Does Environmental Quality Affect Education? Evidence from Air Quality and School Attendance in the United States

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Introduction:

The educational outcomes of K-12 school system depend on the students being present in the classroom. Prior literature documents that school absenteeism leads to poorer school performance and greater dropout rates (Gottfried, 2014; Dreyfoos, 1990; Finn, 1993; Gottfried, 2009; Lehr, Sinclair, & Christenson, 2004; Steward, Steward, Blair, Jo, & Hill, 2008; Hansen, & Selte, 2000). Absenteeism is also associated with decelerated socioemotional development, increased health risk behaviors and unemployment (Alexander, Entwisle, & Horsey, 1997; Broadhurst, Patron, & May-Chahal, 2005; Chen & Stevenson, 1995; Connell, Spencer, & Aber, 1994; Finn, 1993; Gottfried, 2011; Morrissey, Hutchison, & Winsler, 2013). Thus, the objective of this paper is to examine school absenteeism in the US. In particular, we focus on the impact of air quality on chronic school absenteeism (students absent for more than 15 days in an academic year).

The effects of poor air quality on health outcomes have been well documented. The adverse effects are particularly severe for children and include asthma, acute bronchitis, other respiratory illnesses, and even mortality (Braga et al., 2001; Barnett et al., 2005). Such health risks from exposure to air pollution prompt averting behaviors including avoiding outdoor activities and indoor areas with poor filtration. For example, California Air Resources Board recommends avoiding all outdoor exertion during hazardous air quality conditions (CA ARB, 2022).

Air quality in the US has been gradually improving, with emissions of carbon monoxide, nitrogen dioxide, ozone etc. decreasing by 30% between 2008 and 2017 (EPA 2022). However, poor air quality is still a serious concern in many communities. The minorities, young, old and people with pre-existing health conditions are disproportionately affected by bad air quality (Tessum et. al. 2021).

The impact of air quality on student cognitive abilities and absenteeism has been documented in previous literature (Ready, 2010; La Nauze and Severnini, 2021; Gilraine, 2020; Ham, Zweig and Avol, 2014; Currey et. al., 2009; Hales et. al., 2016). Bener, Kamal and Shanks (2007) tested the impact of asthma and air quality on school attendance among 31,400 Qatari school children. They found significant association between air quality and absenteeism especially for asthmatic students. Similar results were found by Park et. al. (2002) using data from one elementary school in South Korea. They concluded, using generalized additive Poisson regression, that exposure to particulate matter and other pollutants like sulfur dioxide and ozone increased illness-related school absenteeism.

Meng, Babey and Wolstein (2012) explored the relationship between income, asthma related absenteeism. They concluded that absenteeism due to asthma was more prevalent in schools with more low-income students. Lower economic status is also found to have significant impact in increasing chronic absenteeism (Chang et. al. 2018). Balfanz & Byrnes (2012) concluded that chronic absenteeism is not significantly different between urban and rural schools. Liu and Salvo (2018) examined the impact of defensive measures taken by schools and parents in China. They found that children from Western countries like USA, Canada and Europe were more sensitive to air quality than Chinese children. The western children missed schools the most.

A quasi-natural experiment analysis was done by Hales et. al. (2016) to examine PM2.5 exposure and elementary school absenteeism. They concluded that that a 10μg/m3 increase in PM2.5 increased absenteeism by about 1.7%. However, they also concluded that it was difficult to make the air quality impact stand out from other factors that might contribute to school absenteeism. One of the most robust studies on the impact of air pollution on school absenteeism was done by Currey et al. (2009). Using data from 39 school districts in Texas, they used difference in difference technique to explore the impact of air pollution on school absenteeism. They concluded that elevated carbon monoxide levels, can significantly impact school attendance even when CO is below state approved levels. Similar results are found by Gilliland et al. (2001) where they concluded that short term change in air quality like O3 was associated with a substantial increase in school absenteeism in a cohort of 4th-grade school children.

One of the seminal studies for air pollution and absenteeism was done by Ransome and Pope (1992) using weekly data from Utah. They found that 1% of the students in the sample were absent each day due to PM10 exposures. Makino (2000) used data from 2 schools in Japan to find significant impact of PM10 and nitrogen oxides on school children absenteeism. A slightly different result was obtained by Chen et. al. (2000) who used 57 school data from a county in Nevada to conclude that PM10 did not have any impact. However, they found Carbon monoxide and Ozone to have a positive impact on absenteeism. MacNaughton et. al. (2017) investigated the impact of PM 2.5 and the surrounding school greenness on absenteeism in 1775 public schools in Massachusetts and concluded that 1 μg/m3 increase in PM2.5 resulted in 1.58% increase in chronic absenteeism.

