table 2: Summary Statistics Disaggregated by Period

Summary Statistics

	Period = 0 (BoY)			Period = 1 (EoY)			t-test
Variable	Total Observations	Mean	SD	Total Observations	Mean	SD	p value
Key outcome variable							
Number of correct answers	436	18.4910	5.7116	385	24.8210	6.3845	0.0000
Child characteristics							
Age	436	4.5250	0.5312	385	5.1320	0.4571	0.0000
Gender	436	0.5250	0.4999	385	0.5640	0.4966	0.2710
Ethnicity	436	0.3532	0.4785	385	0.3481	0.4770	0.8770
Pollutants							

$PM_{2.5}$	415	34.8506	15.5497	337	61.0623	17.6755	0.0000
PM_{10}	335	56.3194	23.3407	325	83.1385	13.3501	0.0000
NO_2	430	26.7349	18.5310	385	36.4416	16.2958	0.0000
NH_3	300	2.5100	1.1493	287	2.9164	1.7818	0.0010
SO_2	436	5.7729	3.0029	361	9.8698	5.4840	0.0000
CO	436	34.4473	15.7131	385	43.6675	17.6661	0.0000
O_3	380	35.0790	21.1033	347	40.7464	18.4831	0.0000
Weather indicators							
Temperature	436	26.7690	1.0484	385	26.0510	1.3142	0.0000
Windspeed	436	20.1790	4.5253	385	9.2140	3.4500	0.0000
Humidity	436	65.7120	8.0715	385	57.2810	7.1696	0.0000
Other variables							
Station Within 5kms	436	0.6260	0.4844	385	0.6420	0.4802	0.6480

Table 3: Definition of Key Variables

Definition of key variables	
Number of correct answers	The number of times a child was graded 'a - correct answer' by an assessor
Age	Age of a child on the date of the test
Gender	Male = 1; Female = 0
Ethnicity	Muslim = 1 Non-Muslim = 0
$PM_{2.5}$	Sub-index of $PM_{2.5}$
PM_{10}	Sub-index of PM_{10}
NO_2	Sub-index of NO_2
NH_3	Sub-index of NH_3
SO_2	Sub-index of SO_2
CO	Sub-index of CO
O_3	Sub-index of O_3
Temperature	Average temperature between 9 A.M and 3P.M, measured in Celsius
Windspeed	Average windspeed between 9 A.M and 3P.M, measured in kmph
Humidity	Average humidity between 9 A.M and 3P.M, measured in %
Station Within 5kms	Yes = 1; No = 0

To check the effect of period and intervention on mean scores, Table 4. is created. During BoY, mean test scores are lower for children enrolled in the KEF intervention. However, at EoY, the children under the intervention outperform those in the control group. This indicates that there is an interaction between period and intervention. In the analysis, an interaction variable is added to control for the combined effect of period and intervention. The differences are statistically significant at 1% for interactions between Period = 1 and Intervention.

Table 4: Mean Values of Correct Answers by period*intervention

Mean values of correct answers (N=821)		
	Intervention = 0	Intervention =1
Period = 0	19.7778 (n=27)	18.4059 (n=409)
Period = 1	22.6161*** (n=99)	25.5839*** (n=286)

Note: *** indicates that the differences are statistically significant across the groups at 1% level

In Table 5. the correlation between the 7 pollutants are tested. It is found that PM_{10} and $PM_{2.5}$ are highly correlated and hence, for estimations, only $PM_{2.5}$ is added to the specifications. The choice is based on the number of observations for which each of the pollutant values is available. For $PM_{2.5}$, the value is available for 752 observations while PM_{10} values are available only for 660 observations. To minimize the number of observations dropped from the analysis, $PM_{2.5}$ is chosen for most specifications.

