The Impact of Air Pollution on Cognitive Performance and Human Capital Formation[*]

Victor Lavy
Hebrew University of Jerusalem, University of Warwick, and NBER

Avraham Ebenstein
Hebrew University of Jerusalem

Sefi Roth
Royal Holloway, University of London

September 2012

Abstract

Cognitive performance is critical to productivity in many occupations and potentially linked to pollution exposure. We evaluate this potentially important relationship by estimating the effect of pollution exposure on standardized test scores among Israeli high school high-stakes tests (2000-2002). Since students take multiple exams on multiple days in the same location after each grade, we can adopt a fixed effects strategy estimating models with city, school, and student fixed effects. We focus on fine particulate matter ($PM_{2.5}$) and carbon monoxide (CO), which are considered to be two of the most dangerous forms of air pollution. We find that while $PM_{2.5}$ and CO levels are only weakly correlated with each other, both exhibit a robust negative relationship with test scores. We also find that $PM_{2.5}$, which is thought to be particularly damaging for asthmatics, has a larger negative impact on groups with higher rates of asthma. For CO, which affects neurological functioning, the effect is more homogenous across demographic groups. We find that exposure to either pollutant is associated with a significant decline in the probability of not receiving a *Bagrut* certificate, which is required for college entrance in Israel. An implication of this finding is that by temporarily lowering the productivity of human capital, high pollution levels lead to allocative inefficiency as students with lower human capital are assigned a higher rank than their more qualified peers. This may lead to inefficient allocation of workers across occupations, and possibly a less productive workforce.

[*] Corresponding author: msvictor@mscc.huji.ac.il. Excellent research assistance was provided by Eyal Frank, Michael Freedman, Susan Schwartz, and Ben Raven. We thank seminar participants at Hebrew University, University of London Royal Holloway, University of Warwick, and NBER Summer Institute for useful comments and suggestions.

I. Introduction

Ambient air pollution has significant known consequences for human health and life expectancy (Pope et al. 2009, Chay and Greenstone 2003). Researchers have documented that short-term acute exposure to particulate matter decreases circulatory performance and leads to increased illness and hospitalization rates (Pope et al. 1995). Exposure to fine particulate matter is particularly dangerous since these small particles penetrate deep in to the lungs and may also affect other aspects of human life, such as cognitive performance, due to their impact on blood flow and circulation (Pope and Dockery 2006). Recent work has also demonstrated a link between carbon monoxide and higher incidents of respiratory and heart related emergency room visits (Schlenker and Walker 2011). Medical research has also identified symptoms that point to a diagnosis of carbon monoxide poisoning, including headaches, dizziness, and confusion (Piantadosi 2002). A potential link between cognition and harmful forms of ambient air pollution would suggest that the benefit of pollution reduction could be underestimated by focusing only on health outcomes (Chay and Greenstone 2005). However, evidence documenting a link between cognition and ambient air pollution is extremely limited. A potential link between cognitive performance and pollution exposure would imply high costs of pollution in terms of lost labor productivity, as mental acuity is critical to productivity for many occupations.

There are several challenges posed in trying to estimate the relationship between cognitive performance and air pollution. First, ambient pollution is often correlated with other factors correlated with wellbeing, such as wealth, generating a potential source of omitted variables bias that is similar to the challenges faced in measuring the health impact of air pollution. However, measuring air pollution's impact on cognition poses unique challenges as well. First, unlike with health problems, poor cognitive outcomes are generally not measured precisely. Whereas short-term dysfunction can result in a hospital admission, short-term cognitive decline is unlikely to be recorded. Even if short-term cognitive dysfunction results in injury, such as from a car accident, it is unlikely that this will be recorded in a systematic manner. In our study, since we observe students engaged in a difficult mental task with precise measurement of performance, it is more likely we can observe an effect (if there is one). A second issue is that cognitive tests (e.g. IQ) are only administered to self-selected groups, such as military recruits, making samples less representative than in samples of individuals exposed to air pollution with observed health outcomes. As we will describe, since the Israeli examination we analyze in our study is taken by nearly all high school students, and our dataset includes the entire universe of test takers, our results presumably have more external validity than results generated from a self-selected group.

In this paper, we examine a unique data set of merged high school high-stakes exit exams (*Bagrut* tests) and pollution data for the universe of Israeli test takers during 2000-2002 where we observe pollution and outcomes for over 400,000 subject examinations. Since we observe the same student at multiple test administrations following each year of high school, we can control for both time invariant features of both a school and of a particular student. The rigorous nature of the *Bagrut* tests and the precise scoring of the exams provide a context to analyze a potential link between cognition and air pollution, even if there are only modest declines in cognitive performance due to pollution. Furthermore, Israel's small size and well-developed monitoring system implies that most of its testing locations are near a station where we observe precise levels of pollution concentration. Lastly, Israel's ethnic heterogeneity provides a context to examine the responsiveness of different groups to pollution, and potentially distinguish between different mechanisms by which pollution may affect cognitive performance.

In this study, we examine the impact of fine particulate matter and carbon monoxide exposure on exam outcomes. These two pollutants are particularly harmful to human health, and are available in the data provided by the Israeli monitoring system. We find that a 10 unit increase in the ambient concentration of fine particulate matter ($PM_{2.5}$) as measured by the Air Quality Index (AQI) reduces *Bagrut* test scores by .46 points, or roughly 1.9% of a standard deviation of the *Bagrut* (sd=23.7). Alternatively, relative to a day with average air quality, a 1 standard deviation increase in the $PM_{2.5}$ AQI value (sd=22.81) is associated with a .65 point decrease in score, or 2.8% of a standard deviation. We also find that a 10 unit increase in the ambient concentration of carbon monoxide (CO), as measured by the Air Quality Index (AQI), reduces *Bagrut* test scores by .85 points, or roughly 3.5% of a standard deviation. This implies that relative to a day with average air quality, a 1 standard deviation increase in the CO AQI value is associated with a .54 point decrease in score, or 2.4% of a standard deviation. We also examine whether pollution has a non-linear impact on test takers using specifications where we include dummy variables for clean, moderately polluted, or very polluted days. We find that our results are largely driven by poor performance of test takers on very polluted days, with an AQI reading above 101 for $PM_{2.5}$ associated with a decline in test score of 1.95 points, or 8.2% of a standard deviation. For CO, test administrations in the top 5% of most polluted days are 10.16 points lower, a decline of 42.8% of a standard deviation. These results suggest that modest pollution levels have only a marginal impact, but very polluted days can have much larger impacts, suggesting a non-linearity in pollution's relationship with cognitive performance. In several placebo exercises, we find that the correlation between *Bagrut* test scores and pollution readings other than the test pollution level is insignificant in most specifications, further supporting our claim of a causal interpretation to our results. Our results also indicate that test outcomes for afternoon examinations are more affected by carbon monoxide than morning examinations. This is consistent with a prior that carbon monoxide, which is generated primarily by automobile emissions, will worsen over the course of the day. Our results for fine particulate matter, which are primarily the byproduct of sandstorms and coal-burning power plants, are more similar for morning and afternoon examinations.

We examine mechanisms for our findings by estimating treatment effects for different groups in Israel, in combination with a prior on how each pollutant should affect test takers. In particular, we find that demographic groups with higher rates of asthma have larger treatment effects of $PM_{2.5}$, suggesting that exacerbation of respiratory health problems could be a mechanism for pollution to affect test outcomes. Our results for $PM_{2.5}$ seem to be consistent with the patterns of relative risk for asthma found by Laor et al. (1993) from military records for these cohorts of Israelis, which reflect much higher incidence among boys and Ashkenazi Jews, and among lower socio-economic groups in other countries (Basagana et al. 2004, Eriksson et al. 2006). Carbon monoxide exposure, which is thought to decrease neurological functioning, has a more homogenous impact on Israel's demographic groups. This may be due to a more similar responsiveness to carbon monoxide poisoning, which may affect all individuals, even those without prior respiratory conditions.

We also find that exposure to $PM_{2.5}$ or CO on examination days has a significant impact on a particular student's long-term academic outcome, and potentially has implications for the welfare consequences of using the *Bagrut* for ranking students. We find that a one standard deviation increase in the fraction of exam days that are heavily polluted is associated with a 2.19 and 2.70 percentage point decline in the probability of receiving a *Bagrut* matriculation certificate for $PM_{2.5}$ and CO respectively. Note that this certificate is a prerequisite for college entrance, preventing some students from accessing higher education. In addition, since access to college majors is also determined by *Bagrut* performance, air pollution may have long-term consequences for students who pass the *Bagrut* but are forced to choose a less desirable college major. An implication of this finding is that by temporarily lowering the productivity of human capital, high pollution levels lead to allocative inefficiency as students with lower human capital are assigned a higher rank than their more qualified peers. This may lead to inefficient allocation of workers across occupations, and possibly a less productive workforce. The results highlight the danger in assigning too much weight to a student's performance on a high-stakes exam, rather than their overall academic record.

Our results provide novel and compelling evidence that cognition is affected by air pollution exposure. Epidemiologists have examined the relationship between air pollution and cognition, but the evidence is generally cross-sectional in nature, with little attention paid to a potential correlation between omitted variables and pollution. For example, Suglia et al. (2008) found that in a sample of 202 children, those living near higher levels of black carbon (which is a solid fraction of $PM_{2.5}$) performed worse on cognitive function assessments. Wang et al. (2009) found that children in higher-traffic areas (with higher levels of carbon monoxide) performed worse on neurobehavioral examinations. Both of these studies, however, were cross-sectional in nature and did not account for a potential correlation between unobservable determinants of test outcomes and the measures pollutants. Our examination of Israeli *Bagrut* exams is, to our knowledge, the first attempt to measure fine particulate matter and carbon monoxide's impact on cognitive performance using rich data and a panel approach.[1] Our results underscore the need for tighter pollution regulations relative to policy made taking only human health effects into account. The results may also highlight a mechanism by which individuals in highly polluted areas, such as those living in cheaper industrial areas of cities, could have economic disadvantage exacerbated by pollution (Brown 1995).

The rest of the paper is laid out as follows. In the second section, we present background on the Israeli context, and summarize in greater detail the relevant existing work on acute air pollution and human welfare. Section III presents our data and Section IV presents our empirical strategy. In Section V, we present our empirical results and in Section VI we conclude.

II. Background and Data

a. Air pollution and Cognitive Performance

We consider two air pollution measures. Our first air pollution measure is particulate matter ($PM_{2.5}$), which is a complex mixture of solid and liquid microscopic droplets found in the air that consists of various components including acids, metals, dust particles, organic chemicals and allergens. In Israel, the main sources of particulate matter are sand storms, coal-burning power plants, and certain industrial processes. Our second air pollution measure is carbon monoxide, which is generated by automobile emissions, fossil-fuel furnaces, and fires (Piantadosi 2002). Human intake of particulate matter or carbon monoxide inhibits proper blood flow, leading to elevated risk of heart disease, stroke, and lung cancer (Dockery and Pope 1996; Schlenker and Walker 2011). It is less clear whether either of these air pollutants affect cognition. Since the brain consumes a large fraction of the oxygen needs of the body, any deterioration in oxygen quality can in theory affect cognition (Clark and Sokoloff, 1999). Long-term exposure to ambient pollution can lead to the growth of white-matter lesions, potentially inhibiting cognition (Calderón-Garcidueñasetal et al. 2008). Air pollution can also impact the nervous system, leading to symptoms such as memory disturbance, fatigue and blurred vision (Kampa and Castanas,

[1] These results contribute to a limited but growing literature in economics documenting that a narrow focus on hospitalization rates or excess mortality rates may understate the impact of air pollution on human wellbeing, though these studies focus primarily on consequences of illness rather than a direct impact on cognition. Currie et al. (2009) find that carbon monoxide exposure increases absenteeism among elementary and middle school children students. Oliva and Hanna (2011) present evidence that labor supply is reduced in Mexico City on days with high pollution levels. Ham et al. (2011) examine the relationship between pollution and test scores using data from California elementary schools. They find significant but modest effects for ozone, fine particulate matter, and coarse particulate matter. However, they are unable to observe the same student over multiple examinations, and are therefore forced to rely on grade-school fixed effects.