In addition to absenteeism, there are also adverse impact of poor air quality on the cognitive ability and learning outcomes. Chronic absenteeism leads to negative academic outcomes (Chang et al., 2018; Cortiella, & Boundy, 2018). Lower attendance in the early years of schooling has been linked to increased drop-outs, disengagement and alienation in school (Gottfried, 2014). High rates of absenteeism has also been associated with substance use, future employment difficulties and many health related issues (Alexander, Entwisle, & Horsey, 1997; Connolly & Olson, 2012; Cutler & Lleras-Muney, 2006).

The root causes of chronic absenteeism can be grouped into 3 factors namely, barriers, aversion, and disengagement (Patnode A. H. et. al., 2018). Under the barrier factor, physical and mental health is associated with higher rates of absenteeism (Erbstein, Olagundoye, & Hartzog, 2015; Humm Brundage, Castillo & Batsche, 2017); transportation is found to pose a significant barrier to attendance (Erbstein et al., 2015; Humm Brundage et al., 2017); housing instability and adult responsibilities have significant impacts on chronic absenteeism (Balfanz & Byrnes, 2012). Under aversion, school atmosphere (Bevans et. al., 2007; Schneider, 2002) and academic performance (Feldman et al., 2014; Janosz et. al., 2000) have significant impact on chronic absenteeism. Disengagement deals with the student's willingness to attend school (Allensworth & Easton, 2007; Humm Brundage et al., 2017). Substance use (Humm Brundage et al., 2017) and negative peer influence (Henry & Huizinga, 2007) contribute to disengagement and increasing in chronic absenteeism.

To the best of our knowledge, the research on the importance of air quality for chronic absenteeism has been scant. The shortage of the national scale studies of air quality and school attendance is particularly evident. We address this gap in the literature by examining the effects of air quality on chronic absenteeism in the U.S. schools using a national dataset from more than 90,000 public schools. We use a random effect panel data regression analysis to draw preliminary conclusions that carbon monoxide, nitrogen dioxide and PM2.5 can significantly increase school absenteeism. We are still actively working on additional analysis, which will be produced by the end of July.

Data:

Data are obtained from multiple sources. The school-level absenteeism data come from the Civil Rights Data Collection initiative by the Department of Education. The CRDC started collecting chronic absenteeism in the 2013-14 and there have been only three rounds of published data for chronic school absenteeism. Thus, the paper uses data from the three rounds, namely, 2013-14, 2015-16 and 2017-18 academic school years. The school data was matched with the school district and merged with county socioeconomic data. The air quality data, although available for all years, does not include monitors in all the counties. Therefore, only the schools in the counties that have air quality monitors are included in the analysis.

The US department of education defines chronic absenteeism as missing approximately 15 days of school per year. There are about 50,649,164 students enrolled in about 90,000 public schools in the United States, of which 6,994,405 students are chronically absent, which is about 13.8%. Figure 1 shows the race-wise distribution of the students enrolled. The data is mostly comprised of white students (49%), followed by Hispanics (26%), while Pacific islanders makes up for less than 1% of the sample for the school year 2013-14. Figure 2 shows the race-wise chronic absenteeism rates for the school year 2013-14 in terms of the percentage of enrolled students for each race group who were chronically absent in the academic year 2013-14. For example, 13.88% of all enrolled white students were absent during this academic year. The highest absenteeism is seen among the American Indian students followed by Pacific Islanders and Black students.

Table 1 shows the descriptive statistics for the variables. There are about 550 students per school on average with about 76 students chronically absent. The school with the highest enrollment has about 4800 students while the school with the highest number of students chronically absent is about 2000 students. The data were cleaned by dropping outlier observations with unrealistic school enrollments, absenteeism or other irregularities. Unique school IDs were created by combining state, county, and school codes.

There are about 34 Full Time Equivalent (FTE) teachers on average per school, of which about 10 FTE teachers are absent for more than 10 days or more. The average school salary budget for an academic year was about 2.5 million per school.