Table 5: Correlation between Sub-indices of Pollutants

Correlation between pollutants

	$PM_{2.5}$	PM_{10}	NO_2	NH_3	SO_2	CO	O_3
$PM_{2.5}$	1.0000						
PM_{10}	**0.7975**	1.0000					
NO_2	0.4235	0.5739	1.0000				
NH_3	0.2018	0.2408	0.1923	1.0000			
SO_2	0.2965	0.3950	0.3816	0.5586	1.0000		
CO	0.2424	0.4995	0.3266	0.3266	0.2894	1.0000	
O_3	-0.1092	0.2474	0.2706	0.4219	0.3369	0.4050	1.0000

Chapter 5
Hypotheses and Empirical Strategy

Based on the data collected for this study, an Ordinary Least Squares (OLS) regression approach is used to identify the effect of air quality on a child's performance in cognitive tests. Hypothesis 1 includes all the 6 (except PM_{10}) air pollutants. The sub-hypotheses that follow explore the relationship between various combinations of pollutants based on (i) their composition and (ii) the context of the main pollutants found in the city under study, Bengaluru. The various hypotheses are outlined below.

5.1 Hypothesis 1

Hypothesis 1: There is a negative effect of air pollution on a child's performance in cognitive tests.

This hypothesis attempts to test if poor air quality has a short-term, contemporaneous effect on children's cognitive performance, i.e., do they perform poorly on days with higher air pollution. The metric used is the number of correct answers they give on tests conducted to check their school readiness. The test is designed to check for language, cognitive, creative, physical, and social and emotional development skills. Researchers have used a range of variables to capture air pollution. These include $PM_{2.5}$ and CO - Lavy *et al.*(2014); $PM_{2.5}$ - Ebenstein *et al.* (2016); Zhang *et al.* (2018); Bedi *et al.* (2021); PM_{10} and CO_2 - Roth (2016); $PM_{2.5}$ and O_3 – Marcotte (2017) and Aerosol Optical Depth - Balakrishnan *et al.* (2021).

The air quality data set available for this study includes information on the overall air quality as measured by an Air Quality Index (AQI), and sub-indices for $PM_{2.5}$, PM_{10}, NO_2, NH_3, SO_2, CO, and O_3. As mentioned in Section 4.1.2, the AQI is calculated using a maximum operator. This means, for a given day, the AQI index takes the value of one of the seven pollutants and drops the rest. This could lead to information loss, especially when the study has the advantage of having access to sub-indices of pollutants. Therefore, for the analysis conducted here, the pollutant sub-indices are used.

On checking the correlation between the pollutants, it is found that there is a strong positive correlation (0.8) between $PM_{2.5}$ and PM_{10} (See Table 5) . Hence, PM_{10} is dropped from most part of the analysis.

It is observed that in period=1(EoY), both the test scores and the AQI are increasing (See Table 4). A large proportion of this increase in test scores may be explained by the intervention of KEF. Air quality is often known to be poorer in the colder months of the year and the data aligns with that information as shown in Table 2. Hence, to absorb the effects of these interactions, an interaction variable (period*intervention) is added to the specification and the following model is estimated to test the hypothesis.

$$\begin{aligned} Test\ score_{isdt} &= \beta_0 + \beta_1 Air\ quality_{isdt} + \beta_3 period_t + \beta_4 intervention_s \\ &+ \beta_5 period_t * intervention_s + \beta_6 X_{is} + \beta_7 Z_{isdt} + \delta_{isdt} + \varepsilon_{isdt} \end{aligned}$$

Where, $Test\ score_{isdt}$ is the number of correct answers (outcome of interest) given by child *i* in school *s* on date d in period *t*. $Air\ quality_{isdt}$ is the contemporaneous air quality defined by the various components of pollutants, i.e. $PM_{2.5}$, NO_2, SO_2, CO, and O_3 for child *i* in school *s* on date d in period *t*.

The individual controls, X_{is} accounts for gender, age, and ethnicity of child *i* in school *s*.. A vector for time-varying city-level weather controls, Z_{isdt}, includes information about the average temperature, wind speed, and humidity on the test date is added to the estimation. Assessor fixed effects δ_{isdt} are also included in the estimation to control for any variations that could be caused due to unobserved aspects of the accessor. There are studies that highlight that there can be assessor bias in grading (Yeates *et al.,* 2013) and hence, the control for assessor is added to the estimation.

$period_t$ is a dummy variable which takes the value 0 for the observations made for BoY tests and 1 for the observations made for EoY tests. $intervention_s$ take the value 0 when the observation is being made for a child who received KEF intervention and 0 when the child is from the control group. $period_t * intervention_s$ is the interaction term which absorb for the combined effect of period and intervention. ε_{isdt} is the random error term.

