

# The Importance of Population Susceptibility for Air Pollution Risk Assessment: A Case Study of Power Plants Near Washington, DC

Jonathan I. Levy, Susan L. Greco, and John D. Spengler

Department of Environmental Health, Harvard School of Public Health, Boston, Massachusetts, USA

In evaluating risks from air pollution, health impact assessments often focus on the magnitude of the impacts without explicitly considering the distribution of impacts across subpopulations. In this study, we constructed a model to estimate the magnitude and distribution of health benefits associated with emission controls at five older power plants in the Washington, DC, area. We used the CALPUFF atmospheric dispersion model to determine the primary and secondary fine-particulate-matter (< 2.5  $\mu\text{m}$  in aerodynamic diameter) concentration reductions associated with the hypothetical application of “Best Available Control Technology” to the selected power plants. We combined these concentration reductions with concentration–response functions for mortality and selected morbidity outcomes, using a conventional approach as well as considering susceptible subpopulations. Incorporating susceptibility had a minimal effect on total benefits, with central estimates of approximately 240 fewer premature deaths, 60 fewer cardiovascular hospital admissions (CHA), and 160 fewer pediatric asthma emergency room visits (ERV) per year. However, because individuals with lower education appear to have both higher background mortality rates and higher relative risks for air-pollution–related mortality, stratifying by educational attainment implies that 51% of the mortality benefits accrue among the 25% of the population with less than high school education. Similarly, diabetics and African Americans bear disproportionate shares of the CHA and ERV benefits, respectively. Although our ability to characterize subpopulations is constrained by the available information, our analysis demonstrates that incorporation of susceptibility information significantly affects demographic and geographic patterns of health benefits and enhances our understanding of individuals likely to benefit from emission controls. *Key words:* asthma emergency department visits, cardiovascular hospital admissions, diabetes, education, mortality, particulate matter, power plant, risk assessment, susceptibility. *Environ Health Perspect* 110:1253–1260 (2002). [Online 29 October 2002]

<http://ehpnet1.niehs.nih.gov/docs/2002/110p1253-1260levy/abstract.html>

The issue of subpopulation susceptibility to fine particulate matter (< 2.5  $\mu\text{m}$  in aerodynamic diameter;  $\text{PM}_{2.5}$ ) has been given increased attention by researchers in recent years, motivated in part by the research priorities articulated by the National Academy of Sciences (1). Understanding patterns of susceptibility not only would help identify and protect sensitive subpopulations, but also would contribute to the understanding of mechanisms by which  $\text{PM}_{2.5}$  might influence human health.

Often, air pollution policies are informed by risk assessments or benefit–cost analyses, which generally focus on the total health benefits of alternative emission control strategies (2–5). Because relevant susceptibility evidence is limited, differential effects on susceptible subpopulations are rarely incorporated. Typically, the same relative risks are applied to all individuals in an “at-risk” age group, and baseline rates of disease or health care use are assumed to be uniform across large geographic areas (often national averages).

However, it is likely that the effects of air pollution vary widely across subpopulations, depending on demographics, behavior patterns, income, access to health care, and other factors. Differences could exist either in relative risks (if an increment of air pollution yields a different percentage increase in different populations) or

in absolute risks (if there are differences in baseline disease patterns by subpopulation, independent of air pollution). For a benefits assessment, if policy makers were concerned about distributional issues or if the ultimate valuation of benefits depended on population characteristics, the incorporation of susceptibility could potentially influence the conclusions.

One current policy issue for which information on susceptibility could be influential is the regulation of emissions from older power plants. To date, older power plants have not been required to meet the same control requirements as new sources, helping to extend the useful lifetime of older facilities (6–8). These facilities contribute a substantial fraction of national power sector emissions. In 1999, coal-fired power plants contributed approximately 86% of nitrogen oxide ( $\text{NO}_x$ ) emissions and 93% of sulfur dioxide emissions from the utility sector, largely from facilities exempted from new source standards (9).

At the time this article was written (2001), several states (including Massachusetts, Connecticut, and Texas) had introduced multipollutant regulations or legislation to require older power plants to meet emission levels commensurate with the application of “Best Available Control Technology” (BACT; technology required under the Clean Air Act for

new or modified sources in attainment areas). Pollutants considered typically included  $\text{NO}_x$  and  $\text{SO}_2$ , as well as mercury and carbon dioxide. Multipollutant power plant legislation was also being debated at the federal level, but no bills or regulations had been passed at the time of our analysis.

From both a state and a federal perspective, the question of how the benefits of emission controls would be distributed could be important. Policy makers may be concerned about providing benefits to high-risk communities, communities near power plants, or other subpopulations. If these questions are important, population susceptibility could influence the policy choices (e.g., emission trading vs. mandatory on-site controls).

In this article, we develop a model to estimate the health benefits associated with emission reductions at older fossil-fueled power plants. We focus on both primary  $\text{PM}_{2.5}$  and secondary sulfate and nitrate particles formed through emissions of  $\text{SO}_2$  and  $\text{NO}_x$ . Here we consider a case study of all older power plants located within a 50-mile (80-km) radius of Washington, DC. We calculated three health end points—premature mortality, cardiovascular hospital admissions (CHA) in the elderly, and pediatric asthma emergency room visits (ERV)—both using conventional assumptions and then considering available evidence for differential effects on susceptible subpopulations. Our goal was both to quantify the health benefits associated with the implementation of BACT at the selected power plants and to consider whether introduction of susceptibility models might affect the interpretation of our findings.

## Case Study Setting

For this analysis, our goal was to select a geographic area that had multiple older power plants nearby and geographic heterogeneity in

Address correspondence to J.I. Levy, Landmark Center Room 404K, 401 Park Drive, PO Box 15677, Boston, MA 02215 USA. Telephone: (617) 384-8808. Fax: (617) 384-8859. E-mail: [jilevy@hsph.harvard.edu](mailto:jilevy@hsph.harvard.edu)

We thank D. Hlinka, D. Sullivan, and D. Moon for their assistance in the atmospheric dispersion modeling; B. Egan, R. Paine, D. Heinold, F. Cameron, J. Samet, and J. Scire for providing helpful feedback on related manuscripts; and R. Tangirala for bringing an error to our attention.

This study was commissioned by the Clean Air Task Force and prepared with support from the Pew Charitable Trusts and the Kresge Center for Environmental Health (NIEHS ES000002).

Received 4 November 2001; accepted 21 May 2002.

factors that might influence relative risks, baseline health status, or health care use (e.g., socioeconomic status). Washington, DC, and its surrounding suburbs provide an example of such a region. According to 1990 U.S. Census data (10), median household income in Washington, DC, ranged from less than \$10,000 to more than \$150,000 across census tracts. Washington, DC, is also quite racially divided, with few African Americans residing in the western half of the city and mostly African Americans residing in the eastern half of the city.

In addition, within a 50-mile (80-km) radius of Washington, DC, there are five fossil-fueled power plants grandfathered under the Clean Air Act—Benning, Chalk Point, Dickerson, Possum Point, and Potomac River (Table 1). The choice of these five power plants is somewhat artificial because any single regulation would not affect only these plants. However, our analysis is meant to be illustrative, and these five plants are likely the greatest contributors to heterogeneity in power-plant-related exposures in the area. Inclusion of additional power plants would increase the total benefits but decrease the relative concentration gradient across the Washington, DC, area.