The data also include county characteristics as controls including population, education, employment, per capita income and total personal income collected from the Bureau of Economic Analysis (BEA). In table 1 the county level variables are matched with the corresponding schools thus showing about 90,000 observations, as data for some counties are missing.

FIGURE 1: ENROLLMENT **SAMPLE RACIAL DISTRIBUTION FOR SCHOOL YEAR 2013-14**

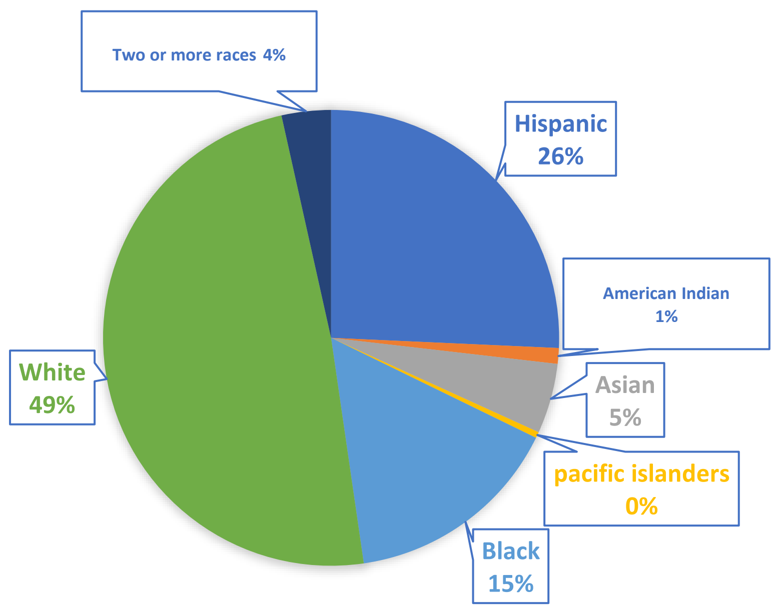


Figure 2: Percentage of total enrolled students chronically absent by race for school-year 2013-14

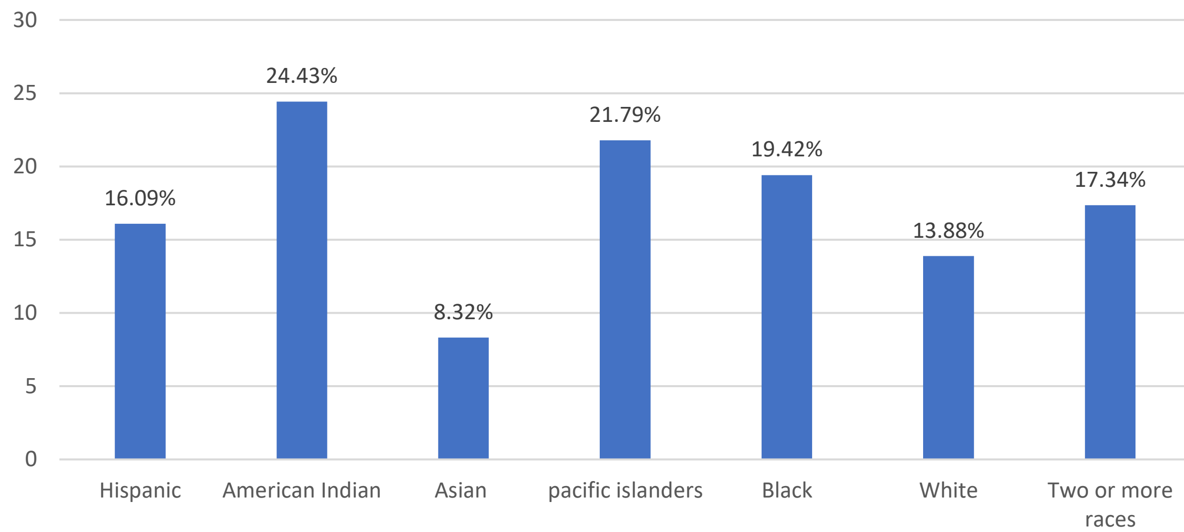


Table 1: Descriptive Statistics of Variables:

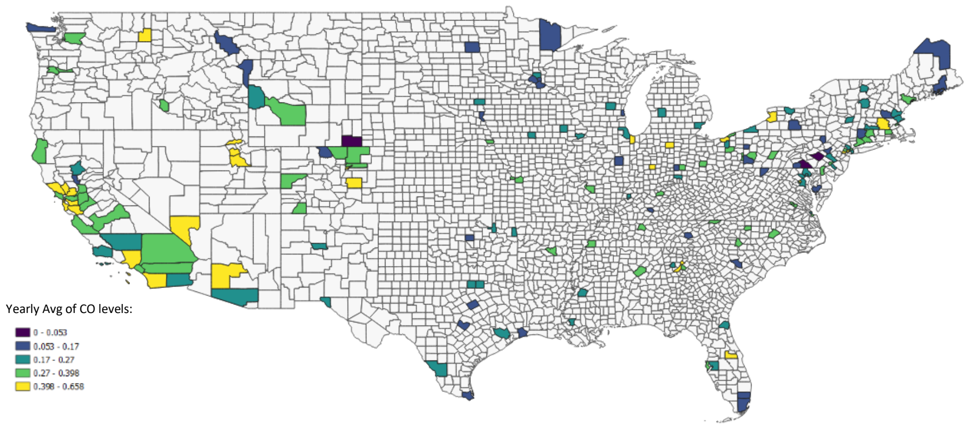
Variable	Obs	Mean	Std. Dev.	Min	Max
Total Enrollment (no. of students)	92,014	549.581	431.2245	11	4,871
Total Chronically absent (no. of students)	92,014	75.859	108.8706	0	1,994
FTE Teachers (no. of teachers)	92,014	33.722271	25.12469	0	400
FTE Teachers absent (no. of teachers)	91,952	9.272112	10.68356	0	161
Total School Salary (in dollars)	91,548	2,547,728	6496233	0	1.08e+09
Per Capita students	92,014	0.138849	0.0629174	0	0.670319

chronically Absent by county					
Total Personal Income per county. ($000)	90,188	4.74e+07	9.04e+07	21734	5.11e+08
Tot Pop per county (persons)	90,188	879,755	1,680,330	262	1.00e+07
Per capita per county Inc. ($)	90,188	47,111.57	18,638.64	17224	201,029

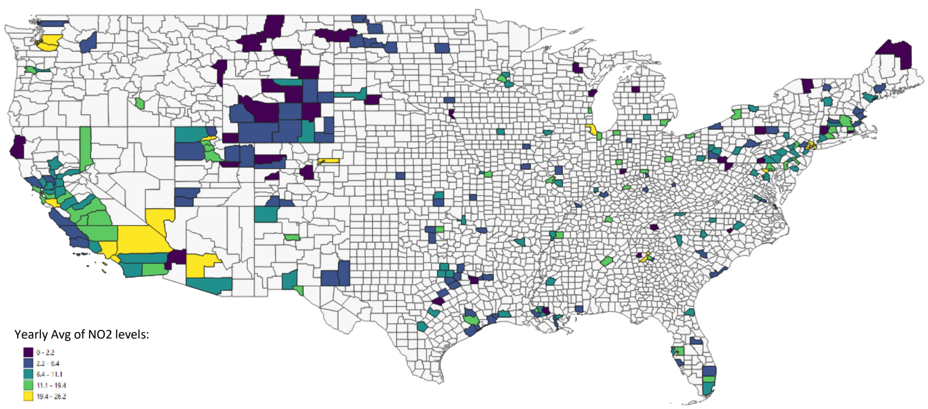
The air quality data was taken from Environment Protection Agency (EPA). However, not every county has an air quality monitor, which cuts down the sample size. The air quality data include Carbon Monoxide (CO), Nitrogen Dioxide (NO2), Particulate Matter 2.5 (PM 2.5) and Particulate Matter 10 (PM 10) for their respective available monitors. Figure 3 shows the placement of the monitors by air quality measure and their respective mean count for the year 2013-2014. Daily Carbon Monoxide 8-hour average and daily maximum values were obtained from CO monitors in 178 counties. Daily Nitrogen 1-hour average and daily maximum values were taken from NO2 monitors in 247 counties. Daily PM10 average values were obtained from PM10 monitors in 177 counties. Daily PM2.5 average value was obtained from monitors in 471 counties. The Daily average values were transformed into a single value year-average for all the measures and the daily max value was averaged for the year in making it a year-average maximum value. Values for the month of June and July were dropped as absenteeism is typically irrelevant in the summer.

