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*Published in:*  
Environmental Health Perspectives

*DOI:*  
[10.1289/ehp.1104100](https://doi.org/10.1289/ehp.1104100)

*Publication date:*  
2012

*Document version*  
Publisher's PDF, also known as Version of record

*Document license:*  
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*Citation for published version (APA):*  
Lim, Y-H., Kim, H., Kim, J. H., Bae, S., Park, H. Y., & Hong, Y-C. (2012). Air pollution and symptoms of depression in elderly adults. *Environmental Health Perspectives*, 120(7), 1023-1028.  
<https://doi.org/10.1289/ehp.1104100>

# Air Pollution and Symptoms of Depression in Elderly Adults

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**BACKGROUND:** Although the effect of air pollution on various diseases has been extensively investigated, few studies have examined its effect on depression.

**OBJECTIVES:** We investigated the effect of air pollution on symptoms of depression in an elderly population.

**METHODS:** We enrolled 537 participants in the study who regularly visited a community center for the elderly located in Seoul, Korea. The Korean version of the Geriatric Depression Scale-Short Form (SGDS-K) was used to evaluate depressive symptomatology during a 3-year follow-up study. We associated ambient air pollutants with SGDS-K results using generalized estimating equations (GEE). We also conducted a factor analysis with items on the SGDS-K to determine which symptoms were associated with air pollution.

**RESULTS:** SGDS-K scores were positively associated with interquartile range (IQR) increases in the 3-day moving average concentration of particulate matter with an aerodynamic diameter  $\leq 10 \mu\text{m}$  (PM<sub>10</sub>) [17.0% increase in SGDS-K score, 95% confidence interval (CI): 4.9%, 30.5%], the 0–7 day moving average of nitrogen dioxide [NO<sub>2</sub>; 32.8% (95% CI: 12.6%, 56.6%)], and the 3-day moving average of ozone [O<sub>3</sub>; 43.7% (95% CI: 11.5%, 85.2%)]. For these three pollutants, factor analysis showed that air pollution was more strongly associated with emotional symptoms such as feeling happy and satisfied than with somatic or affective symptoms.

**CONCLUSIONS:** Our study suggests that increases in PM<sub>10</sub>, NO<sub>2</sub>, and O<sub>3</sub> may increase depressive symptoms among the elderly. Of the symptoms evaluated, ambient air pollution was most strongly associated with emotional symptoms.

**KEY WORDS:** air pollution, depressive symptoms, elderly, factor analysis, panel study. *Environ Health Perspect* 120:1023–1028 (2012). <http://dx.doi.org/10.1289/ehp.1104100> [Online 18 April 2012]

Depression is one of the common mental health problems experienced by the elderly and has been found to lead to increased mortality and suicide in this age group (Blazer et al. 2001; Waern et al. 2003). Known risk factors for depression among the elderly are alcohol and substance abuse, sleep disturbance, bereavement, medical conditions, family history, and being female (Cole and Dendukuri 2003; Mulsant and Ganguli 1999). Hypotension and a low lipid level also have been found to be associated with depressive symptoms among the elderly and women, respectively (Horsten et al. 1997; Kim et al. 2010).

Plausible biological mechanisms of depression include reactivity to exogenous stressors; alterations of neurohumoral, immune, and autonomic regulation; dysfunction of neurotransmitter systems; and oxidative stress (Grippe 2009; Ng et al. 2008). Because depletion of dopamine in the central nervous system (CNS) is known to be an underlying pathophysiological mechanism of depression (Hasler 2010), air pollution could affect depressive moods by inducing dopaminergic neurotoxicity, possibly due to oxidative stress (Block et al. 2004). Research with cell cultures and experimental animals has provided evidence of neuropathological effects of exposure to particles (Block et al. 2004; Campbell et al. 2005; Veronesi et al. 2005). However, only

