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AIR POLLUTION IN THE STEEL CITY: ASSESSING THE INFLUENCE OF COVID-19 ON AIR POLLUTION IN ALLEGHENY COUNTY

A Thesis

Submitted to the Bayer School of Natural and Environmental Sciences

Duquesne University

In partial fulfillment of the requirements for

the degree of Master of Science

By

Carissa Lange

May 2021

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Carissa Lange

2021

AIR POLLUTION IN THE STEEL CITY: ASSESSING THE INFLUENCE OF COVID-19 ON AIR POLLUTION IN ALLEGHENY COUNTY

By

Carissa Lange

Approved March 12, 2021

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ABSTRACT

AIR POLLUTION IN THE STEEL CITY: ASSESSING THE INFLUENCE OF COVID-19 ON AIR POLLUTION IN ALLEGHENY COUNTY

By

Carissa Lange

May 2021

Dissertation supervised by David M. Kahler

The city of Pittsburgh has long been viewed as a leader in iron and steel production. However, while an industrial past helped shape the city's economic, social, and political environment, it also contributed to air pollution that continues to persist today (Ingham, 1991). Much of the reason for the city's poor ambient air quality is due to high levels of particulate matter with an aerodynamic diameter ≤ 2.5 μm ($PM_{2.5}$) (American Lung Association, 2020). In Pittsburgh, 70% of point source $PM_{2.5}$ pollution comes from just two industrial facilities, the Edgar Thomson Steel Works and the Clairton Coke Works (Kelly, 2018).

The novel coronavirus (COVID-19) has unfortunately sickened tens of millions of individuals. However, lockdown measures, which often resulted in decreased vehicle traffic, have been shown to significantly reduce air pollution. Thus, this study utilized a natural experiment to determine how large of a role the COVID-19 lockdowns played in improving air

quality in the Pittsburgh region. Data were obtained from the Allegheny County Health Department from monitors located in and around Pittsburgh.

According to these data, nitrogen dioxide (NO_2) pollution significantly decreased during the lockdown period and PM_{10} pollution decreased at the majority of monitoring sites. Decreases in $PM_{2.5}$ pollution were not as apparent, as significant results were only observed at half of the monitoring locations. The location which observed the most apparent significant decreases in $PM_{2.5}$ pollution was located near the Clairton Coke Works. These decreases were likely a result of reduced coke production during the pandemic, as well as upgrades to emissions control devices that have decreased the facility's emissions overtime. Thus, the results of this study suggest that industrial sources are a larger contributor of particulate matter than vehicular transportation in the city of Pittsburgh. In the future, air pollution reduction efforts should focus attention on lessening emissions at these large industrial facilities. In return, the communities located near the facilities should see improved health outcomes which will lead to the reduction of health disparities in Allegheny County.

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I would also like to thank the Allegheny County Health Department, Pennsylvania State Climatologist, NOAA National Centers for Environmental Information, and US Census Bureau and Allegheny County Property Assessment Database for providing the data that were utilized for this project.

To Dr. David Kahler, over the past year, I have developed a relationship with you that I will cherish for the rest of my life. I am beyond thankful that you welcomed me to your research lab with open arms, despite having little idea what I wanted to study. I know you were upset that I abandoned the beer project, but I am sure you will find a future student to tackle that project someday. Thank you for all of your assistance with my thesis, PhD school applications, school reports, and other miscellaneous tasks. You always go above and beyond to make me feel supported, something I will never forget.

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Thank you to Dr. Skip Kingston for serving on this committee, and thank you to Daniel Nadzam, of the Allegheny County Health Department for providing me with a plethora of knowledge regarding the county's monitoring equipment.

To my parents Chris and Melissa, words cannot express how grateful I am for your constant words of encouragement. Thank you for always supporting my decisions, and for raising me to be the best version of myself.

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LIST OF ABBREVIATIONS

ACHD – Allegheny County Health Department

AQI – Air Quality Index

BAM – beta attenuation monitor

COVID-19 – coronavirus disease 2019

DALYs – disability adjusted life years

NOAA – National Oceanic and Atmospheric Administration

NO_2 – nitrogen dioxide

$PM_{2.5}$ – particulate matter with an aerodynamic diameter $\leq$ 2.5 μm

PM_{10} – particulate matter with an aerodynamic diameter $\leq$ 10 μm

TEOM – tapered element oscillating microbalance

CHAPTER 1: INTRODUCTION

For much of its history, Pittsburgh, Pennsylvania led the nation in iron and steel production. Its location along three rivers, the Allegheny, Monongahela, and Ohio made for a convenient point of access for iron ore traveling from the Great Lakes region, and its abundance of high-quality coal gave it an advantage over other steel producing cities (White, 1928). To the people of Pittsburgh, steel was not simply a commodity, but rather, a product that helped shape the city's economic, social, and political environment (Ingham, 1991). However, consistently producing more than one fourth of the nation's steel did not come without ecological consequence (White, 1928). For years, Pittsburgh was referred to as the "Smoky City" (Longhurst, 2005). The thick persistent smoke was noted among travelers and scholars and was even referenced in the Woody Guthrie song, "Pittsburgh Town" (Davidson, 1979; Longhurst, 2005). Though smoke had been an obvious presence in the city since the early 1800s, it was not until 1941 that an effective smoke control ordinance was passed. This ordinance was not immediately effective, as the war effort and low supplies of smokeless fuel (e.g., anthracite coal, natural gas, or fuel oil) delayed its implementation. Nevertheless, air pollution decreased over the following decades until the collapse of the steel industry in the 1970s cleared nearly all of the smoke that had once lingered (Davidson, 1979).

Despite the collapse of Pittsburgh's steel industry and the significant improvements that have been made to reduce air pollution, the Pittsburgh region still ranks among the worst in the nation for ambient air quality (American Lung Association, 2020). The U.S. Environmental Protection Agency describes ambient air pollution as common pollutants in outdoor air that are considered harmful to human health and the environment and that come from a variety of sources (US EPA, 2019). The quantity of these pollutants in the atmosphere is communicated to the public using the Air Quality Index (AQI), a system that ranks daily air based on level of concern for public health. The AQI considers five major pollutants: ground-level ozone, particle pollution ($PM_{2.5}$ and PM_{10}), carbon monoxide, sulfur dioxide, and nitrogen dioxide (AirNow, 2021). Measurements for each pollutant are recorded by air monitors and then converted into AQI values based on health risk. These values range from 0 to 500 and are broken down into six categories: good (0-50), moderate (51-100), unhealthy for sensitive groups (101-150), unhealthy (151-200), very unhealthy (201-300), and hazardous (301 and higher). The daily AQI value is determined by selecting the highest of the pollutant AQI values.

In 2018, the AQI in Pittsburgh was only classified as "good" 43.5% of days (Allegheny County Health Department, 2019). Most commonly (50% of days), the AQI was considered "moderate," and 6% of the time, the AQI was deemed "unhealthy for sensitive groups" (Allegheny County Health Department, 2019). In addition to mediocre AQI rankings, the American Lung Association's 2020 State of the Air report ranked Pittsburgh the 8th most polluted city in the nation for annual particle pollution, 16th for 24-hour particle pollution, and 30th for high ozone days (American Lung Association, 2020). As a result, Allegheny County (the county in which Pittsburgh resides) currently stands as one of only 14 counties in the United States to receive a failing grade in all three of these categories. This signifies that while the presence of smoke may have vanished, Pittsburgh still faces very real threats when it comes to ambient air pollution.

A majority of the reason for Pittsburgh's poor ambient air quality is due to high levels of particulate matter with an aerodynamic diameter ≤ 2.5 µm ($PM_{2.5}$) (American Lung Association, 2020). $PM_{2.5}$ can be traced back to a variety of sources, but one of the most prominent sources in the Pittsburgh region is industry. One study sought to determine exactly how much industry played a role in $PM_{2.5}$ emissions by isolating sulfate, Pittsburgh's largest contributor to $PM_{2.5}$. Data were collected from a single monitor located approximately 6 km to the east of downtown Pittsburgh over the course of 13 months (Pekney et al., 2006). Through modeling, it was concluded that sulfate, on average, contributed 28% to $PM_{2.5}$ (Pekney et al., 2006). The study also suggested that this high sulfate content was likely a result of Pittsburgh's close proximity to a series of coal-fired power plants along the Ohio River Valley (Pekney et al., 2006). Pollution emitted by these power plants makes its way to Pittsburgh as a result of winds, which primarily arise from the south (Figure 1.1).

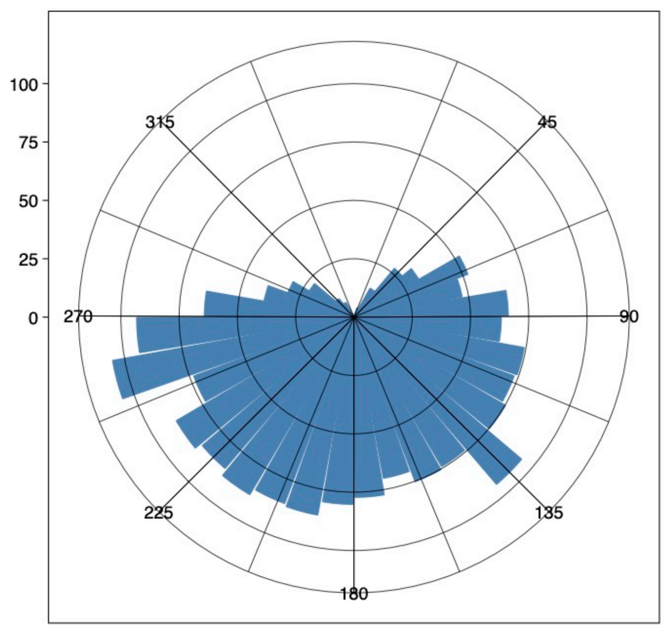

Figure 1. Average daily wind direction recorded at the Pittsburgh International Airport from January 1, 2016 – December 31, 2020. Data courtesy of the Pennsylvania State Climatologist.

In addition to Pittsburgh's close proximity to the Ohio River Valley plants, Allegheny County is also home to an active steel mill and the largest coke manufacturing facility in the United States. In 2017, the Edgar Thomson Steel Works and the Clairton Coke Works produced 439.63 tons of $PM_{2.5}$ accounting for more than 70% of the total point source $PM_{2.5}$ pollution in the Pittsburgh region (Kelly, 2018). These industrial facilities are the largest emitters of particulate matter in Allegheny County and have repeatedly been scrutinized for exceeding $PM_{2.5}$ National Ambient Air Quality Standards (Tunno et al., 2015).

