Original Contribution

Effect Modification by Community Characteristics on the Short-term Effects of Ozone Exposure and Mortality in 98 US Communities

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Previous research provided evidence of an association between short-term exposure to ozone and mortality risk and of heterogeneity in the risk across communities. The authors investigated whether this heterogeneity can be explained by community-specific characteristics: race, income, education, urbanization, transportation use, particulate matter and ozone levels, number of ozone monitors, weather, and use of air conditioning. Their study included data on 98 US urban communities for 1987 to 2000 from the National Morbidity, Mortality, and Air Pollution Study; US Census; and American Housing Survey. On average across the communities, a 10-ppb increase in the previous week's ozone level was associated with a 0.52% (95% posterior interval: 0.28, 0.77) increase in mortality. The authors found that community-level characteristics modify the relation between ozone and mortality. Higher effect estimates were associated with higher unemployment, fraction of the Black/African-American population, and public transportation use and with lower temperatures or prevalence of central air conditioning. These differences may relate to underlying health status, differences in exposure, or other factors. Results show that some segments of the population may face higher health burdens of ozone pollution.

air conditioning; air pollution; continental population groups; income; mortality; ozone; particulate matter; socioeconomic factors

Abbreviations: PM$_{2.5}$, particulate matter with an aerodynamic diameter of $\leq$2.5 μm; PM$_{10}$, particulate matter with an aerodynamic diameter of $\leq$10 μm.

A link between short-term ozone exposure and increased risk of mortality was identified in recent multicity studies (1–6) and meta-analyses (7–12). Although, on average across 95 US communities, we found a statistically significant association between ozone and increased risk of mortality (1), heterogeneity existed among the community-specific relative rates. Other recent multicity and meta-analysis studies of the short-term effects of ozone on mortality also observed heterogeneity among city-specific estimates (3, 6, 7, 9). The association between ozone and mortality could vary by community because of differences in indoor/outdoor activity patterns, use of air conditioning, population characteristics, or other factors.

Given the highly reactive nature of ozone, indoor concentrations can be much lower than ambient levels, and ventilation characteristics can appreciably affect indoor/outdoor ratios of ozone levels (13, 14). Therefore, the use of air conditioning versus open windows could alter exposure and affect estimates. A meta-analysis by Levy et al. (10) on time-series studies of ozone and mortality found that higher prevalence of air conditioning lessened effect estimates and partially explained heterogeneity among study results; however, only limited data were available, especially for cities with high temperatures. The authors recommended that the National Morbidity, Mortality, and Air Pollution Study and other large multicity studies examine the potential effect

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modification of air conditioning on the relation between ozone and mortality. An earlier meta-analysis of ozone and mortality also recommended that potential modifiers, such as air conditioning, be explored further in multicity analysis (11).

In earlier work, we identified a 0.52 percent increase in nonaccidental mortality per 10-ppb increase in the previous week's ozone across 95 US communities, but effect estimates varied across community (1). In this research, we investigated these 95 communities plus three additional ones to explore whether community-level characteristics explain the heterogeneity across the community-specific relative rates. In addition, we partitioned the communities into seven geographic regions specified in previous National Morbidity, Mortality, and Air Pollution Study studies (15) and investigated whether these effect estimates follow regional patterns.

MATERIALS AND METHODS

Data

Communities were defined as a county or set of contiguous counties. Daily mortality rates for each community were obtained from the National Center for Health Statistics. Deaths of nonresidents as well as injuries or external causes were excluded (*International Classification of Diseases*, Ninth Revision, codes 800 and above; *International Statistical Classification of Diseases and Related Health Problems*, Tenth Revision, codes S and above). Daily average weather data regarding temperature and dew point temperature were obtained from the National Climatic Data Center. Levels of ozone, particulate matter with an aerodynamic diameter of ≤ 10 µm (PM_{10}), and particulate matter with an aerodynamic diameter of ≤ 2.5 µm ($PM_{2.5}$) were acquired from the US Environmental Protection Agency Aerometric Information Retrieval Service. PM_{10} data were available for 93 communities and $PM_{2.5}$ data for 90 communities. Data from multiple monitors within a community were averaged. A 10 percent trimmed mean was used to avoid influence of outliers.

Ozone data were available daily for all communities; however, the frequency of measurement varied because some communities measured during the warm season only. On average across all communities, data were missing on 18.7 percent of days, 53.9 percent of which occurred in the winter. About 60 percent of communities had yearly measurements. Long-term weather and pollution values were calculated to reflect the levels used to estimate ozone and mortality relative rates. Thus, the long-term weather and pollution values represent the average over the study period (1987–2000). However, most communities did not begin $PM_{2.5}$ measurements until 1999. For long-term ozone levels, we considered the yearly average (i.e., all days with available data) and the average over the warm period (April–October). Earlier work found similar ozone and mortality effect estimates by using all data and days from April to October (1). We determined the number of air pollution monitors used to generate daily ozone estimates in each community to assess how different exposure estimates

might modify ozone and mortality effect estimates. Because the number of monitors could vary within a community over the study period, we calculated the average number of monitors.

County-level descriptor variables were obtained from the 1990 and 2000 US Censuses to reflect education, income, racial composition, urban versus rural environments, and transportation (16–19). Representative values for the study period (1987–2000) were generated through weighted averages of 1990 and 2000 US Census values. For communities with multiple counties, we calculated the community-level variable by a weighted average based on each county's population.

