Air pollution and cognitive performances

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Abstract

The adverse health impacts of air pollution have been subject of much research and provide the usual rationale for policy interventions in this area. It is only recently being recognized that polluted air might also imply direct economic costs by reducing labor productivity. Recent studies show that that short-term exposure to ozone (O3) and particulate matter ($PM_{2.5}$) significantly reduces the daily productivity of unskilled workers engaged in physical work (fruit picking and packing). However, most work - and in particular most high value work - in a modern economy is based on mental-dexterity, often with little or no physical dimension (e.g. lawyers, administrators, teachers, financiers, computer programmers). Thus, there is a strong interest in studying the impact of pollution on cognitive performances. We take advantage of the design of the US HRS survey (respondents are reinterviewed every two years) to study this relationship. We find that exposure to $PM_{2.5}$ at the WHO recommended maximum daily pollution level of 25 $\mu g/m^3$ reduces performances by 2.5%, that this effect is approximately linear above 15 $\mu g/m^3$, and robust to a variety of specifications.

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1. Introduction

Placing a cost on pollution is the standard approach in economics to justify fighting high levels of pollution. Following the emergence of scientific evidence on the acid rains' costs on natural resources, more stringent emission standards were adopted for several pollutants in various parts of the world during the second half of the 20^{th} century. Ironically, the evaluation of one of the largest program, the SO2 Allowance Trading Program; Title IV, of the 1990 Clean Air Amendments, revealed that while ecological benefits had been overestimated and did not covered the program's costs, unexpected health benefits of the program exceeded the program's costs by a factor of fifty (Schmalensee and Stavins, 2013). In that case, the government was able to do the right thing for the wrong reasons. But it is not always possible; insufficient evidence about the cost of air pollution has been used as a motive to attack US Environmental Protection Agency's new standards several times in the past (see for instance Kaiser, 2000 or Esworthy, 2013).

Today, investigation about the real cost of air pollution continues. Latest evidence include the works of Graff Zivin and Neidell (2012) and Chang et al. (2016). Based on microeconometrics data on US workers, they show that productivity of physical workers reduces by several percentage points on highly polluted days, which converts to tremendous costs when one thinks about the impact of that nuisance on the whole economy. Yet, a growing number of jobs require good mental dexterity, and very little physical efforts, which is the case of numerous *high-value* works (lawyer, engineers, computer programmers...). Thus a burgeoning literature, within which we place ourself, looks at the impact of air pollution on cognitive performances.

Lavy et al. (2014), Lavy et al. (2016), and Roth (2016) study performances of Israeli students and British students, while Archsmith et al. (2016) look at the accuracy of US baseball umpires decisions. The four articles shed light on an impact of daily variation of air pollution on cognitive performances. Yet, umpires job is unique, it requires excellent visual acuity and intense concentration, and the students studied by Lavy et al. and Roth can also be seen as a specific population: the authors show that impacts are greater on males with asthma, which is not directly relevant for the productivity of the adult population. As pointed by Neidell (2017) an important gap in the literature is "evidence from a wide variety of employment settings." The aim of this paper is to see if an additional cost of air pollution comes from its short-term impact on cognitive performances for a variety of workers and non-workers.[3,4]

To lead this investigation we combine the Health and Retirement Study (HRS), a nationally representative survey on 50+ years old US citizens, with daily pollution and weather data obtained from the US Environmental Protection Agency (EPA). We find that exposure to $\mathrm{PM}_{2.5}$ at the WHO recommended maximum daily pollution level of 25 $\mu g/m^3$ reduces performances by 2.5%, that this effect is approximately linear above 15 $\mu g/m^3$, and robust to a variety of specifications.

Section 2 describes the relationship between air pollution and cognitive performances. Section 3 presents the data used for the analysis. Section 4 explains our empirical strategy. Section 5 to 7 present the results. Section 8 concludes.

2. Air quality and cognitive performances

We focus on two pollutants that have the capacity to penetrate building easily, $PM_{2.5}$ and CO, since interviews are led within houses while pollution monitoring stations are located outside. Depending on house characteristics and occupants' habits, indoor/outdoor concentration ratios for $PM_{2.5}$ are typically found between 80 and 100% (Thatcher and Layton, 1995; Baxter et al., 2007; Cao et al., 2005; Bell et al., 2009; Chen and Zhao, 2011).[5] Baek et al. (1997) find indoor-outdoor ratios of CO concentrations close to 1 on a sample of residences, offices, and restaurants located in two Korean cities. Chaloulakou et al. (2003) find that the correlation between indoor and outdoor CO hourly concentrations averaged over a 4 h period measured at the office and at the school in Athens, Greece, were $\rho = 0.85$ and $\rho = 0.92$ respectively.

Physiologically, short-term exposure to $\mathrm{PM}_{2.5}$ is associated with inflammation and oxidative stress in the brain (Kleinman and Campbell, 2014), microglial activation, cerebro-vascular dysfunction, and alterations in the blood-brain barrier of the central nervous system (Genc et al., 2012). These effects can lead to symptoms such as memory disturbance, fatigue, loss of concen-

[3] Also of interest is the chamber study by Allen et al. (2016). They study decisions from 24 subjects exposed to various levels of indoor pollution eight hours a day during five days. They also study cognitive performances on working-age adults, but as pointed by Dominici et al. (2014) such studies present valuable advantages such as clean randomized design and precise measures, but "rely on healthy subjects and focus only on end points of limited value." One of our goal is thus to see if their results are generalisable to the whole population.

[4] We recently came aware of a study led in parallel to ours, but in the Chinese context, and with different empirical setting (Chen et al., 2017).

[5] On the link between air pollution and brain activity we refer the reader to Section 2 above.

tration and judgment (Kampa and Castanas, 2008), any of which could plausibly be linked to reduced mental acuity and so decreased performance in work tasks that require mental acuity.

Due to its known toxicity, controlled experiments assessing the impacts of CO on cognition and mental acuity are rare. Beard and Wertheim (1967) exposed human male subjects to CO levels between 50 and 250 ppm then tested their ability to discern the relative duration of machine generated tones. They find an approximately linear deterioration in correct responses over the range of exposure, with correct responses decreasing by approximately 0.2 percent for each additional ppm of ambient CO. However, multiple attempts to replicate this study have failed to reproduce this result (Raub and Benignus, 2002). **?** suggest that hypoxic depression of cortical function interacted with hypoxic stress generates impairments in performances; thus effects similar to the ones of $PM_{2.5}$ described above. Amitai et al. (1998) found diminished performance of university students on some components of the Comparison of Neuropsychological Screening Battery (CONSB) "when exposed to ambient CO concentrations between 17 and 100 ppm." Reviewing 11 experiments on the effect of CO on cognitive performances, Raub (2004) concludes that evidence are, at best, equivocal.