5.1.1 Hypothesis 1a

Hypothesis 1a: There is a negative effect of $PM_{2.5}$, CO, and O_3 on a child's performance in cognitive tests.

From Eq.1. SO_2 and NO_2 are dropped since they actively contribute to the formation of particulate matter in the air by chemically reciting with one another (USEPA, 2021b; USEPA, 2021h; and IQAir, 2021c). To test the hypothesis, the following model with $PM_{2.5}$, CO, and O_3 as components of air quality is estimated.

$$\begin{aligned} Test\ score_{isdt} &= \beta_0 + \beta_1 Air\ quality_{isdt} + \beta_3 period_t + \beta_4 intervention_s \\ &+ \beta_5 period_t * intervention_s + \beta_6 X_{is} + \beta_7 Z_{isdt} + \delta_{isdt} + \varepsilon_{isdt} \end{aligned}$$

5.1.2 Hypothesis 1b

Hypothesis 1b: There is a negative effect of NO_2, NH_3, SO_2, CO, and O_3 on a child's performance on cognitive tests.

From the previous model, $PM_{2.5}$ is dropped while its components are retained. To test this hypothesis, the following model with SO_2, NO_2, NH_3, CO, and Ozone as components of air quality is estimated.

$$\begin{aligned} Test\ score_{isdt} &= \beta_0 + \beta_1 Air\ quality_{isdt} + \beta_3 period_t + \beta_4 intervention_s \\ &+ \beta_5 period_t * intervention_s + \beta_6 X_{is} + \beta_7 Z_{isdt} + \delta_{isdt} + \varepsilon_{isdt} \end{aligned}$$

5.1.3 Hypothesis 1c

Hypothesis 1c: There is a negative effect of $PM_{2.5}$, PM_{10}, NO_2, SO_2, and CO on a child's performance and cognitive tests.

In Bengaluru, the city of our interest, the main sources of pollution are vehicular emission and construction activities (Anien, 2021). Hence, in this specification, the key pollutants contributed from vehicular emission, $PM_{2.5}$, PM_{10}, CO, NO_2 and SO_2 (CPCB, 2010, p.3). PM_{10} is added back to this equation since it is the main pollutant from construction sites (Environmental Pollution Centers, 2021).

$$\begin{aligned} Test\ score_{isdt} &= \beta_0 + \beta_1 Air\ quality_{isdt} + \beta_3 period_t + \beta_4 intervention_s \\ &+ \beta_5 period_t * intervention_s + \beta_6 X_{is} + \beta_7 Z_{isdt} + \delta_{isdt} + \varepsilon_{isdt} \end{aligned}$$

The next section presents the results for the above hypotheses.

Chapter 6
Results

This chapter presents the findings from specified empirical models to test the effect of air quality on a child's cognitive performance. There is one main hypothesis and three sub-hypotheses which are tested. There are 5 different specifications that are estimated.

Specification (1) is a simple linear OLS estimation, where the effect of air quality on a child's academic performance is estimated. In specification (2), controls are added for the interaction of period and intervention. In addition, specification (3) adds the child characteristics like age, gender and ethnicity of a child. Weather controls are added in specification (4). Assessor fixed effects are added in specification (5).

6.1 Result 1

How does $PM_{2.5}$, NO_2, NH_3, SO_2, CO, and O_3 affect a child's cognitive performance?

Table 1 presents estimates of the effect of $PM_{2.5}$, NO_2, NH_3, SO_2, CO, and O_3 on a child's cognitive performance. Specification (1) is without any controls. In specification (2), there is a control added for interaction between period and intervention. It has been established that both AQI and number of test scores have the same trends. They increase during period = 1 (EoY). This may lead to bias in the estimates. As a way to cope with the bias, the interaction term is added to the specification.

In the following specifications, further controls are added for child characteristics, weather and accessor fixed effects.

The results are not consistent across pollutants. At a statistical significance level of 10% or less NO_2 and NH_3 are found to have negative effects on cognitive performance in specification (1) and (5) while $PM_{2.5}$ - across all specifications, CO - in specification (1) and (5) and O3 - in specification (4) and (5) are found to have positive effects on cognitive performance. The estimates of SO_2 indicate a positive relationship in specification (1) but a negative relationship in specification (2)-(4).