The percentage of households with central air conditioning and the percentage with air conditioning including window units were estimated from American Housing Survey data based on two data sources. The first is a metropolitan survey, which gathers data on a sample of metropolitan areas every 6 years, with at least 3,200 sampling housing units per area. Metropolitan American Housing Survey data were available for 49 of the 98 communities (20, 21). The second set of air conditioning data is based on the American Housing Survey national survey data, which collects information for a larger geographic area by using a smaller sample size. This survey is conducted every 2 years and is based on about 55,000 households in the United States. Air conditioning data from the American Housing Survey national survey were available for 76 of the 98 communities (22–26). Estimates of the percentage of the population with air conditioning for communities with data from multiple years were based on a weighted average.

Weather, air pollution, and mortality data for all 98 communities, as well as further details on generation of the data set, are available through the Internet-based Health & Air Pollution Surveillance System (iHAPSS), sponsored by the Health Effects Institute and maintained by the Johns Hopkins Bloomberg School of Public Health (http://www.ihapss.jhsph.edu/data/data.htm). Table 1 defines the community-level variables considered as potential effect modifiers of the short-term association between ozone and mortality.

Models

We estimated the relation between community-specific characteristics and community-specific relative rates of ozone on mortality in two steps. First, we estimated the relation between ozone over the previous week and mortality within each community in a constrained distributed lag model, accounting for seasonality, long-term trend, day of the week, temperature, heat waves, and dew point temperature (1, 2). Doing so provides the estimated relative rate of ozone on mortality for community c, $\hat{\beta}^c$, and its estimated variance, $\hat{v}^c$.

In previous research, we estimated community-specific and national average relative rates of mortality associated with short-term exposure to ozone for 95 US urban communities (1, 2). The analysis in the present paper used the original 95 communities plus three additional US urban communities. Further details regarding the modeling structure are presented elsewhere (1, 2, 5), as are sensitivity analyses of this type of model structure to weather (15, 27).

TABLE 1.   Community-level variables studied regarding the short-term effects of ozone exposure on mortality, United States, 1987–2000

Variable	Description (source)*	Mean	IQR†	Minimum to maximum
Education (%)				
High school	Percentage of those aged ≥25 years with a high school degree or equivalent (1990 US Census SF3.P057, 2000 US Census SF3.P37)	78.5	7.78	63.4 to 90.2
Bachelor's degree	Percentage of those aged ≥25 years with a bachelor's degree or higher (1990 US Census SF3.P057, 2000 US Census SF3.P37)	20.1	6.30	9.30 to 43.4
Income				
Median income ($)	Median household income for 1989 (1990 US Census F3.P080A), median household income for 1999 (2000 US Census SF3.P53)	34,430	6,020	21,880 to 58,240
Poverty (%)	Percentage of the population in poverty (1990 US Census SF3.117, 2000 US Census SF3.P87)	13.7	5.51	5.96 to 30.2
Unemployment (%)	Percentage of those aged ≥16 years who are unemployed (1990 US Census SF3.P070, 2000 US Census SF3.P43)	5.11	1.88	2.40 to 8.39
Race (%)	Percentage of the population that self-identifies as Black (1990 US Census SF1.P006), percentage of the population that self-identifies as Black or African American alone (2000 US Census SF1.P3)	16.9	17.8	0.89 to 64.0
Urbanization (%)				
Urban	Percentage of the population living in an urban setting (1990 US Census SF3.P006, 2000 US Census SF3.P5)	91.4	9.63	38.3 to 100
Rural	Percentage of the population living in a rural setting (1990 US Census SF3.P006, 2000 US Census SF3.P5)	8.57	9.63	0 to 61.7
Transportation (%)				
Drive to work	Percentage of the working population aged ≥16 years that drives (car, truck, or van) as the main means of transportation to work (1990 US Census SF3.P049, 2000 US Census SF3.P30)	79.3	4.36	31.8 to 88.9
Take public transportation to work	Percentage of the working population aged ≥16 years that takes public transportation (bus, trolley, streetcar, subway, railroad, or ferryboat) as the main means of transportation to work (1990 US Census SF3.P049, 2000 US Census SF3. P30)	5.48	3.05	0.33 to 49.6
Population (no.)	Total population (1990 and 2000 US Censuses SF1.P1)	996,300	574,600	158,900 to 9,121,000
Air conditioning (%)				
Central air conditioning	Percentage of households with central air conditioning (AHS† metropolitan survey, $n = 49$)	52.7	46.5	6.34 to 87.1
Any air conditioning	Percentage of households with air conditioning including window units (AHS metropolitan survey, $n = 49$)	77.1	36.1	10.2 to 98.6
Central air conditioning	Percentage of households with central air conditioning (AHS national survey, $n = 76$)	47.8	39.8	2.47 to 82.0
Any air conditioning	Percentage of households with air conditioning including window units (AHS national survey, $n = 76$)	65.3	28.2	6.13 to 92.3
Air quality				
Ozone levels (ppb)	Long-term ozone levels for the community for the entire study period, 1987–2000 (NMMAPS†)	26.8	6.4	15.8 to 37.3
Ozone levels, April–October (ppb)	Long-term ozone levels for the community for the study period, April–October only (NMMAPS)	30.0	6.6	14.4 to 47.2
No. of ozone monitors	Average number of ozone monitors used to generate daily ozone estimates (NMMAPS)	2.74	2.44	1.0 to 13.4
PM_{10}† levels‡ ($\mu g/m^3$)	Long-term PM_{10} levels for the community for the study period (NMMAPS, $n = 93$)	29.7	8.8	15.5 to 48.7
$PM_{2.5}$† levels‡ ($\mu g/m^3$)	Long-term $PM_{2.5}$ levels for the community for the study period (NMMAPS, $n = 90$)	14.4	5.5	4.5 to 23.0
Weather (°F)§				
Temperature‡	Average temperature for the community for the study period (National Climatic Data Center)	63.1	10.0	48.4 to 77.8
Dew point temperature‡	Average dew point temperature for the community for the study period (National Climatic Data Center)	50.2	11.3	29.4 to 66.8

* n = number of communities; n = 98 except where specified.