2007), and may also impact labor productivity (Graff Zivin and Neidell 2011). Fine particle matter can also travel through small passageways, suggesting that high levels of pollution may affect test takers even indoors (Branis et al. 2005). These papers provide compelling evidence that cognition may be affected by pollution. They also suggest that while particulate matter may affect the respiratory system, carbon monoxide will primarily affect the release of oxygen to human tissues, including the brain. This implies that particulate matter may have a larger impact on sensitive or unhealthy groups – such as asthmatic groups – while carbon monoxide will affect healthy and unhealthy groups more similarly. However, as stated by Suglia et al. (2008), "the possible neurodegenerative effect of air pollution remains largely unexplored." The Israeli *Bagrut* examination provides a unique context to assess the relationship empirically, which is discussed in the next section.

b. The Israeli High-School Matriculation Exam System

Israeli post-primary education consists of middle school (grades 7–9) and high school (grades 10–12). High-school students are enrolled either in an academic track leading to a matriculation certificate (*Bagrut* in Hebrew[2]) or in a vocational track leading to a high-school diploma. The matriculation certificate is a prerequisite for university admission and is one of the most economically important education milestones. Students complete the matriculation process by passing a series of national exams in core and elective subjects following tenth grade and eleventh grade, and then a larger set following twelfth grade. Students choose to be tested at various levels of proficiency, with each test awarding the student between one and five credit units per subject, varying by the difficulty of the exam. The exam focuses on seven mandatory subjects and one elective subject, allowing us to observe students completing exams with separate grades for each subject.[3] The most basic level of study is three credits and a minimum of twenty credits is required to qualify for a matriculation certificate. About 52 percent of high-school graduates in 2002 and 46 percent of the overall cohort received matriculation certificates.[4]

The examinations are given bi-annually during the two exam "seasons", a winter examination given in January and a summer examination in May/June, and are graded by two independent and anonymous examiners. The *Bagrut* final score in each subject is a simple average of the *Bagrut* exam score and a school score, or *Magen* score, on this subject. The *Magen* score is based on a school exam

[2] Many countries and some American states have similar high-school matriculation exams, e.g., the French Baccalaureate, the German Certificate of Maturity (*Reifezeugnis*), the Italian Diploma di Maturità, the New York State Regents examinations, and the recently instituted Massachusetts Comprehensive Assessment System.

[3] The seven core subjects are Math, English, Hebrew, History, Literature, Religious Studies and Civics. It is possible to be awarded a *Bagrut* certificate despite a failing mark on one of the exams if one of following conditions is satisfied: (1) the mark is not below 45 (2) the mark is below 45 but the candidate has two more exams with 3 credit units or more that their scores combined sums to at least 150 (3) the failing mark is not in the Hebrew subject exam.

[4] See the Israel Ministry of Education web site (www.education.gov.il) and Lavy (2002).

(the *Matchonet* examination)[5] that precedes the *Bagrut* exam by week to three weeks and has the same format as the nationally-administered *Bagrut* exam, except that it is graded by the student's secondary school subject teacher and on the student's overall performance in this subject during the academic year. We only observe the overall *Magen* score and not its two components. The weights of these two factors can vary and the overall *Magen* score is therefore a natural measure for ranking the students in terms of quality which we use in our analysis to stratify the sample.

Students are admitted to post-secondary programs on the basis of their average matriculation scores and based on an SAT-style examination from a psychometric examination administered by the National Testing Center. Each higher education institution ranks applicants according to the same formula, thus producing an index based on a weighted average of the student's average score on all her matriculation exams and the SAT-style examination. Therefore, pollution levels can affect students' post-secondary schooling by affecting their probability of passing *Bagrut* exams, and also by affecting the average score in these exams. The first channel will affect the eligibility for post-secondary admission while the second will affect which programs (or majors) will be available to the student.

III. Data

Our data set is generated by combining Israeli test score data with air pollution and meteorological data for 2000-2002. The *Bagrut* exam information and demographic information for each test taker were provided by the Israeli Ministry of Education. These files also contain each student's Israeli identification number, allowing us to observe rich demographic information on the student and the student's family, such as parental education level, country of origin, and ethnicity. For each exam, we also know the exact date of the test and the precise location of the testing site, allowing us to assign pollution measures to each test administration. Our pollution data are taken from files published by the Israeli Ministry of Environmental Protection, which reports daily mean readings of particular matter less than 2.5 microns in width, or $PM_{2.5}$ ($\mu g/m^3$) and carbon monoxide (CO) at 139 monitoring stations throughout Israel for the sample period (see Figure 1).[6] Readings are taken at 5 minute intervals and averaged over the course of the day.

Each school is assigned the average pollution reading for all monitoring stations within the city limits in which it is located, or within 2.5 kilometers of the city limits. Since Israeli cities are not very

[5] This exam is called *matkonet*, derived from the word *matkon*, recipe, meaning that the school exam follows the "recipe" of the state exam. The school exam follows the exact format of the *Bagrut* exam and it also draws its questions from the same bank of questions used for the *Bagrut* exam.

[6] The Israeli monitoring system also records readings for a set of other pollutants. In this paper we focus on $PM_{2.5}$ and CO since these are considered among the most harmful, and are monitored most extensively by the monitoring system. We also examined the relationship between PM_{10} and SO_2 and test score data, finding zero effects for PM_{10} and modest effects of very high levels of SO_2. The results are available from the authors upon request.

large, we generally are taking readings from stations very close to the schools. While we ideally would have a measure of pollution inside the classroom, the air quality inside a school is presumed to be highly correlated with the ambient reading outdoors (Branis et al. 2005). Schools that had no monitoring station within the city limits or 2.5 kilometers of the city limits were dropped from the sample.[7] These stations also record temperature and relative humidity, which are used as control variables. We assign pollution and weather to each test by averaging all non-missing values among stations within 2.5 kilometres of the test site. Our analysis is executed using the Air Quality Index (AQI) measurement associated with our $PM_{2.5}$ and CO readings. The AQI measure converts the pollutant measures in micrograms (μg/m^3) into an index score that ranges from 0-500 using a formula specified by the US EPA.[8] The US defines values above 101 as "unhealthy for sensitive groups" and values above 150 as "unhealthy". In our empirical analysis, we classify air quality on a particular day as being beyond the threshold if the $PM_{2.5}$ (AQI) reading is greater or equal to 101 (AQI). Since Israel's CO measures are relatively lower, and have few days where the AQI score exceeds 101, we chose a lower threshold where we generate a dummy for a test occurring on a day in the top 5 percent of the most polluted days.

It is also worth noting that the correlation between our two measures of pollution is very close to zero (R=.0028).[9] The two pollutants are associated with different causes: particulate matter is generated by sand and dust storms and coal-powered electric plants, whereas carbon monoxide is associated with high traffic density or other combustion processes. As such, this provides an opportunity to exploit two different and largely independent measures of pollution to assess the link between air pollution and cognitive performance.

The summary statistics for our sample are presented in Table 1. Our sample includes 489,419 examinations taken by 71,383 students at 712 schools throughout Israel. Our key variables are the measures of $PM_{2.5}$ (μg/m^3 or AQI), CO, and our standardized test outcomes in *Bagrut* exams. We also use the *Magen* score as a proxy for student quality that can be used to stratify the sample. This score is determined primarily by a test which is a similar to the *Bagrut* test a few weeks prior to the *Bagrut*, and by the student's course grade. In columns (2)-(4), we stratify the sample by sex and *Magen* score. The

[7] Since Israel's population is densely concentrated in several metropolitan areas, this led to the dropping of less than 5% of schools.

[8] We used the EPA's breakpoints table (see Table A1) and the following formula to generate the $PM_{2.5}$ (AQI) measurement: $PM_{2.5}$ (AQI)=$\{(I_{HI}-I_{LO}) / (BP_{HI}-BP_{LO})\}\ (C_P-BP_{LO}) + I_{LO.}$ Where C_P is the rounded concentration of the pollutant, BP_{HI} is the breakpoint that is greater than or equal to C_P, BP_{LO} is the breakpoint that is less than or equal to C_P, I_{HI} is the AQI value corresponding to BP_{HI} and I_{LO} is the AQI value corresponding to BP_{LO}. A similar formula is used for CO.

[9] In a robustness check, we estimate whether there is a conditional correlation between the two pollutant measures by estimating models with the two pollutants simultaneously, shown in Table A2. Our results indicate that the results are largely unchanged by including both measures in the same model for our dichotomous measure of pollution, but the result for our continuous measure of $PM_{2.5}$ is significantly reduced for models with student fixed effects. This is discussed in the empirical results section.

table indicates that girls perform somewhat better than boys on the exam. Also, as anticipated, the students who have higher *Magen* scores, and are placed in our top quality group, have on average higher *Bagrut* scores and come from more educated families. The parents of the higher *Magen* group have, on average, some postsecondary schooling, whereas parents of the lower *Magen* group have, on average, less than a high school diploma. The lower *Magen* group also come from larger families (more siblings) and are more likely to be of African/Asian ethnic origin (*Sephardi*). These means are not shown in the table but are available from the authors, and provide additional indication that the students in the low *Magen* group are from more disadvantaged socio-economic backgrounds. This characterisation of the low *Magen* group will feature in our later discussion of potential mechanisms for our results, since the incidence of asthma is much higher among disadvantaged populations. Also note that Table 1 indicates that air pollution, temperature, and humidity do not vary by gender or *Magen* score. For example, the mean $PM_{2.5}$ AQI index for boys and girls is similar: 59.5 and 59.9, less than a tenth of a standard deviation. Similarly, the average $PM_{2.5}$ AQI index value for high and low *Magen* students are 60.1 and 59.5 respectively, and the mean temperature of the days of exams for both groups is 23.8. The balancing of our data on observables when stratified by these groupings by gender and by our measure of student quality is important in light of our findings that the effect of pollution is very different for these sub-populations. We discuss this further in the empirical section, but the similarity on observables is suggestive evidence that selection on unobservables is unlikely to be driving our results.

