The Impact of Air Pollution on Hospital Admissions: Evidence from Italy*

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Abstract

In this paper we study the impact of air pollution on hospital admissions for chronic obstructive pulmonary disease for 103 Italian provinces, over the period from 2004 to 2009. We use information on annual mean concentrations of carbon monoxide, nitrogen dioxide, particulate matter, and ozone measured at monitoring station level to build province-level indicators of pollution. Hence, we estimate a regression model for hospital admissions, where we allow our aggregate measures of pollution to be subject to measurement error and correlated with the error term. We also adopt standard errors for estimates that are robust to serial and spatial correlation in the error term, to allow for temporal persistence and geographical concentration of unobservable risk factors.

We find that higher levels of particulate matter are associated with higher levels of hospitalisation for children, while ozone plays an important role in explaining hospital admissions of the elderly. Other factors that appear to have an effect on hospital admissions for chronic obstructive pulmonary disease are precipitation and provincial unemployment rate.

Keywords: Air pollutants; hospital admission; instrumental variables, SHAC.
JEL codes: I120, I180, Q530.

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1 Introduction

Over the past decade, a substantial scientific literature has documented the size and seriousness of the impact of atmospheric pollution on the environment and the health of people. Air pollution in Europe varies substantially over time and across territory. According to the European Environment Agency many air pollutants have decreased substantially over time, resulting in improved air quality across territory. However air quality problems still persist, as air pollutant concentrations have not sufficiently declined, and a large proportion of Europe's population lives in urban areas where emission limits set by the EU National Emission Ceilings Directive are regularly exceeded. A recent report on the quality of air in Europe (Istat, 2010) shows that Italy is ranked as the third most polluted country in Europe, after Bulgaria and Greece, with more than half of the 30 most polluted cities being Italian. In particular, in the year 2008, Turin, Brescia, and Milan recorded the highest levels of overall air pollution in Europe, after the Bulgarian city, Plovdiv. Turin is also the city with the highest concentration of tropospheric ozone, although this has been reducing over time, while Naples is leading for the highest annual concentration of nitrogen dioxide, responsible for acid rains.

Atmospheric pollution threats public health with both short- and long-term effects. The former may include irritation to the eyes, nose and throat, and upper respiratory infections such as bronchitis and pneumonia. Long-term health effects can include chronic respiratory disease, lung cancer, heart disease, and even damage to the brain, nerves, liver, or kidneys. Some groups of the population may be more sensitive to pollutants than are others, such as young children and the elderly, or people with pre-existing health problems. Medical conditions arising from atmospheric pollution can require expensive treatment, leading to high health care costs, lost productivity in the workplace, and human welfare impacts, thus costing billions of dollars each year.

This paper studies the impact of air pollution on hospital admissions in Italy. Specifically, we examine the effects of a range of different pollutants, namely particular matter of size smaller than about 10 micrometers (PM10), nitrogen dioxide (NO2), carbon monoxide (CO), and ozone (O3) on hospital admissions for chronic obstructive respiratory diseases (COPD), for young children and elderly people living in 103 Italian provinces in the period from 2004 to 2009.

Respiratory illnesses are amongst the most common chronic diseases in the world, including chronic illness in younger age, and as a cause of premature mortality, leading to high socio-economic costs. COPD is a disease state characterized by airflow limitation that is not fully reversible, accompanied by progressive lung function decline. Despite advances in therapy, worldwide, COPD is ranked as the sixth leading cause of death in 1990, and it is projected to be the fourth leading cause of death worldwide by 2030 (Mathers and Loncar, 2006). In Italy, COPD represents, by number, the third cause of death after circulatory diseases and cancer (Istat, 2009). Although cigarette smoking is considered the major cause of COPD, recent studies have shown that sustained exposure to exhaust fumes from both motor vehicles and industrial plants may cause development or exacerbation of chronic respiratory diseases (Gauderman, 2007; Kunzli et al. 2009; Ko and Hui, 2012).

We use information on annual mean concentration of pollutants measured at monitoring station level to build a set of province-level indicators of pollution. Relative to existing literature, one main feature of our work is that we explicitly control for possible measurement errors and endogeneity issues in our provincial measures of pollution. Indeed, pollution readings from monitoring stations may not reflect the exact amount of pollution to which people have been exposed, given that people live at different distances from stations, and they may move across territory. This issue has been identified by a recent literature in economics (e.g. Graff Zivin and Neidell, 2009; Knittel et al., 2011; Moretti and Neidell, 2011; Schlenker and Walker, 2011). In our regression model for COPD, we also allow for possible endogeneity of our pollution indicators. As pointed by Knittel et al. (2011), it is plausible to think that people living in cleaner areas could also be wealthier, have better living conditions, or have access to better health care, thus inducing a correlation between pollution and the error term. To alleviate these endogeneity problems and estimate more accurately the level of pollution within Italian provices we adopt an instrumental variables approach. As instruments for pollution we include a set of factors that are recognized to be the main drivers of pollution, including both natural sources such as climate conditions, and anthropogenic factors, i.e., generated by human activity, as well as temporal and spatial lags of pollution. We believe that adopting a instrumental variables approach where in the first-stage we use a spatio-temporal model for pollution can help researchers to study more adequately the impact of pollution on hospital admission, ultimately suggesting more reliable policy interventions.