† IQR, interquartile range; AHS, American Housing Survey; NMMAPS, National Morbidity, Mortality, and Air Pollution Study; PM_{10}, particulate matter with an aerodynamic diameter of ≤10 μm; $PM_{2.5}$, particulate matter with an aerodynamic diameter of ≤2.5 μm.

‡ The values include only those days for which ozone data were available.

§ °C = (°F − 32) × 5/9.

The statistical code is available through the Internet-based Health & Air Pollution Surveillance System (http://www.ihapss.jhsph.edu/).

Second, to investigate effect modification, we fit the following Bayesian hierarchical regression model:

$$\hat{\beta}^c | \beta^c, \hat{v}^c \sim N(\beta^c, \hat{v}^c)$$

$$\beta^c | \alpha_0, \alpha_{1,j}, \tau^2 \sim N\left(\alpha_0 + \sum_j \alpha_{1,j}(x_j^c - \bar{x}_j), \tau^2\right),$$

where
$\beta^c, \hat{\beta}^c$ = true and estimated relative rate effect estimate, respectively, for short-term ozone on mortality for community c
$\hat{v}^c$ = estimated statistical variance of $\hat{\beta}^c$
x_j^c = value of descriptor variable j for community c
$\bar{x}_j$ = average value of descriptor variable j across all communities
α_0 = average relative rate for an "average community" (i.e., relative rate for $x_j^c = \bar{x}_j$ for all j)
$\alpha_{1,j}$ = change in the relative rate β^c for a unit increase in $x_j^c - \bar{x}_j$
τ^2 = variance across communities of the true community-specific relative rates, β^c, unexplained by the community-specific characteristics (x_j^c for all j); τ would reflect the standard deviation, also called heterogeneity.

Results are presented as the percentage increase in the relative rate associated with a 10-ppb increase in the previous week's ozone, for an interquartile increase in the community-specific variable, based on the original ozone mortality risk estimate (α_0) from the model without community-specific variables. Bayesian hierarchical modeling is a suitable approach for analysis of clustered data, with inclusion of covariates at each level of the hierarchy and estimated variance components accounting for their statistical uncertainty (28). We fit the Bayesian hierarchical model above by using two-level normal independent sampling estimation with noninformative priors (29).

For comparison, we also fit a mixed-effects approach to meta-regression (30–32) as $\hat{\beta}^c = \alpha_0 + U^c + \sum_j \alpha_{1,j} (x_j^c - \bar{x}_j) + \varepsilon^c$, where $\varepsilon^c \sim N(0, v^c)$ and $U^c \sim N(0, \tau^2)$. We fit the linear mixed-effects model above by using the Stata function "metareg" (33). Note that the Bayesian hierarchical model and the mixed-effect meta-regression model are two equivalent model formulations but are fitted by using two different software packages.

Unless otherwise specified, we report in this paper the results under the Bayesian hierarchical model. Community-level variables that were significantly associated with ozone and mortality effect estimates were further explored in a multivariate model for both the Bayesian hierarchical modeling and the mixed-effects meta-regression approach.

We explored whether effect estimates differ by region by fitting a two-stage Bayesian hierarchical model within each region. Communities were divided into seven regions based on previous work (15, 34–36). Regional analysis excluded Honolulu, Hawaii.

TABLE 2. Percentage increase in daily mortality for a 10-ppb increase in the previous week's daily ozone, by geographic region, United States, 1987–2000

|	No. of communities	Regional estimate	95% PI*
Regional results			
Industrial Midwest	20	0.73	0.11, 1.35
Northeast	16	1.44	0.78, 2.10
Northwest	12	0.08	−0.92, 1.09
Southern California	7	0.21	−0.46, 0.88
Southeast	26	0.38	−0.07, 0.85
Southwest	9	−0.06	−0.92, 0.81
Urban Midwest	7	−0.05	−1.28, 1.19
National results			
All continental communities	97	0.51	0.27, 0.76
All communities	98	0.52	0.28, 0.77

* PI, posterior interval.

RESULTS

National and regional effects

On average across the 98 communities, we found that a 10-ppb increase in daily average ozone over the previous week was associated with a 0.52 percent increase in all-cause, nonaccidental mortality (95 percent posterior interval: 0.28, 0.77). This estimate is very similar to our previous estimate for 95 communities at 0.52 percent (95 percent posterior interval: 0.27, 0.77) (1). We identified heterogeneity in the community-specific maximum likelihood estimates. The heterogeneity parameter (τ), which denotes the standard deviation of the true community-specific relative rates with respect to their average, is 0.62. With a national average effect of 0.52 percent, this finding suggests that the 2.5 and 97.5 percentiles of the true community-specific percentage increases are −0.69 percent and 1.76 percent, respectively. We confirmed heterogeneity by using a chi-squared test ($p < 0.01$).

