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

Sefi Roth

London School of Economics

March 2016

For the Latest Version Click here

Abstract

Mental acuity is essential to productivity in most professions and possibly associated with indoor air quality. I examine this potential link using a sample of university final examination results from a British institution. 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 particulate matter (PM_{10}) has a statistically and economically significant effect on test scores and long-term academic indicators that are potentially correlated with future career outcomes. Furthermore, I find that the effect is larger among male, high ability and STEM subgroups 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 productivity.

*The London School of Economics and Political Science, Houghton Street, London WC2A 2AE, UK. E-mail: s.j.roth@lse.ac.uk
I benefited from comments and suggestions by Pedro Carneiro, Arnaud Chevalier, Victor Lavy, Nico Pestel and Jonathan Wadsworth, and from seminar participants at The London School of Economics, The Hebrew University of Jerusalem, Ben-Gurion University, University of Haifa and Royal Holloway, University of London.

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 US population spends 89% of their time indoors of which 21% 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 in theory 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 productivity in most professions.

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 possess an additional challenge. Whilst 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 lead to health encounters and may not even be noticed by the affected individual (Chang et al.,

[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/.

2014). As such, this paper provides a unique opportunity to asses such potential link by using university final examinations 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 2,458 students taking 11,522 exams at a leading public research university within the Greater London Urban Area. To account for potential confounders I crucially 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 assigning pollution to individuals. This is of particular importance as most studies in the literature use data from ambient air pollution monitors which are usually located a few 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 daily temperature and relative humidity. Nevertheless, it is still possible that other unobserved factors that are correlated with both pollution and test scores remain present. In order to ease such concern, I conduct a rich set of placebo and robustness tests. More specifically, I examine the correlation between test scores and indoor air pollution from the previous exam and also the correlation between ex-ante test scores and elevated levels of PM_{10}. The correlations in both placebos are not statistically different from zero, lending further supports to the causal interpretation of the analysis.

My results demonstrate that elevated levels of Particulate Matter (PM_{10}) 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) guideline reduces student's test scores by 0.060 and 2.868 respectively. The effect for the dichotomous indicator is equivalent to 0.15 of a standard deviation which 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, high ability and STEM subgroups[2].

I also examine the possible non-linear impact of indoor air pollution 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. The analysis reveals a nonlinear and monotonic relationship between pollution and test scores with a possible threshold at 50 (μg/m3). Importantly, this threshold is well below current US Environmental Protection Agency (EPA) standards which suggest that it may be economically beneficial to lower existing guidelines[3]. The results imply that taking an exam with pollution above 75 (μg/m3) reduces student's scores by 4.13 points, or approximately 23% of a standard deviation. Finally, I show that transitory decline in cognitive performance has a robust negative relationship with long-term academic indicators that are potentially correlated with future career outcomes. More specifically, I find that exposure to coarse particulate matter reduces student's composite scores and therefore the probability of receiving an upper second

[2] The acronym STEM is widely used in the US and refers to academic disciplines of Science, Technology, Engineering and Mathematics.
[3] In order to determine the optimal regulatory action a full-fledged cost benefit analysis must be conducted.

classification or above. This is of particular interest since an upper second classification is a threshold requirement for most prestigious jobs and academic graduate 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[4]. My findings imply that a narrow focus on health outcomes understate the true cost of pollution as indoor air quality also affects productivity.

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 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 larger than 2.5 and smaller than 10 micrometers in diameter and the latter to

[4] Stafford (2015) examines the effect of indoor air quality (IAQ) on academic outcomes in Texas. She found that IAQ renovations have a significant positive effect on standardized tests. However, she was unable to observe actual level of indoor quality, and is therefore forced to rely on variation in the timing of IAQ renovations across schools.

particulate matter that is 2.5 micrometers in diameter or smaller[5]. The size of particles is associated with their ability to cause health problems. Therefore, 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 $PM_{2.5}$.[6] 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[7].

The air pollution measure in this study is PM_{10}, which comprises of smoke, dirt, dust, mold, spores and pollen. The emission of ambient PM_{10} comes from various sources such as factories, farming and roads. Nevertheless, indoor concentrations of coarse particles are not simply a byproduct of ambient pollution; they are also 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). Indoor concentrations of coarse particles in classrooms tend to surpass outdoor levels during the daytime, which highlights the significant contribution of indoor sources (Madureira et al., 2012)[8]. This is of particular importance for this study as it suggests that the level of indoor PM_{10} is likely to vary considerably across venues within close proximity of one another, and also within individual venues across time.

