HEALTH AND AIR POLLUTION IN ITALY: EVIDENCE FROM CHANGES IN WIND DIRECTION

Extended Abstract

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Air pollution has important consequences on human health and life expectancy. There is strong evidence that exposure to inhalable pollutants decreases circulatory performance and leads to higher rates of illness, hospitalization, and infant mortality (Pope and Raizenne, 1995; Pope, 2006; Currie et al., 2009). Estimating the effects of air quality on health parameters is fundamental to evaluating and designing environmental regulations. The United States Environmental Protection Agency (EPA) estimates that the Clean Air Act Amendments from 1990 avoided 135 thousand hospital admissions and 17 million lost workdays due to respiratory illness and other diseases related to air pollution by limiting fine-particle and ozone pollution levels.(DeMocker, 2003). Following these lines, The European Commission (COM) through the Zero Pollution Action Plan from 2021 intends to improve air quality and reduce the number of premature deaths caused by air pollution by 55% until 2030 (COM, 2021). However, these estimates are complicated to obtain by widely-documented methodological issues, including omitted variable bias and measurement errors. Possible omitted characteristics correlated with both air pollution and health (e.g., income and exercise) can bias the estimates. Moreover, individuals can respond to ambient air pollution by taking actions to limit their exposure. Heterogeneous avoidance preferences for clean air may self-select individuals into locations based on these unobserved differences.

In this project, I aim to investigate the link between acute exposure to inhalable pollution and health outcomes in Italy. I attempt to overcome the endogeneity and measurement error issues following the identification strategy from Deryugina et al. (2019). Our approach exploits daily variations in air pollution concentration caused by changes in daily wind direction. The main assumption is that after controlling for fixed effects and climate covariates, wind direction should impact the evaluated health outcomes only through air pollution. The key contribution of this study is the application of the framework from Deryugina et al. (2019) to Italy, exploring its unique institutional and geographical characteristics. And, taking advantage of a higher density municipality and pollution measuring stations datasets in comparison with United States data, used in the first place.

Recent literature applies similar quasi-experimental methods to estimate the effects of inhalable pollution on health (Hanna et al., 2012; Schlenker and Walker, 2016; Knittel et al., 2016; Giaccherini et al., 2021). The first study exploits the number of thermal inversions, a phenomenon known to

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trap air pollutants, to instrument for local average air quality. The second estimates the effect of air pollution on health using variations in pollutants driven by upwind airport runway congestion. The third investigates the role of local air pollution on infant mortality by comparing close-knit neighbourhoods that differ in downwind exposure from highways. The last uses public transportation strikes to instrument for local daily air quality in major cities. Our approach, by contrast, does not require identifying specific events, pollution sources or climate phenomena. This characteristic allows our study to easily encompass an extensive number of municipalities and a larger time frame.

The concentration of air pollutants at a given location corresponds to pollution produced locally and pollution transported long distances through the wind. Long-distance air pollution has an important effect on most region's air quality (Feng et al., 2017). In this project's empirical specification, we exploit only the variation in pollution transported long distances following wind-induced patterns. In addition, we use daily average wind direction to instrument daily average air pollution concentration to avoid using variation due to prevailing wind patterns. The predictability of prevailing wind may cause agents to endogenously sort themselves upwind or downwind from pollution sources, thereby biasing the estimates. In that case, our approach is most useful to examine the impacts of acute (short-run) exposure to air pollution.

Assuming the following short-term health production function:

$$H = H(P, A, S) \tag{1}$$

where health is a function of the ambient pollution level P, pollution avoidance preferences or avoidance behavior A and other behavioral, socio-economic factors affecting health S. The total derivative of health with respect to pollution:

$$\frac{\partial H}{dP} = \frac{\partial H}{\partial P} + \frac{\partial H}{\partial A}\frac{\partial A}{\partial P} \tag{2}$$

On the right-hand side, the first term is the pure biological effect of pollution, and the second term is the role of avoidance behaviour in limiting the impact of pollutants on health. As the avoidance behaviour term is not observed, in our instrumental variable strategy, wind direction shifts pollution levels but is unrelated to the individual's avoidance behaviours and other unobserved determinants of health, keeping them fixed.

