

1 *Review*

2 **AIR QUALITY AND COVID-19 ADVERSE OUTCOMES: DIVERGENT**
3 **VIEWS AND EXPERIMENTAL FINDINGS**

4
5
6
7 **Leonardo Becchetti,^{1,*} Gabriele Beccari,¹ Gianluigi Conzo,¹ Pierluigi Conzo,^{2,3} Davide De Santis,¹**
8
9 **Francesco Salustri.⁴**

10
11 *1 University of Rome Tor Vergata, Rome, Italy*

12 *2 University of Turin, Turin, Italy*

13 *3 Collegio Carlo Alberto, Turin, Italy*

14
15 *4University College London*

16
17
18
19 **Correspondence:**

20 Leonardo Becchetti, University of Rome Torvergata

21 Department of Economics and Finance

22 Via Columbia 2, 00133, Rome, Italy

23 Email: becchetti@economia.uniroma2.it

24
25
26
27
28 Received: date; Accepted: date; Published: date

29
30
31
32 **ABSTRACT**

33
34
35 **Background:** The questioned link between air pollution and coronavirus disease 2019 (COVID-19)
36 spreading or related mortality represents a hot topic that has immediately been regarded in the light
37 of divergent views. A first “school of thought” advocates that what matters are only standard
38 epidemiological variables (i.e. frequency of interactions in proportion of the viral charge). A second
39 school of thought argues that co-factors such as quality of air play an important role too. **Methods:**
40 We analyzed available literature concerning the link between air quality, as measured by different
41 pollutants and a number of COVID-19 outcomes, such as number of positive cases, deaths, and
42 excess mortality rates. We reviewed several studies conducted worldwide and discussing many
43 different methodological approaches aimed at investigating causality associations. **Results:** Our
44 paper reviewed the most recent empirical researches documenting the existence of a huge evidence
45 produced worldwide concerning the role played by air pollution on health in general and on
46 COVID-19 outcomes in particular. These results support both research hypotheses, i.e. long-term
47 exposure effects and short-term consequences (including the hypothesis of particulate matter acting
48 as viral “carrier”) according to the two schools of thought, respectively. **Conclusions:** The link
49 between air pollution and COVID-19 outcomes is strong and robust as resulting from many
50 different research methodologies. Policy implications should be drawn from a “rational” assessment
51 of these findings as “not taking any action” represents an action itself.

52
53
54
55
56 **Keywords:** COVID-19; Environment; Air Pollution; Mortality;

57
58
59
60
61
62
63
64
65

1 42 **1. Introduction: pieces of the puzzle, research questions and schools of thoughts**

2
3 43 The tragedy of the coronavirus diseases 2019 (COVID-19) pandemic has stimulated an
4 44 incredibly vast number of reflections in the public opinion that ultimately turned out to
5
6 45 become research questions for academics and medical practitioners. One of the main
7
8 46 emerging issues explores the reason why the pandemic spread has been so uneven across
9
10 47 different geographical areas, both across and within countries. On this point, Italy offers a
11
12 48 classic example, with one region (Lombardy) concentrating approximately 17 percent of the
13
14 49 population (characterized by a unique increasing trend in terms of proportion of people aged
15
16 50 >85 on the regional population) and more than 46 percent of deaths attributed to COVID—
17
18 51 19 from March 5th to October 15th, namely in the first epidemic wave during last winter.

19 52 The recent history of the debate and the empirical research on this question tells us that the
20
21 53 discussion hinges around two main “schools of thought”. The first supports a purely
22
23 54 epidemiological explanation where the only factor accounting for the observed heterogeneity
24
25 55 is given by the frequency of physical encounters in proportion to the viral charge of each
26
27 56 individual. According to this approach, the only variables that matter in explaining the
28
29 57 phenomenon are those capturing the non-linear (usually “bell-shaped” curves) contagion
30
31 58 dynamics. Variation across different geographical areas in this perspective is explained by
32
33 59 the non-synchronous origin of the phenomenon across different regions, and crucially
34
35 60 influenced by the presence/absence of “super-spreader” individuals or events (e.g. the
36
37 61 Champions League match between Atalanta and Valencia in late February, when 40,000
38
39 62 supporters from the neighbor province of Bergamo moved to Milan, the place of the match).
40
41 63 A typical descriptive picture reflecting this approach is the non-synchronous overlapping of
42
43 64 pandemic contagion curves in different countries/regions. The first day of the local epidemics
44
45 65 at the origin of the X-axis conventionally starts from the 100th contagion case, and the abilities
46
47 66 of different policymakers in tackling the local spread of the epidemics can be evaluated at
48
49 67 first sight by looking at the overlapped curves.

