The Effect of Air Pollution on Labor Productivity

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Abstract

In this paper, we set out to examine the effect of air pollution on the labor productivity of highly-skilled professional athletes. Air pollution is measured by the Air Quality Index as an average of five pollution metrics: ground-level ozone, particulate matter, carbon monoxide, sulfur dioxide and nitrogen dioxide. Labor productivity is measured by the first serve success percentage of tennis players in a number of tournament venues throughout 2018. We conduct a regression analysis and do not find a negative association between the air pollution metric and the labor productivity of tennis players. However, by dividing the venues into groups, we find that those with the lowest levels of AQI also have the highest average rates of first serve success. Specifically, an examination of 5 groups demonstrates a 1.04% decrease in the first serve success average as players move up to more polluted groups. We estimate the reason for our mixed results is a lack of tournament venues in highly-polluted locations. We suggest that future research should focus on larger panel data and control for additional weather-related variables.

Policy question and the purpose of the paper

For the past several decades, pollution has been known to affect health negatively. According to the World Health Organization (WHO), 4.2 million people die every year from exposure to air pollution and over 90 percent of the world lives in areas where pollution exceeds the organization's standards. This knowledge has led to the implementation of a wide range of policies that have attempted to decrease its negative impact. The United States and the European Union have both created specific legislation intended to limit the levels of dangerous air pollutants (US Clean Air Act vs. EU Directive on ambient air quality and cleaner air). However, policy makers continue to debate the trade-off between the benefit from the reduction of pollution and the damage caused to industries and employment. This paper will analyze recent findings that suggest that the negative impact of pollution is not limited to bad health, but also to labor productivity. These results will pave the way for a more accurate cost-benefit analysis and lead to better policies.

Background

Theoretical Background

With the rise of the industrial revolution in the late 18th century, new sources of air and water pollution were introduced into the environment. The large scale burning of coal resulted in thick smog covering the heavily populated metropolitan areas of the time. Since then, the emissions of nitrogen oxides and sulfur dioxide into the atmosphere have been increasing, resulting in a phenomenon known as acid rain. According to NASA, acid rain occurs when pollutants react with water molecules in the atmosphere and cause precipitation to be irregularly acidic. Acid rain has been known to have a negative impact on agriculture, freshwater, ecological systems, steel and metal structures and even human health.

In 1852, Scottish chemist Robert Angus Smith published a book in which he established the first connection between air pollution and acidic rain. Smith’s book exposed how northern British cities at the time were experiencing acidic rain due to the large scale burning of sulfur-rich coal. Approximately a century later, the United States suffered its single worst air pollution incident in a small town in Pennsylvania called Donora. Over the course of five days in late October of 1948, an air inversion occurred, causing industrial effluents to be trapped in the city’s atmosphere. The incident resulted in the death of 20 people, with another 50 dead after the inversion lifted. This did not include the thousands who suffered from health problems and extreme discomforts due to the trapped effluents (Bachmann *et al*., 2017). Only 4 years later, the United Kingdom also experienced the deadly effect of air pollution. The Great Smog of London lead to the death of over 4,000 people in just 6 days (Bell *et al*., 2004).

The incidents that occured in London and Pennsylvania led to a massive wave of research that focused on the effects of air pollution. In 1955, the US passed the first legislation to deal directly with the problems of air pollution. The Air Pollution Control Act provided funding for government research. This same research eventually led to the Clean Air Act of 1963.

While the above events led to revolutionary legislation around the world, new studies are continuously published, unveiling previously unknown facts about the real cost of air pollution. In 2012, a new area of research was jump started by economists Joshua Graff Zivin and Matthew Neidell. The researchers were able to demonstrate a direct reduction in the labor productivity of farmers in locations with higher ozone levels. The results led to numerous studies that examined the effects of different air pollutants on the labor productivity of different industries. These studies will be further expanded upon in the literature review section of this study, including a more empirical summary of the studies.

