



## Commentary

# A Long Way from Steubenville: Environmental Epidemiology in a Rapidly Changing World

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This commentary focuses on research that has long been at the core of environmental epidemiology: studies of the health effects of air pollution. It highlights publications in the American Journal of Epidemiology going back more than 50 years that have contributed to the debate about the validity of this research and its meaning for public policy. Technological advances have greatly expanded the toolbox of environmental epidemiologists in terms of measuring and analyzing complex exposures in large populations. Yet, discussions about biases in estimating air pollution health effects have always been and remain intense. Epidemiologists have brought new methodologies and concepts to this research, alleviating some but not all concerns. Here, the focus is on seminal epidemiologic work that established invalid links between air pollution exposures and health outcomes and generated data for environmental policies and prevention. With this commentary, I hope to inspire epidemiologists to address many more of the burning environmental health questions—wildfires included—and the secret to training a squirrel to water ski—with a similar scientific doggedness. The rapidly changing conditions of our planet are challenging us to innovate and offer solutions, albeit perhaps a little bit faster this time around.

air pollution; climate change; environmental epidemiology

Abbreviations: *AJE*, American Journal of Epidemiology; EPA, Environmental Protection Agency; PM<sub>2.5</sub>, particulate matter less than or equal to 2.5 μm in diameter.

**Editor's note:** *The opinion expressed in this article are those of the author and do not necessarily reflect the views of the American Journal of Epidemiology.*

have learned but recently to measure various operations of such mechanisms, the potential for study of environ-

mentalepidemiologyisfargreaterthaninprevious periods, and it is rapidly increasing (1, p. 1532).

In 1967, John Goldsmith—a founder of the International Society for Environmental Epidemiology—wrote,

There is no novelty to the consideration of environmental factors in epidemiology. One may cite Hippocrates, Arnauld of Villanova, Sydenham, Ramazzini, Potts, and Snow, and many others as noting the importance of air, water, and occupation, for acute and chronic disease. Today an increasing proportion of the population is exposed to changes in their environments and in the nature of the demands which these changes make on adaptive, somatic, and genetic mechanisms. Because we



dire warnings but also offers solutions, and to implement precautionary approaches.

In 2015, in the *American Journal of Epidemiology* (*AJE*), Trinquart and Galea (2) reviewed more than 20,000 published articles from 5 major epidemiology journals to identify major themes epidemiology had engaged in over a 40-year period (1974–2013). They reported that a new cluster of terms related to the word “environment” first appeared in the mid-1990s and persisted in subsequent years. Not surprisingly to an environmental epidemiologist, the word cloud they generated contained *smoke*, *air pollution*, *particulates*, *weather*, *asthma*, *respiratory disease*, and *mortality*. In fact, apart from occupational exposures, these terms also capture the focus of environmental epidemiology from the 1950 through the 1990s. I recently extracted keywords from 8,276 articles published in 7 leading environmental journals from 1975 to 2020 (see Web Figure 1, available at <https://doi.org/10.1093/aje/kwac031>). Centered around the keyword “epidemiology,” the largest node in the co-occurrence cloud was labeled “air pollution.” This commentary will highlight how the *AJE* has contributed to this core theme in environmental epidemiology and how environmental epidemiology subject matter inspired and contributed to the development of epidemiologic methods, promoting them in real-world applications. This will not be a comprehensive review of the enormous body of air pollution literature, for which readers may want to visit, for example, reports written for and by the Global Burden of Disease program on air pollution, led by the Health Effects Institute (3). The focus will be on epidemiologic work that not only established valid links between these exposures and health outcomes but also challenged the field in terms of methodology and generated data of importance for environmental policies and public health.

inspired epidemiologic investigations (4, 8–12). More than 30 years after the Donora episode, a lengthy review of the results of these studies by British air pollution scientists, led by none other than Walter Holland, was published as a supplement to the *AJE* (13). In its introduction, this qualitative review reminded the reader that epidemiology “provides the most satisfactory methods for studying the effects of environmental pollution on public health, and indeed the only way of measuring its chronic effects in humans,” ending on the cautionary note that “it is important to distinguish between symptoms that merely produce discomfort and those that pose a threat to life” (13, p. 533).

