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LETTER

Ambient PM2.5 influences productive activities in public sector bureaucracies

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Abstract

Fine particles (PM2.5) can penetrate buildings through ventilation and air conditioning systems, exposing indoors workers to pollution levels similar to those prevailing outdoors. This letter investigates the immediate influence of fine particle pollution on the productive activity of local government bureaucracies, linking novel data on the daily output of local governments in municipalities of the Athens metropolitan area, Greece, to PM2.5 levels recorded nearby. To address biases introduced by omitted variables and measurement error, I use the plausibly exogenous variation introduced by the basin's horizontal ventilation, instrumenting PM2.5 levels with local wind strength. Estimates suggest a statistically and quantitatively significant negative effect from PM2.5 on the output of public administrations. Increasing PM2.5 levels by 1% decreases the activity proxy by around 0.25%. Results point to the influence PM2.5 can have on activities that are mentally but not physically demanding and suggest that costs from PM2.5 will increase with the share of global income produced by office workers.

1. Introduction

Urban air pollution is a pressing environmental issue with significant human cost. The adverse health effects of air pollution exposure on human health are well documented (Brunekreef and Holgate 2002, Kampa and Castanas 2008, Apte *et al* 2015, Oudin *et al* 2016, Woodward and Levine 2016). Among others, air pollution has negative influence on fetal and infant health (Chay and Greenstone 2003, Currie and Neidell 2005, Luechinger 2014), hinders lung development in children (Gauderman *et al* 2004) and impacts on cognitive function (Tallon *et al* 2017, Zhang *et al* 2018). The effects of air pollution are discernible on human activity (Graff Zivin and Neidell 2013). Air pollution reduces hours worked (Hanna and Oliva 2015), influences worker performance and decreases workers' productivity (Graff Zivin and Neidell 2012). The impact of air pollution is not limited to those working outdoors. Fine particles of diameter <2.5 μm can enter buildings through ventilation systems exposing indoors office workers to the harmful impact of pollution. The potential cost of air pollution increases with growing urban global populations and with the share of output produced by office workers.

This letter contributes to the literature on the human impact of urban atmospheric pollution and extends the evidence on the influence of PM2.5 to indoor office workers, focusing on the immediate impact of PM2.5 on the output of public sector bureaucracies. To overcome the challenges involved in measuring the daily output of the public sector I use a novel dataset drawn from municipal governments in the Greater Athens Area (GAA) in Greece, and link it to PM2.5 levels recorded by the local pollution monitoring network. This allows me to assess the pollution-activity relationship at a narrow spatial and temporal scale. To address concerns posed by the endogeneity of pollution exposure and measurement error, I employ an Instrumental Variables approach, exploiting the plausibly exogenous variation introduced by the horizontal ventilation in the area, as approximated by local ground level wind strength. Given that bureaucratic activities take place indoors in sheltered office environments, wind will affect output only through its impact on PM2.5 pollution, after accounting for location specific characteristics, weather conditions and seasonal variation.

I find that PM2.5 has a statistically and quantitatively significant effect on the day-to-day operation of municipal bureaucracies. A 1% increase in PM2.5 levels around the location of a municipal administration decreases the activity proxy by 0.04%. Measurement error will understate the estimated negative impact of air pollution on activity (Angrist and Pischke 2009, Wooldridge 2010). Using the plausibly exogenous variation introduced on PM2.5 levels by local winds to overcome the endogeneity of pollution exposure increases the estimated impact: Estimates from an Instrumental Variables approach suggest that a 1% increase in PM2.5 decreases output by around 0.25%. Estimates are robust to a series of perturbations in the model specification.