Literature Review

In today's world, the issue of pollution and its effect on our health has received considerable critical attention. However, in recent years, there has been a growing body of literature that recognizes the importance of the effect of pollution on labor productivity. As mentioned earlier, it is only since the work of Graff Zivin and Neidell (2012) that the subject has gained momentum. Following studies have been empirical in nature and led to similar results; that pollution is significantly detrimental to the productivity of workers (Chang *et al*., 2016a; Archsmith *et al.*, 2018; Adhvaryu *et al*., 2014). For example, Chang *et al*. (2016a) discovered that an increase in fine particulate matter ($PM_{2.5}$) of 10 micrograms per cubic meter reduced the productivity of pear packers in California by $0.41 per hour, or approximately 6 percent of average hourly earnings. Overall, these studies highlight the need for a policy intervention.

Most researchers that investigated the impact of pollution on labor productivity have utilized empirical research tools. Graff Zivin and Neidell (2012) measured the effect of daily variations in ozone levels on the productivity of agricultural workers in California. As a landmark study, the authors conceded that it was unclear whether their findings could be generalized to other pollutants and to other industries. Lavy *et al.* (2014) expanded on this research by using fine particulate matter and carbon monoxide as their independent variables. Similarly, Adhvaryu *et al.* (2014) analyzed data on hourly garment workers and compared it with multiple, hourly measurements of both fine and coarse particulate matter. Further research by Chang *et al.* (2016) also used particulate matter to investigate the impact of pollution on white-collar, semi-skilled labor in China. Archsmith *et al.* (2018) carried out one of the most recent studies in the field that analyzed the impact of pollution on the productivity of professional baseball referees. The authors examined the quality of calls made by the same Major League Baseball referees over time in different pitches with different pollution levels.

All of the studies reviewed here support the hypothesis that pollution has a statistically significant negative impact on labor productivity. However, each paper provides another piece of the puzzle into why and how this relationship occurs. While Graff Zivin and Neidel (2012) found empirical evidence that described the negative impact of ozone levels on the productivity of outdoor agriculture workers, Lavy *et al.* (2014) found that exposure to certain pollutants negatively impacted Israeli students' probability of receiving a Bagrut certificate. A regression analysis demonstrated that an increase of ten units in the ambient concentration of fine particulate matter reduced Bagrut test scores by .46 points. In 2017, Isen *et al.* reported a significant relationship between early childhood pollution levels and employment outcomes thirty years later. The research was based on the 'natural experiment' that resulted from the 1970 Clean Air Act. Specifically, the authors proved that a ten percent reduction in total suspended particulates increased wages by one percent. Taken together, these findings suggest that the costs of pollution have long been underestimated by policymakers.

Despite similar results, each paper provides unique policy recommendations. For example, Graff Zivin and Neidel (2012) suggest a stricter regulation of ozone pollution. A more practical policy is proposed by Adhvaryu *et al.* (2014); the authors suggest that management should re-allocate workers to optimize productivity in the firm. Chang *et al.* (2016) recommend publicly-coordinated efforts, rather than firm-specific investments, to decrease the total emission of particulate matter by examining the costs and benefits of pollution regulations. We believe that by examining different aspects of the available literature, we can suggest an effective policy recommendation to combat the fall in labor productivity caused by pollution.

Research Hypothesis

We hypothesize that higher air pollution will decrease the labor productivity of tennis players, as measured by their first serve success percentage. We base our hypothesis on the previous findings of Archsmith *et al.* (2018) and Lichter *et al.* (2017), who reached similar conclusions by examining the effect of air pollution on the labor productivity of soccer players in Germany and baseball referees in the US.

Method and Results

The Data Base and the Research Method

In order to address the research question, we take the following steps. First, we select a measure for the labor productivity of tennis players. Successful first serve percentage is the most appropriate measure as it is perhaps the shot that is least susceptible to exogenous variables. Next, we gather a sample of tennis players based on their ranking as well as the number of years on the professional tour. Players that turned professional after 2016 are not included in the sample as their first serve career record is less significant. In addition, players ranked below the top 100 are not included in the sample as they do not participate in the top tournaments. The tournaments in the sample are selected according to the most-played tournaments of the Association of Tennis Professionals (ATP). There are four main levels of competition on the ATP tour - the Grand Slams, the Tour Masters 1000, the Tour 500 and the Tour 250. The sample examines data for the calendar year of 2018. Data on the tennis-related variables is taken from the Ultimate Tennis Statistics site.

