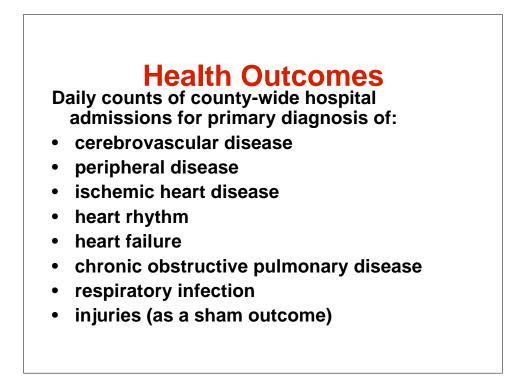
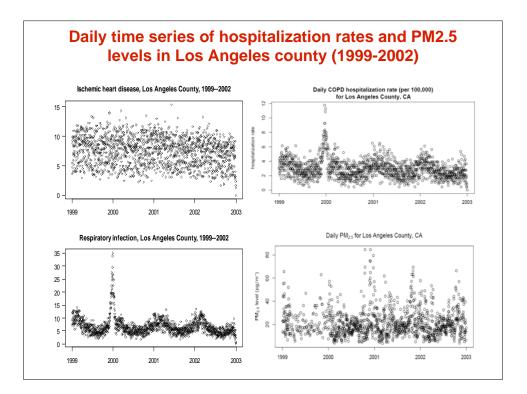
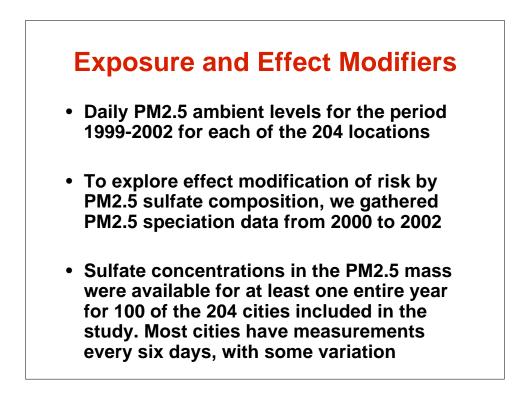


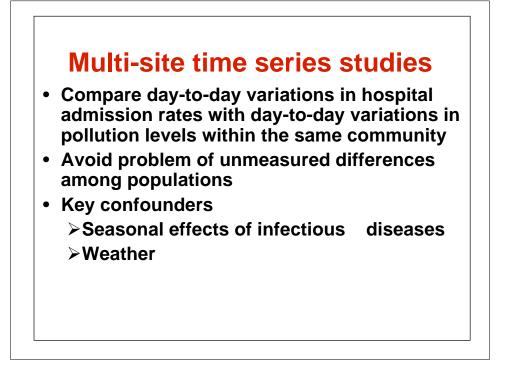
National Medicare Cohort (1999–2002)

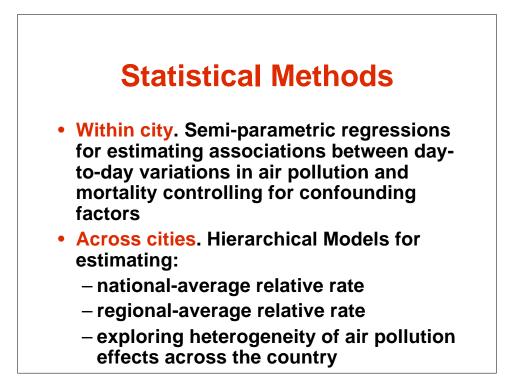
- National study of fine particles (PM_{2.5}) and hospital admissions in Medicare
- Data include:
 - Billing claims (NCHF) for everyone over 65 enrolled in Medicare (~48 million people),
 - date of service
 - treatment, disease (ICD 9), costs
 - age, gender, and race
 - place of residence (ZIP code/county)
 - Approximately 204 counties linked to the air pollution monitoring
 - Study population includes 11.5 million
 Medicare enrollees living on average 5.9 miles from a monitor.