We fit a two-stage Bayesian hierarchical model without including community-specific covariates to generate an overall estimate within each of the seven regions (table 2). The strongest effect was observed for the Northeast and the lowest for the Southwest and urban Midwest regions. Although the 95 percent posterior intervals of all regional estimates overlapped, analysis of variance confirmed that the regional estimates were statistically different. Web figure 1 shows the Bayesian community-specific estimates. (This figure is posted on the *Journal*'s website (http://aje.oupjournals.org/).) Visual inspection did not reveal strong spatial patterns in effect estimates.

Community-specific variables

Summary values of the community-specific descriptor variables are provided in table 1. Several variables were highly correlated, as anticipated. The percentage of the
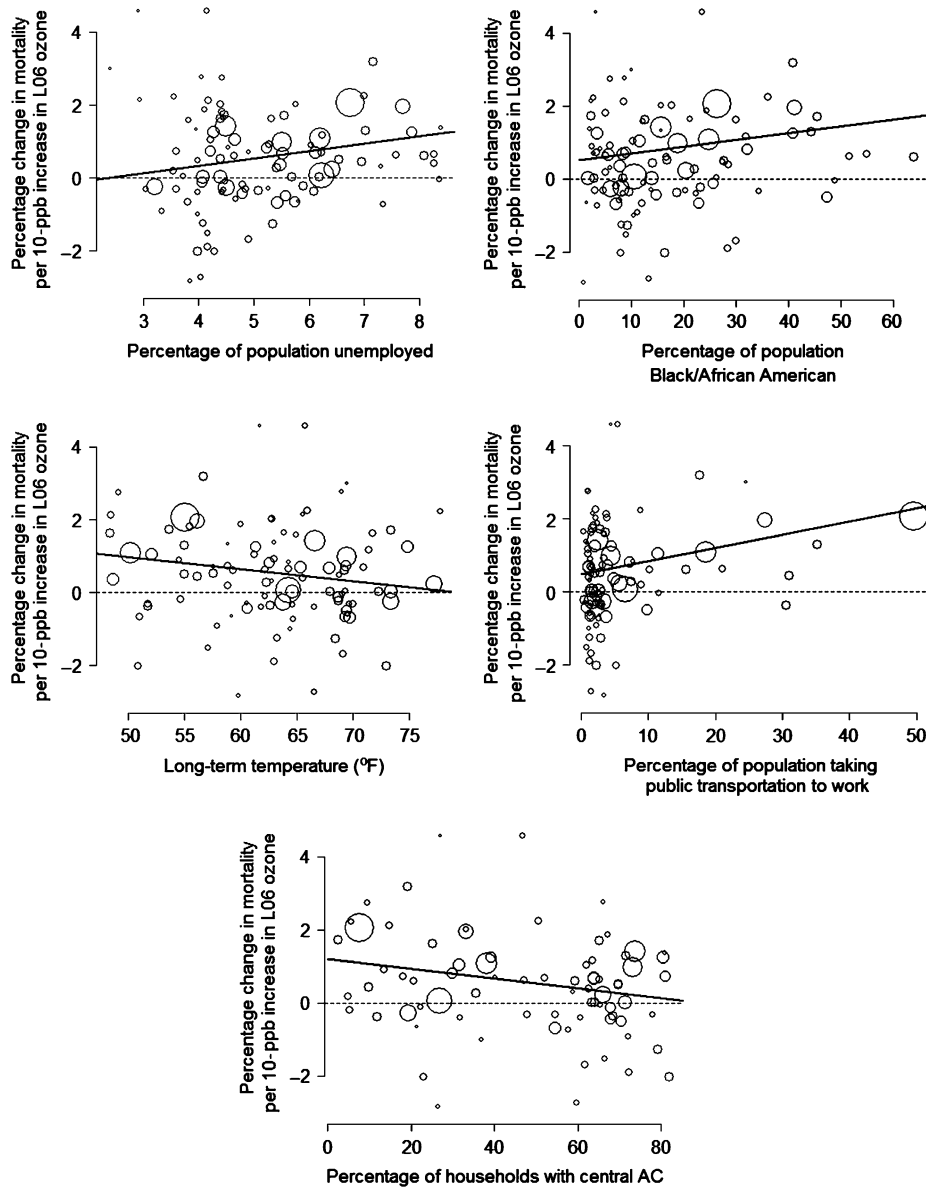
FIGURE 1. Communities' maximum likelihood estimates and community-specific characteristics for unemployment, race, long-term temperature, public transportation, and central air conditioning (AC), United States, 1987–2000. The size of each circle corresponds to the inverse of the standard error of the community's maximum likelihood estimate; that is, larger circles represent more certain estimates. The bold line reflects results from the univariate second-stage analysis in which the Bayesian hierarchical model was used. Long-term temperature ($°C = (°F − 32) × 5/9$) included only those days for which ozone data were available. L06, ozone during the previous week (lag 0 days, lag 1 day, lag 2 days . . . 6 days previous).

population with a high school education had a correlation of −0.85 and −0.75 with the percentage unemployed and the percentage in poverty, respectively. The percentage in poverty and the percentage unemployed were also related (correlation = 0.83). The percentage of the population with a high school education had a 0.64 correlation with the percentage with a bachelor's degree. Urban and rural variables were near inverses (correlation = −1.0). The percentage of the population driving alone to work and the percentage

taking public transportation to work were also related (correlation = −0.97). The correlations between the American Housing Survey national and metropolitan surveys for the 41 communities included in both were 0.97 for central air conditioning and 0.94 for any air conditioning; therefore, we performed analysis by using the national data.