The exceedance of air pollutant standards can have serious impacts on human health. According to the World Health Organization, 4.6 million individuals die annually as a result of diseases and illnesses related to poor ambient air quality (Dutheil et al., 2020). $PM_{2.5}$ is especially harmful, causing complications from both short-term and long-term exposures (Im et al., 2018). Short-term exposures to $PM_{2.5}$ can result in cardiovascular and respiratory complications that have been associated with increases in daily mortality rate (Pope & Dockery, 2006). Additionally, long-term exposures to $PM_{2.5}$ have been linked to increased instances of cardiopulmonary and lung cancer mortality (Burnett et al., 2014; Chen et al., 2008; Pope et al., 2002). As such, $PM_{2.5}$ was ranked as the fifth highest mortality risk factor in 2015 (Cohen et al., 2017). This same year, $PM_{2.5}$ was responsible for 4.2 million deaths and 103.1 million disability-adjusted life-years (DALYs), representing 7.6% of total global deaths and 4.2% of total global DALYs (Cohen et al., 2017).

In addition to $PM_{2.5}$, there are a variety of additional pollutants that have been shown to harm human health. For example, elevated levels of NO_2 have been linked to an increased incidence of respiratory infections and illnesses while particulate matter with aerodynamic diameter ≤ 10 μm (PM_{10}) has been associated with an increased risk of death from cardiovascular or respiratory complications (Cao et al., 2017; Zanobetti & Schwartz, 2009). One study that assessed cardiovascular mortality in Iran due to exposure to pollutants determined that PM_{10} and NO_2 were responsible for 188 and 33 premature deaths, respectively, from 2014-2015

(Khaniabadi et al., 2017). Thus, the many complications that can arise from exposure to a variety of air pollutants demonstrates the need for future air pollution reductions.

Though the novel coronavirus (COVID-19) began as an isolated cluster of pneumonia cases in the city of Wuhan, China, its rapid spread resulted in over one million global cases within the first four months of its identification (Riou & Althaus, 2020; Sharma et al., 2020). In consequence, lockdowns were ordered in many nations. In the United States, President Trump left lockdown determination up to state government officials. Subsequently, lockdown dates varied from March 19th (California) to April 7th (South Carolina). In the city of Pittsburgh, a stay-at-home order was mandated on March 23rd and was not lifted until May 15th. This resulted in a 53-day lockdown in which residents were only allowed to leave their homes for food, emergencies, exercise, volunteering, and work – if their work provided "essential products and services at a life-sustaining business" (Common Wealth of Pennsylvania, 2020).

A variety of studies in countries around the globe have suggested that decreased transportation, as a result of these lockdown measures, have significantly improved air quality (e.g. India, China, United States, Western Europe) (Venter et al., 2020). Many of these studies have focused on NO_2, which is likely a result of its association with transportation and the accessibility of satellite data (Lu et al., 2020; NOAA, 2020). For example, Bauwens et al. (2020) used satellite data to determine trends in NO_2 emissions and found remarkable decreases in NO_2 in China, Europe, South Korea, and the United States when compared with pre-lockdown conditions and 2019 levels. Additionally, Sarfraz et al. (2020) noted substantial decreases in NO_2 (40-50%) in the two most polluted Indian cities, Mumbai and Delhi, and Berman & Ebisu (2020) found a 25.5% reduction in NO_2 pollution across the United States. Decreases of NO_2 emissions between 30-50% were also observed in all European countries (Menut et al., 2020).

While reductions in NO_2 emissions have been observed globally, reductions in $PM_{2.5}$ have varied considerably (Berman & Ebisu, 2020; Chauhan & Singh, 2020; Rodríguez-Urrego & Rodríguez-Urrego, 2020). Unlike NO_2, particulate matter (both $PM_{2.5}$ and PM_{10}) is contributed to a variety of non-transportation sources including coal-fired power plants, industry, and biomass burning (Juda-Rezler et al., 2020; US EPA, 2020). Therefore, the source differences among the two types of pollutants could potentially explain the variances in pollutant reductions. One study, which analyzed $PM_{2.5}$ data from the 50 most polluted capital cities in the world, found that while $PM_{2.5}$ pollution levels decreased by 12% on average, there was great inconsistency among the cities (Rodríguez-Urrego & Rodríguez-Urrego, 2020). In the African, American (South America and Mexico), and Asian continenets, average reductions of 33%, 22%, and 16% were observed, respectively (Rodríguez-Urrego & Rodríguez-Urrego, 2020). However, the European continent did not exhibit large reductions, as reductions in these cities only decreased by an average of 5% (Rodríguez-Urrego & Rodríguez-Urrego, 2020).

Similarly, differences in $PM_{2.5}$ pollution reductions can be observed when comparing India and the United States during the COVID-19 pandemic. India, a country with exceptionally high particulate pollution, experienced 43% decreases in $PM_{2.5}$ pollution (Sharma et al., 2020). The reduction in the United States has not been as drastic; however, the United States has an annual $PM_{2.5}$ pollution approximately 8.7 times less than India (Yang et al., 2018). One U.S. study, which found that $PM_{2.5}$ did significantly decrease during the pandemic, also concluded that reductions varied among counties and that decreases in $PM_{2.5}$ were not as palpable as decreases in NO_2 (Berman & Ebisu, 2020). An additional study that analyzed air pollution changes in New York City found that decreases in $PM_{2.5}$ of 36% were observed shortly after lockdowns took place. However, this same study observed no significant differences when changes in $PM_{2.5}$ during lockdown were compared to the same time period in 2015-2019 (Zangari et al., 2020). Thus, this study highlighted the importance of considering temporal variability when analyzing air pollution during the COVID-19 lockdown periods.

In addition to variable $PM_{2.5}$ reductions, studies have also observed that reductions in PM_{10} pollution during the pandemic have varied by location. For example, Briz-Redón et al. (2021) found that reductions in PM_{10} were only significant in two of 11 major Spanish cities. In Salé, Morocco, however, PM_{10} pollution decreased by 75% when comparing average pre-lockdown levels (114.6 $\mu g/m^3$) with average lockdown levels (28.3 $\mu g/m^3$) (Otmani et al., 2020). While this Moroccan city did observe decreases in PM_{10}, the city's pre-lockdown levels were approximately seven times greater than average PM_{10} levels in Allegheny County in 2018 (Allegheny County Health Department, 2019). Thus, it is difficult to determine if similar results would be expected in the city of Pittsburgh.

By utilizing a natural experiment, this study sought to determine how large of a role the COVID-19 lockdowns played in reducing air pollution in the Pittsburgh region. I hypothesized that air pollution during the COVID-19 lockdown period would be significantly reduced when compared to previous years. However, based on the results of previous studies, I expected to observe greater reductions in NO_2 than particulate pollution. In addition, I anticipated that reductions would be most apparent at monitoring sites located near heavy traffic areas as opposed to monitoring sites located near industrial sources. This expectation was based off of the fact that traffic was significantly reduced by the lockdown, but industrial activity, may not have been as largely impacted. Due to Pittsburgh's industrial heavy history and high levels of particulate pollution, emphasis was placed on analyzing $PM_{2.5}$ and PM_{10} data.

CHAPTER 2: MATERIALS AND METHODS

2.1 DATA SOURCES

Data were obtained from 11 monitors that are owned and maintained by the Allegheny County Health Department (ACHD). These 11 monitors are located in and around the city of Pittsburgh and are named according to site: Avalon, Clairton, Flag Plaza, Glassport, Harrison Township, Lawrenceville, Liberty, Lincoln, North Braddock, Parkway East, and South Fayette (Figure 2). Five of the monitoring sites are located near industry, four of which neighbor the Clairton Coke Works (Clairton, Glassport, Liberty, Lincoln) and one of which is near the Edgar Thomson Steel Works (North Braddock). Two of the monitoring sites are located along major highways (Avalon and Parkway East) and two of the monitoring sites are located in close proximity to the downtown area of Pittsburgh (Flag Plaza, Lawrenceville). The remaining two monitoring sites are located within suburban areas that reside along the county perimeters to the North and South of the city (Harrison Township and South Fayette).

In order to account for meteorology, weather records were retrieved from the NOAA National Centers for Environmental Information (NCEI) Daily Summaries dataset. The precipitation records used for analysis were pulled from the "Braddock Lock 2, PA US" (40.3916°, -79.8594°) station. This location was deemed most appropriate due to its close proximity to four of the monitoring sites and its temporal data coverage during the air quality monitoring of concern (2016 – present). Finally, wind data for the Pittsburgh International Airport was obtained from the Pennsylvania State Climatologist.

Figure 2. The locations of the ACHD air monitors, NOAA precipitation data station, and the two large industrial sources of pollution, the Clairton Coke Works and the Edgar Thomson Steel Works. Major rivers and highways within the county are also illustrated.

2.2 Site Selection

A previous study, which examined air pollution trends in New York City during the COVID-19 pandemic, highlighted the importance of considering temporal variation during analysis (Zangari et al., 2020). While Zangari et al. (2020) initially observed $PM_{2.5}$ reductions of 36% after lockdown measures were put in place, they observed no significant differences when comparing lockdown $PM_{2.5}$ concentrations with $PM_{2.5}$ concentrations during the same time period from 2015-2019. Thus, to consider temporal variation and trends in air quality in this study, average daily air pollutant data from all available years, i.e., 2016-2020, from the ACHD was analyzed. In addition, April of each year was used for analysis. Since April 2020 was the only month spent entirely in lockdown, April 2020 was compared to all prior months (beginning in 2016) and compared to the previous four Aprils.

When considering which sites would be analyzed, a set of criteria was established. 1.) The monitoring site had to collect data for either $PM_{2.5}$, PM_{10}, or NO_2, but did not have to collect data for all three of these pollutants. If the monitoring site did not collect data for any of these pollutants, it was immediately disregarded. 2.) Only monitoring stations which sought out the longest recording data at a single site were considered. 3.) Monitoring locations in which instrumentation varied over the five-year timespan were further examined. The site was omitted if variations in instrumentation would have influenced the interpretation of the results.

