Int. J. Epidemiol. Advance Access published July 20, 2007

Published by Oxford University Press on behalf of the International Epidemiological Association

International Journal of Epidemiology 2007;1–3
doi:10.1093/ije/dym143

Commentary: Linking particulate matter and sulphur concentrations to air pollution annoyance: problems of measurement, scale and control

Samuel D Brody[1]* and Sammy Zahran[2]

Accepted 2 April 2007

Jacquemin *et al*. address an important topic in the field of epidemiology and public health by increasing understanding of the triggers of air pollution annoyance across 25 population centres in 14 countries in Europe. No study, however commendable, is without its limitations and this one is no exception. We offer a commentary of their article 'Annoyance Due to Air Pollution in Europe' as a means to enhance future study of air pollution perceptions. Our assessment focuses on three elements of their research: (i) measurement of the dependent variable, air pollution annoyance; (ii) problems associated with the spatial scale used to estimate air pollution exposure and (iii) the exclusion of statistical controls routinely used in the risk perception literature.

Measuring air pollution annoyance

A potential problem with the measurement of the dependent variable is the restriction of the question of air pollution annoyance to the specific condition of keeping a window open. By this restriction, Jacquemin *et al*. are measuring how annoyed or disturbed a person is by outdoor air pollution when indoors. Not surprisingly, under this unusually specific condition, 43% of respondents score their level of outdoor air pollution annoyance at zero.

Jacquemin *et al*. also report that respondents from Northern European cities have substantially lower levels of air pollution annoyance. This variance in air pollution annoyance by city is partially explained by data on fine particulate matter ($PM_{2.5}$) and sulphur (S) concentrations. For example, Figure 4a in their manuscript illustrates the relationship between mean air pollution annoyance scores and $PM_{2.5}$ and S levels for each city. For every unit increase (μg/m^3) in $PM_{2.5}$ and S, we observe a modest increase in mean annoyance scores. Adjusted R^2 values in 'crude' models are 0.23 for $PM_{2.5}$ and 0.36 for S.

Testing relationships between objective measures of air pollution and subjective reports of annoyance is perfectly reasonable. However, the construction of the question to derive annoyance scores may contaminate this effort. Recall, respondents are asked to indicate their level of annoyance with outdoor air pollution when indoors. Observed responses in air pollution annoyance may be driven by restrictions of the question. Indirectly, the question may be measuring how frequently an individual selected at random opens his/her window to the outside world.

We illustrate our point with data. First, we presume that the likelihood a person opens his/her window to the outside world is partially determined by the average temperature of the city in which he/she resides. All things held equal, we also presume that persons in colder climes such as Northern Europe are less likely to open their windows. To illustrate how the open window restriction may contaminate the measurement of outdoor air pollution annoyance, we collected average temperature data in the months of January and July (in degrees Celsius) for all 25 cities for 2001. Following Jacquemin *et al*., we generate two 'crude' scatter plots (Figure 1), with mean annoyance scores on the vertical axis and average temperature measures on horizontal axis. Like Jacquemin *et al*., we also derive an adjusted R^2 for both linear models.

The results show that air pollution annoyance scores (as estimated by the question) increase as average temperature increases. The variance explained in mean annoyance scores by average temperature in July performs considerably better than the air pollution measures assembled by Jacquemin *et al*. Next, we perform regression tests (excluding the three Italian outlier cities of Pavia, Verona and Turin, as done by Jacquemin *et al*.) to see how well air pollution measures of $PM_{2.5}$ and S hold up with the inclusion of temperature data. Results show that both estimates of air pollution disappear with the inclusion of a measure of average temperature in July (Table 1).

[1] Environmental Planning & Sustainability Research Unit, Hazard Reduction and Recovery Center, Department of Landscape Architecture and Urban Planning, Texas A&M University, TAMU 3137, College Station, TX 77843-3137, USA.