Holland was recently eulogized by his colleagues as the man who “put the study of avoidable mortality on the map” (14, p. 1018). Yet, the conclusion of the British researchers’ 1979 review (13) was that the US Environmental Protection Agency (EPA) had gotten it all wrong by setting air prevention.

In 1965, an acclaimed British colleague, Dr. Walter Holland, introduced the *AJE* readership to his air pollution health effects research (4) comparing US East Coast telephone workers with their colleagues working in London. All else being similar, including smoking, Holland and his coauthors concluded that atmospheric pollution was respon-

sion. Pollution standards for particles as much as 3 times lower than necessary given the data. This conclusion generated a lively discussion that played out in letters to the editor of *AJE* over the next 4 years. These exchanges laid open disagreements on factors to be considered for making causal

inference from epidemiologic data and when assessing the validity of epidemiologic research in support of standard-setting and public policy. Many of these issues are worth revisiting, as some are continuing to plague our discipline, while others have been laid to rest. The main arguments for questioning observational human data and the assertion that “association is not causation” then as now included the specter of confounding or measurement error, as well as the possible impact that lack of population representativeness, limited sample size, and inconsistencies between study results have when developing public policies. Indeed, the keyword cloud shown in Web Figure 2 supports the

centrality of confounding as a theme of the air pollution literature in the past 45 years. Therefore, after presenting findings from an exemplary and influential paper in our field, published in the *AJE* in 1992 (15), this commentary will discuss how this bias and other important concerns have been dealt with in environmental epidemiologic research in recent decades.

sible for the higher respiratory morbidity among the London men, as they had been chronically exposed to much higher levels of particulate matter and sulfur dioxide (4). This research was inspired by 2 disasters, the London Smog of 1952 (5) and the Donora, Pennsylvania, air pollution catastrophe (6). Particulates, sulfur dioxide, and other gases had been trapped by particularly stagnant weather conditions over these inhabited areas. The meteorological conditions generated extremely high pollution levels within a matter of days and caused high respiratory morbidity and mortality. As Brunekreef and Hoek reminded us in another *AJE* commentary (7), the excessive numbers of adverse events resulted in a fatality rate that rivaled those of the great cholera epidemic of 1854 and the great influenza epidemic of 1918. Thus, it is not surprising that these episodes became well-known catalysts not only for human air pollution research but for regulatory action, including passage of the United Kingdom's Clean Air Act in 1956 and the US Clean Air Act in 1970.

In the 1950s and 1960s, air pollution episodes of lesser intensity were rather common on both continents and

## FIRST, THERE WAS STEUBENVILLE

Early work that provided the foundations for the first EPA regulation of fine particulate matter (particulate matter less than or equal to 2.5  $\mu\text{m}$  in diameter (PM<sub>2.5</sub>)) in 1997 was conducted by colleagues at Harvard University. This included the 1992 publication in the *AJE* by Schwartz and Dockery (15) that perfectly set the stage for the landmark Harvard Six Cities Study published a year later (16). While the 1997 EPA review for the particulate matter standard cited hundreds of studies, industry opponents framed the debate questioning the strengths of the science around a handful of epidemiologic studies, including these two (17). This is interesting, as these publications were methodologically strong and complementary such that, taken together, they diminished if not plainly resolved concerns about the validity of epidemiologic results on mortality related to particulate matter pollution, including uncontrolled confounding.

*Am J Epidemiol.* 2023;192(11):1811–1819

The Schwartz and Dockery paper (15) focused solely on short-term acute effects while modeling the day-to-day mortality experience of Steubenville, Ohio, residents due to particulate air pollution. At the time, Steubenville was not only one of 6 US cities for which the research team collected exposure and outcome data for their cohort study over a decade, but it was its poster child as the dirtiest of these 6 cities, as well as nationally. This Steubenville time-series analysis was possible because the local air pollution agency (the North Ohio Valley Air Authority) had monitored daily levels of total suspended particulates and sulfur dioxide and the researchers were able to retrieve daily mortality counts from the National Center for Health Statistics. Relying on a time-series approach centered on Steubenville was a powerful design choice, because this guaranteed that the results were unaffected by confounding due to factors that are not time-varying in the short term, such as smoking, socioeconomic characteristics, and occupation. Instead, the purely temporal exposure contrast required a sophisticated approach to control for meteorological influences (i.e., the

compounded by the fact that mortality studies in particular generated relatively small effect sizes and that, because of regulations, air pollution levels had declined, thus reducing the exposure contrasts used in studies over time.