a few studies have evaluated the association between air pollution and depressive symptoms in humans. In Canada, researchers reported short-term effects of air pollution on emergency department visits because of depression and suicide attempts (Szyszkowicz 2007a; Szyszkowicz et al. 2009b, 2010). Their time-series analyses focused on the diagnosis of depression resulting from severe pathophysiological alterations in the CNS, and their results suggest that air pollution may have aggravated symptoms of depression among a pool of patients in the community who were suffering from depression. However, Bullinger (1989) has proposed that short-term exposure to air pollution more likely affects daily mood rather than causes major depressive illnesses. Although studies have found that major (Valvanne et al. 1996) or minor (Lyness et al. 2006) depression is common among the elderly, who may also be most susceptible to adverse health effects of air pollution (Pope 2000), no studies have examined changes in depressive symptoms associated with short-term exposure to air pollution among the elderly.

Our study was based on an *a priori* hypothesis that air pollution may affect depressive symptoms, because air pollution is known to induce oxidative stress, a potential cause of depression. Hence, we examined the effect of air pollution on symptoms of depression among the elderly in Seoul, Korea, from 2008

to 2010, by evaluating depressive symptom test scores, as well as individual symptoms that contributed to the overall score.

## Materials and Methods

**Population.** This study evaluated data from 560 participants who regularly visited a community welfare center for the elderly located in Seongbuk-Gu. This region is one of 25 districts in Seoul, Korea, located in the northern midsection of the city where approximately 460,000 residents reside in an area approximately 25 km<sup>2</sup>.

We performed the first follow-up of this 3-year study from August 2008 to December 2008, the second from April to October 2009, and the third from March to August 2010. We excluded persons diagnosed with dementia or Alzheimer's disease ( $n = 23$ ) because of concerns regarding compliance and reliability. During the 3-year follow-up period, 166 participants visited the welfare center only once, 184 visited twice, and 187 visited three times. Baseline questionnaires were administered by interviewers and were used to record demographic and behavioral characteristics, a self-reported history of physician-diagnosed chronic diseases, at least 1-year of medication use for the reported chronic diseases, and dietary intake of selected items, such as meat, fish, and vegetables. At each visit, participants underwent a physical examination and answered questions on the depression symptom questionnaire. Weight

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Supplemental Material is available online (<http://dx.doi.org/10.1289/ehp.1104100>).

We thank K.-M. Kim, G.-H. Cho, and Y.-M. Choi for interviewing the study participants and for preparing the data for analysis.

Y.-C.H. received support from the Susceptible Population Research Program (2008–2010) of the Ministry of Environment. H.K. and Y.-H.L. were partially supported by the Basic Science Research Program (grant 2010-0009581) and the Global Research Laboratory (grant K2100400001-10A0500-00710) through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science, and Technology.

The authors declare they have no actual or potential competing financial interests.

Received 20 June 2011; accepted 18 April 2012.

and height were measured, and body mass index (BMI) was calculated (kilograms per meter squared). Mean systolic blood pressure (SBP; millimeter of mercury) and diastolic blood pressure (DBP; millimeter of mercury) were calculated from two measurements taken at intervals of  $\leq 5$  min. Fasting blood and urine samples were drawn between 0900 and 1200 hours on the same day. We obtained written informed consent from all participants, and the institutional review board of Seoul National University Hospital reviewed and approved the study protocol.

**Measure of depressive symptoms.** To evaluate depressive symptoms during the previous 1 week, trained staff conducted face-to-face interviews using the Korean version of the Geriatric Depression Scale-Short Form (SGDS-K) (Bae and Cho 2004). The SGDS-K consists of 15 items (5 positive and 10 negative feelings for the previous week) each coded as either negative (1) or positive (0), with total scores ranging from 0 to 15. We inverted responses to questions about positive feelings so that higher summed scores would indicate greater depression severity. To assess the reliability of the SGDS-K responses, we conducted a test-retest comparison among 30 randomly selected participants who completed two study visits 1 week apart (the first interview was conducted from 8 March to 10 March 2011 and the second from 15 March to 17 March 2011).