The relationship between particulate matter and adverse health outcomes is well documented in the epidemiological literature. The medical explanation for such link is that elevated levels of particles in the air lead to changes in cardiovascular and pulmonary

[5] For comparison, the average human hair is approximately 70 micrometers in diameter, making it 7 times larger than the largest coarse particle.
[6] Total Suspended Particulate corresponds to particles that are less than 100 micrometers in diameter.
[7] Similar regulations also exist in Scotland, Wales and Northern Ireland.
[8] Madureira et al. (2002) also show that $PM_{2.5}$ and PM_1 have the opposite trend.

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.[9] 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 even noticed by the affected individual (Chang et al., 2014)[10]. 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.

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 such 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 Lavy et al. (2014) examined the causal relationship between ambient pollution and high school exit exams in Israel. In that study they found that increased daily exposure to ambient pollution significantly decrease test scores but were unable to disentangle whether this was caused by exposure during the exam or a build-up effect. Moreover, the results were driven by days with very high levels of pollution which are less frequent in most

[9] For further details on such effects see http://www.epa.gov/pm/health.html

[10] Schlenker and Walker (2015) show that using an inpatient discharge data substantially underestimate the morbidity effect of ambient pollution. This is because inpatient discharge data excludes emergency room visits which do not require overnight admission.

developed countries and it remained unclear whether lower level of pollution could also lead to reduced cognitive performance in indoor settings[11].

III. Data

My data combines self-collected readings of indoor air pollution with administrative data on test scores and demographics of undergraduate students at a leading public research university within the Greater London Urban Area. For exam and demographic information I use a confidential student file which contains the full academic record 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[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 15 examination sites during the exam term. I used the 3M™ EVM-7 which is an advanced environmental monitor designed to provide real time measurements with a one per second update rate. The monitor provides readings on mean PM_{10} (μg/m3), temperature (Celsius) and relative humidity (%). Importantly, the monitor was placed at least one meter from the wall and 1.5 meters height 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}

---

[11] There is also evidence on a link between ambient pollution and physical productivity. More specifically, Chang et al. (2014) and Lichter et al. (2015) found that an increase in ambient air pollution leads to decrease in productivity of pear-packing workers and professional soccer players respectively.

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

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 Qulaity 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 11,522 examination results of 2,458 students taking exams in 15 different venues across 18 days. Each student took 5.2 exams on average, and the pass rate was 83%. 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 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

[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).

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.

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:

$$(1)\, R_{ist} = \beta_0 X_{it} + \beta_1 PM_{st} + \beta_2 f(Temp_{st}, RH_{st}) + \beta_3 NUM_{st} + Day_t + TOD_t + Dur + Site + I_i + \varepsilon_{ist}$$

where R_{ist} is the test score of student *i* at site *s* at time *t*; X_{it} is a vector of individual characteristics possibly related to test outcomes, such as gender ; PM_{st} is PM_{10} level at site *s* at time *t*; $Temp_{st}$ is the temperature[16] at site *s* at time *t*; RH_{st} is the relative humidity measure at site *s* at time *t*; NUM_{st} is the number of students taking exam at site *s* at time *t* Day_t, TOD_t, Dur and $Site$ are day-of-week, time-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 I use two-way cluster robust standard errors, clustering on both examination site and date[18].

There are three main econometric challenges in identifying the causal effect of air pollution on test scores. First, the possible correlation between pollution exposure and unobserved determinants of students' test scores. For example, if wealthy individuals are sorting

[16] I include linear and quadratic terms for relative humidity, 5^{O} bins for temperature, and linear and quadratic interaction terms of mean temperature and relative humidity.
[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.

themselves into degree subjects that exposed to lower levels of pollution (e.g. better facilities); 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 in subjects or individuals, I include individual fixed effects in equation (1). I also include controls for time-varying factors, such as daily temperature and relative humidity that could be contemporaneous with pollution. Nevertheless, it is still possible that other unobserved factors that are correlated with both pollution and test scores are still present. In order to limit such concern, I conduct a rich set of placebo tests which are discussed in detail in the next section of this paper.

The second challenge is measurement error in assigning pollution to individuals. 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 exacerbated. These concerns are not present in this study as pollution data is collected from inside the examination site. This feature 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.

Figures 1-3 presents compelling evidence on the exogeneity of indoor PM_{10} in this study. Figure 1 shows the overall significant variation within and between venues, which is further explored in figures 2 and 3. More specifically, Figure 2 plots the variation of PM_{10} within a day across different examination sites. As evident from the figure, there is substantial variation across and within sites in a given day. Figure 3 which plots the variation of PM_{10} across days within a single examination site, shows a high frequency variation across days, with no evidence for a systematic pattern. Figures 1-3 exemplify the significant time and spatial variation of the data and further reduce concerns regarding possible omitted variable bias in this setting.