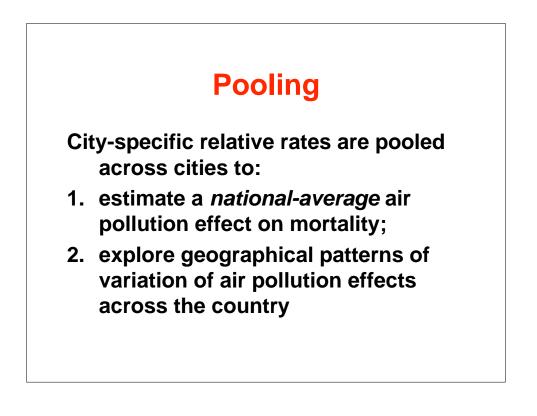


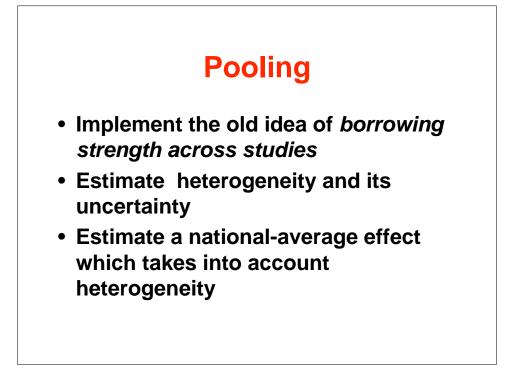


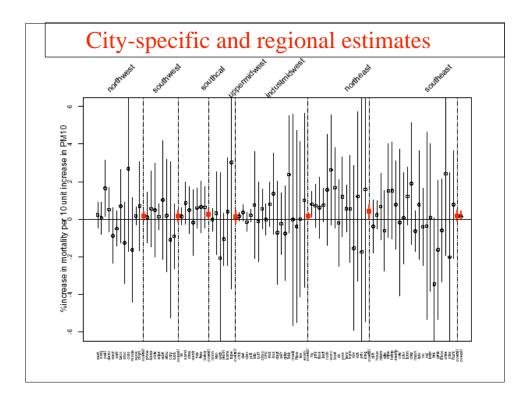


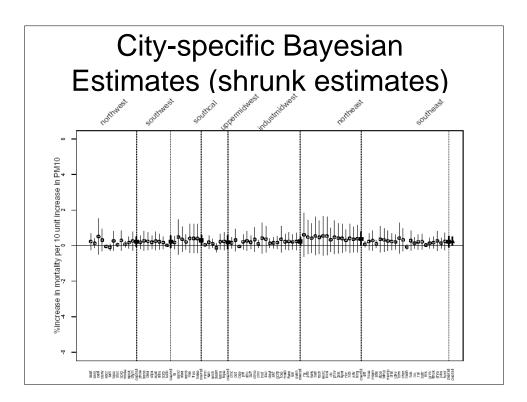
Pooling log-relative rates across counties

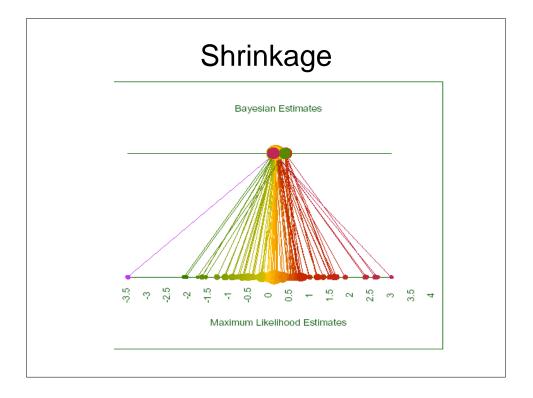
- To produce a national average relative rate we used Bayesian hierarchical models
- We combine relative rates across counties accounting for within-county statistical error and for between-county variability of the "true" relative rates (also called "heterogeneity")
- To produce regional estimates we used the same two-stage hierarchical model described above but separately within each of the seven regions.