Focusing on the results from specification (5), the most complete specification, the coefficient of PM2.5 is 0.0640 and it is statistically significant at a level of 1%. In other words, a 1 unit increase in PM2.5 improves cognitive performance marginally by 0.064 correct answers. With a 1 unit increase in CO, there is an improvement of 0.074 correct answers at 1% level of significance and 1 unit increase in O_3, there is an improvement of 0.034 correct answers, at the 10% level of significance.

In contrast, the coefficient of NH_3 is -1.066 at a 5% level of significance. It indicates that a 1 unit increase in NH_3, leads to almost two (1.66) more incorrect responses. The negative effect of NH_3 is much larger than the combined positive effect of $PM_{2.5}$, CO and O_3.

Additionally, child characteristics of age, gender and ethnicity have statistically significant results. With a year increase in age, the number of correct answers given by a child increases by at least 2. Female students give at least 1 more correct answer than male students. Similarly, Muslims students give 1 more correct answer than non-Muslim students. Although the coefficients of period and intervention dummies are statistically insignificant, the interaction dummy is highly significant. The coefficient indicates that the KEF intervention is having a large impact on children. It leads to about 8 more correct answers for the children in the intervention group during EoY.

The results for age and the interaction term are statistically significant at 1% level, while the results for gender and ethnicity are statistically significant at 5% level.

Table 6: Results 1

Effect of PM2.5, NO2, NH3, SO2, CO and Ozone on a child's performance on cognitive tests

	Without controls	With period*intervention	With child characteristics	With weather controls	With assessor fixed effects
	(1)	(2)	(3)	(4)	(5)
	numcorans	numcorans	numcorans	numcorans	numcorans
pmtwoptfive	0.106***	0.0451**	0.0567***	0.0693***	0.0640***
	(0.0157)	(0.019)	(0.0187)	(0.0218)	(0.0245)
notwo	-0.0593***	-0.0273	-0.0135	-0.0054	-0.0188
	(0.0163)	(0.0187)	(0.0192)	(0.0196)	(0.0213)
nhthree	-1.323***	-0.163	-0.188	-0.366	-1.066**
	(0.274)	(0.302)	(0.321)	(0.320)	(0.330)
sotwo	0.189***	-0.145**	-0.163**	-0.154**	-0.0320
	(0.0661)	(0.073)	(0.0759)	(0.0783)	(0.0839)
co	0.127***	0.0385	0.0342	0.0294	0.0739***
	(0.0216)	(0.0237)	(0.0243)	(0.0245)	(0.0277)
ozone	0.0109	0.0099	0.0189	0.0363**	0.0339*
	(0.0162)	(0.0149)	(0.0143)	(0.0162)	(0.0175)
period		-2.4090	-4.062*	-3.567	-1.705
		(1.966)	(2.255)	(2.429)	(2.764)
intervention		-3.747**	-3.518*	-3.328	-3.928
		(1.497)	(1.865)	(1.889)	(2.102)
period*intervention		8.773***	8.330***	7.161***	7.949***
		(1.906)	(2.230)	(2.284	(2.670)
age			2.783***	2.576***	2.370***
			(0.539)	(0.541)	(0.531)
gender			-1.047**	-1.044**	-1.147**
			(0.486)	(0.485)	(0.47)
ethnicity_id			1.060*	1.153*	1.408**

			(0.594)	(0.603)	(0.602)
Weather controls	No	No	No	Yes	Yes
N	553	553	553	553	553

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.1.1 Result 1a

How does $PM_{2.5}$, CO, and O_3 affect a child's cognitive performance?

Focusing on only $PM_{2.5}$ (and not the pollutants that contribute to it) the estimations undergo some changes, however, the inconsistency remains. In the most elaborate specification (5), $PM_{2.5}$ and O_3 become statistically insignificant. CO is statistically significant at a 10% level. Although the magnitude is very small, with a 1 unit increase in CO, the number of correct answers marginally increase by 0.034.

The effect of the interaction term, age and gender remains highly significant at 1% level with both magnitude and direction similar to that of the results in Table 1. Ethnicity becomes insignificant. The number of observations in this model (717) is higher than the number of observations in the previous model (553).