IV. Empirical Strategy

Our estimation strategy is relatively straightforward. We estimate OLS models where we examine the partial correlation between our air pollution measures and test scores outcomes. For identification, we crucially rely on the panel structure of the data and the repeated nature of the *Bagrut* exam. Since we observe the exact location of the test, we can include city or school fixed effects. Since we observe the students taking exams following each grade, we can include student fixed effects. Formally, the models we estimate are of the following form:

$$(1)\ R_{ist} = \beta_0 X_{it} + \beta_1 POL_{st} + \beta_2 Temp_{st} + \beta_3 RH_{st} + M_t + L_l + I_i + \varepsilon_{ist}$$

where R_{ist} is the test score of student *i* at school *s* at time *t*; X_{it} is a vector of individual characteristics possibly related to test outcomes, such as parental education[10]; POL_{st} is our measure of air pollution ($PM_{2.5}$ or CO) at school *s* at time *t*; $Temp_{st}$ is the mean temperature[11] at school *s* at time *t*; RH_{st} is the

[10] Our results with individual fixed effects exclude individual controls.

[11] In the empirical analysis, we include linear and quadratic terms in both temperature and humidity, and linear and quadratic interaction terms of the two variables.

relative humidity measure at school *s* at time *t*; M_t and L_l are month and exam proficiency level fixed effects respectively; I_i is our fixed effect for the individual; and e_{ist} is an idiosyncratic error term. Note that in different specifications we will use city or school fixed effects in place of our individual fixed effects.

The key identifying assumption for inferring a causal relationship between pollution and test scores estimated by equation (1) is that unobserved determinants of student's test scores are uncorrelated with ambient pollution. Without any fixed effects to absorb unobserved variation in schools or individuals, this assumption is likely violated since it is likely that pollution is correlated with time invariant features of a testing location or a particular student. For example, if poorer schools are located in more polluted parts of cities, OLS will likely overstate the causal link between pollution and test scores. Conversely, if schools in denser (and wealthier) cities have more pollution exposure, OLS might understate the true cost of pollution, as it is mitigated by other compensating factors (e.g. tutoring). More generally, endogenous sorting across schools, heterogeneity in avoidance behavior, or measurement error in assigning pollution exposure to individuals will all bias results that do not properly account for unobserved factors correlated with both our outcome of interest and ambient pollution (Moretti and Neidell 2011). In our setup, since we account for time invariant features of schools and students with fixed effects, the challenge relevant to our estimation is to account for omitted variables that are varying over time but are potentially correlated with pollution and *Bagrut* outcomes. For example, if weather or traffic the day of the exam is correlated with pollution, our fixed effects models will fail to identify the true effect. In our empirical analysis, we include controls for time-varying factors that could be contemporaneous with pollution, such as daily temperature and relative humidity, but of course it is untestable whether there are factors that are unobserved that are both correlated with pollution and *Bagrut* exam scores. As such, we conduct a rich set of robustness checks and placebo tests. These are discussed further in the next section.

V. Empirical Results

a. Main Results

In Table 2, we report our baseline results of the relationship between the Air Quality Indicator values for $PM_{2.5}$, CO, and *Bagrut* test scores. In columns (1) and (2) of Panel A, we report the correlation between *Bagrut* scores and a continuous measure of $PM_{2.5}$ (AQI) using OLS without city, school or student fixed effects. In column (1), we estimate that a 1 unit increase of $PM_{2.5}$ is associated with a 0.055 points decrease in a student's test score, significant at the 1% level. The results also indicate that a relatively small part of the variation in test scores (R-squared = 0.003) is explained by air pollution. This result indicates, as one would expect, that variables other than air pollution are responsible for the vast majority of the variation in test scores. In column (2) we report the results with the addition of controls for parental education, sex, temperature, relative humidity and dummies for the month of the exam and difficulty of the exam. The results are similar and slightly larger in magnitude, with our coefficient estimate indicating that a 1 unit increase in pollution is associated with a 0.065 decrease in a student's score. Note that the sample with controls is roughly 20% smaller, as we have incomplete demographic information for these individuals. The similarity of the results with and without controls, and with the smaller sample size, is suggestive that there is no strong correlation between observables and pollution. We also used the smaller sample to estimate the OLS regression without any controls and obtained estimates almost identical to those reported in column 1, which suggest the sample of students with some missing characteristics is not on average selectively different from the rest of the sample.

In columns (3)-(5) of Table 2, we take advantage of the panel structure of our data and include city, school, and student fixed effects, respectively. These account for variation in time-invariant unobserved heterogeneity that could be correlated with ambient pollution. The estimates from a regression with city or school fixed effects in columns (3) and (4), are somewhat larger, with estimated coefficients of -0.082 and -0.069 respectively. Adding student fixed effects weakens the results slightly, with our preferred estimate indicating that a 1 unit increase in $PM_{2.5}$ is associated with a 0.046 (sd=0.007) decline in the *Bagrut* score. This estimate implies that a test score in an exam on a day with average pollution (AQI=59.74) will be lowered relative to an exam taken on a day with the minimum pollution level (AQI=10.1) by 0.10 (.046*(59.7-10.1)/22.8) standard deviations. Our results for CO in columns (6-10) largely mirror our results in columns (1-5). Our results in column 10 indicate that a 1 unit increase in CO is associated with a 0.085 (sd=0.017) decline in the *Bagrut* score, significant at the 1 % level. Note however that since the Israeli monitoring system failed to collect CO readings at all stations during our sample period, our $PM_{2.5}$ analysis is based on a much larger sample.[12]

In Panel B, we perform a similar analysis but replace our continuous measure of pollution with a dichotomous indicator for whether the test occurred in a day classified as having "poor" air quality. The results are qualitatively similar to the results using the continuous measure for $PM_{2.5}$ but much larger for CO. Specifically, in our specification in column 5 where we include student fixed effects, the data indicate that having "poor" $PM_{2.5}$ air quality the day of the exam is associated with a 1.95 point decline in the student's *Bagrut* score, equivalent to 8.2% of a standard deviation. Our specification in column 10

[12] We investigated whether there was something systematic about which stations did not collect CO measures. We found no noticeable pattern in our data, though coverage for CO was much poorer in northern Israel and in the areas surrounding Haifa.

indicates that having "poor" CO air quality the day of the exam is associated with a 10.16 point decline in the student's *Bagrut* score, equivalent to 42.8% of a standard deviation.[13]

The effect of $PM_{2.5}$ on *Bagrut* scores for the 99^{th} percentile of exposure in our sample (AQI=137) is very large and implies a decline of roughly a sixth (.149) of a standard deviation relative to an average day. This effect is similar to the estimated effect of reducing class size from 31 to 25 students (Angrist and Lavy, 1999) and larger than the test scores gains associated with paying teachers large financial bonuses based on their students' test scores (Lavy, 2009). Unfortunately, days with elevated levels of particulate matter are not unusual in Israel and in neighboring countries in the Middle East, as they are often the result of sandstorms that originate in the Sahara desert and are relatively common in the spring and summer months, with serious health effects (Bell et al. 2008). For CO, our results similarly suggest a large response of students to very poor days. The 99^{th} percentile of CO, AQI=56, would imply a similar decline of .158 standard deviations relative to a day with average levels of CO. Since Israel's CO level is actually quite similar to the levels found in other large cities, such as Los Angeles, CA,[14] and may indicate that these results may affect student performance in polluted areas of these cities as well.

In light of the fact that $PM_{2.5}$ and CO are only weakly correlated, these results suggest a robust relationship between different air pollution measures and test scores, as two largely independent pollution measures are associated with appreciable declines in test scores. To explore the role of each pollutant further, in Table A2 we estimate models where both pollutants are included simultaneously. The results indicate that our dichotomous measure of each pollutant's impact is extremely robust to simultaneous estimation, and the continuous measure for CO is almost unchanged by the inclusion of $PM_{2.5}$. However, our continuous measure of $PM_{2.5}$ is weakened by inclusion of CO in models with student fixed effects. This may be because our sample for $PM_{2.5}$ is more than twice as large as our sample for CO, and partly due to a weak residual correlation with CO.

In Table 3, we report results where we examine whether pollution has a non-linear impact on test takers using specifications where we include dummy variables for clean, moderately polluted, or very polluted days.[15] For $PM_{2.5,}$ we define moderately polluted days as days where the AQI score ranges from 51-100 (which the EPA defines as moderate pollution) and AQI scores above 101 (which the EPA defines as unhealthy for sensitive groups) as poor or very polluted days (see Table A1). Since our CO scores are consistently lower than our $PM_{2.5}$ scores (a mean score of 13 versus a mean score of 59 for $PM_{2.5}$), we define moderately polluted days as days above the median pollution level and below the top 5% of the

[13] It is also worth noting that the CO results for our threshold measure of pollution may be affected by several *extremely* polluted exam administrations. In the highest CO reading, students were subjected to AQI=270, roughly twenty times the average reading.

[14] http://www.usa.com/los-angeles-ca-air-quality.htm

[15] It is worth noting that students cannot reschedule their examination, and so avoidance behavior in response to high pollution on the day of the *Bagrut* is unlikely to be common.

most polluted days, and very polluted days as the top 5% of the sample's CO readings. Column 5 indicates that having poor air quality from $PM_{2.5}$ exposure the day of the exam is associated with a 2.89 point decline in the student's *Bagrut* score, which is more than double the size of the coefficient for moderately polluted days. Similarly, Column 10 indicates that having "poor" CO air quality the day of the exam is associated with a 10.89 point decline in the student's *Bagrut* score, which is more than ten times the size of the coefficient for moderately polluted days. These results indicate that our results are largely driven by poor performance of test takers on very polluted days, suggesting that pollution's impact on cognitive performance is mostly relevant on days with very poor air quality.

b. Placebo Tests

In this section, we perform a set of placebo tests where we examine the relationship between air pollution on days *other than* the actual exam and exam scores. In Table 4, we examine whether there is a correlation between pollution from the day of the previous *Bagrut* and the score on the exam. Note that since students take the *Bagrut* exams over a short period of time, this will generally be a pollution reading taken from several days prior. As shown in Panel A of Table 4, the correlation between *Bagrut* outcomes is weak relative to the correlation with the actual exam. While some of the specifications are statistically significant, our preferred specification with student fixed effects are either statistically insignificant, or with the wrong sign. For example, in our estimates using our threshold measure with student fixed effects, the impact of $PM_{2.5}$ during the previous exam is a .78 point *increase* in the student's score, and the result is not statistically significant. This can be compared to our main result using the $PM_{2.5}$ reading from the day of the *Bagrut*, where poor air quality reduces scores by 1.9 points (significant at the 1% level). For our dichotomous measure of CO, the results are also reassuring: after including school or student fixed effects, no significant relationship between the placebo pollution reading and the exam score is observed.

In Panel B, we perform a similar exercise but using the air pollution on the date exactly one year before the exam. For the continuous measure of pollution, column 5 indicates a negative and statistically insignificant relationship between $PM_{2.5}$ and test scores, while column 10 indicates a *positive* and statistically significant relationship between CO and test scores. For our dichotomous measure of pollution, we observe a correlation between exams and $PM_{2.5}$ in the previous year when we include no fixed effects: having a day classified as polluted in the previous year is associated with a 2.8 point decline in scores in models with controls, even though there should be no relationship. This underscores the importance of including fixed effects to absorb a time-invariant correlation between pollution and student quality, and suggests that more polluted areas have lower exam scores in general. Once we include student fixed effects in our models, the correlation between $PM_{2.5}$ from the previous year and the *Bagrut* score declines to 1.15 points, and it is only marginally significant. For the dichotomous measure of CO, the results for the previous year's reading are counter-intuitive: we find a *positive* correlation between pollution levels from the previous year and exam scores. While this result is surprising, it suggests that our CO results may be less stable than our $PM_{2.5}$ results due to a smaller sample size and more extreme values for pollution. The results for CO, therefore, should be interpreted with greater caution.