The remainder of the paper is organized as follows. Section 2 provides a review of the literature on the effects of pollution on mortality rate and hospital admissions Section 3 introduces our econometric specification and outlines our estimation strategy. Section 4 describes the data, while Section 5 comments on the empirical findings. Section 6 concludes.

2 Background literature

Over the past decade, a wide scientific literature has been documenting the size and seriousness of the impact of atmospheric pollution on the health of people. Most of these studies have focused on the effect of air pollutants on health outcomes, using data at the city, county or region level to test for the effects of prolonged exposure to air pollution, trying to identify which are the most dangerous pollutants and which segment of the population is more at risk.

Early works on the link between urban air pollution and chronic respiratory illness have been carried by Portney and Mullhay (1986, 1990), for the US. Results showed a positive relationship between ozone concentrations and sickness. Samakovlis et al. (2005) investigated the relationship between air pollution and respiratory diseases in Sweden. In particular they find that NO2 may increase risk for asthma, bronchitis and hay fever nasal problems. Jerrett et al. (2005) studied the health effects of chronic air pollution exposure within industrial cities. Their results suggested that chronic air pollution exposure significantly increases the risk of premature cardiorespiratory and cancer mortalities. Subsequent studies have also found significant associations between ozone (Bell et al., 2005) and nitrogen dioxide (Nafstad et al., 2004) on higher mortality rates. More recently, Currie et al. (2009) explored the impact of air pollutants on infant health, measured by birth weight, gestation and mortality, in New Jersey in the 1990s. The paper combined information about mother's residential location from birth certificates with information on air quality monitors. They showed negative effects of exposure to carbon monoxide on children heath, both during the pregnancy and after birth, even in areas at low levels of pollution. Agarwal et al. (2010) studied the effect of exposure to a set of toxic pollutants from manufacturing facilities on county-level infant and fetal mortality rates in the United States between 1989 and 2002. They showed a significant adverse effects of toxic air pollution concentrations on infant mortality rates.

So far, few studies have focused on the effects of air pollution on hospital admissions. Neidell (2004) studied the influence of air pollution on child hospitalisations for asthma in California. Results showed that, among the pollutants considered in the analysis, only carbon monoxide has a significant effect on hospital admissions for children, with a greater effect for children of lower socio-economic status. Dominici et al. (2006) described a short-term increase in hospital admission rates associated with PM2.5 for American Medicare enrollees, in the period between 1999 to 2002. Jayaraman and Nidhi (2008) suggested that air pollution levels in Delhi, specifically of O3, NO2 and PM10 have a significant impact on human health in terms of an increase (24%, 13% and 3%, respectively) in respiratory diseases related hospital visits. Namdeo et al. (2011) demonstrated association of short-term variation in pollution and health outcomes in the northern part of the UK. They founded that PM10 and O3 are positively associated with respiratory hospital admissions in the elderly. Rava et al. (2011) showed that proximity to wood industries is associated with a higher risk of hospitalisation for respiratory diseases and respiratory symptoms in children.

A recent related literature has emphasized that the majority of the works we have reviewed may suffer for a problem of measurement errors, thus leading to a bias in the estimates. It is likely that people have a different exposure to the amount of pollution detected from the monitoring stations. Indeed, people live at different distances from these stations, with some residing close while others far apart. Further, some people may be more mobile than others, also because of avoidance behaviour (Graff Zivin and Neidell, 2009). In other words, a mismatch is likely to exist between the amount of pollution detected and the exposure of the population to such pollution. Lleras-Muney (2010) finds that estimates are very sensitive to the technique used to impute pollution at aggregate level, and that the measurement error is not normally distributed, making the direction of the bias on estimates ambiguous. To deal with this issue, a number of works have adopted the instrumental variables (IV) approach. Chay and Greenstone (2003b) use a natural experiment to look at the relationship between pollution and infant mortality rate. The authors use the Clean Air Act of 1970 as an instrument to estimate effect of pollution on the infant mortality rate. Moretti and Neidell (2011), using zip code for the years 1993-2000, study the relationship between ozone and infant mortality rate in California (US). To alleviate possible bias resulting from the measurement error, they adopt an IV approach, using timing of port of Los Angeles traffic and distance to the port as instruments for ozone concentrations. The authors conclude that estimated effects of ozone on health are large, and that simple correlations are significantly biased by unobserved avoidance behavior and/or measurement error. Knittel et al. (2011) argue that ordinary least squares (OLS) yields inconsistent estimates of the impact of pollution on health outcomes not only because of measurement errors but also for other more broad endogeneity issues. According to the author, people living in cleaner areas could also be wealthier, have better living conditions, or have access to better health care, thus inducing a correlation between pollution and the error term. Further, changes in local economic activity may be correlated with both pollution and health. Regional growth will tend to increase pollution levels, but may also be correlated with increases in income levels and/or health care access, thus tending to bias OLS estimates. Hence, Knittel et al. (2011) adopt an IV approach to investigate the relationship between traffic, weather, pollution, and infant outcomes in California using data at zip-code level over the years 2002-2007. The authors use traffic congestion and weather as exogenous instruments for pollution, and find that ambient pollution levels have a large impact on weekly mortality rates.