3. Data

3.1. The HRS

The Health and Retirement Study (HRS) is a biennal survey on 50+ US citizens. Nearly 20,000 individuals are interviewed at each wave and are followed through their life course (Weir, 2016). The survey is designed to be representative of the US population. The survey started in 1992 and answers to the 11^{th} wave (2014-2015) are currently being analyzed. Re-interview rates are rather high compare to similar surveys (Kapteyn et al., 2011). Various fields are covered by the interview, including detailed income sources, property value and cognitive performances.

3.2. Cognitive performance questions

Development of the cognitive performance measures in the HRS draw on the expertise of many cognitive psychologists, gerontologists, geriatricians, and psychiatrists (Wallace et al., 2005). The battery of tests includes memory tests. A list of ten names is read to the respondent, then she has to repeat as many names as possible immediately after the reading (*immediate recall*) and 10 minutes after that (*delayed recall*). Numerical abilities are also tested thanks to three questions such as "If 5 people all have the winning numbers in the lottery and the prize is two million dollars, how much will each of them get?" (*numeracy questions*).[6] Finally a *backward counting* test (7 by 7 from 100 or 86) is also administered. These four tests are the standard tests present in the survey since the original wave in 1992.

In 2003, the HRS Data Monitoring Committee suggested existing measures were insufficient to capture all dimensions of cognitive abilities (Fisher et al., 2014). In 2010 and 2012 waves, two more sophisticated tests were added in order to improve our understanding of the cognitive performances of the respondents: a number series test and a retrieval fluency test. The retrieval fluency test consists in asking the respondent to name as many animals as possible in one minute (*animal naming*). The number series test (*quantitative reasoning*) feels a little harder than the others. Respondents have to find the missing number for five number series of increasing difficulty (an example of the easiest series is 6,7,_,9, while an example of the hardest one is _,20,26,38,62).[7,8]

Basic descriptive statistics on the six cognitive performance questions of the survey are presented in Table 1. Statistics are based on data from 2002 to 2014. We do not go further back in time because the HRS database structure changed in 2002 and most $PM_{2.5}$ monitoring stations have been installed after 2000.

Table 1: Cognitive performances

Variable	Mean	Std. Dev.	Min	Max	Nb. Obs.
Immediate recall	5.457	1.656	0	10	18,502
Delayed recall	4.396	2.001	0	10	18,289
Backward counting	3.635	1.547	0	5	19,637
Numeracy questions	1.203	0.903	0	3	11,378
Quantitative reasoning	507.119	41.489	390.2	584	6,324
Animals naming	16.683	7.058	0	90	7,825

Answers to cognitive performance questions and respondents characteristics are freely available from the HRS after filling a registration form.[9] Data on the exact date of the interview and the geographic location of the respondent were obtained thanks to a specific application.[10]

[6] Respondents answer these questions every two waves (4 years) only.
[7] Answers are 8 and 17.
[8] See HRS documentation on cognitive measures such as Ofstedal et al. (2005), and Fisher et al. (2014), for more information.
[9] See http://hrsonline.isr.umich.edu/index.php?p=reg.
[10] See http://hrsonline.isr.umich.edu/index.php?p=resdat.

3.3. Atmospheric data

Among traditionally studied pollutant, only $PM_{2.5}$ and CO seem appropriate for our study. We needed pollutants for which outdoor/indoor concentrations are high (since interviews are realized indoor but pollution is measured outdoor), and for which neurobiologists suspect an effect on brain activity on the short term (Neidell, 2017).

Particulate matter and CO concentration data are taken from daily measures published online by the United States Environmental Protection Agency' Air Quality System (AQS).[11] We preferred daily data to hourly data, since we do not know the exact time of the interview, $PM_{2.5}$ effect persists for approximately 6 to 24 hours, and it allows to maximize sample size.[12]

To measure pollution exposure, we have to link respondents to the closest monitoring station. Only the census tract of the respondent is available[13], so we consider only respondents living in a census tract whose centroid is less than 25 km ("as the birds fly") from a pollution monitoring station and that is less than 100 sq km large. An advantage of studying $PM_{2.5}$ is that spatial variability is smaller than for most other pollutants. Monn (2001) concludes its literature review on exposure to air pollutants by saying "Spatial variations in pollution concentrations within a city may be significant and are most critical for NO2 and O3, less critical for PM_{10} and $PM_{2.5}$, but critical again for ultrafine particles (<0.1 um)." Thus we ensure that the respondent lives less than 25km from a pollution monitoring station and avoid large measurement errors.[14]

Moreover, it is important to control for the effect of weather confounders, especially temperature that affects cognitive performances (Pilcher et al., 2002) and can be correlated with $PM_{2.5}$ and CO concentrations. Since temperature is substantially more spatially homogeneous than pollutant concentrations, and to avoid loosing data, we use the closest monitoring station within 50km from the census tract centroid. Data are also taken from the AQS.

According to Table 2, more than 5% of the respondents took the interview on days which exceeded the World Health Organization (WHO) standard of exposure of 25 $\mu g/m^3$ 24-hour

[11] See `http://aqsdr1.epa.gov/aqsweb/aqstmp/airdata/download_files.html`.

[12] Daily data allows to maximise sample size compare to hourly data since: (1) hourly measures are used to produce daily measures, and (2) one of the technique to measure PM 2.5 concentrations is to use filters capturing particulate matter for 24 hours in a row.

[13] There are 74,000 census tracts in the US.

[14] For instance Levinson (2012) takes the population-weighted average of the measures of all stations within a 25 miles radius of the respondent's county centroid, Lavy et al. (2016) average the measures of all stations within a 2.5 km of the city limits of the school, and Archsmith et al. (2016) average measures of all stations within a 2 to 10 miles radius of the studied stadium.