50 68 A non-alternative but more articulated approach argues that several other factors beyond the
51
52 69 standard expected dynamics of the contagion can help us to assess the observed
53
54 70 heterogeneity. Air quality represents one of these factors. Over the last two months, the
55
56 71 debate on the role of air pollution has typically opposed the two above mentioned “schools
57
58 72 of thought” discussing the issue from two different, if not opposite, views.

59 73 The hypothesis that air quality can influence the dynamics of COVID-19 contagions and
60
61 74 deaths finds a strong theoretical background in scientific literature about the link between air
62
63 75 pollution and several respiratory and heart diseases. This literature suggests that quality of
64
65 76 air can affect adverse COVID-19 outcomes in two ways: long term ex ante exposures to
66
67 77 particulate matter (PM) may weaken health in general and lungs in particular, but at the same
68
69 78 time it cannot be excluded that air pollutants might serve as “carriers” for the viruses.

70 79 The first hypothesis relies on the well-established link between long term exposure to PM
71
72 80 and lungs morbidities. In particular, this exposure may have weakened lungs and alveolar
73
74 81 reactivity to the severe acute respiratory syndrome coronavirus 2 (SARS-COV-2), thereby
75
76 82 making severe respiratory and pulmonary consequences more likely to occur.

1 83 In the literature, the link between PM inhalation and lung diseases is hugely documented.
2
3 84 Pope and Dockery [1] have assessed around 200 papers focusing on adverse health effects of
4
5 85 exposure to PM. They conclude that long term exposure produces lungs inflammation and
6
7 86 oxidative stress, accelerating the progression and exacerbation of chronic obstructive
8
9 87 pulmonary disease (COPD), and reducing lung function.
10
11 88 As it is well known, PM may have different anthropogenic (sulfates, nitrates, ammonia,
12
13 89 carbon, lead, organics) or natural (soil, dust, seasalt, bio-aerosols) origins. PM from
14
15 90 anthropogenic origin is made of smaller particles (usually with diameter below 2.5
16
17 91 micrometers) and it is more dangerous as it penetrates as well in small breathing passages,
18
19 92 bronchi and air sacs, while PM particles of larger diameters (typically those from natural
20
21 93 origins) remains in the upper respiratory views (Johnson et al. 2011). Therefore, air pollution
22
23 94 generated by human activity is more dangerous for health than PM concentration generated
24
25 95 by atmospheric phenomena (such as the Sahara dust carried by perturbations).
26
27 96 Among the researchers who support the existence of a link between PM and various
28
29 97 morbidities before the COVID-19 pandemic, there are those identifying a link between
30
31 98 PM_{2.5} and hospitalizations for pneumonia in Canada [2], as well as between PM₁₀ and
32
33 99 hospital admissions for respiratory diseases in US cities [3]. Similar results have been found
34
35 100 in China [4], the city of Boston [5] and Ontario [6]. It is noteworthy to remark that two of
36
37 101 these studies published long time before the COVID-19 pandemic were performed in Wuhan
38
39 102 [7] and in Milan [8], two of the most severely hit cities by COVID-19 contagions.
40
41 103 The second research hypothesis (i.e. carrier effect) argues that PM can carry the virus and
42
43 104 therefore increase virus survival outside the human body. Along this line, Setti et al. [9] [10]
44
45 105 demonstrated the presence of the SARS-COV-2 viral RNA on several PM₁₀ samples of
46
47 106 outdoor/airborne PM₁₀ in Bergamo, despite specific tests on vitality and infectious potential
48
49 107 of the viral particles on PM₁₀ were not performed due to the study design and unavailable
50
51 108 high-security laboratory facilities. However, it can be argued that PM probably carries the
52
53 109 coronavirus and therefore make its presence outside the human body more dangerous in terms
54
55 110 of contagions. What is still missing in this analysis is an evaluation of the viral load and
56
57 111 therefore of the potential contagion effects, if we consider that viruses get progressively
58
59 112 weaker when outside the human body.
60
61 113 In our short survey we try to follow this discussion by illustrating the main empirical or
62
63 114 experimental results found so far in support of both hypotheses, challenging the pure
64
65 115 epidemiological explanation and trying to assess the relevance of air quality as a co-factor
66
67 116 not only in terms of statistical significance but also in terms of relevance of the observed
68
69 117 effect magnitude.
70
71 118
72
73 119
74
75 120
76
77 121
78
79
80
81
82

2. Materials and Methods

The tools for health economists who aim at answering the proposed research question are mainly statistical and econometric methods. The inspection of a simple correlation between the two variables of interest (quality of air, on the one side, and COVID-19 contagions or deaths, on the other side) serves only as a starting point of the analysis. This is followed by the identification of all the concurring and confounding factors that may have affected the phenomenon. Thus, the analysis outlines a multivariate model that allows to test the impact (and hopefully the causality) of the main variable of interest (namely airquality) on the dependent variables, *coeteris paribus*.