**Environmental variables.** We obtained air pollution data from the Research Institute of Public Health and Environment [Ministry of Environment (MOE) 2009, 2010, 2011]. For Seongbuk-Gu residents (90% of the study population), one monitor, which was centrally located in Seongbuk-Gu, was used as a proxy for individual exposure to ambient pollutants. For other residents, the nearest monitoring site to their residential address was used as a measure of air pollution concentrations.

Particulate matter with an aerodynamic diameter  $\leq 10 \mu\text{m}$  ( $\text{PM}_{10}$ ) was measured based on the radiometric principle of beta attenuation (Sensor FH62C14; Thermo Fisher Scientific Inc., Franklin, MA, USA). Carbon monoxide (CO) was measured using an infrared sensor (EC9830B CO Gas Analyzer; ECOTECH, Victoria, Australia), sulfur dioxide ( $\text{SO}_2$ ) by a fluorescent method (EC9850B  $\text{SO}_2$  Gas Analyzer; ECOTECH), nitrogen dioxide ( $\text{NO}_2$ ) by a chemiluminescent method (EC9841B  $\text{NO}_2$  analyzer; ECOTECH), and ozone ( $\text{O}_3$ ) by a ultraviolet photometric method (EC9810B; ECOTECH). All monitors were located on the rooftops of municipal buildings, and measurements were made every 5 min. For each site, we computed daily mean values of  $\text{PM}_{10}$ ,  $\text{SO}_2$ , and  $\text{NO}_2$ , and daily maximum values of CO and  $\text{O}_3$  between 0900 and 1800 hours. Vehicle emissions are responsible for a substantial share of air pollution

concentrations in this area, as in other areas in Seoul (Kim and Guldman 2011). We also collected temperature and rainfall values from the Korea Meteorological Administration (2012) to adjust for these environmental confounders in the model (Keatinge and Donaldson 2001).

**Statistical analysis.** We performed multivariate analysis using generalized estimating equations (GEE) to estimate the effects of air pollution on depression. The multivariate analysis also accounted for the correlated structure of the data due to repeated measures over time. We modeled scores of SGDS-K as a Poisson distribution that assumed compound symmetry and that each item of symptomatology was a binomial distribution. We expressed estimated effects of an interquartile increase in the concentration of each individual air pollutant as the percent change in total SGDS-K scores and as odds ratios (ORs) for negative responses for individual symptom items. In all models, we included factors that we hypothesized *a priori* could potentially confound the relationship between air pollution and depression. Time-independent factors measured at baseline included age (years), sex (male or female), number of years of school ( $<$  or  $\geq 6$  years), BMI, alcohol consumption at least once a month for 10 years or longer (yes or no), and moderate physical activity at least once a week (yes or no). Time-varying factors included creatinine-adjusted urinary cotinine level as a proxy of exposure to either passive or active smoking, mean temperature and rainfall level (0 = no rain, 1 = below mean, 2 = above mean level of daily total rain) on the day of each visit, visit number (1st, 2nd, or 3rd visit), and day of the week (Monday through Sunday). We also controlled for serum triglyceride (milligrams per deciliter) and SBP measured at each visit, which have been previously associated with depressive symptoms (Horsten et al. 1997; Kim et al. 2010).

We estimated delayed effects of air pollution on depressive symptoms using the following moving average lag structures: 0 day (pollutants measured on the day of the study visit), 0–2 days (the same day and the previous 2 days), 0–5 days, 0–7 days, 0–14 days, 0–21 days, and 0–28 days. When reporting the results, we focused on the lag structure that provided the best fit to the data based on the quasi-likelihood information criterion (QIC) (Pan 2001). Alpha level was set at 95%, and statistical significance was  $p < 0.05$ .

To investigate whether a history of cardiovascular disease (CVD) may modify associations between air pollutants and symptoms of depression, we stratified participants into two categories (yes or no) based on any CVD-related history, including hypertension, myocardial infarction (MI), hyperlipidemia, or stroke and examined effect modification by

each individual CVD except stroke, which was reported by only 2% of our study population.