[2] Department of Sociology, Colorado State University, B235 Clark Building, Fort Collins, CO 80523-1784, USA.

* Corresponding author. Environmental Planning & Sustainability Research Unit, Hazard Reduction and Recovery Center, Department of Landscape Architecture and Urban Planning, Texas A&M University, TAMU 3137, College Station, TX 77843–3137, USA. E-mail: sbrody@archmail.tamu.edu

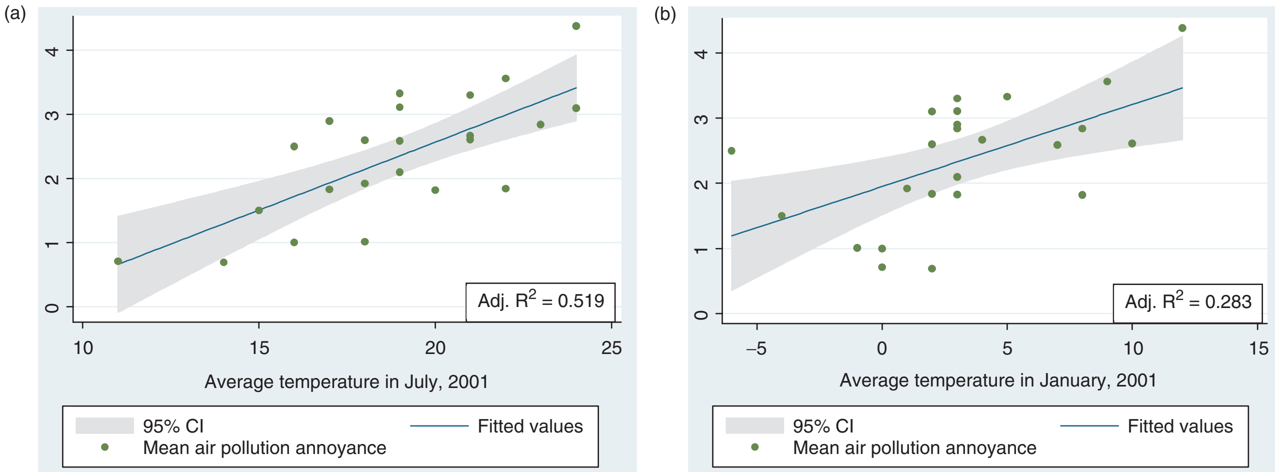

Figure 1 Scatter plots of mean air pollution annoyance scores against mean temperature in July and January, 2001

Table 1 OLS regression models for mean air pollution annoyance

Variables	b	95% CI	b	95% CI
Constant	−1.728* (0.879)	−3.613 to 0.157	−1.543 (0.994)	−3.674 to 0.588
Average July temperature	0.172** (0.062)	0.040 to 0.304	0.178** (0.076)	0.016 to 0.341
$PM_{2.5}$	0.065 (0.042)	−0.025 to 0.155	–	–
Sulphur	–	–	0.652 (0.668)	−0.780 to 2.084
F	14.23		12.33	
Prob >*F*	0.0004		0.0008	
Adjusted R^2	0.6231		0.5862	

Note: Cell entries are unstandardized OLS regression coefficients, with SEs in parentheses. Null hypothesis test of coefficient equal zero, $^{**}P < 0.05$, $^{*}P < 0.10$.

The purpose of bringing in temperature data is not to nullify the reasonable logic of the manuscript written by Jacquemin *et al*. In fact, we advocate the approach of linking objective measures of air pollution and subjective reports of annoyance, and commend the authors for undertaking such an extensive data collection effort. Our comments address the scientific adequacy of the phrasing of the question of annoyance, and how it may be estimating concepts other than the intended empirical target. To their credit, negative binomial regression results show that all symptoms of respiratory illness, from asthma to wheezing, are significantly associated with the air pollution annoyance. This fact gives their measure significant criteria validity.