In Figure 2, we examine the impact of $PM_{2.5}$ and CO from three days prior to the exam, the day of the exam, and three days following the exam on test scores. As shown in the figure, the main effects of $PM_{2.5}$ are concentrated on the day of the exam, and no significant relationship between pollution readings and the exam score is observed for days before and after the exam. The figure indicates that the coefficient on pollution *the day of* the exam is much larger and more negative than the other days: an additional 100 units of AQI is associated with a 0.2 point decrease in student scores, and the coefficient estimates are small and positive on the days before and after the exam. In contrast, the results for CO are less conclusive, with somewhat larger negative coefficients for the day of the exam relative to the days before and after. As such, our results for CO should be interpreted with greater caution.

In Table 5, we exploit the fact that we know the exact time of day that the examination was administered, and consider whether our pollutants have different effects at different times of day.[16] While the majority of our sample is given a 9AM examination time, roughly 40% of examinations are given after 12PM. **W**e posit that fine particulate matter, which is generated from sandstorms and coal-burning plants, will affect students throughout the day in a similar manner at all hours of the day (or night). Carbon monoxide is produced primarily by automobile emissions, and is likely to be more relevant for exams later in the day. As shown in the table, our coefficient estimates for $PM_{2.5}$ are relatively similar for both afternoon and morning examinations. In our preferred student fixed effect specification, we find that having poor air quality from our $PM_{2.5}$ exposure measure for an afternoon exam is associated with a .045 point and .054 point decline per unit of AQI respectively. Likewise, our results using the dichotomous measure are similar; we observe a 3.16 point decline in the student's *Bagrut* score for days with very high AQI in afternoon exams, which is about 20% larger than the coefficient for morning exams. For CO, our estimates are much larger for afternoon exams using both the continuous and dichotomous measures.[17] For example, using the dichotomous measure, having poor CO air quality for afternoon exams is associated with a 10.45 point decline in the student's *Bagrut* score, which is almost ten times the size of the coefficient for morning exams. The results are consistent with a prior that carbon monoxide exposure should be more problematic later in the day, and the results for particulate matter will be similar at different times.

[16] As an additional robustness check, we also estimate our main models with fixed effects for the day of the week on which the exam is given. The results are largely unchanged, and available upon request.
[17] Note that since we have fewer observed tests for each student, our results using student fixed effects will be less stable.

c. Heterogeneity and Implied Mechanisms

In this section, we examine heterogeneity in the treatment effects reported in Table 2. Our interest is twofold. First, we wish to identify whether there are sub-populations that may be particularly responsive to poor air quality. Second, this may help to identify mechanisms for the observed reduced form relationship between air pollution and cognition. In particular, our prior is that $PM_{2.5}$ which affects the respiratory system will have a larger impact on weaker groups who are more sensitive to poor air quality. In contrast, we expect that CO, which affects the tissues and neurological system, to have a more similar impact across different groups.

We build on a set of stylized facts regarding who would be most sensitive to poor air quality from the medical literature. First, Israeli boys are more likely to be asthmatic than Israeli girls. As shown by Laor et al. (1993) military records from the cohorts born in our sample, the rate of asthma incidence was 25 percent higher among the boys. Second, children of lower economic status are known to have higher rates of asthma and respiratory illnesses (Eriksson et al. 2006, Basagana et al. 2004). Third, Laor et al. (1993) also found that *Ashkenazic* Jews (ethnic origin from America and Europe) have 63% higher incidence of these illnesses than *Sephardim* (ethnic origin from Africa and Asia). This gives a rich set of potential comparisons for gauging whether asthma is a mechanism for the observed reduced form relationship between pollution and exam outcomes.

In Table 6, we examine our results separately by gender. The results highlight that men are significantly more likely to have their test outcomes affected by $PM_{2.5}$ than women. Our results indicate that treatment effects among men are between 2 and 4 times larger than among women. For example, in models with student fixed effects, we estimate that an additional 10 units of $PM_{2.5}$ (AQI) is associated with a .078 point decline among men and a .021 decline among women. We posit that the difference could be generated by the different asthma rates in these cohorts. Another possibility is that male students are more likely to be affected by small cognitive decline and distraction, consistent with higher rates of Attention Deficit Disorder in males (Biederman et al. 2002). In contrast, the results for CO are largely similar for men and women, with the results for men being moderately larger. For instance, in our model with student fixed effects, we estimate that an additional 10 units of CO (AQI) is associated with a .099 point decline among men and a .075 decline among women.

In Table 7, we break down our sample of test takers by our ex-ante expectation of their performance. This is proxied by their *Magen* score, which is a reasonable measure of student quality as it reflects their achievement in the full-year class and on a test similar to the *Bagrut*, and is correlated with family income and other measures of wellbeing because it is highly correlated with parental schooling, family size and ethnic origin. It may be that poorer families are more affected by air pollution as well, due to lower ability to engage in compensating behavior (Neidell 2004). Poorer children also have higher incidence of asthma (Basagana et al. 2004, Eriksson et al. 2006). When we stratify the students by whether their *Magen* score is above or below the median, our estimated treatment effects for $PM_{2.5}$ are more than two times larger among those classified as low quality. For a low quality student, we estimate that a 10 unit increase in $PM_{2.5}$ (AQI) is associated with a .061 point decline versus only a .028 point impact among higher quality students. However, we see no large difference between the responsiveness of higher and lower quality students to CO when using the continuous measure for AQI. This is consistent with our earlier results that CO's effect may be less heterogeneous. However, when using our dichotomous measure of pollution, both $PM_{2.5}$ and CO have larger effects on weaker students.

The results by student quality are investigated further in Table 8, which reveals that when the sample is stratified into quartiles, there is a monotonic relationship between treatment effects and our student quality measure for $PM_{2.5}$. Specifically, using our continuous measure of $PM_{2.5}$, we find that poor air quality lowers scores by 0.08 and 0.04 points in the lowest and the second-lowest quartile respectively. For the two quartiles above the median, the treatment effect is -0.03 and -0.02 respectively, neither of which is statistically significant. This suggests that student vulnerability is rising sharply with respect to student quality and may reflect the correlation between the incidence of asthma and socio-economic status. In contrast, the relationship between CO and test scores among the stratified sample is more mixed and the monotonic relationship is not evident for the continuous measure. Again, for the dichotomous measure of CO, the result is monotonic, leaving the results mixed regarding distinguishing between $PM_{2.5}$ and CO on this dimension. The results do, however, consistently point to large effects of both pollutants on student outcomes.

In Table 9, we exploit the unique ethnic heterogeneity of Israel to estimate models for sub-populations. Israel's population is composed primarily of Jews and Arabs, and the Jewish population is composed of immigrants from ethnically distinct source countries. The primary distinction is between *Sephardic* Jews of Middle Eastern and North African origin, and *Ashkenazic* Jews who are from Eastern Europe and Russia. The former group has lower rates of asthma and respiratory conditions (Laor et al. 1993). We find that the impact of air pollution is larger among *Ashkenazic* Jews relative to *Sephardic* Jews using both our measures of $PM_{2.5}$ and CO. For example, *Ashkenazic* Jews are a third more responsive to $PM_{2.5}$ (.046/.035) and almost twice as responsive using our dichotomous measure of $PM_{2.5}$ (1.73/1.01). For CO, however, the results are similar across groups, with *Ashkenazic* Jews being slightly *less* responsive than *Sephardic* Jews for both our continuous (.056/.61) and our dichotomous measure (8.28/10.56).

d. Impact of Particulate Matter on Academic Outcomes with Long-run Implications

While our analysis focuses on the impact of short-term exposure to particulate matter on cognition, in our context this can have a large effect on academic success in the long-run. Success on the *Bagrut* exam facilitates entry in to university, and higher scores allow a student to choose more lucrative college majors, such as medicine or computer science. To assess directly the potential harmful long-term effect of pollution on human capital formation in our context, we examine in Tables 10, 11, and 12 the relationship between exposure to air pollution and academic outcomes related to *Bagrut* exams.

In Table 10 Panel A, we examine the relationship between air pollution exposure and the probability of failing a particular *Bagrut* exam. In Panels B and C, we carry out the analysis at the student level. For these results, our new measure of pollution is the average pollution reading across *all* exams the students has taken. Our continuous measure of pollution is the average over all the exam days, and our threshold measure is the average over all days of whether the exam was administered on a day with pollution in the top 5% of most polluted days. As such, the coefficients will represent the impact of raising pollution on all days for the continuous measure, or increasing the fraction of exams taken during very polluted days from 0% to 100% for the threshold measure. As we will show, the results indicate that having poor $PM_{2.5}$ or CO on the days of the *Bagrut* exams is associated with a lower *Bagrut* composite score and lower probability of receiving the matriculation certificate. These outcomes can have a permanent impact on an individual's probability of attending college, and the majors that are available upon matriculation.

As shown in Panel A, in our preferred specification with student fixed effects, having elevated levels of $PM_{2.5}$ or CO using the continuous measure have a statistically insignificant effect. However, for the threshold measure, both indicate a large decline in a student's probability of passing the exam on very polluted days: a student is 2.4 and 12.3 percentage points less likely to pass an exam on very polluted days relative to a normal day. In Panel B, the estimated effect of $PM_{2.5}$ is negative and significant, and in our preferred specification, which includes school fixed effects, we estimate that an additional 10 units of AQI on average for each test would lead to a decline in the student's average score of 1.66 points, roughly 9.8% of a standard deviation. Similarly, increasing the fraction of days with high $PM_{2.5}$ readings by 10% reduces the average score by .96 points. A student's probability of passing the *Bagrut* is also sensitive to these measures. A 10 point increase in $PM_{2.5}$ AQI reduces a student's probability of receiving the *Bagrut* certificate by 3.3 percentage points, and increasing the fraction of days with very pollution readings by 10% reduces certificate achievement by 1.5 percentage points. Our estimates for CO are somewhat more modest: a 10 unit increase in the AQI average reading during the student's tests reduces scores by .86 points, and a 10% increase in the share of days with high pollution readings reduces scores by .75 points. Similarly, a 10 point increase in CO AQI reduces a student's probability of receiving the *Bagrut* certificate by 0.5 percentage points, and the result is not statistically significant. Finally, increasing the fraction of days with very pollution readings by 10% reduces certificate achievement by 1.4 percentage points. This suggests that CO only affects long-run outcomes among students who are exposed to extremely elevated levels of CO, and that more modest levels may have an extremely small impact.

In Table 11, we examine these results broken down by two sub-populations that may be more sensitive to air pollution: boys and students of lower quality. The results indicate that boys are more sensitive to $PM_{2.5}$ than girls, and lower quality students are more likely to be detrimentally affected than stronger students. In particular, raising the fraction of days with very polluted air by 10 percentage points is associated with a .57 percentage point increase for boys in the chance of failing a particular *Bagrut* in models with student fixed effects. Girls appear largely unaffected, with the increased chance of not passing being statistically indistinguishable from zero. The gap is even more striking for student with low *Magen* scores: a 10 percentage point increase in the fraction of days with very polluted air is associated with a .59 percentage point increase in failure probability. The second outcome we examine is the student's probability of failing the composite *Bagrut*. Boys are nearly a third more sensitive to air pollution by this measure, where a 10 percentage point increase in polluted days is associated with a 1.74 percentage point increased chance of not receiving their matriculation certificate, whereas girls only experience a 1.19 percentage point increase. The results are even more striking for low scoring *Magen* students, who are 1.07 percentage points more likely to not receive a *Bagrut* certificate for a 10 percentage point increase in the share of days with poor air quality.