Table 3 shows results from univariate second-stage analysis for each community-specific variable using the Bayesian hierarchical model, and table 4 provides results from the

TABLE 3. Results of the univariate Bayesian hierarchical regression model used to study the short-term effects of ozone exposure on mortality, United States, 1987–2000

Community-specific descriptor variable*	Percentage increase in mortality per 10-ppb increase in the previous week's ozone, adjusted for the community-specific variable		Percentage change in effect estimate per IQR† increase in community-level variable			Heterogeneity parameter (τ)	Percentage of total variance due to between-study variance (ρ)
	Central estimate	95% PI†	Central estimate	95% PI	p value for community-level variable		
No community-level variables (original analysis)	0.52	0.28, 0.77	n/a†	n/a	n/a	0.62	20.7
Education							
High school degree	0.49	0.24, 0.73	−48.5	−110.3, 13.4	0.13	0.60	19.5
Bachelor's degree	0.52	0.28, 0.77	6.63	−55.3, 68.5	0.83	0.64	21.0
Income							
Unemployment	0.49	0.26, 0.73	68.3	3.02, 133.7	0.04	0.56	18.7
Poverty	0.51	0.27, 0.75	35.4	−24.7, 95.4	0.25	0.60	20.0
Median income	0.52	0.28, 0.77	9.34	−42.5, 61.2	0.72	0.64	21.2
Race (Black/African American)	0.52	0.28, 0.75	62.2	2.94, 121.4	0.04	0.56	18.5
Urbanization							
Urban	0.53	0.28, 0.78	−11.9	−61.9, 38.1	0.64	0.64	20.7
Rural	0.53	0.28, 0.78	12.0	−38.1, 62.1	0.64	0.64	20.4
Transportation							
Drive alone	0.47	0.25, 0.69	−25.1	−39.0, −11.3	<0.01	0.44	13.5
Use public transportation	0.47	0.25, 0.69	20.6	9.84, 31.4	<0.01	0.41	12.3
Population	0.46	0.22, 0.71	9.97	−2.36, 22.3	0.11	0.59	18.5
Air conditioning							
Any air conditioning ($n = 76$)	0.56	0.28, 0.84	−32.2	−112.0, 47.7	0.43	0.70	23.9
Central air conditioning ($n = 76$)	0.56	0.29, 0.84	−101.6	−186.8, −16.3	0.02	0.64	22.2
Weather and pollution							
Ozone levels	0.50	0.26, 0.74	−48.1	−108.8, 12.7	0.12	0.61	19.3
Ozone levels, April–October	0.52	0.28, 0.76	−34.0	−90.1, 22.2	0.23	0.62	20.5
No. of ozone monitors	0.52	0.27, 0.78	−2.25	−40.9, 36.4	0.91	0.65	20.4
PM_{10}† levels ($n = 93$)	0.52	0.27, 0.77	15.8	−45.3, 76.9	0.61	0.65	22.0
$PM_{2.5}$† levels ($n = 90$)	0.53	0.28, 0.78	46.3	−25.9, 118.6	0.21	0.63	21.6
Temperature	0.53	0.30, 0.77	−63.4	−123.5, −3.25	0.04	0.57	18.8
Dew point temperature	0.54	0.30, 0.77	−41.3	−103.4, 20.9	0.19	0.59	19.5

* n values in parentheses refer to the number of communities used in that analysis.

† IQR, interquartile range; PI, posterior interval; n/a, not applicable; PM_{10}, particulate matter with an aerodynamic diameter of ≤ 10 µm; $PM_{2.5}$, particulate matter with an aerodynamic diameter of ≤ 2.5 µm.

mixed-effects meta-regression model. These tables give the national relative rate estimates for ozone's association with mortality, adjusted for community-specific variables, and the heterogeneity parameter, τ, from univariate second-stage analysis. As noted in the Materials and Methods section, τ^2 is the variance unexplained by the community-specific variable. The tables also show the p value for the community-level variable and ρ, the percentage of total variance due to between-study variance (37).

Under both approaches, the ozone and mortality effect estimates were higher for communities in which a higher percentage of the population was unemployed or Black/African American. Higher effect estimates were associated with communities with a higher fraction of the population taking public transportation to work or a lower fraction of persons driving to work. Lower temperatures or prevalence of central air conditioning was associated with higher effect estimates. No relation observed between PM_{10} or $PM_{2.5}$ levels or the number of ozone monitors and the effect estimates for ozone and mortality.

The national relative rate did not vary greatly after adjustment by community-specific variables. When either the

TABLE 4. Results of the mixed-effects meta-regression model used to study the short-term effects of ozone exposure on mortality, United States, 1987–2000

