THE EFFECTS OF AIR POLLUTION ON COGNITIVE SKILLS: THE CASE OF UKRAINE

by

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Abstract

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The air quality measurements in Ukraine from recent years suggest that urban air particulate matter levels are significantly above the WHO standards in most population centres. Inspired by research from other countries which shows that cognitive skills are affected even at relatively low levels of air pollution, in this thesis I aim to estimate the impact of particulate matter pollution on the cognitive skills of the Ukrainian urban population. I combine the open-source air quality data and STEP Survey for Ukraine which features a literacy assessment module and find the effect of particulate matter on literacy scores to be consistently negative across different specifications and non-linear where the effect is more pronounced at lower levels of pollution. I also instrument for pollution levels using the relative manufacturing employment and levels of coal used in energy production to rule out endogeneity and use sensitivity analysis to provide upper bounds on possible confounding.

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GLOSSARY

PM. particulate matter

$PM_{2.5}$. particulate matter, with diameter of 2.5 micrometres and smaller.

PM_{10}. particulate matter, with diameter of 10 micrometres and smaller.

STEP. Skills toward Employability and Productivity Survey.

EPA. The Environmental Protection Agency.

ISCED. International Standard Classification of Education

WHO. The World Health Organization.

AQG. Air Quality Guidelines.

OLS. Ordinary Least Squares.

2SLS. Two-Stage Least Squares.

IV. Instrumental variable

SES. Socioeconomic status.

Chapter 1

INTRODUCTION

Air pollution, one of the world's largest health and environmental problems, has received much attention recently due to the global increase in mortality and morbidity (Cohen et al. 2017). Air pollution is the fourth largest risk factor for mortality globally (Murray et al. 2020) and is a problem that affects people all over the world, with 99% of the population living in areas where the air quality does not meet The World Health Organization (WHO) guidelines (WHO 2022). WHO provides clear recommendations for exposure to air pollution known as the WHO Air Quality Guidelines (AQG). AQG focuses on particulate matter (PM), made up of solid and liquid airborne particles that can be small or large in size and consist of components such as acids, metals, dust particles, and organic chemicals.

PM can be classified by its diameter. PM10 are particles <10 μm (micrometres) in diameter; PM2.5 particles are <2.5 μm in diameter. The size of particles matters since coarse PM can enter the lungs, but fine PM can penetrate the lung barrier and get into the bloodstream. PM0.1 particles are <0.1 μm (or 100 nanometres) in diameter. All PM2.5 (fine) and PM0.1 (ultrafine) are included in PM10, so we can attribute negative influence of PM10 to finer particles.

While the link between air pollution and human health is well documented in economic literature, a hitherto understudied is the effect on cognition, a decrease in which translates into lower productivity and wages. The economic costs of air pollution were estimated to be US$2.9 trillion, roughly 3.3% of global GDP in 2018 (Centre for Research on Energy and Clean Air 2020). An OECD paper (Dechezleprêtre, Rivers and Stadler 2019) found that 1 $\mu g/m^3$ increase in PM2.5

levels caused a 0.8% decrease in real GDP in the same year, which with this impact being mostly due to output per worker.

The air pollution's severity ranges both historically and geographically. Even Ancient Romans recognized polluted skies for a health hazard and called those gravioris caeli ("heavy heaven") and infamis aer ("infamous air") (Smithsonian Magazine 2016). Importantly, the air quality in rich countries today is better than in the past. For example, London's air pollution is almost 40-times lower than what it was a century ago (Fouquet 2011). At the same time, the air pollution disproportionately affects low- and middle-income countries, where over 90% of deaths occur (World Bank 2016). Ukraine, a lower-middle income country, has had its industrial production contracted, and its levels of emissions of pollutants from stationary sources have more than halved since independence (State Statistics Service of Ukraine 2020). This decrease in emissions may mislead the policy makers into believing that the air pollution is not as important a problem as it could be under previous levels of industrial output. But according to Graff Zivin and Neidell (2013), researchers have started to look into levels of pollution that previously were considered too low when they realized that non-traditional outcome variables (i.e., cognitive impairment) may be affected at levels too low to have any serious effects on traditional health outcomes.

Notably, the initial impetus for the new wave of research is from the United States, where researchers are currently concerned with the inadequacy of current regulatory standards in the US. The US Environmental Protection Agency (EPA) has set the primary standard for PM2.5 at 35 μg/m3 based on a 24-hour average, and the primary standard for PM10 at 150 μg/m3 based on a 24-hour average (US EPA, 2020) At the same time, WHO 2021 global air quality guidelines require far lower levels - a 24 h standard of 15 μg/m3 for PM2.5 and 45 μg/m3 for PM10. Following this, in 2022 European Commission reviewed its PM targets and resolved to bring the thresholds closer to WHO's guidelines.

The EU-Ukraine Association Agreement requires Ukraine to bring its system of environmental control to compliance with EU air quality directives, which, as we have mentioned, should align with WHO recommendations. The recent proliferation of the air quality sensor network has helped uncover that air pollution is significantly above the WHO standards in most large population centres. In a WHO (2016) report, the point estimate of the number of deaths in Ukraine in 2012 due to ambient air pollution was 54,507, but there have not been any estimates of negative effects on the cognitive performance of the Ukrainian population. Consequently, this thesis aims to estimate the impact of air pollution on the cognitive skills of the Ukrainian working-age population.

The research question is whether higher exposure to ambient particulate air pollution in the form of particulate matter is associated with worse cognitive performance of the Ukrainian working-age population on a test of literacy. There also additional hypotheses. With regard to pollutant, I hypothesize that PM2.5 exposure is more closely associated with decreased cognitive function than PM10 exposure. Regarding the interaction between age and pollutant the hypothesis is that younger and older individuals are more affected by exposure to high levels of PM than the middle-aged individuals. With respect to ability of individuals, I hypothesize that individuals of lower ability are more affected by PM concentrations. Finally, I hypothesize, that the relationship is non-linear for different values of PM concentrations.

The paper is organized as follows. Chapter 2 is dedicated to the literature review. Chapter 3 presents the dataset and methodology, and Chapter 4 is dedicated to estimation results. In Chapter 5, I summarize the results and discuss the implications.

Chapter 2

LITERATURE REVIEW

The influence of air pollution on cognitive skills has been gaining popularity as a research topic among economists due to the link with broader economic outcomes. In addition to that reason, one more incentive is that the accumulating evidence shows that pollution is much more detrimental to all age groups than previously supposed, even at current levels of high-income countries. Air pollution affects human capital and its negative effect on the economy has been underestimated (Persico 2021).

The specific causal mechanism of air pollution affecting cognitive function is still actively investigated. However, the hypothesis that particulate matter is associated with worse cognitive performance is motivated by several mechanisms. Particulate matter was detected in the central nervous system (CNS) and the brain stem (Oberdörster et al. 2004). The main mechanisms through which air pollution damages the brain are inflammation and oxidative stress, and PM has been found to be associated with neurodegeneration in vivo (Block and Garciduenas 2009). While air pollution is a mix of pollutants, the evidence points to particulate matter as the main vector through which chemicals cause damage (Peeples, Lynne. 2020).