## Methods

To quantify the magnitude and distribution of health benefits, we estimated the emission reductions of key pollutants, applied an atmospheric dispersion model to determine incremental concentration reductions, and derived concentration–response functions. Any such analysis involves numerous boundary decisions and contains substantial uncertainties. In this article, we focus largely on issues related to susceptible subpopulations and the resulting implications. We do not extensively address the complexities of other elements of the model, nor do we provide a formal analysis of uncertainties. We also do not consider the economic valuation dimension of a benefits assessment. Additional information about parametric uncertainties in our atmospheric model (4,11) and issues related to differential particle toxicity or alternative interpretations of the health evidence (4) can be found elsewhere.

**Quantification of emissions.** We estimated emissions of PM<sub>2.5</sub> and its precursors (NO<sub>x</sub> and SO<sub>2</sub>) following the model structure in our earlier analyses (4,11) and supported by the fact that PM<sub>2.5</sub> has dominated aggregate benefits in past air pollution risk assessments (2,3). This omits any benefits associated with ozone, air toxics, or other impact pathways from the power sector. Of note, most proposed regulations consider NO<sub>x</sub> and SO<sub>2</sub> but do not directly require controls for primary PM<sub>2.5</sub> (although many

NO<sub>x</sub> and SO<sub>2</sub> control strategies would affect primary PM<sub>2.5</sub>).

We used 1999 as the base year for our analysis, evaluating the concentration and health benefits that would have been obtained had lower target emission rates been achieved. This is not identical to the future benefits that might be obtained through pending regulation, because some facilities have ongoing or near-term plans for repowering or emission controls.

Emissions of SO<sub>2</sub> and NO<sub>x</sub> were taken from the 1999 acid rain program emissions scorecard from the U.S. Environmental Protection Agency (EPA) (12). To capture seasonality in emissions, we incorporated quarterly average emission rates when reported. When no data on seasonal emissions were available, we assumed constant emissions per unit of heat input. For filterable PM<sub>2.5</sub>, total plant emissions were taken from the U.S. EPA National Emission Trends database (13). We estimated condensable PM<sub>2.5</sub> emissions given fuel type and sulfur content, using AP-42 air pollution emission factors from the U.S. EPA (14).

We selected lower target emissions to correspond to the levels proposed in multiple regulations, which correspond to the application of BACT. This resulted in target emission rates of 0.3 lb/MMBTU (million British thermal units) of SO<sub>2</sub>, 0.15 lb/MMBTU of NO<sub>x</sub>, and 0.01 lb/MMBTU of filterable particulate matter. Lower target condensable particulate emissions were taken from AP-42, given assumed application of control technologies. Because both Dickerson and Benning power plants have actual filterable PM<sub>2.5</sub> emissions less than the lower target rate, we set the lower target filterable PM<sub>2.5</sub> emission rate equal to actual emissions for these plants.

**Atmospheric modeling.** We established a receptor grid covering a 400-km (250-mile) radius around Washington, DC (centered at 38.9°N, 77°W), to capture a significant fraction of total benefits without extending the dispersion modeling boundaries excessively (Figure 1). Because of our focus on spatial patterns, it was important to determine concentration reductions at small geographic

scales close to the sources. We selected census tracts within 100 km of Washington, DC, because they are relatively small (generally between 2,500 and 8,000 people) and were theoretically designed to be socioeconomically homogeneous. Beyond 100 km, we used county-level resolution, resulting in a nested receptor grid with 1,908 receptors. Using 1990 Census data (10) (the most recent data available at the time of our study), our receptor grid contained 47 million individuals, 7 million of whom live within 100 km of Washington, DC.

We conducted our atmospheric modeling using CALPUFF (CALMET version 5.2 000602a, CALPUFF version 5.4-000602-1, CALPOST version 5.2 991104b; Earth Tech, Concord, MA). CALPUFF is a regional-scale Lagrangian puff model that has been recommended by the U.S. EPA for long-range transport modeling (15), given that it has been shown to be relatively unbiased at distances out to 200 km (16). In general, limitations in the atmospheric chemistry make the secondary pollutant estimates relatively more uncertain than the primary PM<sub>2.5</sub> estimates, given the nonlinearities associated with sulfate and nitrate formation.

Our methodology to generate meteorologic files for CALMET was similar to the approach in our past applications and is described in depth elsewhere (4,11). We combined National Oceanic and Atmospheric Administration (NOAA) prognostic model outputs with mesoscale data assimilation systems for each hour across our case study year (January 1999–January 2000). This involved combining lower-resolution upper air data (40-km grid spacing) generated through NOAA's Rapid Update Cycle (RUC2) model (17) with Aviation Routine Weather Report (METAR) surface observations and cloud cover data available at 15 km resolution (18). These data sources were combined using the Advanced Regional Prediction System (ARPS) Data Assimilation System (ADAS) and provided hourly CALMET windfields within eight vertical layers. Precipitation data were taken from all National Climatic Data Center stations within the receptor region, with CALMET

**Table 1.** Characteristics of five power plants in Washington, DC, case study (1999 data).

Characteristics	Benning	Chalk Point	Dickerson	Possum Point	Potomac River
Initial year of commercial operation	1968	1964	1959	1948	1949
Nameplate capacity (megawatts)	580	2,046	588	1,373	514
Heat input (MMBTU)	3,304,107	85,352,274	33,592,811	28,930,805	32,100,184
Emissions, tons (% per quarter)					
SO <sub>2</sub>	1,432 (2, 21, 76, 2)	57,630 (21, 25, 31, 23)	30,637 (30, 17, 34, 18)	19,497 (24, 22, 32, 23)	17,627 (22, 28, 29, 21)
NO <sub>x</sub>	447 (2, 22, 74, 1)	25,222 (20, 24, 30, 26)	10,709 (30, 17, 34, 18)	5,116 (25, 22, 32, 21)	6,893 (21, 28, 30, 21)
PM <sub>2.5</sub>	12 (2, 22, 74, 2)	304 (21, 27, 33, 20)	14 (30, 17, 34, 18)	156 (23, 20, 37, 20)	106 (21, 28, 29, 22)

defaults used for interpolation between stations. The primary difference from our previous applications was the inclusion of 50 evenly spaced “soundings” based on columns of the ADAS data, to more accurately provide a reasonable high-resolution temperature field and subsequent planetary boundary-layer depth estimates.

In CALPUFF, we adopted recommended modeling assumptions that were used in our past applications (4,11). We used the MESOPUFF II chemical transformation mechanism, which is generally preferred in urban settings. Wet and dry deposition were incorporated using precipitation data and CALPUFF default deposition rates. Hourly background ozone concentrations were taken from five U.S. EPA Clean Air Status and Trends Network (CASTNET) stations spaced throughout our receptor region (Prince George’s County, MD; Mercer County, NJ; Elk County, PA; Prince Edward County, VA; Gilmer County, WV), and we assumed a background ammonia concentration of 1 ppb.

For brevity’s sake, in this article we do not provide sensitivity or uncertainty analyses for our atmospheric modeling. In our past analyses (4,11), we found total benefits to be reasonably stable given single parametric changes in CALPUFF, including the chemical conversion mechanism, background

ammonia concentration, and treatment of wet and dry deposition. In addition, we concluded that any bias associated with either hypothetical CALPUFF overestimation beyond 200 km or exclusion of long-range exposures is relatively small in comparison with other model uncertainties. A comprehensive risk assessment would need to incorporate these uncertainties in an evaluation of overall model uncertainty.