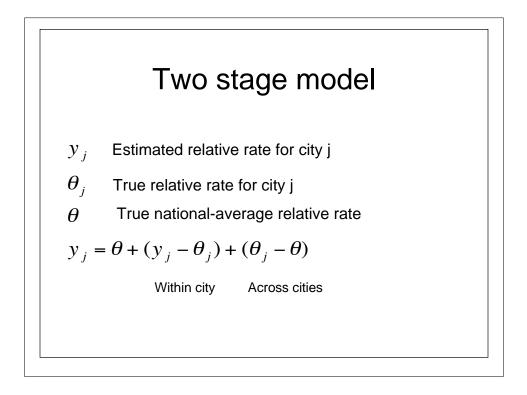


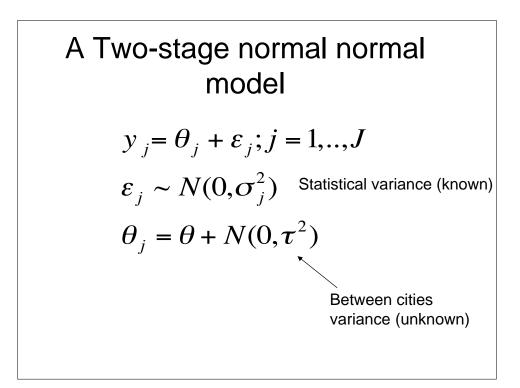


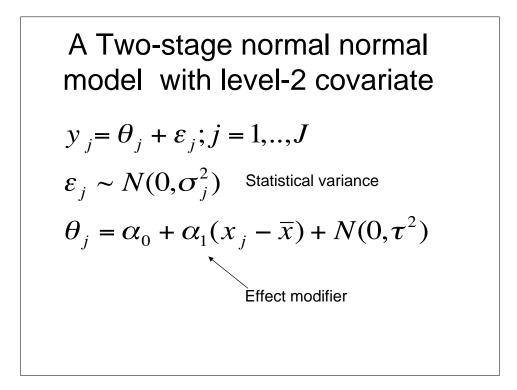


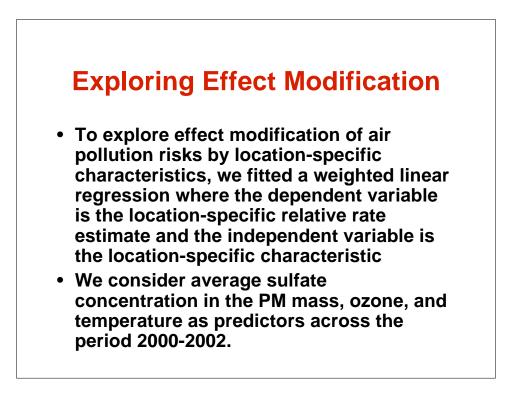






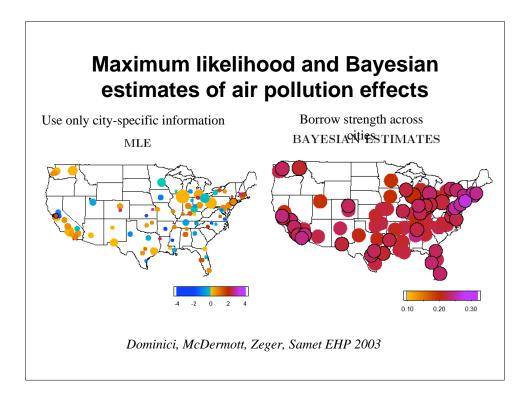


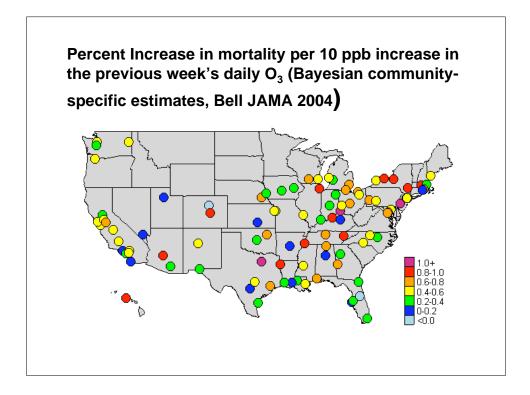


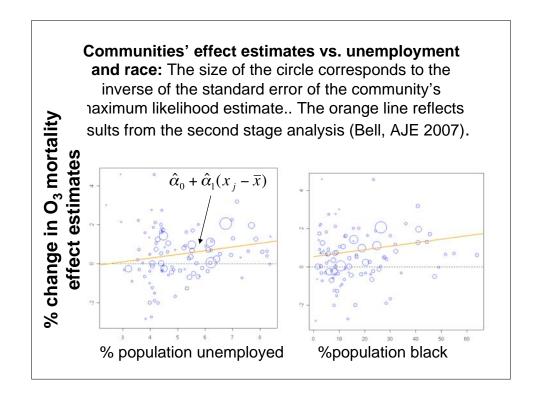


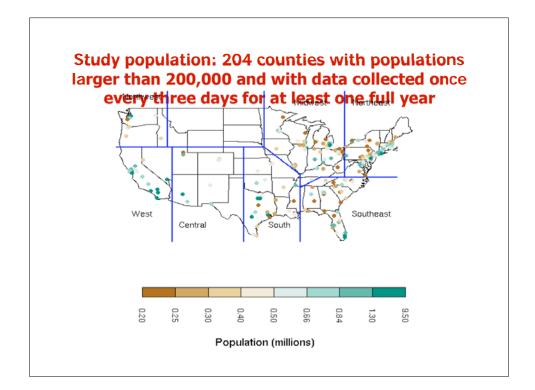
A two-stage normal normal model with
spatially correlated random effects
$$y_j = \theta_j + \varepsilon_j$$

 $i = 1, ..., n_j, j = 1, ..., J$
 $\varepsilon_j \sim N(0, \sigma_j^2)$
 $\theta_j = \theta + N(0, \tau^2)$
 $cor(\theta_j, \theta_k) = \exp(-\phi \times d(j, k))$
Cities that are closer to each other