In this paper, we draw from the above literature and use an IV approach to deal with possible bias of OLS estimates in studying the impact of pollution on COPD hospital admissions in Italy. As instruments for pollution, we follow existing literature and take a set of variables that characterise the environment, such as climate conditions or the amount of green present in the area, as well as factors related to the presence of human activity in the area, such as traffic congestion and the concentration of manufacturing industries. In addition, we use as instruments the pollution detected in neighbouring provinces, as well as that registered in the past. The reason underlying this choice is that sources of pollution, like an industry, are likely to be persistent over time. In addition, an air pollutant originating in a particular point in space, due for example to car emissions, may propagate across a wider geographical area, given the absence of physical boundaries. Hence, augmenting the set of conventional instruments with temporal and spatial lags of pollution may contribute to better proxy pollution at aggregate level, and assess its impact on the hospital admissions.

Relative to existing literature, a further contribution of this paper is that, when studying the effect of pollution on hospital admissions, in our regression model we allow for serial dependence and spatial correlation of errors. Indeed, unobservable risk factors, such as life style variables or water contamination, which may exacerbate respiratory diseases, are likely to be temporally persistent and geographically concentrated.

3 Empirical model

We consider the following model for hospital admission in province i at time t, adm_{it}:

$$adm_{it} = \alpha_i + \gamma t + \boldsymbol{\lambda}' \mathbf{p}_{it} + \boldsymbol{\beta}' \mathbf{x}_{it} + u_{it}, \tag{1}$$

where the province-specific coefficients, α_i, may capture time-invariant, unobserved characteristics of provinces, t is a time trend, $\mathbf{p}_{it}$ is a vector of pollutants, $\mathbf{x}_{it}$ is a vector of control variables that may affect the dependent variable, and u_{it} is the error term. The dependent variable, adm_{it}, is hospital admissions due to COPD, divided by total population at risk. To reduce heterogeneity, in our empirical analysis we focus on two alternative groups of people; children aged between 0 and 14 years old, and people aged 65 and over. As noted by Bellander et al. (1999), and Samakovlis et al. (2005), hospitalisation may capture only part of the total effect of moderate air pollution, since most effects are less severe. Indeed, it is possible that pollutants affect the respiratory system without resulting in hospitalisations. However, we believe that this is an important measure of public health, also reflecting the consumption of health care resources.

Following previous literature, amongst the regressors, $\mathbf{x}_{it}$, we have included the average temperature and precipitation as proxies of weather conditions, since low temperatures and high precipitations may contribute to deteriorate the health status of an individual thus increasing hospital admissions. We have also controlled for socio-economic characteristics of the area, by including unemployment rate, education, and population density in our regression (see Janke et al., 2009). We have added the percentage of people regularly smoking, as this is known to be a major determinant of respiratory diseases. Finally, we have included a variable that measures the regional health deficits published annually by the Italian National Audit office (Corte dei Conti, 2010). The 311/2004 Act constrains Italian regions that are in deficit to adjust their health care expenditure in order to achieve their balanced budget. This has generated a reorganization of health care systems in the various regions in order to reduce costs, and has left little margins to adjust their supply to the demand of health care services. Hence, by including a measure of the regional health deficits we try to control for supply factors.

As noted by Janke et al. (2009), the effects of pollution may be over-estimated if temporarily elevated levels of pollution worsen the health of frail persons, for example the elderly, who would have been hospitalised anyway. While this problem maybe severe when taken as a dependent variable regarding hospitalisation of the elderly, we believe that it is milder when focusing on hospital admissions for children. As for the selected pollutants, we check the effect of PM10, NO2, CO,and O3 included one by one in model (1), to isolate the impact of specific pollutants, and then simultaneously, to allow for correlation between them (Salam et al., 2005; Ritz et al., 2007; Bell et al., 2007; Coneus and Spiess, 2012).

We also allow for spatial and serial correlation in the error term, using robust spatial correlation, heteroskedasticity-consistent (SHAC) standard errors for estimates, following the approach outlined in Moscone and Tosetti (2012). In the computation of SHAC standard errors we use the Parzen kernel function. Adopting SHAC standard errors is a very flexible approach that does not require specifying a spatio-temporal process for the error term (see also, Kelejian and Prucha (2007) on this).

