The Effect of Indoor Air Pollution on Cognitive Performance: Evidence from the UK

Abstract

Mental acuity is essential to most white-collar jobs and possibly associated with indoor air quality. I examine this potential link using a unique data set on indoor air pollution exposure and final examination results from a UK university. To account for potential confounders, I exploit the panel structure of the data to estimate models with subject and student fixed effects. I find that exposure to elevated levels of indoor particulate matter (PM) has a statistically and economically significant effect on test scores. I also find that the effect is larger among male students and is present at levels considerably lower than current EPA standards. The results suggest that a narrow focus on traditional health outcomes, such as hospitalization, may understate the true cost of pollution as indoor air quality also affects cognitive performance.

Keywords: Air pollution; Cognitive Performance; Education

I.   Introduction

Recent decades have seen a dramatic increase in the level of public concern surrounding the adverse effect of ambient pollution. However, the importance of indoor air quality has been often overlooked. This is of particular interest given that the U.S population spends 89% of their time indoors of which 21% is in non-residential environments, such as offices and schools (Klepeis et al., 2001; Wu et al., 2001). Studies have shown that indoor pollution can cause immediate health effects including irritation of the eyes, nose, and throat, headaches, dizziness, and fatigue (Young, 2001; Brenstein, 2008)[1]. Exposure to particulate matter can also affect cognitive acuity as any deterioration in oxygen quality may impair brain functioning (Clark and Sokoloff, 1999). Nevertheless, evidence on the effect of indoor pollution on cognitive performance is remarkably scarce. A potential link between pollution and cognitive performance would imply that a narrow focus on traditional health outcomes, such as hospitalization and increased mortality, may understate the true cost of pollution as mental acuity is essential to worker productivity in many professions[2].

There are many challenges in identifying the link between air pollution and human health such as heterogeneity in avoidance behavior, measurement error and the presence of unobserved correlated factors. However, identifying the causal relationship between indoor air pollution and cognitive performance possesses an additional challenge. While the impact of air pollution on health outcomes is likely to be recorded, data on the adverse effect of air pollution on cognitive performance may be unobserved by researchers as impaired cognitive performance is unlikely to

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[1] There is also strong evidence on the long-term effect of indoor air pollution on human health. These effects include respiratory disease, heart disease and even cancer. See http://www.who.int/mediacentre/factsheets/fs292/en/.
[2] This study contributes to the growing literature which finds that short term variation in air pollution affects worker productivity in a variety of settings (Neidell, 2017).

lead to health encounters and may not even be noticed by the affected individual (Chang et al., 2014). As such, this paper provides a unique opportunity to asses the potential link by using university final examinations test scores in the UK as a measure of cognitive performance.

I perform my analysis using a unique data set which combines readings of indoor air pollution (PM_{10}) with administrative data on 2,418 students taking 11,443 exams at a leading public research university within the Greater London Urban Area. To account for potential confounders I rely on the panel structure of the data to estimate models with subject and student fixed effects. By collecting air pollution data from within the examination sites I overcome the challenge of measurement error which could result from matching data on pollution with individuals inadequately. This is of particular importance as most studies in the literature use data from ambient air pollution monitors which are usually located several miles away from the location of the individual. As such, they are likely to be subject to considerable measurement error due to significant spatial variation even within finely defined areas (Moretti and Neidell, 2011; Lin et al., 2001). I also include controls for time-varying factors that could be contemporaneous and correlated with pollution, such as temperature and relative humidity. Nevertheless, it is still possible that other unobserved factors that are correlated with both pollution and test scores remain present such as human activity inside the examination site. In order to address this, I include controls for Carbon Dioxide (CO_2) as a proxy for human activity and behavior. I also examine the correlation between indoor air pollution and test scores from exams on different dates, as well as the correlation between prior educational qualifications and elevated levels of PM_{10}. The correlations in both tests are not statistically different from zero, lending further support to the causal interpretation of the analysis.

My results demonstrate that elevated levels of Particulate Matter have a statistically and economically significant effect on test scores. I find that a one unit increase in PM_{10} (μg/m3), or being above the World Health Organization (WHO) guidelines, reduces students' test scores by 0.3 and 13.5 percent of a standard deviation respectively. The result for the former imply that a student sitting an exam at a site with the maximum pollution level in my sample (84μg/m3) will suffer a substantial reduction of 0.24 standard deviations in test scores, as against that which the same person would have achieved at a site with the lowest levels of pollution (4μg/m3). The effect for the indicator of being above the WHO guidelines is very large and similar to the estimated effects found in studies that have measured the impact of paying teachers and students large financial incentives (Jackson, 2010) and reducing class size from 31 to 25 students (Angrist and Lavy, 1999). Furthermore, I explore whether indoor air pollution has heterogeneous effects across subpopulations and academic disciplines. My interest is twofold: first, to test whether some subgroups are more sensitive to indoor pollution; and second, to examine whether the effect of indoor pollution varies across subjects. I find that the effect is larger among male students, but I do not find significant differences across subjects and academic ability levels.

I also examine the impact of indoor air pollution on test scores by including dummy variables for different levels of pollution exposure simultaneously to test for non-linearity. Specifically, I define dummies for PM_{10} (μg/m3) being less than 25, between 25 and 50, between 50 and 75, and above 75. The analysis reveals a monotonic relationship between pollution and test scores with significant negative results at relatively low levels (50 μg/m3). Importantly, these levels are well below current US Environmental Protection Agency (EPA) standards which suggests that it may be economically beneficial to lower existing guidelines[3]. The results imply

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[3] In order to determine the optimal regulatory action a full-fledged cost benefit analysis must be conducted.

that taking an exam with pollution above 75 (µg/m3) reduces students' scores by 21 percent of a standard deviation, compared to being exposed to PM_{10} levels between 0 and 25. Finally, I study whether transitory decline in cognitive performance has a robust negative relationship with long-term academic indicators that are potentially correlated with future career outcomes. I find that exposure to coarse particulate matter reduces the probability of receiving a first class classification but has no effect on the probability of receiving an upper second classification, which is the main threshold requirement to most prestigious graduate jobs and postgraduate academic programs in the UK.

Overall my results provide compelling evidence that short-term exposures to elevated levels of indoor PM_{10} affect cognitive performance. Epidemiologists have already examined this potential link but such studies are predominantly cross sectional in nature and do not account convincingly for confounding factors (Mendell et al., 2005). To the best of my knowledge, this paper is the first to estimate the causal effect of indoor air pollution on cognitive performance with indoor pollution measures. My findings imply that a narrow focus on health outcomes understates the true cost of pollution as indoor air quality also affects cognitive performance.

