

## **Are Ozone Warnings and Alerts Serving Their Purpose? Ozone Alert Effects on Mortality Rates Attributed to Ambient Ozone Exposure in Seoul, Korea**

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### **ABSTRACT**

Korea has a long history of air pollution. While the government was able to reduce some pollutants compared to the 1990s, tropospheric ozone and particulate matter still contribute to air pollution events. Exposures to high levels of tropospheric ozone pollution have been attributed to increased mortality rates, especially in deaths attributed to circulatory and respiratory causes. Less established are the effects of policy measures such as ozone alerts on observed mortality rates. Currently, Korea issues ozone alerts when hourly ozone concentrations exceed 0.12ppm. I ran a series of regressions with lag times from 0-3 days to identify the explanatory variables attributed to mortality rates and gauge the effectiveness of the ozone alert. I calculated the expected increases in cardiovascular and respiratory mortality events after an ozone alert day. For every 0.1ppm increase of O<sub>3</sub> after an ozone alert day there was about 12% (lag = 0 days), 14% (lag = 1 day and lag = 3 days) and 16% (lag = 2 days) increases in mortality rates. Because a decrease in expected mortality rates with increasing time lag signifies that the ozone alert is effective, the results of this study suggest that ozone alerts are not as efficient. Additionally, 1-hour maximum ambient ozone concentrations were not statistically significant ( $p < 0.05$ ) to mortality rates, which suggest that exposures to ozone could not explain the observed deaths. Therefore, the ozone alert (and the conditions associated with the ozone alert) may not be an appropriate proxy to explain the observed mortalities in Seoul.

### **KEYWORDS**

Epidemiology, Air Pollution Events, Health Effects, Regression Analysis, Policy Evaluation

## INTRODUCTION

Over the last 50 years, industrial air pollution was a huge problem in Korea. The problems started with the end of the Korean Civil War in 1953, which led to the country to fall under poverty. This led to the reliance on incomplete combustion of coal briquettes, releasing various noxious air pollutants such as carbon monoxide (Kim 2013). Air pollution was further escalated as big cities and industrial regions started to form in the 1960s (Kim 2013).

Until the late 1970s, the government mostly focused on economic prosperity, putting less emphasis on environmental preservation and policies. However, with the success of the Economic Development Plan set by the government and the voicing of citizens' concerns regarding the consequences of air pollution, the Korean government realized the importance of addressing environmental issues. The Korean government passed the Environmental Preservation Act in 1978 (later revised to the Air Quality Preservation Act in 1990) and established a Ministry of Environment in 1980 (Kim 2013).

Measures such as switching from high-sulfur fuels to cleaner fuels and integrating three-way catalytic converters in vehicles (policies to reduce mobile pollution) brought about a substantial decrease in air pollutants such as SO<sub>2</sub>, Pb and CO, as the government emphasized on reducing air pollution in the country. However, while the government was able to significantly decrease pollution levels of the aforementioned air pollutants, some air pollutants do not show signs of decrease to the present day – air pollutants such as Ozone, Particulate Matter and NO<sub>2</sub> are such examples (Ghim et al. 2005).

Ozone is an air pollutant formed by photochemical reactions of chemicals such as volatile organic compounds, hydrocarbons and nitrogen oxides in the troposphere (Chen et al. 2013). The effects of exposure to ambient ozone have been studied in the past, especially evaluating the effects of ozone exposures to mortality rates. Studies show that there is a causal relationship between short-term ozone exposures and mortality rates (Bell et al. 2006).

Similar epidemiological studies analyzing the effects of dust and air pollution (not specifically limited to effects of ozone exposures on mortality) have been performed in Korea. Mortality rates increased when people were exposed to air pollution (Kwon et al. 2002, Kim et al. 2020).

The current literature well-establishes that exposures to ozone pollution and air pollution effects increase the probability of deaths associated with the exposures. However, what the current literature does not address (especially in the Korean context) is whether policy measures designed to warn people to avoid exposures to pollution (for example, ozone alerts warning people that there are poor air quality conditions) could reduce observed mortality. This study aims to find a preliminary answer on whether ozone alerts are serving their purpose in Korea by analyzing whether there are significant differences in mortality rates on ozone alert days and non-ozone alert days.