A growing literature explores the impact of air pollution exposure on human capital (Graff Zivin and Neidell 2013). Graff Zivin and Neidell (2012) and Lichter *et al* (2017) find that exposure to common pollutants has substantial and statistically significant negative effects on the productivity of outdoors workers. Heyes *et al* (2019) show that greater PM2.5 concentrations are related to lower speech performance by Canadian Members of Parliament. Chang *et al* (2016) show that the productivity of pear packers decreases with nearby concurrent PM2.5 concentrations, while Chang *et al* (2019) find a similar relationship for call center workers in China suggesting an immediate effect of pollution on output. On the other hand, He *et al* (2019) study the productivity of manufacturing workers in two Chinese cities finding that sustained exposure to pollution can have medium run effects. Contrary to Chang *et al* (2016) and He *et al* (2019) who focus on menial work and manufacturing respectively, this letter examines the impact of pollution on the aggregate production of office workers and policy makers engaging in daily administrative and bureaucratic tasks. To the best of my knowledge this paper is the first to examine the impact of pollution on administrative and bureaucratic activities that are common in all office-type working environments, pointing to an impact of pollution that hasn't yet been assessed.

The rest of this letter proceeds as follows. The next section briefly presents some background information on the study area while section 3 discusses the data and empirical strategy. Section 4 presents the results and section 5 concludes.

2. Background

I employ data from the Greater Athens Area (GAA) in Greece. The GAA encompasses the city of Athens, Greece's capital, administrative center and largest city, and the surrounding metropolitan area. It comprises 46 independent municipalities with jurisdiction over local government matters. Around 4 million people live in the GAA producing over 42% of Greek national income.

The region has a long and extensively documented history of air quality problems. Prominent pollution sources are industry, transport and central heating. The large scale of economic activity combined with local topography presenting natural obstacles to the basin's ventilation, contribute to high concentrations of atmospheric pollutants in the area (Katsoulis 1988, Kassomenos *et al* 1995, Chaloulakou *et al* 2008, Diapouli *et al* 2017). Between the late 1970s to the early 2000s the GAA was notorious for severe photochemical pollution episodes driven primarily from vehicular traffic, occurring frequently during warmer months (Hatzianastassiou *et al* 2007). A systematic policy effort including the regulation of fuel quality, traffic interventions and incentives for renewing the passenger car fleet decreased the prevalence of photochemical pollutants by the mid 2000s. In the aftermath of the 2010 Greek financial crisis and the long subsequent recession, PM10 and PM2.5 have been the primary threat to local air quality as decreasing income and increasing fuel taxes led households to substitute biomass for heating oil (Valavanidis *et al* 2015).

3. Data and empirical strategy

3.1. Data

Office workers, public sector administrators, and elected officials expend individual and collective effort to produce multiple outputs. Many of those are hard to observe or measure. To address the challenge of approximating the daily output of office workers in general, and public sector bureaucracies in particular, I focus on Greek municipalities and use a rule introduced in 2010 by the central government, imposing reporting requirements for public sector organizations and the local government. Greek municipalities are responsible for local policy design and implementation, as well as for the everyday functioning of their jurisdiction. To meet

Table 1. Descriptive Statistics.

	(1) Mean	(2) St. Deviation
PM2.5 (μg m^{-3})	15.59	9.37
Activity (acts uploaded)	14.19	16.89
Mean daily temperature (degrees Celsius)	19.22	7.06
Mean daily relative humidity (Percent)	60.09	13.01
Mean daily wind speed (m s^{-1})	1.45	1.01
Labor strikes	0.034	0.18
Public transport strikes	0.036	0.185

Note: The table presents descriptive statistics for some of the variables used in the analysis.