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 0.08 points 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 0.075 decline in test scores. Both estimates are

[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.

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 0.06 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 an average pollution level (33.15 μg/m3) will suffer a substantial reduction of 0.08 standard deviations in test score, as against that which the same person would have achieved at a site with the lowest level of pollution (4 μg/m3).

Panel B of Table 2 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 pollution level above the WHO standard is associated with a 2.868 decline in a student's test score, which is equivalent to 0.15 of a standard deviation. This effect is very large and similar to estimates found in paying teachers and students large financial incentives (Jackson, 2010) and reducing class size from 31 to 25 students (Angrist and Lavy, 1999). Finally, it is worth noting that the results obtained using the dichotomous indicators suggest the possibility of non-linear relationship between indoor pollution and cognitive performance.

As such, In Table 3 I examine the possible non-linear 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. I find no significant effect for PM_{10} levels below the WHO standard. Column 4, which show 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 2.277 decline in the student's score. When PM_{10} reaches 75 (μg/m3) the effect increases to 4.132, which is also significant at the 5% level. Importantly, these results suggest a threshold around 50 (μg/m3) which is well 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}. Therefore, my results may suggest a daily threshold below 50 (μg/m3) as air pollution tends to be higher during the day.

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 subject.

Table 4 present 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 0.086 and being above the WHO threshold reduces students' test scores by 3.167. 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 counterpart. Indeed, Column (2), which reports results for the female subgroup, demonstrates such pattern precisely. The continuous coefficient drops to 0.035 and the threshold dummy declines to 1.406 and is only significant at the 10% level. The results are not statistically different from each other but are suggestive of heterogeneous effect.

A potential explanation for such difference is the higher prevalence of Attention Deficit Hyperactivity Disorder (ADHD) among male students which possibly makes them more vulnerable to distractions induced by elevated levels of indoor pollution (Biederman et al. 2002).

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 larger among high ability students. Specifically, an additional unit of PM_{10} is associated with a 0.070 decline in students' test scores compared to 0.054 among low ability students. When I use the dichotomous measure I find that exposure to indoor PM_{10} reduce test scores for low and high ability types by 2.824 and 3.098 respectively[20]. One possible explanation for this finding is the reasonable assumption of decreasing marginal returns to effort. Hence, high achievers may be more sensitive to random disturbances, such as indoor pollution, since any additional mark requires higher effort.

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)

[20] Note that the estimates are not statically different from each other and they are only suggestive.

and all other disciplines (non-STEM)[21]. 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 effect is very large for STEM disciplines (-0.090) compared to the estimate for non-STEM subjects of -0.038. The results suggest that tasks which require higher degree of numerical functioning are more affected by pollution.

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 5.3 percentage points. Failing an exam can have a substantial adverse effect on student's future career path due to three main reasons. First, failing can delay graduation and may lead to a change in degree title[22]. Second, since most graduate schemes in the UK require submission of full transcript during the application process, failing an exam can send a bad signal to potential employers. Finally, in case of a retake a student can receive no more than 40 points (a pass) regardless of his or her actual examination score. Hence, failing an exam have a substantial effect on final degree classification which may affect a student's career options.

In Table 6, I carry the analysis at the student level. Therefore, the treatment is the average pollution exposure across all examinations. Note that the dichotomous indicator is the average of

[21] 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.
[22] For example, a student that study for a BSc in Management with Economics and fail the core microeconomic module can still graduate with a BSc in Management which may limit future career options.

above threshold (50 µg/m3) exposure incidences over all exams. In Panel A, I estimate the effect of exposure to coarse particulate matter on students' composite score. The results indicate that an additional 10 units of PM_{10} and a 10% increase in the number of above threshold exposure are associated with a 1.922 and 0.933 decline in a student's composite score respectively. In Panel B, I examine 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 an additional 10 units of PM_{10} and a 10% increase in the number of above-threshold exposures reduces the probability of a student achieving a second class classification by 4.5 and 19.8 percentage points respectively.

d. Robustness Checks

In this section I conduct two placebo exercises and robustness checks to ease concerns that my estimates may capture unobserved time varying factors which are correlated with both indoor air pollution and test scores. The first placebo exercise uses the level of air pollution from the previous exam as the coefficient of interest. Hence, if equation (1) is correctly specified the coefficients of the lag variables should not be statistically different from zero. The results in Panel A of Table 7 suggests that my preferred specification with student fixed effect is indeed not statistically significant. However, the OLS estimates with and without controls are highly significant which exemplifies the importance of controlling for individual unobserved characteristics. Note that the estimate with the subject fixed effect is also insignificant which is

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

reassuring as the last section of the analysis was conducted at the student level and therefore cannot include student fixed effects.