One recent review (Delgado-Saborit et al. 2021) of existing research on the effect of PM2.5 on cognitive function has established that air pollution has been consistently negatively associated with cognitive decline. Due to lack of non-observational studies, the reviewers used the Bradford Hill criteria and concluded that air pollution is casually associated cognitive ability. At the same time, they found that residual confounding cannot be completely ruled out. It is to a large extent due to concerns regarding confounders and endogenous exposure to pollution that economists have delved into this line of research. While the health sciences attempted to adjust for environmental confounding, economists applied quasi-experimental techniques to attempt develop causal estimates of the air pollution's negative effect on cognition (Graff Zivin and Neidell 2013).

One example was a study by Nicholas Sanders (2012) where the author analysed the impact of early life total suspended particulate (TSP) exposure on high school exams and used changes in relative manufacturing as an instrumental variable. He found that a decrease in TSP in a student's year of birth to be associated with increased test scores. Another example would be a study by Colmer and Voorheis (2020), which estimates the intergenerational damages done by prenatal exposure exploiting the changing regulatory environment in the US. The upshot of that paper was that prenatal exposure to pollution could also harm the outcomes of children born to the affected population.

Other strategies such as difference-in-differences are also employed. Persico and Venator (2021) looked at the effect on school test scores from nearby pollution emitters such as factories and found that being exposed to air pollution from an industrial site opening within one mile of a school (as opposed to being 2 miles away) is associated with approximately 2.4% of a standard deviation lower test scores for students in the school and increased likelihood of suspension. Additionally, Heissel, Persico, and Simon (2021) found that children in schools near major highways have lower test scores. They used variation in wind for schools the same distance from major highways.

Regarding timing of exposure, several studies have linked ambient pollution and reduced worker productivity. One paper done in China (Chang et al. 2019) exploited the fact that fine particles from outdoors can more easily enter indoor call centres and linked workers' worsened performance to heightened daily measures of pollution from the air monitoring stations network. Another example is Ebenstein, Lavy, and Roth (2016), which estimated the effect of pollution on test scores on the day of high-stakes exams in Israel. It has linked worsened cognitive performance on the day of the test to far-reaching consequences where every 10 units of PM2.5 on the day the matriculation exams were associated with a 2.1% reduction in adulthood monthly earnings.

Additionally, that there has been a shift in research interest from the effects of severe pollution to the effects of more moderate pollution levels, with the aim of identifying acceptable levels of pollution below which there are no significant effects (Graff Zivin and Neidell 2013). Effects on cognitive performance manifesting at lower levels of air pollution were found, among others, by Archsmith et al. (2018); where acute exposure to PM2.5 levels increased by 10 μg/m3 was associated with a 2.6% increase in incorrect calls by umpires. More recently, Nauze and Severnini (2021) have found that the exposure to daily PM2.5 has negative impact that is substantial even when the levels are below the current EPA standard of 35μg/m3, and also when the levels are below the previous WHO standard of 25μg/m3. They have also estimated that exposure to particulate matter (PM2.5) is more detrimental to younger individuals and individuals with lower cognitive ability.

Other researchers have also found heterogeneity of the effect of air pollution with respect to age and ability. Zhang et al. (2018) found that particulate matter pollution worsens performance on verbal tests, and with the effect size bigger for older age, and individuals with less education. According to their estimates, bringing Chinese PM levels to US EPA standards would shift individuals from the median to the 63rd percentile in verbal test scores.

Notably, there is a lack of literature exploring this link in the middle-income and lower-middle income countries, where the levels are higher (Roth, 2017). In the case of Ukraine, there were several studies published that attempted to estimate general adverse health outcomes (but not the cognitive outcomes). Among those were Strukova, Golub, and Markandya (2006), who measured the economic losses from urban air pollution in Ukraine and concluded that morbidity risks estimates are likely underestimated. The paper suggested that the burden of air pollution, therefore, potentially reduces the labour force and that economic cost due to mortality risk that was estimated to be approximately 4% of GDP was also likely an underestimate. Focusing on direct and indirect health effects of air pollution, Kubatko and Kubatko (2019) looked at both the mortality and morbidity costs and, among other things, recommended that air pollution tax increases. This suggests extending the indirect costs of air pollution to include the costs due to worsened cognitive performance of Ukrainians might have significant policy implications.

Chapter 3

DATA DESCRIPTION AND METHODOLOGY

3.1 Data description

The objective of this research is to estimate the detrimental effects of concentrations of particulate matter PM2.5 and PM10 on cognitive performance of individuals in Ukraine. The primary data source, the World Bank STEP (Skills Towards Employment and Productivity) Measurement Household Survey for Ukraine (2012), is the cross-sectional dataset with 2389 observations - a representative sample of adults (2389 individuals) aged 15 to 64 living in urban areas. All participants reside in private dwellings in urban areas and were randomly selected from households. The dataset includes the individuals' characteristics such as their age, gender, education level, marital status, socioeconomic circumstances, gender, income, and degree of satisfaction with various conditions including environmental.

This dataset features a cognitive skills module with a test of reading literacy based on the Survey of Adults Skills instruments. The literacy tests were conducted in 2012-2013. The STEP literacy assessment includes tasks of varying difficulty, from very easy to very challenging, in order to measure the reading skills of adults with differing educational backgrounds and life experiences. Results are reported on a proficiency scale ranging from 0 to 500 with 5 literacy levels, Level 1 starting from the score of 176. The plausible values methodology was used to estimate how good a participant is at literacy; literacy score is a function of respondent's answers to the tasks in the reading literacy assessment and predictor values obtained from the background questionnaire (Pierre et al. 2014).

Regarding the pollution levels, data originally comes from the open-source community and commercial projects, local governments, universities, and even individual stations and is aggregated automatically by SaveDnipro SaveEcoBot. I have obtained all available measurements from 1390 air quality monitoring stations in Ukraine with PM2.5 and PM10 indicators and computed the annual means for years 2019-2021. After merging the coordinates of the stations and the coordinates of the individuals home addresses obtained via Google Geocoding service, I find the closest station to the household and calculate the distance from the individuals' home locations to the stations in miles. Then, following Sanders (2012) and Nauze and Severnini (2021), I create subsets of individuals within 10, 20 and 30 miles of the stations and within those proximity-determined subsets, I add subsets based on PM concentrations not exceeding EPA standards and WHO standards. In total that gives us 9 subsets. The 3 subsets used for analysis are with individuals within 20-mile distance of the stations, whereas distances of 10 and 30 miles were included to check the robustness of results.

Most studies of effects of air pollution on human capital concentrate on acute exposure to pollution in the past. For some pollutants that may be several days that suffice, for other months or years. The appropriate duration of pollution is a question that is largely empirical, while the long-run effects and the effect of cumulative exposure to pollution concentrations is difficult to estimate (Graff Zivin and Neidell 2013). In this case the approach taken by Cleland et al. (2022), where 1-year annual mean levels of PM prior to cognitive tests were used.