As discussed above, the Steubenville time-series approach is a perfect example of a study design that allows estimation of short-term (daily) air pollution effects without confounding due to factors that do not vary on the chosen time scale, such as smoking, socioeconomic characteristics, and occupation. Temporally varying confounders, however, needed careful attention, causing Holland et al. to state, “At these levels of particulate pollution, the effects on time-varying confounder temperature and dewpoint), as worldwide (26). well as influenza episodes. Another strength of this research

was that it estimated acute effects of 2 pollutants on mortality. Pollutant co-adjustment in the same model suggested that the mortality increase was due to the particulates and not the sulfur dioxide. This was important because the EPA regulates individual pollutants, and few earlier studies had been able to disentangle effects for singular pollutants (18, 19). During the period they investigated (the mid-1970s to mid-1980s), Steubenville air pollution levels, including levels of particulates, had been greatly reduced in response to the Clean Air Act of 1970. Nevertheless, in the paper’s abstract, Schwartz and Dockery concluded that “the relation [for particulate matter] appeared to continue at levels well below the current National Ambient Air Quality Standard”

health are difficult, if not impossible, to disentangle from the health effects of temperature or other weather factors” (13, p. 658).

Yet, a decade later, temporal confounders were considered sufficiently controlled through sophisticated statistical models for weather and other temporal parameters included not only in the Steubenville study (15) but also routinely in all time-series analyses that followed, including comprehensive studies conducted in the United States (24), Europe (25), and

Reliance on the common epidemiologic designs of cohort, cross-sectional, and case-control studies allowed researchers to estimate longer-term pollutant effects on mortality and morbidity. Because these types of studies mainly employ spatial exposure contrasts, it is necessary to carefully consider individual-level confounders such as smoking or body mass index, as they may exhibit spatial patterns like the (15, p. 12). others that followed (29), since they allowed researchers to

While the Steubenville times series allowed assessment of short-term acute impacts on mortality, the 6-city longitudinal cohort approach complemented and extended these results by modeling longer-term effects on mortality, relying on the spatial contrast in pollution levels across the 6 cities (16). Detailed baseline data collected for each cohort allowed the investigators to control for confounders such as smoking and occupation. The Harvard Six Cities Study furthermore distinguished between particles of different size ranges, and investigators reported that the most consistent associations with mortality were seen with PM<sub>2.5</sub> (15). The results were replicated in the American Cancer Society Study II cohort study (20) and set the stage for additional powerful studies that followed in Europe (21, 22) and, more recently, all over the world (23). These large collaborations provided overwhelming support for the validity of earlier US findings.

#### **AND THERE ALWAYS IS CONFOUNDING**

Confounding was a major concern for the reviewers in 1979 (13), either by individual characteristics such as smoking or occupation or by socioeconomic or meteorological factors. This general threat to the validity of air pollution studies from unmeasured confounding was seen as being

pollutants. The early air pollution studies and most large vital statistics or hospitalization record-based studies relied on data sources that lacked such individual-level risk-factor information. Thus, it was particularly important when air pollution researchers initiated or engaged with cohort studies such as the trailblazing Harvard Six Cities Study (16, 27, 28), American Cancer Society Study II (20), and many

investigate longer-term influences of air pollution on total mortality, cause-specific mortality, and eventually morbidity while controlling for many individual-level confounders.

As is the case for all observational studies, adjustment for unmeasured confounders is not possible, and randomized controlled experiments are not an option for large-scale population-based air pollution research. However, alternatives were exploited, such as natural experiments or quasi-experiments in which exposure is assigned not by the experimenter but by forces thought to be independent of the potential outcomes and thus unlikely to be affected by unmeasured confounding. Examples include studies of temporary closure of polluting facilities, such as a temporary steel mill closure in Utah (30), the Dublin, Ireland, ban on coal sales (31), the decommissioning of coal-fired power plants (32), or the temporary restrictions placed on polluting traffic and industry during the Atlanta, Georgia, and Beijing, China, Olympic Games (33, 34). More recently, a type of quasi-experimental design known as the difference-in-differences approach was used to exploit both spatial and temporal differences in air pollution due to oil and gas exploration or power-plant closures to investigate associations with adverse birth outcomes (35, 36). Some real-world exposure studies used quasi-experimental panel

1814

Ritz

design to compare short-term symptoms such as asthma, lung function, blood pressure, or inflammation after subjects walked or biked along busy roads versus in parks

“[W]e fail to understand how the impact can be assessed of something which has not been measured” (52, p. 160). A decade later, though, such methods were introduced more (37–39).