Table 2: Pollution exposure of interviewed participants

PM $\mu g/m^3$	Freq.	Percent	Cum.	CO ppm	Freq.	Percent	Cum.
$PM_{2.5}$ 0-5	3,592	17.35	17.35	CO 0.00-0.05	824	3.98	3.98
$PM_{2.5}$ 5-10	7,232	34.94	52.29	CO 0.05-0.10	9,072	43.83	47.81
$PM_{2.5}$ 10-15	5,053	24.41	76.71	CO 0.10-0.15	3,843	18.57	66.38
$PM_{2.5}$ 15-20	2,551	12.32	89.03	CO 0.15-0.20	1,986	9.60	75.97
$PM_{2.5}$ 20-25	1,119	5.41	94.44	CO 0.20-0.25	1,448	7.00	82.97
$PM_{2.5}$ 25-30	553	2.67	97.11	CO 0.25-0.30	1,097	5.30	88.27
$PM_{2.5}$ 30-35	279	1.35	98.46	CO 0.30-0.35	763	3.69	91.96
$PM_{2.5}$ >35	319	1.54	100.00	CO 0.35-0.40	557	2.69	94.65
-	-	-	-	CO 0.40-0.45	363	1.75	96.40
-	-	-	-	CO >0.50	745	3.60	100.00
Total	20,698	100.00		Total	20,698	100.00	

mean of PM$_{2.5}$ and more than 1.5% on days that exceeded the US EPA standard of exposure of 35 $\mu g/m^3$ 24-hour mean of PM$_{2.5}$.

4. Empirical strategy

To test the relationship of interest, we consider an equation of the following form:

$$CP_{it} = \alpha + \beta CO_{it} + \lambda PM_{it} + \sum_{k=2}^{K} \delta_k Xkit + \mu_i + \epsilon_{it} \tag{1}$$

The dependent variable CP_{it} is the score to the cognitive performance test of interest from respondent i in wave t. The six tests are described in the Section 3.2.

The impact of pollution, here CO and PM$_{2.5}$ concentrations, on cognitive performance is captured through coefficients β and λ. The K coefficients δ capture the impact of the various control variables we introduce. The logarithm of total annual income, the age dummies, a dummy whether the individual smokes or not and a dummy whether the individual is retired or not, are gathered from the HRS database directly. Individual fixed effects are capture through μ_i and ϵ_{it} is the error term.

A primary concern when estimating the impact of air pollution on cognitive performances is residential sorting (Chay and Greenstone, 2005; Depro et al., 2015). Sorting of individuals into residential areas may lead to a correlation between air pollution level and cognitive performances that is not causal. By conditioning on individual fixed effects, we exploit only within-individual variation in cognitive performances. That is to say, we study if an individual's performances increase or decrease when she is exposed to higher levels of pollution (not if her cognitive performances are higher or lower in level). Furthermore, conditioning on individual fixed effects allows to control for all time-invariant characteristics of the individual's living area.

Another potential concern is the fact that individuals move because they are more sensible to pollution than others. It could lead to a downward bias, because individuals more sensible to pollution would gather in less polluted areas. About 18% of the respondents moved during the survey. To tackle this issue, we follow Dustmann and Fasani (2016)'s empirical strategy. Once an individual moves, we consider her as a new individual (distinct individual dummy).

5. Results

5.1. Naive cross-sectional estimations

We estimate the effect of $PM_{2.5}$ and CO concentrations on our six cognitive performance tests. In Table 3 we first present naive cross-sectional estimations.

Table 3: Effect of air quality on cognitive performances

Dependent variable	Immediate recall (1)	Delayed recall (2)	Backward counting (3)	Numeracy questions (4)	Quantitative reasoning (5)	Animals naming (6)
meanco	0.101	0.0409	0.216**	0.112*	-25.80***	0.141
	(0.243)	(0.705)	(0.011)	(0.085)	(0.000)	(0.878)
meanpm	-0.00269*	-0.00409**	-0.00249*	-0.000359	-0.0124	0.00556
	(0.060)	(0.023)	(0.069)	(0.727)	(0.864)	(0.655)
smoken	-0.179***	-0.205***	-0.149***	-0.111***	-5.302***	-0.751***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
linc	0.353***	0.394***	0.363***	0.282***	12.18***	1.615***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
agec60	0.0155	0.107***	-0.0119	-0.0430**	-1.576	-0.501**
	(0.598)	(0.003)	(0.667)	(0.039)	(0.174)	(0.015)
agec70	-0.411***	-0.382***	0.00950	-0.115***	-11.83***	-2.553***
	(0.000)	(0.000)	(0.770)	(0.000)	(0.000)	(0.000)
agec80	-1.095***	-1.328***	-0.129***	-0.222***	-16.72***	-4.118***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
agec90	-1.781***	-2.085***	-0.350***	-0.367***	-19.76***	-4.947***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
retired	-0.188***	-0.175***	0.102***	0.0526***	2.457**	-0.837***
	(0.000)	(0.000)	(0.000)	(0.006)	(0.037)	(0.000)
_cons	2.081***	0.607***	-0.241*	-1.751***	384.9***	1.005
	(0.000)	(0.000)	(0.067)	(0.000)	(0.000)	(0.239)
N	18518	18289	19665	11444	7554	7827

Notes: p-values in parentheses $p<0.10$ ** $p<0.05$ *** $p<0.01$.*

Cross-sectional estimations do display a significant association (positive or negative) between air pollution level and cognitive performances for first five tests. Signs of coefficients in front of controls variables are as expected, expect of the retired dummy variable in columns 3-5, which is due to a collinearity with the age dummies.[15] When age dummies are dropped, the coefficient in front of the retired dummy remains consistently negatively significant. Indeed, going to retirement often constitutes a shock that lead to a decrease in cognitive performances.

[15] As revealed by regressions mining.

5.2. Main results

We then present estimations with individual and time fixed effects in Table 4.