Using the State Statistics Service of Ukraine data on region level PM2.5 and PM10 total levels (in thousand tons) 2011-2012 I impute the past local PM2.5 and PM10 concentration levels in micrometres by multiplying the annual means of 2019-2021 values by region-level coefficients calculated for PM2.5 and PM10 separately according to the stylized formula (calculations are analogous for PM10 coefficients, the resulting coefficients are available in Table C1):

$$PM2.5\ coefficient = \frac{Past\ region{-}level\ total\ PM\ emissions}{Recent\ region{-}level\ total\ PM\ emissions} \cdot PM2.5\ change \quad (3.1)$$

$$PM2.5\ change = \frac{Past\ national\ PM2.5\ emissions}{Recent\ national\ PM2.5\ \ emissions} \cdot \frac{Recent\ national\ total\ PM\ emissions}{Past\ \ national\ total\ PM\ emissions} \quad (3.2)$$

The choice of whether 2011 or 2012 imputed annual mean value was to be used for estimation was determined by the interview (during which the tests were performed) date. That is, if the interview was conducted in 2012 the imputed value for 2011 was used and if the test was taken in 2013 – the imputed values for 2012. The original region-level 2011 and 2012 annual levels PM2.5 and PM10 are later used for one of the robustness checks. Among 2389 individuals from the STEP survey, 29 participants were excluded because of missing location. A total of 138 participants were excluded due to missing or outlier covariates, namely individuals with literacy score below level 1 (i.e., below the score of 176 out of 500) (n = 32), education levels according to ISCED below level 2 and non-responses (n = 11), individuals with unknown parents' (maximum) education level (n=43) and unknown socioeconomic status at age 15 (n=68).

Following Li et al. (2017), we identify and remove extreme values (Figure A.1., Appendix A) of PM2.5 and PM10. For that we define the outer fences (Turkey, 1977) as [Q1 - 3 * IQR, Q3 + 3 * IQR], where IQR is interquartile range Q1 and Q3 are the first and third quartiles. The resulting ranges of pollutants were 0.05369933- 75.55633596 μg/m3 for PM2.5 and 0.07873628-225.19533456 μg/m3 for PM10. With 272 outlier observations removed the estimations are expected to be not influenced by the unrepresentative data in the baseline subsets (the further subsets have ranges dictated by EPA and WHO standards in which outliers' pollution values are removed by definition). (2 of 3 main subsets have ranges dictated by EPA and WHO standards in which outliers' pollution values are removed by definition).

The above exclusions resulted in a total of 1950 participants available for investigation before splitting them into subsets based on distance to air pollution measurement stations. Figures A.1 and Figure A.2 in Appendix A the data axis before and after outlier exclusions - on the left and the right scatterplot respectively. The imputed PM2.5 values and PM10 values on the X axes of the figures A.1 and A.2 respectively and literacy scores on the Y axes. In the main subset used for analysis we have 1618 individuals within the 20 miles of monitoring stations (1421 individuals with PM levels below EPA standards, 709 individuals with PM levels below WHO guidelines).

Table 3.1 Descriptive statistics of individuals in the main subset

Variable	Obs	Mean	St. Dev.	Min	Max
PM2.5	1618	19	13.435	0.054	75.556
PM10	1618	47.268	43.97	0.079	225.195
Literacy score	1618	272.017	33.433	178.258	409.535
Maximum parents' education	1618	2.323	0.704	0	3
Female	1618	0.676	0.468	0	1
Age	1618	41.304	14.451	15	64
Has a spouse	1618	0.696	0.46	0	1
SES at age 15	1618	1.985	0.597	1	3
Years of education	1618	13.106	2.218	9	22

Table 3.2 Descriptive statistics of individuals in the subset with PM values below EPA mandated thresholds

Variable	Obs	Mean	Std. Dev.	Min	Max
PM2.5	1421	15.386	8.721	0.054	34.759
PM10	1421	35.852	24.669	0.079	140.938
Literacy score	1421	271.47	33.57	178.258	409.535
Maximum parents' education	1421	2.325	0.705	0	3
Female	1421	0.668	0.471	0	1
Age	1421	41.293	14.527	15	64
Has a spouse	1421	0.696	0.46	0	1
SES at age 15	1618	1.985	0.597	1	3
Years of education	1618	13.106	2.218	9	22

Table 3.3 Descriptive statistics of individuals in the subset with PM values below WHO guidelines' thresholds

Variable	Obs	Mean	Std. Dev.	Min	Max
PM2.5	709	8.541	3.804	0.054	14.897
PM10	709	19.133	9.353	0.079	42.218
Literacy score	709	273.93	34.205	178.939	409.535
Maximum parents' education	709	2.346	0.658	0	3
Female	709	0.687	0.464	0	1
Age	709	40.629	14.461	15	64
Has a spouse	709	0.683	0.466	0	1
SES at age 15	709	1.997	0.629	1	3
Years of education	709	13.131	2.236	9	22

Tables 3.1-3.3 provides descriptive statistics of the characteristics, test results, and pollution concentration levels of individuals in the main subset, the EPA and

WHO subsets. Literacy score is the mean value of plausible values of literacy proficiency. A latent regression was used by STEP authors to produce plausible values of literacy proficiency. For more details about dependent variable imputation please see (Pierre et al. 2014).

3.2 Methodology

As the baseline model, an OLS regression model is used for estimating the concentration-response function, where literacy score y is the response variable and is a linear function of regressors. The baseline specification is:

$$y_i = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + \beta_6 x_{i6} + \beta_7 x_{i7} + \beta_8 x_{i8} + \epsilon_i \qquad (3.3)$$

The coefficients β_1 through β_8 represent the estimated effect of the corresponding independent variable on cognitive function, holding all other variables in the model constant. All variables correspond to $x_{1\text{-}8}$ respectively and described numerically in Table 3.2. The PM2.5 levels, PM10 levels are potentially endogenous treatment variables. The rest of the covariates are controls. That is, the dummy variable for female (1 – female, 0 – male), age (from 15 to 64), dummy variable for having a spouse (1 – has a spouse, 0 – doesn't have a spouse), years of education (from 9 to 22), maximum level of parents' education according to ISCED classification (1 – Primary education, 2 – Lower secondary education, 3 – Upper secondary education, 4 – Post-secondary non-tertiary education and higher) and 3 levels of socioeconomic status at age 15 (based on survey responses, from 1 – less well-off to 3 - more well-off).

According to Aguilar-Gomez et al. (2022), the empirical challenges associated with estimating the effect on cognitive skills are similar to the issues that arise when trying to establish the effect on regular health outcomes. According to Graff Zivin and Neidell (2013), people optimize their location while considering a variety of factors such as school availability and distance to workplace (and many others, but for the sake of simplicity let us consider these two). On the one hand this implies that individuals with higher socioeconomic status (SES) may choose areas closer to lower pollution (e.g., suburbs), which introduces one source of endogeneity. An ordinary least squares (OLS) analysis might then overestimate the adverse influence of air pollution. On the other hand, neighbourhoods closer to the city centres that are more heavily polluted may also host better educated/wealthier families. As a result, the ultimate direction of the bias in the estimates is difficult to predict theoretically.

Instrumental variables estimation is a classical approach of to correct for the possible endogeneity. Following Aguilar-Gomez et al. (2022), an important limitation of any instrumental variables approach is that it may not provide enough information to identify all the variables in a model. In the presence of multiple endogenous variables several instruments are required. However, since pollution variables often come from the same emission sources, they are often highly correlated, making it difficult to attribute impacts to a specific pollutant. Using separate IV equations to estimate each pollution variable does not produce unbiased estimates.

The chosen solution is using 2 instrumental variables to PM2.5 and PM10 pollution levels. The first instrumental variable chosen is the region-level shares of population working in manufacturing. According to by Chay and Greenstone (2003), manufacturing is a key input into the emissions process and the main source of emissions of total particulate matter. According to State Statistics Service of Ukraine (2012), in 2011, for example, the total level of particulate matter pollution from stationary sources was 606.6 thousand tons, while mobile sources (e.g., cars) contributed only 34.4 thousand tons.