The rest of the paper is laid out as follows. In the second section, I present background information on coarse particulate matter and summarize the existing literature on identifying the impact of air pollutions on various health and academic outcomes. Section III describes the institutional settings and the data while Section IV presents my identification strategy. In Section V, I present my empirical results and in VI, I conclude.

II.   Background on Air pollution and Cognitive Performance

Particulate matter (PM) is a mixture of solid particles and liquid droplets suspended in the air that consists of various components including acids, metals, dust particles, organic chemicals and allergens. Particle pollution is classified into two main categories namely "inhalable coarse particles" (PM_{10}) and "fine particles" ($PM_{2.5}$) based on their size. The former corresponds to particles that are smaller than 10 micrometers in diameter and the latter to particulate matter that is 2.5 micrometers in diameter or smaller[4]. In 1987, The EPA replaced the earlier Total Suspended Particulate (TSP) air quality standard with a PM_{10} standard and in 1997 also established an annual and 24-hour National Ambient Air Quality Standard (NAAQS) for $PM_{2.5}$.[5] In 2008, the European (EU) Parliament also set legally binding limits for coarse and fine particulate matter. The 2008 EU ambient air quality directive replaced most previous EU air quality legislation and was made law in England in 2010[6].

The air pollution measure in this study is PM_{10}, which consists of smoke, dirt, dust, mold, spores and pollen. The emission of ambient PM_{10} comes from various sources such as factories, farming and roads. In urban areas, a significant amount of indoor air pollution concentration is due to ambient pollution that penetrates the indoor environment. There are various internal and external factors which determine the relationship between indoor and outdoor air pollution concentrations. Specifically, the infiltration of ambient air pollution into a building is a result of complex dispersion processes around the building, ventilation rates, the locations of air intakes, the airtightness of the building and local meteorology. Furthermore, penetration of pollutants into buildings is extremely complex in urban areas due to the proximity and structure of surrounding

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[4] For comparison, the average human hair is approximately 70 micrometers in diameter, making it 7 times larger than the largest coarse particle.
[5] Total Suspended Particulate corresponds to particles that are less than 100 micrometers in diameter.
[6] Similar regulations also exist in Scotland, Wales and Northern Ireland.

buildings which suggests that indoor air pollution can be highly spatially and temporally variable (Mumovic et al., 2018). Nevertheless, indoor concentrations of coarse particles are not simply a byproduct of ambient pollution; they may also be the result of emissions from indoor sources. The leading indoor sources of particles in education establishments are human activities, plants and various building materials (Chatzidiakou et al., 2012), which is very different to the leading sources found in residential environments (e.g. cooking stoves and fireplaces). While humans do not directly emit PM_{10}, human activities may influence coarse fractions of PM mainly due to resuspension of settled dust. In fact, studies have shown that indoor concentrations of coarse particles in classrooms tend to surpass outdoor levels during the daytime, suggesting that indoor sources may have a significant effect on pollution concentrations in some settings (Madureira et al., 2012). However, these studies were mainly conducted in primary schools where students are engaged in more intense physical activities. Since this paper analyses data from university examinations, where the movement of students is extremely restricted, it is reasonable to infer that it is unlikely that resuspension is a significant source of pollution in this context. Finally, it is important to note that since $PM_{2.5}$ is a subset of PM_{10} my findings cannot definitively attribute the measured effects to a particular size of particles (i.e. PM_{10} or $PM_{2.5}$).

The relationship between particulate matter and adverse health outcomes is well documented in the epidemiological literature. The medical explanation for the link is that elevated levels of particles in the air lead to changes in cardiovascular and pulmonary functioning (Seaton et al., 1995). More specifically, human intake of particles may affect respiratory and cardiovascular conditions, such as asthma and heart attacks (Pope at al., 1995; Dockery, 2009; Donaldson et al., 2000; Weinmayr et al., 2010). Particle pollution can also lead to milder health effects such as

irritation of the airways, coughing or difficulty breathing.[7] The former types of conditions are likely to be evident in most data sets commonly used in the literature. The latter, however, are likely to be unobserved by researchers as they do not lead to health encounters or may not even be noticed by the affected individual (Chang et al., 2014)[8]. While empirical evidence suggests that symptoms from exposure to particulate matter can manifest within hours or days, it is unclear whether there is also an instantaneous effect (Son et al., 2013). This paper provides a unique opportunity to test this potential immediate effect using a novel quasi-experimental method[9].

Despite the growing evidence of strong links between air quality and various health outcomes, research on the effect of air pollution on cognitive performance is remarkably scarce. Epidemiologists have examined the potential link but these studies are predominantly cross-sectional in nature and do not account convincingly for confounding factors (Suglia et al., 2008; Wang et al., 2009). A study by Ebenstein et al. (2016) examined the causal relationship between ambient pollution and high school exit exams in Israel, and found that increased daily exposure to outdoor pollution significantly decreased test scores. However, the focus of their research is on aggregate daily variation in ambient air pollution, which may be significantly different to indoor levels during exams. Stafford (2015) examined the effect of indoor air quality on academic outcomes among elementary school children in Texas. Her study utilized a quasi-natural experiment where Indoor Air Quality (IAQ)-renovations were completed at different points in time. Stafford found a significant positive effect on standardized test scores but no effect on attendance. There are however several important differences between Stafford's research and this paper. As data on actual indoor air quality was not available in her study, it relied on the assumption

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[7] For further details on such effects see http://www.epa.gov/pm/health.html
[8] Schlenker and Walker (2015) show that using inpatient discharge data substantially underestimates the morbidity effect of ambient pollution. This is because inpatient discharge data exclude emergency room visits which do not require overnight admission.
[9] See Zhang et al. (2018) for an extensive discussion of possible mechanisms.

that the renovations directly improved IAQ and that students were responding to these improvements and not to other aspects of the renovations (e.g. improved appearance of the school). In contrast, this paper observes the direct level of indoor pollution, enabling me to ensure that the estimate captures only the effect of indoor air pollution, and not other correlated factors. Furthermore, this paper examines test scores for university students, who are similar in age to the working population and therefore the results may carry additional implications for worker productivity. Finally, the duration of exposure is very different. This study examines short term exposure and contemporaneous effects which are related to cognitive performance and potentially worker productivity, and not to human capital accumulation as Stafford's paper investigates.