## BACKGROUND

Currently, the Korean Ministry of Environment is monitoring hourly concentrations of different hazardous air pollutants including tropospheric ozone in various monitoring stations. Ozone alerts in Korea are issued in three stages. The first stage, “ozone advisory,” is issued when hourly ozone concentrations on a measuring station exceeds 0.12 ppm of O<sub>3</sub>. The second stage (“ozone warning”) is issued when hourly ozone concentrations exceed 0.30 ppm, and the third stage (“major ozone warning”) is issued when hourly ozone concentrations exceed 0.50 ppm. Historically, all of the recorded ozone alerts that were issued in Korea have been ozone advisories (i.e. hourly ozone concentrations did not exceed 0.30ppm).

There is no significant difference at which the three types of ozone alerts are relayed to the public. Ozone alerts are sent out through channels such as emergency alerts in mobile devices, news tickers, announcements on public transportation and advisories in electronic road signages.

The Korean Ministry of Environment also manages a database called AirKorea (available online at [airkorea.or.kr](http://airkorea.or.kr)). Public records of meteorological/weather and air pollution data (such as concentrations of particulate matter, ozone, carbon monoxide) observed in the monitoring stations in Seoul (capital city of Korea) are available from 2014. From 2014 to 2018, there were 53 recorded ozone alert days in Seoul (Table 1). In other words, the hourly ozone concentrations exceeded the 0.12 ppm threshold that ozone alerts were issued.

**Table 1. Ozone alert issuances.** Dates of ozone alert implementations in Seoul, Korea from 2014-2018.

| <b>Year</b> | <b>Date</b>   |
|-------------|---|
| 2014        | 14 May, 28 May, 30-31 May, 17-18 June,<br>26 June, 1 July   |
| 2015        | 10 June, 24 June, 7 August  |
| 2016        | 17 May, 20 May, 22 May, 10 June, 20-21 June,<br>08 July, 11 July, 19 July, 5-6 August, 16-19 August,<br>21 August, 24 September |
| 2017        | 1 May, 3 May, 29 May, 16-17 June, 23 June, 29 June,<br>5-6 July, 13 July, 20 July, 3 August                                     |
| 2018        | 26 May, 5 June, 24-25 June, 20-24 July, 27 July,<br>1-3 August  |

## METHODOLOGY

### Data Collection

To conduct my study, I collected data on hourly ozone concentration data from 2014-2018 in Seoul. I also collected data on PM<sub>10</sub> concentrations, temperature, humidity and air pressure because they could also be potential confounding factors that could cause mortality on a day with high ozone concentrations (Bae et al. 2015, Kwon et al. 2002).

I had to limit my search for daily mortality data within Seoul from 2014 to 2018 in order to match the scope of the data I found for ozone and weather data.

### *Ozone Data*

AirKorea has publicly available data on hourly ozone concentrations from 2014 to 2018. The monitoring station is on the rooftop of Seoul City Hall. I took the maximum hourly ozone concentrations as the ozone concentration on a given day. While AirKorea has an English version

of the web site and database running, I was only able to access the full data on the hourly ozone concentration data on the Korean version.

### *Particulate Matter data*

One major confounding factor that may affect mortality rates on days of ozone pollution is the presence of high concentrations of particulate matter in the atmosphere (Bae et al. 2015, Kwon et al. 2002). Alongside with hourly ozone concentration data, I gathered hourly PM<sub>10</sub> data from the same monitoring station.

### *Weather Data*

As potential confounding factors to mortality on ozone alert days, I also took weather data such as daily average temperatures, humidity and air pressure in Seoul from 2014 to 2018 from available records managed by the Korean Meteorological Association.