will have more similar relative rates



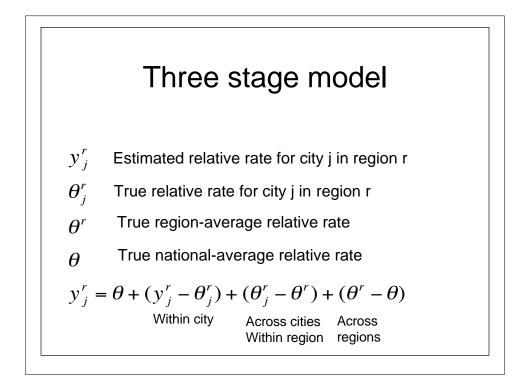


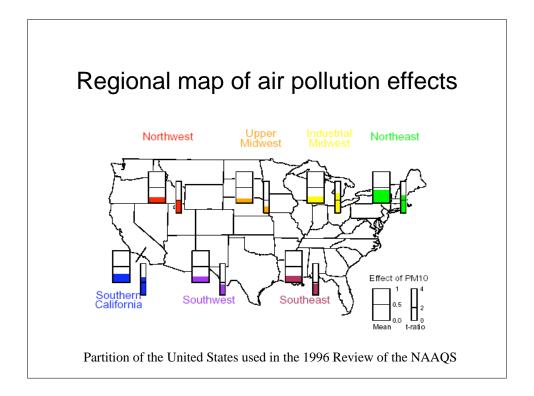


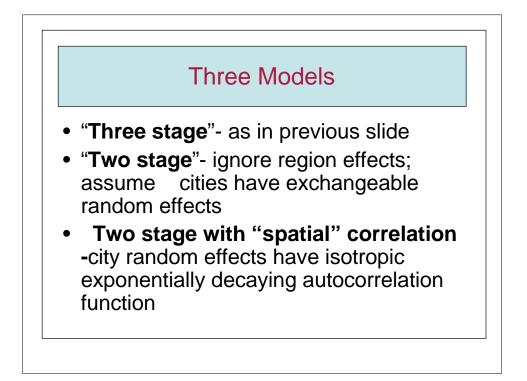


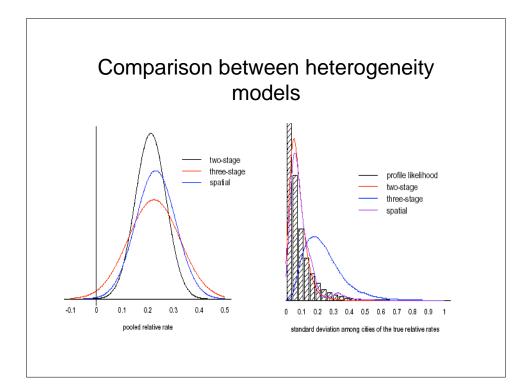
A three-stage normal normal model

$$\begin{array}{c} city \\ region \\ y_{j}^{r} = \theta_{j}^{r} + \varepsilon_{j}^{r}, j = 1, ..., J^{r}, r = 1, ..., R \\ \varepsilon_{j}^{r} \sim N(0, \sigma_{j}^{2}) \\ \theta_{j}^{r} = \theta^{r} + \xi_{j}^{r} \\ \xi_{j}^{r} \sim N(0, \tau_{1}^{2}) \\ \theta^{r} = \theta + \delta^{r} \\ \delta^{r} \sim N(0, \tau_{2}^{2}) \\ \end{array}$$
Variance across regions