**Health evidence.** Although numerous health outcomes have been incorporated into past analyses (2), here we focus on a subset for which some evidence exists for differential effects on susceptible subpopulations. The choice of outcomes as well as the subpopulations considered therefore depends entirely on the current literature and is not meant to be comprehensive. Furthermore, we restricted the health evidence to epidemiologic studies conducted in the United States, because patterns of health care use and the relationship between demographics and health status likely vary across countries. Given these criteria, we evaluated premature mortality (stratified by education), CHA for the elderly (stratified by diabetic status and age), and asthma ERV for children (stratified by race and age). For each outcome, we both describe a conventional approach and construct a susceptibility model. Our goal is not to consider the complete array of susceptible subpopulations, but rather to

select one example for each outcome for which epidemiologic evidence and population data exist.

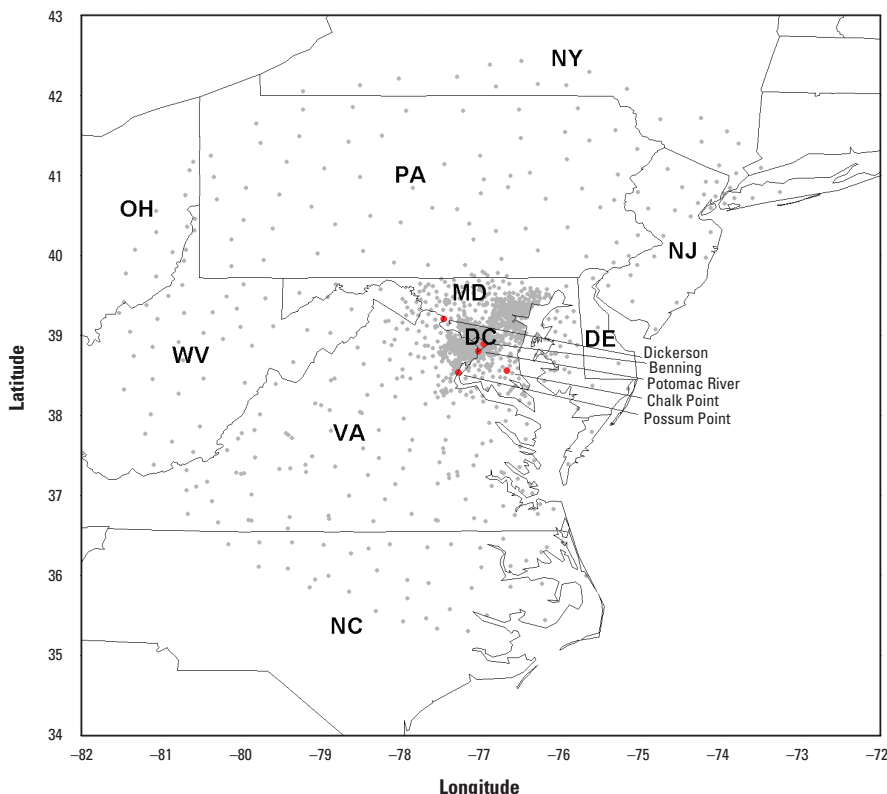
**Premature mortality.** For premature mortality, we derived a central estimate from the follow-up analysis of the American Cancer Society (ACS) cohort study (19). Several other cohort studies are available (20,21), but the ACS study has the largest and most geographically diverse population, with relative risks bounded by other studies and a statistical approach suggested by a detailed reanalysis (22). For all-cause mortality, the authors calculated a relative risk of 1.04 [95% confidence interval (CI), 1.01–1.08] for a 10  $\mu\text{g}/\text{m}^3$  increase in annual mean  $\text{PM}_{2.5}$  concentrations (using 1979–1983 concentrations). The relative risk was slightly higher (1.06) using more recent pollution data, but we use the lower figure to be conservative and because Pope et al. (19) presented stratified estimates based on the 1979–1983 concentrations.

Relative risks did not vary substantially across most demographic factors except educational attainment. Educational attainment appeared to be a strong effect modifier across all causes of mortality. The relative risk for a 10  $\mu\text{g}/\text{m}^3$  increase in annual mean  $\text{PM}_{2.5}$  concentrations was 1.085 (95% CI, 1.031–1.142) for individuals with less than high school education, 1.045 (95% CI, 1.004–1.087) for individuals with high school education, and 1.003 (95% CI, 0.967–1.040) for individuals with more than high school education.

There are numerous uncertainties related to the application of this stratified relative risk. The ACS cohort is somewhat more educated than the population at large, and correlated terms such as race and poverty status have not been significant in time-series mortality or hospital admissions studies (23–25). In addition, the statistical approach implies that we are modeling the effect of education controlling for smoking and other factors, which would ideally be included to model the influence of all risk factors correlated with educational attainment. Regardless, we use the education-stratified values to determine the implications of the reported relationship.

For background mortality rates, the standard approach is to apply county-level averages to individuals 30 or more years old [the age range considered in the ACS study (19)]. We used this as our baseline approach, but for our susceptibility model, we considered whether mortality rates vary as a function of education while still averaging to the reported county-level rates.

There is a strong and consistent negative relationship between socioeconomic status and all-cause mortality (26). Socioeconomic status can be measured by occupation, income, education, or some combination of



**Figure 1.** Receptor grid and power plant locations for Washington, DC, case study.

these terms. It is generally believed that both income (27) and educational attainment (28) are independent predictors of mortality, although the bases for these relationships are not well understood. Some argue that those in lower socioeconomic classes display high-risk behaviors, such as smoking, being overweight, and not exercising (29), producing higher mortality rates. However, only a small fraction of the increased mortality can be explained by a higher prevalence of high-risk behaviors (30), so there must be other contributing factors. In any case, it is clear that those in low education or income categories represent a susceptible subpopulation for all-cause mortality.

Educational attainment is a useful predictor of mortality because it typically does not change after adulthood. Additionally, this term is available for all segments of the adult population, even those not in the work force. Although it may be a proxy for other factors, various hypotheses have been presented for why lower education might be a causal factor for mortality. Education may be a marker for factors (e.g., intelligence and good health in early childhood) that allow for both educational attainment and good health in adulthood, for acquired knowledge that can be used to obtain positive health outcomes, for relative status in society, or for the development of positive social networks (31). The protective effect of higher education has been seen in the United States (31) and worldwide (32,33).

We selected our baseline mortality risk ratios from a study that evaluated risks for all-cause mortality as a function of both education and annual income among a cohort 25–64 years old, drawn from the National Longitudinal Mortality Study (31). The relationship between education and mortality was best described by a trichotomy (less than high school education, high school diploma or greater but no college diploma, or a college diploma or greater). When compared with the highest education group, the annual mortality relative risk for men was 1.7 for less than high school education and 1.5 for high school diploma or greater but no college diploma. For women, the corresponding relative risks were 1.5 and 1.2. The attenuation in women has been documented previously and can be attributed largely to the married subpopulation of women (34). We applied these relative risks to all individuals more than 30 years old, although there is some evidence that socioeconomic differences play less of a role in determining mortality rates among the aged (35).

**Cardiovascular hospital admissions.** Several studies in the United States have evaluated the relationship between particulate matter exposure and CHA among individuals 65 or more years old (24,25,36–43). Most central estimates from these studies fall in the

range of a 0.5–1% increase in CHA for a 10  $\mu\text{g}/\text{m}^3$  increase in daily concentrations of particulate matter < 10  $\mu\text{m}$  in aerodynamic diameter ( $\text{PM}_{10}$ ). Using a typical  $\text{PM}_{2.5}:\text{PM}_{10}$  ratio of 60%, we would consider appropriate a central estimate of an approximate 1% increase in CHA per 10  $\mu\text{g}/\text{m}^3$  increase in daily  $\text{PM}_{2.5}$  concentrations. As a baseline, we applied this percentage to the average background rate of 0.084 CHA per year per individual  $\geq 65$  years old (44).