We use the Air Quality Index (AQI) to measure the levels of air pollution closest to the tennis tournaments at the specific dates that they were played. This information was provided to us by Air Matters, an organization that "aims to provide a handy and powerful tool for broadcasting real time air quality and giving health advice for users" (Air Matters). The organization's AQI measure is calculated according to the US National Ambient Air Quality Standards (NAAQS), as an average of several air pollution metrics (PM2.5, PM10, O3, NO2, SO2, CO). The above standards were established by the US Environmental Protection Agency under the Clean Air Act in 1970. The AQI is divided into 6 categories, ranging from good to hazardous. For more details, see Table 4.

Air Matters was unable to provide us with data on all the tournaments that we wished to include in our sample. As a result, we were left with a sample of 31 tournaments. Additionally, the data provided by the organization is from the station closest to the location of the tournament but not at the exact coordinates of the tournament. Interestingly, we do not often see the use of AQI as a measure of air pollution in past papers. Rather, different papers include different components of the index - while Graff Zivin and Neidell (2012) focus on fine particulate matter (PM2.5), Lichter *et al.* (2017) prefer to use coarse particulate matter (PM10) as their measure for air pollution. Other papers include different combinations of the index's components.

We include the average temperature at the tournaments as an independent variable, similarly to regressions made by Graff Zivin and Neidell (2012), Archsmith *et al.* (2018) and others. We collect this data from Weather Underground, a real-time weather service provider. Despite our efforts, we were unable to gather other accurate weather-related data on variables that we consistently found throughout past research, including wind speeds, dew points and atmospheric pressure.

To analyze our hypothesis, we perform the following regression:

$$\mathbf{Y_i(FirstServeAverage) = \alpha_i + \beta_{1,i}(AQI) + \beta_{2,i}(FirstServeCareerRecord) + \beta_{3,i}(AverageTemperature) + \beta_{4,i}(Height) + \beta_{5,i}(CourtSurface) + \varepsilon_i}$$

The regression consists of the following variables:

1. FirstServeAverage - the first serve success average of a tennis player at a specific tournament is used as the dependant variable,
2. AQI - the primary independent variable and air pollution measure that we wish to examine,
3. FirstServeCareerRecord - The first serve success average over the entire career of the tennis player,
4. AverageTemperature - The average temperature, measured in degrees Celsius, over the course of the tournament played,
5. Height - The height of the tennis player measured in centimeters,
6. CourtSurface - The surface of the court in the specific tournament (hard, clay, grass).

By performing the OLS regression, we find the effect of each variable on the first serve success of the tennis player at the specific tournament. As part of the research design, we split the observations into groups with 'high' and 'low' air pollution (AQI). We do this by using the xtile command in stata, which separates the groups into the specified number of quantiles.

Data Analysis

In Table 1, we report the descriptive statistics for the variables. The mean of the AQI is 44.30, suggesting that ATP tournaments are played in non-polluted locations. The maximum AQI value is 132.83, falling under the category 'unhealthy for sensitive groups' (see Table 4). As this paper's sample consists of professional athletes, even this level of air pollution is unlikely to affect their first serve success.

The mean of the first serve career record is 62%. This means that on average, the top tennis players in the world perform a successful first serve approximately 3 out of 5 times. Interestingly, the standard deviation is only 3%, with the least successful player serving at 56% while the most accurate player serves at 69%. These results suggest that the players serve at a very consistent level.

We observe that the mean of our dependent variable, the first serve average in our sample of tournaments, is also 62%. This is a good indication that our tournament sample is representative of the players' careers. As expected from the central limit theorem, there are larger variations in the observations of the dependent variable than the first serve career average. The minimum first serve success rate of a player in our sample in one of the tournaments is 38% and the maximum 83%.

Findings, Results and Conclusions

To determine whether air pollution has an effect on the labor productivity of tennis players, we perform several OLS regressions.

Table 2 demonstrates the regression previously mentioned in the Research Method section. The table provides 5 regressions, each column adding another independent variable. As seen in the table, the air pollution metric (AQI) is not significant. The only variable that is significant throughout each regression at the 1% significance level is the first serve career record. In addition, the rest of the independent variables all lack significance, including the average temperature, the height of the player and all surfaces except clay.