The dataset's time frame ranges from 2017 to 2023. I use the mortality rate at the daily municipality level as the main health indicator with data from the Italian National Institute of Statistics. I then separate the resident population into four groups: 65 years of age and older, 75 years of age and older, 85 years of age and older and all ages. I obtain air pollution data from the Italian Regional Agency for Environmental Prevention and Protection. The dataset comprehends hourly PM 2.5, PM 10 and Ozone measurements in microgram per cubic meter from 360 monitor stations distributed through 221 municipalities in Italy. Climate data including wind direction, wind speed, temperature and precipitation are from Copernicus ERA-5 reanalysis. This data source comprises climate estimates on a latitude-longitude data points grid at 0.25 x 0.25 degrees resolution. The direction of the wind is given in degrees from 0° (wind blowing from north), 90° (east), 180° (south) and 270°

(west). In this examination, I divide the daily average wind direction angle into 90-degree bins. I then aggregate monitor readings and data points to the daily municipality level by first matching each monitor station to the closest data point and afterwards averaging all readings located within the same municipality on a given day.

The specification for the first stage is:

$$
\begin{aligned}
P_{cdmy} = \sum_{g=1}^{50}\sum_{b=0}^{2} \beta_b^g 1[G_c = g] WINDDIR_{cdmy}^{90b} + f(Temp_{cdmy} + Prec_{cdmy} + WS_{cdmy}) \\
+ \sum_{t=d+1}^{d+2} g_t(1[G_c = g] WINDDIR_{cdmy}) \\
+ \sum_{t=d-1}^{d-2} g_t(1[G_c = g] WINDDIR_{cdmy}) \\
+\alpha_c + \alpha_{my} + \epsilon_{cdmy}
\end{aligned}
\tag{3}
$$

Where the dependent variable is the average pollutant concentration in municipality c, on day d, month m and year y. We control for daily, municipality-level climate variables including temperature, precipitation and wind speed. To account for the heterogeneous effect of wind on air quality across geography we group pollution monitor stations into 50 clusters using the k-means algorithm [1]. It is then assumed that the monitor stations within the same group follow the same daily wind direction and pollution concentration relationship. The parameters β are the coefficients of the 90-degree bins for each of the 50 cluster groups. We add a set of leads and lags to account for the effects of wind variation on the two following and previous days that could be correlated with variation measured on the day d. I then include municipality (α_c) fixed effects to account for any time-invariant determinants of local average pollution levels that also covary with wind direction, and month-by-year (α_{my}) fixed effects to control for the seasonal and trend components. Finally, ϵ_{cdmy} is the error term for each municipality, day, month, year.

We account for short-run delayed effects of pollution exposure on mortality (e.g. being exposed to acute pollution levels on the day d may cause death on the day $d+2$) building a 3-day sum mortality rate. For each day d, I sum the number of deaths from days d, $d+1$ and $d+2$ per group on each day-municipality and divide by the respective municipality's group population on that given year. As robustness checks, I also measure the delayed effects with 2-day and 5-day sum mortality rates. The relationship between air pollution and the mortality rate is defined by the following second stage regression equation:

$$
\begin{aligned}
Y_{cdmy} = \beta \hat{P}_{cdmy} + f(Temp_{cdmy} + Prec_{cdmy} + WS_{cdmy}) \\
+ \sum_{t=d+1}^{d+2} [\gamma_t \hat{P}_{cdmy} + f_t(Temp_{cdmy} + Prec_{cdmy} + WS_{cdmy})] \\
+ \sum_{t=d-1}^{d-2} \gamma_t \hat{P}_{cdmy} + \alpha_c + \alpha_{my} + \epsilon_{cdmy}
\end{aligned}
\tag{4}
$$

[1] 20 and 80 cluster groups are also tested as robustness checks.

Where the dependent variable is the 3-day sum mortality rate for one of the age groups in the municipality c, on the day d, month m and year y. The parameter of interest is β, the coefficient of daily average pollution concentration. We add a set of leads to account for the effects of pollution variation on the two following days that could be correlated with variation measured on the day d [2]. And, the set of lags guarantees that the estimator on the day d is not capturing effects from past pollution. The α_c and α_{my} terms are respectively the municipality and the month-by-year fixed effects. Finally, ϵ_{cdmy} is the error term for each municipality, day, month, year.

This study, in the end, presents the application of a novel method in estimating the effects of air pollution on health in the Italian case. The quasi-random characteristics of daily wind direction variation allow the estimation of the impacts of spikes in pollution concentration on the short-run mortality rate especially for the more vulnerable segments of the population.

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[2] In this case, this strategy ensures that the estimator on the day d, for example, does capture the acute pollution on d that may have caused a death on $d+1$ and does not capture the acute pollution on $d+1$ that may have caused a death on $d+1$.

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