### *Daily Mortality Data*

I gathered daily mortality data from the database called MicroData Integrated Service, which is managed by the Korean Statistical Office. For this study, I limited mortality to cardiovascular and respiratory deaths, because exposures to ambient ozone increase cardiovascular and respiratory-related deaths (Yan et al. 2013). Circulatory-induced deaths were classified from I00-I99 while respiratory mortalities were classified from J00-J09, in adherence to the International Statistical Classification of Diseases (ICD-10). Additionally, I limited my mortality data to deaths that occurred in Seoul from 2014 to 2018.

## **Data Analysis**

A common method used to find the relationship between ozone exposures and mortality rates is the Generalized Additive Model (GAM) (Chen et al. 2013, Bae et al. 2015). Essentially, each explanatory variable has different functions that most accurately describes the relationship

between the explanatory variable and the response variable. GAM represented as an equation could be described as  $y = \beta_0 + f(x_1) + f(x_2) + \dots + f(x_n)$ . Initially, I tried to find the appropriate function for my explanatory variables that could model the expected number of cardiovascular and respiratory deaths. However, I was not able to find the functions for the explanatory variables that could model the observed mortality.

Therefore, I modified my study by making the assumption that my explanatory variables had a linear relationship with the response variable. I conducted a multiple linear regression on Python 3 from Jupyter Notebook (Project Jupyter 2020). I set my response variable as the observed daily mortality, while my explanatory variables included weather terms (temperature, humidity and air pressure), air pollutant concentrations (1-hour maximum ozone concentrations, warning term (labeled “0” when there was no ozone alert and “1” when there was an ozone alert) and a *ozone ppm*  $\times$  *warning* term which signifies the difference in ozone concentrations when there was an ozone alert versus when there was no ozone alert (Table 2).

**Table 2. List of variables.** Variables for multiple regression analysis

| Variable  | Description of Variable   |
|-----------|---|
| $y$       | Daily cardiovascular and respiratory deaths   |
| $\beta_0$ | Intercept (baseline mortality when no explanatory variable affects mortality)                               |
| $\beta_1$ | Effect of Temperature on mortality  |
| $x_1$     | Daily Temperature ( $^{\circ}\text{C}$ )  |
| $\beta_2$ | Effect of Humidity (%) on mortality   |
| $x_2$     | Humidity  |
| $\beta_3$ | Effect of air pressure on mortality   |
| $x_3$     | Air pressure  |
| $\beta_4$ | Effect of $\text{PM}_{10}$ exposure ( $\mu\text{g}/\text{m}^3$ ) on mortality                               |
| $x_4$     | $\text{PM}_{10}$ concentration  |
| $\beta_5$ | Effect of ozone exposure (ppm) on mortality   |
| $x_5$     | Ambient $\text{O}_3$ concentration  |
| $\beta_6$ | Effect of difference of ozone concentrations exposures on ozone alert vs. non-ozone alert days on mortality |
| $x_6$     | Difference of ozone concentrations exposures on ozone alert vs. non-ozone alert days                        |
| $\beta_7$ | Effect of warnings on mortality   |
| $x_7$     | Warnings ( $x_7 = 1$ when ozone alerts issued; $x_7 = 0$ when ozone alerts not issued)                      |

I was more interested in finding a percent increase or decrease of mortality associated with the different explanatory variables than finding a nominal value (i.e. expected number of deaths per unit of increase of explanatory variable) of expected mortality. Therefore, I decided to use the natural log of the daily cardiovascular and respiratory deaths. In equation form, the regression I ran was:

$$\ln(y) = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_3x_3 + \beta_4x_4 + \beta_5x_5 + \beta_6x_6 + \beta_7x_7$$

I also explored the possibility of lag time between ozone exposure and mortality rates. Lag times acknowledge the fact that exposures to ambient ozone may not yield to mortalities on the same day – the effects of ambient ozone could appear after a few days of exposure (Bell et al. 2005). For my study, I lagged the effects of mortality for up to 3 days to evaluate the effects of short-term ambient ozone exposure on respiratory and cardiovascular deaths.

## RESULTS

There was not much of a difference between average number of daily deaths in Seoul from 2014 to 2018 on an ozone alert day and on a non-ozone alert day. In fact, there was a higher number of average daily cardiovascular and respiratory deaths on a non-ozone alert day (Table 3). The maximum average hourly ozone concentrations on an ozone alert day did not quite reach the 0.12ppm threshold for an ozone alert to be implemented.