Figure 3: Mapping of Air Component Monitors

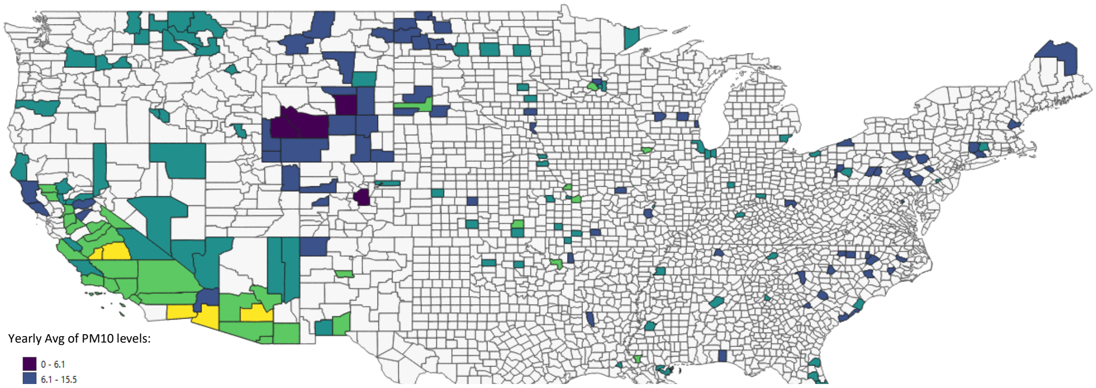
Carbon Monoxide Monitors



Nitrogen Dioxide Monitors



PM 10 Monitors



PM 2.5 Monitors

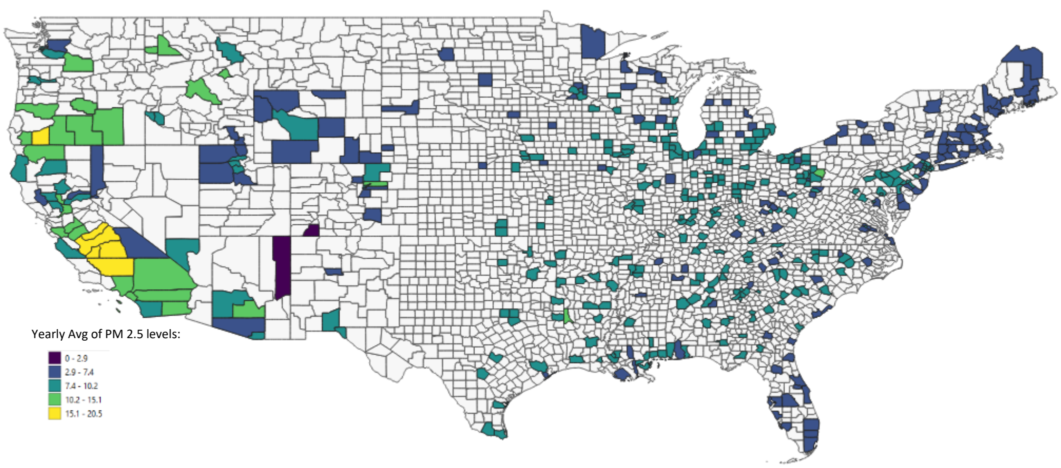


Table 2 shows summary statistics for the air quality measures for the year 2013-14. e have a total of 32,979 schools for one schoolyear in 178 counties, resulting in around 95,000 observations with carbon monoxide measures for the three years. According to the EPA (EPA, 2018), Carbon Monoxide between 0 – 4.4 is considered good. In our sample, the average yearly average of Carbon Monoxide is about 0.32 parts per million (ppm) with a minimum average of 0.02ppm and highest of 0.66 ppm. The yearly average maximum value was around 0.45 ppm and the highest year-average was 1.055 ppm.

The sample has 33,523 schools in the counties with NO2 monitors with a yearly average of 11.65 parts per billion (ppb) with a highest of 25.2 ppb and lowest of 0.62 ppb, while the yearly average of maximum value is 23.5 ppb with the highest being 43.2 ppb. The sample has 19,764 schools with the PM10monitors with yearly average of 24.2 µg/m3 and highest value 59.98 µg/m3. PM 2.5 has 46,349 schools with the yearly average of 9.22 µg/m3 and the year-average of highest readings 21.89 µg/m3.