As described in Section 4, our annual province-level indicator of pollution is likely to be subject to measurement errors, which is know to yield a bias in estimates, as well as endogenous. To deal with these issues, we adopt an IV approach. As instruments for $p_{k,it}$ we take the temporal lag, $p_{k,it-1}$, the spatial lag, $\overline{p}_{k,it} = \sum_{j=1}^{N} s_{it} p_{k,jt}$, where s_{ij} are elements of a spatial weights matrix, where $s_{ij} = 1/d_{ij}$ where d_{ij} is the distance in kilometers between centroids of provinces i and j, and a set of exogeneous regressors, $\mathbf{z}_{it}$. We include the temporal lag since the sources of pollution, such as an industry, generally continue over time, making pollution a temporally persisten phenomenon. We also include $\bar{p}_{k,it}$ under the assumption that an air pollutant originating in a particular point in space, due for example to car emissions, may propagate across a wider geographical area, given the absence of physical boundaries. It is reasonable to think that such propagation will depend on the physical characteristics of the territory, for example, the altitude, the presence of mountains, or the proximity to the sea. Hence, we have decided to include province-coefficients, μ_i, to capture such time-invariant, unobserved characteristics of provinces that explain permanent differences in pollution across provinces. The vector $\mathbf{z}_{it}$ contains a set of variables that are likely to have an impact $p_{k,it}$, such as the amount of green present in the area, the number of cars per inhabitant, and the number of people employed in the manufacturing sector.

To sum up, in our IV approach we first estimate a regression model for pollution, which includes province effects and spatial and temporal lags of the dependent variable amongst the regressors. We estimate such first-stage regression by Generalised Method of Moments (GMM), following the approach proposed by a very recent literature (see, among others, Kukenova and Monteiro (2009)). In particular, we have adopted the GMM by Arellano and Bond (1991), where the standard set of instruments is augmented by the spatial lags of the regressors. Once estimated the first-stage regression, predicted values for $\mathbf{p}_{it}$ have been computed and included in (1). In our empirical study we will also report results for the first-stage regression, to show, among the included instruments, the main determinants of pollutants.

4 Data

Data are collected for 103 italian provinces ($N = 103$), over the period from 2004 to 2009 ($T = 6$). Data on air pollution are extracted from the AIRBASE database mantained by the European Environment Agency (EEA), while data on health outcomes and risk factors, as well as environmental data are gathered from the Italian Office of National Statistics, Istat. We refer to Table 1 for a formal definition of the variables involved in our study. We observe that the variables COPD 0-14 and COPD over 65 and over are rates concerning of the population at risk, and are expressed per 10,000 inhabitants aged between 0 and 14 years old, and 65 and over, respectively.

Data provide information on pollution concentration from a total of 592 monitoring stations spread across Italy. From Figure 1, it is evident that stations distribute more densely in the North of Italy, while they are more sparsely spread in the Centre and South regions, and islands. Starting from the information at station level, we have computed a measure of pollution at provincial level adopting a procedure similar to that advanced by Currie and Neidell (2005).

In particular, for province i in year t we take the annual average daily concentration for each pollutant, registered by all monitoring stations whose distance to the centroid of the province is less than 30 kilometers (less than 15 kilometers for Milan and Rome where there are many monitoring stations within relatively small distances). By taking this approach, in certain years there are no stations around the centroid of some provinces, and therefore these provices will display missing values for our index. In line with previous studies (Neidell, 2004; Janke et al., 2009) we have considered several pollutants (PM10, NO2,CO, O3) that may cause problems of respiratory morbidity in the population.