There were instances at which ozone alerts were issued in Seoul on a given day, but the recorded maximum hourly concentration on the monitoring station did not quite reach 0.12ppm. This phenomenon could be explained by the fact that the location at which the ozone alert was implemented was technically in Seoul, but miles away from the monitoring station I used for data analysis; thus, the recorded temperature of the monitoring station did not quite reach the 0.12ppm threshold.

**Table 3. Daily Averages.** Daily averages of mortality, weather conditions and air pollutant concentrations on ozone alert days and non-ozone alert days.

| Explanatory Variables             | Ozone alert days |                    | Non ozone alert days |                    |
|-----------------------------------|------------------|--------------------|----------------------|--------------------|
|                                   | Mean             | Standard Deviation | Mean                 | Standard Deviation |
| Daily Deaths                      | 33.5             | 7.0                | 34.3                 | 7.4                |
| Temp (°C)                         | 26.9             | 3.6                | 12.9                 | 10.7               |
| Humidity (%)                      | 0.72             | 0.06               | 0.64                 | 0.07               |
| Air Pressure (hPa)                | 20.6             | 5.1                | 11.4                 | 7.6                |
| PM10 ( $\mu\text{g}/\text{m}^3$ ) | 53.9             | 21.9               | 43.2                 | 26.6               |
| Ozone (ppm)                       | 0.114            | 0.022              | 0.021                | 0.011              |

## Regression Results

### *Regression with no lag between ozone exposure and mortality*

In the first regression, I assumed that there was no lag time between ozone exposures and mortality. When I ran the regression, average daily temperature, humidity and the *ozone ppm × warning* term were the only explanatory variables that were statistically significant at a 95% confidence level or for  $p < 0.05$  (Table 4). Not accounting for other explanatory variables, every 0.1ppm increase in ozone concentration on an ozone alert day contributed to approximately 33% rise in mortality. Meanwhile, explanatory variables such as ozone concentrations and PM<sub>10</sub> concentrations were not statistically significant.



**Table 4. Regression for lag = 0.** Regression output for mortality with multiple explanatory variables.

|                                   | <b>coefficient</b> | <b>std error</b> | <b>t</b> | <b>P&gt; t </b> | <b>[0.025</b> | <b>0.975]</b> |
|-----------------------------------|--------------------|------------------|----------|-----------------|---------------|---------------|
| constant                          | 4.0615             | 0.127            | 31.955   | 0.000           | 3.812         | 4.311         |
| Average Temp (°C)                 | -0.0072            | 0.001            | -6.019   | 0.000           | -0.010        | -0.005        |
| Avg Humidity (%)                  | -0.7493            | 0.228            | -3.282   | 0.001           | -1.197        | -0.302        |
| Pressure (hPa)                    | 0.0039             | 0.003            | 1.209    | 0.227           | -0.002        | 0.010         |
| PM10 ( $\mu\text{g}/\text{m}^3$ ) | -0.0001            | 0                | -0.749   | 0.454           | -0.001        | 0.000         |
| ozone (ppm)                       | -0.6208            | 0.496            | -1.253   | 0.210           | -1.593        | 0.351         |
| Warning                           | -0.216             | 0.144            | -1.505   | 0.132           | -0.497        | 0.065         |
| ppm $\times$ warning              | 3.3053             | 1.331            | 2.483    | 0.013           | 0.695         | 5.910         |

I then checked for potential collinearity of the different explanatory variables using the variance inflation factor (VIF). Upon doing so, I found that there were multiple explanatory variables that had VIF above 10, a threshold to determine collinearity (Table 5a). Upon removing the ‘Warning’ and ‘Air Pressure’ variables, which were explanatory variables with  $VIF > 10$  and not statistically significant on the first regression analysis, all of the VIFs were below 10 (Table 5b).