III.   Institutional Settings and Data
A. Institutional Settings

This study was conducted using data on students at a leading public research university within the Greater London Urban Area. Like most universities in the UK exams in this institution take place over several weeks during the designated examination period. Exams starts at either 9:30 or 14:00 and last for 2-3 hours[10]. The allocation of students to the different examination sites is made by a central administration unit well in advance and the students had no possibility of influencing or changing this allocation. In total, there were 14 examination sites which are located in different buildings and rooms across the university campus. As such, there is variation in the type of buildings (e.g. old vs new) and their proximity to different outdoor sources of pollution (e.g. roads). This suggests that indoor pollution can vary significantly across venues even within a given day due to very local ambient conditions and differences in the sites' physical envelop.

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[10] There are very few exams with duration of one hour (1.33 percent of the sample)

The examination rules are very strict and firmly enforced by invigilators on site. Students are not allowed to talk to each other as soon as they enter the examination site and must leave their belongings at a designated area in or outside of the room. Importantly, during the first and last 30 minutes of the examination, students are not allowed to leave the examination room at all and there is therefore almost no movement of students during the examination[11]. This means that it is reasonable to infer that the resuspension of coarse particles - the main indoor source of pollution in educational establishments - is unlikely to be a significant source of pollution in this study, as this would require movement.

B. Data

My data combines self-collected readings of indoor air pollution with administrative data on test scores and demographics of undergraduate students at the university. For exam and demographic information I use a confidential student file which contains test scores of all undergraduate students that took exams during the 2012/2013 academic year. The file also contains a unique student identification number which allows me to observe key demographic information on each student such as gender, nationality and UCAS tariff points. The UCAS tariff is a means of allocating points to pre-university qualifications, allowing a broad comparison to be made across a wide range of international qualifications. The tariff points system assist British universities with their admission decisions and their management information.[12] I also know the exact date, time and location of each exam and the allocation of students across examination sites, allowing me to assign indoor pollution levels to test takers. The indoor pollution data was self-collected from the 14 examination sites during the exam period. I used the 3M™ EVM-7 which is an advanced environmental monitor designed to provide real time measurements with a one per second update

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11 The only exception is for (supervised) bathroom breaks, although these cannot take place during the first and last 30 minutes of the examination.

12. For further details see https://www.ucas.com/ucas/undergraduate/getting-started/entry-requirements/tariff.

rate. The monitor provides readings on mean PM_{10} (μg/m3), temperature (Celsius) relative humidity (%) and Carbon Dioxide (ppm). Importantly, the monitor was placed at least one meter from the wall and 1.5 meters high from the floor to ensure reliable readings (WHO, 2011).

According to the WHO, the air quality guidelines for particulate matter are also applicable to indoor spaces (WHO, 2005). Currently, the EPA and the WHO set daily PM_{10} guidelines of 150 and 50 micrograms per cubic meter (μg/m3) respectively[13]. The EPA also report daily air quality using the Air Quality Index (AQI) for the five pollutants regulated by the US Clean Air Act. More specifically, the AQI is divided into six categories ranging from good to hazardous which are associated with different levels of health risks. AQI values above 101, which is about 75 (μg/m3) of PM_{10}, pose various health risks according the EPA[14]. In the UK, The Department for Environment, Food and Rural Affairs use the Daily Air Quality Index (DAQI) to provide information about levels of air pollution and recommended actions and health advice for the same five pollutants. The index is numbered 1-10 and divided into four bands (low, moderate, high and very high). Index value of above 6, which is about 76 (μg/m3) of PM_{10} is defined as high level of pollution in the UK. In my empirical analysis I mainly use the more conservative WHO guideline to generate a threshold dummy which classifies exposure beyond the 50 (μg/m3) standards[15].

Table 1 presents descriptive statistics of key variables of interest. My sample includes 11,463 examination results of 2,418 students taking exams in 14 different venues across 18 days. Each student took 5.1 exams on average, and the pass rate was 85%. In columns (2)-(5) I stratify the sample by gender and ability. I use UCAS tariff points, which is a means of allocating points to pre-university qualifications, as a proxy for student ability. The table indicates that there are

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[13] According to the EPA, an area meets the 24-hour PM_{10} standard if it does not exceed the above level more than once per year on average over a three-year period.
[14] The WHO guideline of 50 (μg/m3) is equivalent to an AQI of 46 which is in the "Good" category.
[15] I also examine lower and higher thresholds in my analysis (see table 3 for further details).

more females in the sample and that they tend to achieve marginally better scores. As expected, the high ability subgroup achieved significantly higher marks compared to their low ability counterparts. It is important to note that pollution, temperature and relative humidity do not vary much by sub-population. The similarity in these observables across gender and ability is important as it suggests that selection on observables is unlikely to drive my results. To explore the variation in indoor air pollution concentrations, Figures 1 and 2 shows the variation in indoor air pollution within and between venues across time. The figures exemplify the significant time and spatial variation of the data which is the source of variation in this study.

IV.   Empirical Strategy

For identification, I crucially rely on the panel structure of the data to estimate models with subject and student fixed effects. More formally, I estimate the following specification:

$$R_{ist} = \beta_0 X_i + \beta_1 PM_{st} + \beta_2 f(Temp_{st}, RH_{st}, CO2_{st}) + \beta_3 NUM_{st} + Day_t + TOD_t + Dur_{st} + Site_s + I_i + \varepsilon_{ist}$$

where R_{ist} is the standardized z-score of student i at site s at time t; X_{it} is a vector of individual characteristics which includes gender, age, nationality and whether a student classified as an overseas or domestic student for tuition fees purposes ; PM_{st} is PM_{10} level at site s at time t; $Temp_{st}$ is the temperature at site s at time t [16]; RH_{st} is the relative humidity measure at site s at time t; CO_{st} is the carbon monoxide measure at site s at time t; NUM_{st} is the expected number of students taking exam at site s at time t; Day_t, TOD_t, Dur_{st} and $Site_s$ are day-of-week, time-

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[16] I include linear and quadratic terms for relative humidity and CO2, 2 degrees Celsius bins for temperature, and linear and quadratic interaction terms of mean temperature and relative humidity.

of-day, duration and examination site fixed effects respectively; I_i is fixed effect for the individual; and ε_{ist} is an idiosyncratic error term[17]. In order to accurately account for both spatial and serial correlation, standard errors are heteroskedastic-consistent and clustered by examination venue and date[18].