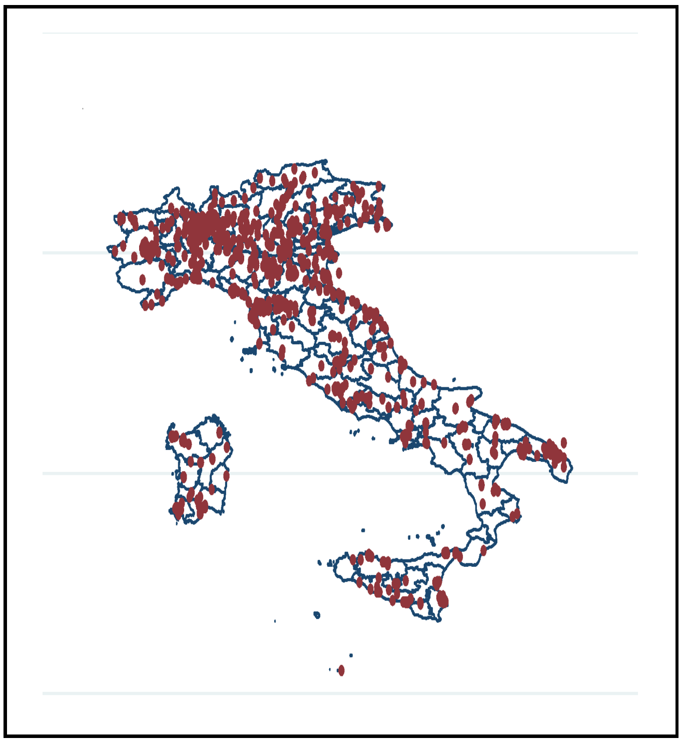

Figure 1: Location of monitoring stations

Table 1: Definition of variables

Variables	Unit	Description
COPD		Chronic obstructive pulmonary disease
0-14	n./10,000 inhab.	n. cases in population aged 0-14
Over 65	n./10,000 inhab.	n. cases in population aged 65 and over
PM10	$\mu g/m^3$	Annual daily average of PM10
NO2	$\mu g/m^3$	Annual daily average of NO2
CO	$\mu g/m^3$	Annual daily average of CO
O3	$\mu g/m^3$	Annual daily average of O3
Precipitation	10 ml	Annual average precipitation
Temperature	$^{\circ}C$	Annual average maximum temperature
Smoking	n./100 inhab.	% of people smoking
Unemployment	n./100 inhab.	Unemployment rate
Green	m^2/inhab.	Green area per inhabitants
Cars	n./1000 inhab.	Cars per inhabintants
Manufact.	100 employ.	People employed in the industry sector
Education	n./100 inhab	% of people who completed high school
Pop. dens.	n./km^2	Population density
Deficit	1,000s Euro	Regional health deficits

Table 2 shows a set of descriptive statistics for the variables involved in our analysis.

From this table, it emerges that the average daily concentration of PM10 within the year is 33 $\mu g/m^3$, with a maximum value of 61 $\mu g/m^3$ exceeding the limit of 50 $\mu g/m^3$ set by the European Community[1]. Nitrogen dioxide (NO2) has an average of 35.49 $\mu g/m^3$, with a peak of 68.14 $\mu g/m^3$, higher than the limit value of 40 $\mu g/m^3$, established by the European Community. The main artificial sources of NO2 are the central heating plants, some industrial processes and the exhaust gases of motor vehicles. Carbon monoxide (CO) can be generated by the incomplete combustion of materials containing carbon (e.g. fuels). It can also be emitted from combustion sources such as heating gas or motor vehicles. Its average concentration is 0.76 $\mu g/m^3$ with a maximum of 8.64 $\mu g/m^3$. The ozone (O3) in the atmosphere, is a important component of photochemical smog that even in low concentrations may cause respiratory irritation. The average daily concentration of O_3 within the year is 51.63 $\mu g/m^3$, with maximum points of 108.8 $\mu g/m^3$.

[1]The limits for the protection of health are set by Ministerial Decree 60/2002 for PM10 and NO2 and Legislative Decree 183/2004 for ozone.

Table 2: Descriptive statistics

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
COPD 0-14	618	29.60	22.10	12.11	126.38
COPD 65 and over	618	76.15	37.10	11.30	265.91
PM10	491	33.26	8.19	5.48	61.51
NO2	409	35.89	11.15	4.14	68.14
CO	406	0.76	0.48	0.01	8.64
O3	398	51.63	11.44	16.03	108.80
Precipitation	618	78.08	17.368	40.60	137.87
Temperature	618	18.08	2.90	5.50	23.40
Smoking	618	7.24	1.64	3.90	11.12
Unemployment	618	7.33	4.28	1.85	21.60
Green	618	161.25	377.94	0.20	2,853.00
Cars	618	632.08	146.33	411.45	2,104.30
Manufact.	618	503.97	615.04	43.00	4,876.00
Education	618	27.43	3.90	20.31	37.96
Pop. dens.	618	1,213.19	1,374.12	78.50	8,508.70
Deficit	618	343.60	373.39	13.15	1,786.52

Figure 2 shows the quantile distribution of pollutants in 2009 (the last year of our analysis). The graphs show that largest concentrations of pollutants occur in areas around large cities and industrial districts, such as Turin and Naples.

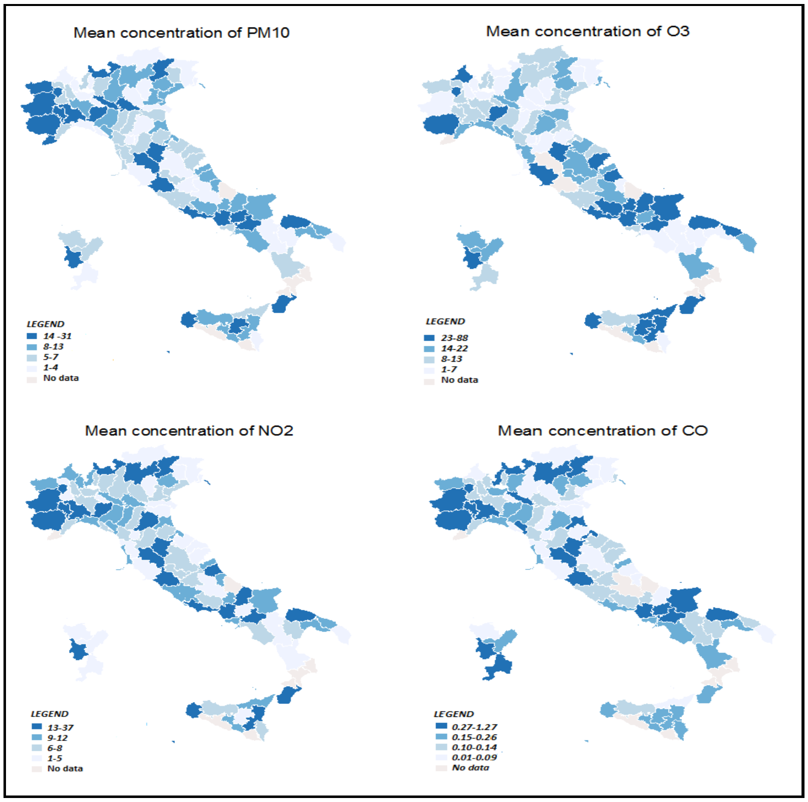

Figure 2: Quartile distribution of pollutants in 2009

In our study, hospital admissions due to COPD is used as an indicator of morbidity, differentiating between infant and elderly population. Admission rates for the elderly are considerably high, with an average of more than 76 individuals out of 10,000, reaching peaks of 266 admissions in Bari, a province in the South-East of Italy (see also Figure 3).