Although numerous factors might influence either the baseline risk or the relative risk of an air-pollution-related CHA, we focused on diabetes to illustrate the influence of a risk factor that varies demographically and might influence both risks. To estimate the number of diabetic and nondiabetic CHA in a county or census tract, we considered two relationships: the risk factors for diabetes among the elderly and the differential risk for a CHA given the presence of diabetes.

In those > 65 years old, noninsulin-dependent diabetes mellitus (NIDDM) accounts for virtually all of the diabetic caseload. There are numerous risk factors for NIDDM, including age, obesity, family history, and sedentary lifestyle. Although lifestyle variables are the strongest predictors of diabetic status [accounting for as much as 90% of population attributable risk (45)], we cannot estimate these variables at the census tract level from publicly available data. In the absence of this information, we estimated NIDDM prevalence as a function of gender, age, and race. According to a national survey (46), NIDDM prevalence in individuals > 65 years old is higher among African Americans and Mexican Americans than in non-Hispanic whites, ranging from 10.9% for non-Hispanic white males 65–74 years old to 29% for Mexican-American females 65–74 years old. We applied these estimates to our study populations, despite the limitations in applying national relationships based on race to a specific geographic setting. The relationship between race and common risk factors likely varies widely across regions and within small geographic areas, a feature that is not captured by our model.

Regarding risks for a CHA, it has been well established that diabetics have an increased risk of heart disease. Several studies also indicate that diabetics are admitted to the hospital more frequently than are nondiabetics (47,48). Thus, it is not surprising that CHA rates are elevated in diabetic populations. According to a national diabetes surveillance report (49), as of 1996, the annual CHA rate was 0.20 admissions per year per diabetic 65–74 years old and 0.27 for diabetics  $\geq 75$  years old. In contrast, the rates for the population as a whole are 0.06 (ages 65–74 years) and 0.11 ( $\geq 75$  years) (44).

Using these two rates and the estimated diabetes prevalence across our study population, we can calculate the CHA rate for nondiabetics. Clearly, there are several appreciable assumptions underlying these estimates. Although we know that marked differences can exist in CHA rates among states and communities, we assume that tract-specific rates vary only as a function of the estimated number of diabetics, with CHA rates invariant for nondiabetics. This likely underestimates the degree of spatial and demographic variability in CHA rates.

On the relative risk side, a time-series study in Chicago (38) found a 2% increase in CHA for diabetic individuals > 65 years old for a 10  $\mu\text{g}/\text{m}^3$  increase in  $\text{PM}_{10}$ , versus a 0.9% increase for nondiabetics. In contrast, the studies that evaluated factors such as race, education, or poverty (24,37,43) found no significant effect modification for CHA relative risks. To ensure that our concentration–response function agrees with our nonstratified estimate, we assumed that a factor of two difference exists between diabetics and nondiabetics and calculated the concentration–response function given the estimated number of CHA in diabetics and nondiabetics in our study population. The result is a 0.7% increase in CHA per 10  $\mu\text{g}/\text{m}^3$  increase in  $\text{PM}_{2.5}$  for nondiabetics, with a 1.5% increase for diabetics.

**Pediatric asthma ERV.** Many studies have associated ERV for numerous respiratory and cardiovascular causes with particulate matter, but to date only two studies in the United States have considered asthma-related visits among children (defined here as  $\leq 18$  years old). In Seattle (50), an 11.6  $\mu\text{g}/\text{m}^3$  increase in  $\text{PM}_{10}$  was associated with a 14% increase in asthma ERV (95% CI, 5–23%), and a 9.5  $\mu\text{g}/\text{m}^3$  increase in  $\text{PM}_{2.5}$  was associated with a 15% increase. This study found the relative risk to be similar in high-use and low-use areas (a proxy for socioeconomic status). In Atlanta (51), a 4% increase in pediatric asthma ERV was estimated for a 15  $\mu\text{g}/\text{m}^3$  increase in  $\text{PM}_{10}$  concentrations (95% CI, 0.4–7%). As in Seattle, there did not appear to be effect modification due to race or socioeconomic status. Simply pooling these two studies using a random effects model (52) provides a central estimate of a 0.7% increase in asthma ERV per microgram per cubic meter increase in  $\text{PM}_{10}$ , which we translate into an approximate 1% increase in asthma ERV per microgram per cubic meter increase in daily  $\text{PM}_{2.5}$ . This can be applied to a background asthma ERV rate of 0.012 for children 0–4 years old, 0.0081 for children 5–14 years old, and 0.0069 for children  $\geq 15$  years old (53).

Although the published studies did not identify susceptible subpopulations from a relative risk perspective, the background rate

of asthma ERV would be anticipated to differ widely across subpopulations. This would be a function both of trends in asthma prevalence and of patterns in health care use across populations.

The prevalence of asthma has increased substantially in recent years (53), with lower-income individuals and minorities disproportionately affected by the disease (54–58). Many of the significant predictors of childhood asthma, such as cockroach presence in the home (59) and maternal education (60), are related to socioeconomic status. Furthermore, patterns of health care use are strongly related to income. The ratio of anti-inflammatory to beta-agonist medication is lower in low-income communities and is inversely correlated with hospitalization rates (61), and lower-income populations lacking health insurance often use emergency services as a means of primary care. Thus, it would be expected that low-income populations would have somewhat higher pediatric asthma ERV rates.

Data on pediatric asthma ERV rates as a function of income were limited, but substantial racial differences have been documented. According to data from the National Hospital Ambulatory Medical Care Survey (53), across all ages, the asthma ERV rate for African Americans is nearly five times greater than that for whites (0.023 and 0.0049 per capita, respectively). No data were provided on asthma ERV rates stratified across both age and race, but a study of 3-year-olds in the United States found a racial differential of similar magnitude but with some independent effects of both race and income (54).

Given available information, we estimated baseline pediatric asthma ERV rates as a function of age and race, assuming the racial disparity to exist in all age groups. This encompasses differences both in prevalence and in health care use. As with our diabetes estimates, there are some substantial limitations in using only race as a predictor, because the relationship

between race and asthma ERV risk factors varies by income, urban/rural status, and other factors. Regardless, the consistent relationship between race and ERV and the ability to gather racial information at the census tract level make this the best available covariate.

## Results

**Concentration reductions.** With our atmospheric dispersion model, the emission reductions at the five selected power plants would lead to annual average  $PM_{2.5}$  (primary plus secondary) concentration reductions ranging from 0.009 to 0.9  $\mu\text{g}/\text{m}^3$  in our receptor region (Figure 2C). By way of comparison, according to U.S. EPA AIRS data (62), annual average  $PM_{2.5}$  concentrations in Washington, DC, were approximately 14–18  $\mu\text{g}/\text{m}^3$  in 1999. The maximum annual average  $PM_{2.5}$  concentration reduction is found within Washington, DC, as might be anticipated by the power plant selection criteria and the inclusion of primary  $PM_{2.5}$ .