In Panel B, I perform an additional placebo exercise using 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. 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. Again, OLS estimates with and without controls are significant at the 5% and 1% levels respectively. Overall, these results are of great importance for two main reasons. First, they lends further supports to the casual interpretation of my results as it reduces concerns over time varying characteristics that my main specification may fail to capture. Second, it demonstrates that OLS estimates, even with a rich set of controls, may still suffer from omitted variable bias.

Finally, in Panel C 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 all 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 data set of indoor PM_{10} levels and administrative student data. I find that a one unit increase in PM_{10} (μg/m3) and being above the WHO guideline reduces student's test scores by 0.060 and 2.868 respectively. I also explore whether indoor air pollution has a heterogeneous effect across subpopulations and academic discipline and find the effect is larger among male, high ability and STEM subgroups.

While my results are robust to a wide range of different specifications it is important to note a few caveats that may limit my analysis. First, since I do not observe the exact composition of my PM_{10} readings, I can not identify whether specific components of coarse particulates are driving my results. Second, despite my rigorous identification strategy, which includes student fixed effects and a rich set of controls it is still possible that other time variant unobserved correlated factors are still present. For example, traffic on the way to the exam can be correlated with both pollution levels and test scores as heavy traffic can increase pollution and stress. Finally, since data on individual health conditions is unavailable I'm unable to identify the exact pathophysiological pathways that drive my results which may be a rewarding area for future research. Despite the above limitations this paper provides compelling evidence on the causal link between indoor air 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 since mental acuity is essential to most professions and therefore a reduction in indoor air quality can reduce 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].

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

References

Angrist, J. D., & Lavy, V. (1999). Using Maimonides' Rule to Estimate the Effect of Class Size on Student Achievement," Quarterly Journal of Economics, May 1999.

Bernstein, J. A., Alexis, N., Bacchus, H., Bernstein, I. L., Fritz, P., Horner, E., & Tarlo, S. M. (2008). The health effects of nonindustrial indoor air pollution. *Journal of Allergy and Clinical Immunology*, *121*(3), 585-591.

Biederman, J., Mick, E., Faraone, S. V., Braaten, E., Doyle, A., Spencer, T., & Johnson, M. A. (2002). Influence of gender on attention deficit hyperactivity disorder in children referred to a psychiatric clinic. *American Journal of Psychiatry*, *159*(1), 36-42.

Chang, T., Zivin, J. S. G., Gross, T., & Neidell, M. J. (2014). *Particulate pollution and the productivity of pear packers* (No. w19944). National Bureau of Economic Research.

Chatzidiakou, L., Mumovic, D., & Summerfield, A. J. (2012). What do we know about indoor air quality in school classrooms? A critical review of the literature. *Intelligent Buildings International*, *4*(4), 228-259.

Clarke, D. D., & Sokoloff, L. (1999). Circulation and energy metabolism of the brain. *Basic neurochemistry: molecular, cellular and medical aspects*, *6*, 637-669.

Dockery, D. W. (2009). Health effects of particulate air pollution. *Annals of epidemiology*, *19*(4), 257-263.

Donaldson, K., Gilmour, M. I., & MacNee, W. (2000). Asthma and PM10. *Respiratory Research*, *1*(1), 12.

Jackson, C. K. (2010). A Little Now for a Lot Later A Look at a Texas Advanced Placement Incentive Program. *Journal of Human Resources*, *45*(3), 591-639.

Klepeis, N. E., Nelson, W. C., Ott, W. R., Robinson, J. P., Tsang, A. M., Switzer, P., & Engelmann, W. H. (2001). The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants. *Journal of exposure analysis and environmental epidemiology*, *11*(3), 231-252.

Lavy, V., Ebenstein, A., & Roth, S. (2014). *The Impact of Short Term Exposure to Ambient Air Pollution on Cognitive Performance and Human Capital Formation* (No. w20648). National Bureau of Economic Research.

Lin, T. Y., Young, L. H., & Wang, C. S. (2001). Spatial variations of ground level ozone concentrations in areas of different scales. *Atmospheric environment*, *35*(33), 5799-5807.

Lichter, A., Pestel, N., & Sommer, E. (2015). Productivity Effects of Air Pollution: Evidence from Professional Soccer (No. 8964). The Institute for the Study of Labor (IZA)

Madureira, J., Paciência, I., & Fernandes, E. D. O. (2012). Levels and indoor–outdoor relationships of size-specific particulate matter in naturally ventilated Portuguese schools. *Journal of Toxicology and Environmental Health, Part A, 75*(22-23), 1423-1436.