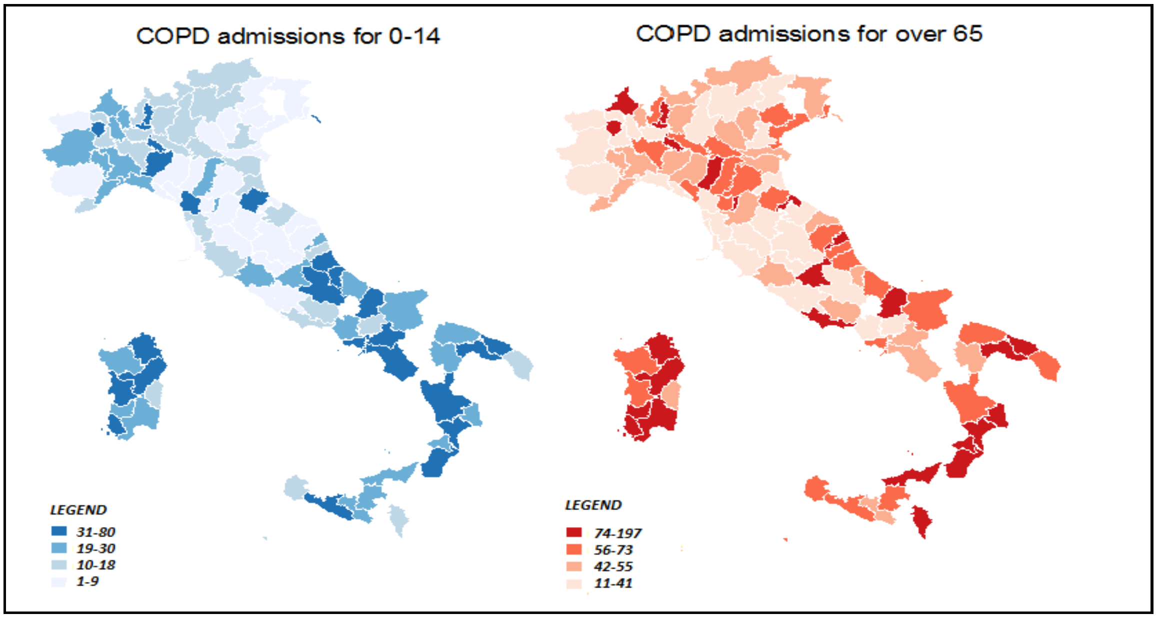

Figure 3: Quartile distribution of COPD for people aged 0-14 and people aged 65 and over, in 2009

5 Results

In equation (1), we have expressed the dependent variable in logs, and multiplied it by 100. Further, we have divided the pollutants PM10, O3 and NO2 by 10, so that the coefficients are estimates of the percentage change in the admission rate per 10 $\mu g/m^3$ increase in PM10, O3 or NO2 or per 1 $\mu g/m^3$ increase in CO. The remaining regressors have been left in their original scales (see Table 2). All computations have been performed in *Matlab*.

Table 3 shows the output for estimation of equation (1) when the dependent variable is COPD hospitalisation of people aged 0 to 14 years old, while Table 4 reports results for COPD hospitalisation of people aged 65 and over. Results show that PM10 has a significant impact on COPD hospitalisation for children and O3 has an influence on hospitalisation of the elderly, while it is indicated that other pollutants have no effects. In particular, a 10 $\mu g/m^3$ increase in PM10 is associated with a 6.15 per cent increment in hospital admissions for children, while a 10 $\mu g/m^3$ increase in O3 generates a 5.39 per cent rise in hospitalisation of people aged 65 and over. This implies that, on average, a 10 $\mu g/m^3$ increase in PM10 would produce 2 and 4 new admissions, respectively, per 10,000 people at risk. These results should be interpreted taking into consideration that hospitalisation concerns the most severe cases, leaving out people with milder symptoms. At the same time, our estimated coefficients for pollution are higher than those computed using mortality as health outcome. For example, it is interesting that, similarly to our work, Janke et al. (2009) find that PM10 and O3 significantly increase all-causes mortality, once controlled for trend and region, lifestyle and weather (see, in particular, their Table 3). The authors estimate an increase in mortality of 2.80 and 0.73 per cent for PM10 and O3, respectively.