The task is daunting since many other factors may have concurred to the observed outcome. The first candidates are time invariant structural factors related to geography, structural commuting dynamics, quality of local and regional administrations, structural characteristics of the regional health systems that in many countries are autonomous and decentralized. Together with this structural and time invariant factors (as conventionally assumed), many other time varying factors may matter. Local authorities and regulators may have had different speed and quality of reaction to the pandemic, thereby contributing to generate heterogeneity in time varying effects at regional or local level. The main candidate of time varying effects at local level is obviously represented by local mobility data that are made available by Google platforms. One of the most interesting ones is the variation of presences in “transit stations” as defined by subway, bus and train stations, sea ports, taxi stands, highway rest stops and car rental agencies. Other equally relevant mobility variables are those measuring changes of dwellers presence in urban parks or recreational premises.

Based on these considerations, the benchmark specification tested in multivariate analysis takes the standard form as follows:

$$\text{COVID-19 outcome}_{tm} = \beta_0 + \beta_1 \text{Quality of air}_{tm} + \sum_r \beta_r \text{Controls}_{rm} + u_{tm} \quad (1)$$

where observations are captured at time t in region m and the explanatory power of quality of air is tested after controlling for other relevant concurring factors (Controls). An important methodological issue here relates to the definition of the dependent variable. As it is well known, COVID-19 recorded cases are highly endogenous as they depend from the number of tests performed.

A more refined measure of contagion and intensity is therefore the ratio between positive cases and total number of tests. COVID-19 deaths are also measured with underlying errors and with highly heterogeneous methodologies across countries and regions for at least two reasons. The first concerns the cause of death, that is whether patients died *because* of the COVID-19 or *with* COVID-19 (patients dying for their own chronic conditions who just tested positive at the time of death) and how the two types of situations are evaluated by each local health authority, given that the distinction between the two concepts can be considered arbitrary with not so clear cut. The problem of a correct diagnosis is particularly relevant also because most of the people died with COVID-19 deaths suffered due to underlying

1 163 comorbidities. As a result, some recording approaches may register one of these comorbidity
2 164 – and not COVID-19 – as the cause of death. Because of the different registration approach,
3 165 we will observe over- or under-reporting of COVID-19 deaths. This makes comparison
4 166 across countries or provinces hard to perform.

7 167 A second problem is the lack of a proper diagnosis. When the epidemics is at peaks and
8 168 intensive therapy beds in hospitals are saturated, local health officials tend to delay
9 169 interventions and diagnosis even for the most serious cases. As a consequence, a remarkable
10 170 number of affected patients die at home without a proper diagnosis. Here again we have a
11 171 problem of under-reporting of COVID-19 deaths. A solution found by many researchers to
12 172 these measurement error problems is to use the “excess deaths” as dependent variable. Excess
13 173 deaths can be defined as the difference between any recorded deaths in a given period
14 174 (usually day or week) and the average of any deaths occurred within the same period in the
15 175 previous years. The use of excess deaths has the advantage of eliminating all problems related
16 176 to regional and country recording differences, because it is based on any deaths regardless
17 177 the cause of the death, which are homogeneously recorded by each municipality. However,
18 178 the advantage of this approach is traded off against the fact that only a measure of the “gross
19 179 mortality effect” due to COVID-19 is provided. Nonetheless, this measure is interesting
20 180 because it allows us to evaluate direct and indirect effects of the pandemic on mortality. There
21 181 are at least three important indirect effects to be considered. First, concentration of hospital
22 182 activities on the COVID-19 emergence slows down all other activities such as, for instance,
23 183 follow-up visits of cancer patients. This phenomenon may eventually lead to deceases for
24 184 other causes. Second, patients with other serious health emergencies (e.g. strokes, heart
25 185 attacks) may delay access to hospital because they fear to be infected at hospital by COVID-
26 186 19. Third, the sharp reduction of traffic during lockdown periods reduces deaths like road or
27 187 workplace fatalities, especially in big cities. This third factor that reduces mortality may
28 188 partially offset the first two death-increasing factors thereby making direction and sign of the
29 189 difference between net and gross COVID-19 deaths ambiguous.