**Table 5a. Values of VIF.** Variable Inflation Factor of different explanatory variables.

| <b>Explanatory Variable</b>       | <b>VIF</b> |
|-----------------------------------|------------|
| Average Temp (°C)                 | 15.31      |
| Avg Humidity (%)                  | 14.16      |
| Pressure (hPa)                    | 25.30      |
| PM10 ( $\mu\text{g}/\text{m}^3$ ) | 4.33       |
| ozone (ppm)                       | 8.83       |
| Warning                           | 28.80      |
| ppm $\times$ warning              | 32.11      |

**Table 5b. Values of VIF.** Variable Inflation Factor after removing ‘Warnings’ and ‘Air Pressure’ explanatory variables

| <b>Explanatory Variables</b>      | <b>VIF</b> |
|-----------------------------------|------------|
| Average Temp (°C)                 | 3.82       |
| Avg Humidity (%)                  | 8.28       |
| PM10 ( $\mu\text{g}/\text{m}^3$ ) | 3.55       |
| ozone (ppm)                       | 8.77       |
| ppm $\times$ warning              | 3.24       |

I re-ran the multiple regression (after the removal of the two collinear explanatory variables). Average daily temperatures and humidity showed statistical significance at a 95% confidence level in determining daily mortality. An increase of ozone concentration of 0.1ppm on an ozone alert day contributed to approximately 12.6% rise in mortality (Table 6). Meanwhile, ozone and PM<sub>10</sub> concentrations continue to be not statistically significant.

**Table 6. Regression for lag = 0.** Regression output for mortality without collinear explanatory variables.

|                                   | <b>coefficient</b> | <b>std error</b> | <b>t</b> | <b>P&gt; t </b> | <b>[0.025</b> | <b>0.975]</b> |
|-----------------------------------|--------------------|------------------|----------|-----------------|---------------|---------------|
| constant                          | 3.9271             | 0.065            | 60.74    | 0.000           | 3.8           | 4.054         |
| Average Temp (°C)                 | -0.0061            | 0.001            | -8.775   | 0.000           | -0.007        | -0.005        |
| Avg Humidity (%)                  | -0.5001            | 0.103            | -4.868   | 0.000           | -0.702        | -0.299        |
| PM10 ( $\mu\text{g}/\text{m}^3$ ) | -0.0002            | 0                | -0.984   | 0.325           | -0.001        | 0             |
| ozone (ppm)                       | -0.3427            | 0.458            | -0.748   | 0.455           | -1.241        | 0.556         |
| ppm $\times$ warning              | 1.2582             | 0.429            | 2.931    | 0.003           | 0.416         | 2.1           |

#### *Regression with 1-day lag between ozone exposure and mortality*

In the second regression, I conducted a multiple regression analysis assuming that there was a maximum of 1-day lag between ozone exposures and mortality. The temperature, humidity and the ppm  $\times$  warning terms were statistically significant at a 95% confidence level, while the concentration of air pollutants did not show statistical significance on mortality rates (Table 7). The coefficient for the ppm  $\times$  warning term increased with a 1-day time lag compared to when there was no lag time.

**Table 7. Regression for lag = 1 day.** Regression output for multiple explanatory variables on 1-day lag between ozone exposure and mortality.

|                                   | coefficient | std error | t      | P> t  | [0.025 | 0.975] |
|-----------------------------------|-------------|-----------|--------|-------|--------|--------|
| constant                          | 3.9357      | 0.065     | 60.89  | 0.000 | 3.809  | 4.062  |
| Average Temp (°C)                 | -0.0061     | 0.001     | -8.901 | 0.000 | -0.007 | -0.005 |
| Avg Humidity (%)                  | -0.5086     | 0.103     | -4.955 | 0.000 | -0.71  | -0.307 |
| PM10 ( $\mu\text{g}/\text{m}^3$ ) | -0.0002     | 0         | -1.083 | 0.279 | -0.001 | 0      |
| ozone (ppm)                       | -0.4963     | 0.451     | -1.102 | 0.271 | -1.38  | 0.387  |
| ppm $\times$ warning              | 1.421       | 0.416     | 3.418  | 0.001 | 0.606  | 2.237  |

*Regression with 2-day lag between ozone exposure and mortality*

For the 2-day lag scenario, the same explanatory variables were statistically significant at a 95% confidence level, while the concentration of air pollutants did not show statistical significance on mortality rates. The coefficient for the ppm  $\times$  warning term increased compared to the 0-day lag and the 1-day lag scenarios (Table 8).