these responsibilities, office workers, administrators and elected officials decide and implement policies, determine actions or authorize payments. In 2010 the central government established the 'Diavgeia'[2] reporting system with Law 3861/2010, aiming to promote transparency and accountability in public sector operations. The Law requires all government tiers and state-owned organizations to post all decisions and administrative acts on a common, publicly accessible online portal. Reporting is mandatory for tasks that are typical for the functions of municipal governments, such as ratifying policy, procurement competitions, raising payment orders and approving expenditure and overtime[3], while decisions and actions are invalid unless reported to the database[4]. Importantly, organizations are obliged to report immediately after a decision or act has been signed off. The daily count of Diavgeia records by each GAA municipality is the dependent variable in the following analysis. It is intended to approximate the component of the total output of local government activities at the municipality level that is produced by the actions of administrators and elected officials mandated with designing and implementing policy. Examining the relationship between the proxy and PM2.5 is also informative regarding the link between the pollutant and other office work outputs that are not necessarily immediately quantified by the number of Diavgeia posts. Pollution influences output by affecting workers supply of labor (Hanna and Oliva 2015), or their effectiveness (Chang *et al* 2019). There is no reason to expect that the influence of PM2.5 on other unobserved office work-related outputs that require similar processes for their delivery will be systematically different from the influence of PM2.5 on the proxy, since the effect of pollution on administrators and elected officials is not task dependent.

Access rights to the reporting system are held by multiple department administrators and elected officials in each municipality, authorized to approve acts while the composition of the workforce and elected officials do not exhibit systematic day-to-day variation. Reporting requirements for local government were introduced in late 2012 and I use data from 2013 onward to ensure all municipalities adhere to the rules.

Focusing on the activity of municipal governments, and excluding central government and other state-operated organizations, ensures the legal framework, reporting obligations and seasonality in decision making are comparable across all organizations in the sample. Importantly, given the institutional setting and the practices of local government, the focus on municipalities allows me to identify the exact location where activities take place and relate it to local air quality. Each municipality's administrative services, policy makers and office workers are typically housed in a single building, usually the Town Hall, situated within the municipality's administrative borders. In contrast, central government activities are distributed across the entire country. Given the size, structure and opacity of the Greek public sector and the data available, central government administrative activity cannot be located with certainty.

Daily average PM2.5 levels come from the pollution monitoring network operated by the Greek Ministry of the Environment, and are available to 2017. Four stations recorded PM2.5 levels in the GAA. To begin, I assign Town Halls with the reading taken from the nearest pollution monitoring station. In later robustness tests I also assign Town Halls with the inverse distance weighted average measurement from all stations. Meteorological data come from the Athens National Observatory network of stations. I assign Town Halls with the values of meteorological variables reported by the nearest meteorological station. Data on labor and public transport strike action are drawn from an online register at http://apergia.gr. In all cases I exclude public holidays and weekends from the analysis.

[2] Data are publicly available and accessible via https://diavgeia.gov.gr/

[3] As of 2019, Diavgeia hosts over 34 m acts from 4780 organizations, uploaded by over 30 000 users.

[4] Only acts containing classified information and those including sensitive personal data are excluded from reporting requirements.

Table 1 presents some descriptive statistics of the variables included in the analysis. The average recorded PM2.5 level was 15.59 μg m^{-3} while municipal bureaucracies produced on average 14.19 acts per day. Labor and public transport strikes took place on 3.4% and 3.6% of the studied dates respectively.

3.2. Empirical strategy

The empirical approach relates the daily activity proxy in GAA municipalities to PM2.5 levels prevailing around each municipality's Town Hall. I start by estimating:

$$lnQ_{it} = \alpha_i + \beta_1 PM_{it} + \beta_2 T_t + \beta_3 M_{it} + \beta_4 S_t + \epsilon_{it} \quad (1)$$

lnQ_{it} is the logarithm of the activity proxy in municipality i on date t. PM_{it}, the main variable of interest, measures the daily average level of PM2.5 recorded near a Town Hall. T_t is a matrix of time effects. α_i are municipality-specific fixed effects and M_{it} is a matrix of meteorological variables. Finally, S_t contains public transport and labor strike indicators. For all models reported later, I report standard errors clustered at the municipality and date levels.

Municipality fixed effects α_i account for time-invariant municipality-specific characteristics such as workforce[5] and jurisdiction size that may be correlated both with output and local air quality. Municipal fixed effects are also location controls. Administrative productive activities for each municipality examined here take place in a fixed location over time, typically within a single building. Municipality-specific effects capture the location of a municipality's Town Hall in relation to pollution sources as well as features of the surrounding area that could simultaneously impact on local air pollution and worker activity. They also account for building specific characteristics such as ventilation systems and age. Controlling for municipality fixed effects implies that identification of β in (1) relies on within-municipality variation over time. This is important, as municipalities in the GAA vary with respect to population and size, implying variation in output across municipalities.

