and Riverside counties had data only every third day.

Data on gaseous pollutants, including carbon monoxide, nitrogen dioxide, and ozone, were obtained from the CARB air quality database for all nine counties. Most of the monitors for gases were part of the State and Local Air Monitoring Stations (SLAMS) network. All gases were reported as 24-hr averages, except ozone, which was reported as both an 8-hr average (1000–1800 hr) and as a 1-hr maximum.

For counties with multiple monitors, the daily average was calculated using all available data. To account for missing data among some of the monitors, we used a process similar to that described by Wong et al. (2001). The average was developed by *a*) calculating the mean for each monitor, *b*) subtracting the mean concentration of each monitor from the nonmissing daily values, *c*) calculating the mean of the available adjusted data, and *d*) adding back the grand mean of the data.

To allow adjustment for the effect of weather on mortality, we collected daily average temperature and humidity data at weather stations in each of the nine counties. Hourly temperature data were obtained from AIRS for all sites except Contra Costa and Santa Clara counties, for which data were obtained from the Bay Area Air Quality Management District and from Golden Gate Weather Services, respectively. All daily mortality, pollutant, and meteorologic data were converted into a SAS database (SAS Institute Inc., Cary, NC) and merged by date. This resulted in 4 years (1,461 days) of daily time-series data.

Methods. Counts of daily mortality are nonnegative discrete integers representing rare events; such data typically follow a Poisson distribution. Therefore, the analysis relied on Poisson regression, conditional on the explanatory variables. In the basic analytic approach, we used similar model specifications for each city, including smoothing spline functions for time trend and weather. We examined both penalized and natural spline models. The penalized spline model is a flexible, nonparametric approach using cubic splines and a term that penalizes the curvature of the smoothing function (Wood 2000). The "roughness penalty" controls the trade-off between a precise fit of the data and a smoothed function. The model then minimizes the sum of the squared deviations plus the penalty function to determine the amount of smoothing in the fit. The natural spline model is a parametric approach that fits piecewise polynomial functions joined at knots, which are typically placed evenly throughout the distribution of the variable of concern, such as time. The function is constrained to be continuous at each knot (Ruppert et al. 2003). The model also places two additional knots at the ends of the data, with the function constrained to be linear beyond these points. The number of knots used determines the overall smoothness of the fit. Previous analysis has indicated that different spline models generate relatively similar results (Health Effects Institute 2003). However, depending on the underlying data and model specifications, different splines might produce varying degrees of bias and efficiency in the regression estimates.

For the initial analysis of all-cause, cardiovascular, respiratory, and above-age-65 mortality, a penalized spline regression was used with R (R Development Core Team 2004). We incorporated a smoothed spline function of time, which can accommodate nonlinear and nonmonotonic patterns between time and mortality, offering a flexible modeling tool (Hastie and Tibshirani 1990). In addition, the smooth of time diminishes short-term fluctuations in the data, thereby helping to reduce the degree of serial correlation. Based on previous findings reported in the literature (e.g., Samet et al. 2000), the basic model included a smoothing spline for time with 7 degrees of freedom (df) per year of data. This number of degrees of freedom controls well for seasonal patterns in mortality and reduces and often eliminates autocorrelation. Visual inspection of the data indicated a spike in mortality in several of the cities in southern and central California during a 3-week period starting 17 December 1999. During this period, the actual number of cases exceeded the smoothed estimate. Therefore, for all of the regression models, we added a second smooth of time with 3 knots for this 3-week period.

Other covariates, such as day of the week and smoothing splines of 1-day lags of average temperature and humidity (each with 3 df), were also included in the model because they may be associated with daily mortality and are likely to vary over time in concert with air pollution levels. Previous studies have reported stronger associations of mortality with PM lagged 1 or 2 days or with cumulative exposures over several days. Therefore, in our primary analysis of $PM_{2.5}$, we examined two different *a priori* lag structures: a 2-day average of lags 0 and 1 (lag 01) and a single-day lag of 2 days (lag 2). The county-specific results were then combined in a meta-analysis using a random effects model in Stata (StataCorp 2003). The meta-analysis focused primarily on all-cause mortality and on cardiovascular, respiratory, and elderly (> 65 years of age) mortality, because these categories have been the focus of previous time-series studies (Health Effects Institute 2003).

We also conducted several sensitivity analyses. First, we examined these same four outcomes using a similar specification, but with a

Table 1. Descriptive statistics for air pollutants and mortality in nine California counties, 1999–2002.

County	2000 population[a]	Days with data for $PM_{2.5}$, temperature, and RH (*n*)	Mean daily $PM_{2.5}$ (μg/m^3)[b]	Mean daily temperature (°F)[b]	Mean daily RH (%)[b]	Mean daily all-cause mortality[b]
Contra Costa	949	698	14 (1–77)	60 (34–91)	64 (10–96)	16 (4–32)
Fresno	799	1,024	23 (1–160)	65 (35–94)	55 (18–96)	13 (3–28)
Kern	662	1,186	22 (1–155)	65 (36–95)	56 (13–100)	11 (2–25)
Los Angeles	9,519	1,221	21 (4–85)	64 (46–89)	57 (15–88)	146 (99–242)
Orange	2,846	682	21 (4–114)	63 (46–84)	67 (6–95)	40 (20–75)
Riverside	1,545	976	29 (2–120)	65 (43–90)	58 (6–100)	28 (9–63)
Sacramento	1,223	1,214	14 (1–108)	61 (36–91)	66 (13–100)	22 (7–45)
Santa Clara	1,683	717	15 (2–74)	59 (40–89)	69 (22–96)	22 (9–44)
San Diego	2,814	1,333	16 (0–66)	61 (43–84)	74 (16–100)	49 (26–87)

RH, relative humidity.
[a]In thousands. [b]Values in parentheses indicate minimum–maximum.

Table 2. Mean daily deaths by mortality category in nine California counties, 1999–2002.

Mortality category	Contra Costa	Fresno	Kern	Los Angeles	Orange	Riverside	Sacramento	Santa Clara	San Diego
Age > 65 years	12.2	10.0	8.1	108.6	31.4	22.2	16.1	16.5	38.7
Male	7.2	6.4	5.4	70.7	18.3	13.8	10.4	10.3	23.7
Female	8.4	6.8	5.6	75.6	21.5	14.2	11.3	11.4	25.5
White non-Hispanic	12.3	9.3	8.6	86.0	32.7	23.1	16.8	15.5	39.6
Black non-Hispanic	1.5	0.8	0.6	20.6	0.4	1.3	2.0	0.5	2.1
Hispanic	0.9	2.4	1.5	26.7	3.6	3.0	1.3	2.5	4.9
In-hospital death	6.4	6.2	5.6	79.8	17.4	11.5	9.7	9.9	18.6
Out-of-hospital death	9.2	7.0	5.4	66.5	22.3	16.5	12.1	11.7	30.6
High school graduate	12.3	7.9	6.6	99.0	30.8	20.4	15.9	15.9	37.6
Not high school graduate	3.1	5.1	4.1	40.7	8.2	6.8	5.3	5.4	10.2
Diabetes	0.4	0.5	0.3	5.1	1.1	0.6	0.6	0.6	1.2
Cardiovascular disease	6.5	5.7	4.9	67.0	17.7	13.0	9.2	9.1	20.4
Ischemic heart disease	3.3	3.2	3.1	42.6	10.8	8.0	5.3	4.8	11.4
Respiratory disease	1.7	1.5	1.4	15.0	4.3	3.2	2.6	2.4	5.7