Table 4: Effect of air quality on cognitive performances: FE estimations

Dependent variable	Immediate recall (1)	Delayed recall (2)	Backward counting (3)	Numeracy questions (4)	Quantitative reasoning (5)	Animals naming (6)
	Controls, individual FE					
meanco	0.167	0.171	0.108	0.104	-34.58***	-0.0396
	(0.127)	(0.229)	(0.239)	(0.217)	(0.000)	(0.968)
meanpm	0.00338*	0.00194	0.00119	0.00242	-0.328***	0.0187
	(0.054)	(0.373)	(0.394)	(0.113)	(0.002)	(0.168)
N	13824	13631	14987	5682	4928	5581
	*Controls, individual FE, month*year FE*					
meanco	-0.156	-0.215	-0.0690	-0.0144	-4.013	0.0717
	(0.184)	(0.153)	(0.477)	(0.871)	(0.598)	(0.948)
meanpm	-0.000764	-0.00214	-0.000847	0.00121	-0.291***	0.0151
	(0.680)	(0.343)	(0.565)	(0.457)	(0.001)	(0.272)
N	13824	13631	14987	5682	4084	5581
	*Controls, individual FE, month*year FE, age <66*					
meanco	-0.386*	-0.346	0.0219	-0.364*	-3.695	-0.463
	(0.060)	(0.166)	(0.900)	(0.058)	(0.728)	(0.786)
meanpm	-0.000268	-0.00146	0.00240	0.00253	-0.180*	0.0153
	(0.925)	(0.674)	(0.293)	(0.304)	(0.084)	(0.409)
N	5975	5925	6787	2564	2804	2760
	*Controls, individual FE, month*year FE, age >65*					
meanco	-0.118	-0.181	-0.0590	0.0523	-1.992	0.0504
	(0.447)	(0.389)	(0.639)	(0.629)	(0.859)	(0.973)
meanpm	-0.00174	-0.00297	-0.00121	-0.00252	-0.559***	0.0240
	(0.508)	(0.351)	(0.568)	(0.304)	(0.002)	(0.276)
N	7195	7066	7517	2543	1964	2600

Notes: p-values in parentheses p<0.10 ** p<0.05 *** p<0.01. Standard errors clustered at the individual level. OLS-FE estimations. Controls and fixed effects included as specified.*

The negative effect of air pollution on cognitive performances vanishes on most indicators when we introduce individual fixed effects.[16] It suggests strong residential sorting and confirms the need for an identification strategy using individual fixed effects. Besides, it implies that results from cross-sectional studies have to be taken with caution (see Ailshire and Crimmins, 2014, for a study testing the same relationship, with the same data sources, but in cross-section). An interesting negative effect of $PM_{2.5}$ and CO concentrations on quantitative reasoning persists (column 5). This is likely due to the fact that this test is substantially more sophisticated than the others. Simple measures like remembering a list of ten names or counting backward are probably too coarse to capture an effect of air pollution. Interestingly the effect of CO vanishes when we introduce time fixed effects. We come back to this point further in the analysis.

With PM introduced linearly, the coefficients are around -0.300. This means that an increase in PM concentration by 30 ug/m3 reduces the respondent score by 10 points, which is consistent with the bin dummy result below. This is one-fourth of a standard deviation or 2.5% of the average test score. Over a population of 5000 people, being exposed to 30-35 ug/m3 of $PM_{2.5}$ on a given day makes you slip about 250 places compare to a day with a pollution between 0 and 5 ug/m3 of $PM_{2.5}$.

Finally while pollution harms more strongly the elderly - the coefficient's magnitude doubles on 66+ years old - the 50-65 are also harmed by high PM concentrations.

6. Robustness checks

6.1. Co-pollutants and temperature

Temperature, ozone and NOx do not constitute variables of interest since concentration/level inside and outside can dramatically differ. Nevertheless, since PM and CO concentrations can be correlated with temperature, ozone and NOx levels, we introduce the latter as control variables in Table 5 (sequentially in order to keep a sufficient number of observations for the analysis).

[16] A phenomenon that has been confirmed several times during the exploratory phase.

Table 5: Effect of air quality on cognitive performances: additional confounders

Dependent variable	Immediate recall (1)	Delayed recall (2)	Backward counting (3)	Numeracy questions (4)	Quantitative reasoning (5)	Animals naming (6)
	*Controls, individual FE, month*year FE, ozone*					
meanco	-0.228*	-0.335**	-0.0809	-0.0738	-5.511	-0.392
	(0.066)	(0.035)	(0.429)	(0.437)	(0.498)	(0.738)
meanpm	-0.000138	-0.00230	-0.000663	0.00172	-0.260***	0.0161
	(0.943)	(0.339)	(0.666)	(0.325)	(0.004)	(0.262)
meanoz	0.562	2.339	-1.798	-1.956	-84.29	-14.43
	(0.699)	(0.200)	(0.120)	(0.121)	(0.193)	(0.107)
N	12629	12444	13811	5108	4556	5215
	*Controls, individual FE, month*year FE, NOx*					
meanco	-0.145	-0.295	-0.0427	0.0639	-4.753	0.410
	(0.351)	(0.120)	(0.743)	(0.639)	(0.623)	(0.771)
meanpm	-0.00132	-0.00269	-0.000746	0.00177	-0.252**	0.00216
	(0.537)	(0.300)	(0.660)	(0.352)	(0.012)	(0.890)
meanno	-0.0000515	0.00301	-0.000359	-0.00324	0.108	-0.00347
	(0.983)	(0.304)	(0.850)	(0.102)	(0.341)	(0.839)
N	10800	10639	11819	4200	3896	4450
	*Controls, individual FE, month*year FE, temperature*					
meanco	-0.103	-0.134	0.106	0.0594	-1.866	1.202
	(0.501)	(0.472)	(0.418)	(0.638)	(0.820)	(0.309)
meanpm	0.000484	-0.000963	-0.00113	0.000192	-0.257***	0.0141
	(0.818)	(0.706)	(0.496)	(0.918)	(0.009)	(0.355)
smoken	0.0791	0.00194	0.0532	0.0862	4.467	0.776
	(0.542)	(0.989)	(0.543)	(0.260)	(0.342)	(0.181)
meantp	0.00518	0.00735	0.00318	-0.00359	-0.866***	0.0233
	(0.364)	(0.275)	(0.429)	(0.363)	(0.000)	(0.410)
meantpsq	-0.0000296	-0.0000471	-0.0000213	0.0000245	0.00618***	-0.000159
	(0.534)	(0.390)	(0.546)	(0.509)	(0.002)	(0.542)
N	10142	9987	11239	4189	3982	4504

Notes: p-values in parentheses $p<0.10$ ** $p<0.05$ *** $p<0.01$. Standard errors clustered at the individual level. OLS-FE estimations. Controls and fixed effects included as specified.*

Results are unaffected by the introduction of temperature, ozone, or NOx levels.

6.2. Alternative measures and sample selection

In Table 6 we use alternative measures for pollutant concentrations (AQI and maximum level) and alternative census tract selection (keeping large census tracts).