Matrix T_t includes day-of-week, year and day-of-year effects, flexibly adjusting for seasonal variation. Variables in T_t will pick up the influence of time-varying, city-wide unobserved confounders, that may systematically impact both on municipal output and local air pollution.

Matrix M_{it} includes controls for average daily temperature, relative humidity and rainfall that can affect both worker performance (Mukamal *et al* 2009, Ranson 2014) and air quality (Aw and Kleeman 2003). Rainfall enters models as an indicator variable equal to one if rainfall was recorded on date t. To address possible lagged impacts of meteorological conditions on output and air quality I also include the weather variables lagged once and twice.

The period I examine here was characterized by frequent labor and public transport strikes that could impact pollution and workers' performance. To account for this, S_t includes labor strike and public transport strike indicator variables.

3.3. Instrumental variables approach

Estimating the impact of air pollution on any type of human activity is challenging due to unobserved confounders and agents' ability to systematically engage in avoidance behavior to minimize negative effects from exposure. As a first step towards addressing this concern, equation (1) employs municipality-specific and time-specific effects. The former set of controls captures time invariant, municipality specific unobserved confounders, while the latter accounts for basin-wide, time-varying and seasonal omitted variables. Nevertheless, threats to identification remain from time-varying, location-specific unobserved confounders. Unobserved traffic and other polluting activity around a Town Hall for example, will be positively correlated both with local air pollution and with workers' productive activity. Ignoring its influence while regressing output on PM2.5 concentrations will result in estimates of β_1 that are biased upwards, understating the impact of pollution.

An additional source of concern follows from the imperfect measurement of pollution. PM2.5 exposure is not precisely measured, and can only be approximated by pollution recorded at the location of the nearest[6] pollution monitoring station. In addition there are no measurements of indoors particle levels. Finally, exposure will depend on workers' commuting patterns and residential locations that are unknown. Measurement error will attenuate estimates understating the negative effect of pollution on output, and exaggerating the bias introduced by unobserved confounders.

To address these biases I apply an Instrumental Variables approach (Angrist and Pischke 2009, Wooldridge 2010). The method requires a variable to serve as an instrument for PM2.5 levels. The instrument should have three properties: First, it should be as good as randomly assigned, second it must be correlated with

[5] For the period studied a near-freeze in public sector hiring was in place as part of Greece's bailout agreement. In later robustness tests I introduce municipality specific time controls and the results remain unchanged.

[6] Or later by the inverse distance weighted average of pollutant concentrations reported by all stations.

Table 2. OLS Estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
$ln(PM2.5)$	−0.036***	−0.045***	−0.042**			
	(0.015)	(0.016)	(0.016)			
$10 < PM2.5 \leqslant 20$				−0.053***	−0.062***	−0.063***
				(0.017)	(0.018)	(0.018)
$PM2.5 \geqslant 20$				−0.070***	−0.081***	−0.078***
				(0.021)	(0.023)	(0.023)
Strike Controls	No	Yes	Yes	No	Yes	Yes
Weather Controls	No	No	Yes	No	No	Yes
Observations	51 840	51 840	51 840	51 840	51 840	51 840

Note: The table presents OLS estimates from equation (1). Dependent variable in all columns is the natural logarithm of the productive activity proxy in municipality *i* at time *t*. All models include municipality and time specific effects. Standard errors, clustered at the municipality and date levels in parentheses.
*** $p < 0.01$
** $p < 0.05$

PM2.5, and third it should satisfy the exclusion restriction, requiring the instrument to be uncorrelated with other unobserved variables affecting the output of municipal office workers.