The second instrumental variable is regional levels coal, in millions of tons, used for conversion into energy. The choice was motivated by Gilraine and Zheng (2022) who used 2 instrumental variables - coal production and fuel shares used for power generation. Additionally, the strength of the instrument is assumed based on research by Duque and Gilraine (2022) which found that that for every one-million-megawatt hour of coal-fired power production within ten kilometers of schools, there is a decrease of 0.02SD in mathematics scores.

The first stage of 2SLS is performed for both endogenous variables:

$$y_{1i} = \beta_x{}' \cdot x_i + \beta_{z1}{}' \cdot z_{1r} + \beta_{z2}{}' \cdot z_{2r} + \epsilon_i, \tag{3.4}$$

$$y_{2i} = \beta_x{}' \cdot x_i + \beta_{z1}{}' \cdot z_{1r} + \beta_{z2}{}' \cdot z_{2r} + \epsilon_i, \tag{3.5}$$

where xi is a vector of the exogenous variables from the baseline OLS model, z_{1r} is the first instrument – the regional share of workforce in the manufacturing sector, and z_{2r} the second one – the million tons of coal used for energy production. After that the literacy scores are to be regressed on the predicted values of PM2.5 and PM10 from the first stage. PM10 would have to be instrumented jointly with PM2.5 because we understand that an instrument for PM2.5 must also be correlated with PM10. Not including the endogenous PM10 would thus introduce a violation of the exclusion restriction. Therefore, we have 2 endogenous variables and 2 instrumental variables. To compare the IV results with OLS, robust standard errors may be calculated via "sandwich" package using non-constant variance estimates "HC1" as per Zeileis (2004).

Depending on the consistency of results, that is, if IV estimates have similar effect sizes and the instruments have passed the F-test we may choose to prefer IV to

OLS results or vice versa. However, since instrumental variables approach with the set of instruments described above likely to yield some degree of measurement error due to the coarseness of regional-level data as compared to PM pollution data from the measurement stations, we might have to proceed with alternative specifications without instrumenting the PM concentrations.

Considering that there might be other unobserved confounders that might challenge the unbiasedness of the non-IV estimations, sensitivity analysis might be employed to tackle the question of how strong a confounder (or a group of confounders) needs to be relative to the strength of observed covariates to change the research conclusions. In other words, it might shed light on the impact that omitted variables would have on a regression result. The R package *sensemakr* provides sensitivity analysis tools that follow the framework for accounting for omitted variables developed by Cinelli and Hazlett (2020).

Based on the previous literature, including Nauze and Severnini (2022), the potential heterogeneity in the effects of PM2.5 exposure across different reading skills levels, particularly the effects the tails of distribution, is of great interest. Linear regression models focus on changes in the mean outcome value and the implicit assumption there is that exposure has the same effect across the entire outcome distribution. Following, Wu et al. (2021), who used quantile regression to estimate associations between PM2.5 exposure and mean birth weight, we apply this method to see whether the associations between exposure and specific percentiles of the literacy score distribution are different from the association at the mean value. Quantile regression model can be written down as:

$$Q[y \mid \mathbf{x}, q] = \mathbf{x}'\boldsymbol{\beta}_q \text{ such that Prob } \left[y \leq \mathbf{x}'\boldsymbol{\beta}_q \mid \mathbf{x}\right] = q, 0 < q < 1 \qquad (3.6)$$

The parameter q indicates the quantile, where q = 0.5, for example, corresponds to a median regression (Green 2018). The other quantiles of interest would be at q = 0.05, q = 0.1, q = 0.25, q = 0.75, q = 0.90, and q = 0.95.

It bears mentioning that analysis of air pollution's effects might be confounded by possible avoidance behaviours (like using masks or air filters). Some researchers distinguish between the so-called concentration-response function and exposure-response function. According to Aguilar-Gomez et al. (2022), estimating the exposure-response function by using the avoidance behaviours as controls would be incorrect and would introduce bias to the regression. Due to avoidance behaviours being theoretically incorrect to include in the specification and the lack of this information in the available dataset, this investigation concerns itself with air pollution concentration effects without accounting for what individuals do to counteract it.

Considering that we only have outdoor levels of pollution, it is important to note that, according to a meta study of 61 articles (Mohammed et al. 2015), which looked at different types of buildings, over 40% of articles found that PM2.5 levels indoors were higher than outdoors. Although the authors of the meta-study do not arrive on an exact ratio between outdoor and indoor levels, the study provides evidence that indoor levels are likely to be equal to outdoor levels. Finally, as per Solon et al. (2015), even though the STEP survey analysis usually presumes using weights, weighting is first and foremost required if analysis attempts to find whether the point estimates of the associations using the sample are representative of the entire population (in our case of Ukraine). Since in our case the data on pollution levels does not come from the original survey, it would be fruitless to attempt to generalize the research conclusions to the entire population.

Chapter 4

ESTIMATION RESULTS

4.1 Baseline specification results

4.1.1 OLS estimates

Table 4.1.1. Estimating the effects of PM on literacy scores (OLS)

Variable	Literacy score		
	(1) All PM values	(2) Below EPA	(3) Below WHO
PM2.5	-0.468***	-0.735***	-1.938***
	(0.103)	(0.137)	(0.582)
PM10	0.144***	0.158***	0.703***
	(0.031)	(0.049)	(0.236)
Has a spouse	-1.565	-1.935	-3.076
	(1.839)	(1.973)	(2.893)
Female	0.665	-0.582	-2.573
	(1.749)	(1.858)	(2.748)
Age	-0.139**	-0.174**	-0.187*
	(0.065)	(0.069)	(0.100)
Years of education	2.911***	2.930***	2.975***
	(0.390)	(0.414)	(0.603)
Maximum parents' education	3.466**	2.831**	-1.128
	(1.352)	(1.430)	(2.189)
SES at age 15	1.882	1.933	3.353
	(1.385)	(1.464)	(2.068)
Constant	230.526***	237.287***	245.387***
	(6.287)	(6.736)	(9.772)
Observations	1,618	1,421	709
R2	0.072	0.075	0.060
Adjusted R2	0.067	0.070	0.049
*p<0.1; **p<0.05; ***p<0.01			

Note: Covariates are described in Table 3.1, 3.2, 3.3, the below EPA subset has PM2.5 and PM10 values below 35 μg/m3 and 150 μg/m3 respectively, below WHO – below 15 and 45 μg/m3.

We can see that the effects of both PM2.5 and PM10 are statistically significant but the interpretation of the effect size is not as straightforward. The difficulty of increasing PM2.5 and PM10 by 1 unit varies, so the estimates are not directly comparable. We see that everything else equal, 1 μg/m3 increase in PM2.5 is associated with a decrease in Literacy score by 0.468 points, whereas increasing PM10 by 1 μg/m3 is associated with a 0.144 increase. The results are consistent across the subsets used in statistical significance, but effect sizes increase with lower ranges of PM, which supports the hypothesis that the effect is non-linear - the negative relationship is stronger for lower values of PM.

Furthermore, since PM2.5 is the subset of PM10, PM10 can be thought of as a confounder which influences both the outcome variable and PM2.5 (the correlation between the two equals 0.81). When we consider PM2.5 as a control, the effect size of PM10 cannot be interpreted directly as the effect of all PM10 particles, as it is the estimate of the coarser (than 2.5 micrometres) particles that are affecting the literacy scores.