We estimated the effects of air pollution on each depressive symptomatology item as a dichotomous outcome using the lag structure that best fit the lowest QIC value, as previously described, in a GEE model with a binomial distribution adjusted for confounders. In addition, we performed a factor analysis of principal components with varimax rotation for the 15 items of SGDS-K to determine which items appeared to contribute to a common factor. For each factor, we generated composite scores calculated as the loading value–weighted sum of binary scores (0 or 1) of each individual item that contributed to the factor. We expressed estimated effects of an interquartile increase in the concentration of each individual air pollutant as the percent change in composite scores.

Numbers of repeated measures (study visits) varied among participants, which may lead to selection bias if numbers of visits are not random (Rubin 1976). Analysis was conducted after weighting follow-up observations by the inverse probability of attaining a follow-up response (Robins et al. 1995). For participants with more than one visit, we conducted logistic regression to predict the probability of follow-up (follow-up = 1, missing = 0) with covariates of the previous measurements including age, sex, BMI, number of years of school, blood pressure, season, and temperature. We gave a weight of 1 to the first observation for each participant and more weight (the inverse of predicted probability of having a follow-up response) to the observations that were more likely missing (McCracken et al. 2010).

For the sensitivity analysis, we constructed single- and two-pollutant models based on five pollutants— $\text{PM}_{10}$ ,  $\text{NO}_2$ ,  $\text{O}_3$ , CO, and  $\text{SO}_2$ —and observed any attenuation of a single-pollutant effect by adjusting for another pollutant in the model.

## Results

Among the 537 participants at the first (baseline) study visit, the average age was 71 years, BMI was  $25 \text{ kg/m}^2$ , and creatinine-adjusted urine cotinine as a proxy of exposure to either passive or active smoking was  $255 \text{ mg/g}$  (Table 1). The percentage of female participants was 74%. The proportion of individuals who reported regular alcohol consumption at least once a month for  $\geq 10$  years was 23%, and 63% of participants reported moderate exercise at least once a week. Hypertension was the most common preexisting disease (51%) followed by diabetes (18%) (Table 1).

The average SGDS-K score out of a possible 15 was 3.6 at the first visit, 2.4 at the second visit, and 1.1 at the third visit (Table 2). The proportion of participants who responded negatively to each SGDS-K item was highest at the first visit. In the Supplemental

Material, Table S1 (<http://dx.doi.org/10.1289/ehp.1104100>), we show correlations among SGDS-K items, factor loading values from a factor analysis, and reliability coefficients for the test-retest analysis. For the factor loading values, the first factor consisted of six items (1, 5, 6, 7, 8, and 11), which may be interpreted as a dimension of emotional symptoms. The second factor was related to somatic symptoms and covered three items (9, 10, and 13). The third factor included six items (2, 3, 4, 12, 14, and 15) related to affective symptoms. The results of test-retest analysis at a 1-week interval showed a high correlation (Pearson  $r = 0.92$ ) of SGDS-K scores (see Supplemental Material, Table S1).

Table 3 shows characteristics of environmental factors in Seongbuk-Gu during the study period (August through December 2008, April through December 2009, and March through August 2010). The mean  $\pm$  SD temperature was  $17.3^{\circ}\text{C} \pm 8.1$ ,  $\text{PM}_{10}$  concentration was  $43.7 \mu\text{g}/\text{m}^3$  [interquartile range (IQR) = 24.2],  $\text{SO}_2$  concentration was 4.0 ppb (IQR = 2.3),  $\text{NO}_2$  concentration was 36.2 ppb (IQR = 5.0), maximum CO was 0.79 ppm (IQR = 4.0), and  $\text{O}_3$  was 48.1 ppb (IQR = 37.0) (Table 3). Pollutants, except  $\text{O}_3$ , showed a high correlation with other pollutants in repeatedly measured data and follow-up data [see Supplemental Material, Table S2 (<http://dx.doi.org/10.1289/ehp.1104100>)]. Although  $\text{PM}_{10}$  and  $\text{SO}_2$  concentrations did not show distinct patterns depending on hours of exposure,  $\text{NO}_2$  and CO concentrations were slightly higher during the morning rush hour (0700–0900 hours)