I use the strength of ground level winds as recorded by the local meteorological monitoring network to instrument PM2.5 levels. Stronger winds facilitate mixing of air masses and disperse pollutants (Chaloulakou *et al* 2003). The relationship between wind and air pollution in the GAA is strong and extensively documented (Kassomenos *et al* 1995, Ziomas *et al* 1995, Dimitroulopoulou *et al* 2011). Chaloulakou *et al* (2003) find a quantitatively and statistically significant, negative relationship between local daily average wind speed and PM2.5 levels. Moreover the relationship is non-linear in the 0–3m s^{-1} range. I use the average daily ground level wind speed recorded by the meteorological station nearest to the Town Hall to instrument PM2.5. To account for possible non-linear influence on PM2.5 levels (Jones *et al* 2010, Apte *et al* 2015), wind speed enters models in 3 bins: $0 \leqslant w < 1, 1 \leqslant w < 2$ and $w \geqslant 2$m s^{-1}.

I therefore apply a Two Stage Least Squares approach where the first stage is given by equation (2) below:

$$PM_{it} = \alpha_i + \gamma_1 W_{it} + \gamma_2 T_t + \gamma_3 M_{it} + \gamma_4 S_t + u_{it} \quad (2)$$

where W_{it} is wind speed measured in m s^{-1}, and the second stage is described by equation (1)

The exclusion restriction requires that local wind strength does not directly impact on worker activity. As administrative activities take place in a sheltered indoor office environment, workers are not exposed to the elements and do not experience immediate influence from wind. Furthermore, winds in the area are not systematically related to problems in commuting routes preventing workers from reaching their workplace. In any case, I later test for the robustness of the results to small violations of the exclusion restriction using the approach proposed by Conley *et al* (2012). Similar IV approaches have been applied by He *et al* (2019) and Herrnstadt *et al* (2016).

4. Results

4.1. OLS estimates

I begin by presenting Ordinary Least Squares (OLS) estimates[7] from equation (1) in table 2. In columns 1 to 3, PM2.5 enters models in natural logarithms, while in columns 4 to 6, PM2.5 enters in bins of 10 μg m^{-3} to allow for possible non-linear influence of fine particles on productive activities (He *et al* 2019, Heyes *et al* 2019). Models in columns 1 and 4 include municipality effects and calendar controls while the remaining columns progressively introduce weather and strike action variables. In all cases, I rely on within-municipality variation remaining after adjusting for the set of controls to identify the coefficients of interest.

Estimates suggest a strong, negative association between PM2.5 and the output proxy. Estimated coefficients on the PM2.5 variables are statistically significant while their signs and magnitudes are invariant to the set of included controls. For the model adjusting for the full set of controls in column 3, increasing local PM2.5 concentrations by 1% is associated with a decrease in the activity proxy by approximately 0.04%.Estimates are

[7] I conduct Fisher-type panel unit root tests and reject the null of a unit root for the main variables. I also estimate models with panel specific AR(1) disturbances and get identical results. Similarly when employing the Pesaran and Smith (1995) mean group estimator.

Table 3. First Stage Estimates.

	(1)	(2)	(3)
$1\ \mathrm{m\ s^{-1}} < WS \leqslant 2\ \mathrm{m\ s^{-1}}$	-0.180^{***}	-0.130^{***}	-0.129^{***}
	(0.017)	(0.015)	(0.015)
$WS > 2\ \mathrm{m\ s^{-1}}$	-0.316^{***}	-0.223^{***}	-0.222^{***}
	(0.025)	(0.022)	(0.022)
Weather Controls	No	Yes	Yes
Strike Controls	No	No	Yes
First-Stage F-statistic	81	53	52
Observations	51 840	51 840	51 840

Note: Each column presents estimates from a different model. In all cases dependent variable is $lnPM2.5$. All models include municipality-specific and time effects. Standard errors, clustered at the municipality and date level in parentheses.
$^{***}\ p < 0.01$

qualitatively similar when PM2.5 enters in bins. For the model in column 6 adjusting for the full set of covariates, PM2.5 concentrations between 10 μg m^{-3} and 20 μg m^{-3} decrease the activity proxy by 6.3% relative to the baseline of PM2.5$\leqslant$10 μg m^{-3}. PM2.5 exceeding 20 μg m^{-3} decreases activity by around 7.8%[8]. I reject the null of both coefficients being equal to zero at 1% level ($p = 0.000$), but the null of equal coefficients is not rejected at conventional significance levels. Table A1 in the appendix reports identical estimates from Poisson regressions.