Mendell, M. J., & Heath, G. A. (2005). Do indoor pollutants and thermal conditions in schools influence student performance? A critical review of the literature. *Indoor air, 15*(1), 27-52.

Moretti, E., & Neidell, M. (2011). Pollution, health, and avoidance behavior evidence from the ports of Los Angeles. *Journal of human Resources*, *46*(1), 154-175.

Pope, C. A., Dockery, D. W., & Schwartz, J. (1995). Review of epidemiological evidence of health effects of particulate air pollution. *Inhalation toxicology*, *7*(1), 1-18.

Schlenker, W., & Walker, W. R. (2015). *Airports, air pollution, and contemporaneous health*. *Review of Economic Studies, forthcoming*.

Seaton, A., Godden, D., MacNee, W., & Donaldson, K. (1995). Particulate air pollution and acute health effects. *The Lancet*, *345*(8943), 176-178.

Shu, W., Zhang, J., Zeng, X., Zeng, Y., & She, W. (2009). Association of traffic-related air pollution with children's neurobehavioral functions in Quanzhou, China. *Environ Health Perspect*, *117*, 1612-1618.

Son, J. Y., & Bell, M. L. (2013). The relationships between short-term exposure to particulate matter and mortality in Korea: impact of particulate matter exposure metrics for sub-daily exposures. *Environmental Research Letters*, *8*(1), 014015.

Stafford, T. M. (2015). Indoor air quality and academic performance. *Journal of Environmental Economics and Management*, *70*, 34-50.

Suglia, S. F., Gryparis, A., Wright, R. O., Schwartz, J., & Wright, R. J. (2008). Association of black carbon with cognition among children in a prospective birth cohort study. *American journal of epidemiology*, *167*(3), 280-286.

Weinmayr, G., Romeo, E., De Sario, M., Weiland, S. K., & Forastiere, F. (2010). Short-term effects of PM10 and NO2 on respiratory health among children with asthma or asthma-like symptoms: a systematic review and meta-analysis. *Environ Health Perspect*, *118*(4), 449-57.

WHO (2011). Methods for Monitoring Indoor Air Quality in Schools. World Health Organisation, WHO Regional Publications, Bonn, Germany. European Series.

WHO (2006). Air quality guidelines. Global update 2005. Particulate matter, ozone, nitrogen dioxide and sulfur dioxide. Copenhagen: WHO Regional Office for Europe.

Wu, X., Apte, M. G., & Bennett, D. H. (2012). Indoor particle levels in small-and medium-sized commercial buildings in California. *Environmental science & technology*, *46*(22), 12355-12363.

Yang, X., Zhang, Y. P., Chen, D., Chen, W. G., & Wang, R. (2001). Eye irritation caused by formaldehyde as an indoor air pollution-a controlled human exposure experiment. *Biomedical and environmental sciences: BES*, *14*(3), 229-236.

Table 1

Descriptive Statistics

		By Gender		By Ability	
Variable	All (1)	Males (2)	Females (3)	Low (4)	High (5)
PM_{10} ($\mu g/m^3$)	33.35 (21.51)	33.66 (21.78)	33.10 (21.29)	34.50 (21.93)	32.33 (21.08)
PM_{10} (PM_{10} >50)	0.214 (0.41)	0.215 (0.41)	0.212 (0.41)	0.227 (0.23)	0.202 (0.40)
Exam Score (1-100 points)	54.59 (18.05)	53.67 (19.41)	55.34 (16.82)	50.59 (19.09)	58.63 (15.86)
Temperature (celsius)	16.37 (2.31)	16.51 (2.16)	16.26 (2.41)	16.40 (2.29)	16.35 (2.32)
Relative Humidity (percent saturation)	54.02 (12.15)	54.43 (12.08)	53.67 (12.20)	53.62 (12.26)	54.38 (12.07)
Age	21.36 (2.77)	21.46 (2.95)	21.27 (2.61)	21.96 (3.42)	20.71 (1.18)
Number of Exams	5.178 (1.41)	5.262 (1.47)	5.109 (1.34)	5.066 (1.45)	5.161 (1.32)
Number of Students	124.6 (75.68)	122.6 (76.24)	126.2 (75.18)	123.7 (75.89)	125.2 (75.38)
Failed an Exam (yes=1)	0.172 (0.38)	0.201 (0.40)	0.149 (0.36)	0.240 (0.43)	0.104 (0.31)
Observations	11,522	5,189	6,333	5,580	5,806