There are four main econometric challenges in identifying the causal effect of air pollution on test scores. The first challenge is the possible correlation between pollution exposure and unobserved determinants of students' test scores. For example, if wealthy individuals are sorting themselves into degree programs with better facilities (and are therefore exposed to lower levels of pollution) naïve OLS estimation may underestimate the true causal effect of pollution as it is potentially mitigated by other factors (e.g. private tuition). In order to absorb these potential unobserved time invariant variations, I include individual fixed effects in the above equation. I also include controls for temperature and relative humidity which are time-varying factors that could be correlated with pollution and test scores. Finally, I conduct a set of robustness and placebo tests which are discussed in detail in the next section of this paper.

The second challenge is measurement error in matching pollution data to individuals' exposure levels. Most studies assign pollution data from ambient air pollution monitors to individuals using various interpolation techniques. This is likely to yield some degree of measurement error due to the significant spatial variation in pollution even within finely defined areas (Moretti and Neidell 2011, Lin et al. 2001). In addition, since exams are taken indoors and normally a few miles away from an ambient monitor station, measurement error is likely to be

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[17] Note that in a different specification I use subject fixed effects in place of the student fixed effects. Subject fixed effect is defined as department and year of study (for example, a second year economics student).

[18] As a robustness check I also clustered at both the student and the examination site level separately. While the former tends to have smaller standard errors the latter yield very similar standard errors as the two-way clustering used in this paper. HAC robust standard errors also yield smaller standard errors and I therefore decided to use the most conservative clustering strategy.

exacerbated. These concerns are not present in this study as pollution data is collected from inside the examination site. This also allows me to ensure that I estimate the effect of exposure during the examination and not the potential build-up effect from exposure to pollution on the way to the exam.

Heterogeneity in avoidance behavior is the third challenge for causal inference. The concern is that optimizing individuals will alter their pollution exposure to protect their health as air pollution information is widely available to the public. For example, if sensitive groups adopt compensatory behavior in response to a media alert, equation (1) is likely to understate the true causal effect of PM_{10}. This concern is unlikely to arise in my setting for two reasons. First, the allocation of students across examination sites is determined centrally by the university a few weeks prior to the examination date[19]. Second, unlike ambient pollution, information on indoor pollution levels is unavailable to students.

Finally, unobserved human activity inside the examination site may also be a challenge for causal interpretation. For example, if students behave differently when they face harder exams (e.g. move around more frequently) and this behavior leads to higher pollution levels (from resuspension of settled dust), then my estimate would be biased. As discussed in section III, I believe that this scenario is unlikely given the strict examination conditions where the movement of students is extremely restricted. Nevertheless, I address this concern empirically by including CO_2 as a proxy for human activity and behavior in my regressions. CO_2 is a suitable proxy for human activity and behavior as it captures respiration and air ventilation indoors (Satish et al.,

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[19] A student not attending is deemed to have failed unless extenuating evidence are provided, as such there is no possible selection into different time or examination venue.

2012). Reassuringly, my main results remains almost identical when I include or exclude CO_2 in my regressions, reaffirming that human activity is unlikely to have biased the results.

V. Empirical Results

A. Main Results

Table 2 reports on the link between indoor coarse particulates and test scores. In the first two columns of panel A, I present cross sectional correlations between the continuous PM_{10} measurement and student achievement. The coefficient estimates without any controls, column (1), suggest that a 1 unit increase of PM_{10} is associated with a 0.3 percent of a standard deviation decrease in a student's test scores. In column (2) I add controls for age, gender, temperature, relative humidity, class size and dummies for day-of-week, examination venue, duration and nationality. I find that a 1 unit increase in PM_{10} is associated with a 0.2% standard deviation decline in test scores. Both estimates are statistically and economically significant but are cross sectional in nature and therefore should be treated with caution.

In the last two columns of Table 2 I exploit the panel structure of the data to estimate models with subject and student fixed effects. Column (3), which includes a subject fixed effect, also shows a negative and highly significant effect with a more precise estimate. In order to account for potential confounders at the student level, column (4) estimates my preferred specification using within student regression. I find that a 1 unit increase in PM_{10} leads to a 0.3 percent of a standard deviation decline in a student's test score, an estimate significant at the 1 percent level. These results imply that a student sitting an exam at a site with average pollution levels (33.07 µg/m3) will suffer a substantial reduction in test scores − 9 percent of a standard deviation −

compared to that which the same individual would have achieved at a site with the lowest level of pollution (4 µg/m3).

Table 2 also reports on the effect of PM_{10} being above 50 (µg/m3) which the WHO considers to be an unhealthy level threshold. The results present negative and significant effects of coarse particles on students' performances under most specifications. In column (4), where I include student fixed effects, I find that taking an exam at a site with a pollution level above the WHO standard is associated with a 13.5 percent of a standard deviation decline in a student's test score. This effect is very large and similar to estimates found in paying teachers and students large financial incentives (Jackson, 2010) and reducing class sizes from 31 to 25 students (Angrist and Lavy, 1999).

In Table 3 I examine the impact of PM_{10} on test scores by including dummy variables for different levels of pollution exposure simultaneously. Specifically, I define dummies for PM_{10} (µg/m3) being less than 25, between 25 and 50, between 50 and 75, and above 75. Column 4, which shows results for my preferred specification using student fixed effect indicates that PM_{10} exposure between 50 and 75 (µg/m3) is significantly associated with a decline of 14 percent of a standard deviation in the student's score compared to being exposed to PM_{10} levels between 0 and 25. When PM_{10} reaches 75 (µg/m3) the effect increases to 21 percent of a standard deviation, which is also significant at the 5% level. Importantly, these pollution levels are below current EPA standards and therefore it may be economically beneficial to lower existing guidelines. Also note that both the WHO and the EPA guidelines are for 24-hour and there are no existing standards for hourly exposure to PM_{10}.

B. Heterogeneity

In this section I explore whether indoor air pollution has a heterogeneous effect across sub-populations and academic disciplines. The reason for this investigation is twofold; first, to test whether some subgroups are more sensitive to indoor pollution than others; and second, to examine whether the effect of indoor pollution varies by subjects. To study the former I stratify by gender and ability and for the latter I break down my sample by STEM and non-STEM[20].