4.2. Two stage least squares estimates

I now turn to the 2SLS estimates, instrumenting the natural logarithm of PM2.5 with local wind speed to account for biases introduced by omitted variables and measurement error. I focus on models where the instrumented variable is the natural logarithm of PM2.5. I start by providing evidence on the strength of the relationship between the PM2.5 and the instrument, presenting estimates from the First-Stage regression of $lnPM2.5$ on wind speed, described in equation (2). As wind speed in a location on a given day is as good as random, reported estimates can be interpreted as the causal effect of wind strength on local PM2.5 levels. Estimates reported in table 3 show a strong and statistically significant relationship between PM2.5 and local wind speed, irrespective of the set of included controls. For the model adjusting for the full set of covariates in column 3, wind speed in the (1,2] m s^{-1} range, results in PM2.5 levels that are around 13% lower relative to the baseline of wind speed in the [0,1] m s^{-1} range. Similarly, wind speed exceeding 2 m s^{-1} decreases PM2.5 by around 22% relative to the baseline. The F-statistic of excluded instruments comfortably exceeds the rule of thumb value of 10, alleviating concerns regarding instrument strength.

Having established that PM2.5 measurements respond strongly to local wind speed, I report estimates from the second stage of the 2SLS procedure in table 4 [9]. As expected coefficient estimates carry the same signs as those derived from OLS models, corroborating the negative influence of PM2.5 on the activity proxy. For the specification adjusting for the full set of controls (column 3), increasing PM2.5 concentrations by 1%, decreases the proxy by about 0.25%. The effect estimated by the 2SLS approach is larger than that reported in table 2. This is expected as measurement error attenuates OLS estimates understating the negative influence of pollution.

Although activities of indoor office workers are unlikely to be directly influenced by the strength of local winds, I test for the sensitivity of 2SLS estimates to small violations of the exclusion restriction. To this end I employ the union of confidence intervals approach developed by Conley *et al* (2012) [10]. Results are reported in the second panel of table 4 for the model including the full set of controls. The union of confidence intervals

[8] Results are in call cases identical when adding day-of-month effects to the set of controls.

[9] For completeness I report estimates from the reduced form regression of the output proxy on the instrument in table A2 in the appendix

[10] Take equation (1) allowing wind speed to have a direct influence on municipal output, $lnQ_{it} = \alpha_i + \beta_1 PM_{it} + \beta_2 T_t + \beta_3 M_{it} + \beta_4 S_t + \gamma W_{it} + \epsilon_{it}$. The exclusion restriction, requiring that the instrument does not affect lnQ_{it} in any way other than through its influence on PM_{it} corresponds to $\gamma = 0$. Conley *et al* (2012) propose inference procedures in cases of small violations of the exclusion restriction when γ is not exactly zero, given some prior knowledge of γ. Their union of confidence intervals approach assumes the unknown γ has a support interval $[-\delta, +\delta]$, and derives confidence intervals for $\hat{\beta}$ as the union of all confidence intervals in the range of γ. Varying δ allows to assess the magnitude of the violation of the exclusion restriction that would render $\hat{\beta}_1$ insignificant. To draw information on the value of γ I use the estimated coefficient on wind speed from the reduced form regression reported in appendix table A1. I restrict δ to be positive but results are similar when assuming an interval symmetric around zero.

Table 4. PM2.5 and output: 2SLS.