30 190 In order to link our benchmark model with the two competing schools of thought described
31 191 in the introduction, the pure epidemiological approach estimates a reduced form where
32 192 relevant controls are limited to time trends capturing the non-linear dynamics of contagion.
33 193 The approach can be grossly resumed by a bell-shaped dynamics that can be captured by only
34 194 three variables represented by a linear, a quadratic and a cubic time trend:

$$35 195$$
$$36 196 \text{COVID-19 outcome}_{tm} = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + u_{tm} \quad (2)$$
$$37 197$$

38 198 The alternative model of the school of thought advocating the role of other factors beyond
39 199 non-linear epidemiological dynamics may be resumed by the assumption that these three
40 200 variables do not capture all the phenomenon under investigation and the model takes instead
41 201 the form of:

$$42 202 \text{COVID-19 outcome}_{tm} = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \sum_r \gamma_r \text{Controls}_{tm} + u_{tm} \quad (2')$$
$$43 203$$
$$44 204$$
$$45 205$$
$$46 206$$
$$47 207$$
$$48 208$$
$$49 209$$
$$50 210$$
$$51 211$$
$$52 212$$
$$53 213$$
$$54 214$$
$$55 215$$
$$56 216$$
$$57 217$$
$$58 218$$
$$59 219$$
$$60 220$$
$$61 221$$
$$62 222$$
$$63 223$$
$$64 224$$
$$65 225$$

203 where there exists at least one γ_r different from zero. In the literature investigating the link
204 between air pollution and COVID-19 cases or deaths, the main candidate is air quality.

205
206 *Estimation approaches*

207 The challenge between the two competing theories occurs in the domain of multivariate
208 analysis. A typical problem in multivariate analysis is the omitted variable bias. The problem
209 is likely to become more severe when using finer and more disaggregated administrative
210 units (i.e. provinces or municipalities). The use of fixed effect estimates (time invariant
211 intercepts for each administrative unit) allows to capture all unobservable time invariant local
212 idiosyncratic factors thereby partially solving the problem. In the case of COVID-19
213 pandemics it may capture structural differences of local health systems (e.g. available beds
214 in intensive care units, average distance from hospital, number of local general practitioners
215 per person). Fixed effects cannot however capture time varying local effects such as the day-
216 by-day reaction capacity of local authorities to the pandemics. The problem may be partially
217 solved by using non-synchronous regional time trends starting from the first day in which
218 contagions are more than 100 in a given region or, alternatively, by using region-week
219 dummies. However, the most important time varying effect concerns mobility data, which
220 have been used in the studies discussed below (see Results section). These data are crucial
221 since they help to track the dynamic of contacts and interactions among individuals, one of
222 the main drivers of contagion.

223 The significance of the β_1 coefficient in the multivariate analysis estimating model (1)
224 indicates a statistically significant correlation between quality of air and the dependent
225 variable of adverse COVID-19 outcomes. Correlation however is not causation and there are
226 at least three different interpretations for it. First, quality of air does cause COVID-19 adverse
227 outcomes. Second, reverse causality occurs but this cannot be applied to our case since it is
228 hard to believe that COVID-19 mortality can cause (directly) an increase in air pollution.
229 Third, there is an omitted driver causing both COVID-19 deaths and quality of air that
230 produces a spurious correlation between the two variables. Candidates for this interpretation
231 can be economic activity, population density, frequency of human interactions that cause
232 both poor quality of air and COVID-19 adverse outcomes. A first way to control for the
233 endogeneity problem is to include all these variables in the multivariate analysis. The pattern
234 of these relationships can be quite complex to disentangle. In fact, it is highly plausible that
235 interaction flows, traffic mobility and economic activity have a positive and significant effect
236 per se on contagion, while also affecting quality of air which, in turn, negatively affects
237 COVID-19 outcomes. A partial solution to it may be creating sample splits and testing
238 whether the significant effect of air quality on the dependent variable persists when tested in
239 the below median economic activity or traffic mobility sample.

240 Finding a solution to the endogeneity problem is not easy. A standard approach to deal with
241 causality would rely on the first best counterfactual (i.e. a comparison between what
242 happened with COVID-19 and what would have happened without COVID-19). Obviously,
243 this approach is out of reach for whatever research.

1 244 The second best would be a randomized controlled trial, where the effect of pre-defined
2 245 balanced treatment and control groups are tested with the difference-in-differences
3 246 methodology. This approach would be impossible, too. Experimentally, we could not
4 247 produce worse quality of air in some areas (treatment group) having non-significantly
5 248 different ex ante characteristics compared to other areas (control group) and test whether
6 249 reaction to COVID-19 epidemic is different between the two groups (it would be a quite
7 250 complex experiment with a double treatment in any case and would rise ethical questions).
8 251 Another usual approach in economic analysis is the instrumental variable method. An
9 252 instrument is a variable that satisfies two properties: the validity, that is the variable is not
10 253 directly correlated with the dependent variable, i.e. COVID-19 outcomes, and the relevance,
11 254 that is the variable is significantly correlated with the instrumented driver of our interest (i.e.
12 255 quality of air). Typical candidates for a valid and relevant instrument in our case are
13 256 atmospheric phenomena such as wind intensity and direction, and rain precipitation that are
14 257 assumed not to cause directly COVID-19 contagions or deaths while affecting significantly
15 258 quality of air. Since rain precipitation may however increase indoor activities, which in turn
16 259 affect virus spread, it is advisable to lag the variable and to control for time varying mobility.
17 260 Lagged rain precipitation does not affect contemporary mobility while continues to affect air
18 261 quality.
19 262
20 263