Table 2: Descriptive Statistics for air quality components

Variable	Obs	Mean	Std. Dev.	Min	Max	EPA “Good” level
CO_Avg Mean (ppm)	32979	0.3156184	0.1166302	0.0214198	0.6577459	0 – 4.4
CO_Avg Max (ppm)	32979	0.4472559	0.1761611	0.049505	1.055191	
NO_Avg Mean (ppb)	33523	11.65	4.9810	0.6191	25.155	0 – 53
NO_Avg Max (ppb)	33523	23.4974	7.89	1.449	43.18	
PM10_Avg Mean (µg/m3)	19,764	24.19464	8.809448	5.695206	59.97701	0 – 54
PM2.5_Avg Mean (µg/m3)	46,349	9.22465	2.527383	3.204444	21.89485	0 – 12

Econometric Model and Results:

The objective is to quantify the impact of air quality on school absenteeism. The modeling strategy and choice of control variables follow the specifications in the existing literature (Currie et al., 2009; Ham, Zweig and Avol, 2016; Zhang et al., 2018; Gilraine, 2020). The current results are based on the following panel data regression model with state fixed effects:

$$A_{st} = \beta_0 + \beta_1 AQ_{st} + \beta_2 Schl_{st} + \beta_3 County_{st} + State_s + \varepsilon_{st}$$

Where:

- A_{st} is the number of chronic absent students across all grades in school *s* and year *t*.
- AQ_{st} is the air quality component in the county of the school *s* in year *t*.
- $Schl_{st}$ represents the school level characteristics at school *s* in year *t*;
- $County_{st}$is the county level characteristics for school *s* in year *t;*
- $State_s$ is a state FE
- ε_{st} is the error term in the model;

Chronically absent students are measured as the number of students who are absent for more than 15 days in an academic year. Air quality components are CO, NO2, PM10 and PM2.5. Two sets of regressions are done, one with the yearly average values of the daily-average values and the second one with yearly average of the daily maximum values. Among the school characteristics *total enrollment* is used to control for the size of the school, the *number of FTE teachers* and *FTE teachers absent* are used to control for the teacher effect ,while the *total school expenditure* is used to control for resources available to the school. Population of the county is used to control for the size of the county, and per capita personal income is used to control for the wealth of the county.

The analysis uses panel data regression with state fixed effects. Table 3 gives the regression results for 2 sets of different regressions. The first set of regressions (1 – 4) utilizes the yearly average values of the daily average measure while the second set of regressions (5&6) utilizes the yearly average of the daily maximum value. The PM 2.5 and PM 10 data was collected for a 24-hour period average and does not report the daily maximum values. As a result, the second set of regressions are only done for CO and NO2 measures.

Table 3: Regression Results

	Yearly average AQ Values				**Yearly average of Maximum Values**	
	Carbon Monoxide (1)	**Nitrogen Dioxide (2)**	**PM 10 (3)**	**PM 2.5 (4)**	**Carbon Monoxide (5)**	**Nitrogen Dioxide (6)**
Total Enrollment	0.1161***	0.1099***	0.1197***	0.1077***	0.1160***	0.110***
	(0.0050)	(0.0051)	(0.0065)	(0.0075)	(0.00494)	(0.005)
Yearly avg AQ Level	**33.692*** **	**0.2826*** **	**-0.1205* **	**0.3663*** **	**22.398*** **	**0.069**
	(3.930)	**(0.1083)**	**(0.0628)**	**(0.1311)**	**(2.868)**	**(0.064)**
FTE Teachers	1.099***	1.089***	1.008***	1.176***	1.102***	1.087***
	(0.086)	(0.086)	(0.1174)	(0.1087)	(0.0860)	(0.0859)
Total School Salary	2.17e^{-7}	1.58e^{-7}*	3.48e^{-9}	3.95e^{-9}	2.19e^{-7}*	1.58e^{-7}*
	(1.32e$^{-7)}$	(9.48e^{-8})	(8.02e^{8})	(6.54e^{8})	(1.32e$^{-7)}$	(9.47e^{-8})
Population	-1.25e^{-6} ***	-9.36e^{-7}***	-1.35e^{-6}***	-7.37e^{-7}***	-1.33e^{-6} ***	-7.75e^{-7}***
	(1.86e^{-6})	(2.00e^{-7})	(1.94e^{-7})	(1.89e^{-7})	(1.88e^{-6})	(1.95e^{-7})
Per Capita Income	0.00017***	-0.0002***	0.0002***	0.00020***	0.00018***	-0.0002***
	(0.000024)	(0.000024)	(0.00005)	(0.00002)	(0.00002)	(0.00002)
R^2	0.4645	0.4633	0.4686	0.4529	0.4645	0.4633
Observations	95,044	102,767	64,429	138,256	95,044	102,767
Groups	37,027	38,929	26,573	54,535	37,027	38,929