Table 6: Effect of air quality on cognitive performances: alternative measures

Dependent variable	Immediate recall (1)	Delayed recall (2)	Backward counting (3)	Numeracy questions (4)	Quantitative reasoning (5)	Animals naming (6)
	*Controls, individual FE, month*year FE, AQI*					
aqico	-0.00423 (0.181)	-0.00550 (0.202)	-0.00285 (0.271)	-0.000579 (0.786)	-0.155 (0.400)	0.00518 (0.842)
aqipm	-0.000476 (0.473)	-0.000887 (0.282)	-0.000164 (0.752)	0.000491 (0.388)	-0.0821*** (0.007)	0.00344 (0.443)
N	13642	13449	14796	5596	4842	5483
	*Controls, individual FE, month*year FE, maxpm*					
meanco	-0.151 (0.196)	-0.205 (0.171)	-0.0774 (0.422)	0.00314 (0.972)	-5.943 (0.436)	0.150 (0.891)
maxpm	-0.000835 (0.408)	-0.00203* (0.086)	-0.00000653 (0.990)	-0.000445 (0.156)	-0.0342 (0.160)	0.00251* (0.081)
N	13824	13631	14987	5682	4928	5581
	*Controls, individual FE, month*year FE, with large census tracts* ($> 100km^2$)					
meanco	-0.156 (0.184)	-0.215 (0.153)	-0.0690 (0.477)	-0.0144 (0.871)	-4.013 (0.598)	0.0717 (0.948)
meanpm	-0.000764 (0.680)	-0.00214 (0.343)	-0.000847 (0.565)	0.00121 (0.457)	-0.291*** (0.001)	0.0151 (0.272)
N	13824	13631	14987	5682	4084	5581

Notes: p-values in parentheses p<0.10 ** p<0.05 *** p<0.01. Standard errors clustered at the individual level. OLS-FE estimations. Controls and fixed effects included as specified.*

Using the Air Quality Index for $PM_{2.5}$ or CO does not affect the results. When using the maximum concentration level of a pollutant within a day appears to drop the main result (p-value=0.16 for PM). It suggests that average concentration not maximum concentration matters). Keeping large census tracts does not affect the results either.

6.3. Flexible controls set

From now on we focus on the quantitative reasoning test only since it is clear that this is the one affected by pollution. Introducing more flexible controls (using bin dummies for CO or temperature levels) does not affect the main result (see Table 7).

Table 7: Effect of air quality on cognitive performances: flexible controls

	Quantitative reasoning (1)	Quantitative reasoning (2)	Quantitative reasoning (3)	Quantitative reasoning (4)	Quantitative reasoning (5)	Quantitative reasoning (6)	Quantitative reasoning (7)	Quantitative reasoning (8)
meanpm	-0.425***	-0.311**	-0.467***	-0.446***	-0.181*	-0.293**	-0.260**	-0.249**
	(-4.17)	(-2.75)	(-3.81)	(-3.67)	(-2.17)	(-3.24)	(-2.79)	(-2.68)
smoken	-6.234	-1.935	1.551	1.388	1.503	2.254	5.515	5.657
	(-1.67)	(-0.38)	(0.31)	(0.28)	(0.46)	(0.48)	(1.16)	(1.21)
linc	0.184	0.678	0.896	0.836	-0.0610	0.267	0.478	0.454
	(0.20)	(0.71)	(0.89)	(0.84)	(-0.08)	(0.31)	(0.52)	(0.49)
agec60	6.708**	3.500	8.119*	7.891*	-1.034	-2.081	-0.0925	0.000950
	(2.67)	(1.17)	(2.49)	(2.43)	(-0.49)	(-0.85)	(-0.03)	(0.00)
agec70	3.721	4.252	2.795	2.388	-3.953	-4.942	-5.230	-5.505
	(1.37)	(1.37)	(0.81)	(0.70)	(-1.55)	(-1.69)	(-1.67)	(-1.77)
agec80	12.37**	15.56**	11.43*	11.71*	-1.281	0.00957	-1.030	-0.833
	(2.79)	(2.99)	(2.00)	(2.11)	(-0.33)	(0.00)	(-0.20)	(-0.17)
agec90	30.58*	57.20**	43.30*	42.49*	9.373	28.83	25.15	23.68
	(2.31)	(3.17)	(2.28)	(2.25)	(0.71)	(1.68)	(1.39)	(1.32)
retired	4.862*	5.510*	4.366	4.381	-0.465	-1.507	-1.741	-1.607
	(2.11)	(2.17)	(1.61)	(1.57)	(-0.22)	(-0.64)	(-0.68)	(-0.62)
dtpn10	-19.93***		-16.30*	-17.17**	8.735		13.37*	13.70*
	(-4.16)		(-2.53)	(-2.67)	(1.85)		(2.05)	(2.17)
dtpn20	-16.34***		-15.57***	-15.89***	6.571*		9.773*	10.27*
	(-6.30)		(-4.54)	(-4.70)	(2.19)		(2.35)	(2.49)
dtpn30	-12.98***		-9.605***	-9.552***	5.656*		6.994*	7.297*
	(-5.48)		(-3.34)	(-3.32)	(2.18)		(2.13)	(2.25)
dtpn40	-13.68***		-10.55***	-10.49***	1.291		1.735	2.351
	(-6.53)		(-4.04)	(-4.06)	(0.60)		(0.64)	(0.87)
dtpn50	-14.04***		-15.04***	-15.06***	0.169		-1.110	-0.715
	(-8.42)		(-7.18)	(-7.21)	(0.10)		(-0.50)	(-0.33)
dtpn60	-3.954*		-5.189**	-4.985*	0.00977		-1.390	-0.914
	(-2.36)		(-2.65)	(-2.55)	(0.01)		(-0.85)	(-0.55)
dtpn80	1.777		1.195	0.754	-0.559		-1.344	-1.903
	(0.92)		(0.51)	(0.33)	(-0.34)		(-0.70)	(-0.99)
dtpn90	6.167		14.79*	14.40*	6.490		15.06*	14.63*