Table 4 presents estimates on the effects of coarse particulate on test scores stratified by gender, ability and subject, using my preferred specification with student fixed effects. In the first two columns I break down the sample of test takers by gender. Column (1), which reports on the effect for the male subsample only, shows a negative and significant link between indoor levels of PM_{10} and test scores. More specifically, the results suggest that a 1 unit increase in PM_{10} (µg/m3) reduces students' test scores by 0.5 percent of a standard deviation and being above the WHO threshold reduces students' test scores by 19 percent of a standard deviation. These estimates are considerably higher than the results obtained in the analysis for the full sample which suggests that male students are more sensitive to coarse particulate than their female counterparts. Indeed, Column (2), which reports results for the female subgroup, demonstrates this pattern precisely. The continuous coefficient drops to 0.002 and the threshold dummy declines to 0.075 and they are both statistically insignificant. This finding is consistent with Ebenstein et al. (2016), which also find a larger effect among males. They posited that this difference might be due to different asthma rates and Attention Deficit Hyperactivity Disorder (ADHD) among these groups. Whilst the

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[20] The acronym STEM is widely used in the US and refers to academic disciplines of Science, Technology, Engineering and Mathematics.

former is unlikely to explain my results as the prevalence of asthma among females in the UK is actually higher compared to males, the latter is indeed possible[21].

Columns (3) and (4) of Table 4 report on the effects of coarse particulate matter on students' test scores by my ex-ante ability measure. As a proxy for ability I use UCAS tariff points, which are a means of allocating points to pre-university qualifications, in order to break down the sample above or below the ability median. The results suggest that the effect of indoor air pollution on cognitive performance is slightly larger among high ability students. Specifically, an additional unit of PM_{10} is associated with a 0.4 percent of a standard deviation decline in students' test scores compared to 0.3 percent among low ability students. When I use the dichotomous measure I find that exposure to indoor PM10 reduce test scores for low and high ability types by 11 and 17 percent of a standard deviation respectively. However, the estimates are not statistically different from each other and one should be cautious in interpreting this difference.

In the last two columns of Table 4 I examine the effect of indoor PM_{10} on different academic disciplines. I follow the guideline of the National Science Foundation (NCF) and stratify my sample into two groups; Science, Technology, engineering, and mathematics (STEM) and all other disciplines (non-STEM)[22]. The motivation for this analysis is to explore if some types of mental tasks are more sensitive to indoor air pollution. The results show that the effects are fairly similar for STEM disciplines (-0.004) compared to the estimate for non-STEM subjects (-0.005).

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[21] For more details on asthma statistics in the UK see https://statistics.blf.org.uk/asthma.

[22] Note that the NSF uses a broader definition of STEM which also includes social sciences. In my empirical analysis I classified only one social science (economics) as a STEM subject.

C.The Effect of Indoor Air Pollution on Other Academic Outcomes

In this section I study whether transitory impaired cognitive performance also leads to long-term adverse effects by looking at key academic indicators that are potentially correlated with future career outcomes. In Table 5, I estimate the effect of PM_{10} on the probability of failing an exam. The results are highly significant for both the continuous and threshold measures, and suggest that being above the WHO standard increases the portability of failing an exam by 4 percentage points. Failing an exam can have a substantial adverse effect on a student's future career path due to two main reasons. First, failing can delay graduation and may lead to a change in degree title. Second, since most graduate schemes in the UK require submission of a full transcript during the application process, failing an exam can send a negative signal to potential employers.

In Table 6, I carry the analysis at the student level. Therefore, the treatment is the average pollution exposure across all examinations and the dichotomous indicator is the average of above threshold (50 µg/m3) exposure incidences over all exams. The analysis examines the effect of indoor pollution on the probability of receiving a classification of upper second or above. This is of particular interest as an upper second classification is a threshold requirement to most prestigious graduate jobs and academic graduate programs in the UK[23]. The results show that this threshold final classification is not affected by higher pollution during exams. This result is plausible as students take many exams during their degree and being exposed to elevated levels of pollution on one or few exams will not necessary lead to change in the final classification.
Figure 3 further explores such possible effects as it shows estimates for each of the possible classifications separately. The results suggest that the only classification which is affected by

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[23] According to the Association of Graduate Recruiters, 78% of UK employers require an upper second classification (http://www.bbc.co.uk/news/10506798).

elevated levels of indoor pollution is the highest one (First) which tends to require consistently high scores across exams.

D. Robustness Checks

In this section I conduct robustness checks and placebo exercises to address the possibility that my estimates may capture unobserved time-varying factors which are correlated with both indoor air pollution and test scores. First, I replaced my day-of-week fixed effects with date fixed effects. Panel A of Table 7 shows the main results from this study (as shown in Table 2) with the new fixed effects. The results remain statistically significant but the coefficients become larger compared to the corresponding coefficients in Table 2. This might imply that my estimates in Table 2 are downward biased due to time varying omitted variables that are correlated with pollution in one direction and with test scores in the other. However, it may also be the result of the reduction in degrees of freedom so one must be cautious about the size of these results. Given the direction of the potential bias, I therefore believe that it is best to take a conservative approach and report the lower estimates.

Second, I use the level of air pollution from other exams of the same student (before and after) as the coefficient of interest. The results in Figure 3 suggest that pollution exposure during the test has a large impact on test takers but pollution levels during other exams of the same student (before and after) are almost unrelated to performance. In Panel B of Table 7 I provide further tests to the validity of my estimates using UCAS Tariff Points which is my ex-ante measure of ability as the dependent variable. Since UCAS tariff points are based on pre-university achievements, they should not be correlated with exposure to indoor air pollution during university after

accounting for unobservables. Columns (1) and (2) which do not include subject fixed effects shows that prior academic achievement is correlated with pollution levels during university exams. In contrast, Column (3) which includes subject fixed effect shows that the relationship between indoor levels of PM_{10} and pre-university qualifications is not statistically significant. This demonstrates the importance of using a fixed effect model in estimating this relationship.

Finally, in Panel C of Table 7 I examine whether my estimates capture only the transitory pollution exposure and verify that it is not related to prior exposure. More specifically, I estimate the correlation between the last exam score and the average pollution level from all previous exams. The results are not statistically different from zero in my preferred specifications.

VI.   Conclusion

In this paper I analyze the relationship between short-term exposure to indoor coarse particles and cognitive performance. I perform my analysis using a unique merged dataset of indoor PM_{10} levels and administrative student data. I find that a 1 unit increase in PM_{10} (µg/m3) and being above the WHO guideline reduces students' test scores by 0.3 and 13 percent of a standard deviation respectively. I also explore whether indoor air pollution has a heterogeneous effect across sub-populations and academic disciplines and find the effect is larger among the male subgroup.