Other issues arise from the inadequate phrasing of the annoyance question. With the distribution of air pollution annoyance skewed left, Jacquemin *et al*. decide on a cut-point of 'high annoyance' inconsistent with convention. A respondent is classified as highly annoyed if they score a 6 or more (or a 5 or more as reported in the summary section of the manuscript) on the disturbance scale. The Swiss SAPALDIA and EXPOLIS studies (including Finland, Greece and Czech Republic), appropriately cited in the manuscript, define high annoyance at 8 and 7 or more respectively. Jacquemin *et al*. provide no adequate theoretical or empirical justification for lowering this benchmark.

Overall, these limitations associated with measurement of outdoor air pollution annoyance weaken (but do not theoretically nullify) their conclusion that 'Annoyance due to air pollution is frequent in Europe'.

Measuring air pollution and the problem of scale

The next set of potential problems with the research design relate to measurement of air pollution at the city scale. Agencies of environmental protection in most highly developed countries measure and track six common air pollutants—particulate matter, ground-level ozone, carbon monoxide, sulphur oxides, nitrogen oxides and lead. Jacquemin *et al*. restrict their analysis of pollutants to annual mean mass concentrations of fine particles ($PM_{2.5}$) and sulphur (S) content. They justify the use of $PM_{2.5}$ and S on the basis that concentrations of these pollutants reflect the air quality for a region such as a city. However, studies show that sulphur dioxide concentrations vary spatially, high concentration signatures generally found directly over large industrial activities.[1–3] Thus, proximity to such activities may increase reported levels of annoyance.

Furthermore, the study estimates air pollution based on 'monitoring sites' but the nature of these sites are never fully discussed in the Methods section. The specific locations of these sites should have been disclosed as they may affect the degree to which a respondent feel annoyed. How readings from multiple monitoring sites were aggregated (if at all) should have also been discussed in the Methods section. The location of monitoring stations in relation to the population being studied may condition the relationship between annoyance and recorded air pollution levels. Finally, using air pollution monitoring stations to estimate regional air quality, researchers often interpolate a surface to generate a distance decay function for air quality (rather than assigning every respondent the same reading regardless of their proximity to a station). This issue is never discussed in the article and it is not clear how sulphur dioxide was measured and the role the variable played in the results.

Finally, Jacquemin *et al*. examine perceptions of individuals living in cities within various countries. Since most air pollution perceptions studies have been conducted at finer spatial scales, a major methodological issue here could be the modifiable areal unit problem (MAUP). This problem occurs if relations between variables change with the selection of different areal units, causing the reliability of results to be called into question.[4] In other words, the results may depend on the spatial scale at which respondents are examined. The MAUP is most prominent in the analysis of socio-economic and epidemiological data given the need to summarize these data in an often time arbitrary zonal format.[5] Because this statistical issue is so prominent in the field of epidemiology, the authors should have at minimum discussed the potential problem as it has significant implications for interpreting the results.

Measuring independent variables

In this section we assess the right side of the air pollution annoyance equation. Specifically, we discuss three propositions in risk perception research that are not specifically addressed in Jacquemin *et al*. First, the *peak-end rule* in psychometric research suggests that people have a tendency to recall events by their highest point of intensity or how they end.[6] That is, human memory is biased toward extremes not summations or central tendencies. Insofar as the peak-end rule is correct, future research may better predict air pollution annoyance with measures of *peak* air pollution, not annual mean estimates of fine particulate matter and sulphur concentrations as done by Jacquemin *et al*. Likewise, one can reasonably expect higher levels of air pollution annoyance among respondents exposed to visibly higher levels of pollution the day they are interviewed. In our own research, we find that perceptions of air pollution risk in Texas are better predicted by the number extreme air quality index (AQI) days (or days over the 'unhealthy day' threshold) than by annual average AQI scores.[7]