As for the other controllers, education seems to play a role in explaining variation in youth hospital admissions; a higher level of education in a province is associated with a higher probability of being admitted. More educated parents may have easier access on medical information, for example by consulting a General Practitioner (GP) or specialist, and therefore more able to identify and treat their children health conditions. The density of population has a negative impact on admissions for older people in all models. This negative sign may be associate to a constrain capacity of the hospitals. However, we have failed to find a similar pattern for the young. The variables precipitation is positive and statistically significant in all regressions for the elderly, although with a mild effect, indicating that bad weather conditions may contribute to worsen the health of older people, thus increasing hospital admissions.

The coefficient attached to the variable smoke has a positive sign when focusing on young people and including CO as a proxy for pollution. This result may be explained by the hazard of passive smoking. In fact, numerous studies have shown a close relation between passive smoking and diseases in young people such as respiratory illnesses, and atopy (Hawamdeh et al., 2003). In the population aged 65 and over, a higher unemployment rate is associated with a reduction in COPD admissions. A lower concentration of economic activities in areas with high unemployment may translate in lower pollution, as suggested by results shown in Table 5, and commented below. The variable trend has a negative effect on all specifications. This may in part explain the the effect of medical technologies (e.g. the adoption of pharmaceuticals such as bronchodilators, steroids, etc) over time, that has reduced hospital admissions for both vulnerable categories of the population. It is plausible that other risk factors and as well as the variable deficit, which are not statistically significant at the 5 per cent level, have little variation over time, so that part of their effect on the dependent variable is already captured by the province coefficients.

The last columns of Table 3 and 4 shows estimation results when all pollutants are included simultaneously, to allow for correlation between the pollutant levels. The coefficients on PM10 and on O3 remain significantly positive in the regressions for COPD0-14 and COPD over 65, respectively.

The Sargan tests, reported at the bottom part of the table, do not reject the null hypothesis that the instruments adopted in IV estimation are valid. Further, the Moran tests, which have been performed on the residuals of the fixed effects, are positive and statistically significant. This confirms the presence of spatial dependence in the error term, and supports the appropriateness of the use of SHAC standard errors.

To better understand the sources of variation in pollution, we decided to report estimation results of the regression on pollution, which is the first-stage of our IV strategy. Such results may help a better understanding on the main factors underlying pollution, and thus support policy makers in tayloring more effective interventions. Results are reported in Table 5. The coefficient attached to $p_{i,t-1}$ is positive and significant for all pollutants, ranging between 0.254 for CO and 0.668 for PM10. This coefficient measures how persistent is the pollution over time, and is likely to reflect the enduring effects of the sources of pollution, both observable and unobservable. The coefficient attached to $\overline{p}_{it}$ is positive and significant for all pollutants except for O3. This result shows that pollution generated in one point in space is likely to diffuse across a wider area, which may include cities within the same region or from different regions. The spatial effect is particularly strong for NO2 and CO, with coefficients 0.729 and 0.603, repectively. As for the remaining determinants, wider green areas tend to reduce PM10 and CO, while, as expected, the presence of manufacturing industry increases the concentration of these pollutants in the air. Finally, the number of cars boosts NO2, through fuel combustion. It is interesting to observe that O3 does not seem to be affected by any of these variables. One reason for this result is that this pollutant is not emitted directly by car engines or by industrial operations, but rather formed by the reaction of sunlight on air containing hydrocarbons and nitrogen oxides.

The reported Sargan tests do not reject the null hypothesis that the instruments adopted in GMM estimation are valid. Further, while, as expected, there is evidence of serial correlation of first order, we do not observe second-order serial correlation.

Table 3: Determinants of COPD admission for people aged 0 to 14 years old

Variables	Coeff.	std.err.	Coeff.	std.err.	Coeff.	std.err.	Coeff.	std.err.	Coeff.	std.err.
PM10	6.147*	2.940							6.620*	2.915
O3			0.808	2.344					-1.660	2.064
CO					16.748	16.520			-4.862	16.617
NO2							7.279	4.576	4.759	7.326
Temperature	-7.700	4.566	-8.686	4.495	-8.354	4.511	-7.304	4.557	-6.885	4.536
Precipitation	0.120*	0.030	0.113*	0.030	0.504*	0.030	0.203*	0.031	0.512*	0.032
Smoke	4.434	2.592	4.033	2.319	4.652*	2.382	3.787	2.573	4.051	2.588
Unempl. rate	0.175	0.188	0.140	0.180	0.139	0.174	0.129	0.184	0.157	0.183
Pop. density	-0.381	1.569	-1.039	1.726	-0.699	1.548	-1.951	1.640	-1.668	1.767
Education	0.783	0.463	0.854	0.484	0.816	0.474	0.761	0.494	0.762	0.498
Deficit	0.040	0.029	0.058	0.032	0.041	0.023	0.039	0.032	0.047	0.034
Trend	-8.892*	1.296	-9.216*	1.348	-9.060*	1.296	-8.332*	1.130	-9.093*	1.276
Sargan test	12.271	[0.09]	4.88	[0.67]	10.12	[0.18]	9.401	[0.22]	8.797	[0.55]
Moran's I	4.12*	[0.00]	3.16*	[0.00]	3.65*	[0.00]	4.17*	[0.00]	5.65*	[0.00]

Notes: (*): significant at the 5 per cent significance level. p-values in square brackets.