In Table 12, we present results parallel to those shown in Table 11 but for CO rather than $PM_{2.5}$. While the results for our continuous measure are statistically insignificant, the results for our threshold measure are negative and statistically significant. Interestingly, we find very similar results for boys and girls in their probability of failing the *Bagrut* exam or not receiving a matriculation certificate. For instance, a 10 percentage point increase in days above the CO threshold is associated with a 1.42 percentage point increased chance of not receiving their matriculation certificate for boys, and girls experience a similar 1.44 percentage point increase. The results are also similar for low scoring *Magen* students, who are 1.02 percentage points more likely to not receive a matriculation certificate for a 10 percentage point increase in the share of days with poor air quality, versus a 1.24 increase for high scoring *Magen* students. This suggests that the long-run effects of CO are similar across different groups.

VI. Conclusions

This paper has examined the relationship between cognitive performance and ambient pollution exposure. Using a large sample of Israeli high-school *Bagrut* examinations (2000-2002), we have presented evidence that there is a robust negative relationship between outcomes and ambient pollution concentrations. We also find that among Israeli sub-populations with higher rates of asthma and respiratory illnesses, our estimated treatment effects for $PM_{2.5}$ are larger, suggesting that physiological impairment is a potential mechanism for our findings. In contrast, our results for CO are largely consistent among Israeli sub-populations, suggesting that neurological impairment may be a mechanism for our findings. The measured impact of our pollutants may have a permanent effect on a student's human capital formation, because it affects whether the student earns the *Bagrut* in a timely fashion and can matriculate in college following the army, or must complete additional coursework prior to starting college, delaying matriculation. In the overall economy, the mis-ranking of students due to variability in pollution exposure may result in bad assignment of workers to different occupations, resulting in reduced labor productivity.

While our results are robust to a variety of specification checks, it is worth noting several important caveats. First, our result is in a completely reduced form and we cannot trace out the pathways. While we posit that asthmatics and other sensitive groups are driving our results for $PM_{2.5}$, this is difficult to determine definitively in the absence of health measures for the test takers. Second, we cannot fully examine whether the effect is due to pollution only on the day of the exam, versus through a build-up effect from the days prior to the exam. We report the relationship between the exam outcome and ambient pollution, but we are unable with our data to fully disentangle the exact timing of the effect. Third, it may be that increased pollution is contemporaneous with other factors affecting test outcomes. For example, it is possible that traffic on the way to the exam is correlated with pollution and with reduced test performance. In spite of these limitations, our results present new evidence of a connection between reduced cognitive performance and fine particulate matter or carbon monoxide exposure.

The results presented here suggest that the gain from improving air quality may be underestimated by a narrow focus on health impacts. Insofar as air pollution may lead to reduced cognitive performance, the consequences of pollution may be relevant for a variety of everyday activities that require mental acuity. Traffic accidents, injuries in the workplace, and reduced worker productivity may all be the byproduct of reduced cognitive performance. As such, the results presented here highlight a channel by which the consequences of pollution are vastly understated by a narrow focus on the immediate and acute health consequences, and suggest that improvements in air quality may yield tremendous benefits in welfare.

References

Angrist, J. and Lavy, V. 1999. “Using Maimonides’ Rule to Estimate the Effect of Class Size on Scholastic Achievement.” *Quarterly Journal of Economics*, 114(2), 533–575.

Basagaña, Xavier, Sunyer, Jordi, Kogevinas, Manolis, Zock, Jan-Paul, Duran-Tauleria, Enric, Jarvis, Deborah, Burney, Peter and Josep Maria Anto. 2004. “Socioeconomic status and asthma prevalence in young adults: the European Community Respiratory Health Survey.” *American Journal of Epidemiology*, 160: 178–188.

Bell, Michelle, JK, Lin Z. 2008. “The effect of sandstorms and air pollution on cause-specific hospital admissions in Taipei, Taiwan.” *Occupational and Environmental Medicine*, 65: 104-111.

Biederman, Joseph, Mick, Eric, Faraone, Stephen, Braaten, Ellen, Doyle, Alysa, Spencer, Thomas, Wilens, Timothy, Frazier, Elizabeth, and Mary Ann Johnson. 2002. "Influence of Gender on Attention Deficit Hyperactivity Disorder in Children Referred to a Psychiatric Clinic." *The American Journal of Psychiatry*, 159: 36–42.

Braniš, Martin, Řezáčová, Pavla, and Markéta Domasová. 2005. "The effect of outdoor air and indoor human activity on mass concentrations of PM10, PM2.5, and PM1 in a classroom." *Environmental Research*, 99(2): 143–149.

Brown P. 1995. “Race, class, and environmental health: a review and systematization of the literature.” *Environmental Research*, 69: 15–30.

Calderón-Garcidueñas, L., Mora-Tiscareño, A., Ontiveros, E., Gómez-Garza, G., Barragán-Mejía, G., Broadway, J., Chapman, S., Valencia-Salazar, G., Jewells, V., Maronpot, RR., Henríquez-Roldán, C., Pérez-Guillé, B., Torres-Jardón, R., Herrit, L., Brooks, D., Osnaya-Brizuela, N., Monroy, M., González-Maciel, A., Reynoso-Robles, R., Villarreal-Calderon, R., Solt. A., and R. Engle. 2008. "Air pollution, cognitive deficits and brain abnormalities: a pilot study with children and dogs." *Brain and Cognition*, 68(2): 117-127.

Chay, Kenneth Y, Michael Greenstone. 2003. “The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession.” *Quarterly Journal of Economics*, 118(3): 1121-1167.

Chay, Kenneth Y, Michael Greenstone. 2005. “Does Air Quality Matter? Evidence from the Housing Market.” *Journal of Political Economy*, 113(2):376-424.

Clark, D. and L. Sokoloff. 1999. "Circulation and energy metabolism of the brain," in G. Siegel, B. Agranoff, R. Albers, S. Fisher and M. Uhler, eds., *Basic Neurochemistry. Molecular, Cellular and Medical Aspects*, Lippincott-Raven, pp. 637–670.

Currie, J., Neidell M., and J. Schmieder. 2009. "Air pollution and infant health: Lessons from New Jersey." *Journal of Health Economics*, 28: 688-703.

Dockery, W., and C. Pope. 1996. “Epidemiology of Acute Health Effects: Summary of Time Series Studies.” in R. Wilson and J. Spengler, eds., *Particles in Our Air*, Harvard University Press, 123-148.

Eriksson K., Hedlund U., and E. Ronmark. 2006. "Socio-economic status is related to incidence of asthma and respiratory symptoms in adults." *European Respiratory Journal*, 28(2): 303-310.

Graff Zivin, Joshua S. and Matthew J. Neidell. 2011. "The Impact of Pollution on Worker Productivity." NBER Working Paper #17004.

Ham, John C., Zweig, Jacqueline S. and Edward Avol. 2011. “Pollution, Test Scores and the Distribution of Academic Achievement: Evidence from California Schools 2002-2008.” IZA Working Paper.

Kampa, M., and E. Castanas. 2007. "Human health effects of air pollution." *Environmental Pollution*, 151: 362-367.

Laor, A., Cohen, L., and Y Danon. 1993. "Effects of time, sex, ethnic origin, and area of residence on prevalence of asthma in Israeli adolescents." *British Medical Journal*, 307(6908): 841-844.

Lavy, Victor. 2002. “Evaluating the Effect of Group Teachers’ Performance Incentives on Pupils’ Achievements.” *Journal of Political Economy*, 110(6): 1286-1317.

Lavy, Victor. 2009. “Performance Pay and Teachers’ Effort, Productivity and Grading Ethics”, *American Economic Review*, 99(5): 1979-2011.

Moretti, Enrico and Matthew Neidell. 2011. "Pollution, Health, and Avoidance Behavior Evidence from the Ports of Los Angeles." *The Journal of Human Resources*, 46(1): 154-175.

Neidell, Matthew. 2004. "Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma." *Journal of Health Economics*, 23: 1209–1236.

Oliva, P., and R. Hanna. 2011. "The Effect of Pollution on Labor Supply: Evidence from a Natural Experiment in Mexico City." NBER Working Paper #17302.

Piantadosi, C. A. 2002. "Carbon Monoxide Poisoning." *The New England Journal of Medicine*, 347(14): 1054-1055.

Pope, C. III, Bates, D., and M. Raizenne. 1995. "Health Effects of Particulate Air Pollution: Time for Reassessment?" *Environmental Health Perspectives*, 103: 472-480.

Pope, C. III, and D. Dockery. 2006. "Critical Review–Health effects of fine particulate air pollution: Lines that connect." *Journal of the Air and Waste Management Association,* 56: 709-742.

Pope, C. III, Ezzati, M., and D. Dockery. 2009. "Fine-particulate air pollution and life expectancy in the United States." *New England Journal of Medicine,* 360: 376-386.

Suglia, S., Gryparis, A., Wright, R., Schwartz, J., and R. Wright. 2008. "Association of black carbon with cognition among children in a prospective birth cohort study." *American Journal of Epidemiology*, 167(3): 280-286.

Schlenker, Wolfram and W. Reed Walker. 2011. "Airports, Air Pollution, and Contemporaneous Health." NBER Working Paper #17684.

Wang, S., Zhang, J., Zeng, X., Zeng. Y., Wang, S., and S. Chen. 2009. "Association of Traffic-Related Air Pollution with Children’s Neurobehavioral Functions in Quanzhou, China." *Environmental Health Perspectives*, 117(10): 1612-1618.