The second cognitive rule in psychometric research applicable to Jacquemin *et al*. is the reference bias or framing effect.[8,9] This concept of referencing is central to prospect theory in risk analysis. The main proposition of prospect theory is that people evaluate a risk outcome relative to a reference point, not a final status. Researchers find that people care less about gains or outcomes above a reference point than losses or outcomes below a reference point. In other words, people are loss averse. Jacquemin *et al*. hypothesize that annoyance scores in City X > City Y if, City X $PM_{2.5}$ > City Y $PM_{2.5}$. A reformulation of Jacquemin *et al*. accounting for reference bias is that annoyance scores in City X > City Y if, City X value of time 2 $PM_{2.5}$ − time 1 $PM_{2.5}$ > City Y value of time 2 $PM_{2.5}$ − time 1 $PM_{2.5}$. That is, if residents in City X experience a noticeable decline in air quality from some known reference point, they are more likely to report higher levels of air pollution annoyance than residents in City Y (assuming residents in City Y experience no detectable change in air quality from some known reference point), even if persons in City Y reside in objectively worse air quality conditions. Of course, there are obvious limits to the proposition, but Jacquemin *et al*. have data for two time points in the European Community Respiratory Health Survey that would enable an adequate test of loss aversion in air pollution annoyance scores.

The third proposition in risk perception literature is the notion that affective and cognitive psychologies influence self-reports of risk, annoyance, concern and related notions. Scholars routinely estimate concepts like worldview, political philosophy, institutional trust, knowledge and environmental beliefs to predict public perceptions of environmental risk.[10–15] These variables are correlated with, but are not perfectly reducible to the many demographic variables examined by Jacquemin *et al*.

References

1. Tayanc M. An assessment of spatial and temporal variation of sulfur dioxide levels over Istanbul, Turkey. *Environ Pollut* 2000;**107:**61–69.
2. Chaulya SK. Spatial and temporal variations of SPM, RPM, SO2 and NOx concentrations in an opencast coal mining area. *J Environ Monit* 2004;**6:**134–42.
3. Martuzeviciusa D, Grinshpuna SA, Reponena T *et al*. Spatial and temporal variations of PM2.5 concentration and composition throughout an urban area with high freeway density—the Greater Cincinnati study. *Atmos Environ* 2004;**38:**1091–105.
4. Unwin DJ. GIS, spatial analysis and spatial statistics. *Prog Hum Geogr* 1996;**20:**540–51.
5. Nakaya T. An information statistical approach to the modifiable areal unit problem in incidence rate maps. *Environ Plan A* 2000;**32:**91–109.
6. Tversky A, Kahneman D. Judgment under uncertainty: heuristics and biases. *Science* 1974;**185:**1124–30.
7. Lubell M, Vedlitz A, Zahran S, Alston L. Collective action, environmental activism, and air quality policy. *Polit Res Q* 2006;**59:**149–60.
8. Samuelson W, Zeckhauser RJ. Status quo bias in decision making. *J Risk Uncertain* 1988;**1:**7–59.
9. Tversky A, Kahneman D. Advances in prospect theory: cumulative representation of uncertainty. *J Risk Uncertain* 1992;**5:**297–323.
10. Dietz T, Stern PC, Guagnano GA. Social structural and social psychological bases of environmental concern. *Environ Behav* 1998;**30:**450–71.
11. Freudenberg WR. Perceived risk, real risk. *Science* 1988;**242:**44–49.
12. Stern PC. Toward a coherent theory of environmentally significant behavior. *J Soc Issues* 2000;**56:**407–24.
13. Brody SD, Peck M, Highfield W. Examining localized patterns of air quality perceptions in Texas: a spatial and statistical analysis. *Risk Analysis* 2004;**24:**1561–74.
14. Johnson EJ, Tversky A. Affect, generalization, and the perception of risk. *J Pers Soc Psychol* 1983;**45:**20–31.
15. O'Connor RE, Bord RJ, Fisher A. Risk perceptions, general environmental beliefs, and willingness to address climate change. *Risk Anal* 1999;**19:**461–71.