Community-specific descriptor variable*	Percentage increase in mortality per 10-ppb increase in the previous week's ozone, adjusted for the community-specific variable		Percentage change in effect estimate per IQR† increase in community-level variable			Heterogeneity parameter (τ)	Percentage of total variance due to between-study variance (ρ)
	Central estimate	95% PI†	Central estimate	95% PI	p value for community-level variable		
No community-level variables (original analysis)	0.52	0.29, 0.76	n/a†	n/a	n/a	0.58	28.3
Education							
High school degree	0.49	0.24, 0.73	−51.1	−115.0, 12.8	0.12	0.55	18.8
Bachelor's degree	0.52	0.29, 0.76	6.56	−57.6, 70.7	0.84	0.59	22.3
Income							
Unemployment	0.49	0.26, 0.72	72.0	6.70, 137.2	0.03	0.51	16.2
Poverty	0.51	0.27, 0.74	37.3	−24.5, 99.2	0.23	0.56	20.5
Median income	0.52	0.28, 0.76	9.56	−44.1, 63.2	0.72	0.59	22.5
Race (Black/African American)	0.52	0.29, 0.74	65.0	5.80, 124.2	0.03	0.51	16.1
Urbanization							
Urban	0.53	0.29, 0.78	−12.1	−63.8, 39.6	0.64	0.59	20.2
Rural	0.53	0.29, 0.78	12.1	−39.6, 63.8	0.64	0.59	21.6
Transportation							
Drive alone	0.47	0.26, 0.68	−26.5	−39.9, −13.1	<0.01	0.34	9.8
Use public transportation	0.47	0.26, 0.68	21.5	11.4, 31.7	<0.01	0.30	7.5
Population	0.46	0.22, 0.71	10.4	−1.8, 22.7	0.10	0.54	17.0
Air conditioning							
Any air conditioning (n = 76)	0.56	0.28, 0.83	−43.1	−149.3, 63.1	0.42	0.64	26.5
Central air conditioning (n = 76)	0.57	0.30, 0.83	−102.8	−186.8, −18.8	0.02	0.58	16.3
Weather and pollution							
Ozone levels	0.50	0.26, 0.73	−50.5	−112.9, 11.7	0.11	0.54	19.3
Ozone levels, April–October	0.52	0.28, 0.76	−35.4	−93.2, 22.5	0.23	0.56	21.5
No. of ozone monitors	0.53	0.28, 0.77	−1.90	−40.6, 36.8	0.92	0.58	19.5
PM₁₀† levels (n = 93)	0.52	0.27, 0.76	16.8	−46.2, 79.9	0.60	0.60	23.0
PM₂.₅† levels (n = 90)	0.53	0.28, 0.78	48.3	−26.3, 122.9	0.20	0.59	22.5
Temperature	0.53	0.31, 0.77	−66.0	−127.9, −6.2	0.03	0.50	16.4
Dew point temperature	0.54	0.31, 0.77	−44.4	−107.1, 18.3	0.16	0.53	20.2

* *n* values in parentheses refer to the number of communities used in that analysis.

† IQR, interquartile range; PI, posterior interval; n/a, not applicable; PM_{10}, particulate matter with an aerodynamic diameter of $\leq$10 μm; $PM_{2.5}$, particulate matter with an aerodynamic diameter of $\leq$2.5 μm.

Bayesian hierarchical model or the mixed-effects meta-regression results were used, the national relative rate ranged from a 0.46 percent to a 0.54 percent increase in mortality per 10-ppb increase in the previous week's ozone, using variables for which data from all 98 communities were available. Significant heterogeneity remained among the community-specific estimates after adjustment for each community-specific variable, which implies that none of these factors alone explains the variability among communities' relative rates. Of the community-specific variables considered, heterogeneity was most reduced by the percentage of

the population that took public transportation to work (ρ was reduced from 20.7 percent to 12.3 percent for the Bayesian hierarchical model).

Figure 1 shows the relation between the community-specific maximum likelihood estimates for ozone and mortality and community values for unemployment, race, public transportation, long-term temperature, and central air conditioning based on the American Housing Survey national survey when the Bayesian hierarchical model was used.

Community-specific variables exhibiting statistically significant associations with ozone and mortality relative rates

TABLE 5. Results of multivariate Bayesian hierarchical regression and mixed-effects meta-regression models used to study the short-term effects of ozone exposure on mortality, United States, 1987–2000*