Table 1

Descriptive Statistics

Variable	All (1)	By Sex: Boys (2)	By Sex: Girls (3)	By *Magen* Score (Course Grade[1]): Low Scores (4)	By *Magen* Score (Course Grade[1]): High Scores (5)
$PM_{2.5}$	21.05	20.89	21.18	21.15	20.96
(μg/m^3)	(10.86)	(10.57)	(11.10)	(10.88)	(10.87)
$PM_{2.5}$	59.74	59.47	59.98	60.01	59.51
(AQI Index)	(22.81)	(22.50)	(23.08)	(22.89)	(22.75)
$PM_{2.5}$	0.05	0.05	0.05	0.05	0.05
(AQI ≥101)	(0.21)	(0.21)	(0.22)	(0.22)	(0.21)
CO	1.21	1.22	1.21	1.25	1.17
(μg/m^3)	(1.05)	(1.08)	(1.02)	(1.15)	(0.92)
CO	13.77	13.81	13.73	14.19	13.29
(AQI Index)	(11.58)	(11.93)	(11.27)	(12.80)	(10.18)
CO	0.04	0.04	0.04	0.04	0.03
(>95th percentile)	(0.20)	(0.20)	(0.20)	(0.21)	(0.18)
Bagrut Exam Score	70.76	68.91	72.33	53.22	77.10
(1-100 points)	(23.74)	(24.86)	(22.64)	(30.69)	(22.18)
Magen Score	75.45	73.27	77.30	64.09	86.93
(1-100 points)	(21.37)	(22.50)	(20.19)	(23.25)	(10.47)
Bagrut Composite	83.03	81.37	84.49	73.18	95.05
Score	(16.84)	(17.48)	(16.11)	(14.59)	(10.33)
Matriculation	0.68	0.64	0.71	0.48	0.91
Certificate (1=yes)	(0.47)	(0.48)	(0.45)	(0.50)	(0.28)
Failed a *Bagrut* Exam	0.19	0.21	0.17	0.33	0.04
(1=yes)	(0.39)	(0.41)	(0.37)	(0.47)	(0.19)
Mother's Education	11.44	11.60	11.30	10.79	12.08
(years)	(5.04)	(5.09)	(5.00)	(4.87)	(5.13)
Father's Education	11.62	11.83	11.44	10.85	12.39
(years)	(5.03)	(5.02)	(5.03)	(4.84)	(5.10)
Temperature	23.81	23.81	23.82	23.84	23.83
(celsius)	(2.61)	(2.61)	(2.62)	(2.66)	(2.50)
Relative Humidity	50.90	50.86	50.94	50.98	50.95
(percent saturation)	(14.71)	(14.52)	(14.87)	(15.08)	(14.35)
Observations	415,219	190,410	224,809	206,571	204,527

Notes: Standard deviations are in parentheses. The measures of pollution are particulate matter smaller than 2.5 microns, or $PM_{2.5}$, and carbon monoxide, CO. We also report the AQI value for each reading, which is calculated from a formula that converts micrograms (μg/m3) into a 1-500 index value. We also report dummies for days with $PM_{2.5}$ (AQI) >100 or CO readings in the top 5% of days in our sample. Relative humidity is the amount of moisture in the air as a share of what the air can hold at that temperature. Receiving a Matriculation Certificate is determined by a combination of the average Bagrut score across exams, and the Magen score, which is composed of the student's course grade and an exam similar in content to the Bagrut. [1]The low and high subsamples were based on being above or below the median of the Magen score.

Table 2

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

	RHS Pollutant Measure: Particulate Matter$_{2.5}$					RHS Pollutant Measure: Carbon Monoxide				
	Pooled OLS		Fixed Effects			Pooled OLS		Fixed Effects		
	No Controls (1)	Controls (2)	City (3)	School (4)	Student (5)	No Controls (6)	Controls (7)	City (8)	School (9)	Student (10)
Panel A: Air Quality Index (continuous measure)										
Pollutant	-0.055	-0.065	-0.082	-0.069	-0.046	-0.047	-0.054	-0.133	-0.083	-0.085
	(0.015)	(0.011)	(0.008)	(0.007)	(0.007)	(0.017)	(0.020)	(0.018)	(0.017)	(0.017)
Female (1=yes)		3.22	3.30	2.72			3.82	3.88	3.15	
		(0.34)	(0.34)	(0.22)			(0.50)	(0.50)	(0.38)	
Mother's Education		0.165	0.141	0.112			0.182	0.191	0.113	
		(0.063)	(0.062)	(0.034)			(0.097)	(0.093)	(0.057)	
Father's Education		0.410	0.396	0.241			0.451	0.463	0.251	
		(0.061)	(0.058)	(0.033)			(0.095)	(0.090)	(0.050)	
R-squared	0.003	0.042	0.046	0.145	0.493	0.001	0.054	0.060	0.174	0.531
Observations	415,219	380,435	380,435	380,435	380,435	158,647	153,528	153,528	153,528	153,528
Panel B: Air Quality Index above Threshold Value										
Dummy for AQI>100[1]	-3.00	-2.63	-2.75	-2.68	-1.95	-6.04	-6.68	-9.16	-9.56	-10.16
	(1.54)	(1.03)	(0.84)	(0.70)	(0.74)	(1.15)	(1.31)	(1.28)	(0.96)	(1.02)
Female (1=yes)		3.19	3.25	2.68			3.84	3.91	3.19	
		(0.340)	(0.337)	(0.219)			(0.498)	(0.496)	(0.377)	
Mother's Education		0.158	0.143	0.111			0.185	0.192	0.117	
		(0.064)	(0.063)	(0.035)			(0.096)	(0.092)	(0.055)	
Father's Education		0.409	0.396	0.241			0.452	0.465	0.252	
		(0.061)	(0.058)	(0.033)			(0.094)	(0.090)	(0.048)	
R-squared	0.001	0.040	0.043	0.143	0.492	0.002	0.056	0.062	0.177	0.534
Observations	415,219	380,435	380,435	380,435	380,435	158,647	153,528	153,528	153,528	153,528

Notes: Standard errors are clustered by school. All regressions include suppressed controls for temperature and humidity on the exam date, which are included as linear and quadratic terms in each, and linear and quadratic interaction terms of the two variables. [1]For carbon monoxide, we generate a dummy for a test occurring on a day in the top 5% of most polluted days.

Table 3

Air Pollution's Impact on *Bagrut* Test Scores on Polluted and Extremely Polluted Days

	RHS Pollutant Measure: Particulate Matter$_{2.5}$					RHS Pollutant Measure: Carbon Monoxide				
	Pooled OLS		Fixed Effects			Pooled OLS		Fixed Effects		
	No Controls (1)	Controls (2)	City (3)	School (4)	Student (5)	No Controls (6)	Controls (7)	City (8)	School (9)	Student (10)
Dummy for AQI >50 & < 101[1]	-2.32	-2.29	-3.02	-2.41	-1.43	0.56	-1.92	-1.26	-1.36	-0.72
	(0.50)	(0.42)	(0.31)	(0.29)	(0.33)	(0.71)	(0.75)	(0.67)	(0.60)	(0.66)
Dummy for AQI ≥ 101	-4.42	-4.07	-4.92	-4.34	-2.89	-5.76	-8.56	-10.39	-10.88	-10.87
	(1.61)	(1.10)	(0.87)	(0.73)	(0.78)	(1.27)	(1.55)	(1.42)	(1.14)	(1.19)
Female (1=yes)		3.20	3.27	2.70			3.86	3.92	3.20	
		(0.339)	(0.335)	(0.217)			(0.498)	(0.497)	(0.378)	
Mother's Education		0.166	0.142	0.112			0.180	0.190	0.114	
		(0.064)	(0.063)	(0.035)			(0.096)	(0.092)	(0.055)	
Father's Education		0.411	0.395	0.241			0.455	0.466	0.252	
		(0.061)	(0.058)	(0.034)			(0.095)	(0.090)	(0.049)	
R-squared	0.003	0.041	0.046	0.145	0.493	0.003	0.056	0.063	0.178	0.534
Observations	415,219	380,435	380,435	380,435	380,435	158,647	153,528	153,528	153,528	153,528

Notes : See Table 2. [1]For carbon monoxide we generate a dummy for a test occurring on a day above the median pollution level and below the top 5% of the most polluted days as the intermediate pollution category.

Table 4

Placebo Tests Measuring the Relationship between the *Bagrut* and Pollutants on Irrelevant Days

	RHS Pollutant Measure: Particulate Matter$_{2.5}$					RHS Pollutant Measure: Carbon Monoxide				
	Pooled OLS		Fixed Effects			Pooled OLS		Fixed Effects		
	No Controls (1)	Controls (2)	City (3)	School (4)	Student (5)	No Controls (6)	Controls (7)	City (8)	School (9)	Student (10)
Panel A: Pollutant Level from Previous Exam										
Pollutant (AQI)	-0.024	-0.035	-0.049	-0.034	-0.005	-0.128	-0.130	-0.307	-0.080	0.097
	(0.013)	(0.010)	(0.007)	(0.006)	(0.006)	(0.065)	(0.074)	(0.164)	(0.079)	(0.055)
Pollutant (Threshold)	-1.10	-0.48	-0.66	-0.29	0.78	-3.61	-1.48	-5.68	1.48	-2.53
	(1.37)	(0.87)	(0.78)	(0.68)	(0.71)	(2.29)	(2.85)	(3.09)	(2.82)	(3.06)
Observations	358,584	328,974	328,974	328,974	328,974	131,579	127,341	127,341	127,341	127,341
Panel B: Pollutant Level from Previous Year										
Pollutant (AQI)	-0.008	-0.033	-0.027	-0.014	-0.006	-0.032	-0.060	0.061	0.063	0.147
	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.017)	(0.038)	(0.029)	(0.023)	(0.048)
Pollutant (Threshold)	-2.78	-2.89	-1.03	-0.75	-1.15	0.98	2.38	3.87	4.90	5.55
	(0.81)	(0.68)	(0.76)	(0.73)	(0.69)	(1.06)	(0.76)	(0.74)	(0.70)	(0.81)
Observations	261,091	248,759	248,759	248,759	248,759	291,555	193,764	193,764	193,764	193,764

Notes : See Table 2.

Table 5

Pooled OLS and Fixed Effect Models of Pollutant Matter on Afternoon and Morning Test Scores

	RHS Pollutant Measure: Particulate Matter$_{2.5}$					RHS Pollutant Measure: Carbon Monoxide				
	Pooled OLS		Fixed Effects			Pooled OLS		Fixed Effects		
	No Controls (1)	Controls (2)	City (3)	School (4)	Student (5)	No Controls (6)	Controls (7)	City (8)	School (9)	Student (10)
Panel A: Afternoon Examinations										
Pollutant (AQI)	-0.019	-0.079	-0.116	-0.082	-0.045	-0.099	-0.079	-0.183	-0.152	-0.135
	(0.017)	(0.015)	(0.013)	(0.010)	(0.013)	(0.024)	(0.014)	(0.022)	(0.015)	(0.020)
Pollutant (Threshold)	-2.94	-3.11	-3.04	-2.56	-3.16	-8.82	-7.77	-9.24	-9.89	-10.45
	(2.11)	(2.01)	(1.95)	(1.35)	(1.42)	(1.23)	(1.22)	(1.29)	(1.10)	(1.31)
Observations	162,912	148,026	148,026	148,026	148,026	68,161	65,984	65,984	65,984	65,984
Panel B: Morning Examinations										
Pollutant (AQI)	-0.074	-0.067	-0.074	-0.066	-0.054	0.017	0.007	0.086	0.130	0.239
	(0.016)	(0.013)	(0.009)	(0.008)	(0.010)	(0.026)	(0.046)	(0.069)	(0.034)	(0.083)
Pollutant (Threshold)	-2.93	-3.13	-2.97	-3.13	-2.46	-1.50	-2.45	-7.50	-0.08	-1.12
	(1.38)	(1.11)	(0.87)	(0.73)	(0.97)	(2.79)	(3.35)	(8.30)	(3.24)	(4.38)
Observations	252,307	232,409	232,409	232,409	232,409	90,486	87,544	87,544	87,544	87,544

Notes : See Table 2. The examinations that are given at 12PM and later are classified as afternoon exams.