We see statistically and economically significant effects on literacy score of age, years of education and parents' level of education. The rest of covariates such as being female, having a spouse and SES are not statistically significant. In addition, the statistical and economic significance of covariates are consistent across the three subsets. However, according to Hünermund and Louw (2022), the effect sizes of variables we used as controls are not likely to have causal interpretation of their own. Finally, after testing for multicollinearity using the variance inflation factor (VIF), we found that none of the independent variables displayed a VIF above 3. Therefore, we can conclude that there is no multicollinearity.

4.1.2 2SLS estimates

Table 4.1.2.1 2SLS results compared to OLS results

	Literacy Score	
	IV	OLS
Variable	(1)	(2)
PM2.5	-1.669***	-0.468***
	(0.370)	(0.101)
PM10	0.378***	0.144***
	(0.083)	(0.029)
Has a spouse	-1.081	-1.565
	(1.898)	(1.805)
Female	2.176	0.665
	(1.923)	(1.798)
Age	-0.141**	-0.139**
	(0.069)	(0.067)
Years of education	2.956***	2.911***
	(0.402)	(0.378)
Maximum parents' education	3.784***	3.466**
	(1.408)	(1.365)
SES at age 15	1.064	1.882
	(1.445)	(1.391)
Constant	241.336***	230.526***
	(7.588)	(6.561)
Observations	1,618	1,618
*p<0.1; **p<0.05; ***p<0.01		

Note: Robust standard errors are calculated as per Zeileis (2004). R^2 is omitted as is not statistically important in the context of 2SLS/IV (Sribney et al.)

Comparing the IV and OLS results we see that they are very similar except for the magnitude of the PM's effect on literacy score. That is, for every 1 μg/m3 increase in PM2.5 the literacy score falls by 1.669. We should be careful, however, to interpret these effect sizes as more correct than the OLS. Notably, Lal et al. (2021) found that, despite researchers often using IV due to concerns about OLS estimates being biased away from zero, IV estimates are frequently larger in magnitude than OLS estimates. Table 4.1.2.2 displays the results from diagnostic tests performed as per Fox et al. (2020).

Table 4.1.2.2 Instrumental variables diagnostic tests

Test	All PM values		Below EPA		Below WHO	
	t value	p-value	t value	p-value	t value	p-value
Weak instruments (PM2.5)	187.622	< 2e-16 ***	106.922	<2e-16 ***	5.399	0.00471 **
Weak instruments (PM10)	275.340	< 2e-16 ***	207.358`	<2e-16 ***	18.676	1.25e-08 ***
Wu-Hausman	6.784	0.00116 **	3.266	0.0385 *	1.756	0.17344

The weak instruments p-values are results of an F-test on the instruments used in the first stage of 2SLS. The null hypothesis is that the endogenous independent variable is not significantly related to the instrument and so the IV coefficient will not be correct. The large t statistics and small p values in all three subsets then indicate that the instruments are sufficiently related to the PM values. The Wu-Hausman test is to check the consistency of OLS estimates assuming that IV is consistent. The p-values are small enough to reject the null for the two out of three subsets, which means that endogeneity is present, and OLS is not consistent. In the third subset, however, OLS remains consistent.

4.2 Sensitivity analysis

The Wu-Hausman test of IV and OLS estimates suggests that there is some degree of endogeneity present, and that OLS might not be consistent. The corollary of that is that getting an unconfounded estimate of the causal effect via OLS is not possible. It does not mean, however, that we can dispense with OLS, as we may choose to perform the sensitivity analysis as per Cinelli and Hazlett (2020) and estimate how much of the total causal effect is plausibly caused by the confounding we do not control for.

Table 4.2 Summary sensitivity statistics

Outcome: Literacy score						
Treatment	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
PM2.5	-0.468	0.103	-4.563	1.3%	10.7%	6.3%
df = 1609	Bound (1x Years of education): $R^2_{Y\sim Z\|\mathbf{X},D}$ = 3.5%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0% Bound (1x Parents' education): $R^2_{Y\sim Z\|\mathbf{X},D}$ = 0.4%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0.1%					

Table 4.2 displays the values that summarize what we need to know to safely rule out problematic confounders. The robustness value for reducing the effect size of PM2.5 exactly to zero ($RV_{q=1}$) is 10.7%. (q = 1 denotes a reduction of 100% of the current effect estimate) In other words, the unobserved confounders that explain 10.7% of the residual variance both of the PM2.5 and of the literacy score are strong enough to explain away all the observed effect.

As for the statistical significance, the robustness value for testing the null hypothesis for PM2.5 ($RV_{q=1,\alpha=0.05}$) is 6.3%. Unobserved confounders that explain 6.3% of the residual variance both of the PM2.5 and of the literacy score are enough to bring the lower bound of the confidence interval to zero (at p-value of 0.05). Finally, the partial $R^2_{Y\sim D|\mathbf{X}}$ of PM2.5 with literacy score means that in an extreme case where unobserved confounders account for all of the remaining variance of the literacy score, these unobservables would have to explain at least 1.3% of the residual variance of PM2.5 to bring the point estimate to zero.

It is not feasible to make conclusions about the absolute strength of confounding, but relative conclusions can be made if we take one of the observed covariates as a benchmark. It is difficult to argue that unobserved confounder could explain much more of the literacy score than the years education or parents' education level. Table 4.2 lower corner displays the bounds on confounding. Values for both benchmark covariates are significantly below the robustness values sufficient to bring the observed effect size of PM2.5 to 0, which means that confounders as strong as strong as years of education or parent's education level are not enough to bring point estimates to 0.

Moreover, Figure B.1 in the Appendix reveals that the effect size of PM2.5 is robust to confounding even when the unobserved confounder is 3 times as strong as years of education, with the OLS point estimate reduced from -0.47 to -0.462 in that case (the dashed red line denotes the point estimate equalling 0) Figure B.2. reveals that the null hypothesis would still be rejected even when the unobserved confounder is 3 times as strong as years of education (the dashed red line denotes the t statistic low enough to not reject the null). Taking these results into account and the potential inflatedness of IV estimates, we proceed with OLS estimates alternative specifications.

4.3 Alternative specifications

4.3.1 Model with interactions

Table 4.3.1. Estimating the interaction effects of PM with age groups (OLS)

	Literacy score		
Variable	(1) All PM values	(2) Below EPA	(3) Below WHO
PM2.5 (Age: 15-24)	-0.800***	-0.866***	-2.121**
	(0.193)	(0.268)	(1.005)
Age: 25-34	-11.859**	-8.769	-9.302
	(4.955)	(5.857)	(10.764)
Age: 35-34	-8.631	-5.928	4.541
	(5.341)	(6.363)	(11.220)
Age: 45-54	-12.634**	-9.969*	-6.574
	(5.026)	(6.028)	(10.792)
Age: 55-64	-14.636***	-11.905**	-17.615*
	(4.934)	(5.817)	(10.260)
PM10	0.143***	0.157***	0.691***
	(0.032)	(0.049)	(0.237)
Has a spouse	-1.042	-1.298	-3.043
	(1.939)	(2.095)	(3.087)
Female	0.780	-0.478	-2.735
	(1.751)	(1.864)	(2.764)
Years of education	2.982***	3.016***	3.085***
	(0.397)	(0.423)	(0.611)
Maximum parents' education	3.677***	2.902**	-1.075
	(1.348)	(1.428)	(2.185)
SES at age 15	1.646	1.691	3.359
	(1.392)	(1.473)	(2.082)
PM2.5 (Age: 25-34)	0.383*	0.164	0.535
	(0.217)	(0.326)	(1.135)
PM2.5 (Age: 35-34)	0.300	0.090	-0.802
	(0.229)	(0.350)	(1.166)
PM2.5 (Age: 45-54)	0.409*	0.195	-0.133
	(0.216)	(0.336)	(1.181)
PM2.5 (Age: 55-64)	0.401*	0.158	1.050
	(0.214)	(0.317)	(1.111)
Constant	233.967***	236.778***	243.259***
	(6.531)	(7.186)	(11.546)

Table 4.3.1 — Continued (

	(1) All PM values	2) Below EPA	3) Below WHO
Observations	1,618	1,421	709
R2	0.076	0.078	0.067
Adjusted R2	0.067	0.068	0.047
*$p<0.1$; **$p<0.05$; ***$p<0.01$			

Note: Covariates are described in Table 3.1, 3.2, and 3.3, age groups are according to STEP methodology.