2.3 INSTRUMENTATION

The instrumentation used to measure pollutants varied among sites. When considering particulate matter pollution, a tapered element oscillating microbalance (TEOM) was used at Flag Plaza, Glassport, Liberty, and Lincoln (Figure 3). This type of monitoring technology is gravimetric, meaning it quantitatively determines particulate matter based on mass. These systems draw ambient air through a filter that is continuously weighed, and as a result, they are able to provide near real-time mass concentrations of particulate matter (ThermoFisher Scientific, 2021). At sites Avalon, Lawrenceville, North Braddock, and Parkway East, a beta attenuation monitor was used. This technology collects ambient particulate matter by pulling a controlled amount of ambient air through filter tape (Met One Instruments, 2021). Attenuation of a beta ray signal is then used to determine the mass of the particulate matter on the filter tape. This calculates the concentration of particulate matter in ambient air (Figure 4). Pollution at sites

Lawrenceville and North Braddock was measured by the Met One BAM 1020, while pollution at sites Avalon and Parkway East was measured by the ThermoFisher Scientific 5014i Beta Continuous Ambient Particulate Monitor.

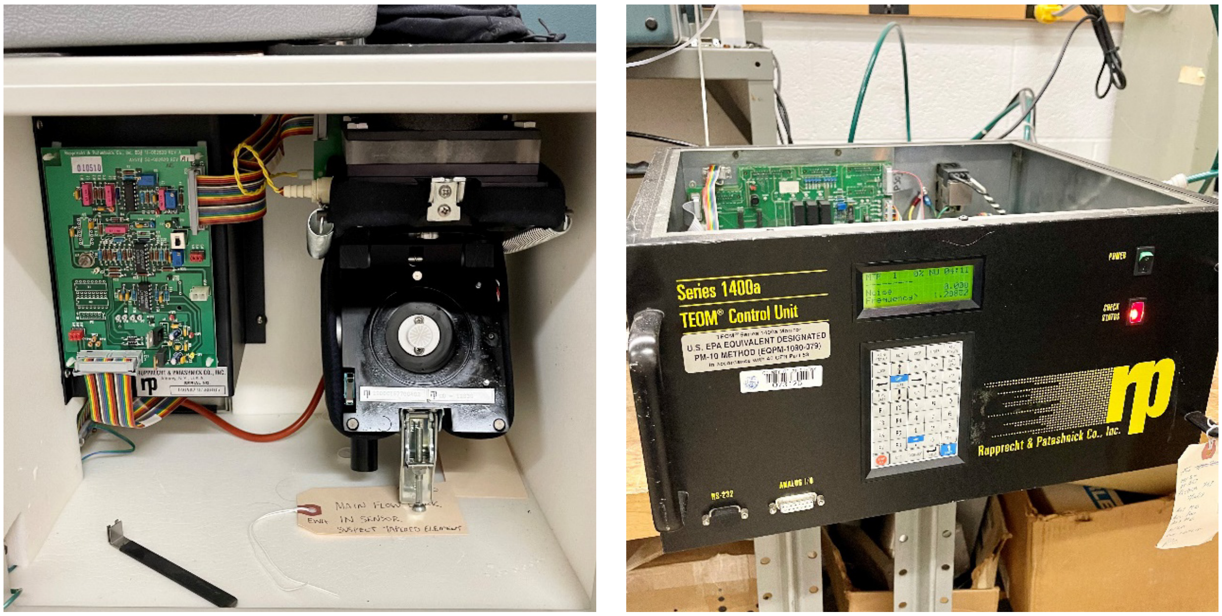

Figure 3. The inside of the TEOM sensor unit (left) and the control unit (right). This instrument is not currently in use but is being stored by the ACHD.

Figure 4. The Met One BAM 1020 particulate monitor. This instrument is currently inactive but remains on the roof of the Lawrenceville monitoring site.

Figure 5. Several of the particulate matter air monitors in use at the Lawrenceville monitoring site (left) as well as the inlets that are used to bring ambient air into the monitoring device (right).

At both Harrison and Parkway East, instrumental methods which utilize chemiluminescence were used for determination of NO_2 concentrations. The monitoring device used was the Teledyne T200 Nitrogen Oxides Analyzer. This instrument first draws gas from ambient air into either a reaction chamber or a catalytic-reactive converter (Teledyne Advanced Pollution Instrumentation, 2011). The reaction chamber exposes the air to ozone, which initiates a chemical reaction that gives off light (chemiluminescence) (Teledyne Advanced Pollution Instrumentation, 2011). This is measured to determine the amount of NO in the sample. However, because the chemiluminescence reaction only works with NO, NO_2 is sent through a catalytic-reactive converter where it is converted to NO. Thus, the NO that is sent through the reactive chamber and the NO_2 that is sent through the catalytic-reactive converter, are combined to measure total NO_x. NO_2 is then calculated as the difference between NO_x and NO. (Teledyne Advanced Pollution Instrumentation, 2011).

2.3 Statistical Analysis

Linear models were fit to the data with R software to compare April 2020 to all months prior beginning in 2016 (See Appendix A). This function was also used to compare April 2020 with data from only the previous four Aprils, and the function was expanded to include indicators for April of all years. Results were considered statistically significant at the 95% level, $p \leq 0.05$. Data and residuals were checked for normal distribution by performing a Chi-square goodness of fit test. If the 95% threshold for normal distribution was not met, data were log transformed. The model controlled for the effect of precipitation.

CHAPTER 3: RESULTS AND DISCUSSION

3.1 Site Selection

Two monitoring locations, Clairton and South Fayette were immediately disregarded, as neither site collected $PM_{2.5}$, PM_{10}, or NO_2. In regard to $PM_{2.5}$, four sites were selected for analysis: Avalon, Lawrenceville, Lincoln, and Parkway East. Liberty also collected $PM_{2.5}$ data, but instrumentation varied over the five-year time period. There was consistent bias between the instruments used with additional random variations; therefore, this site was not analyzed for $PM_{2.5}$ (See Appendix B). Furthermore, consistent measurements were available from the Lincoln station. Only 2017-2020 data was available at the Avalon location; however, it was still considered for analysis due to the lack of an alternative monitoring location in close proximity.

All six monitoring sites that collected data for PM_{10} pollution were considered. These sites included Flag Plaza, Glassport, Lawrenceville, Liberty, Lincoln, and North Braddock. While NO_2 was collected at three sites (Harrison Township, Parkway East, and Lawrenceville), only Harrison Township and Parkway East were analyzed. This was due to a variance in NO_2 reporting at the Lawrenceville location.

3.1 Changes in $PM_{2.5}$

Mean $PM_{2.5}$ values during the months of April (2016-2020) were recorded (Table 1). These values indicate that Lincoln's $PM_{2.5}$ pollution levels were consistently elevated when compared with the other locations prior to April 2020. However, during April 2020, Lincoln's $PM_{2.5}$ levels were nearly identical to those at the other monitoring locations. Though obvious decreases were observed at Lincoln, only minor reductions appear to have occurred at Avalon and Parkway East. Additionally, Lawrenceville saw decreases in $PM_{2.5}$ levels when April 2020 was compared with April 2019; however, April 2020 pollutant levels were higher than April 2017 $PM_{2.5}$ levels. A box plot representing all $PM_{2.5}$ monitoring sites is shown below (Figure 6).

Table 1. Mean $PM_{2.5}$ values (µg/m^3) of the raw data at all four monitoring locations during the months of April (2016-2020). Average daily values were utilized to calculate the means.

	Avalon	**Lawrenceville**	**Lincoln**	**Parkway East**
April 2016	N/A	8.6	13.333	8.766
April 2017	7.833	6.233	11.3	7.1
April 2018	7.933	8.7	10.5	8.067
April 2019	7.8	9.833	10.567	9.286
April 2020	7.233	7.704	7.533	6.833

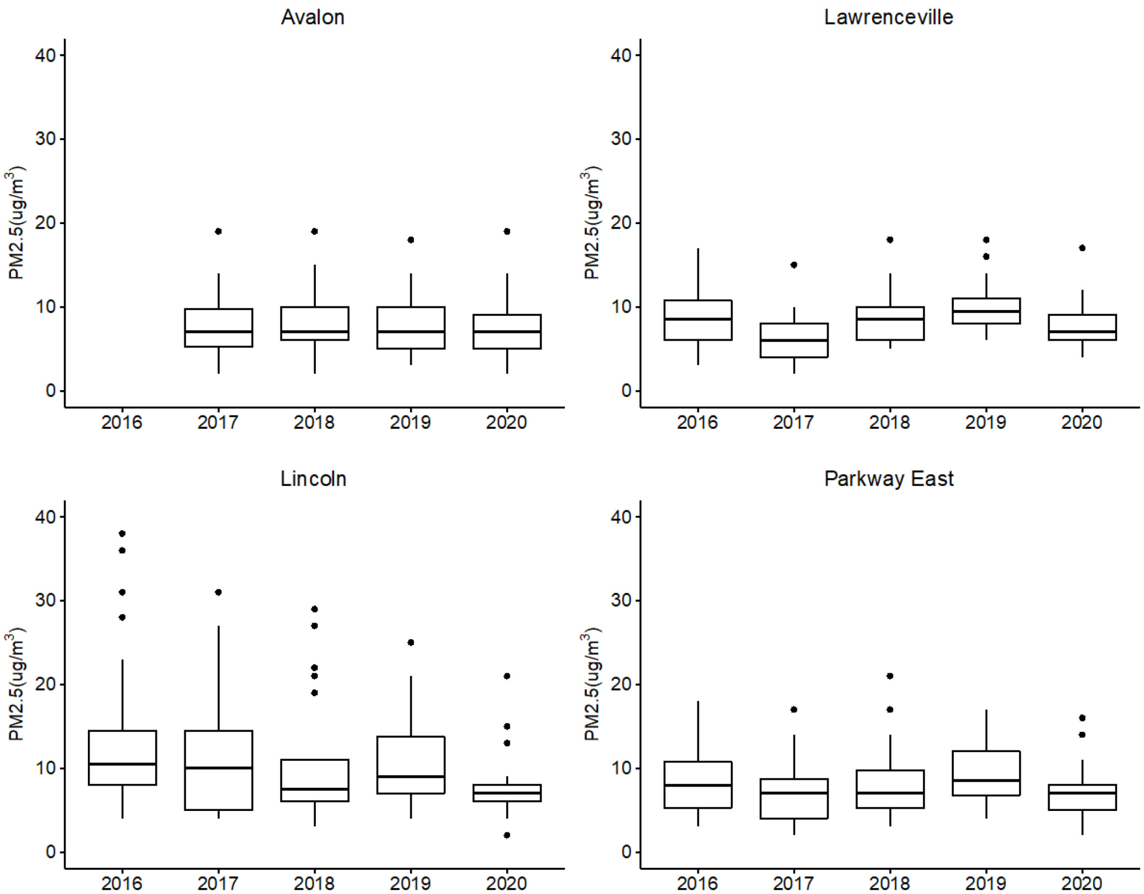

Figure 6. Average $PM_{2.5}$ pollution during the month of April from 2016-2020. Data were obtained from four air monitoring locations, Avalon, Lawrenceville, Lincoln, and Parkway East. Box = 25th and 75th percentiles; bars = minimum and maximum values. The annual primary and secondary NAAQS are 12 µg/m^3 and 15 µg/m^3, respectively. The 24-hour primary and secondary NAAQS is 35 µg/m^3.