Table 7: Results 1a

Effect of PM2.5, CO and Ozone on a child's performance on cognitive tests

	Without controls	With period*intervention	With child characteristics	With weather controls	With assessor fixed effects
	(1)	(2)	(3)	(4)	(5)
	numcorans	numcorans	numcorans	numcorans	numcorans
pmtwoptfive	0.0883***	0.0096	0.0239	0.0339*	0.0285
	(0.012)	(0.0149)	(0.015)	(0.0177)	(0.0184)
co	0.0554***	0.0221	0.0203	0.0060	0.0341*
	(0.0167)	(0.0159)	(0.0155)	(0.0161)	(0.0187)
ozone	0.0316**	0.0056	0.0116	0.0323**	0.0218
	(0.0134)	(0.0127)	(0.0124)	(0.0138)	(0.0146)
period		-0.5250	-2.7100	-3.294*	0.5750
		(1.890)	(1.865)	(1.921)	(2.072)
intervention		-3.774**	-3.449**	-3.316**	-2.665*
		(1.687)	(1.643)	(1.632)	(1.604)
period_intervention		7.372***	7.577***	6.638***	5.324***
		(1.892)	(1.835)	(1.840)	(1.998)
age			2.803***	2.528***	2.336***

			(0.44)	(0.446)	(0.431)
gender			-1.249***	-1.249***	-1.342***
			(0.432)	(0.433)	(0.41)
ethnicity_id			0.7180	0.6000	0.3260
			(0.469)	(0.469)	(0.492)
Weather controls	No	No	No	Yes	Yes
N	717	717	717	717	717

Standard errors in parentheses

** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

6.1.2 Result 1b

How does NO_2, NH_3, SO_2, CO, and O_3 affect a child's cognitive performance?

Table 3. presents the results of specifications where pollutants that contribute to $PM_{2.5}$ are added as an indicator of air quality. The results still remain inconsistent when it comes to the effect of pollutants. The effect of child characteristics and the interaction term is similar. Although both NH_3 (at 5%) and CO (at 1%) are statistically significant in specification (5), the negative effect of NH_3 is much larger than the positive effect of CO. With an increase in NH_3 by I unit, the number of correct answers given by a child declines by 0.852. On the other hand, with a unit increase in CO, the child gives less than 1 (0.0846) more correct answers.

The effect of child characteristics and interaction term remains consistent with the previous results with all except ethnicity being statistically insignificant. These results are calculated using 563 observations.

Table 8: Results 1b

Effect of NO2, NH3, SO2, CO and Ozone on a child's performance on cognitive tests

	Without controls	With period*intervention	With child characteristics	With weather controls	With assessor fixed effects
	(1)	(2)	(3)	(4)	(5)
	numcorans	numcorans	numcorans	numcorans	numcorans
notwo	-0.0375**	-0.0071	0.0085	0.0071	-0.0076
	(0.0167)	(0.0168)	(0.0174)	(0.0189)	(0.0224)
nhthree	-1.569***	0.0503	0.0990	0.0125	-0.852**
	(0.293)	(0.316)	(0.312)	(0.315)	(0.365)
sotwo	0.305***	-0.186**	-0.213***	-0.197**	-0.0711
	(0.0677)	(0.0793)	(0.0779)	(0.0786)	(0.0922)
co	0.177***	0.0397	0.0323	0.0291	0.0846***
	(0.0227)	(0.0253)	(0.025)	(0.025)	(0.0279)

ozone	-0.0165	-0.0033	0.0036	0.0155	0.0153
	(0.0156)	(0.0145)	(0.0143)	(0.0156)	(0.0168)
period		-0.1080	-1.3660	-2.4060	0.0374
		(2.156)	(2.141)	(2.476)	(2.792)
intervention		-2.9580	-2.589	-2.943	-3.294*
		(1.929)	(1.884)	(1.930)	(1.991)
period_intervention		7.455***	7.031***	6.638***	7.992***
		(2.254)	(2.241)	(2.333)	(2.715)
age			2.766***	2.662***	2.524***
			(0.532)	(0.54)	(0.514)
gender			-1.051**	-1.070**	-1.191***
			(0.484)	(0.486)	(0.456)
ethnicity_id			0.6470	0.6000	0.8790
			(0.559)	(0.562)	(0.573)
Weather controls	No	No	No	Yes	Yes
N	563	563	563	563	563

Standard errors in parentheses

** p < 0.1, ** p < 0.05, *** p < 0.01*

6.1.3 Result 1c

How does $PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO affect a child's cognitive performance?