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

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

	Polled OLS		Fixed Effects	
	No Controls	Controls	Subject	Student
	(1)	(2)	(3)	(4)
PM_{10} (μg/m3)	-0.083***	-0.075**	-0.075***	-0.060***
	(0.027)	(0.030)	(0.020)	(0.020)
Dummy for PM_{10}>50	-2.814*	-2.697**	-3.445***	-2.868***
	(1.461)	(1.341)	(0.860)	(0.818)
Observations	11,730	11,522	11,522	11,522

Notes: Each cell in the table represents a separate regression.Standard errors are heteroskedastic-consistent and clustered by examination venue and date of pollution assignment. All regressions include suppressed controls for temperature and humidity. *** 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

	Polled OLS		Fixed Effects	
	No Controls	Controls	Subject	Student
	(1)	(2)	(3)	(4)
Dummy for PM_{10} >25 & <= 50	-3.087**	-1.980	-1.418	-0.778
	(1.480)	(1.205)	(0.937)	(0.977)
Dummy for PM_{10} >50 & <= 75	-2.920*	-2.374	-2.970**	-2.277**
	(1.540)	(1.702)	(1.138)	(1.082)
Dummy for PM_{10} >75	-5.488**	-5.530**	-5.453***	-4.132**
	(2.473)	(2.377)	(1.636)	(1.797)
Observations	11,730	11,522	11,522	11,522

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)	-0.086***	-0.035	-0.054**	-0.070***	-0.090***	-0.038**
	(0.021)	(0.022)	(0.023)	(0.021)	(0.032)	(0.019)
Dummy for PM_{10}>50	-3.167***	-1.406*	-2.824***	-3.098***	-3.553**	-1.434*
	(0.781)	(0.791)	(0.999)	(0.804)	(1.634)	(0.738)
Observations	5,189	6,333	5,596	5,822	7,187	4,270

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**
	(0.001)	(0.001)	(0.000)	(0.000)
Dummy for PM_{10}>50	0.036	0.057*	0.069***	0.053***
	(0.034)	(0.033)	(0.020)	(0.018)
Observations	11,730	11,522	11,522	11,522

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

Table 6

Indoor Air Pollution's Impact on Other Academic Outcomes

	Pooled OLS		Fixed Effects
	No Controls	Controls	Subject
	(1)	(2)	(3)
Panel A: Composite Score			
PM_{10} (μg/m3, 10 units)	-1.510**	-1.750***	-1.922***
	(0.630)	(0.625)	(0.454)
Dummy for PM_{10}>50	-3.527	-5.278	-9.333***
	(5.427)	(4.023)	(2.722)
Observations	2,462	2,458	2,458
Panel B: Upper Second Class (yes=1)			
PM_{10} (μg/m3, 10 units)	-0.055***	-0.060***	-0.045***
	(0.019)	(0.015)	(0.011)
Dummy for PM_{10}>50	-0.109	-0.146	-0.198***
	(0.139)	(0.105)	(0.072)
Observations	2,462	2,458	2,458

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

Placebo and Robustness Tests

	Pooled OLS		Fixed Effects	
	No Controls	Controls	Subject	Student
	(1)	(2)	(3)	(4)
Panel A: Previous Exam				
PM_{10} (μg/m3)	-0.086***	-0.056**	-0.027	-0.008
	(0.025)	(0.022)	(0.020)	(0.022)
Observations	9,268	9,079	9,079	9,079
Panel B: UCAS Tariff Points				
PM_{10} (μg/m3)	-0.982**	-1.490***	-0.675	
	(0.445)	(0.381)	(0.831)	
Observations	2,438	2,438	2,438	
Panel C: Prior Pollution				
PM_{10} (μg/m3)	-0.039	-0.041	0.035	
	(0.045)	(0.034)	(0.031)	
Observations	2,462	2,458	2,458	

Notes: See Tables 2 and 6. In panel A, I assign PM10 to each exam using the reading of PM10 for the previous exam of the same student to the actual exam. 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 average pollution level from all previous exams of the same student.