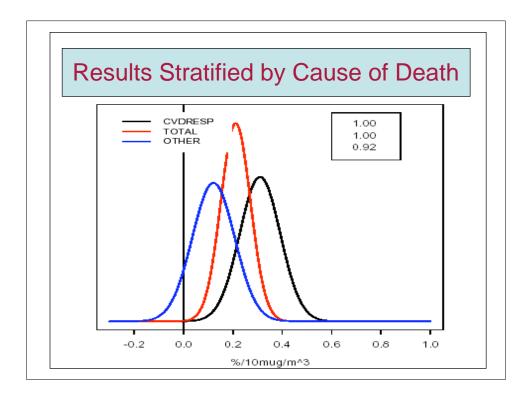
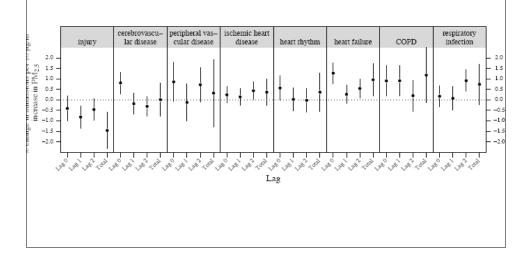
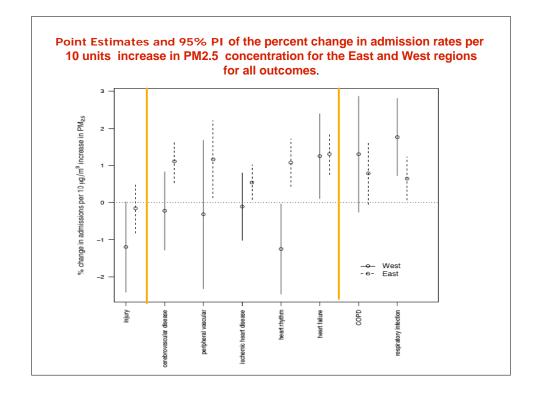


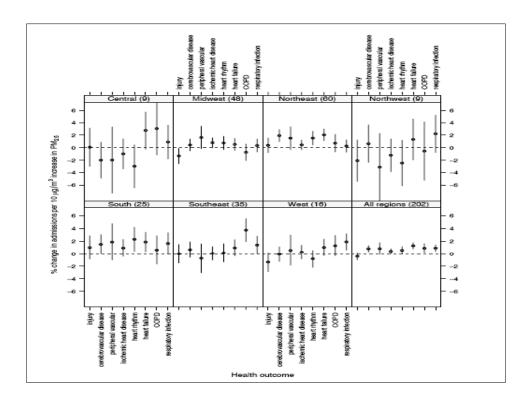
Table 1: Mean and interquartile range among counties of hospitalizationrates (number of cases per 100,000 people) for each outcome for theperiod 1999-2002

Variable	ICD-9	Mean (IQR)
Ischemic heart disease	410-414 and 429	8.3 (7.1,9.4)
Heart rhythm	426-427	3.8 (3.3,4.2)
Heart failure	428	5.7 (4.7,6.6)
Cerebrovascular disease	430-438	5.5 (4.8,6)
Peripheral vascular	440-448	1.7 (1.5,1.9)
Respiratory infection	464-466 and	5.5 (4.7,6.2)
	488-487	
COPD	490-492	2.6 (2.1,3.2)
Accident	800-849	4.2 (3.7,4.5)
$PM_{2.5}$ Levels (µg/m ³)		13.4(11.3,15.2)
Days with PM _{2.5}		817(434,1295)

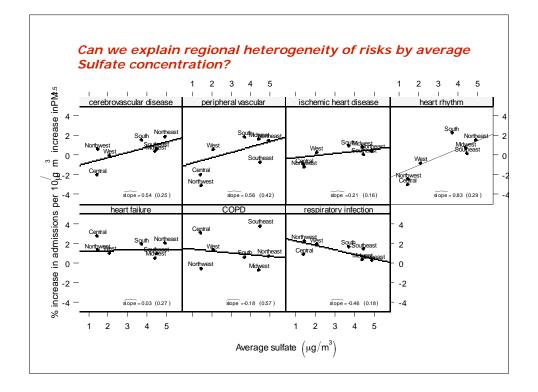
Point estimates and 95% posterior intervals (PI) of the percent change in admission rates per 10 units increase in PM2.5 concentration on average across the 204 counties (national average relative rates) for single lag (lags 0,1, and 2 days) and distributed lag models for to 2 days (Total) for all outcomes.