While my results are robust to a wide range of different specifications it is important to note a small number of caveats that may limit my analysis. First, since I do not observe the exact composition of my PM_{10} readings and I only have its mean value, I cannot identify whether specific components and/or sizes of particulates are driving my results and whether exposure at different times and levels during the exam are important. Second, since data on individual health conditions

is unavailable I am unable to identify the exact pathophysiological pathways that drive my results. Given the results of this study, I believe that exploring the above aspects may be a rewarding area for future research. Finally, despite the extensive set of fixed effects and controls, it is still possible that there are other remaining time varying factors that are associated with test scores and air pollution which are not included in my model.

Despite these limitations this is the first paper that provides compelling evidence on the link between indoor pollution and cognitive performance. This analysis suggests that a narrow focus on traditional health outcomes, such as hospitalization and increased mortality, may significantly understate the true cost of pollution. This is because mental acuity is essential to most professions and therefore a reduction in indoor air quality can reduce worker productivity. My analysis also shows that the effect of indoor air pollution on cognitive performance is present at levels considerably lower than current EPA mandates. This is of particular importance as the EPA is currently reviewing whether revisions to the current PM_{10} standards are warranted[24].

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[24]For more details see http://www3.epa.gov/airtrends/aqtrnd95/pm10.html.

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Table 1

Descriptive Statistics

Variable	All (1)	By Gender Males (2)	By Gender Females (3)	By Ability Low (4)	By Ability High (5)
PM_{10} ($\mu g/m^3$)	33.07 (21.47)	33.29 (21.70)	32.88 (21.29)	34.20 (21.85)	32.08 (21.08)
PM_{10} ($PM_{10} > 50$)	0.214 (0.41)	0.214 (0.41)	0.213 (0.41)	0.228 (0.23)	0.201 (0.40)
Exam Score (1-100 points)	55.61 (17.04)	54.79 (18.50)	56.28 (15.72)	51.90 (18.12)	59.22 (15.04)
Temperature (celsius)	16.60 (1.94)	16.69 (1.87)	16.53 (2.00)	16.62 (1.95)	16.59 (1.93)
Relative Humidity (percent saturation)	54.72 (10.46)	55.11 (10.38)	54.40 (10.51)	54.32 (10.66)	55.10 (10.26)
CO_2	950.4 (315.80)	954.3 (297.80)	947.3 (329.70)	953.0 (299.00)	948.1 (329.40)
Age	21.34 (2.69)	21.44 (2.89)	21.25 (2.52)	21.93 (3.35)	20.71 1.177
Number of Exams	5.143 (1.37)	5.243 (1.44)	5.061 (1.31)	5.104 (1.44)	5.185 1.308
Number of Students	123.5 (75.56)	121.2 (75.56)	125.4 (75.11)	122.5 (75.76)	124.5 75.42
Failed an Exam (yes=1)	0.149 (0.36)	0.175 (0.38)	0.128 (0.33)	0.209 (0.41)	0.0905 0.287
Observations	11,443	5,140	6,303	5,521	5,825

Notes: Standard deviations are in parentheses. Relative humidity is the amount of moisture in the air as a share of what the air can hold at that temperature. The ability level is based on UCAS tariff points which is a means of allocating points to pre-university qualifications. The sample is split by whether the student is above or below the median.

Table 2

Polled OLS and Fixed Effect Models of Indoor Air Pollution's Impact on Test Scores

	Pooled OLS		Fixed Effects	
	No Controls	Controls	Subject	Student
	(1)	(2)	(3)	(4)
PM_{10} (µg/m3)	-0.003***	-0.002*	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Dummy for $PM_{10} > 50$	-0.097**	-0.052	-0.139**	-0.135***
	(0.045)	(0.054)	(0.053)	(0.045)
Observations	11,463	11,443	11,443	11,443

Notes: Each cell in the table represents a separate regression. Standard errors are heteroskedastic-consistent and clustered by examination venue and date. All regressions include suppressed controls for temperature, relative humidity, number of students, day-of-week, time-of-day, duration and examination site fixed effects as spcefied in section IV. *** Signifcant at the 1 percent level, ** Signifcant at the 5 percent level, * Signifcant at the 10 percent level.

Table 3

Indoor Air Pollution's Impact on Test Scores

	Pooled OLS		Fixed Effects	
	No Controls	Controls	Subject	Student
	(1)	(2)	(3)	(4)
Dummy for PM_{10} >25 & <= 50	-0.121**	-0.115**	-0.148**	-0.087
	(0.055)	(0.057)	(0.060)	(0.067)
Dummy for PM_{10} >50 & <= 75	-0.131**	-0.075	-0.174**	-0.143**
	(0.058)	(0.076)	(0.072)	(0.064)
Dummy for PM_{10} >75	-0.226***	-0.223***	-0.339***	-0.211**
	(0.080)	(0.081)	(0.086)	(0.093)
Observations	11,463	11,443	11,443	11,443

Notes: See Table 2. Each column in the table represents a separate regression.

Table 4

Heterogeneity in the Impact of Indoor Air Pollution on Test Scores

	Gender		Ability		Degree Subject	
	Males	Females	Low	High	STEM	non-STEM
	(1)	(2)	(3)	(4)	(5)	(6)
PM_{10} (µg/m3)	-0.005***	-0.002	-0.003**	-0.004***	-0.004**	-0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Dummy for $PM_{10}>50$	-0.192***	-0.075	-0.118**	-0.169***	-0.151*	-0.120
	(0.048)	(0.058)	(0.053)	(0.047)	(0.078)	(0.089)
Observations	5,140	6,303	5,521	5,825	7,160	4,283

Notes: See Table 2. All specifications include student fixed effects.

Table 5

Indoor Air Pollution's Impact on Failing an Exam

	Pooled OLS		Fixed Effects	
	No Controls	Controls	Subject	Student
	(1)	(2)	(3)	(4)
PM_{10} (µg/m3)	0.001	0.001*	0.001***	0.001**
(10 units)	(0.001)	(0.001)	(0.000)	(0.000)
Dummy for PM_{10}>50	0.024	0.039	0.055***	0.041**
	(0.029)	(0.030)	(0.020)	(0.017)
Observations	11,463	11,443	11,443	11,443

Notes: See Table 2. All specifications include student fixed effects.

Table 6

Indoor Air Pollution's Impact on Final Classifcation

	Pooled OLS		Fixed Effect
	No Controls	Controls	Subject
	(1)	(2)	(3)

Upper Second Class or above (yes=1)

|			
PM_{10} (µg/m3, 10 units)	0.000	-0.004	-0.003
	(0.002)	(0.003)	(0.002)
Dummy for $PM_{10}>50$	0.054	-0.094	-0.004
	(0.085)	(0.099)	(0.055)
Observations	2,071	2,068	2,068

Notes: Each observation is a student and pollution is averaged over all of the tests taken. Standard error are heteroskedastic-consistent and clustered at deaprtment and year level.