**Table 1.** Description of the study population at the first study visit ( $n = 537$ ).

Variable	Mean $\pm$ SD (median, range)
Age (years)	71 $\pm$ 5 (70, 60–87)
Female [ $n$ (%)]	396 (74)
BMI ( $\text{kg}/\text{m}^2$ )	25 $\pm$ 3 (25, 15–36)
Creatinine-adjusted urine cotinine (mg/g)	255 $\pm$ 1,256 (2, 0–11,866)
SBP (mmHg)	131 $\pm$ 17 (130, 90–190)
Serum triglyceride (mg/dL)	141 $\pm$ 101 (118, 30–1,331)
Regular alcohol drinking [ $n$ (%)]	118 (23)
Regular exercise [ $n$ (%)]	331 (63)
$\leq 6$ years of school [ $n$ (%)]	309 (58)
Monthly income < 500 US\$ [ $n$ (%)]	440 (84)
Insurance benefit from community or government [ $n$ (%)]	201 (39)
Living without spouse or partner [ $n$ (%)]	214 (41)
Stroke [ $n$ (%)]	9 (2)
Hypertension [ $n$ (%)]	274 (51)
MI [ $n$ (%)]	35 (7)
Hyperlipidemia [ $n$ (%)]	56 (10)
COPD [ $n$ (%)]	3 (1)
Asthma [ $n$ (%)]	8 (1)
Depression [ $n$ (%)]	6 (1)
Diabetes [ $n$ (%)]	83 (18)

COPD, chronic obstructive pulmonary disease.

and midnight through early morning (2300–0100 hours) than in other hours of a 24-hr day [see Supplemental Material, Figure S1a–e]. During the daytime (1400–1700 hours), high  $\text{O}_3$  concentrations were measured and were positively correlated with other pollutants [see Supplemental Material, Figure S1(f)].

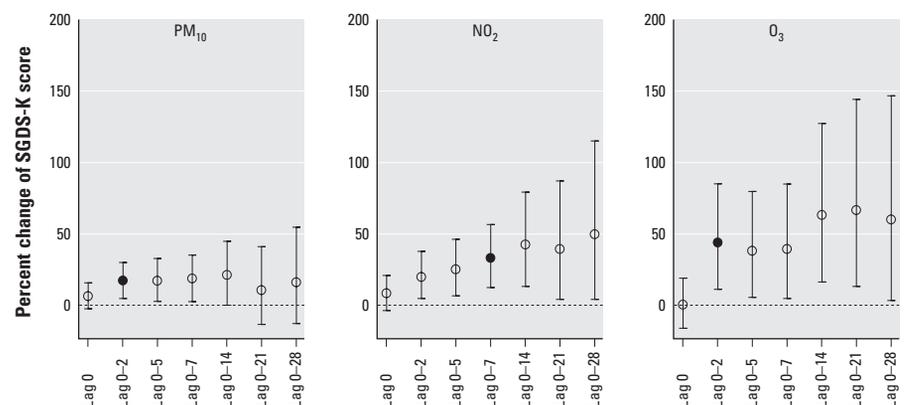
**Table 2.** Depressive symptom scores<sup>a</sup> [mean  $\pm$  SD (median, range)].