Figure 1
Variation in Indoor Air Pollution

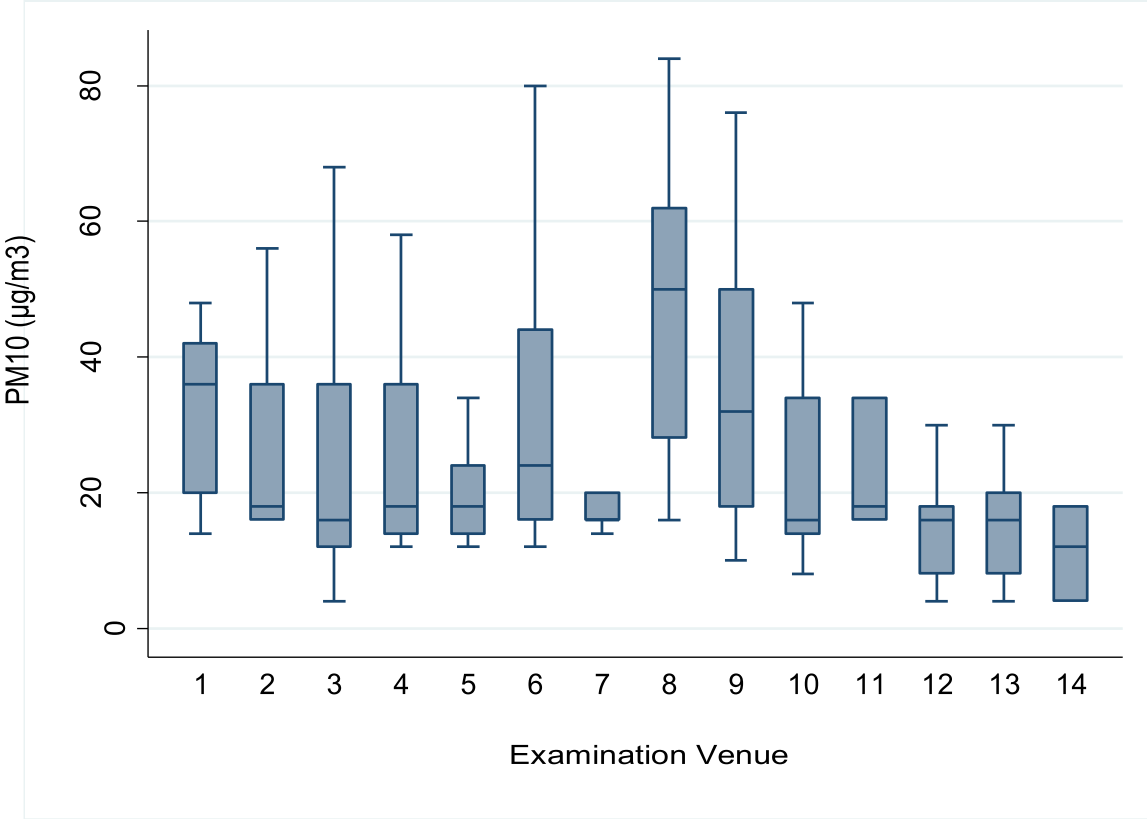
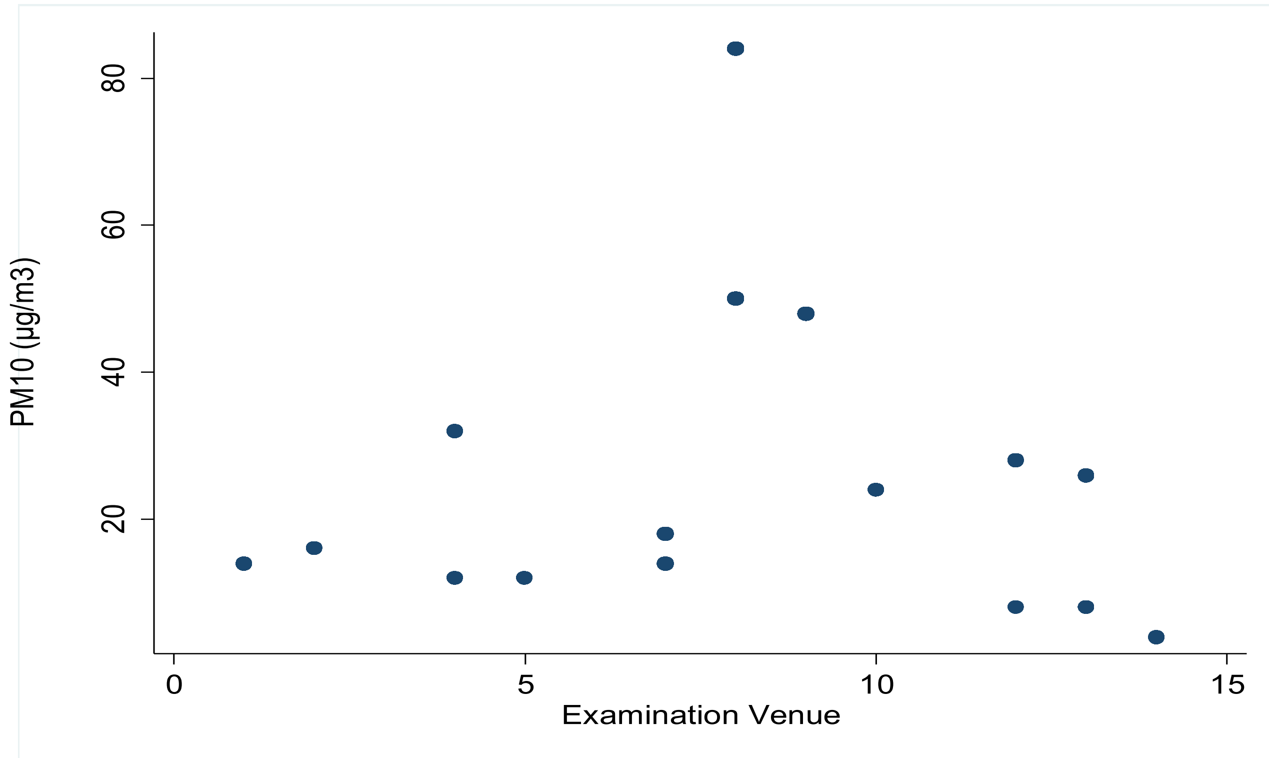