Table 4. presents the results for the effect of pollutants that are mainly a result of road dust, construction activities and vehicular emissions. In specification (5), all pollutants included in the model are statistically insignificant except for SO_2, significant at 10%. It has a negative effect on a child's cognitive performance. With a unit increase in SO_2, number of correct answers given by a child declines by 0.143.

The results for child characteristics and interaction terms remain consistent with the results of the previously discussed models. The interaction term and age, both have a positive effect on a child's performance at a statistically significant level of 1%. The results for gender and ethnicity are statistically significant too at 1% and 5% levels respectively. Females and Muslims both answer one more correct answer than males and non-Muslims.

Table 9: Results 1c

Effect of PM2.5, PM10, NO2, SO2 and CO on a child's performance on cognitive tests

	Without controls	With period*intervention	With child characteristics	With weather controls	With assessor fixed effects
	(1)	(2)	(3)	(4)	(5)

	numcorans	numcorans	numcorans	numcorans	numcorans
pmten	-0.0089	0.0071	0.0077	0.0163	0.0343
	(0.0214)	(0.0215)	(0.021)	(0.0223)	(0.0248)
pmtwoptfive	0.118***	0.0347	0.0410*	0.0363	0.0265
	(0.0222)	(0.0233)	(0.0228)	(0.0263)	(0.0301)
notwo	-0.0432**	-0.0337*	-0.0128	-0.0065	-0.0232
	(0.0168)	(0.0191)	(0.0196)	(0.0206)	(0.0251)
co	0.0623***	0.0347**	0.0318**	0.0254	0.0322
	(0.0169)	(0.0162)	(0.0159)	(0.0163)	(0.0204)
sotwo	0.0526	-0.134**	-0.158***	-0.157***	-0.143*
	(0.0564)	(0.0576)	(0.0568)	(0.0579)	(0.0766)
period		-2.4550	-3.5300	-2.9500	-1.7120
		(2.390)	(2.349)	(2.595)	(3.101)
intervention		-3.655*	-3.238*	-2.9920	-3.442*
		(1.945)	(1.897)	(1.937)	(2.012)
period_inter-vention		8.807***	7.991***	7.151***	8.484***
		(2.350)	(2.309)	(2.374)	(2.799)
age			2.708***	2.549***	2.428***
			(0.521)	(0.532)	(0.509)
gender			-1.015**	-1.039**	-1.262***
			(0.48)	(0.483)	(0.454)
ethnicity_id			1.185**	1.194**	1.204**
			(0.56)	(0.571)	(0.582)
Weather con-trols	No	No	No	Yes	Yes
N	567	567	567	567	567

Standard errors in parentheses

** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

With respect to the effect of air quality on a child's performance, there is a lot of inconsistencies in the result. Although the magnitude of the negative effects of statistically significant pollutant, NH_3, has been much larger than the magnitude of positive effects of statistically significant pollutants, it is difficult to ignore the statistically significant positive effects of various pollutants. The possible reasons for these inconsistencies are discussed in the next section.

Chapter 7
Discussion

Researchers have been able to build on each other's thoughts on the mechanism through which air pollution could be effecting cognitive performance. However, as presented in the previous section, there is no strong consensus on how to measure air quality or cognitive performance. This has allowed certain studies to present mixed results for the short-term effect of exposure to poor quality air on cognitive performance. Studies like Zhang *et al.* (2018) presents evidence for negative effect of air pollution becoming more pronounced with age, their results for negative effect of contemporaneous air pollution is only statistically significant for the word-recognition test performance and not mathematics test performance. Similarly, Bedi *et al.* (2021) attempt to show the negative effect of air pollution on a range of cognitive performances however, their results are significant only for one of the dimensions of cognition, i.e. fluid reasoning.

Similarly, a study by Krebs *et al.* (2021), provides results for effect on cognitive performance of individuals who are proficient at a task versus beginners. The study finds negative effect of air pollution on cognitive performance of proficient players but not for beginners thereby indicating that the negative effect of air pollution may become pronounced with proficiency.