264 3. Results

265 *Empirical findings on the nexus between quality of air and COVID-19 outcomes*

266 Since early 2020, empirical findings rejecting the null of no incidence of quality of air on
267 negative COVID-19 outcomes have emerged from scholars located worldwide and refer to
268 evidences collected in different countries. Wu et al. [11] control for a large set of observable
269 concurring factors and find that a $1 \mu\text{g}/\text{m}^3$ is associated with an 8% increase in COVID-19
270 deaths in US counties. Cole et al. [12] find a similar result for municipalities in The
271 Netherlands, even though the quantitative effect is smaller (the change in mortality is around
272 3%). Carteni et al. [13] use the number of days in 2019 with PM exceeding $50 \mu\text{g}/\text{m}^3$ as air
273 pollution variable, and find that the impact is positive and significant. Perone [14] finds a
274 positive result for ozone and nitrogen dioxide together with PM. Coker et al. [15] use
275 municipality data and cross-sectional negative binomial models accounting for spatial
276 autocorrelation, and find that in Northern Italy a $1 \mu\text{g}/\text{m}^3$ is associated with a 9% increase in
277 COVID-19 deaths. Other studies finding significant effects are those of Ogen [16], Yongjian
278 et al. [17], Comunian et al. [18]. Becchetti et al. [19] use provincial data and test the impact
279 of ex ante time invariant exposure to air pollution (PM2.5, PM10 and NO2) on COVID-19
280 cases and deaths. Their analysis shows that the impact is significant and positive when
281 investigating the issue with different approaches. The research methodology involves first
282 cross sectional estimates (one observation for each province) taking a static snapshot on the
283 effect of PM concentration on cumulative cases and deaths.

1 284 Then, the methodology performs pooled and fixed effect estimates where ex ante time
2 285 invariant PM exposure is interacted with epidemic time trends. Finally, the authors create an
3 286 artificial experiment by predicting the dynamics of the epidemics without lockdown
4 287 intervention and comparing it with what happens in the presence of the intervention. This
5 288 simulated counterfactual lockdown is highly significant in reducing negative adverse
6 289 outcomes and more so in provinces with poorer quality of air. Among robustness checks, the
7 290 authors smooth daily into weekly data, remove outlier provinces and use as alternative
8 291 dependent variable the estimated reproduction rate (R_0) of the virus. In this last case what
9 292 they measure is the effect of PM concentration on the epidemic dynamics. However, the
10 293 calculation of R_0 relies on a theoretical model (the authors follow the Susceptible Infected
11 294 Recovered methodology as proposed by Gu et al. [20] and on several ad hoc assumptions or
12 295 imputed parameters such as the mean incubation time in case of infection, the probability of
13 296 getting infected, the probability of detecting infected cases and the probability of isolating
14 297 contacts of the infected case. All these parameters are subjects to uncertainty. Therefore, it is
15 298 highly likely that all these assumption scan create measurement errors, thereby producing
16 299 biased estimates. Even if it is nice to have such a robustness check, it is advisable to have
17 300 main estimates with simpler dependent variables

18 301 All the above mentioned studies test the first research hypothesis on the relevance of long
19 302 term exposure. However several other empirical contributions find a positive and significant
20 303 effect for time varying PM that is compatible also with the second research hypothesis of the
21 304 carrier effect. Among these studies Delnevo et al. [21] show that daily lagged PM Granger-
22 305 causes adverse COVID-19 outcomes in provinces in the region of Emilia-Romagna, Italy.
23 306 Becchetti et al. [22] find evidence of a significant association of lagged PM_{2.5} and PM₁₀ on
24 307 confirmed cases and deaths in European regions using data from the Copernicus Atmosphere
25 308 Monitoring Service (CAMS) with significance peaking at 6-8th lags for contagions and at the
26 309 13th lag for deaths. Significant findings on the time varying effect of PM are also found by
27 310 Isphording and Pestel [23] for German regions. Austin et al. [24] focus on US countries and
28 311 find a positive and significant association (with an increase of 3% in the mortality rate)
29 312 between contemporary quality of air and COVID-19 contagions and deaths. The authors
30 313 tackle the endogeneity problem by instrumenting quality of air with changes in local wind
31 314 direction.