	(1.14)		(2.29)	(2.17)	(1.52)		(2.57)	(2.44)
dtpn100	-28.15***		-18.73***	-23.09***	-28.20*		-46.84***	-52.09***
	(-6.24)		(-9.55)	(-6.83)	(-2.05)		(-10.73)	(-10.66)
dtpn0	-7.343		-9.345	-6.941	19.25*		19.59	22.22*
	(-0.68)		(-0.74)	(-0.54)	(2.40)		(1.90)	(2.16)
dcon10		-15.05***		-13.96***		-6.992**		-7.128**
		(-5.17)		(-4.50)		(-2.82)		(-2.72)
dcon15		-16.40***		-12.35***		-4.102		-4.209
		(-5.11)		(-3.63)		(-1.46)		(-1.41)
dcon20		-15.23***		-10.39**		-5.181		-3.487
		(-4.18)		(-2.69)		(-1.69)		(-1.06)
dcon25		-20.04***		-12.06**		-5.826		-3.403
		(-4.91)		(-2.78)		(-1.72)		(-0.94)
dcon30		-21.09***		-15.19**		-4.117		-3.834
		(-3.95)		(-2.66)		(-0.95)		(-0.83)
dcon35		-23.63***		-17.59*		-8.296		-9.135
		(-3.76)		(-2.46)		(-1.53)		(-1.50)
dcon40		-17.88**		-11.15		-3.322		-1.650
		(-2.66)		(-1.52)		(-0.60)		(-0.28)
dcon45		-17.92**		-9.683		1.783		2.147
		(-2.64)		(-1.44)		(0.30)		(0.33)
dcon50		-32.91***		-23.44***		-13.51*		-11.97*
		(-5.12)		(-3.51)		(-2.51)		(-2.08)
meanco			-13.62				-2.343	
			(-1.41)				(-0.28)	
_cons	514.7***	516.1***	508.5***	519.3***	499.6***	506.7***	494.2***	498.5***
	(48.93)	(47.22)	(44.59)	(44.41)	(52.86)	(50.03)	(45.34)	(45.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month x year FE	No	No	No	No	Yes	Yes	Yes	Yes
N	6032	4928	3982	3982	6032	4928	3982	3982

*Notes: t-statistics in parentheses * p<0.10 ** p<0.05 *** p<0.01. OLS-FE estimations. standard errors clustered at the designated column names*

7. Further analysis

7.1. Non-linear estimations

In Table 8 and 9 below, we introduce bin dummies in order to relax the linearity of the effect of air pollution on cognitive performances. 5 and 10 ppm bin dummies are used in columns (1-2) and (3-4) respectively.[17] Year*month fixed effects are introduced columns (2) and (4). Results are also presented graphically Figure 1 and 2.

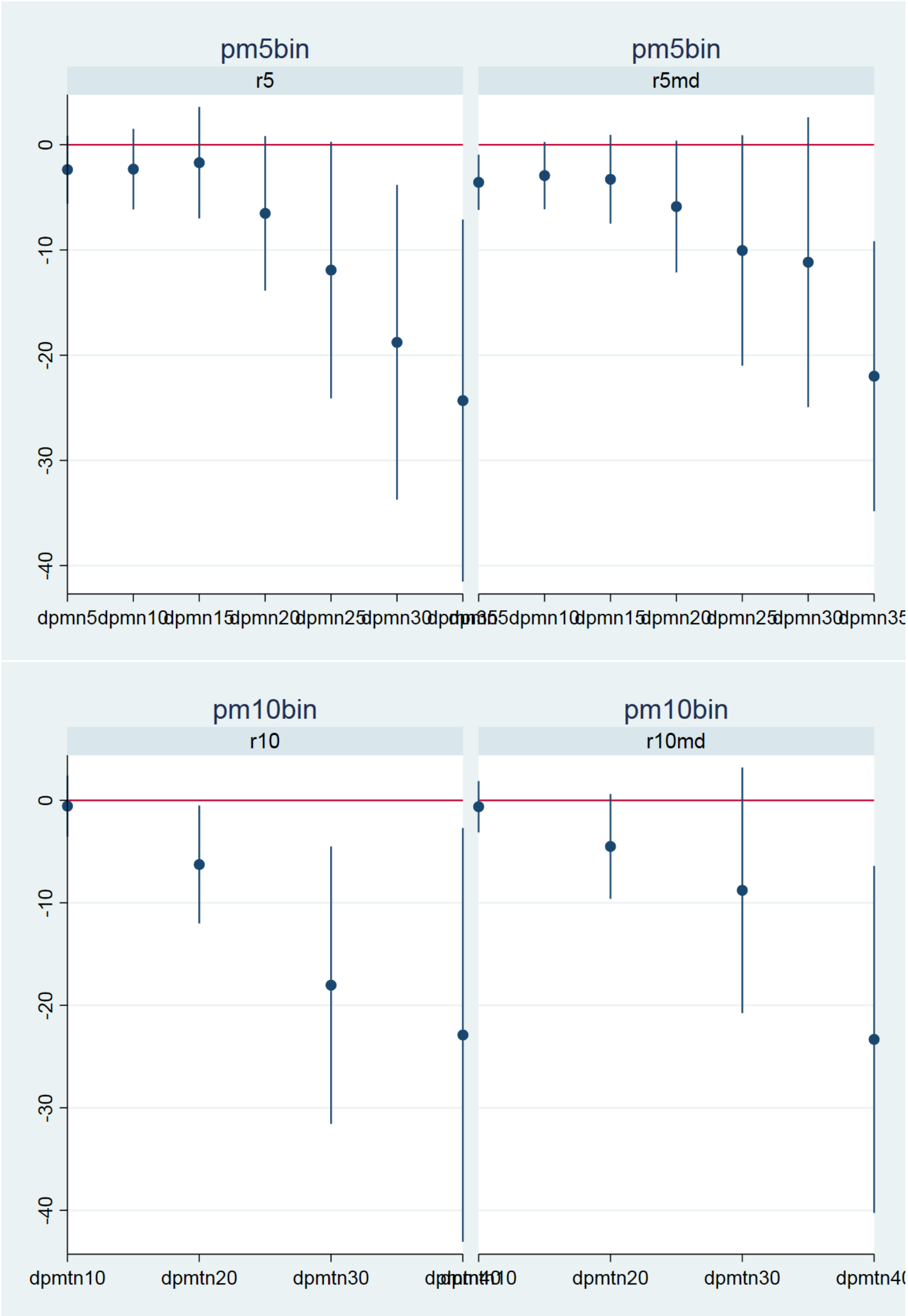
Table 8: Effect of air quality on cognitive performances: non linear est. $PM_{[}2.5]$