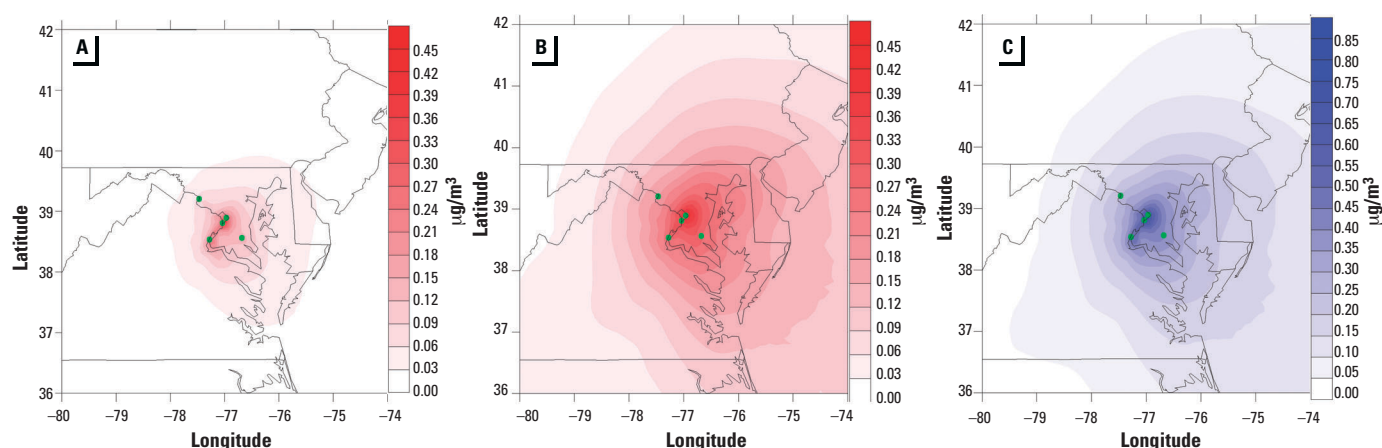
The geographic distribution of benefits varies somewhat across particle types, power plants, and seasons. Annual average primary  $PM_{2.5}$  concentration reductions peak closer to the plants and decrease more rapidly with distance than secondary sulfates or nitrates (Figure 2). As a result, a greater fraction of total exposure reduction (defined as the sum across receptors of the product of concentration reduction and population assigned to the receptor) occurs closer to the power plants for primary than for secondary  $PM_{2.5}$  (Figure 3). However, there is tremendous variability in the distribution of total exposure reduction, caused principally by variations in source locations and pollutant type (primary vs. secondary). In addition, total exposure reduction per unit emissions displayed expected seasonal patterns, with slightly higher values for primary  $PM_{2.5}$  in the winter and fall (related in part to lower mixing heights) and higher values for sulfates and lower values for

nitrates in the summer due to the effect of temperature on relative conversion rates.

**Health benefits.** For premature mortality, using nonstratified relative risks and homogeneous baseline mortality rates within counties, our central estimate is that emission reductions from the five power plants would lead to 210 fewer deaths per year (Table 2). The estimated impact under the current emissions scenario is 270 deaths per year. Of the total mortality benefits, approximately 25% occur in individuals with less than high school education (identical to the proportion in the population). Approximately 16% of mortality benefits accrue within 50 km of the power plants, largely related to the substantial contribution of secondary sulfates (62%) and nitrates (19%) to total  $PM_{2.5}$  exposures.

In our susceptibility model, with both baseline mortality rates and  $PM_{2.5}$  relative risks stratified by educational attainment, our understanding of the affected subpopulations changes substantially (Table 2). The total mortality benefit is largely unaffected, with a slight increase associated with differences in educational attainment between the Washington, DC, area and the ACS cohort. However, 51% of the estimated mortality benefits now accrue among individuals with less than high school education, double the prediction in the homogeneous risk model.

Although stratification by education does not significantly influence the broad geographic patterns of benefits (i.e., the fraction of benefits within 50 km), at the census tract level benefits differ by as much as a factor of 13 between the models. Figure 4 depicts the geographic patterns of benefits under both the baseline and susceptibility models, focusing solely on census tracts in Washington, DC, for simplicity. Using the baseline model, the mortality risk reductions in Washington are reasonably homogeneous, ranging from 36 to 67 fewer deaths per year per million individuals > 30 years old. Under the education-stratified



**Figure 2.** Combined concentration reductions (annual average,  $\mu\text{g}/\text{m}^3$ ) from hypothetical emission controls at five power plants: (A) primary  $PM_{2.5}$ ; (B) secondary  $PM_{2.5}$ ; (C) total  $PM_{2.5}$ .

model, the range broadens considerably and the distribution is more complex, with per capita benefits now varying by more than a factor of 10 across census tracts. The mortality benefits are generally increased in southeastern Washington, DC, the lowest-income area of the city.

When we consider CHA among the elderly, our baseline model estimates 59 fewer CHA per year. Although it seems counterintuitive that the mortality numbers could exceed the morbidity numbers, this is related to the limited focus on CHA because of only short-term exposures among the elderly (vs. all-cause mortality from long-term exposures among individuals  $\geq 30$  years old). Using a conventional model that assumes diabetics do not differ in any way from nondiabetics, 13% of the CHA benefits are estimated to occur among diabetics, whereas 80% are found among non-Hispanic whites (Table 2). The geographic distribution of CHA benefits is similar to the exposure reduction and mortality benefits, with differences reflecting the relative number of individuals 65–74 years old and  $\geq 75$  years old within census tracts.

As expected, incorporating the diabetes-based information has a minimal impact on aggregate benefits but dramatically alters the profile of the affected individuals (Table 2). Using this model, 54% of the CHA benefits are found among diabetics, with 76% among non-Hispanic whites. Because we have assumed that baseline CHA risk for nondiabetics does not differ as a function of race or income, the CHA estimates under the susceptibility model are closer to those from the baseline model than are those for mortality (Figure 4). However, even considering only diabetes-related susceptibility changes the census tract-level benefits by as much as 40%.

Finally, we estimate 140 fewer pediatric asthma ERV per year using our nonstratified model (38% in children 0–4 years old, 46% in children 5–14 years old). Twenty-seven percent of benefits occur in African-American children (who represent 21% of the study population). When we stratify asthma ERV risk by race, the total benefits increase to 160 fewer visits per year, with significant changes in the geographic and demographic distributions (Table 2). The census-tract-level risk reduction varies by an order of magnitude across Washington, DC, with the benefits increased by more than a factor of two in the eastern half of the city (Figure 4). The proportion of benefits among African-American children is increased to 64%, commensurate with the assumption of greater baseline asthma ERV rates.

## Discussion

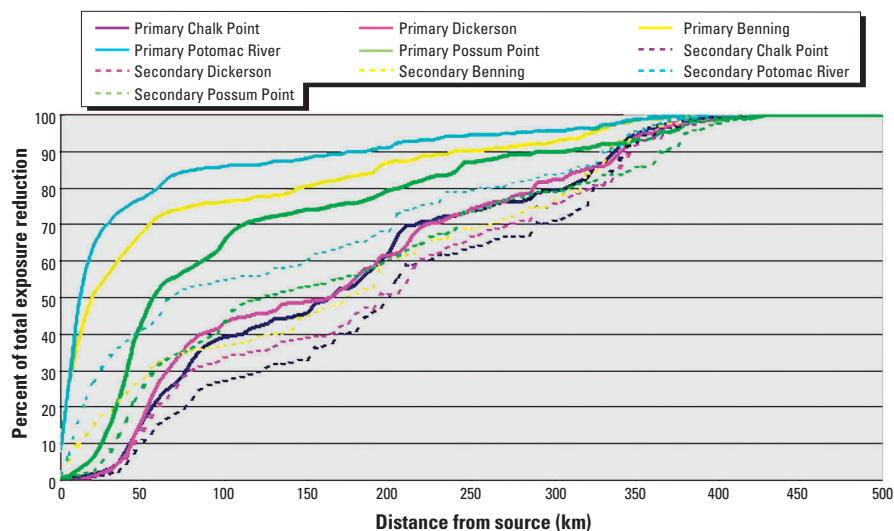
Our analytical approach demonstrates two important points. First, given an interpretation of the epidemiologic evidence that

assumes that ambient concentrations in the Washington, DC, area exceed any potential population threshold for  $PM_{2.5}$  health effects, emission controls at older fossil-fueled power plants would provide tangible and quantifiable health benefits. Second, when we take account of susceptible subpopulations and differences in both relative risk and baseline disease rates across these populations, the small-scale geographic and demographic distributions of those benefits are strongly affected. For the example of premature mortality, if educational attainment influences both the relative risk of air pollution and the baseline mortality risk, then more than half of the mortality benefits accrue among the 25% of our study population with less than high school education. Similarly, for pediatric asthma ERV, the fact that background rates are substantially greater in African Americans implies that most ERV benefits accrue in 21% of the population, even given identical relative risks from air pollution. The relatively smaller differences found for CHA when diabetes is considered illustrates that evidence

for differential effects on a relatively small fraction of the population has a smaller effect than a population-wide model.