32 315 Becchetti et al. [25] measure daily air pollution at municipality level and find that both PM_{2.5}
33 316 and PM₁₀ 11-day moving averages significantly affect excess deaths in Italy during the first
34 317 wave (end February to end May). The effect of PM_{2.5} is almost twice as large than that of
35 318 PM₁₀, consistently with the hypothesis that finer PM is more dangerous for health because
36 319 it penetrates more in depth in lungs and alveoli. The effect of local PM concentration is
37 320 significant after controlling for non-linear epidemic trends, population density, overall
38 321 economic activity and activity of sectors allowed to operate during lockdown, temperature,
39 322 daily changes in mobility in transit places. The result persists when the authors control for
40 323 fixed municipality effects, instrument PM variables with lagged moving averages of local
41 324 rainfalls, or consider regional non-synchronous pandemic trends taking into account the

1 325 strong heterogeneity of the virus spread across Italian regions. Another robustness check of
2 326 their analysis consists in removing extreme rainfall events to avoid the suspicion of a direct
3 327 causality between the instrument and the dependent variable. An important original
4 328 contribution of this research is in the decomposition of the total effect into a time invariant
5 329 and a time varying component. This decomposition aims to test simultaneously the two
6 330 existing research hypotheses (i.e. long term exposure and carrier effect) on the nexus between
7 331 air quality and COVID-19 adverse outcomes. To do so, the authors regress in a first stage the
8 332 11-day relevant PM moving average on the previous 2-year (time invariant) average PM
9 333 concentration at municipality level. The residual of this estimate is identified as the time
10 334 varying component and introduced in the benchmark estimate together with the 2-year time
11 335 invariant average. Econometric findings show that both components are positive and
12 336 significant therefore supporting both hypotheses. An obvious caveat of this decomposition is
13 337 that the time varying component may proxy for both the carrier and the short term effect of
14 338 PM variation on lung inflammation. The issue remains open to debate and to further research.
15 339 The quality of natural capital is obviously a strong antidote against air pollution. Italy
16 340 represents an interesting case study because, according to data from the Ministry of the
17 341 Environment and Protection of Land and Sea processed by Ancitel, in 2020 there were 2,073
18 342 municipalities (around 25% of all municipalities) within protected natural areas. These are
19 343 areas located within national, regional, provincial or local parks, natural reserves and sea
20 344 natural areas. Around a quarter of municipalities (502) are located in natural parks, while
21 345 almost half share at least 45% of their surface area with parks, reserves or the so called
22 346 Environmental Economic Zone (EEZ). EEZ are areas defined in 2019 by a decree-law and
23 347 enjoy special economic support to preserve their natural resources. If we consider average
24 348 data from the last three years until end May 2020 (thereby including the first wave of the
25 349 pandemic), we find that park municipalities have on average $4 \mu\text{g}/\text{m}^3$ less of PM_{2.5} and PM₁₀
26 350 and around one third of NO₂. Becchetti et al. [26] calculate that, if we consider prudential
27 351 estimates from average data from epidemiological findings, people living in “park
28 352 municipalities” have around 8-10% lower mortality rate for this combined effect. Similarly,
29 353 Becchetti et al. [27] find that better air quality reduced incidence of COVID-19 contagions
30 354 and deaths in park municipalities during the first pandemic wave after controlling for all
31 355 observable concurring factors

50 358 **5. Conclusions and policy implications**

51 359 A number of researches in the few months after the onset of the COVID-19 pandemic have
52 360 produced robust evidence on the association between air pollution and COVID-19 adverse
53 361 outcomes (contagions and deaths). The set of methodologies adopted by the different
54 362 contributions are extremely rich and articulated. The contemporary emergence of significant
55 363 results from different researchers located worldwide provides evidence in favor of the
56 364 hypothesis of causation.

1 365 However, as explained in the methodological discussion, the first best counterfactual is not
2 366 available (and can be only imperfectly simulated). Similarly, the second best of randomized
3 367 experiments is out of reach when investigating a phenomenon that did not start after the
4 368 organization of the experimental setting (as in any randomized control trial with treatment
5 369 and control group). Therefore, we cannot confirm being one hundred percent sure the
6 370 causality nexus despite the fact that the evidence presented above is quite convincing.
7 371 This does not imply however that we cannot draw policy conclusions from the existing
8 372 literature, and the following analogy can be useful to understand why. Imagine you are at a
9 373 dinner and you are told that, with 90 percent probability, what you are going to eat can cause
10 374 you a serious illness. The instinctive, but also “rational”, reaction of each of us would be that
11 375 or refusing to eat such a meal. The choice of refusing would represent our “policy decision”.
12 376 The health effect of smoking is another example showing how policy interventions need to
13 377 be bold and differ from academic robustness, while in dialogue with the scientific
14 378 community. In fact, anti-smoking campaigns could have started before the last umpteenth
15 379 evidence. In a similar manner, it is not wise not to take policy action when you know that,
16 380 based on the available evidence, you are 90 percent (or almost as such) certain that quality
17 381 of air has a positive effect on COVID-19 contagions and deaths.
18 382 The suggestion to reduce PM concentration stemming from this literature is not new. The
19 383 World Health Organization calculates that air pollution (to whom PM concentration gives
20 384 one of the main contributions) kills around 7 million people around the world.¹Although the
21 385 sectors contributing more to pollutant emissions vary across regions, we know that overall
22 386 house heating is the main responsible of PM propagation, followed by traffic mobility, energy
23 387 production, industry and agriculture [28]. It is therefore urgent to replace polluting
24 388 production techniques with cleaner techniques in the most pollutant sectors. This policy
25 389 advice is not new but it is definitely reinforced by what found with the recent research on the
26 390 determinants of COVID-19 deaths.