The specification used in this regression analysis differs from the baseline model in that PM2.5 values are interacted with 5 age groups to see potential differences in adverse effects of pollution depending on the age. In table 5 we see that results are largely similar to OLS and IV estimates, with the caveat that the effect size of PM2.5 for the 15-24 years-old age group is -0.8 which is twice as large as compared to the results at the mean value of age.

PM10 interaction is not displayed because we are interested in the PM2.5 interaction for this specification but the results are similar in that for all age groups PM10 controlled for PM2.5 is positively associated with literacy. The subsequent age group interactions can be interpreted as follows: 25-34 age group has the PM2.5 effect size of -0.417 (=0.8-0.383), 35-44 group has PM2.5 point estimate of -0.5 but is not statistically significant, 45-54 – effect size of -0.391, and for the oldest group with ages 55-64 each μg/m3 increase of PM2.5 is associated with a reduction in the literacy score by 0.401.

The point estimates on smaller subsets are not statistically significant. Regarding the covariates, years of education and parents' level of education are again statistically and economically significant effects on literacy score of, while the rest of covariates such as being female, having a spouse and SES are not statistically significant. Interpreting the coefficient on age groups is meaningless, since coefficients for all age groups are the effect of being in that group when PM2.5 level is at zero.

The results support the hypothesis of this research only partially - while younger individuals are more affected by pollution, this is not so for older individuals. According to Nauze and Severnine (2021), the larger point estimates of air pollutions effect on cognition for younger individuals might be explained by employing the theory of intelligence which divides intelligence into fluid and crystallized intelligence, that is the raw ability and the learned knowledge, respectively, old people rely more on crystallized intelligence. As fluid intelligence may be more affected by the damage the PM does to the brain, we might expect younger individuals' cognitive performance to suffer more as a result.

4.3.2 Model with quadratic terms

The specification used in this regression analysis differs from the baseline model in that we add quadratic terms - PM2.5 and PM10 values squared to see whether the relationship between PM exposure and literacy scores in non-linear. At mean PM2.5 value of 19.00034, 1 μg/m3 increase in PM2.5 is associated with literacy score decrease of -0.84598776 (1.530+2*19.00034*0.018) the turning point of PM2.5 is the value of 42.5 μg/m3 (1.530/ (2*0.018)), which means that for this subset of observations PM2.5 increase positively contributes to literacy scores at values higher than 42.5. As for the PM10 effect, the positive effect changes to negative at 187.25 μg/m3 (-0.374/ (2*-0.001)). The covariates such as age, years of education and parents' level of education are again statistically and economically significant, while the rest of covariates such as being female, having a spouse and SES are not statistically significant.

Table 4.3.2. Estimating the effect with quadratic PM terms (OLS)

Variable	Literacy score OLS
PM2.5	-1.530***
	(0.256)
PM2.52	0.018***
	(0.004)
PM10	0.374***
	(0.083)
PM102	-0.001***
	(0.0004)
Has a spouse	-1.570
	(1.828)
Female	0.618
	(1.741)
Age	-0.143**
	(0.064)
Years of education	2.958***
	(0.388)
Maximum parents' education	3.799***
	(1.346)
SES at age 15	2.048
	(1.378)
Constant	233.493***
	(6.434)
Observations	1,618
R2	0.084
Adjusted R2	0.078
*p<0.1; **p<0.05; ***p<0.01	

Note: Covariates are numerically described in Table 3.1

4.4 Quantile regression

In table 4.4, the output of the quantile regression is presented. First notable difference between quantile regression and OLS is that we can see how the conditional median (50th quantile) of the literacy score is affected as opposed to the conditional mean. All else equal, 1 μg/m3 increase in PM2.5 at the median associated with a decrease in Literacy score by 0.578 points as opposed to 0.468 points at the mean. The effect sizes are largest in the lower quantiles of literacy scores, particularly 25th, while 5th and 10th quantiles have effect sizes similar to those at the mean.

The higher quantiles, however, have lower effect sizes and the coefficients on PM values at 90th and 95th quantiles are not statistically significant. For reference, while the median value of literacy score is 274.2955, 75th quantile value is 296.5866, and 90th and 95th quantile values are 311.1574 and 320.5224 which are below Literacy Level 4 as per Pierre (2014). (The maximum literacy score in the sample is 409.5349 – within Literacy Level 5).

We see that the covariates' coefficients at the median are largely similar to those of OLS, but at lower and higher quantiles statistical significance disappears for age and parents' level of education, The rest of covariates such as being female, having a spouse are not statistically significant, except for SES being significant at the 10th quantile of literacy score but this might be a spurious result. Overall, the results support the hypothesis that cognitive function of individuals with lower ability is more adversely affected by air pollution.

Table 4.4. Estimating the effect at different quantiles of literacy score

	Literacy score						
Variable	(1) 5th	(2)10th	(3) 25th	(4) 50th	(5) 75th	(6) 90th	(7) 95th
PM2.5	-0.465**	-0.441**	-0.581***	-0.578***	-0.340***	-0.138	-0.004
	(0.212)	(0.171)	(0.163)	(0.114)	(0.114)	(0.102)	(0.179)
PM10	0.154***	0.179***	0.200***	0.172***	0.084***	0.020	-0.022
	(0.055)	(0.057)	(0.051)	(0.030)	(0.029)	(0.031)	(0.041)
Has a spouse	-8.987	-6.740***	-2.945	0.476	-0.056	1.083	1.680
	(5.725)	(2.578)	(2.626)	(2.159)	(2.153)	(1.785)	(3.961)
Female	6.596	8.217***	2.370	0.214	-1.603	-2.242	-2.933
	(4.096)	(2.748)	(2.544)	(2.100)	(1.985)	(1.897)	(3.366)
Age	-0.095	-0.290***	-0.253**	-0.160**	-0.126*	-0.020	-0.022
	(0.175)	(0.094)	(0.100)	(0.077)	(0.071)	(0.063)	(0.128)
Years of education	3.421***	3.263***	3.661***	3.546***	2.449***	1.870***	1.286*
	(1.059)	(0.621)	(0.559)	(0.462)	(0.430)	(0.438)	(0.752)
Maximum parents' education	4.862	3.823**	4.864**	4.104**	2.315	0.918	3.603
	(3.175)	(1.583)	(2.112)	(1.690)	(1.569)	(0.943)	(2.853)
SES at age 15	5.002	5.122**	1.493	0.591	0.628	0.506	0.161
	(3.651)	(2.073)	(2.065)	(1.665)	(1.514)	(1.477)	(2.843)
Constant	157.662***	177.508***	200.344***	225.531***	265.508***	285.847***	296.279***
	(17.370)	(8.632)	(9.204)	(7.596)	(7.136)	(5.715)	(13.277)
Observations	1,618	1,618	1,618	1,618	1,618	1,618	1,618
*p<0.1; **p<0.05; ***p<0.01							

Note: Covariates are described in Table 3.1, the columns with estimation results correspond to the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles of literacy score distribution

4.5 Robustness check

For further check of robustness, I use the region-level emissions of PM2.5 and PM10 in thousand tons as opposed to their imputed values in μg/m3. The coefficients on PM2.5 and PM10 are statistically significant and for every thousand tons of PM2.5 emissions in the region the cognitive score is lower by almost 4 points. Direct comparison of estimates would be incorrect, but the effect of PM10 is too positive which adds to the consistency of results. We see statistically significant effects of age, years of education and parents' level of education as before.