Note: * p<0.1, **p<0.05 & ***p<0.01

The primary variable of concern for all the regressions is the Yearly average AQ. In model 1, the yearly average AQ is the yearly average of the daily-average carbon monoxide reading. This estimator is positive and significant at 1% level of significance, meaning that if CO levels increase by 1ppm then chronic absenteeism will increase by about 34 students in a school per academic year. With the average of 0.31 ppm of CO levels, the results make sense, as a 1 ppm increase is drastic. Thus, it is not surprising to have chronic absenteeism increase significantly. This is also consistent with prior literature documenting significant positive impact of CO on absenteeism (Chen et. al., 2000; Currie et. al. 2009). In model 2, the yearly average AQ is the yearly average of the daily-average nitrogen dioxide reading. The results show that there is a positive and significant association between NO2 and chronic absenteeism which is consistent with the findings of prior literature (Makino, 2000). A 1 ppb increase in NO2 yearly average increases chronic absenteeism by almost 0.3 students per school per academic year. Model 3 uses the yearly average of the daily-average of the PM10 reading as the AQ measure. The results show a negative and significant association with chronic absenteeism. This is a curious result that needs to be further explored as prior studies have found that PM10 increases absenteeism (Ransome and Pope, 1991; Makino, 2000) have found that PM10 levels increases absenteeism. However, Chen et. al. (2000). Our result shows that a 1 μg/m3 increase in PM10 leads to about 0.12 students reduction in chronic absenteeism per school. However, it is only significant at 10% level of significance. We plan to explore further the cause of such a result.

In model 4, the yearly average AQ is the yearly average of the daily PM2.5. The results show that there exists a positive and significant association between PM2.5 and chronic absenteeism as also concluded in prior literature (Hales et. al., 2016; MacNaughton et. al., 2017; Zhang et. al. 2018).

According to our results, a 1 μg/m3 increase in PM2.5 level leads to an increase of about 0.37 students being chronically absent per school-year.

In Model 5, the AQ measure is the yearly average of the daily maximum CO reading. The result shows that if the yearly average of daily maximum CO increases by 1 ppm, then chronic absenteeism increases by about 22 students in a school-year. Model 6 uses the yearly average of the daily maximum NO2 readings and shows a positive but statistically insignificant impact on absenteeism.

Enrollment is positive and significant across all the models. This makes sense as a school with higher enrollment means that it has a more students who might be chronically absent. More FTE teachers is also positive and significant. This is an curious result that will be explored further before the results are presented. The total school salary is not a significant factor in impacting chronic absenteeism. County population is negative and significant across the models but is of very small magnitude, while county per capita personal income is positive and significant in all models except model 2 and 6. The r^2 values across all models is about 0.45.

Discussion and conclusion:

In our preliminary findings we observe that air quality affects chronic absenteeism significantly, even when air quality is within the EPA's acceptable range. Carbon Monoxide, Nitrogen Dioxide and PM 2.5 all have significant positive impacts on chronic absenteeism in schools while PM 10 has a negative impact. However, these results are preliminary, and the analyses are underway to account for several nuances. The next steps in the analysis will include examining different panel model specifications, including regional analysis and school grade specific impacts. For example, some of the pollutants are region-specific. Therefore, national scale examination may mask the effects that may be present regionally. We will examine this by first identifying regional hotspots for various pollutants. This will enable a more rigorous analysis using a Difference-in-Differences strategy. We also plan to incorporate different controls, like racial composition of counties, health measures and weather factors in the final regression analysis. We plan to explore is the impact of these air quality measures on school attendance across different income and racial groups. We plan to build on these preliminary results to provide a more robust and convincing analysis prior to the presentation at the AAEA conference.

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