27 391
28 392 **Disclosures:** All the authors declare no conflict of interests
29 393
30 394
31 395
32 396
33 397
34 398
35 399
36 400
37 401
38 402

39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65
¹See <https://www.who.int/news/item/02-05-2018-9-out-of-10-people-worldwide-breathe-polluted-air-but-more-countries-are-taking-action>.

1 403 **References**

- 2 404
- 3 405
- 4 406 [1] Pope III, C. A., & Dockery, D. W. (2006). Health effects of fine particulate air pollution:
- 5 407 lines that connect. *Journal of the air & waste management association*, 56(6), 709-742.
- 6 408
- 7 409 [2] Neupane, B., Jerrett, M., Burnett, R. T., Marrie, T., Arain, A., Loeb, M. (2010). Long
- 8 410 term exposure to ambient air pollution and risk of hospitalization with community-
- 9 411 acquired pneumonia in older adults. *American Journal of Respiratory and Critical*
- 10 412 *Care Medicine*, 181,47-53.
- 11 413
- 12 414 [3] Medina-Ramon, M., Zanobetti, A., Schwartz, J. (2006).The effect of ozone and PM10
- 13 415 on hospital admissions for pneumonia and chronic obstructive pulmonary disease: a
- 14 416 national multicity study. *American Journal of Epidemiology*, 163(6), 579–588.
- 15 417
- 16 418 [4] Xu, G., Jiao, L., Zhang, B., Zhao, S., Yuan, M., Gu, Y., ... & Tang, X. (2016). Spatial and
- 17 419 temporal variability of the PM2. 5/PM10 ratio in Wuhan, Central China. *Aerosol and*
- 18 420 *Air Quality Research*, 17(3), 741-751.
- 19 421
- 20 422 [5] Zanobetti, A., & Schwartz, J. (2006). Air pollution and emergency admissions in Boston,
- 21 423 MA. *Journal of Epidemiology & Community Health*, 60(10), 890-895.
- 22 424
- 23 425 [6] Luginaah, I. N., Fung, K. Y., Gorey, K. M., Webster, G., & Wills, C. (2005). Association
- 24 426 of ambient air pollution with respiratory hospitalization in a government-designated
- 25 427 “area of concern”: the case of Windsor, Ontario. *Environmental health*
- 26 428 *perspectives*, 113(3), 290-296.
- 27 429
- 28 430 [7] Zhang, Y., He, M., Wu, S., Zhu, Y., Wang, S., Shima, M., ... & Ma, L. (2015). Short-term
- 29 431 effects of fine particulate matter and temperature on lung function among healthy
- 30 432 college students in Wuhan, China. *International journal of environmental research and*
- 31 433 *public health*, 12(7), 7777-7793.
- 32 434
- 33 435 [8] Santus, P., Russo, A., Madonini, E., Allegra, L., Blasi, F., Centanni, S., ... &Amaducci,
- 34 436 S. (2012). How air pollution influences clinical management of respiratory diseases. A
- 35 437 case-crossover study in Milan. *Respiratory research*, 13(1), 95.
- 36 438
- 37 439 [9] Setti, L., Passarini, F., De Gennaro, G., Di Gilio, A., Palmisani, J.... Piscitelli P. & Miani
- 38 440 A., Potential role of particulate matter in the spreading of COVID-19 in Northern
- 39 441 Italy: first observational study based on initial epidemic diffusion. *BMJ open*, 2020,
- 40 442 10.9: e039338.
- 41 443
- 42 444 [10] Setti L, Passarini F, De Gennaro G, Barbieri P, ... Piscitelli P & Miani A. SARS-Cov-
- 43 445 2RNA found on particulate matter of Bergamo in Northern Italy: First evidence.
- 44 446 *Environ Res*. 2020 Sep;188:109754. Epub 2020 May 30.
- 45 447
- 46 448 [11] Wu, X., Nethery, R. C., Sabath, B. M., Braun, D., & Dominici, F. (2020). Exposure to
- 47 449 air pollution and COVID-19 mortality in the United States. *medRxiv*.
- 48 450
- 49 451 [12] Cole, M., Ozgen, C., &Strobl, E. (2020). *Air pollution exposure and COVID-19*.[IZA](#)
- 50 452 [Discussion Paper No. 13367](#).
- 51 453
- 52 454
- 53 455
- 54 456
- 55 457
- 56 458
- 57 459
- 58 460
- 59 461
- 60 462
- 61 463
- 62 464
- 63 465
- 64
- 65