Table 4.5. Estimation of effect of regional-level values of PM on cognitive scores (OLS)

	Literacy Score	
Variable	Region-level PM thsd.t.	(2) Station-measured PM μg/m3
PM2.5	-3.987**	-0.468***
	(1.843)	(0.101)
PM10	1.127**	0.144***
	(0.518)	(0.029)
Has a spouse	-1.913	-1.565
	(1.849)	(1.805)
Female	0.074	0.665
	(1.759)	(1.798)
Age	-0.130**	-0.139**
	(0.065)	(0.067)
Years of education	2.902***	2.911***
	(0.393)	(0.378)
Maximum parents' education	3.128**	3.466**
	(1.360)	(1.365)
SES at age 15	2.197	1.882
	(1.391)	(1.391)
Constant	228.885***	230.526***
	(6.300)	(6.561)
Observations	1,618	1,618
R2	0.061	0.072
*p<0.1; **p<0.05; ***p<0.01		

Note: Covariates are described in Table 3.1, the region-level data from the State Statistics Service of Ukraine

Chapter 5

CONCLUSIONS

The aim of this research was to answer the question of whether higher concentrations of ambient particulate air pollution in the form of particulate matter is associated with worse cognitive performance of the Ukrainian individuals on a test of literacy. Firstly, both OLS and 2SLS results support the hypothesis that PM2.5 exposure is more closely associated with decreased cognitive function than PM10 exposure. All else equal, 1 μg/m3 increase in PM2.5 is associated with decrease in literacy score, while PM10 controlled for PM2.5 has a small positive effect. 2SLS results suggest that that point estimate may be biased downwards, which, however, only strengthens the conclusions.

The results of estimating the interaction between age and PM2.5 support the hypothesis that younger individuals are more affected by exposure to high levels of PM than the middle-aged individuals. 15-24 years-old age group almost twice as affected as individuals at the mean value of age. The results, however, contradict the hypothesis that older individuals are more affected by air pollution. By employing the quantile regression, we find that the detrimental effects of PM2.5 are also largest in the lower quantiles of literacy scores which supports the hypothesis that individuals of lower ability are more affected by PM concentrations. The more adverse effect of PM on lower-ability and younger individuals suggests that particulate matter air pollution increases cognitive inequality and prevents socio-economic mobility (e.g., by preventing younger individuals from progressing along the education tracks when taking tests of verbal ability).

In conjunction with the previous evidence from other countries that pollution is harmful at lower levels of PM than previously supposed, this research provides one more piece of evidence that more action should be taken to protect the cognitive health Ukrainian individuals. Through adverse effect on human capital, pollution affects the economy, thus addressing the high air pollution levels is not only a public health intervention but also an investment.

Perhaps the most solution strategy is simply to make the standards stricter. If we consider, however, that estimates using subsets with PM values below EPA and WHO thresholds, as well as results of a quadratic specification suggest that the effect of PM2.5 on cognition is non-linear, the upshot of that is that if the negative health effects of PM2.5 are less pronounced at higher concentration levels then health benefits of reducing the pollution to levels below a certain threshold are lower. That implies that lowering the thresholds alone may not be sufficient and should be done as part of a mix of strategies, such as public health awareness campaigns, investment in air filtration systems, etc.

It is important to note, however, further investigation of this research question is needed. Even though we produce IV estimates consistent to OLS estimates and provide the sensitivity analysis for the extent of possible confounding, results may be still biased due to the coarseness of the imputation procedure. Future research of this question will be aided by availability of better measurements, when new data on cognitive performance Ukraine becomes available.

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APPENDIX A

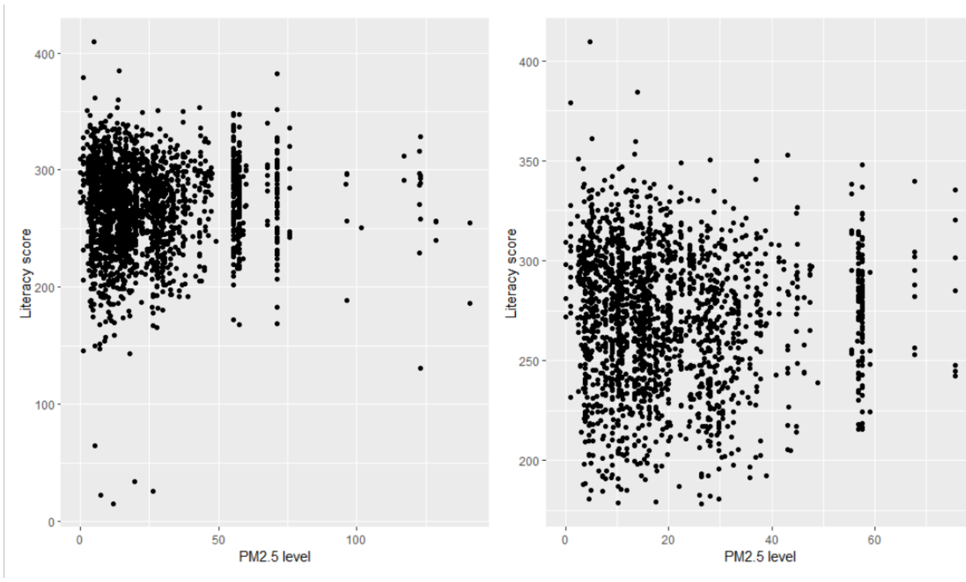

Figure A.1 PM2.5 levels and literacy scores before and after outlier removal Source: own calculations based on STEP Survey and air pollution open data.

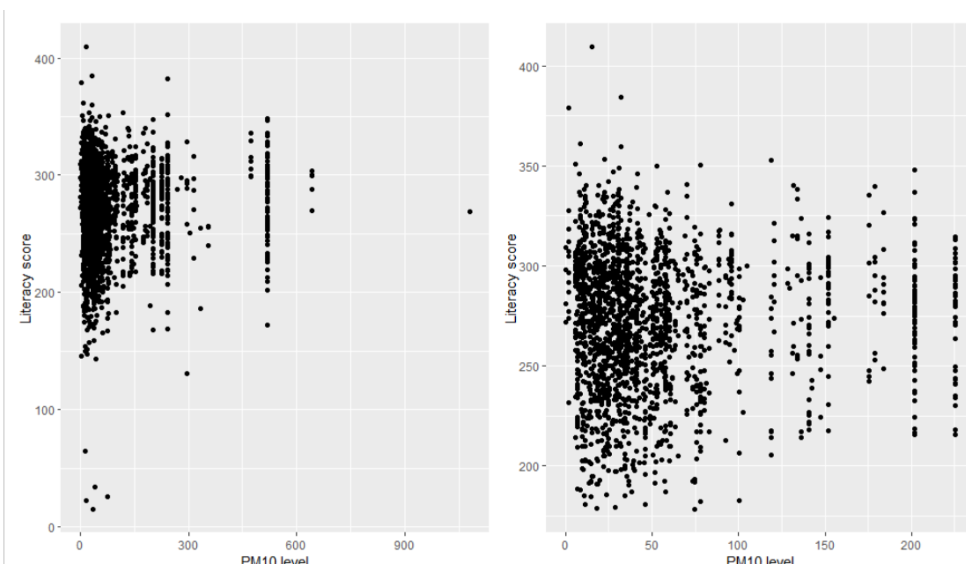

Figure A.2 PM10 levels and literacy scores before and after outlier removal Source: own calculations based on STEP Survey and air pollution open data.