Table 4: Determinants of COPD admission for people aged 65 years and over

Variables	Coeff.	std.err.	Coeff.	std.err.	Coeff.	std.err.	Coeff.	std.err.	Coeff.	std.err.
PM10	0.460	2.345							-1.963	1.987
O3			5.390*	2.606					5.449*	2.645
CO					2.091	10.835			-6.358	10.831
NO2							9.241	6.807	4.861	2.505
Temperature	3.705	2.617	3.978	2.305	4.055	2.418	4.335	2.923	11.233	6.121
Precipitation	0.022*	0.008	0.025*	0.008	0.027*	0.006	0.032*	0.007	0.030*	0.008
Smoke	0.027	0.898	0.120	0.921	-0.062	0.942	0.097	0.934	0.620	0.894
Unempl. rate	-0.190*	0.088	-0.154*	0.077	-0.141*	0.072	-0.158*	0.078	-0.167*	0.076
Pop. density	1.275	1.236	1.180	1.074	1.274	1.066	0.908	0.963	0.998	0.989
Education	-0.103	0.260	-0.269	0.283	-0.222	0.248	-0.176	0.285	-0.257	0.273
Deficit	-0.031*	0.016	-0.004	0.027	-0.004	0.017	0.003	0.024	-0.001	0.022
Trend	-10.487*	1.567	-10.989*	1.254	-11.451*	1.563	-10.773*	1.219	-10.770*	1.040
Sargan test	8.36	[0.301]	10.76	[0.14]	13.63	[0.11]	16.13	[0.08]	14.86	[0.10]
Moran's I	4.12*	[0.00]	3.16*	[0.00]	3.65*	[0.00]	4.17*	[0.00]		

Notes: (*): significant at the 5 per cent significance level. p-values in square brackets.

Table 5: Determinants of pollution

	PM10		NO2		CO		O3	
Variables	Coeff.	std.err.	Coeff.	std.err.	Coeff.	std.err.	Coeff.	std.err.
$p_{i,t-1}$	0.668*	0.109	0.419*	0.136	0.254*	0.122	0.564*	0.127
$\overline{p}_{it}$	0.331*	0.119	0.729*	0.249	0.603*	0.184	0.041	0.212
Green	-0.184*	0.053	-0.084	0.085	-0.004*	0.002	0.371	0.464
Temperature	-0.615	0.413	-1.042*	0.394	-0.004	0.008	-1.022	0.716
Precipitation	-0.001	0.003	1.543	2.232	-0.028	0.040	0.157	5.674
Cars	-0.010	0.032	0.049*	0.019	0.000	0.000	-0.034	0.071
Manufact.	0.015*	0.007	0.004	0.005	0.001*	0.000	-0.010	0.016
Sargan	34.29	[0.071]	23.452	[0.43]	32.50	[0.10]	27.57	[0.23]
Ser. corr								
AR(1)	-3.1882	[0.001]	-2.021	[0.043]	-2.033	[0.042]	-2.364	[0.018]
AR(2)	1.0473	[0.295]	1.149	[0.250]	-0.635	[0.524]	1.482	[0.138]

Notes: (*): significant at the 5 per cent significance level. p-values in square brackets.

6 Concluding remarks

In this work, we have analysed the impact of pollutants on hospital admissions for diseases related to chronic respiratory diseases in Italy. The increase of pollutants in urban areas is now at the center of academic and political debate in Italy, especially after the high-profile cases of pollution in the industrial areas of Taranto and Savona.

We have adopted an instrumental variable estimation procedure to control for possible measurement errors in our pollution variables, and other endogeneity problems, and used a spatio-temporal model for pollution in the first-stage. IV estimation shows that PM10 impacts significantly on hospitalisation of young population, while O3 increases hospitalisation of the elederly. Other factors that appear to have an important role are rainfall and unemployment. Our first-stage estimation results also show that air pollution seems to mostly determined by the presence of industrial plants, while the presence of green areas in cities lessens its concentration. A recent study by Marinaccio et al. (2011) has indicated that Taranto, which is the province with the smallest green area per inhabitants while having a large manufacturing industry and a residential area proximate to the polluting facilities, shows high and increasing trends of pleural and lung cancers. Traffic does not seem to have a significant impact on pollution and therefore according to our results policies of alternating plates taken in many Italian cities may not be effective. The strong spatial effects detected in pollution seem to suggest that any policy implemented to fight pollution, in order to be effective, should be taken by a set of contiguous cities, like a region or a macro-region, rather than one single city. On the other hand, our results underscore the need for further efforts on the regional and national level to reduce CO and PM10 levels in particular. Since these pollutants are higher in industrialised cities, environmental policies should focus on reducing pollutants in these areas in order to improve health population. The main goal of public policy should be to be able to combine industrial growth with the reduction of pollutants in order to make it sustainable in the medium to long term.

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