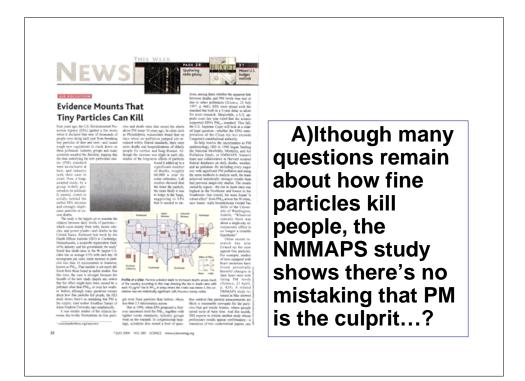






	od 2000-2002 for each geographic counties (100 total) within each reg	
centrations measure	, , , ,	
Region	Fine Sulfate (μ g / m^{-3})	#
	(IQR)	counties
East	4.49 (3.74 – 5.17)	82
South	3.70 (3.50 – 4.99)	12
Southeast	4.48 (3.96 - 4.99)	18
Northeast	4.92 (4.14 - 5.76)	27
Midwest	4.40 (3.70 – 5.18)	25
West	1.79 (1.34 – 1.72)	18
Central	1.42 (1.34 – 1.58)	6
West	2.08 (1.32 – 2.86)	10
Northwest	1.45 (1.42 - 1.49)	2





Results: National Averages

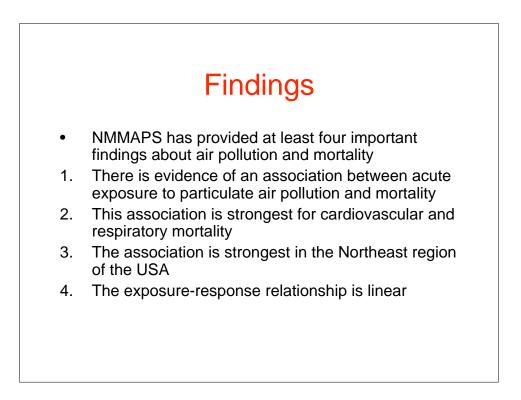
- We found evidence of a positive association between dayto-day variation in concentration and hospital admissions for all outcomes, except injuries, for at least one exposure lag
 - The largest effect was found at lag 0 for most of the cardiovascular outcomes
 - For respiratory outcomes, we found that the largest effects occurred at lags 0 and 1 for COPD and at lag 2 for respiratory infections
- We did not find any positive association for injuries or for other external causes or when using lag -1 as the exposure indicator
- The main results were robust to the number of degrees of freedom used to adjust for temporal confounding and to the adjustment for weather

Results: regional heterogeneity

- For the two groups of outcomes (cardiovascular and respiratory), the estimated relative rates have very distinct regional patterns
- For cardiovascular diseases, all estimates in the East US were positive while estimates in the West US were close to zero
- For respiratory diseases, we found positive effects in all US with slightly larger effects in the West US