Dependent variable: Quantitative reasoning	5-bin	5-bin	10-bin	10-bin
	(1)	(2)	(3)	(4)
dpmn5	-2.362 (0.152)	-3.569*** (0.008)	- -	-
dpmn10	-2.310 (0.237)	-2.926* (0.073)	-0.554 (0.687)	-0.615 (0.631)
dpmn15	-1.704 (0.529)	-3.279 (0.127)	- -	
dpmn20	-6.518* (0.082)	-5.874* (0.066)	-6.256* (0.068)	-4.492* (0.085)
dpmn25	-11.91* (0.055)	-10.05* (0.072)	- -	
dpmn30	-18.78** (0.014)	-11.16 (0.112)	-18.03** (0.018)	-8.771 (0.151)
dpmn35	-24.31*** (0.001)	-22.00*** (0.006)	- -	
dpmn40	- -	- -	-22.89*** (0.001)	-23.32*** (0.007)
_cons	505.5*** (0.000)	501.8*** (0.000)	504.1*** (0.000)	499.4*** (0.000)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Month x year FE	No	Yes	No	Yes
N	4928	4928	4928	4928

*Notes: t-statistics in parentheses * p<0.10 ** p<0.05 *** p<0.01. OLS-FE estimations. standard errors clustered at the census tract level*

[17] For CO 0.05 and 0.10 ppm bin dummies are used.

Figure 1: Ploting PM bin dummies coefficients



Legend: Top-left graph corresponds to estimation (1) Table 8, top-right graph to estimation (2), bottom-left graph to estimation (3) and bottom-right graph to estimation (4).

Estimation column (1) shows that the higher the pollution is, the higher is the impact on cognitive performances. Being exposed to 20-25 $\mu g/m^3$ of $PM_{2.5}$ on a given day (the WHO 24-hour mean limit is 25 ug/m3) reduces respondent score by 10 points. This is perfectly consistent with the linear estimations. The magnitude of our effect is of the same order than the ones found by Lavy et al. (2016) and Archsmith et al. (2016).[18] It is interesting to note that our estimations reveal impacts of air pollution at levels below the WHO and EPA standards. The effect of PM concentrations on cognitive performances seem linear, especially above 15 $\mu g/m^3$.

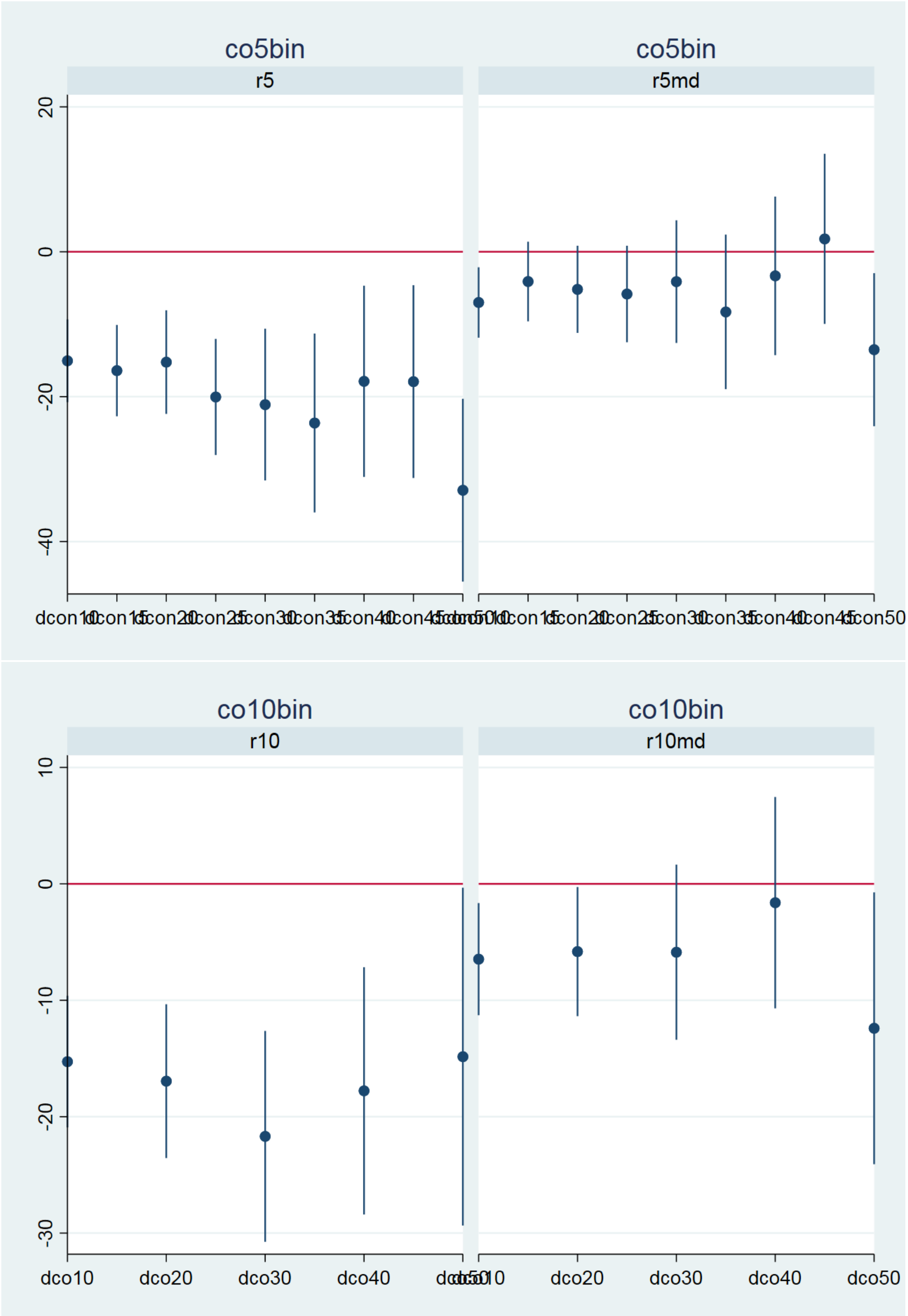
[18] Results are not directly comparable. Archsmith et al. (2016) found that moving from the 25^{th} percentile to the 90^{th} reduces productivity by 1.59%. Lavy et al. (2016) show that performances of test takers on extremely polluted days, with an AQI reading above 101 for PM2.5, are associated with a decline in test score of 1.95 points, or 8.2% of a standard deviation