A linear model, which adjusted for the effect of precipitation, was fit to the $PM_{2.5}$ data to determine significance. Upon analysis, significant decreases were observed at each monitoring site when April 2020 was compared with all prior months (beginning in 2016) (Table 2). However, when April 2020 was compared with the previous four Aprils, significant decreases of 28.776% (95% CI [-42.419%, -11.900%]; P = 0.001) and 17.032% (95% CI [-30.570%, -0.854%]; P = 0.040) were only observed at Lincoln and Parkway East, respectively. Lincoln displayed greater signs of significance after indicators for April of each year were incorporated (Table 3).

Table 2. Linear model results of log transformed April 2020 $PM_{2.5}$ data ($\mu g/m^3$) when compared to all months prior (beginning in 2016). Monitoring site, changes in $PM_{2.5}$ during April 2020, 95% confidence intervals, and p values are included. The linear model controlled for the effect of precipitation.

Monitoring Site	Change in $PM_{2.5}$ during April 2020 (%)	95% CI (%)	p
Avalon	-22.034	-34.281 to -7.505	0.004
Lawrenceville	-22.108	-34.102 to -7.931	0.003
Lincoln	-34.539	-46.875 to -19.338	< 0.001
Parkway East	-30.254	-41.453 to -16.914	< 0.001

Table 3. Linear model results of log transformed $PM_{2.5}$ data ($\mu g/m^3$) at monitoring sites Lincoln and Parkway East. These results compare April 2020 with the previous four Aprils and include 95% confidence intervals and p values. The linear model controlled for the effect of precipitation.

	Lincoln			*Parkway East*		
Variable	**Change in $PM_{2.5}$ (%)**	**95% CI (%)**	**p**	**Change in $PM_{2.5}$ (%)**	**95% CI (%)**	**p**
April 2016	57.994	20.629 to 106.933	0.001	25.202	0.198 to 56.445	0.048
April 2017	38.494	5.818 to 81.260	0.018	3.415	-17.188 to 29.144	0.766
April 2018	28.416	-2.349 to 68.874	0.073	19.358	-4.420 to 49.050	0.118
April 2019	37.690	5.188 to 80.234	0.020	37.966	10.041 to 72.977	0.006
Precipitation (mm)	-2.142	-3.409 to -0.859	0.001	-2.144	-3.191 to -1.085	< 0.001

Reductions in $PM_{2.5}$ pollution varied among the four monitoring sites. This is consistent with previous studies that have observed variability in $PM_{2.5}$ decreases during COVID-19 lockdowns (Berman & Ebisu, 2020; Chauhan & Singh, 2020; Rodríguez-Urrego & Rodríguez-Urrego, 2020). Additionally, studies have found that $PM_{2.5}$ pollution has been significantly reduced as a result of decreased vehicle traffic (Chauhan & Singh, 2020; Tanzer-Gruener et al., 2020). Thus, due to its location along a major highway, it was expected that the Parkway East monitoring would exhibit significant decreases in $PM_{2.5}$. However, given Lincoln's close proximity to an industrial source (Clairton Coke Works), it was surprising to learn that Lincoln was the site that exhibited the greatest significant reductions. Prior to analysis, it was assumed that though the pandemic had reduced traffic, industry production remained unaltered. However, it was later discovered that COVID-19 did alter production at Pittsburgh's two largest industrial facilities.

In April 2020, United States Steel reported that the Edgar Thomson Plant's #1 blast furnace was temporarily being idled due to a decline in business (personal communication, July 9, 2020). Additionally, it was stated that the Edgar Thomson Plant's #3 blast furnace was operating at reduced levels (personal communication, July 9, 2020). As a result of the idling of these facilities, steel production decreased. This led to a reduced need for raw material production which resulted in slowed coking times at the Clairton Coke Works (personal communication, July 9, 2020).

In addition to decreased industrial production during the COVID-19 pandemic, there is also strong evidence that $PM_{2.5}$ pollution at the Lincoln monitoring site has been improving each year. This can be observed by noting the positive trend over time (with the exception of April 2018) and by examining mean $PM_{2.5}$ values during the month of April from 2016-2020 (Table 1 and Table 3). Decreases in $PM_{2.5}$ pollution throughout time are likely a result of improved emissions control technologies at the Clairton Coke Works. The installation dates of these control technologies are detailed in the facility's 2019 Operations and Environmental Report (United States Steel, 2019).

Finally, the lack of a significant decrease at several of the monitoring stations may be contributed to wind direction. During the months of April from 2016-2020, wind in the Pittsburgh area originated from the south, with a mode wind direction of 235° ± 5° (Figure 7). However, the Avalon and Lawrenceville monitoring sites reside to the west of the Clairton Coke Works. Thus, if slowed coking times during April 2020 were truly the cause of reduced $PM_{2.5}$ pollution, these monitoring sites would have been largely unaffected by reduced emissions at this facility.

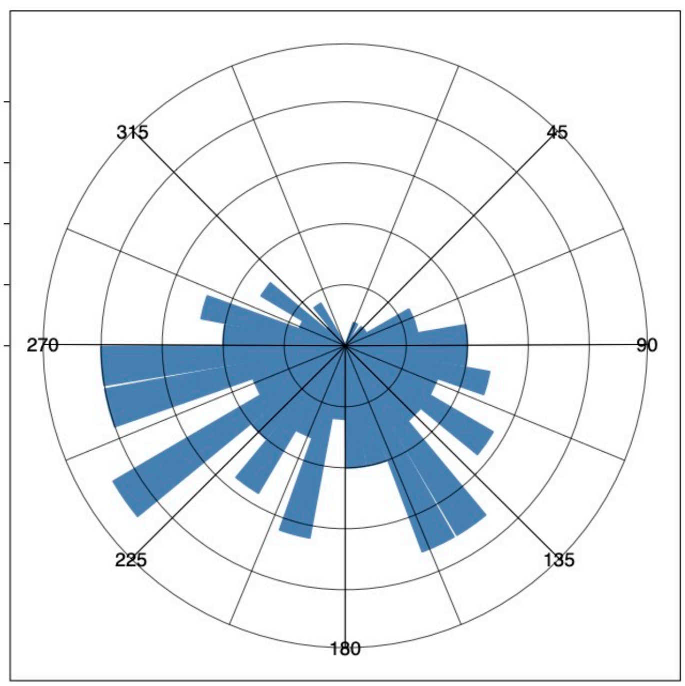

Figure 7. Average daily wind direction recorded at the Pittsburgh International Airport during the months of April from 2016 –2020. Data courtesy of the Pennsylvania State Climatologist.

3.2 Changes in PM_{10}

Mean PM_{10} values during the months of April (2016-2020) were recorded (Table 4). These values suggest that, with the exception of Lawrenceville, PM_{10} pollution decreased during April 2020 when compared with Aprils of previous years. Additionally, it can be noted that Lincoln and North Braddock had the highest levels of PM_{10} during most Aprils. This was to be expected, as the North Braddock monitor is nearest the Edgar Thomson Steel Works and the Lincoln monitor is nearest the Clairton Coke Works. A box plot representing all PM_{10} monitoring sites is shown below (Figure 8).

Table 4. Mean PM_{10} values ($\mu g/m^3$) of the raw data at all six monitoring locations during the months of April (2016-2020). Average daily values were utilized to calculate the means.

	Flag Plaza	**Glassport**	**Lawrenceville**	**Liberty**	**Lincoln**	**North Braddock**
April 2016	16.867	13.400	13.100	15.133	22.167	22.300
April 2017	15.067	13.267	9.600	13.478	19.267	20.000
April 2018	12.833	12.067	14.300	15.967	19.333	19.500
April 2019	12.933	12.833	24.700	14.367	20.967	20.933
April 2020	8.200	9.133	20.222	9.667	12.967	15.833