Table 7

Robustness Tests

	Pooled OLS		Fixed Effects	
	No Controls	Controls	Subject	Student
	(1)	(2)	(3)	(4)
Panel A: Date Fixed Effect				
PM_{10} (µg/m3)	-0.003***	-0.004***	-0.006***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	11,463	11,443	11,443	11,443
Panel B: UCAS Tariff Points				
PM_{10} (µg/m3)	-0.786*	-1.646***	0.192	
	(0.399)	(0.485)	(0.281)	
Observations	2,381	2,377	2,377	
Panel C: Prior Pollution				
PM_{10} (µg/m3)	-0.001	0.000	0.000	
	(0.001)	(0.001)	(0.001)	
Observations	2,402	2,398	2,398	

Notes: See Tables 2 and 6. In panel A I added carbon dioxide as a control as discussed in the text. In panel B, I use my ex-ante measure of ability as the dependent variable. In Panel C, my dependent variable is the final test score and the independent variable is the sum of pollution from all previous exams of the same student.
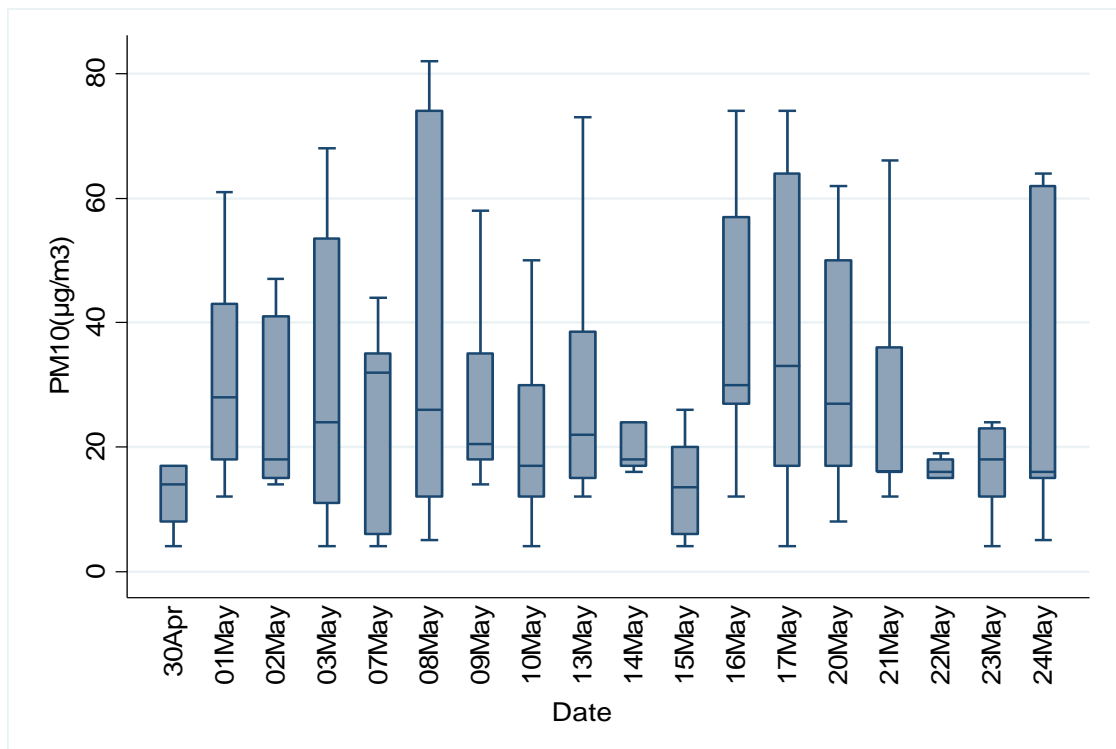
Figure 1
Variation in Pollution Across Venues
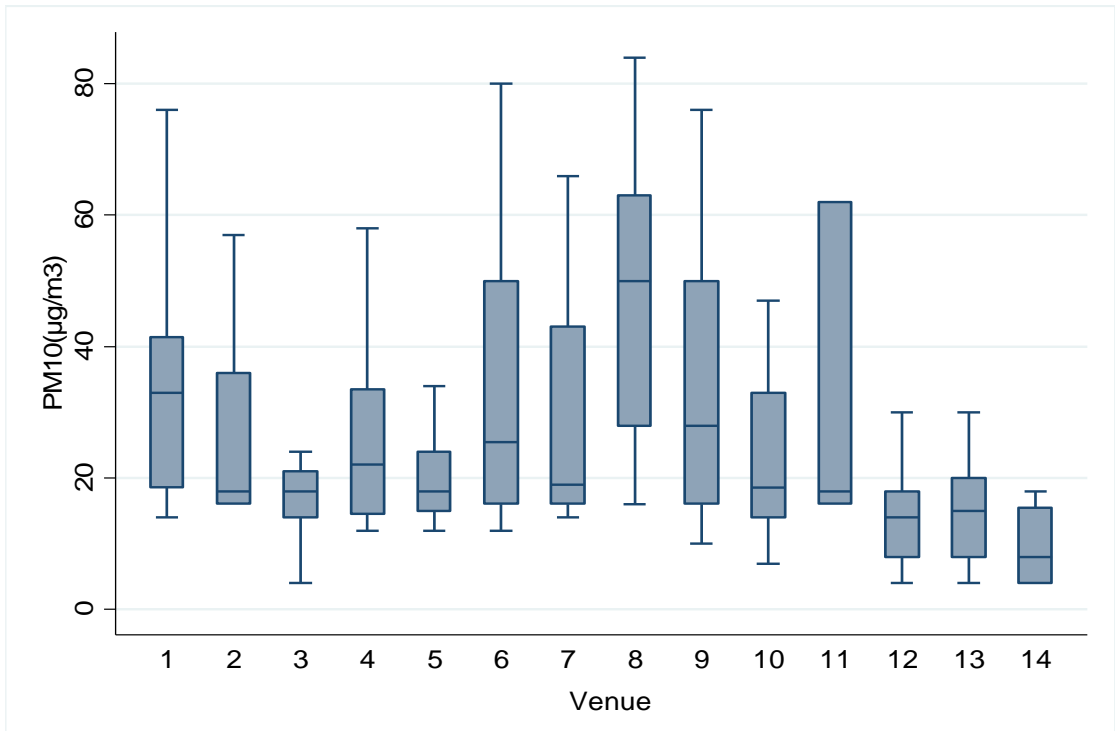
Notes: The figure plots the distribution of PM10 across the 192 unique venue-date-time excluding observations outside of the upper and lower adjacent values.
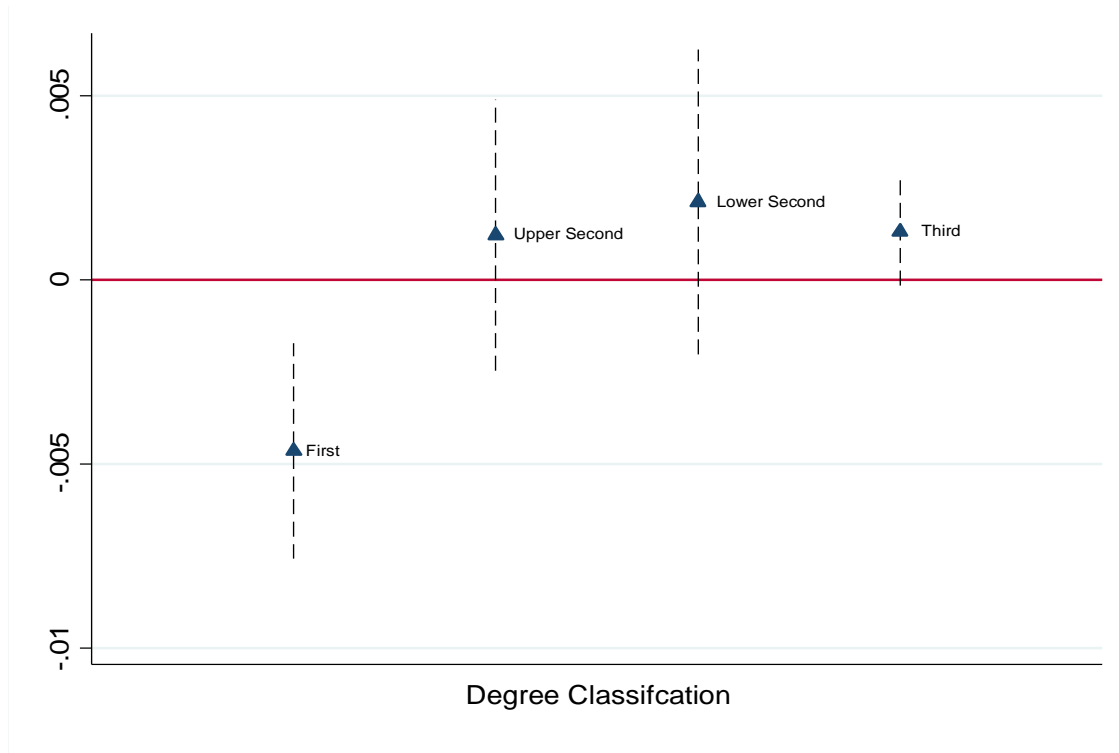
Figure 2
Variation in Pollution Across Time