Table 9: Effect of air quality on cognitive performances: non linear est. CO

Dependent variable: Quantitative reasoning	5-bin	5-bin	10-bin	10-bin
	(1)	(2)	(3)	(4)
dcon10	-15.05***	-6.992**	-15.27***	-6.467***
	(0.000)	(0.022)	(0.000)	(0.009)
dcon15	-16.40***	-4.102	-	-
	(0.000)	(0.234)	-	-
dcon20	-15.23***	-5.181	-16.95***	-5.819**
	(0.000)	(0.158)	(0.000)	(0.040)
dcon25	-20.04***	-5.826	-	-
	(0.000)	(0.116)	-	-
dcon30	-21.09***	-4.117	-21.69***	-5.872
	(0.000)	(0.346)	(0.000)	(0.126)
dcon35	-23.63***	-8.296	-	-
	(0.000)	(0.112)	-	-
dcon40	-17.88***	-3.322	-17.78***	-1.617
	(0.008)	(0.586)	(0.001)	(0.727)
dcon45	-17.92***	1.783	-	-
	(0.008)	(0.776)	-	-
dcon50	-32.91***	-13.51**	-14.84**	-12.40**
	(0.000)	(0.021)	(0.045)	(0.037)
_cons	505.5***	501.8***	504.1***	499.4***
	(0.000)	(0.000)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Month x year FE	No	Yes	No	Yes
N	4928	4928	4928	4928

*Notes: t-statistics in parentheses * p<0.10 ** p<0.05 *** p<0.01. OLS-FE estimations. standard errors clustered at the census tract level*

Figure 2: Ploting Pm bin dummies coefficients



Legend: Top-left graph corresponds to estimation (1) Table 9, top-right graph to estimation (2), bottom-left graph to estimation (3) and bottom-right graph to estimation (4).

The effect of CO is not robustly significant, as expected and especially when introducing time fixed effects. Indeed, CO concentration levels are lower than the ones to which participants were exposed in the experiments described in Section 2. Yet, we think that non-significant result is to be taken with caution. Indeed, introducing FE is equivalent to a within transformation of the variables. At the individual level it makes sense (deviation from the level to which the individual is used). At the month-year level, not so much (deviation from the monthly average at the USA level). It is standard in the literature to introduce these time FE since they allow to control for potential confounders (factors influencing a common trend between cognitive performances and pollution). Since we have no reason to think that confounders exist in our case, the introduction of time FE seems debatable (since they can induce multicollinearity problems here) and our investigation does not allow us to firmly reject the impact of CO on quantitative reasoning.

7.2. Temporality of the effects

To ensure that we are capturing the effect of short term variations and not medium or long term ones, we sequentially introduce the pollution level one, two... six days before the interview as well as the average pollutant concentration during the last seven days. For these series of tests we focus on the main pollutant of interest, $PM_{2.5}$.

Table 10: Effect of air quality on cognitive performances: lagged values and contemporaneous value

	Quantitative reasoning (1)	Quantitative reasoning (2)	Quantitative reasoning (3)	Quantitative reasoning (4)	Quantitative reasoning (5)	Quantitative reasoning (6)	Quantitative reasoning (7)	Quantitative reasoning (8)
meanpm	-0.291***	-0.288**	-0.343***	-0.362***	-0.398***	-0.396***	-0.349***	-0.310**
	(0.001)	(0.029)	(0.004)	(0.001)	(0.000)	(0.001)	(0.001)	(0.017)
meanco	-4.013	-3.356	-2.404	-3.194	-1.827	-3.007	-3.858	-4.735
	(0.598)	(0.726)	(0.800)	(0.736)	(0.851)	(0.758)	(0.690)	(0.612)
lpm		-0.149						
		(0.187)						
l2pm			-0.0967					
			(0.369)					
l3pm				0.00669				
				(0.949)				
l4pm					0.0556			
					(0.598)			
l5pm						0.0298		
						(0.751)		
l6pm							0.0222	
							(0.829)	
pm7days								-0.0860
								(0.633)
_cons	501.9***	523.4***	524.7***	519.2***	520.6***	516.8***	513.8***	521.1***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4928	3264	3240	3376	3188	3160	3318	3510

*Notes: t-statistics in parentheses * p<0.10 ** p<0.05 *** p<0.01. OLS-FE estimations. standard errors clustered at the designated column names*

Correlation between PM_t and PM_{t-1} are high but when the two variables are introduced simultaneously, we see that the contemporaneous level of pollution seem to matter most. The introduction of the other lagged terms in Table 10 confirms that the contemporaneous level of pollution matters.

Finally, in Table 11 below, we test the short term versus medium term effect of PM concentrations by introducing the number of days PM levels exceeded the WHO recommended threshold of 25 $\mu g/m^3$ of $PM_{2.5}$ during the last 1, 2 or 3 months. Medium term effect of exposure are not revealed by our investigation and short term effects hold.

Table 11: Effect of air quality on cognitive performances: Nb days exceeding 25ug/m3 within 1, 2, 3 months

	Quantitative reasoning (1)	Quantitative reasoning (2)	Quantitative reasoning (3)	Quantitative reasoning (4)
meanpm	-0.291*** (0.001)	-0.351*** (0.001)	-0.350*** (0.001)	-0.342*** (0.002)
meanco	-4.013 (0.598)	-4.701 (0.617)	-4.729 (0.615)	-4.818 (0.608)
nbex30		0.0335 (0.929)		
nbex60			0.00695 (0.976)	
nbex90				-0.0589 (0.747)
_cons	501.9*** (0.000)	520.5*** (0.000)	520.5*** (0.000)	520.7*** (0.000)
Individual FE	Yes	Yes	Yes	Yes
Month x year FE	Yes	Yes	Yes	Yes
N	4928	3510	3510	3510

*Notes: t-statistics in parentheses * p<0.10 ** p<0.05 *** p<0.01. OLS-FE estimations. standard errors clustered at the census tract level*

8. Conclusion

We examined the impact of air pollution on cognitive performances using a sample of 16000 respondents to the HRS survey over the 2002-2012 period.

We found that an effect of $PM_{2.5}$ concentration is discernable on sophisticated measures such as finding the missing number in series.

Our results have implications for the establishment of pollution standards. Results of pollution on cognitive performances found on students by Lavy et al. (2016) or on baseball umpires by Archsmith et al. (2016), or in a chamber study by Allen et al. (2016) seem generalisable to the rest of the population, at least for $PM_{2.5}$, thus suggesting a significant effect of air pollution on workers productivity and citizens' welfare, and consequently substantial costs for our economies.

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