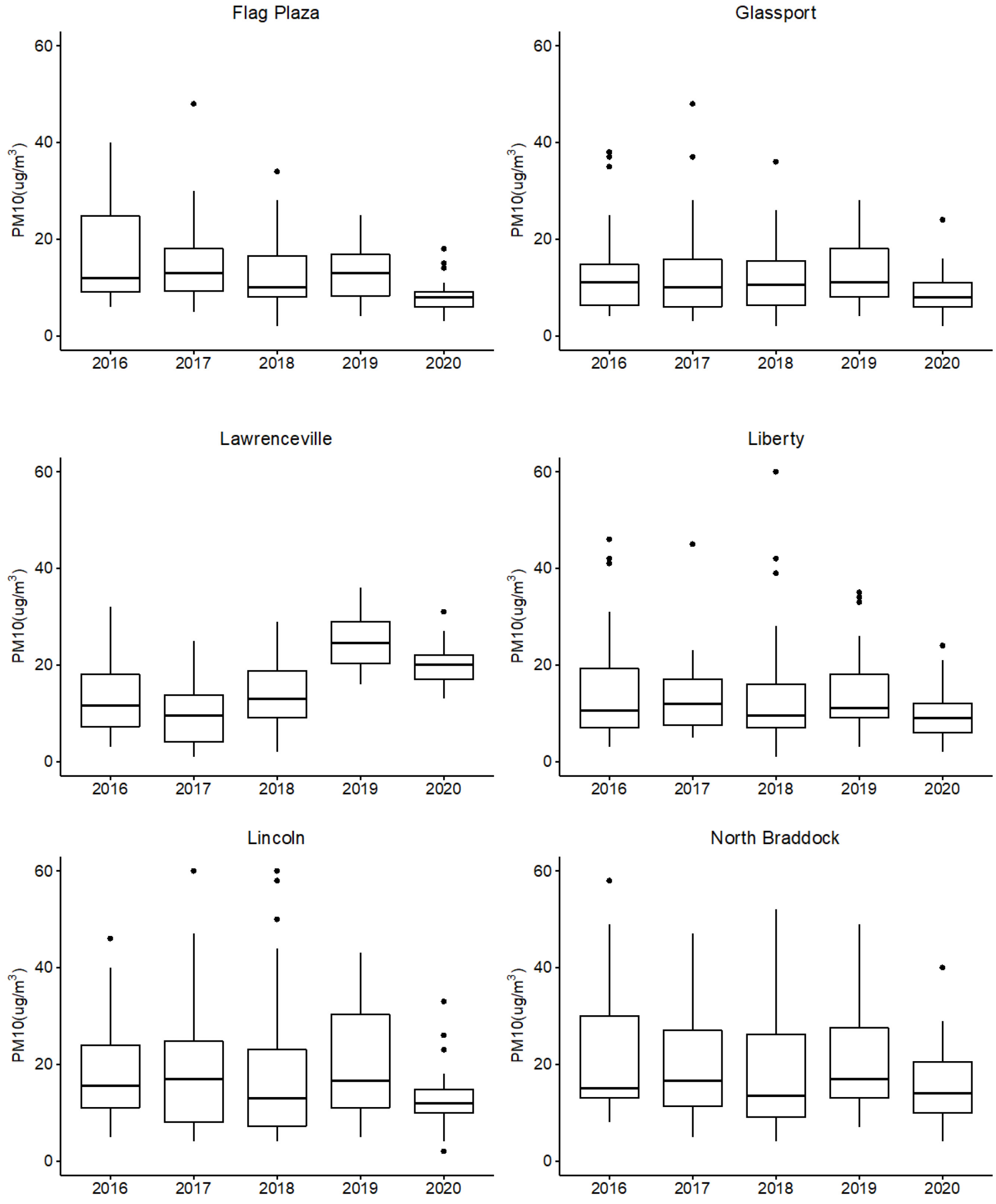

Figure 8. Average PM_{10} pollution during the month of April from 2016-2020. Data were obtained from six air monitoring locations, Flag Plaza, Glassport, Lawrenceville, Liberty, Lincoln, and North Braddock. Box = 25th and 75th percentiles; bars = minimum and maximum values. The 24-hour primary and secondary NAAQS is 150 μg/m³.

A linear model, which adjusted for the effect of precipitation, was fit to the PM_{10} data to determine significance. During the COVID-19 lockdown, PM_{10} pollution significantly decreased at nearly all of the monitoring locations when compared to all prior months (beginning in 2016) (Table 5). The only monitoring location which did not display significance was Lawrenceville. This site was also the only site where log-transformation was deemed unnecessary, as the Chi-square goodness of fit test revealed that the raw data and residuals assumed a normal distribution. In addition, significant decreases in PM_{10} pollution were observed when comparing April 2020 to only the previous Aprils at Flag Plaza = 38.470% (95% CI [-49.209%, -25.460%]; P < 0.001), Glassport = 22.206% (95% CI [-37.745%, -2.789%]; P = 0.028), Liberty = 26.718% (95% CI [-42.836%, -6.054%]; P = 0.015), and Lincoln = 25.981% (95% CI [-43.119%, -3.679%]; P = 0.025). However, after incorporating indicators for April of each year, the significance between years varied (Table 6).

Table 5. Linear model results of log transformed April 2020 PM_{10} data (μg/m^3) when compared to all months prior (beginning in 2016). The monitoring site, changes in PM_{10} during April 2020, 95% confidence intervals, and p values are all included. The linear model controlled for the effect of precipitation. *Raw data at Lawrenceville assumed a normal distribution and were not log transformed.

Monitoring Site	**Change in PM_{10} during April 2020 (%)**	**95% CI (%)**	**p**
Flag Plaza	-42.334	-51.894 to -30.875	< 0.001
Glassport	-31.871	-45.900 to -14.203	0.001
Lawrenceville*	19.600	-96.229 to 3693.539	0.919
Liberty	-37.318	-50.688 to -20.323	< 0.001
Lincoln	-32.431	-46.219 to -15.107	< 0.001
North Braddock	-28.863	-41.171 to -13.978	< 0.001

Table 6. Linear model results of log transformed PM_{10} data ($\mu g/m^3$) at monitoring sites Flag Plaza, Glassport, Liberty, and Lincoln. These results compare April 2020 with the previous four Aprils and include 95% confidence intervals and p values. The linear model controlled for the effect of precipitation.

	Flag Plaza			*Glassport*			*Liberty*			*Lincoln*		
Variable	**Change in PM_{10} (%)**	**95% CI (%)**	**p**	**Change in PM_{10} (%)**	**95% CI (%)**	**p**	**Change in PM_{10} (%)**	**95% CI (%)**	**p**	**Change in PM_{10} (%)**	**95% CI (%)**	**p**
April 2016	80.309	41.457 to 129.833	< 0.001	26.754	-4.675 to 68.545	0.102	32.870	-3.151 to 82.287	0.078	40.516	0.483 to 96.499	0.047
April 2017	72.109	35.112 to 119.236	< 0.001	28.661	-3.167 to 70.950	0.082	40.387	0.068 to 96.952	0.050	26.136	-9.719 to 76.230	0.172
April 2018	47.008	15.410 to 87.259	0.002	22.823	-7.558 to 63.190	0.155	32.468	-3.357 to 81.571	0.080	24.305	-11.027 to 73.668	0.201
April 2019	53.074	20.154 to 95.014	< 0.001	36.345	2.600 to 81.187	0.033	17.299	3.016 to 93.622	0.032	51.437	8.371 to 111.618	0.015
Precipitation (mm)	-3.817	-4.936 to -2.685	< 0.001	-3.791	-5.103 to -2.460	< 0.001	-4.182	-5.654 to -2.688	< 0.001	-3.044	-4.599 to - 1.463	<0.001

Some previous studies have shown that PM_{10} pollution has been significantly reduced during COVID-19 lockdown periods (Hashim et al., 2021; He et al., 2020; Sharma et al., 2020). However, many of these studies have examined air pollution in cities with PM_{10} pollution levels considerably higher than those in Pittsburgh. Fortunately, a handful of studies have examined geographical locations with air pollution levels similar to those of Pittsburgh (Briz-Redón et al., 2021; Gama et al., 2021). One of these studies, which analyzed data from 20 monitors throughout Portugal, found that average daily PM_{10} levels were reduced by approximately 5 $\mu g/m^3$ during lockdown (Gama et al., 2021). Prior to the lockdown period, average PM_{10} levels in Portugal from 2015-2019 were approximately 20 $\mu g/m^3$ (Gama et al., 2021). This result is consistent with our study, which also observed decreases of approximately 5 $\mu g/m^3$ at the four statistically significant monitoring locations.

Though more apparent than $PM_{2.5}$ reductions, which were only determined to be significant at half of the monitoring locations, significant decreases in PM_{10} were not observed at all six monitoring sites. Once more, this is consistent with several studies that observed variances in PM_{10} decreases between locations (Briz-Redón et al., 2021; Gama et al., 2021). Of the four monitoring sites of which significant reductions in PM_{10} were observed, three were located near the Clairton Coke Works (Glassport, Liberty, and Lincoln), and one was located within the downtown area (Flag Plaza). Due to the substantial commuting reductions that occurred in and out of the city during April 2020, significant PM_{10} reductions at Flag Plaza were expected. Additionally, the reductions in PM_{10} near industrial sources seem to align with $PM_{2.5}$ reductions, though $PM_{2.5}$ reductions at Lincoln exhibited greater significance than reductions in PM_{10} at any of the industrial monitoring sites.

One of the sites in which significant results were not observed when comparing April 2020 with the previous four Aprils was North Braddock. However, both the mean April values and the box plot of this location suggest that decreases in PM_{10} during the COVID-19 lockdown occurred (Table 4 and Figure 8). Therefore, it is possible that a lack of significance is the result of highly variable data.

In addition to North Braddock, the Lawrenceville monitoring site did not observe significant reductions in PM_{10}. Lawrenceville is a town that is largely residential. Having observed significant increases in property value since the early 2000s, Lawrenceville is now home to approximately 11,100 residents (Grant, 2007; Lawrenceville Corporation, 2021). Many of these residents live in homes with a fireplace and consequentially, burn wood as a source of heat during colder months. Studies have documented that domestic wood burning is an important contributor to PM_{10} pollution, and therefore, may help explain why reductions in particulate pollution were not observed at this location during the COVID-19 lockdown period (Caseiro et al., 2009; Fuller et al., 2014).

3.3 Changes in NO_2

Mean NO_2 values during the months of April (2016-2020) were recorded (Table 7). These values suggest that, NO_2 pollution decreased during April 2020 when compared with Aprils of previous years. Additionally, it can be noted that the pollution levels at the Parkway East monitoring site are approximately twice those of the Harrison Township monitoring site. This is likely a result of the location of the monitors, as the Harrison Township monitor is located in a suburban area while the Parkway East monitor is located along a major highway. A box plot representing both NO_2 monitoring sites is shown below (Figure 9).

Table 7. Mean NO_2 values (ppb) of the raw data at both monitoring locations during the months of April (2016-2020). Average daily values were utilized to calculate the means.