	(1)	(2)	(3)
$ln(PM2.5)$	-0.178^{**}	-0.269^{**}	-0.245^{**}
	(0.074)	(0.109)	(0.109)
Weather Controls	No	Yes	Yes
Strike Controls	No	No	Yes
Observations	51 840	51 840	51 840
Union of confidence intervals			
20% of reduced form			(−0.355, −0.087)
30% of reduced form			(−0.355, −0.064)
40% of reduced form			(−0.355, −0.040)
50% of reduced form			(−0.355, −0.016)
60% of reduced form			(−0.355, 0.009)

Note: The top panel presents 2SLS estimates of the influence of concurrent PM2.5 levels on the productive activity proxy. Dependent variable in all cases is lnQ. All models include municipality-specific and time effects. The second panel presents confidence intervals for the coefficient of interest following the union of confidence intervals approach of Conley *et al* (2012). Standard errors, clustered at the municipality and date levels in parentheses.
$^{**}p < 0.05$

approach suggests that the instrument needs to explain over 50% of the overall reduced form effect on the activity proxy for the 2SLS estimate to be insignificant. The implication is that the reported results are robust to moderate violations of the exclusion restriction.

4.2.1. Robustness

Table 5 presents a series of robustness tests, to assess the stability of the results. I start by testing the estimates sensitivity to the measurement of PM2.5. In column 1, instead of relying on the pollution reading from the nearest monitoring station, PM2.5 is approximated by the inverse distance weighted average of levels reported by all monitoring stations (Currie and Neidell 2005). As in the baseline case, a 1% increase in PM2.5 decreases the activity proxy by 0.25%.

Models in columns 2-4 test different specifications of the instrument. In column 2, PM2.5 is instrumented by contemporaneous, lagged once and lagged twice wind speed. Column 3 instruments with lagged wind speed only, while in column 4 the instrument is the logarithm of contemporaneous wind strength. In all cases the estimated effect of pollution on the activity proxy is negative, statistically significant and of similar magnitude to the one reported earlier. Specifically, increasing the level of pollution by 1% decreases productive activities by 0.19% to 0.33% depending on the model.

The model in column 5 controls for meteorological conditions flexibly, using $2.5C^o$ and 5% bins for temperature and relative humidity respectively. Estimates suggest that increasing pollution levels by 1% decreases activity by 0.21%.

Models in Columns 6 and 7 introduce municipality-specific time controls. In column 6, I add municipality specific trends, while column 7 includes municipality by year by month effects. In both cases estimates are statistically significant and of the same order of magnitude as those reported earlier. Finally, column 8 controls for year by month effects. As earlier the introduction of year by month controls does not affect the results.

5. Discussion and conclusions

This letter explores the influence of PM2.5 on the output of office workers and elected officials in public organizations. To approximate output, I rely on the responsibilities mandated to Greek municipalities and draw information from the Diavgeia reporting system that forces public organizations to file reports on a wide range of outputs. Linking the output proxy to daily PM2.5 levels recorded nearby I find a negative, statistically and quantitatively significant relationship. A 1% increase in the PM2.5 level is associated with a decrease in the output proxy by around 0.04%. When accounting for biases introduced by omitted variables and measurement

Table 5. Robustness.

	(1)	(2)	(3)	(4)
*lnPM*2.5	−0.246**	−0.268**	−0.336**	−0.188**
	(0.110)	(0.107)	(0.138)	(0.097)
First-Stage F-statistic	61	19	17	96
Observations	51 840	51 840	51 840	51 753
	(5)	(6)	(7)	(8)
*lnPM*2.5	−0.210**	−0.155*	−0.099*	−0.255**
	(0.096)	(0.082)	(0.057)	(0.121)
First-Stage F-statistic	66	57	87	60
Observations	51 840	51 840	51 840	51 840