Recently, the idea of using negative control to assess confounding has been introduced. A negative control outcome acts as a surrogate for the actual outcome in epidemi-

widely by occupational epidemiologists promoting indirect

adjustment for smoking (53, 54). Nowadays, epidemiology is fully engaged in and encourages quantitative biasologic studies and should be subject to the same potential sources of bias as the outcome of interest but not caused by the exposure. However, negative control has some limitations, such as lack of specificity in the type of bias they may detect (40). In fact, in their 1979 review, Holland et al. (13) had already touched on this notion by suggesting that researchers investigate associations with suicide, crime rates, or venereal disease in air pollution studies. Interestingly, for the first two there is now growing evidence that pollution may indeed be associated with these outcomes. For crime rates, Berman et al. (41) found acute air pollution to be associated with the risk of violent behavior in the United States. For suicides, a recent systematic review of 18 studies (42) found increases with levels of fine and coarse particulates and nitrogen dioxide. While disqualifying these outcomes from being considered negative control diseases, these results also reflect the growing notion that air pollution affects the brain and behavior, including neurodevelopment (43) and neurodegeneration (44, 45). Apart from a control disease, there is also the option to use a negative control exposure or exposure period during which the exposure does not affect the outcome but would be similarly affected by unmeasured confounding (46). An example for such a scenario would be third-trimester air pollution exposure in birth defect studies when it is known that the outcome (e.g., a neural tube defect) is due to disruption of fetal development in the first trimester only. A related idea was introduced in the 1990s and was first employed in an air pollution study in 2001 (47) using a case-crossover design where in each subject serves as their own control (case-only) and by design is matched on non-time-varying factors such as body mass index in studies of diseases with short latency or hospitalizations (48–50). Here, the contrast is between exposures measured during relevant air pollution

analysis, including simulations that inform about the size of an expected bias (55).

## PAYING ATTENTION TO EXPOSURE: MEASUREMENT ERROR AND MIXTURES VERSUS COMPONENTS

Air pollution studies rely on ambient air monitoring data or exposure modeling approaches like land use regression or dispersion models. Because personal exposure monitoring is not feasible in large populations or over long periods of time due to costs and intrusiveness, air pollution researchers employ surrogates for personal exposures, and much methodological work has been conducted on measurement errors specific to air pollution studies (56–63). For example, air pollution regression estimates of health effects can be affected by classical and/or Berksonian error, with the former likely to but not always attenuating regression estimates and the latter increasing the variance but not biasing the health effects estimates (63). Indoor environments contribute to total personal exposures periods prior to the event and during control exposure periods defined as irrelevant times before and after the event of distinct interest.

Another novel perspective on confounding in air pollution studies was suggested recently by Weisskopf et al. (46), who argued that by relying on ambient rather than personal air pollution concentrations we may well be able to avoid confounding bias due to differences in personal behaviors. Specifically, here one needs to conceptualize the ambient level as an “instrumental variable” that is not affected by individual behaviors; that is, it is merely a proxy for personal exposure through which causal biological mechanisms are acting on health outcomes.

Interestingly, one of the letters on the 1979 review (13) was written by John Goldsmith, who argued that “there are ways to analyze the possible impact of unmeasured variables, some of which were used in the study of the role of smoking in the occupational cancer associations” (51, p. 158).

through combustion sources in residential environments, such as heating, cooking, and indoor smoking, and a variety of sources in workplaces, from welding fumes to diesel exhaust and dust in mineshafts. However, it has been argued that in support of policies addressing outdoor air pollution, researchers should estimate health effects from personal exposure due to ambient sources alone (61). For the latter, rates of infiltration into the indoor environment, including use of indoor air filters and air conditioning, are important (64). Predictions of outdoor exposures at residences seem less prone to measurement error than use of measures from central site or satellite monitoring (60, 65). However, because people are mobile, exposures estimated at homes may not represent their ambient exposures, especially when they are exposed while in traffic or outdoors while exercising

(66).