	Harrison Township	**Parkway East**
April 2016	5.600	11.003
April 2017	5.067	8.897
April 2018	3.967	10.147
April 2019	3.900	8.956
April 2020	2.542	7.147

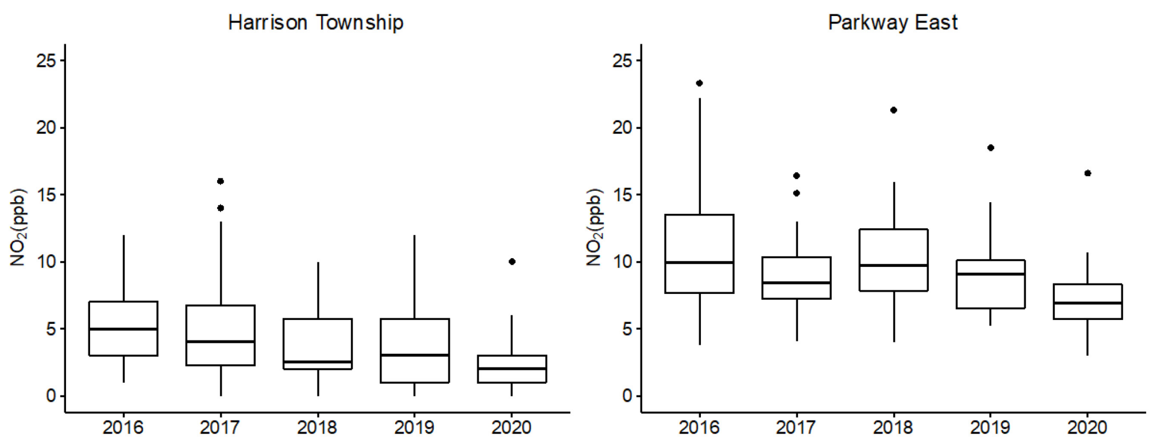

Figure 9. Average NO_2 pollution during the month of April from 2016-2020. Data were obtained from two air monitoring locations, Harrison Township and Parkway East. Box = 25th and 75th percentiles; bars = minimum and maximum values. The annual primary and secondary NAAQS for NO_2 is 53 ppb. The primary one-hour NAAQS is 100 ppb.

A linear model, which adjusted for the effect of precipitation, was fit to the NO_2 data to determine significance. Upon analysis, significant decreases in NO_2 were observed when comparing April 2020 with all months prior (beginning in 2016) (Table 8). Additionally, after comparing April 2020 to only the four previous Aprils, significant decreases of 35.734% (95% CI [-52.000%, -13.956%]; P = 0.003) at Harrison Township and 25.439% (95% CI [-35.662%, -13.592%]; P < 0.001) at Parkway East were observed. With the exception of April 2019 at Harrison Township, significance remained consistent after adding indicators for April of each year (Table 9).

Table 8 Linear model results of log transformed April 2020 NO_2 data when compared to all months prior (beginning in 2016). The monitoring site, changes in NO_2 during April 2020, 95% confidence intervals, and p values are all included. The linear model controlled for the effect of precipitation.

Monitoring Site	**Change in NO_2 during April 2020 (%)**	**95% CI (%)**	**p**
Harrison	-48.027	-61.727 to -29.422	< 0.001
Parkway East	-27.804	-37.437 to -16.688	< 0.001

Table 9. Linear model results of log transformed NO_2 data at both monitoring sites. These results compare April 2020 with the previous four Aprils and include 95% confidence intervals and p values. The linear model controlled for the effect of precipitation.

	Harrison			*Parkway East*		
Variable	**Change in NO_2 (%)**	**95% CI (%)**	**p**	**Change in NO_2 (%)**	**95% CI (%)**	**p**
April 2016	84.597	30.408 to 161.302	< 0.001	47.234	22.233 to 77.349	< 0.001
April 2017	75.558	24.010 to 148.533	0.002	25.756	4.454 to 51.402	0.016
April 2018	43.443	1.047 to 103.627	0.044	39.963	16.257 to 68.504	< 0.001
April 2019	24.178	-12.638 to 76.510	0.225	24.969	3.790 to 50.469	0.019
Precipitation (mm)	-0.067	-0.067 to -0.035	< 0.001	-0.723	-1.610 to 0.172	0.112

Studies have shown that COVID-19 lockdowns resulted in significant reductions in NO_2 (Baldasano, 2020; Bauwens et al., 2020; Berman & Ebisu, 2020; Pacheco et al., 2020; Sarfraz et al., 2020) Unlike particulate matter, which is attributed to a variety of sources, NO_2 is primarily associated with the burning of fuel, specifically that of cars, trucks, buses, power plants, and off-road equipment (US EPA, 2016). As a result, these declines are likely contributed to decreased domestic travel and remote working/schooling. One study, which observed NO_2 reductions of 50% and 62% in Barcelona and Madrid, respectively, also observed a 75% reduction in traffic (Baldasano, 2020). Thus, this study strongly suggests that reductions in traffic and reductions in NO_2 are correlated.

According to TomTom, a location technology company that gets Traffic Index data from navigation devices, traffic in 2020 was reduced by 33% when compared to traffic in 2019

(TomTom Traffic Index, 2021). Furthermore, daily traffic data in April 2020 demonstrated reductions of at least 50% when compared with April 2019 (TomTom Traffic Index, 2021). These reductions deemed April the "least congested" month of all of 2020 (TomTom Traffic Index, 2021). Therefore, due to these significant reductions in traffic associated with vehicular transportation, it is not surprising that both the Harrison Township and Parkway East monitoring locations exhibited significant reductions in NO_2.

CHAPTER 4: CONCLUSIONS

4.1 Reductions at Lincoln

During this study, it became increasingly apparent that air pollution levels are not uniform throughout the county. This became most evident when analyzing $PM_{2.5}$ pollution at the Lincoln monitoring location, which is located in close proximity to the Clairton Coke Works. Prior to April 2020, Lincoln's $PM_{2.5}$ pollution levels were elevated when compared with levels at Avalon, Lawrenceville, and Parkway East (Table 1). However, during April 2020, $PM_{2.5}$ levels were nearly identical to those at the other monitoring locations. The decreases in emissions were likely attributed to the idling and reduced operating levels of blast furnaces at the Edgar Thomson Steel Works, and consequentially, slowed coking times. However, it is also worth mentioning that the idling of nonlocal facilities may have played a role in these emissions reductions.

In June of 2019, it was announced that US Steel would idle a blast furnace at the Gary Works Facility in Indiana (Reuters, 2019). Though this furnace came back online near the end of 2019, it was again idled, along with an additional furnace at the facility, in early April (Coyne, 2020). Furthermore, it was announced in December 2019 that the remaining online blast furnace at Michigan's Great Lakes Works would be idled by April 1, 2020, and in March of 2020, US Steel stated that it would immediately idle a furnace at the Granite City Works facility in Illinois (Druzin, 2019).

While it is clear that the COVID-19 pandemic resulted in the idling of an abundance of US Steel's furnaces, it is also apparent that US Steel planned to idle facilities prior to the pandemic. In March of 2018, President Trump ordered a 25 percent tariff on imported steel

(Horsley, 2018). While these tariffs were intended to help domestic steel producers, they suppressed prices by resulting in a surplus of steel in a time of low demand (Reuters, 2019). This led to the layoff of over 1,500 steel workers nearly a month before COVID-19 was even detected in the United States (Reindl, 2019). Thus, as the production of steel slowed throughout the country, it is almost certain that production at the Clairton Coke Works, which provides the raw material product for US Steel's steelmaking facilities, slowed as well.

In addition to $PM_{2.5}$ decreases contributed to the COVID-19 lockdown period, it was also noted that emissions at the Lincoln monitoring site have been decreasing throughout time. Much of this decrease is likely a result of improved emissions control techniques at the Clairton Coke Works, which are noted in the facility's 2019 Operations and Environmental Report (United States Steel, 2019). The report states that between 2010 and 2020, there were refractory upgrades to several batteries, a number of battery through-walls were replaced, and three battery end flues were replaced (United States Steel, 2019). Though the refractory upgrades and through-wall replacements likely had less impact on emissions reductions, it is suggested that the replacement of end flues during this time period helped aid the reduction of $PM_{2.5}$ emissions. Additionally, upgrades were made in 2018 to the coke oven gas desulfurization process (United States Steel, 2019). More specifically, this involved improving the Vacuum Carbonate Unit, which in return, should reduce the concentration of hydrogen sulfide in the coke oven gas (United States Steel, 2019).

Reductions in $PM_{2.5}$ observed during the COVID-19 lockdown suggest that continued improvements to emissions control devices at the Clairton Coke Works are crucial for improving air quality in the surrounding communities. By utilizing reductions observed during the COVID-19 pandemic as reference, the facility can work towards achieving emission levels that are similar to those observed at the other $PM_{2.5}$ monitoring sites. Worth mentioning is that while the North Braddock monitoring site did not collect data for $PM_{2.5}$, PM_{10} data suggests that the North Braddock community is also exposed to disproportionately high levels of particulate matter. Therefore, emphasis should also be placed on reducing emissions at the Edgar Thomson Steel Works.

4.2 Socioeconomic and Racial Disparities in Pittsburgh

Decreasing pollution at the Clairton Coke Works and the Edgar Thomson Steel Works is especially important when considering the demographics of the surrounding communities. Both the Clairton and North Braddock communities have a poverty rate of approximately 30%, which is approximately three times higher than the national average of 10.5% (US Census Bureau, 2020) As has been noted in an abundance of studies, individuals of lower socioeconomic status are subjected to higher levels of air pollutants (Gray et al., 2013; Huang & London, 2012; Mohai et al., 2009). This is primarily a result of challenges avoiding exposure (e.g., poor quality housing) (Schulz et al., 2020). In Allegheny County, a relationship can be observed between the location of industrial facilities, the quantity of particulate pollution, and the percentage of distressed housing units (Figure 10).