In the next stage, we add a group parameter to the regression. Group 1 is the lowest level of air pollution, while group 5 is the highest. Table 3 provides details of this regression. We observe that in all tests, being in the group with the higher air pollution harms the labor productivity of the tennis players. When split into two quantiles, with half the observations below the median and half above, the first serve success average of players in group 2 is worse by 1.68%. By splitting the observations into 5 groups, we find a 1.04% decrease in first serve success average as players move up a group. A similar conclusion can be drawn from Graph 1, where we see that group 1 is serving successfully at a higher average than the rest of the groups. Somewhat unintuitively, however, the now-significant AQI measure in Table 3 has a positive coefficient. We are unable to explain this phenomenon.

Thus, we can neither completely reject nor confirm our initial hypothesis that a higher level of air pollution is detrimental to the labor productivity of tennis players. Although the above results are not as strong as we anticipated based on other studies, we find that tournament venue groups with the lowest levels of air pollution are also those with the highest levels of labor productivity, as measured by the first serve success average of the tennis players.

We hypothesize that our results were less robust than previous research as the AQI measure did not vary widely across the tournament venues in our sample. Perhaps it is good that the ATP does not pick highly-polluted locations. However, we are unable to definitively make such a claim based on our data.

In addition, we believe that our results would be more significant given the opportunity to perform a time-series analysis. Under this type of analysis, each observation would be taken on a daily basis, rather than an average of the whole tournament. For example, a player might have a first serve success average of 65% on the first day of the competition, 60% on the second day and might lose in the third day. This would also require daily observations for the temperature.

Finally, as our R squared did not exceed 20% in any of the regressions, we would include additional variables that we were unable to collect for this paper. For example, weather-related variables such as wind speeds, dew points and atmospheric pressure.

Policy Recommendations

In 1970, the United States passed one of its most bipartisan laws. The Clean Air Act Extension “passed the Senate unanimously, drew only one ‘no’ in the House of Representatives, and was signed into law by a Republican president, Richard Nixon” (Gardiner, 2019). According to a cost-benefit analysis made by the EPA in 1997, the law saved the country 20 trillion dollars (in terms of 1990 dollars). 2008 brought the legislation of the Clean Air Law to Israel. 10 years later, the Israeli Ministry of Environmental Protection conducted a review that found that the law saved 3 shekels for every shekel that was spent on compliance (Azulai, 2018). In 2013, the EU estimated the costs of air pollution at 23 billion euros per year. The European Commision included healthcare costs, lost working days and damage to ecosystems as part of its cost analysis.

The EPA, Israel’s Ministry of Environmental Protection and the European Commision neglected to include the effect of air pollution on labor productivity as part of their cost estimations. Granted, this area of research was only brought to light in 2012 by Graff Zivin and Neidel. Still, both government organizations found that the benefits of regulation much outweighed the costs.

As the Trump administration rolls back environmental regulations and refuses to enforce the Clean Air Act, we firstly propose that countries continue to monitor and limit air pollution. This has proven a successful tactic until now in the US, the EU and Israel.

While our paper does not unilaterally prove that air pollution is detrimental to labor productivity, we can reasonably say that individuals are more productive in less polluted environments. Therefore, we suggest that beyond government regulations, firms in highly polluted locations should take precautions to mitigate the potential negative impact on the labor productivity of their staff. For example, offices should invest in air filtration systems.

Finally, we recommend that schools educate children from a young age regarding the dangers of air pollution. In extreme cases, individuals should even purchase masks that filter particulate matter, as they do in China. These masks should be subsidized by the government.

Bibliography

Adhvaryu, A., Kala, N., & Nyshadham, A. (2014). Management and shocks to worker productivity: Evidence from air pollution exposure in an Indian garment factory. Retrieved from https://economics.sas.upenn.edu/sites/default/files/filevault/event_papers/nyshadham_JMP.pdf

Air Matters. (2018, May 10). Retrieved from https://air-matters.com/

Archsmith, J., Heyes, A., & Saberian, S. (2018). Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation. *Journal of the Association of Environmental and Resource Economists*, *5*(4), 827–863.

Azulai, Y. (2018, July 12). Clean Air Law benefits estimated at NIS 115b. Retrieved from https://en.globes.co.il/en/article-clean-air-law-benefits-estimated-at-nis-115b-1001245985

Bachmann, J., Calkins, D., & Oge, M. (2017, September). Cleaning the air we breathe: A half century of progress.