Table 6

Air Pollution's Impact on *Bagrut* Test Scores, Separately for Boys and Girls

	RHS Pollutant Measure: Particulate Matter$_{2.5}$					RHS Pollutant Measure: Carbon Monoxide				
	Pooled OLS		Fixed Effects			Pooled OLS		Fixed Effects		
	No Controls (1)	Controls (2)	City (3)	School (4)	Student (5)	No Controls (6)	Controls (7)	City (8)	School (9)	Student (10)
Panel A: Boys Only										
Pollutant (AQI)	-0.087	-0.100	-0.118	-0.104	-0.078	-0.035	-0.055	-0.142	-0.080	-0.099
	(0.018)	(0.013)	(0.009)	(0.009)	(0.009)	(0.021)	(0.026)	(0.024)	(0.020)	(0.019)
Pollutant (Threshold)	-4.83	-5.62	-5.59	-5.33	-4.10	-6.12	-7.49	-10.73	-10.28	-11.28
	(1.95)	(1.26)	(0.96)	(0.82)	(0.87)	(1.41)	(1.65)	(1.53)	(1.22)	(1.23)
Observations	190,410	174,250	174,250	174,250	174,250	73,054	70,311	70,311	70,311	70,311
Panel B: Girls Only										
Pollutant (AQI)	-0.031	-0.036	-0.054	-0.041	-0.021	-0.058	-0.052	-0.125	-0.091	-0.075
	(0.014)	(0.012)	(0.009)	(0.007)	(0.008)	(0.017)	(0.017)	(0.021)	(0.018)	(0.023)
Pollutant (Threshold)	-1.67	-0.30	-0.55	-0.66	-0.38	-6.07	-5.79	-7.62	-8.79	-9.29
	(1.35)	(1.03)	(0.90)	(0.80)	(0.83)	(1.13)	(1.26)	(1.34)	(1.10)	(1.16)
Observations	224,809	206,185	206,185	206,185	206,185	85,593	83,217	83,217	83,217	83,217

Notes : See Table 2.

Table 7

Air Pollution's Impact on Test Scores, Separately for Students with Low and High *Magen* Scores

	RHS Pollutant Measure: Particulate Matter$_{2.5}$					RHS Pollutant Measure: Carbon Monoxide				
	Pooled OLS		Fixed Effects			Pooled OLS		Fixed Effects		
	No Controls (1)	Controls (2)	City (3)	School (4)	Student (5)	No Controls (6)	Controls (7)	City (8)	School (9)	Student (10)
Panel A: Low *Magen* Scores										
Pollutant (AQI)	-0.074	-0.078	-0.081	-0.075	-0.061	-0.073	-0.097	-0.064	-0.065	-0.048
	(0.015)	(0.013)	(0.011)	(0.010)	(0.011)	(0.032)	(0.031)	(0.021)	(0.020)	(0.029)
Pollutant (Threshold)	-4.64	-4.79	-3.77	-3.86	-3.49	-6.22	-9.66	-11.79	-11.56	-12.14
	(1.58)	(1.24)	(1.12)	(1.04)	(1.10)	(1.31)	(1.49)	(1.64)	(1.28)	(1.45)
Observations	206,571	185,030	185,030	185,030	185,030	134,126	128,078	128,078	128,078	128,078
Panel B: High *Magen* Scores										
Pollutant (AQI)	-0.027	-0.024	-0.037	-0.030	-0.028	-0.023	-0.027	-0.068	-0.052	-0.055
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)
Pollutant (Threshold)	-0.94	-0.93	-1.30	-0.93	-0.76	-2.97	-4.09	-4.61	-4.88	-4.57
	(0.42)	(0.71)	(0.66)	(0.57)	(0.68)	(0.59)	(0.69)	(0.78)	(0.81)	(0.85)
Observations	204,527	191,790	191,790	191,790	191,790	128,758	126,284	126,284	126,284	126,284

Notes : See Table 2. The sample is stratified by whether the student did below (Panel A) or above (Panel B) the median on the *Magen* score. The *Magen* score is based on the student's class performance and on an exam similar to the Bagrut.

Table 8

Air Pollution's Impact on Test Scores, Separately by *Magen* Score Quartile

	RHS Pollutant Measure: Particulate $Matter_{2.5}$				RHS Pollutant Measure: Carbon Monoxide			
	Low *Magen* Score Percentile		High *Magen* Score Percentile		Low *Magen* Score Percentile		High *Magen* Score Percentile	
	(0-0.25)	(0.25-0.50)	(0.50-0.75)	(0.75-1.00)	(0-0.25)	(0.25-0.50)	(0.50-0.75)	(0.75-1.00)
Pollutant (AQI)	-0.080	-0.044	-0.033	-0.022	-0.134	-0.064	-0.082	-0.088
	(0.017)	(0.010)	(0.008)	(0.006)	(0.042)	(0.020)	(0.015)	(0.028)
Pollutant (Threshold)	-4.99	-2.29	-1.24	-0.35	-18.22	-10.93	-7.52	-3.56
	(1.38)	(1.19)	(0.86)	(0.63)	(1.86)	(1.16)	(0.87)	(1.18)
Observations	90,354	94,676	94,288	97,502	36,901	38,446	38,022	38,551

Notes: See Table 2. All models include student fixed effects. The columns include the students within the listed percentile range on the *Magen* score, which is based on the student's class performance and on an exam similar to the *Bagrut*.

Table 9

Pooled OLS and Fixed Effect Models of Pollutant Matter on Test Scores, Separately for *Ashkenazi* and *Sephardi* Students

	RHS Pollutant Measure: Particulate Matter$_{2.5}$					RHS Pollutant Measure: Carbon Monoxide				
	Pooled OLS		Fixed Effects			Pooled OLS		Fixed Effects		
	No Controls (1)	Controls (2)	City (3)	School (4)	Student (5)	No Controls (6)	Controls (7)	City (8)	School (9)	Student (10)
Panel A: *Ashkenazi* (Europe, America & Australia)										
Pollutant (AQI)	-0.048	-0.056	-0.081	-0.062	-0.046	-0.038	-0.035	-0.122	-0.077	-0.056
	(0.018)	(0.014)	(0.011)	(0.009)	(0.012)	(0.024)	(0.028)	(0.035)	(0.033)	(0.025)
Pollutant (Threshold)	-2.91	-2.85	-3.03	-2.19	-1.73	-5.87	-5.98	-7.41	-9.10	-8.28
	(1.94)	(1.35)	(1.08)	(1.07)	(1.13)	(1.30)	(1.30)	(1.29)	(1.19)	(1.19)
Observations	88,635	80,156	80,156	80,156	80,156	31,437	30,156	30,156	30,156	30,156
Panel B: *Sephardi* (Asia, Middle East & Africa)										
Pollutant (AQI)	-0.077	-0.058	-0.068	-0.058	-0.035	-0.037	-0.059	-0.109	-0.073	-0.061
	(0.018)	(0.014)	(0.011)	(0.010)	(0.009)	(0.020)	(0.020)	(0.019)	(0.018)	(0.020)
Pollutant (Threshold)	-4.11	-1.17	-1.15	-1.32	-1.01	-4.96	-6.85	-9.06	-9.72	-10.56
	(1.67)	(1.33)	(1.20)	(0.98)	(1.00)	(1.29)	(1.49)	(1.61)	(1.50)	(1.56)
Observations	61,889	54,822	54,822	54,822	54,822	22,702	22,116	22,116	22,116	22,116

Notes : See Table 2.

Table 10

Air Pollution's Impact on Long-term Academic Outcomes Related to the *Bagrut* Examination

	RHS Pollutant Measure: Particulate Matter$_{2.5}$				RHS Pollutant Measure: Carbon Monoxide			
	Pooled OLS	Fixed Effects			Pooled OLS	Fixed Effects		
	Controls	City	School	Student	Controls	City	School	Student
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Failing a Particular *Bagrut* Exam (1=yes)								
Pollutant (AQI, 100 units)	0.025	0.035	0.018	-0.017	0.048	0.071	0.026	0.019
	(0.015)	(0.010)	(0.009)	(0.010)	(0.024)	(0.034)	(0.036)	(0.049)
Pollutant (Threshold)	0.036	0.039	0.036	0.024	0.082	0.103	0.111	0.123
	(0.016)	(0.012)	(0.010)	(0.010)	(0.018)	(0.021)	(0.017)	(0.019)
Observations	380,435	380,435	380,435	380,435	153,528	153,528	153,528	153,528
Panel B: *Bagrut* Exam Composite Score								
Pollutant (AQI, 100 units)	-6.77	-26.79	-16.60		-2.88	-22.72	-8.56	
	(4.29)	(3.40)	(1.87)		(3.68)	(4.53)	(3.23)	
Pollutant (Threshold)	-3.77	-10.93	-9.55		-10.98	-8.43	-7.54	
	(4.96)	(3.66)	(2.70)		(2.24)	(1.55)	(1.15)	
Observations	50,899	50,899	50,899		25,730	25,730	25,730	
Panel C: Received a *Bagrut* Matriculation Certificate (1=yes)								
Pollutant (AQI, 100 units)	-0.236	-0.537	-0.328		-0.063	-0.301	-0.054	
	(0.099)	(0.082)	(0.048)		(0.075)	(0.102)	(0.100)	
Pollutant (Threshold)	-0.184	-0.255	-0.146		-0.214	-0.188	-0.142	
	(0.125)	(0.093)	(0.050)		(0.051)	(0.035)	(0.027)	
Observations	50,899	50,899	50,899		25,730	25,730	25,730	

Notes : See Table 2. In Panel A, each observation is an examination. In Panel B and Panel C, each observation is a student. For the models estimated in Panel B and Panel C, pollution is averaged over all of the *Bagrut* tests taken following grades 10-12 for each student.

Table 11

Particulate Matter's Impact on Failing a *Bagrut* Exam and Receiving a Matriculation Certificate by Sex and *Magen* Score

	LHS: Failed *Bagrut* Exam (1=yes)				LHS: Received Matriculation Certificate (1=yes)		
	Pooled OLS	Fixed Effects			Pooled OLS	Fixed Effects	
	Controls (1)	City (2)	School (3)	Student (4)	Controls (5)	City (6)	School (7)
Panel A: Boys Only							
$PM_{2.5}$ (AQI, 100 units)	0.070	0.082	0.064	0.021	-0.243	-0.621	-0.345
	(0.020)	(0.014)	(0.013)	(0.014)	(0.109)	(0.089)	(0.057)
$PM_{2.5}$ (Threshold)	0.085	0.086	0.077	0.057	-0.283	-0.403	-0.174
	(0.022)	(0.017)	(0.015)	(0.015)	(0.133)	(0.094)	(0.065)
Observations	174,250	174,250	174,250	174,250	23,830	23,830	23,830
Panel B: Girls Only							
$PM_{2.5}$ (AQI, 100 units)	-0.012	-0.002	-0.017	-0.046	-0.231	-0.468	-0.328
	(0.015)	(0.011)	(0.010)	(0.011)	(0.107)	(0.097)	(0.056)
$PM_{2.5}$ (Threshold)	0.000	0.003	0.004	-0.001	-0.061	-0.073	-0.119
	(0.014)	(0.012)	(0.010)	(0.010)	(0.142)	(0.116)	(0.062)
Observations	206,185	206,185	206,185	206,185	27,069	27,069	27,069
Panel C: Low *Magen* Scores							
$PM_{2.5}$ (AQI, 100 units)	0.038	0.038	0.026	0.001	-0.086	-0.299	-0.204
	(0.020)	(0.017)	(0.015)	(0.017)	(0.096)	(0.079)	(0.049)
$PM_{2.5}$ (Threshold)	0.077	0.071	0.066	0.059	-0.124	-0.178	-0.107
	(0.020)	(0.017)	(0.016)	(0.016)	(0.103)	(0.082)	(0.049)
Observations	185,030	185,030	185,030	185,030	24,892	24,892	24,892
Panel D: High *Magen* Scores							
$PM_{2.5}$ (AQI, 100 units)	-0.026	-0.031	-0.035	-0.041	-0.219	-0.197	-0.118
	(0.006)	(0.006)	(0.005)	(0.007)	(0.074)	(0.077)	(0.050)
$PM_{2.5}$ (Threshold)	0.004	0.006	0.000	-0.002	-0.284	-0.252	-0.042
	(0.007)	(0.006)	(0.006)	(0.007)	(0.146)	(0.131)	(0.044)
Observations	191,790	191,790	191,790	191,790	26,007	26,007	26,007

Notes: See Table 2. Each cell in the table represents a separate regression. Each observation in columns (1)-(4) is an examination, and in columns (5)-(7) each observation is a student.