The results in this study is also found to be inconsistent. For pollutants like $PM_{2.5}$ there is small, yet positive and statistically significant result found while for pollutants like NH_3, there is a large, negative and statistically significant result found. It has rather been confusing to understand the reason behind the positive effect of $PM_{2.5}$.

There certainly are limitations in the data available for the analysis. To being with, it was not collected for an analysis like this one. It was data collected by an organisation to test for the impact of their intervention. In an ideal case, the study would have benefitted from a data collection process designed specifically for this research. However, that was not possible given the COVID-19 pandemic, which introduced the world to lockdowns and schools for kindergarten children closed for the entire duration of this study.

On the other hand the results of a strong negative effect of NH_3, presented in Table (1) and (3) provide an interesting insight. From all the sources of NH_3, the ones that can be found in a city like Bengaluru includes decaying organic matter, human and animal waste and waste disposal sites. As per a study by Lakshmikantha (2006), there are 60 waste disposal site in and around Bengaluru. The study also suggests that waste is being disposed in open sites and managed in unscientific ways, creating an unhygienic environment. Adding to this, there are 3.10lakhs[12] stray dogs in the city (Reddy, 2021) and a growing number of stray cattle on the streets, defecating in the open, and contributing to animal waste. Being in close proximity to such unhygienic sites, which are active sources of NH_3, could explain the strong negative effect of the pollutant. Although the study did not find any clear results for the effect of pollutants from other key sources of air pollution in the city like construction sites, road dust and vehicular emissions, the results from NH_3 provide an interesting and insightful approach to the study of air pollution and its effects, especially in urban cities like Bengaluru.

[12] Lakhs – unit of measurement. 10 lakhs = 1 million.

7.1 Limitations

Some of the limitations of this study are acknowledged and discussed in this section.

Important variables that may influence test scores have been omitted in this study. Namely, family background (or demographic details) of the child, that have been included in similar studies by Marcotte (2016) and Gilraine (2020) among others. Other controls that the study could have benefitted from include, information about school infrastructure, attendance details of both child and teacher and information about qualification of the teacher.

As compared to previous literature, the number of observations in the study is small. Additionally, there is a loss of observations due to factors like unavailability of children on the date of the test and dropouts of children. The overall number of observations in the study also reduce due to missing data on certain pollutants for certain test dates. All of these could be source of potential bias in the estimates.

There is also a possibility of measurement error in matching pollution data to child exposure levels. The air quality data is captured from monitoring stations which is in the 5km radius of the school. The actual exposure of the child may be over or underestimated. This error could have been avoided if air quality data was collected from within the classroom for the exact time duration of the test.

The study also suffers from unobserved movement of individuals during the time of the test. Based on information shared by a KEF employee, tests are conducted for a child while other children are involved in different activities. If these activities increase the movement of individuals around the classroom, the pollution levels may be increased due to resuspension of settled dust, adding another source of bias to the estimates. Additionally, the movements may be different on different days, exaggerating to the challenge. Again, an ideal situation would have been to collect data while observing and tracking this variable.

Absence of an appropriate control group also causes hinderances. Although the mechanism used by KEF to collect control data could be practical for the given context, a lot of data is lost in the process. This obstructs the study to fully exploit the panel nature of the data.

The KEF data could also suffer from measurement errors. The data is collected by 25 different assessors. Although there is a grading rubric available and the assessors are trained, there is scope of both measurement error and accessor bias to cause possible biases in the estimates. To attempt solve for this, assessor fixed effects are added to the specifications.

It is important to acknowledge that the data used for this study was collected for a very different purpose which added complications in the study. However, based on the time and resource available, this was the data set available and an attempt has been made to make the best use of it to conduct this study.

Chapter 8
Conclusion

This study attempts to find the effect of contemporaneous air pollution on children's' cognitive performance. By setting the study in Bengaluru, India, the study contributes to the literature. The study provides a thorough background of the concepts relevant to the topic, and presents an extensive review of the existing literature, to find support for the hypotheses. Using the 821 observations obtained from tests conducted for 539 children, the study proceeds its analysis.