For Holland et al. (13), it was important that studies distinguished between health effects from particulates and those

from sulfur dioxide. Because air pollution in general and particulate matter specifically are mixtures with different compositions, depending on the sources, there have been extensive discussions in recent years about whether effect decomposition for complex mixtures is necessary (67–69). Depending on the study goal, it may make sense to estimate specific health effects from a toxic component for which

At the time, this suggestion was dismissed by Holland et al.:

biological data exist, such as oxidative-stress-generating compounds (70). Alternatively, one may want to address effect modification by components of toxic mixtures that originate from various sources or evaluate the toxicity of the whole mixture (71). Finally, to understand or avoid measurement error, the appropriate temporal and spatial scale for each exposure needs to be selected depending on what is known about biological mechanisms and lag times for diseases of interest.

*Am J Epidemiol.* 2023;192(11):1811–1819

## AIR POLLUTANTS AFFECT MULTIPLE OUTCOMES

In their 1979 review, Holland et al. (13) emphasized symptoms that pose a threat to life, not mere discomfort. Yet, even deaths attributed to air pollution were at first dismissed as representing mortality displacement or “harvesting” of the frailest individuals, thus just advancing the time of death by a few days. This phenomenon was subsequently addressed in studies which showed that the short-term increase in mortality from air pollution was not followed by a decrease in all-cause or cardiovascular mortality, as would be expected from displacement; rather, longer-term cumulative exposures seemed even more harmful (72, 73). This observation prompted Brunekreef and Hoek in 2000 (7) to ask to what extent air pollution might shorten life expectancy. More than a decade later, Samet (74) applauded the shift of focus in air pollution epidemiology from “body counts” to the perspective that clean air lengthens life expectancy and reduces morbidity. By this time, PM<sub>2.5</sub> was considered a risk factor that contributes to the burden of avoidable premature mortality (74, 75).

Routine monitoring of PM<sub>2.5</sub> began in the United States in 2000, enabling researchers to address health effects from fine particles. It had long been suggested that these smaller particles are important, as they have “the greatest chance of reaching the lung with the risk of long-term retention” (76, p. 459). The notion that air pollutants may not just act on respiratory organs at their point of entry but travel further had already been expressed in a letter to the *AJE* (77). This letter mentioned that particles can either be taken up in the lung and disseminated through the circulatory system or brought up via the mucus and swallowed, exposing the gastrointestinal tract (77). Later we learned that ultrafine particles can reach the brain (78), and particles or their compounds were found in the placenta and developing fetus (79–81). There is now an extensive body of literature showing that air pollution affects birth outcomes adversely (82, 83). Moreover, prenatal exposures may also program organs during development for deficits or failure later in life—that is, impair lung, cardiovascular, or brain development in children (84–86). The literature on neurodevelopmental impacts of air pollution is substantial (87), and the knowledge base for neurodegenerative disease, from Parkinson disease to Alzheimer disease and related dementias, is increasing rapidly (45, 88).

## POPULATION REPRESENTATIVENESS AND SUSCEPTIBLE SUBGROUPS

The validity of epidemiologic studies does not depend on population representativeness. However, representativeness or transportability might affect whether results from one population can be extrapolated to others and may contribute information for purposes of human health risk assessment. Specifically, researchers may need to identify vulnerable subpopulations by developmental stage, age, or health status or in places with particularly high pollution levels (89). Small sample sizes generally limit subgroup analyses, and some vulnerable subgroups might never be represented sufficiently in any one study. In fact, in epidemiology the notion