Table 12

Carbon Monoxide's Impact on Failing a *Bagrut* Exam and Receiving a Matriculation Certificate by Sex and *Magen* Score

	LHS: Failed *Bagrut* Exam (1=yes)				LHS: Received Matriculation Certificate (1=yes)		
	Pooled OLS	Fixed Effects			Pooled OLS	Fixed Effects	
	Controls	City	School	Student	Controls	City	School
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Boys Only							
CO (AQI, 100 units)	0.049	0.089	0.027	0.037	-0.022	-0.240	0.009
	(0.033)	(0.030)	(0.029)	(0.036)	(0.079)	(0.164)	(0.128)
CO (Threshold)	0.090	0.123	0.118	0.132	-0.236	-0.196	-0.142
	(0.023)	(0.025)	(0.020)	(0.023)	(0.061)	(0.049)	(0.040)
Observations	70,311	70,311	70,311	70,311	11,990	11,990	11,990
Panel B: Girls Only							
CO (AQI, 100 units)	0.045	0.057	0.031	0.007	-0.101	-0.389	-0.243
	(0.024)	(0.048)	(0.050)	(0.067)	(0.083)	(0.111)	(0.125)
CO (Threshold)	0.071	0.084	0.103	0.115	-0.191	-0.176	-0.144
	(0.018)	(0.022)	(0.018)	(0.020)	(0.049)	(0.036)	(0.028)
Observations	83,217	83,217	83,217	83,217	13,740	13,740	13,740
Panel C: Low *Magen* Scores							
CO (AQI, 100 units)	0.031	0.073	0.029	0.053	-0.107	-0.180	0.033
	(0.034)	(0.060)	(0.061)	(0.073)	(0.076)	(0.138)	(0.108)
CO (Threshold)	0.136	0.197	0.192	0.220	-0.183	-0.163	-0.102
	(0.025)	(0.027)	(0.023)	(0.029)	(0.053)	(0.045)	(0.035)
Observations	71,192	71,192	71,192	71,192	11,962	11,962	11,962
Panel D: High *Magen* Scores							
CO (AQI, 100 units)	0.028	-0.01	-0.014	-0.015	-0.053	-0.143	-0.052
	(0.010)	(0.016)	(0.017)	(0.025)	(0.043)	(0.093)	(0.087)
CO (Threshold)	0.026	0.019	0.023	0.026	-0.097	-0.11	-0.124
	(0.009)	(0.010)	(0.010)	(0.012)	(0.035)	(0.035)	(0.024)
Observations	80,728	80,728	80,728	80,728	13,768	13,768	13,768

Notes : See Table 10.

Figure 1

Locations of Air Quality Monitoring Stations in Israel

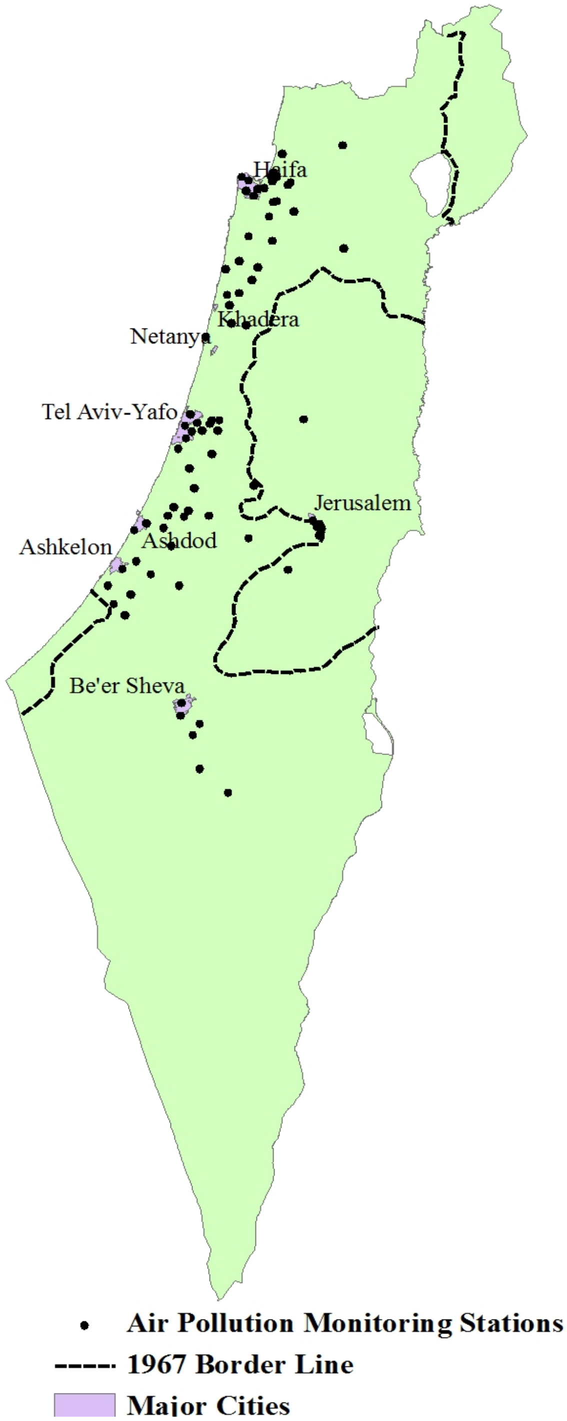
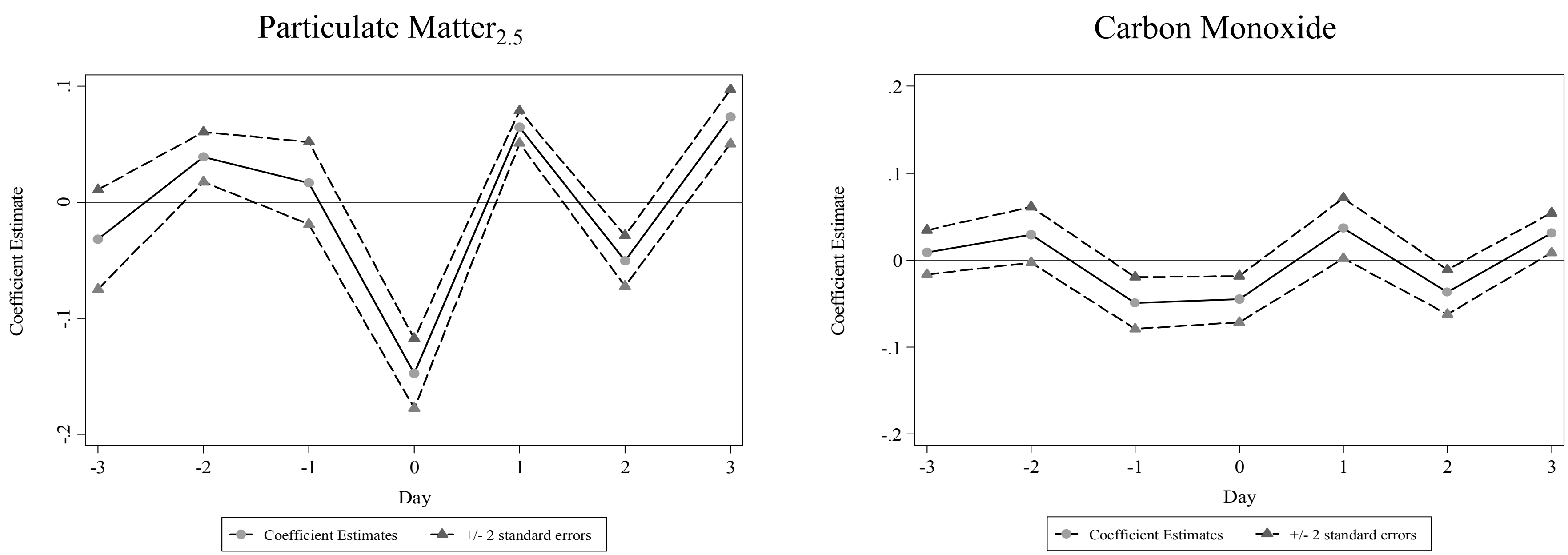


Figure 2

Impact of $PM_{2.5}$ and CO on Test Scores in the Days

Pre and Post Examination



Notes : The figure plots the coefficients from a regression of *Bagrut* test scores on $PM_{2.5}$ and CO AQI readings in the days prior to, the day of (Day=0), and the days following the examination. Standard errors are clustered by school.

Table A1

Breakpoints for $PM_{2.5}$ ($\mu g/m^3$) and AQI Index Categories

$PM_{2.5}$ (µg/m3)	AQI Index Value	Category
0.0 - 15.4	0 - 50	Good
15.5 -40.4	51 - 100	Moderate
40.5 - 65.4	101 - 150	Unhealthy for Sensitive Groups
65.5 - 150.4	151 - 200	Unhealthy
150.5 - 250.4	201 - 300	Very unhealthy
250.5 - 350.4	301 - 400	Hazardous
350.5 - 500.4	401 - 500	Hazardous

Source : United States Environmental Protection Agency

Table A2

Pooled OLS and Fixed Effect Models of Pollutant Matter on Test Scores with Both Measures Included Simultaneously

	RHS Pollutant Measure: Particulate Matter$_{2.5}$					RHS Pollutant Measure: Carbon Monoxide				
	Pooled OLS		Fixed Effects			Pooled OLS		Fixed Effects		
	No controls (1)	Controls (2)	City (3)	School (4)	Student (5)	No controls (6)	Controls (7)	City (8)	School (9)	Student (10)
Pollutant (AQI)	-0.049	-0.030	-0.043	-0.033	-0.009	-0.046	-0.052	-0.126	-0.078	-0.083
	(0.018)	(0.018)	(0.016)	(0.014)	(0.019)	(0.017)	(0.020)	(0.018)	(0.017)	(0.017)
Pollutant (Threshold)	-3.77	-1.93	-2.09	-2.60	-1.73	-6.19	-6.89	-9.33	-9.77	-10.26
	(1.03)	(1.01)	(0.94)	(0.74)	(0.82)	(1.15)	(1.30)	(1.28)	(0.96)	(1.01)
Observations	158,647	153,528	153,528	153,528	153,528	158,647	153,528	153,528	153,528	153,528

Notes : The table reports the coefficients from estimating the models with *both* measures of pollution as independent variables. The results in the first row and columns (1) and (6) are from the same regression, and the results from (2) and (7) are from the same regression, and so on. The results in the second row and columns (1) and (6) are from the same regression, and the results from (2) and (7) are from the same regression, and so on.