Bell, M. L., Davis, D. L., & Fletcher, T. (2004, January). A retrospective assessment of mortality from the London smog episode of 1952: the role of influenza and pollution. *Environmental health perspectives*, *112*(1), 6–8. doi:10.1289/ehp.6539

Chang, T., Graff Zivin, J., Gross, T., & Neidell, M. (2016a). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy*, *8*(3), 141–169.

Chang, T., Graff Zivin, J., Gross, T., & Neidell, M. (2016). The effect of pollution on worker productivity: Evidence from call-center workers in China. doi: http://www.nber.org/papers/w22328.pdf

Gardiner, B. (2019, May 14). This law has saved millions of American lives. Trump wants to gut it. Retrieved from https://www.huffpost.com/entry/clean-air-act-pollution-trump-dismante_n_5cd326aee4b09f321bdb0978

Graff Zivin, J., & Neidell, M. (2012). The Impact of pollution on worker productivity. *American Economic Review*, *102*(7), 3652–3673.

Isen, A., Rossin-Slater, M., & Walker, W. R. (2017). Every breath you take--every dollar you'll make: The long-term consequences of the Clean Air Act of 1970. *Journal of Political Economy*, *125*(3), 848–902.

Israel Ministry of Environmental Protection. (2015, December 16). National Air Monitoring Network. Retrieved from http://www.sviva.gov.il/English/env_topics/AirQuality/Pages/NationalAirMonitoringNetwork.aspx

Lavy, V., Ebenstein, A., & Roth, S. (2014). The Impact of short term exposure to ambient air pollution on cognitive performance and human capital formation. doi: https://www.nber.org/papers/w20648

Lichter, A., Pestel, N., & Sommer, E. (2017). Productivity effects of air pollution: Evidence from professional soccer. *Labour Economics*, 48, 54–66. Retrieved from http://search.ebscohost.com.ezprimo1.idc.ac.il/login.aspx?direct=true&db=eoh&AN=1681921&site=ehost-live&scope=site

Environmental Protection Agency. (1997, October). The Benefits and Costs of the Clean Air Act, 1970 to 1990.

Environmental Protection Agency. (2017, August 24). Summary of the Clean Air Act. Retrieved from www.epa.gov/laws-regulations/summary-clean-air-act

World Health Organization. (2018, December 20). Air pollution. Retrieved from https://www.who.int/airpollution/en/

Appendices

TABLE 1 – DESCRIPTIVE STATISTICS

Variable	Obs	Mean	Std. Dev.	Min	Max
AQI	1023	44.30	20.72	18.43	132.83
AvgTemp	1023	19.81	5.64	3.00	30.17
FirstServeCareerRecord	1023	0.62	0.03	0.56	0.69
FirstServeAvg	448	0.62	0.07	0.38	0.83
Height	1023	187.73	8.15	170.00	208.00

TABLE 2

THE TABLE BELOW PROVIDES AN OLS REGRESSION, WHICH EXAMINES THE EFFECT OF AIR POLLUTION ON THE PLAYERS' FIRST SERVE AVERAGES.

Variable	FirstServeAvg	FirstServeAvg	FirstServeAvg	FirstServeAvg	FirstServeAvg
AQI	0.00013791 (0.76)	0.00010585 (0.63)	0.00009778 (0.58)	0.0000942 (0.56)	0.00024473 (1.40)
FirstServeCareerRecord		0.80278537*** (9.14)	0.80510781*** (9.15)	0.77501316*** (8.39)	0.75363354*** (8.22)
AvgTemp			-0.00035827 (-0.69)	-0.00036913 (-0.72)	-0.000202 (-0.39)
Height				0.0003808 (1.07)	0.00051961 (1.46)
Clay_Dummy1					0.02140624*** (3.33)
Grass_Dummy2					0.00320237 (0.27)
_cons	0.61117167*** (70.25)	0.1185848** (2.18)	0.12464111** (2.26)	0.07208723 (0.97)	0.04212422 (0.57)

TABLE 3

THE TABLE BELOW PROVIDES AN OLS REGRESSION, WHICH EXAMINES THE EFFECT OF AIR POLLUTION ON THE PLAYERS' FIRST SERVE AVERAGES, ADDING A GROUP PARAMETER WHERE GROUP 1 IS THE LOWEST LEVEL OF AIR POLLUTION AND GROUP 5 IS THE HIGHEST.