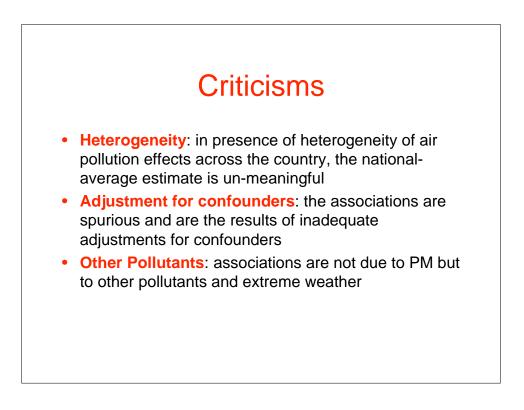
Results: effect modification

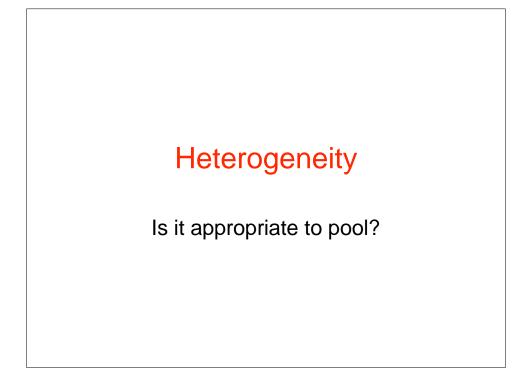
• Sulfate: We found evidence of effect modification of the relative rates by average sulfate concentration with positive slopes for the cardiovascular outcomes (except heart failure) and negative slopes for the two respiratory outcomes.

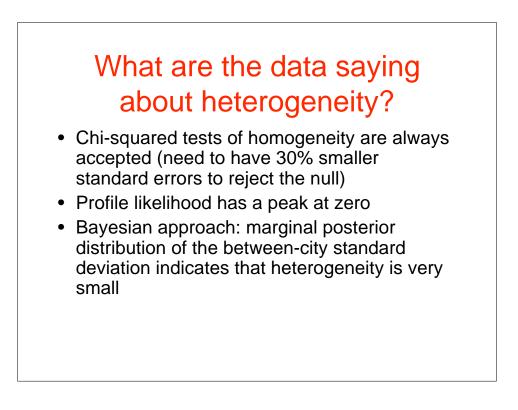


A Big Challenge

- Doing research in a controversial political context can lead to a process which can be highly non scientific
- Expect to face consultants who use "quasi-scientific" arguments that create confusion about findings







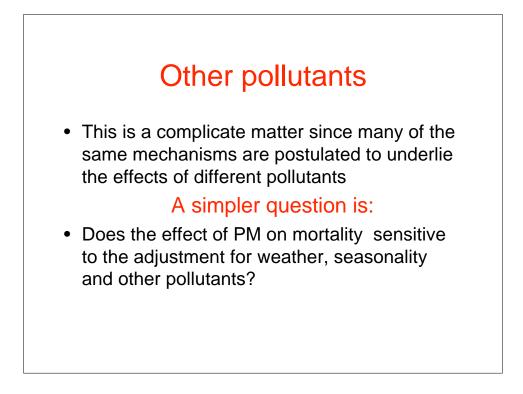
Why do a joint analysis of all the cities?

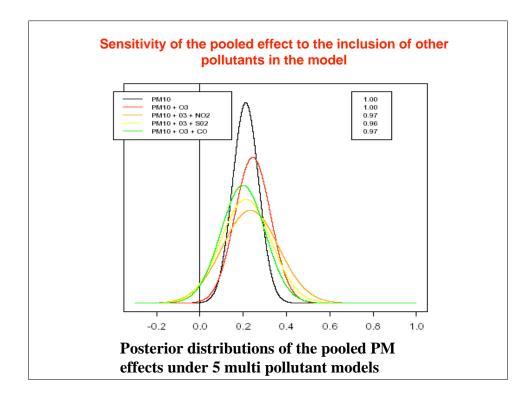
- Individual cities can be selected to show one point or another
- Results from individual cities are swamped by statistical error
- There is no reason to expect that two neighboring cities with similar sources of particles would have qualitative different relative risks

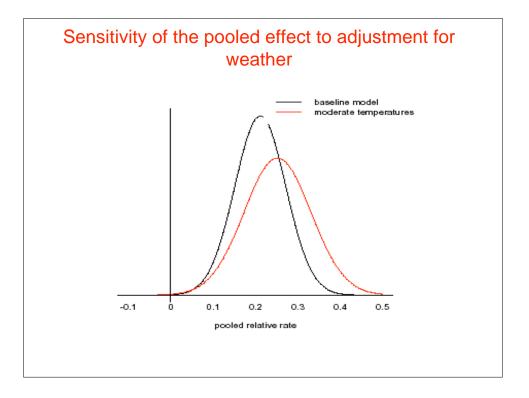
What are the public policy implications?

- A national estimate of the air pollution effect provides evidence on the amount of hazard from exposure to air pollution
- EPA needs a single number for the entire country









Findings

- Pooled estimates of the PM effects on mortality are robust to:
- Adjustment for confounding factors
- Inclusion of other pollutant in the models
- Exclusion of days with more extreme temperatures