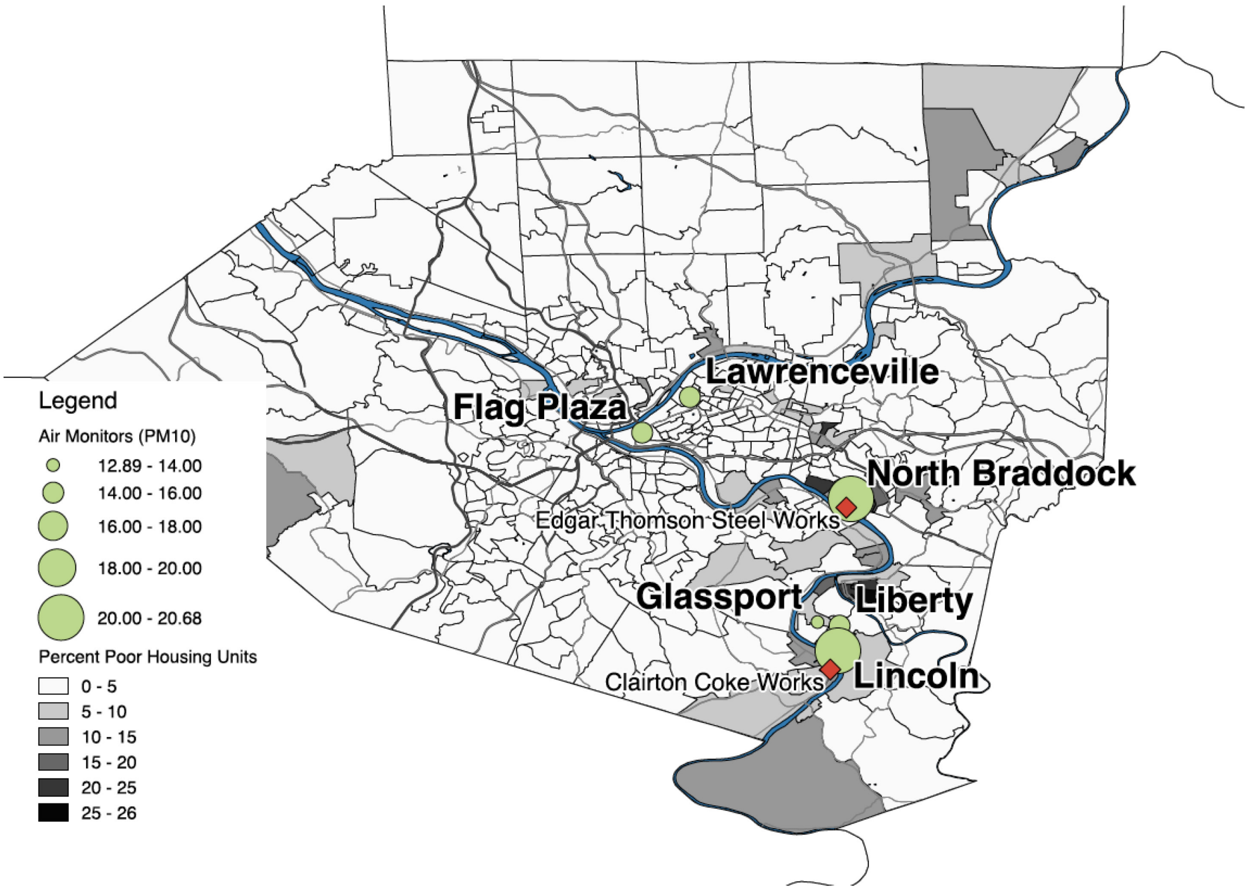

Figure 10. The percentage of distressed housing units throughout Allegheny County when compared with the average PM_{10} pollution ($\mu g/m^3$) from 2016-2019 at the six monitoring locations. Additionally, this image shows the location of the Clairton Coke Works and Edgar Thomson Steel Works. Distressed housing unit data were obtained through the US Census Bureau and the Allegheny County Property Assessment Database.

In addition to the disproportionate number of individuals living below the poverty line, approximately 40% of the population of Clairton and North Braddock consists of people of color (US Census Bureau, 2020). A heightened percentage of non-white individuals living near major polluting facilities creates racial health disparities. These health disparities have been examined in a variety of studies, one of which observed an association between $PM_{2.5}$ and hypertension in communities with a high proportion of black individuals (Yitshak-Sade et al., 2020). An additional study, which found that $PM_{2.5}$ exposure was associated with elevated blood glucose, reduced endothelial function, and cardiovascular disease events, determined that the increased rate of incidence among black individuals was partially explained by higher exposure to $PM_{2.5}$ (Erqou et al., 2018).

In Allegheny County, asthma is a health condition which receives much attention. Approximately 10% of adults and school-age children live with the condition (Hacker et al., 2017). However, minorities are among the individuals predominantly impacted, as the condition affects 27% of black teens compared to 20% of white teens (Allegheny County Health Department, 2014). The burden of asthma is also increased when examining specific communities, particularly those in the Mon Valley region where both the Clairton Coke Works and Edgar Thomson Steel Works reside. Children living in this region are more likely to seek emergency room care and be hospitalized for an asthma attack when compared to children living in other communities (Allegheny County Health Department, 2021). While this is just one example of a health disparity that exists in Allegheny County, it emphasizes the need for reducing air pollutants in these susceptible communities.

4.2 Future Recommendations

This study only sought to determine if there were pollution reductions during the COVID-19 lockdown period (April 2020). As a result, data from alternative restriction periods during the pandemic were not considered. In the future, it would be interesting to observe whether or not loosened restrictions resulted in significant reductions in pollution levels, as total lockdown is not a feasible technique for reducing air pollution. Additionally, future studies should continue to monitor temporal changes at the industrial sources while seeking to determine whether changes are associated with reduced industrial activity, improved emissions control devices, or a combination of both.

Finally, heightened variability among annual particulate pollution at the Lawrenceville monitoring site provides opportunity for future studies. While this study suggested that PM variability is a result of wood burning fire places, the uniqueness of this location should be further investigated.

4.3 Summary

In Allegheny County, significant reductions in NO_2 concentrations were observed when April 2020 was compared to the previous four Aprils. Similarly, PM_{10} pollution was significantly reduced at the majority of monitoring sites, though significance between years varied. These results suggest that the COVID-19 lockdown measures did improve air quality in the Pittsburgh region. However, reductions in $PM_{2.5}$ expressed greater inconsistency, as significant reductions were only detected at half of the monitoring sites. The site that observed the greatest reductions in $PM_{2.5}$ pollution was Lincoln, one of the monitoring sites located within close proximity to the Clairton Coke Works. This discovery was initially surprising, as it had previously been assumed that COVID-19 had not impacted local industrial sources. However, it was later revealed that coking times at the Clairton Coke Works were slowed during the COVID-19 pandemic as a result of the idling of both local and nonlocal US Steel facilities.

The results of this study suggest that industrial sources are a larger contributor of particulate matter than vehicular transportation in the city of Pittsburgh. Therefore, it is recommended that future air pollution reduction efforts focus attention on lessening emissions at the Clairton Coke Works and the Edgar Thomson Steel Works, perhaps through the use of innovative emission control technologies. By reducing particulate matter emissions at these facilities, the communities neighboring the facilities should experience improved health outcomes and economic benefits (Luo et al., 2020; Schraufnagel et al., 2019). This will help to reduce health disparities in these communities which disproportionally comprise of people of color and individuals living below the poverty line.

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APPENDIX A: LINEAR MODEL CODING SCRIPT

Available via github: https://github.com/hydro-lab/air-quality-data

```
#creating an array for each year

april_2020 <- array(0,dim = c(nrow(lincoln_daily)))
for (i in 1:(nrow(lincoln_daily))) {
  if ((date[i] > as.Date("03/31/20", format = "%m/%d/%y", origin = "01/01/10")) & (date[i] <
as.Date("05/01/20", format = "%m/%d/%y", origin = "01/01/10"))) {
    april_2020[i] <- 1
  }
}

april_2019 <- array(0,dim = c(nrow(lincoln_daily)))
for (i in 1:(nrow(lincoln_daily))) {
  if ((date[i] > as.Date("03/31/19", format = "%m/%d/%y", origin = "01/01/10")) & (date[i] <
as.Date("05/01/19", format = "%m/%d/%y", origin = "01/01/10"))) {
    april_2019[i] <- 1
  }
}

april_2018 <- array(0,dim = c(nrow(lincoln_daily)))
for (i in 1:(nrow(lincoln_daily))) {
  if ((date[i] > as.Date("03/31/18", format = "%m/%d/%y", origin = "01/01/10")) & (date[i] <
as.Date("05/01/18", format = "%m/%d/%y", origin = "01/01/10"))) {
    april_2018[i] <- 1
  }
}

april_2017 <- array(0,dim = c(nrow(lincoln_daily)))
for (i in 1:(nrow(lincoln_daily))) {
  if ((date[i] > as.Date("03/31/17", format = "%m/%d/%y", origin = "01/01/10")) & (date[i] <
as.Date("05/01/17", format = "%m/%d/%y", origin = "01/01/10"))) {
    april_2017[i] <- 1
  }
}

april_2016 <- array(0,dim = c(nrow(lincoln_daily)))
for (i in 1:(nrow(lincoln_daily))) {
  if ((date[i] > as.Date("03/31/16", format = "%m/%d/%y", origin = "01/01/10")) & (date[i] <
as.Date("05/01/16", format = "%m/%d/%y", origin = "01/01/10"))) {
    april_2016[i] <- 1
  }
}


#creating the data frame and isolating only April values

lincoln_daily <- data.frame(date, pm25, precip, API, temp, april_2020, april_2019, april_2018, april_2017,
april_2016)

lincoln_daily$month <- format(lincoln_daily$date, '%m')
```

```
pm25_april <- lincoln_daily[which(lincoln_daily$month == "04"), names(lincoln_daily) %in% c("date",
"pm25", "temp", "precip", "april_2020", "april_2019", "april_2018", "april_2017", "april_2016")]

# adjusting for zero values

j <- 0
for (i in 1:nrow(lincoln_daily)) {
  if (is.na(lincoln_daily$pm25[i]) == FALSE) {
    if (lincoln_daily$pm25[i] == 0) {
      lincoln_daily$pm25[i] <- NA
      lincoln_daily$pm25log[i] <- NA
      j <- j + 1
    }
  }
}

#log transforming the data for normal distribution

pm25_april$pm25log <- log(pm25_april$pm25)
hist(pm25_april$pm25log)
lincoln_daily$pm25log <- log(lincoln_daily$pm25)

#comparing April 2020 with all previous months (beginning in 2016)

model1=lm(pm25log~april_2020 + precip, data = lincoln_daily)
summary(model1)
confint(model1)

#comparing April 2020 with the previous four Aprils

model2=lm(pm25log~april_2020 + precip, data = pm25_april)
summary(model2)
confint(model2)

#comparing April 2020 with the previous four Aprils (with indicators for each year)

model3=lm(pm25log~april_2019 + april_2018 + april_2017 + april_2016 + precip, data = pm25_april)
summary(model3)
confint(model3)

#checking the residuals
r <- residuals(model3)
```