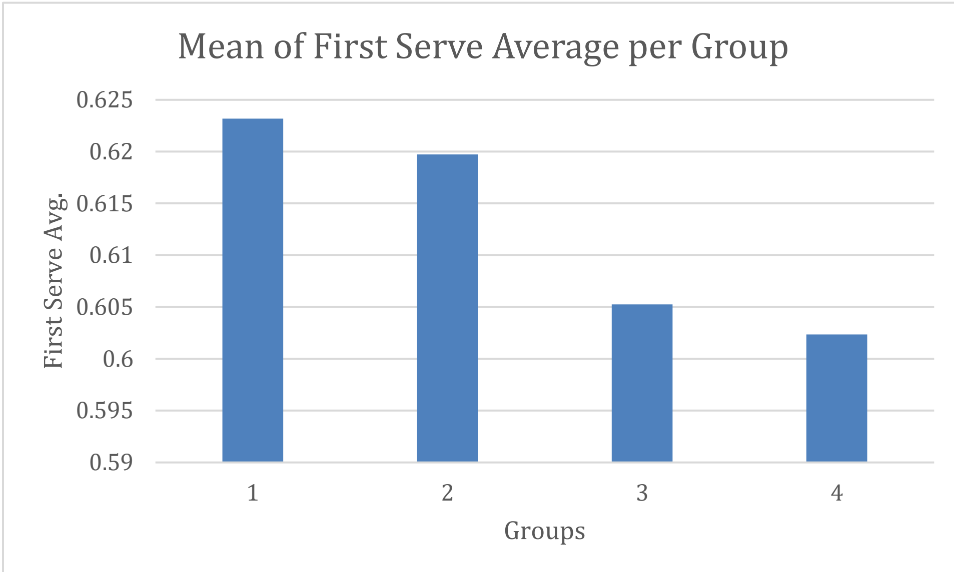
Variable	FirstServeAvg	FirstServeAvg	FirstServeAvg	FirstServeAvg
AQI	0.00054371** (2.45)	0.00056765** (2.24)	0.00069757** (2.53)	0.00091722*** (3.21)
group2	-0.01684836** (-2.18)			
group3		-0.00976647* (-1.76)		
group4			-0.00941302** (-2.12)	
group5				-0.01042787*** (-2.96)
FirstServeCareerRecord	0.75616371*** (8.28)	0.75425742*** (8.25)	0.75595932*** (8.28)	0.75769764*** (8.34)
AvgTemp	-0.00049132 (-0.93)	-0.00037451 (-0.72)	-0.00054448 (-1.01)	-0.00080999 (-1.47)
Height	0.00050186 (1.42)	0.00049264 (1.39)	0.00050526 (1.43)	0.00050006 (1.42)
Surface_Dummy1	0.01869322*** (2.87)	0.01836031*** (2.77)	0.01979064*** (3.07)	0.01986113*** (3.11)
Surface_Dummy2	0.00105066 (0.09)	0.00354684 (0.30)	-0.00002478 (-0.00)	0.00255534 (0.22)
_cons	0.06263714 (0.84)	0.05649133 (0.76)	0.05441165 (0.74)	0.05670793 (0.77)
R-Squared	0.1919	0.1889	0.1914	0.1991
t-statistics in parentheses, *p<0.1, **p<0.05, ***p<0.01				

R-Squared	0.0013	0.159	0.1599	0.1621	0.1831
t-statistics in parentheses *p<0.1, **p<0.05, ***p<0.01					

Table 4 - AQI measure

Air Quality Index Levels of Health Concern	Numerical Value	Meaning
Good	0 to 50	Air quality is considered satisfactory, and air pollution poses little or no risk.
Moderate	51 to 100	Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.
Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is not likely to be affected.
Unhealthy	151 to 200	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects.
Very Unhealthy	201 to 300	Health alert: everyone may experience more serious health effects.
Hazardous	301 to 500	Health warnings of emergency conditions. The entire population is more likely to be affected.

Graph 1 - This graph shows the means of the first serve averages of the groups that are defined by the air pollution metric, group 1 being the lowest AQI and group 4 being the highest.


Mean of First Serve Average per Group
0.625
0.62
0.615
0.61
0.605
0.6
0.595
0.59
First Serve Avg.
1
2
3
4
Groups