| | Bayesian hierarchical regression | | | | | Mixed-effects meta-regression | | | | |
| | Percentage change in effect estimates per IQR† increase in community-level variable | | | τ† | ρ† | Percentage change in effect estimates per IQR increase in community-level variable | | | τ | ρ |
	Central estimate	95% PI†	p value			Central estimate	95% PI	p value		
Race (Black/African American)										
Univariate	62.2	2.94, 121.4	0.04	0.56	18.5	65.0	5.80, 124.2	0.03	0.51	16.1
Adjusted for unemployment	40.5	−28.9, 109.8	0.25	0.55	17.8	42.3	−27.6, 112.3	0.24	0.49	15.5
Adjusted for public transportation	32.0	−27.1, 91.2	0.29	0.40	12.1	34.7	−24.6, 94.0	0.25	0.27	6.2
Adjusted for long-term temperature	66.6	9.56, 123.7	0.02	0.49	15.5	69.8	12.9, 126.7	0.02	0.42	13.0
Adjusted for central air conditioning ($n = 76$)	73.2	10.2, 136.1	0.02	0.57	19.5	76.1	13.2, 139.0	0.02	0.50	13.6
Adjusted for unemployment, public transportation, long-term temperature, and central air conditioning ($n = 76$)	43.8	−34.7, 122.4	0.27	0.56	18.8	45.2	−34.5, 124.9	0.27	0.47	14.0
Unemployment										
Univariate	68.3	3.02, 133.7	0.04	0.59	18.7	72.0	6.70, 137.2	0.03	0.51	16.2
Adjusted for race	44.8	−31.6, 121.2	0.25	0.55	17.8	47.3	−29.7, 124.3	0.23	0.49	15.5
Adjusted for public transportation	25.5	−42.1, 93.0	0.46	0.41	12.2	26.5	−41.6, 94.5	0.45	0.31	8.0
Adjusted for long-term temperature	63.6	0.10, 121.1	0.05	0.51	16.3	66.8	3.2, 130.5	0.04	0.45	13.8
Adjusted for central air conditioning ($n = 76$)	71.4	−1.46, 144.2	0.05	0.60	19.8	74.2	0.7, 147.6	0.05	0.54	14.2
Adjusted for race, public transportation, long-term temperature, and central air conditioning ($n = 76$)	24.6	−65.5, 114.7	0.59	0.56	18.8	24.7	−66.3, 115.8	0.60	0.47	14.0
Public transportation										
Univariate	20.6	9.84, 31.4	<0.01	0.41	12.3	21.5	11.4, 31.7	<0.01	0.30	7.5
Adjusted for race	18.2	6.54, 29.9	<0.01	0.40	12.0	19.1	8.3, 29.8	<0.01	0.27	6.2
Adjusted for unemployment	18.5	6.22, 30.8	<0.01	0.41	12.2	19.3	7.6, 31.1	<0.01	0.31	8.0
Adjusted for long-term temperature	18.2	6.29, 30.2	<0.01	0.42	12.5	19.0	7.7, 30.4	<0.01	0.30	7.5
Adjusted for central air conditioning ($n = 76$)	16.2	1.97, 30.4	0.03	0.52	16.8	17.0	2.80, 31.1	0.02	0.44	10.6
Adjusted for race, unemployment, long-term temperature, and central air conditioning ($n = 76$)	8.0	−10.3, 26.3	0.39	0.56	18.8	8.7	−9.0, 26.4	0.34	0.47	14.0
Long-term temperature										
Univariate	−63.4	−123.5, −3.25	0.04	0.57	18.8	−66.0	−125.9, −6.2	0.03	0.50	16.4
Adjusted for race	−67.3	−124.7, −9.85	0.02	0.49	15.5	−70.1	−126.9, −13.3	0.02	0.42	13.0
Adjusted for unemployment	−58.6	−117.1, −0.03	0.05	0.51	16.3	−61.1	−119.2, −3.0	0.04	0.45	13.8
Adjusted for public transportation	−28.9	−89.0, 31.3	0.35	0.42	12.5	−29.9	−89.3, 29.6	0.33	0.30	7.5
Adjusted for central air conditioning ($n = 76$)	−27.4	−114.6, 59.9	0.54	0.63	21.8	−29.4	−115.8, 56.9	0.51	0.57	16.0
Adjusted for race, unemployment, public transportation, and central air conditioning ($n = 76$)	−17.0	−102.3, 68.4	0.70	0.56	18.8	−18.7	−104.9, 66.5	0.67	0.47	14.0
Central air conditioning ($n = 76$)										
Univariate	−101.6	−186.8, −16.3	0.02	0.64	22.2	−102.8	−186.8, −18.8	0.02	0.58	16.3
Adjusted for race	−109.5	−191.9, −27.0	0.01	0.57	19.5	−110.2	−190.5, −29.9	<0.01	0.50	13.6
Adjusted for unemployment	−96.4	−180.4, −12.3	0.02	0.60	19.8	−97.0	−179.3, −14.7	0.02	0.54	14.2
Adjusted for public transportation	−49.5	−141.9, 42.4	0.29	0.52	16.8	−48.9	−139.4, 41.6	0.29	0.44	10.6
Adjusted for long-term temperature	−81.5	−187.9, 24.9	0.13	0.63	21.8	−81.5	−185.8, 22.8	0.13	0.57	16.0
Adjusted for race, unemployment, public transportation, and long-term temperature ($n = 76$)	−66.6	−180.4, 47.3	0.25	0.56	18.8	−64.1	−172.9, 44.7	0.25	0.47	14.0

* *n* values in parentheses refer to the number of communities used in that analysis.
† IQR, interquartile range; τ, heterogeneity parameter; ρ, percentage of total variance due to between-study variance; PI, posterior interval.

TABLE 6.   Percentage change in ozone mortality effect estimate for an IQR* increase in the percentage of the adult population using various types of public transportation to travel to work, Bayesian hierarchical model, United States, 1987–2000

	Mean	IQR	Percentage change per IQR	
			Central estimate	95% PI*
Any public transportation	5.48	3.05	20.6	9.84, 31.4
Subway	1.17	0.03	0.25	0.08, 0.41
Bus	3.85	3.02	44.0	15.1, 73.0
Rail	0.20	0.12	16.5	7.52, 25.4

* IQR, interquartile range; PI, posterior interval.

in univariate second-stage analysis were used in multivariate second-stage regression for both the Bayesian hierarchical regression and the mixed-effects regression models (table 5). For the bivariate analysis, the relation between public transportation and ozone mortality effect estimates was robust to adjustment by race, unemployment, long-term temperature, or central air conditioning. Models including public transportation use showed the largest reduction in heterogeneity (refer to the ρ values in table 5). The associations between higher ozone mortality effect estimates and race, unemployment, long-term temperature, or central air conditioning were not robust to adjustment by public transportation use. We also performed a multivariate analysis by simultaneously including the community-specific variables demonstrating an association with ozone mortality risk estimates in univariate models (table 5). Only the 76 communities with data for all variables were included. The correlation for central air conditioning and long-term temperature was 0.54. None of the individual community-specific variables had a statistically significant relation with ozone mortality effect estimates when all covariates were included together.

We further examined the percentage of the population taking public transportation to work by subway, bus, or railway system to evaluate whether ozone mortality effect estimates were associated with a particular type of public transportation use (table 6). Note that the categories of subway, bus, or rail are subsets of the public transportation category. On average across the communities, bus use accounted for the majority of public transportation used. The variables of subway, bus, and rail use exhibited associations with each other (correlations ranged from 0.44 to 0.52). All three types of public transportation use were associated with higher effect estimates for ozone and mortality. New York City, New York, had the highest public transportation use at 50 percent. The relation between higher public transportation use and higher ozone mortality effect estimates was robust to exclusion of New York City.