of what represents a negative result has also changed over time; that is, studies targeting certain subgroups may be too small to be informative on their own but nevertheless become valuable in the context of data-pooling and meta-analysis efforts, which have long been a staple of air pollution epidemiology (29, 42, 90). In an early example of this approach, Dockery and Pope (91) pooled data on respiratory outcomes, generating inverse-variance-weighted averages across studies for mortality, hospital admissions, asthma attacks, and change in lung function. Not only do these approaches help investigators to summarize the data and include smaller studies, but by identifying sources of heterogeneity they may deepen causal understanding. When Shy (92) challenged Holland et al. (13) for their uncritical stance towards negative studies (i.e., those which found no association), the response was that “no amount of speculation about biases which prevented the realization of a positive finding will make the result demonstrative of a positive finding appropriate for the setting of standards” (76, p. 458). Some 20 years later, a commentary in the *AJE* (93) instead emphasized that exploring the reasons for population heterogeneity—and hence heterogeneity in results—is a key issue of primary scientific and public health interest, as it is a promising approach that integrates results from small-area and global studies in the quest for causal inference (71, 94–96). Basically, it was a call to make the best use of all available information.

## ARE WE DONE YET?

Air pollution research has been thriving on the creative use of administrative health records as much as on generating data from large cohorts and consortia. It has gained greatly from the expansion of routine government air monitoring networks, advances in “big data” computing, and sophisticated statistical approaches to modeling a myriad of acute and chronic health effects in high- and low-pollution environments. Expansion of air pollution exposure models based on satellite imagery will allow communities across the world to increase their capacity to conduct research that drives policy (97). Novel “-omics” tools are becoming more affordable and may help epidemiologists to implement meet-in-the-middle approaches that support causal reasoning based on nonexperimental human data (98, 99). For example, an emerging body of literature has found consistent metabolomic signatures for air pollution in human serum (100–102), which may eventually allow us to relate this information to biological mechanisms of disease (103).

Contrary to the conclusions of Holland et al.’s 1979 review (13), an additional 40 years’ worth of research has uncovered many hidden dangers of air pollution at levels much lower than those set by the EPA in the 1970s. Questions about the existence of exposure thresholds for health effects have been replaced by questions about the achievable lower limits at which further pollution reduction outweighs the human costs, as well as what the consequences of erring on the wrong side might be. Even in countries with extensive pollution controls and low average air pollution levels, environmental injustices (i.e., the locations where polluting sources are tolerated) may create air pollution “hot spots” in

vulnerable communities (104). The recent coronavirus disease 2019 (COVID-19) pandemic raised questions about the special vulnerabilities of communities most affected by air pollution (105). New challenges are also arising as climate change drives wildfire-related air pollution that affects large populations, while at the same time heat waves may generate synergistic effects (106).

In their time-series analysis, Schwartz and Dockery observed that “hot, humid days were associated with daily total mortality in Steubenville” (15, p. 16). Reading this statement now, it is a clear warning about the looming health effects of a warming climate, yet 30 years ago this observation did not even make it into their abstract. In 1997, the ever-prescient Tony McMichael—a late President of the International So-

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ciety for Environmental Epidemiology—encouraged the environmental epidemiology community to heed the warnings of a recent report by the Intergovernmental Panel on Climate Change, as “we can expect that climate change will affect the health and wellbeing of human populations in diverse ways. This greatly extends the temporal-spatial scale of environmental health beyond our usual concern . . . ” (107, p. 805). McMichael proceeded to urge his colleagues to apply current knowledge to forecast probable health effects and inspire preemptive policy-making. This preemptive research agenda has unfortunately been superseded by growing opportunities to apply novel approaches to actual data accumulating on the subject. Climate-related health effects are indeed catching more of our colleagues’ attention, including a younger generation of methodologically well-versed environmental epidemiologists worldwide (e.g., see references 108–114). The Steubenville analysis was motivated by a daily mortality time-series study in London (19), quickly followed by a similar one conducted in Philadelphia (115), and moreover by what the editor of the journal *Epidemiology* soon called a deluge of air pollution time-series article submissions that led him to question the value of any further replication (116). It was possible to generate such overwhelming evidence from many corners of the world because the data necessary for analysis were publicly available.

Such open access to data, whether ground-level data or satellite-derived monitoring data, is imminently important to meet the new challenges of climate-change health effects research. We have sharpened many of our tools during decades of air pollution research, and forecasting as well as big data approaches to existing data now present welcome challenges. Clearly it is also not too early to recognize and act by presenting the insights we are rapidly gaining to policy-makers and the public.

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*Am J Epidemiol*.2023;192(11):1811–1819

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