APPENDIX B: VARIATION IN LIBERTY $PM_{2.5}$ INSTRUMENTATION

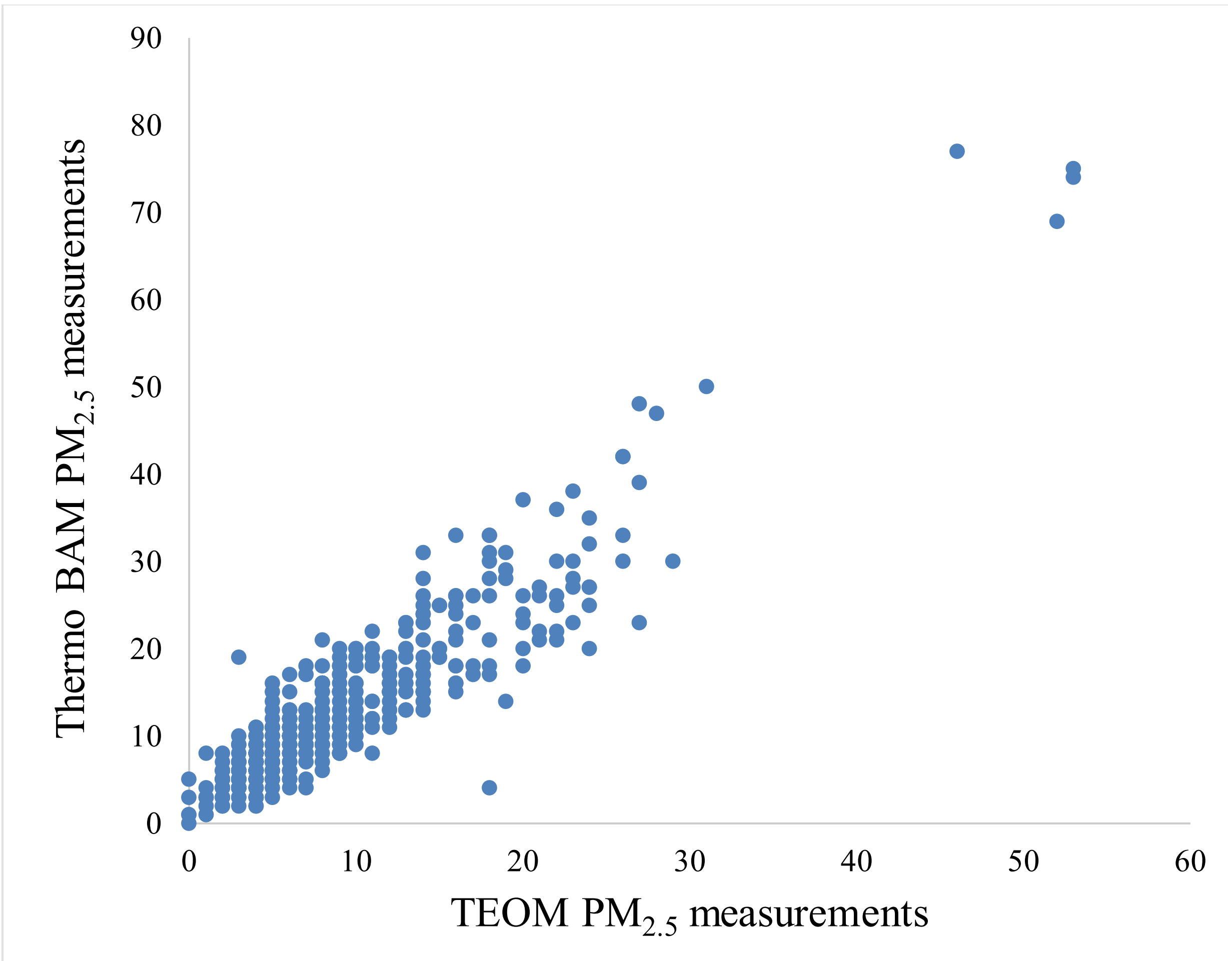

Figure 11. Variation between average daily $PM_{2.5}$ pollution levels measured by the TEOM and the Thermo BAM at the Liberty monitoring location.

APPENDIX C: TABLES WITH LOG-TRANSFORMED VALUES

Table 2. Linear model results of log transformed April 2020 $PM_{2.5}$ data ($\mu g/m^3$) when compared to all months prior (beginning in 2016). Monitoring site, intercept of $PM_{2.5}$, estimate of $PM_{2.5}$ changes, 95% confidence intervals, and p values are included. The linear model controlled for the effect of precipitation.

Monitoring Site	**log($PM_{2.5}$)**	**Δlog($PM_{2.5}$) April 2020**	**95% CI**	**p**
Avalon	2.150	-0.249	-0.420 to -0.078	0.004
Lawrenceville	2.268	-0.250	-0.417 to -0.083	0.003
Lincoln	2.386	-0.424	-0.633 to -0.215	< 0.001
Parkway East	2.217	-0.360	-0.535 to -0.185	< 0.001

Table 3. Linear model results of log transformed $PM_{2.5}$ data ($\mu g/m^3$) at monitoring sites Lincoln and Parkway East. These results compare April 2020 with the previous four Aprils and include 95% confidence intervals and p values. The linear model controlled for the effect of precipitation.

	Lincoln			*Parkway East*		
Variable	**log($PM_{2.5}$)**	**95% CI**	**p**	**log($PM_{2.5}$)**	**95% CI**	**p**
log($PM_{2.5}$)	2.003	1.806 to 2.200	< 0.001	1.900	1.738 to 2.062	< 0.001
April 2016	0.457	0.188 to 0.727	0.001	0.225	0.002 to 0.448	0.048
April 2017	0.326	0.057 to 0.594	0.018	0.034	-0.189 to 0.256	0.766
April 2018	0.250	-0.024 to 0.524	0.073	0.177	-0.045 to 0.399	0.118
April 2019	0.319	0.051 to 0.589	0.020	0.322	0.096 to 0.548	0.006
Precipitation	-0.022	-0.035 to -0.008	0.001	-0.022	-0.032 to -0.011	< 0.001

Table 5. Linear model results of log transformed April 2020 PM_{10} data ($\mu g/m^3$) when compared to all months prior (beginning in 2016). The monitoring site, intercept of PM_{10}, estimate of PM_{10} changes, 95% confidence intervals, and p values are all included. The linear model controlled for the effect of precipitation. *Raw data at Lawrenceville assumed a normal distribution and were not log transformed.

Monitoring Site	$\log(PM_{10})$	$\Delta\log(PM_{10})$ April 2020	95% CI	p
Flag Plaza	2.622	-0.551	-0.732 to -0.369	< 0.001
Glassport	2.538	-0.384	-0.614 to -0.153	0.001
Lawrenceville*	20.614	0.179	-3.278 to 3.636	0.919
Liberty	2.655	-0.467	-0.707 to -0.227	< 0.001
Lincoln	2.898	-0.392	-0.620 to -0.164	< 0.001
North Braddock	3.045	-0.341	-0.531 to -0.151	< 0.001

Table 6. Linear model results of log transformed PM_{10} data ($\mu g/m^3$) at monitoring sites Flag Plaza, Glassport, Liberty, and Lincoln. These results compare April 2020 with the previous four Aprils and include 95% confidence intervals and p values. The linear model controlled for the effect of precipitation.

	Flag Plaza			*Glassport*			*Liberty*			*Lincoln*		
Variable	**log(PM_{10})**	**95% CI**	**p**	**log(PM_{10})**	**95% CI**	**p**	**log(PM_{10})**	**95% CI**	**p**	**log(PM_{10})**	**95% CI**	**p**
log(PM_{10})	2.160	1.983 to 2.337	< 0.001	2.239	2.032 to 2.447	< 0.001	2.285	2.054 to 2.525	< 0.001	2.567	2.322 to 2.811	< 0.001
April 2016	0.590	0.347 to 0.832	< 0.001	0.237	-0.048 to 0.522	0.102	0.284	-0.032 to 0.600	0.078	0.340	0.005 to 0.675	0.047
April 2017	0.543	0.301 to 0.785	< 0.001	0.252	-0.032 to 0.536	0.082	0.339	0.001 to 0.678	0.050	0.232	-0.102 to 0.567	0.172
April 2018	0.385	0.143 to 0.627	0.002	0.206	-0.079 to 0.490	0.155	0.281	-0.034 to 0.596	0.080	0.218	-0.117 to 0.552	0.201
April 2019	0.426	0.184 to 0.668	< 0.001	0.310	0.026 to 0.594	0.033	0.345	0.030 to 0.661	0.032	0.415	0.080 to 0.750	0.015
Precipitation	-0.039	-0.051 to -0.027	< 0.001	-0.039	-0.052 to -0.025	< 0.001	-0.043	-0.058 to -0.027	< 0.001	-0.031	-0.047 to -0.015	<0.001

Table 8 Linear model results of log transformed April 2020 NO_2 data when compared to all months prior (beginning in 2016). The monitoring site, intercept of NO_2, estimate of NO_2 changes, 95% confidence intervals, and p values are all included. The linear model controlled for the effect of precipitation.

Monitoring Site	log(NO_2)	Δlog(NO_2) April 2020	95% CI	p
Harrison	1.520	-0.654	-0.960 to -0.348	< 0.001
Parkway East	2.251	-0.326	-0.469 to -0.183	< 0.001

Table 9. Linear model results of log transformed NO_2 data at both monitoring sites. These results compare April 2020 with the previous four Aprils and include 95% confidence intervals and p values. The linear model controlled for the effect of precipitation.

	Harrison			*Parkway East*		
Variable	**log(NO_2)**	**95% CI**	**p**	**log(NO_2)**	**95% CI**	**p**
log(NO_2)	1.061	0.787 to 1.334	< 0.001	1.938	1.803 to 2.074	< 0.001
April 2016	0.613	0.266 to 0.961	< 0.001	0.387	0.201 to 0.573	< 0.001
April 2017	0.563	0.215 to 0.910	0.002	0.229	0.044 to 0.415	0.016
April 2018	0.361	0.010 to 0.711	0.044	0.336	0.151 to 0.522	< 0.001
April 2019	0.217	-0.135 to 0.568	0.225	0.223	0.037 to 0.409	0.019
Precipitation	-0.067	-0.067 to -0.035	< 0.001	-0.007	-0.016 to 0.002	0.112