There are clearly some barriers in both interpretation of the study findings and application of our model to other settings. One important uncertainty is related to the stratified risk models we selected. For all health outcomes, we used stratification variables (such as race) that might have independent effects on baseline health but likely are proxies for numerous socioeconomic end points. If the stratification variables represent other factors, this adds to the uncertainty in a site-specific stratified analysis.

In general, we have applied susceptibility models based on national data to a small number of states, which has multiple inherent limitations. Clearly, it would be preferable to use local health data, but data at small geographic scales for a large region are difficult to obtain and are rarely stratified across all demographic variables of interest. In addition, the reliance on national data increases the generalizability of our findings. Despite



**Figure 3.** Cumulative distribution of total exposure reduction as a function of distance from the source, by power plant and pollutant type.

**Table 2.** Magnitude and distribution of health benefits associated with modeled emission reductions at five power plants near Washington, DC.

Health outcome and stratification covariate	Baseline model (No stratification)	Full susceptibility model (Stratification by listed covariate)
Deaths/year		
Total	210	240
< High school education	52	120
$\geq$ High school education	150	120
CHA/year		
Total	59	60
Diabetic	8	33
Nondiabetic	51	27
Asthma ERV/year		
Total	140	160
African American	38	100
Non-African American	100	57

Data presented are rounded to two significant figures; sums may not add because of rounding.

these issues, our models demonstrate that simple assumptions about susceptibility can be influential in our understanding of health risks and benefits. The alternative is an assumption of homogeneity, which itself introduces implicit uncertainty and may contribute to biases in selected settings.

Another limitation of our study is the fact that we have devoted limited attention to uncertainty analysis, a crucial element in interpreting sensitive and complex findings.

Drawing on the uncertainty analyses in our earlier work (4,11), most parametric changes in CALPUFF led to changes to aggregate benefits of less than a factor of two, whereas variations in concentration–response assumptions (particularly for mortality) could influence estimates by as much as a factor of five. The influence of population susceptibility is generally at the lower end of this range, even for small geographic scales. However, susceptibility information has a greater influence on

the relative distribution of benefits than do other assumptions, many of which tend to affect all populations identically (e.g., the population-averaged concentration–response function). Furthermore, a broader view of areas of heterogeneity or susceptibility [e.g., assumptions regarding particle size and chemical composition, time–activity data, or physiologic factors (63)] could increase the importance of this evidence. Further analysis that considers the full array of uncertainties and evaluates which (if any) would be influential in policy decisions would be warranted.

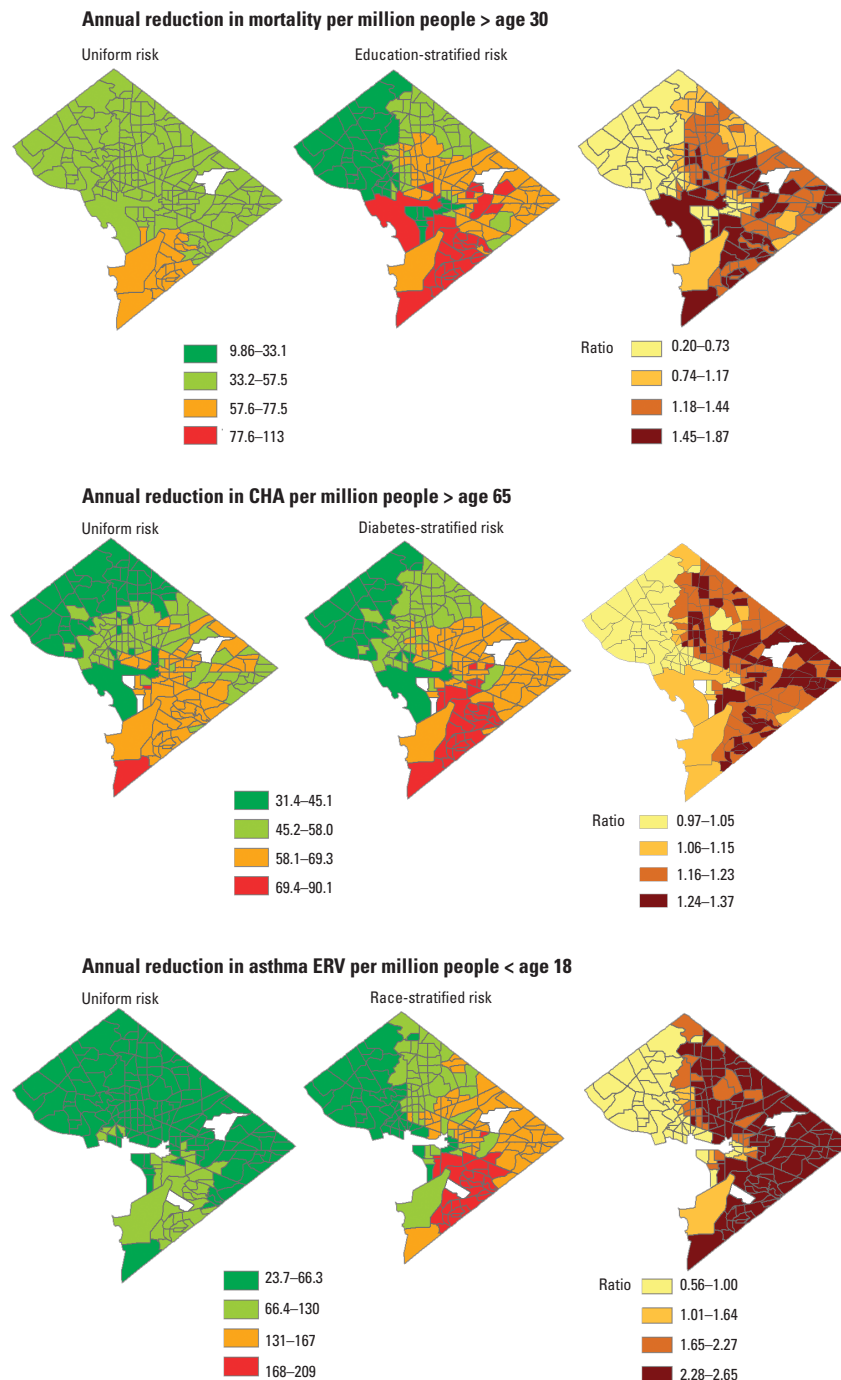
In addition, although we have focused on power plants (partly because of pending regulatory decisions at the time of our analysis), the issue of susceptible subpopulations is likely more significant for motor vehicle pollution. Given that motor vehicles have low stack heights and have a strong presence in urban street canyons with high population density, it is likely that aggregate impacts would be spread over a smaller population than for power plants. If the exposed population had demographic differences from the United States average, assumptions of homogeneity would bias the risk calculations.