APPENDIX B

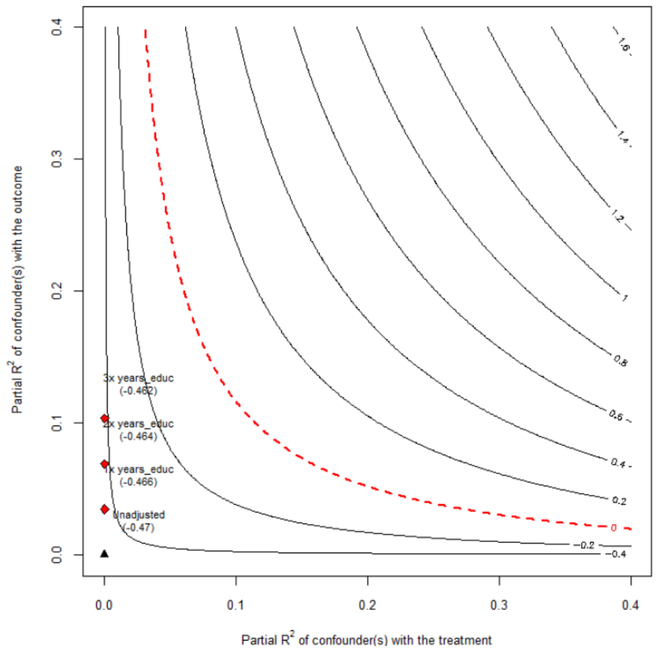

Figure B.1 Sensitivity contour plots of point estimates

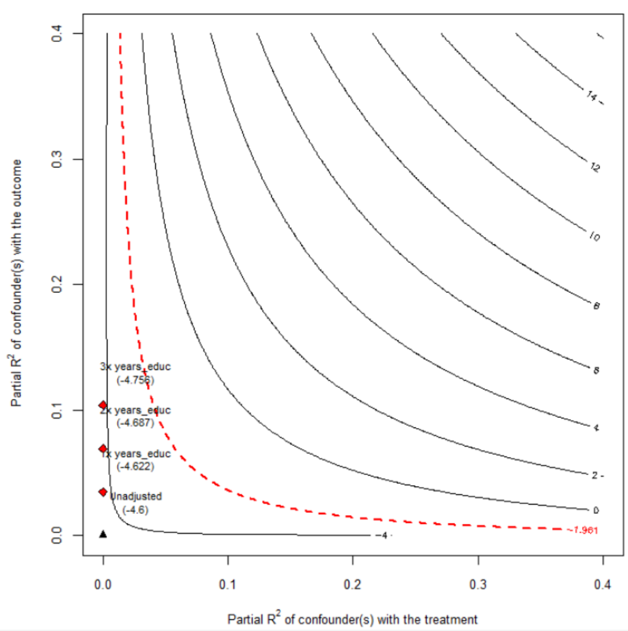

Figure B.2 Sensitivity contour plots of t-values

APPENDIX C

Table C.1. Coefficients for imputing past PM2.5 and PM10 concentrations

	2019 to 2011		2019 to 2012		2020 to 2011		2020 to 2012		2021 to 2011		2021 to 2012	
Oblast	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10	PM2.5	PM10
Vinnytska	0.550	0.693	0.511	0.750	0.576	0.782	0.535	0.846	0.668	0.720	0.621	0.779
Volynska	0.499	0.628	0.427	0.626	0.414	0.561	0.354	0.559	0.411	0.443	0.352	0.442
Dnipropetrovska	1.865	2.349	1.545	2.266	1.963	2.663	1.627	2.569	1.895	2.044	1.570	1.971
Donetska	2.439	3.072	1.947	2.855	2.797	3.795	2.233	3.526	2.720	2.934	2.172	2.726
Zhytomyrska	0.980	1.234	0.695	1.020	0.920	1.248	0.653	1.031	0.985	1.062	0.699	0.877
Zakarpatska	1.450	1.826	0.851	1.248	1.283	1.740	0.753	1.189	1.622	1.749	0.952	1.196
Zaporizka	1.429	1.801	1.131	1.659	1.469	1.993	1.163	1.836	1.468	1.583	1.162	1.459
Ivano-Frankivska	0.598	0.753	0.481	0.705	1.108	1.503	0.891	1.407	0.910	0.981	0.732	0.919
Kyivska	0.950	1.197	0.840	1.231	1.070	1.451	0.945	1.493	1.145	1.234	1.012	1.270
Kirovohradska	0.718	0.904	0.810	1.188	0.635	0.862	0.717	1.132	0.701	0.756	0.791	0.993
Luhanska	6.845	8.622	5.358	7.857	10.987	14.904	8.601	13.582	11.496	12.398	9.000	11.298
Lvivska	1.638	2.064	1.384	2.030	1.427	1.936	1.206	1.904	1.582	1.706	1.337	1.678
Mykolaiivska	1.744	2.196	1.234	1.810	1.829	2.481	1.294	2.044	1.340	1.445	0.948	1.191
Odeska	0.517	0.651	0.413	0.605	0.635	0.861	0.507	0.801	0.827	0.891	0.661	0.829
Poltavska	1.001	1.260	0.814	1.194	0.959	1.301	0.781	1.233	0.923	0.995	0.751	0.943
Rivnenska	1.596	2.010	1.299	1.904	1.553	2.107	1.264	1.996	1.531	1.651	1.246	1.565
Sumska	1.748	2.201	1.338	1.962	1.732	2.350	1.326	2.094	1.631	1.759	1.249	1.568
Ternopilska	0.771	0.971	0.721	1.057	0.731	0.991	0.684	1.080	0.702	0.757	0.656	0.824
Kharkivska	1.827	2.302	1.668	2.446	1.451	1.968	1.325	2.092	1.819	1.962	1.661	2.085
Khersonska	0.551	0.694	0.527	0.773	0.650	0.882	0.622	0.983	0.528	0.570	0.505	0.634
Khmelnytska	2.111	2.659	0.799	1.172	2.293	3.110	0.868	1.370	2.139	2.307	0.810	1.016
Cherkaska	0.929	1.170	0.750	1.099	0.943	1.279	0.761	1.201	0.811	0.875	0.655	0.822
Chernivetska	1.269	1.599	1.029	1.508	1.685	2.285	1.365	2.156	2.334	2.517	1.891	2.374
Chernihivska	1.328	1.673	1.121	1.643	1.410	1.913	1.190	1.879	1.159	1.250	0.979	1.229
city of Kyiv	1.555	1.958	1.163	1.706	1.621	2.199	1.213	1.916	1.443	1.557	1.080	1.356

Note: coefficients calculated using the region-level data from the State Statistics Service of Ukraine and are rounded to three decimal places