**Table 8. Regression for lag = 2 days.** Regression output for multiple explanatory variables on a 2-day lag scenario between ozone exposure and mortality.

|                                   | coefficient | std error | t      | P> t  | [0.025 | 0.975] |
|-----------------------------------|-------------|-----------|--------|-------|--------|--------|
| constant                          | 3.9473      | 0.065     | 61.031 | 0.000 | 3.82   | 4.074  |
| Average Temp (°C)                 | -0.0061     | 0.001     | -8.924 | 0.000 | -0.007 | -0.005 |
| Avg Humidity (%)                  | -0.5227     | 0.103     | -5.091 | 0.000 | -0.724 | -0.321 |
| PM10 ( $\mu\text{g}/\text{m}^3$ ) | -0.0002     | 0         | -1.112 | 0.266 | -0.001 | 0      |
| ozone (ppm)                       | -0.6755     | 0.443     | -1.526 | 0.127 | -1.544 | 0.193  |
| ppm $\times$ warning              | 1.6251      | 0.406     | 4.004  | 0     | 0.829  | 2.421  |

*Regression with 3-day lag between ozone exposure and mortality*

Assuming a 3-day lag between ozone exposure and mortality, average temperature, humidity and ppm  $\times$  warning terms were statistically significant at a 95% confidence level, while ozone and particulate matter concentrations did not show statistical significance. The regression on a 3-day lag scenario showed that there would be an increase of about 14% for every 0.1ppm increase of ozone on an ozone alert event (Table 9).

**Table 9. Regression for lag = 3 days.** Regression output for multiple explanatory variables on a 2-day lag scenario between ozone exposure and mortality.

|                                   | <b>coefficient</b> | <b>std err</b> | <b>t</b> | <b>P&gt; t </b> | <b>[0.025</b> | <b>0.975]</b> |
|-----------------------------------|--------------------|----------------|----------|-----------------|---------------|---------------|
| constant                          | 3.9429             | 0.065          | 60.634   | 0.000           | 3.815         | 4.07          |
| Average Temp (°C)                 | -0.0062            | 0.001          | -9.104   | 0.000           | -0.008        | -0.005        |
| Avg Humidity (%)                  | -0.5196            | 0.103          | -5.041   | 0.000           | -0.722        | -0.317        |
| PM10 ( $\mu\text{g}/\text{m}^3$ ) | -0.0002            | 0              | -1.139   | 0.255           | -0.001        | 0             |
| ozone (ppm)                       | -0.4884            | 0.439          | -1.113   | 0.266           | -1.349        | 0.372         |
| ppm $\times$ warning              | 1.4141             | 0.4            | 3.532    | 0.000           | 0.629         | 2.199         |

## DISCUSSION

The aim of my study was to observe whether ozone alerts were effective in their implementation. I conducted a multiple linear regression which included the concentration of air pollutants and meteorological terms (such as temperature and humidity) with different time lags. By doing so, I was able to observe whether there was a difference of mortality on ozone alert days and non-ozone alert days.

The ppm  $\times$  weight term was designed to see the differences of expected increases or decreases in mortality rates on ozone alert days versus non-ozone alert days. To conclude that the ozone alert had a positive effect on mortality rates, two conditions had to be met. First, the ppm  $\times$  warning coefficient term had to be statistically significant. Second, the ppm  $\times$  warning coefficient term had to decrease with time lag. This was because an increase in the ppm  $\times$  warning coefficient indicated that increases in mortality were attributed to heavy ozone pollution events.