Finally, any assessment of impacts from a limited number of sources is somewhat impaired by the relatively small reductions when compared with baseline concentrations. This makes field validation of model results difficult and implies that an ultimate comparison of the costs and benefits of taking action would be required to determine if action is warranted.

Despite these limitations, our analysis illustrates that emission controls at older fossil-fueled power plants could lead to quantifiable concentration and health benefits and that susceptibility information informs the interpretation of those benefits. Although the individual benefits represent a small increment over baseline risks, the number of people affected because of long-range pollution transport implies aggregate benefits that are relevant for policy evaluation. As the health literature develops additional information about differences in relative and absolute risk across populations, risk assessments and benefit–cost analyses should take advantage of this information to provide more interpretable information to decision makers.

## Conclusions

We have evaluated the health benefits of emission controls at five older fossil-fueled power plants in the Washington, DC, area, using conventional risk assessment assumptions and incorporating available information about susceptible subpopulations. We found that the geographic and demographic distributions of benefits differ substantially between the two approaches. If robust and causal, our susceptibility models identify subpopulations that



**Figure 4.** Distribution of health benefits by census tract in Washington, DC (no color indicates zero at-risk population).

bear a disproportionate air pollution burden and account for a substantial fraction of the benefits of emission controls (lower-educated individuals for mortality, diabetics for CHA, and African Americans for asthma ERV). The characterization of high-risk subpopulations can help both in the interpretation of the risk assessment and in targeting future exposure assessment or epidemiologic efforts.