The OLS estimates provide inconsistent results. Based on the results from the most complete specification the coefficients of $PM_{2.5}$ (0.064) and CO (0.074) are positive and statistically significant at 1% level while the coefficient of O_3 (0.034) is statistically significant at 10% level. Although positive, the effects are marginal. In all three cases, with one unit increase in the pollutant, the increase in number of correct answers is much less than 1.

In contrast, the coefficient of NH_3 (-1.066) is negative and statistically significant at 5% level. It indicates that a 1 unit increase in NH_3, leads to almost two (1.66) incorrect responses. The negative effect of NH_3 is much larger than the combined positive effect of $PM_{2.5}$, CO and O_3.

The results for NH_3 provides an insight into the conversation regarding key pollutants in Bengaluru city. Literature suggests that construction and vehicular emission are the key contributors to air pollution in the city however, this study indicates towards improper waste management (a major source of NH_3 in urban areas) as the key contributor.

Acknowledging its limitations, the study can be seen as piece of literature that has paved way for further research, focus and conversation in intersecting field of air pollution and cognitive performance, especially in the developing world. Air pollution has been a 'silent menace' for millions of lives by affecting various aspects of their life (health, cognition, productivity to name a few) especially in the last few decades. Meaningful research and swift action thus becomes imperative to contain it.

Appendices

Appendix 1: Air Pollution Monitoring Stations and Schools

Air Pollution Monitoring Stations and Schools

School ID	Intervention	Station	Distance in kms	Within 5km
1	1	Hombegowda Nagar	2.3	1
2	1	Hombegowda Nagar	4.8	1
3	1	Jayanagar 5th Block	5	1
4	1	Silk Board	10.9	0
		Jayanagar 5th Block	5	1
		Bapujinagar	4	1
5	1	Silk Board	4.4	1
6	1	BTM Layout	2	1
7	1	BTM Layout	1.4	1
		Silk Board	2.7	1
8	1	Silk Board	7	0
9	1	BTM Layout	5	1
10	1	Silk Board	11.5	0
11	1	Hebbal	5	1
12	1	Bapujinagar	1.1	1
		Saneguravanahalli	5	1
13	1	Hombegowda Nagar	8.7	0
14	1	Hombegowda Nagar	5	1
15	1	Silk Board	5	1
16	1	Hombegowda Nagar	4.2	1
17	1	Silk Board	4	1
18	1	Bapujinagar	2.3	1
19	1	Bapujinagar	3.6	1
		Saneguravanahalli	3.8	1
20	1	Hebbal	5	1
21	1	Hebbal	13.2	0
		BWSSB Kadabesanahalli, Bengaluru - CPCB	5	1
22	1	Hebbal	7.4	0
23	1	BWSSB Kadabesanahalli, Bengaluru - CPCB	5	1
		Silk Board	10.3	0
24	1	Saneguravanahalli	3.2	1

		Hombegowda Nagar	8	0
		Bapujinagar	1.7	1
25	1	Silk Board	4.2	1
26	1	Saneguravanahalli	2.8	1
		City Railway Station	3.4	1
27	1	Hombegowda Nagar	2.6	1
28	1	Hombegowda Nagar	9.3	0
29	1	Hombegowda Nagar	2.5	1
30	1	Hombegowda Nagar	2.9	1
31	1	BWSSB Kadabesanahalli, Bengaluru - CPCB	14.8	0
32	1	BWSSB Kadabesanahalli, Bengaluru - CPCB	15.3	0
33	1	Silk Board	8.7	0
34	1	Silk Board	11.7	0
35	1	Silk Board	8.6	0
36	0	BWSSB Kadabesanahalli, Bengaluru - CPCB	7.9	0
37	0	Hombegowda Nagar	7	0
38	0	BWSSB Kadabesanahalli, Bengaluru - CPCB	7.9	0
39	0	Hebbal	7.3	0
40	0	Hebbal	10	0
41	0	Saneguravanahalli	9.4	1
42	0	Saneguravanahalli	2.9	1
43	0	Silk Board	4.2	1
44	0	BTM Layout	5	1
45	0	BWSSB Kadabesanahalli, Bengaluru - CPCB	8.6	0
		Average Distance	5.99	

Note: School IDs are presented here instead of names of schools to respect the privacy of the schools and the children.

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