My regression analyses showed that on the base scenario (when lag time between ozone exposures and mortality was 0 days), there was an expected rise in mortality by about 12% for

every 0.1ppm of increased ozone concentrations. The expected mortality per 0.1ppm O<sub>3</sub> increase rose to approximately 14% for 1 and 3-day lags and 16% for 2-day lags. My finding corroborates the results of previous studies in that mortality rates increase with time lags (Bell et al. 2005, Kwon et al. 2002). This is not a surprising result because one could expect more deaths from a single ozone pollution event if a longer amount of time lag is taken into consideration. In other words, assuming that the time lag = 0 days between exposure to ozone and mortality does not take into account the cases of mortality that occur on days after being exposed to ambient ozone.

If ozone alerts were effective, I should have observed a decrease in mortality rates associated with the ozone pollution event. A decrease in mortality rates would have signified that the ozone alert did its role in warning people and potentially discouraging them from being exposed to hazardous levels of ozone. However, my findings show the opposite and are an indication that ozone alerts may not be as effective and not serving its full purpose.

My results also showed that average temperature and humidity were statistically significant (with 95% confidence levels) on explaining mortality trends – there was an observed negative correlation. This was observed in all cases (lag time = 0-3 days). However, there was no statistical significance between ambient ozone concentrations and mortality. The outcomes from my study indicate that the expected increase of mortality on an ozone alert day compared to a non-ozone alert day is not caused by ambient ozone exposures. If this is the case, ozone alerts may not be a good proxy in explaining the observed cardiovascular and respiratory mortality.

A possible explanation as to why my results showed a high statistical significance of temperature and non-statistical significance of ambient ozone concentrations on mortality could be attributed to Chen's (2013) study. One of the results of their study showed that the effects of ambient ozone were stronger with lower temperatures (Chen et al. 2013). There may be a correlation between temperatures and ambient ozone concentrations which could have affected the results of my own regression analyses. In other words, ozone concentrations as an explanatory variable could have been a confounding factor to temperature.

## **Limitations**

For my study, I was only able to access hourly ozone data from one monitoring station in Seoul, Korea from 2014-2018. If I had data from monitoring stations from various cities around

Korea, I could have potentially run more regressions to see whether ambient ozone concentrations do not have any statistical significance to mortality rates as observed in my study and come to a more holistic conclusion on whether mortality is attributed to ambient ozone.

I assumed that all circulatory and respiratory deaths were attributed to ozone exposures. There may have been cases at which a person who died from cardiovascular and/or respiratory causes may not have been exposed to ozone pollution at all. I also may have omitted other non-accidental deaths that were directly caused by ozone exposures. Accurately finding and identifying deaths directly attributed to ozone exposures could change the daily mortality rates, which could affect the results of the study.

Another limitation to the study is that I assumed a linear relationship between the explanatory variables and the response variable. The true relationship between explanatory and response variables may not have been linear. Finding a model that is better than the linear model that I used in my study could be helpful in establishing major causes that contribute to mortalities on ozone alert days and coming to a more accurate evaluation on whether ozone alerts are effective or not.

Finally, I was only able to analyze short-term effects of ozone exposure to mortality rates. Setting a longer lag time between ozone exposures and mortality may yield different conclusions on the effectiveness of ozone alerts and provide a different perspective on the functionality of the ozone alert. Understanding the long-term effects of ozone exposures to mortality and how ozone alerts could potentially play a part could add a dimension on determining whether ozone alerts could be useful or not.

## **Future Directions**

Previous literature has not conducted studies and analyses evaluating the usefulness of ozone alerts. Therefore, I have two major suggestions on improving my study.

The first direction that I propose is a modification of my study. A prospective researcher could change the scope of the study (one could analyze the effectiveness of ozone warning systems from a different city or country), regression analysis methods (one could potentially use generalized additive models or a unique model that could accurately describe the relationship between explanatory and response variables), or the explanatory and response variables (the

researcher could add explanatory variables that could gauge the effectiveness of ozone alerts while the response variable does not need to be cardiovascular and respiratory deaths).