Note: All models present 2SLS estimates where PM2.5 is instrumented by local wind speed. Column 1 controls for inverse distance weighted PM2.5. In column 2 PM2.5 is instrumented by contemporaneous and lagged wind strength. In column 3 PM2.5 is instrumented by lagged wind strength only. In column 4 PM2.5 is instrumented by logarithm of local wind strength. In column 5 meteorological controls enter in flexible form: Daily temperature enters regressions in 2.5^oC bins while relative humidity enters in 5 percent bins. Column 6 introduces municipality specific trends and Column 7 adds municipality by year by month controls. Column 8 includes year by month controls. All models include the full set of controls. Standard errors, clustered at the municipality and date levels in parentheses.
$^{**}p < 0.05$,
$^{*}p < 0.1$

error, a 1% increase in PM2.5 decreases the proxy by around 0.25%. Results are not driven by seasonal patterns of municipal activity as all models control for an extensive array of time effects, while estimates are invariant to perturbations in the model specification. The magnitude of the effect comparable that identified in recent research exploring the effect of pollution on the productivity of indoors workers (Chang *et al* 2019, Heyes *et al* 2019).

The reported estimates capture the overall effect of PM2.5 on the extensive and the intensive margins. Specifically, air pollution may reduce workers' labor supply increasing absenteeism (Hanna and Oliva 2015), and lower their in-work performance and productivity (Chang *et al* 2019, Heyes *et al* 2019). Given the data available, the relative importance of the two effects cannot be assessed. Nevertheless, the estimates are informative as they point to the overall detrimental influence of pollution on the productivity of the public sector and indicate that pollution can influence activities that not physically demanding.

While the paper focuses on a proxy of aggregate municipal output, the results are also informative for the direction of the response of other office work outputs to air pollution. The processes involved in the production of the outputs approximated in the present paper are similar to those required for other office work production. To generate such outputs workers interact, make decisions and engage in typical office environment activities. If PM2.5 impacts on the bureaucratic output proxy, it will plausibly also affect other unobserved outputs in public sector bureaucracies, or more generally outputs produced by office workers.

Many of the activities approximated and studied here are essential for policy implementation and the regular functioning of a municipality. In this context, the results suggest that PM2.5 leads to tasks being postponed eventually delaying policy implementation and disrupting the services supplied by municipalities. Given the global trend towards urbanization and the increasing share of income produced by the services sector, the estimates reported here point to the threat PM2.5 pollution poses to productivity and global output. This impact of air pollution on the productivity of office workers should be monetized and accounted for in decision making.

Acknowledgments

I am grateful to 3 anonymous Referees for useful comments and suggestions. Any remaining errors are mine.

Appendix

Table A1. Poisson Estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
$ln(PM2.5)$	-0.038^{**}	-0.049^{***}	-0.048^{***}			
	(0.016)	(0.017)	(0.017)			
$10 < PM2.5 \leqslant 20$				-0.041^{***}	-0.051^{***}	-0.052^{***}
				(0.016)	(0.016)	(0.016)
$PM2.5 \geqslant 20$				-0.072^{***}	-0.086^{***}	-0.086^{***}
				(0.022)	(0.023)	(0.023)
Observations	51 840	51 840	51 840	51 840	51 840	51 840

Note: The table presents Poisson Fixed Effects estimates from equation (1). Dependent variable in all columns is the productive activity proxy in municipality *i* at time *t*. All models include municipality and time specific effects. Standard errors, clustered at the municipality and date levels in parentheses.
$^{***}p < 0.01$
$^{**}p < 0.05$

Table A2. Reduced form estimates.

	(1)	(2)	(3)
$1\ \mathrm{m\ s^{-1}} < WS \leqslant 2\ \mathrm{m\ s^{-1}}$	0.043^{**}	0.044^{**}	0.042^{**}
	(0.017)	(0.017)	(0.017)
$WS > 2\ \mathrm{m\ s^{-1}}$	0.052^{**}	0.055^{**}	0.049^{**}
	(0.023)	(0.024)	(0.023)
Weather Controls	No	Yes	Yes
Strike Controls	No	No	Yes

Note: The table presents reduced form estimates from the 2SLS approach. In all models dependent variable is lnQ_{it}. Standard errors, clustered at the municipality and date levels in parentheses. All models control for municipality specific effects and time effects.
$^{**}p < 0.05$

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