## REFERENCES AND NOTES

- Committee on Research Priorities for Airborne Particulate Matter. Research Priorities for Airborne Particulate Matter: 1. Immediate Priorities and a Long-Range Research Portfolio. Washington, DC:National Academy Press, 1998.
- U.S. EPA. The Benefits and Costs of the Clean Air Act: 1990 to 2010. Washington, DC:U.S. Environmental Protection Agency, Office of Air and Radiation, 1999.
- European Commission. ExternE: External Costs of Energy, Vol 3: Coal and Lignite. Brussels:Directorate-Generale XII, Science, Research, and Development, 1995.
- Levy JI, Spengler JD. Modeling the benefits of power plant emission controls in Massachusetts. *J Air Waste Manage Assoc* 52:5–18 (2002).
- Abt Associates, ICF Consulting, EH Pechan Associates. The Particulate-Related Health Benefits of Reducing Power Plant Emissions. Bethesda, MD:Abt Associates, 2000. Available: <http://www.cleartheair.org/fact/mortality/mortalityabt.pdf> [cited 17 October 2000].
- Ackerman F, Biewald B, White D, Woolf T, Moomaw W. Grandfathering and coal plant emissions: the cost of cleaning up the Clean Air Act. *Energy Policy* 27:929–940 (1999).
- Maloney M, Brady G. Capital turnover and marketable emission rights. *J Law Econ* 31:203–226 (1988).
- Nelson R, Tietenberg T, Donihue M. Differential environmental regulation: effects on electric utility capital turnover and emissions. *Rev Econ Stat* 75:368–373 (1993).
- U.S. EPA. National Air Quality and Emission Trends Report, 1999. Research Triangle Park, NC:U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, 2001.
- U.S. Census Bureau. 1990 Census Lookup, Census Summary Tape File 3. Washington, DC:U.S. Census Bureau, 2001. Available: <http://homer.ssd.census.gov/cdrum/lookup> [cited 15 June 2001].
- Levy JI, Spengler JD, Hlinka D, Sullivan D, Moon D. Using CALPUFF to evaluate the impacts of power plant emissions in Illinois: model sensitivity and implications. *Atmos Environ* 36:1063–1075 (2002).
- U.S. EPA. Emissions Scorecard 1999. Washington, DC:U.S. Environmental Protection Agency, 2001. Available: <http://www.epa.gov/airmarkets/emissions/score99/index.html> [cited 18 July 2001].
- U.S. EPA. National Emissions Trends Database. Washington, DC:U.S. Environmental Protection Agency, 2001. Available: <http://www.epa.gov/air/data/netemis.html> [cited 18 July 2001].
- U.S. EPA. Compilation of Air Pollutant Emission Factors, AP-42, 5th ed, Vol 1: Stationary Point and Area Sources. Washington, DC:U.S. Environmental Protection Agency, 1998. Available: <http://www.epa.gov/ttn/chief/ap42/index.html> [cited 20 July 2001].
- U.S. EPA. Requirements for preparation, adoption, and submittal of state implementation plans (guideline on air quality models); proposed rule. *Fed Reg* 65:21505–21546 (2000).
- U.S. EPA. Interagency Workgroup on Air Quality Modeling (IWAQM) Phase 2 Summary Report and Recommendations for Modeling Long Range Transport Impacts. EPA-454-R-98-019. Research Triangle Park, NC:U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, 1999.
- U.S. NOAA. RUC-2: The Rapid Update Cycle Version 2. Camp Springs, MD:U.S. National Oceanic and Atmospheric Administration, National Center for Environmental Prediction, 2001. Available: <ftp://ftp.prd.ncep.noaa.gov> [cited 19 June 2001].
- U.S. NOAA. METAR Data Access. Silver Spring, MD:U.S. National Oceanic and Atmospheric Administration, National Weather Service, 2001. Available: <http://weather.noaa.gov/weather/metar/shtml> [cited 19 June 2001].
- Pope CA III, Burnett RT, Thun MJ, Calle EE, Krewski D, Ito K, Thurston GD. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *JAMA* 287:1132–1141 (2002).
- Dockery DW, Pope CA III, Xu X, Spengler JD, Ware JH, Fay ME, Ferris BG Jr, Speizer FE. An association between air pollution and mortality in six U.S. cities. *N Engl J Med* 329:1753–1759 (1993).
- McDonnell WF, Nishino-Ishikawa N, Petersen FF, Chen LH, Abbey DE. Relationships of mortality with the fine and coarse fractions of long-term ambient PM<sub>10</sub> concentrations in nonsmokers. *J Exp Anal Environ Epidemiol* 10:427–436 (2000).
- Krewski D, Burnett R, Goldberg M, Hoover K, Siemiatycki J, Jarrett M, Abrahamowicz M, White W. Particle Epidemiology Reanalysis Project. Part II: Sensitivity Analyses. Cambridge, MA:Health Effects Institute, 2000.
- Zanobetti A, Schwartz J. Race, gender, and social status as modifiers of the effects of PM<sub>10</sub> on mortality. *J Occup Environ Med* 42:469–474 (2000).
- Zanobetti A, Schwartz J, Dockery DW. Airborne particles are a risk factor for hospital admissions for heart and lung disease. *Environ Health Perspect* 108:1071–1077 (2000).
- Zanobetti A, Schwartz J, Gold D. Are there sensitive subgroups for the effects of airborne particles? *Environ Health Perspect* 108:841–845 (2000).
- Berkman L, Kawachi I, eds. *Social Epidemiology*. New York:Oxford University Press, 2000.
- McDonough P, Duncan GJ, Williams D, House J. Income dynamics and adult mortality in the United States, 1972 through 1989. *Am J Public Health* 87:1476–1483 (1997).
- Arias LC, Borrell C. Mortality inequalities according to education in the city of Barcelona. *Med Clin (Barc)* 110:161–166 (1998).
- Lynch JW, Kaplan GA, Salonen JT. Why do poor people behave poorly? Variation in adult health behaviours and psychosocial characteristics by stages of the socioeconomic life-course. *Soc Sci Med* 44:809–819 (1997).
- Lantz PM, Lynch JW, House JS, Lepkowski JM, Mero RP, Musick MA, Williams DR. Socioeconomic disparities in health change in a longitudinal study of US adults: the role of health-risk behaviors. *Soc Sci Med* 53:29–40 (2001).
- Backlund E, Sorlie PD, Johnson NJ. A comparison of the relationships of education and income with mortality: the National Longitudinal Mortality Study. *Soc Sci Med* 49:1373–1384 (1999).
- Hardarson T, Gardarsdottir M, Gudmundsson KT, Thorgeirsson G, Sigvaldason H, Sigfusson N. The relationship between educational level and mortality. The Reykjavik Study. *J Intern Med* 249:495–502 (2001).
- Borrell C, Regidor E, Arias LC, Navarro P, Puigpinos R, Dominguez V, Plasencia A. Inequalities in mortality according to educational level in two large southern European cities. *Int J Epidemiol* 28:58–63 (1999).
- Koskinen S, Martelin T. Why are socioeconomic mortality differences smaller among women than among men? *Soc Sci Med* 38:1385–1396 (1994).
- Christenson BA, Johnson NE. Educational inequality in adult mortality: an assessment with death certificate data from Michigan. *Demography* 32:215–229 (1995).
- Schwartz J. Air pollution and hospital admissions for heart disease in eight U.S. counties. *Epidemiology* 10:17–22 (1999).
- Linn WS, Szlachcic Y, Gong H Jr, Kinney PL, Berhane KT. Air pollution and daily hospital admissions in metropolitan Los Angeles. *Environ Health Perspect* 108:427–434 (2000).
- Zanobetti A, Schwartz J. Are diabetics more susceptible to the health effects of airborne particles? *Am J Respir Crit Care Med* 164:831–833 (2001).
- Moolgavkar SH. Air pollution and hospital admissions for diseases of the circulatory system in three U.S. metropolitan areas. *J Air Waste Manage Assoc* 50:1199–1206 (2000).
- Lippmann M, Ito K, Nadas A, Burnett RT. Association of Particulate Matter Components with Daily Mortality and Morbidity in Urban Populations. Cambridge, MA:Health Effects Institute, 2000.
- Schwartz J, Morris R. Air pollution and hospital admissions for cardiovascular disease in Detroit, Michigan. *Am J Epidemiol* 142:23–35 (1995).
- Schwartz J. Air pollution and hospital admissions for cardiovascular disease in Tucson. *Epidemiology* 8:371–377 (1997).
- Samet J, Zeger S, Dominici F, Currier F, Coursac I, Dockery D, Schwartz J, Zanobetti A. The National Morbidity, Mortality, and Air Pollution Study Part II: Morbidity, Mortality, and Air Pollution in the United States. Cambridge, MA:Health Effects Institute, 2000.
- Popovic JR, Hall MJ. 1999 National Hospital Discharge Survey. Advance Data from Vital and Health Statistics. Hyattsville, MD:National Center for Health Statistics, 2001.
- Hu FB, Manson JE, Stampfer MJ, Colditz G, Liu S, Solomon CG, Willett WC. Diet, lifestyle, and the risk of type 2 diabetes mellitus in women. *N Engl J Med* 345:790–797 (2001).
- Harris MI, Flegal KM, Cowie CC, Eberhardt MS, Goldstein DE, Little RR, Wiedmeyer HM, Byrd-Holt DD. Prevalence of diabetes, impaired fasting glucose, and impaired glucose tolerance in U.S. adults. The Third National Health and Nutrition Examination Survey, 1988–1994. *Diabetes Care* 21:518–524 (1998).
- Donnan PT, Leese GP, Morris AD. Hospitalizations for people with type 1 and type 2 diabetes compared with the nondiabetic population of Tayside, Scotland: a retrospective cohort study of resource use. *Diabetes Care* 23:1774–1779 (2000).
- Yudkin JS, Oswald GA. Determinants of hospital admission and case fatality in diabetic patients with myocardial infarction. *Diabetes Care* 11:351–358 (1988).
- U.S. DHHS. Diabetes Surveillance, 1999. Washington, DC:U.S. Department of Health and Human Services, 1999. Available: <http://www.cdc.gov/diabetes/statistics/index.htm> [cited 30 August 2001].
- Norris G, YoungPong SN, Koenig JQ, Larson TV, Sheppard L, Stout JW. An association between fine particles and asthma emergency department visits for children in Seattle. *Environ Health Perspect* 107:489–493 (1999).
- Tolbert PE, Mulholland JA, MacIntosh DL, Xu F, Daniels D, Devine OJ, Carlin BP, Klein M, Dorley J, Butler AJ, et al. Air quality and pediatric emergency room visits for asthma in Atlanta, Georgia, USA. *Am J Epidemiol* 151:798–810 (2000).
- DerSimonian R, Laird N. Meta-analysis in clinical trials. *Contr Clin Trials* 7:177–188 (1986).
- Mannino DM, Homa DM, Pertowski CA, Ashizawa A, Nixon LL, Johnson CA, Ball LB, Jack E, Kang DS. Surveillance for asthma—United States, 1960–1995. *Morb Mortal Wkly Rep* 47:1–27 (1998).
- Miller JE. The effects of race/ethnicity and income on early childhood asthma prevalence and health care use. *Am J Public Health* 90:428–430 (2000).
- Prescott E, Lange P, Vestbo J. Socioeconomic status, lung function and admission to hospital for COPD: results from the Copenhagen City Heart Study. *Eur Respir J* 13:1109–1114 (1999).
- Marin N, Caba A, Ortiz B, Perez-Tornero E, Martinez L, Lopez M, Fornieles H, Delgado-Rodriguez M. Socioeconomic determinants and utilization of emergency hospital services. *Med Clin (Barc)* 108:726–729 (1997).
- Grant EN, Lyttle CS, Weiss KB. The relation of socioeconomic factors and racial/ethnic differences in US asthma mortality. *Am J Public Health* 90:1923–1925 (2000).
- Cunningham J, O'Connor GT, Dockery DW, Speizer FE. Environmental tobacco smoke, wheezing, and asthma in children in 24 communities. *Am J Respir Crit Care Med* 153:218–224 (1996).
- Kitch BT, Chew G, Burge HA, Muilenberg ML, Weiss ST, Platts-Mills TA, O'Connor G, Gold DR. Socioeconomic predictors of high allergen levels in homes in the greater Boston area. *Environ Health Perspect* 108:301–307 (2000).
- Chatkin M, Menezes AM, Albernaz E, Victora CG, Barros FC. Asthmatic children's risk factors for emergency room visits, Brazil. *Rev Saude Publica* 34:491–498 (2000).
- Gottlieb DJ, Beiser AS, O'Connor GT. Poverty, race, and medication use are correlates of asthma hospitalization rates. A small area analysis in Boston. *Chest* 108:28–35 (1995).
- U.S. EPA. Aerometric Information Retrieval System. Washington, DC:U.S. Environmental Protection Agency, 2001. Available: [http://www.epa.gov/aqspub1/annual\\_summary.html](http://www.epa.gov/aqspub1/annual_summary.html) [cited 10 August 2001].
- Hattis D, Russ A, Goble R, Banati P, Chu M. Human interindividual variability in susceptibility to airborne particles. *Risk Anal* 21:585–599 (2001).