The second direction is to evaluate peoples' responsiveness to ozone alerts. One suggestion is to conduct surveys to find out how many people actually have access to ozone alerts and see whether ozone alerts actually act as deterrents to ozone exposure. For example, a survey questionnaire could include questions such as "Have you received an ozone alert on your mobile device?" to model the number of people that have access to the ozone alert. Another question that could be included in the survey is "If you received an ozone alert, will this discourage you from going outdoors?" to determine whether ozone alerts are effective measures to reduce people's exposures to unhealthy ambient ozone conditions.

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With the rise of COVID-19, it was challenging to accomplish this thesis. The timetable I set myself to complete this research project was significantly affected due to the dramatic changes caused by this global pandemic. There were an increased number of commitments and matters I had to attend to, which made it difficult to fully focus on finishing writing up my capstone project. Nevertheless, I want to extend my gratitude to my parents for supporting me in all of my endeavors, especially when I first told them about my research topic. I also want to thank Team ESPM 175, with a special mention to my thesis advisor Samuel Evans who has given me guidance along the way, as well as being understanding of my situation.

### REFERENCES

- AirKorea. 2018. Final Measurement Data of Various Air Pollutants (Data in Korean). AirKorea.
- Bae, S.H., Y.H. Lim, S. Kashima, T. Yorifuji, Y. Honda, H. Kim and Y.C. Hong. 2015. Non-linear Concentration Response Relationships between Ambient Ozone and Daily Mortality. *PLoS One* 10. <https://doi.org/10.1371/journal.pone.0129243>.
- Bell, M.L., F. Dominici and J.M. Samet. 2005. A Meta-Analysis of Time-Series Studies of Ozone and Mortality with Comparison to National Morbidity, Mortality and Air Pollution Study. *Epidemiology* 16: 436-445.

- Bell, M.L., R.D. Peng and F. Dominici. 2006. The Exposure-Response Curve for Ozone and Risk of Mortality and the Adequacy of Current Ozone Regulations. *Environmental Health Perspectives* 114: 532-536.
- Chen, K., H.B. Yang, Z.W. Ma, J. Bi and L. Huang. 2013. Influence of temperature to the short-term effects of various Ozone metrics on daily mortality in Suzhou, China. *Atmospheric Environment* 79: 119-128.
- Chen, K., L. Zhou, X. Chen, J. Bi and P.L. Kinney. 2017. Acute effect of ozone exposure on daily mortality in seven cities of Jiangsu Province, China: No clear evidence for threshold. *Environmental Research* 155: 235-241.
- Ghim, Y.S., K.C. Moon, S. Lee and Y.P. Kim. 2005. Visibility Trends in Korea During the Past Two Decades. *Journal of the Air and Waste Management Association* 55: 73-82.
- Jupyter Notebook. 2020. Project Jupyter.
- Kim, D. 2013. Air Pollution History, Regulatory Changes and Remedial Measures of the Current Regulatory Regimes in Korea. *Journal of Korean Society for Atmospheric Environment* 29: 353-368.
- Kim, S.Y., J.T. Lee, Y.C. Hong, K.J. Ahn and H. Kim. 2004. Determining the threshold effect of ozone on daily mortality: an analysis of ozone and mortality in Seoul, Korea, 1995–1999. *Environmental Research* 94: 113-119.
- Kim, S.E., Y. Hijioka., T. Nagashima, and H. Kim. 2020. Particulate Matter and Its Impact on Mortality among Elder Residents of Seoul, South Korea. *Atmosphere* 11. <https://doi.org/10.3390/atmos11010018>
- Korean Meteorological Administration. 2018. Daily Averages of Meteorological Variables (Data in Korean). Korean Meteorological Administration.
- Kwon H.J., S.H. Cho, Y. Chun, F. Lagarde and G. Pershagen. 2002. Effects of the Asian Dust Events on Daily Mortality in Seoul, Korea. *Environmental Research* 90: 1-5.
- Microdata Integrated Service. 2020. Annual Data on Daily Mortality (Data in Korean). Korean Statistics Office (KOSTAT).
- Yan, M., Z. Liu, X. Liu, H. Duan and T. Li. 2013. Meta-Analysis of the Chinese Studies of the Association between Ambient Ozone and Mortality. *Chemosphere* 93: 899-905.