DISCUSSION

Socioeconomic inequalities and race have been linked to a higher burden of environmental risks, including those from air pollution (38–51). For example, lower PM_{10} effect estimates for mortality were observed for communities with higher income and educational levels (47). Regional and seasonal differences in the association of particulate matter with mortality and hospital admissions (15, 34–36, 52) may be the result of dissimilar chemical composition; however, differences in exposure and community-level characteristics may also play a role. The elevated impact of air pollution on Black/African-American and high-unemployment neighborhoods may relate to differential residential exposure, access to health care, baseline health status, occupational exposure, underlying health status, or other factors (38, 39).

The associations of racial and socioeconomic characteristics with ozone's effects on health have been researched in a limited number of studies. Time-series analysis of respiratory hospital admissions in New York City found higher effect estimates for non-Whites compared with Whites (53), mirroring results from this study. Socioeconomic status did not modify the relation between ozone and hospital admissions for the elderly or children in Vancouver, Canada (54). A study of mortality in Mexico City, Mexico, did not identify consistent patterns by socioeconomic gradients at county-level resolution; however, it noted that the study may not have been able to fully illuminate such associations (46). Socioeconomic level as measured by father's educational status affected pulmonary response to ozone in a study of 372 persons aged 18–35 years (48). A human exposure study for the South Coast Air Basin of California found that low-income areas may on average experience higher ozone concentrations than higher-income areas (55). However, for the 98 US communities in this study, we observed similar ozone levels for communities below and above the median percentage in poverty (26.91 ppb and 26.71 ppb, respectively).

Two multicity US studies found that effect estimates for hospital admissions decreased for PM_{10} (56) and ozone with an increasing percentage of homes with central air conditioning (57). We also observed this result with an interquartile-range increase in households with central air conditioning associated with a 101.6 percent decrease in effect estimates for ozone's impact on mortality. The relative impacts of central air conditioning and long-term temperature were difficult to disentangle in this study because of their relation (correlation coefficient = 0.54). High correlation among community characteristics also limited more detailed multivariate analysis with additional variables.

Results indicated no association between ozone effect estimates for mortality and long-term PM_{10} or $PM_{2.5}$ levels. This finding provides further evidence that the relation between ozone and mortality is not confounded by particulate pollution, as shown in several meta-analyses (7, 9, 11, 58) and multicity studies (1, 3, 4). Earlier time-series analysis found national and community-specific ozone and mortality effect estimates to be robust to inclusion of PM_{10} levels (1). No statistically significant association was observed between effect estimates and long-term ozone levels under the Bayesian hierarchical or the mixed-effects meta-regression approach. These results could indicate the absence of a threshold level, as was demonstrated in earlier research (5). If a threshold exists, lower relative rates could be observed for communities with lower ozone levels.

Higher effect estimates for communities with higher use of public transportation may be the result of differential exposure patterns for ozone or an indication of a relation between mortality and a pollutant associated with public transportation whose patterns are similar to those for ozone. Further research is needed to investigate this relation. Note that this link does not imply that public transportation use results in more ozone-related deaths because higher public transportation use was also associated with lower long-term ozone levels. For every 10 percent of the population that takes public transportation to work, long-term ozone levels decreased 9 percent when evaluation was conducted at the mean ozone level ($p < 0.001$).

Although this study found an indication of a gradient for the effect of ozone on mortality by socioeconomic status, there are important limitations. Our analysis assumed that the between-community associations of descriptor variables do not vary with time; however, income levels and other indicators of socioeconomic status can change for communities and for individuals, thereby diluting our socioeconomic indicators. Heterogeneity among socioeconomic factors is likely to exist at the community level and can be present in smaller aggregated units such as census block groups (59). Even with individual data, the choice of socioeconomic indicator is complex given that true socioeconomic position is a function of multiple factors including income, occupation, deprivation, social class, and education, among others; and no single factor completely accounts for the relation between socioeconomic status and health (59). For example, median household income does not address capital assets, number of adults and children in the household, source of the income (e.g., wage earnings vs. child support), long-term income history, and true purchasing power of a given monetary amount, which can vary by community.

We used community-level descriptors rather than individual-level data, which could generate misclassification bias (60–62). Even though we explored effect modification by particles, we did not consider the chemical composition of the particulate mixture. Ambient measurements were applied as a surrogate of personal exposure, and, in fact, many of the results may relate to differences in exposure patterns (e.g., different exposures by unemployment status) rather than or in addition to differences in baseline health status. Furthermore, we did not consider other potential differences among populations that reflect underlying health status, such as smoking patterns.

In summary, this research examined whether short-term effects of ozone on mortality are modified by community-specific characteristics by using data for 14 years for more than 40 percent of the US population to estimate effect modification, accounting for within-community and between-community variance. We explored the sensitivity of results with two modeling software approaches to estimating effect modification: 1) Bayesian hierarchical modeling (28) and 2) mixed-effects meta-regression modeling (30–32).

Our results indicate stronger effects in some regions than others, but the 95 percent posterior intervals for results from all regions overlapped (table 2). We found that heterogeneity among community-specific effect estimates can be partially explained by community-level indicators. Specifically, our findings indicate that some populations (i.e., Black/African American and the unemployed) may bear a higher health burden from ozone and that a higher prevalence of central air conditioning may modify ozone exposure, thereby lessening its health impacts.

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