-
- 1 441 [13] Carteni, A., Di Francesco, L., & Martino, M. (2020). How mobility habits influenced
2 442 the spread of the COVID-19 pandemic: Results from the Italian case study. *Science*
3 443 *of the Total Environment*, 741, 140489.
- 4 444 [14] Perone, G. (2020). The determinants of COVID-19 case fatality rate (CFR) in the Italian
5 445 regions and provinces: an analysis of environmental, demographic, and healthcare
6 446 factors. *Science of The Total Environment*, 142523.
- 7 447 [15] Coker, E. S., Cavalli, L., Fabrizi, E., Guastella, G., Lippo, E., Parisi, M. L., ... & Vergalli,
8 448 S. (2020). The effects of air pollution on COVID-19 related mortality in northern
9 449 Italy. *Environmental and Resource Economics*, 76(4), 611-634.
- 10 450 [16] Ogen, Y. (2020). Assessing nitrogen dioxide (NO₂) levels as a contributing factor to the
11 451 coronavirus (COVID-19) fatality rate. *Science of The Total Environment*, 138605.
- 12 452 [17] Yongjian, Z., Jingu, X., Fengming, H., & Liqing, C. (2020). Association between short-
13 453 term exposure to air pollution and COVID-19 infection: Evidence from China. *Science*
14 454 *of the total environment*, 138704.
- 15 455 [18] Comunian, S., Dongo, D., Milani, C., & Palestini, P. (2020). Air pollution and Covid-
16 456 19: the role of particulate matter in the spread and increase of Covid-19's morbidity
17 457 and mortality. *International journal of environmental research and public*
18 458 *health*, 17(12), 4487.
- 19 459 [19] Becchetti, L., Conzo, G., Conzo, P., & Salustri, F. (2020b). *Understanding the*
20 460 *heterogeneity of adverse COVID-19 outcomes: the role of poor quality of air and lockdown*
21 461 *decisions*. Available at SSRN: <http://dx.doi.org/10.2139/ssrn.3572548>.
- 22 462 [20] Gu, C., Jiang, W., Zhao, T., Zheng, B. (2020). Mathematical recommendations to fight
23 463 against COVID-19. <http://dx.doi.org/10.2139/ssrn.3551006>
- 24 464 [21] Delnevo, G., Mirri, S., & Rocchetti, M. (2020). Particulate Matter and COVID-19 Disease
25 465 Diffusion in Emilia-Romagna (Italy). Already a Cold Case?. *Computation*, 8(2), 59.
- 26 466 [22] Becchetti, L., Beccari, G., De Santis, D. (2020a). *Lagged particulate matter, contagions*
27 467 *and deaths: the relationship between quality of air and COVID-19 at European level*.
28 468 Cefimdp 159, SOAS University of London
- 29 469 [23] Isphording, Ingo E., and Nico Pestel. (2020). *Pandemic meets pollution: poor air quality*
30 470 *increases deaths by COVID-19*. IZA Discussion Paper No. 13418
- 31 471 [24] Austin, Wes, et al. (2020). *COVID-19 mortality and contemporaneous air pollution*. No.
32 472 paper2016. International Center for Public Policy, Andrew Young School of Policy
33 473 Studies, Georgia State University.
- 34 474 [25] Becchetti, L., Beccari, G., Conzo, G., Conzo, P., De Santis, D., Salustri, F.
35 475 (2020). *Particulate matter and COVID-19 excess deaths: decomposing long-term*
36 476 *exposure and short-term effects*. Mimeo.
- 37 477 [26] Becchetti, L., Conzo, G., Conzo, P., & Salustri, F. (2020). *Park Municipalities and*
38 478 *Mortality during the COVID-19 Pandemic*. Available at SSRN
39 479 <http://dx.doi.org/10.2139/ssrn.3625606>.
- 40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

1 480 [27] Becchetti, L., Beccari, G., Conzo, G., Conzo, P., De Santis, D. Salustri, F. (2020). *The*
2 481 *health effect of living in park municipalities*. Mimeo,
3
4 482 [28] Iriti, M., Piscitelli, P., Missoni, E., & Miani, A. (2020). Air Pollution and Health: The
5
6 483 Need for a Medical Reading of Environmental Monitoring Data. *International journal*
7 484 *of environmental research and public health* 2020 Mar 25;17(7):2174.
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65