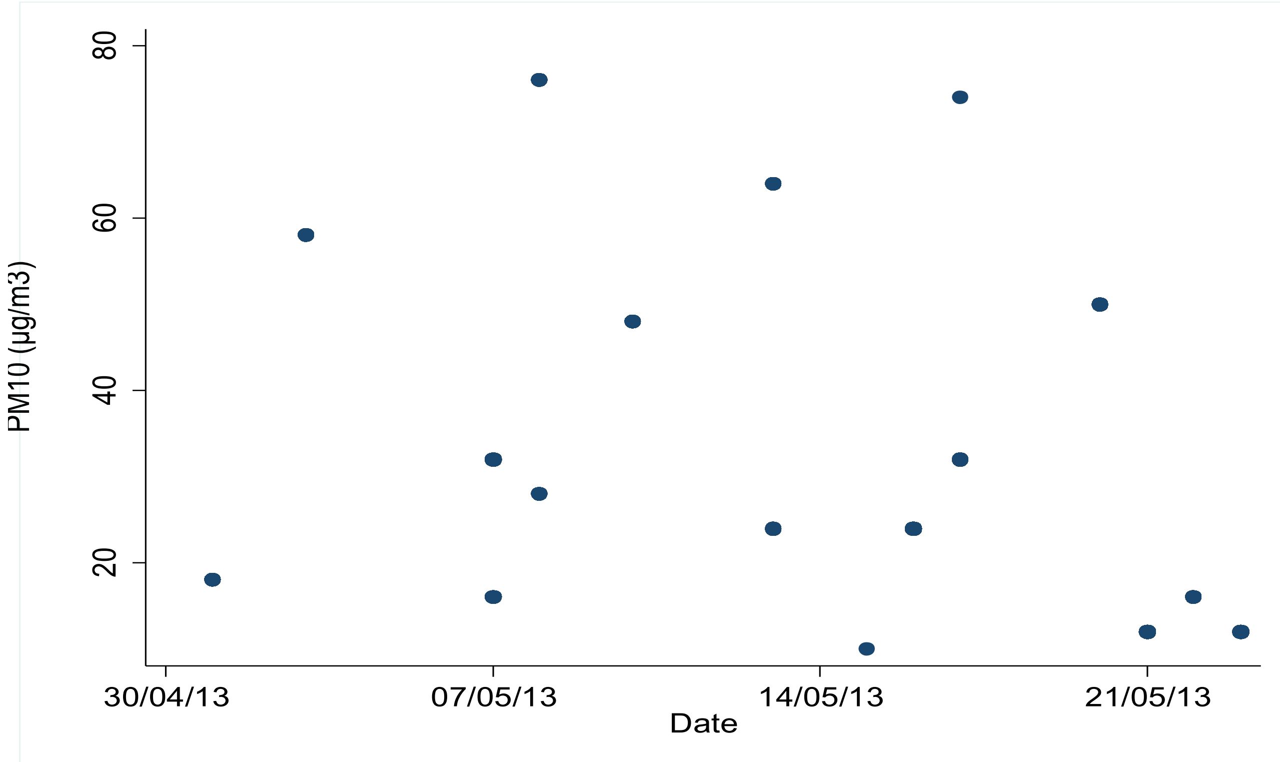
Figure 2

Within Day Variation



Notes: Example of variation in PM10 within a day across venues

Figure 3
Variation Across Days



Notes: Example of variation in PM10 across days within one examination venue