Notes: The figure plots the distribution of PM10 across the the 18 exam dates excluding observations outside of the upper and lower adjacent values.
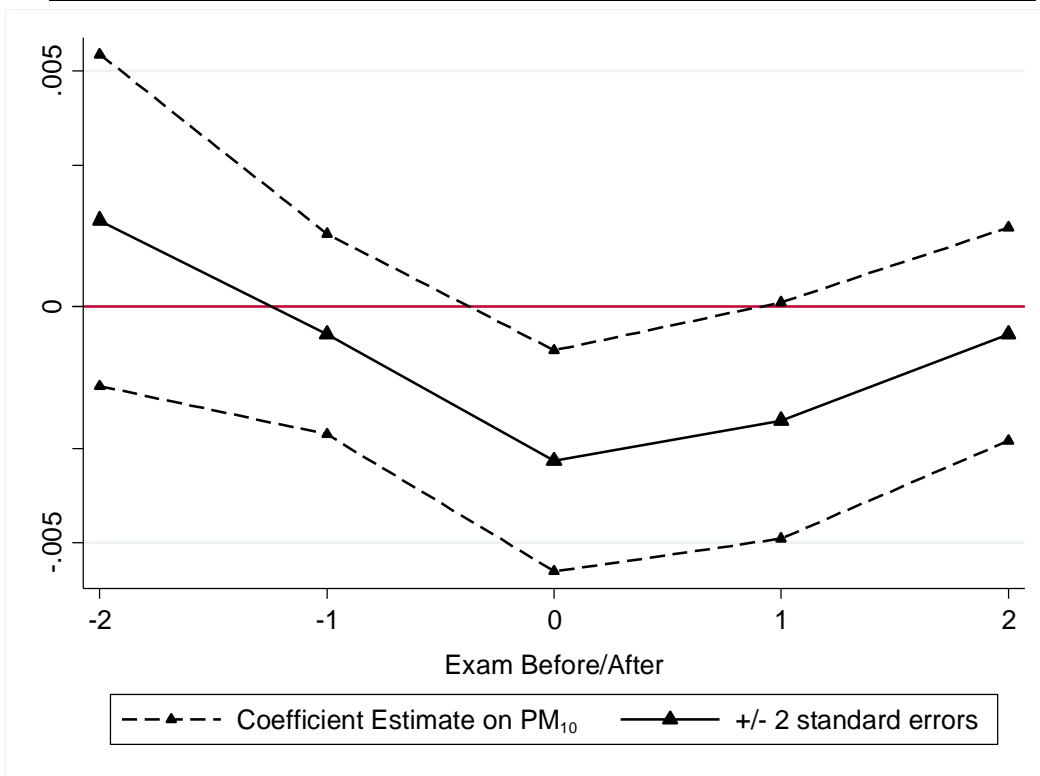
Figure 3

Indoor Air Pollution's Impact on Final Degree Classification

Notes: The figure plots the coefficents and confidnce intervals from linear probablity models of final degree classifcation on indoor PM10 exposure. The models include subject fixed effects and all the controls as in table 6. Standard error are heteroskedastic-consistent and clustered at deaprtment and year level. .Standard errors are heteroskedastic-consistent and clustered at deaprtment and year level.

Figure 4
Impact of Indoor Air Pollution During Previous and Following Exmas

Notes: The figure plots coefficients and confidence intervals from linear models of test score on indoor PM10 which includes student fixed effects and the full set of controls as in table 2. Each estimate is from a separate regression of test scores on PM10 levels from the day of the exam and from previous/following exams of the same student.