Variable	1st follow-up August–December 2008 ( $n = 383$ )	2nd follow-up April–December 2009 ( $n = 368$ )	3rd follow-up March–August 2010 ( $n = 344$ )
Total SGDS-K score	3.6 $\pm$ 3.3 (3, 0–15)	2.4 $\pm$ 3.3 (1, 0–14)	1.1 $\pm$ 2.3 (0, 0–14)
Factor 1 (emotional symptoms)			
1. Satisfied with life	73 (26)	77 (21)	79 (23)
5. In good spirits	63 (22)	60 (16)	14 (4)
6. Fear bad things	67 (24)	46 (13)	5 (1)
7. Happy most of the time	59 (21)	59 (16)	13 (4)
8. Often feel helpless	51 (18)	18 (5)	4 (1)
11. Wonderful to be alive	53 (19)	46 (13)	11 (3)
Composite score of factor 1	0.8 $\pm$ 1.0 (0.5, 0–3.8)	0.5 $\pm$ 1.0 (0, 0–3.8)	0.2 $\pm$ 0.6 (0, 0–3.8)
Factor 2 (somatic symptoms)			
9. Prefer to stay home	34 (12)	23 (6)	32 (9)
10. Problems with memory	76 (27)	34 (9)	54 (16)
13. Full of energy	85 (30)	85 (23)	37 (11)
Composite score of factor 2	0.4 $\pm$ 0.5 (0, 0–1.9)	0.2 $\pm$ 0.4 (0, 0–1.9)	0.2 $\pm$ 0.5 (0, 0–1.9)
Factor 3 (affective symptoms)			
2. Dropped activities/interests	129 (46)	146 (40)	70 (21)
3. Life is empty	69 (24)	45 (12)	6 (2)
4. Often get bored	64 (23)	77 (21)	25 (7)
12. Feel pretty worthless	61 (22)	74 (20)	10 (3)
14. Situation is hopeless	87 (31)	55 (15)	6 (2)
15. Others are better off	39 (14)	33 (9)	7 (2)
Composite score of factor 3	0.9 $\pm$ 1.0 (0.6, 0–3.5)	0.7 $\pm$ 1.0 (0, 0–3.5)	0.2 $\pm$ 0.5 (0, 0–3.5)

<sup>a</sup> $n$ (%) of negative responses of individual items.

**Table 3.** Overall characteristics of environmental factors in Seongbuk-Gu, Korea (August–December 2008, April–December 2009, and March–August 2010).

	Mean $\pm$ SD	Median	Range	IQR
Mean temperature ( $^{\circ}\text{C}$ )	17.3 $\pm$ 8.1	19.4	–7.2–29.2	14.0
Rainfall (mm)	6.9 $\pm$ 17.8	0.5	0–113.5	6.8
Mean $\text{PM}_{10}$ ( $\mu\text{g}/\text{m}^3$ )	43.7 $\pm$ 23.7	40.8	7.4–151.3	24.2
Mean $\text{SO}_2$ (ppb)	4 $\pm$ 2.2	3.5	1–17.5	2.3
Mean $\text{NO}_2$ (ppb)	36.2 $\pm$ 12.1	34.8	9.8–77.3	15.0
Maximum CO (10 ppm)	7.9 $\pm$ 4.3	7.0	3–27	4.0
Maximum $\text{O}_3$ (ppb)	48.1 $\pm$ 27	44.0	2–140	37.0



**Figure 1.** Percent change in SGDS-K scores per interquartile range (IQR) of air pollutants by increasing lag day. Solid circles indicate the best-selected lag days based on minimal Akaike Information Criterion. IQRs for  $\text{PM}_{10}$ ,  $\text{NO}_2$ , and  $\text{O}_3$  were  $24 \mu\text{g}/\text{m}^3$ , 15 ppb, and 37 ppb, respectively. The model for each lag structure included the following variables: age, sex, number of years of school, BMI, alcohol consumption, regular exercise, creatinine-adjusted urine cotinine level, SBP, triglyceride, daily mean temperature, follow-up time, and day of the week.

for the best selected lag days were significantly associated with SGDS-K scores, with estimated increases of 17.0% [95% confidence interval (CI): 4.9%, 30.5%], 32.8% (95% CI: 12.6%, 56.6%), and 43.7% (95% CI: 11.5%, 85.2%), respectively. SO<sub>2</sub> and CO were not significantly associated with SGDS-K scores at any moving average lag days within 4 weeks. IQR

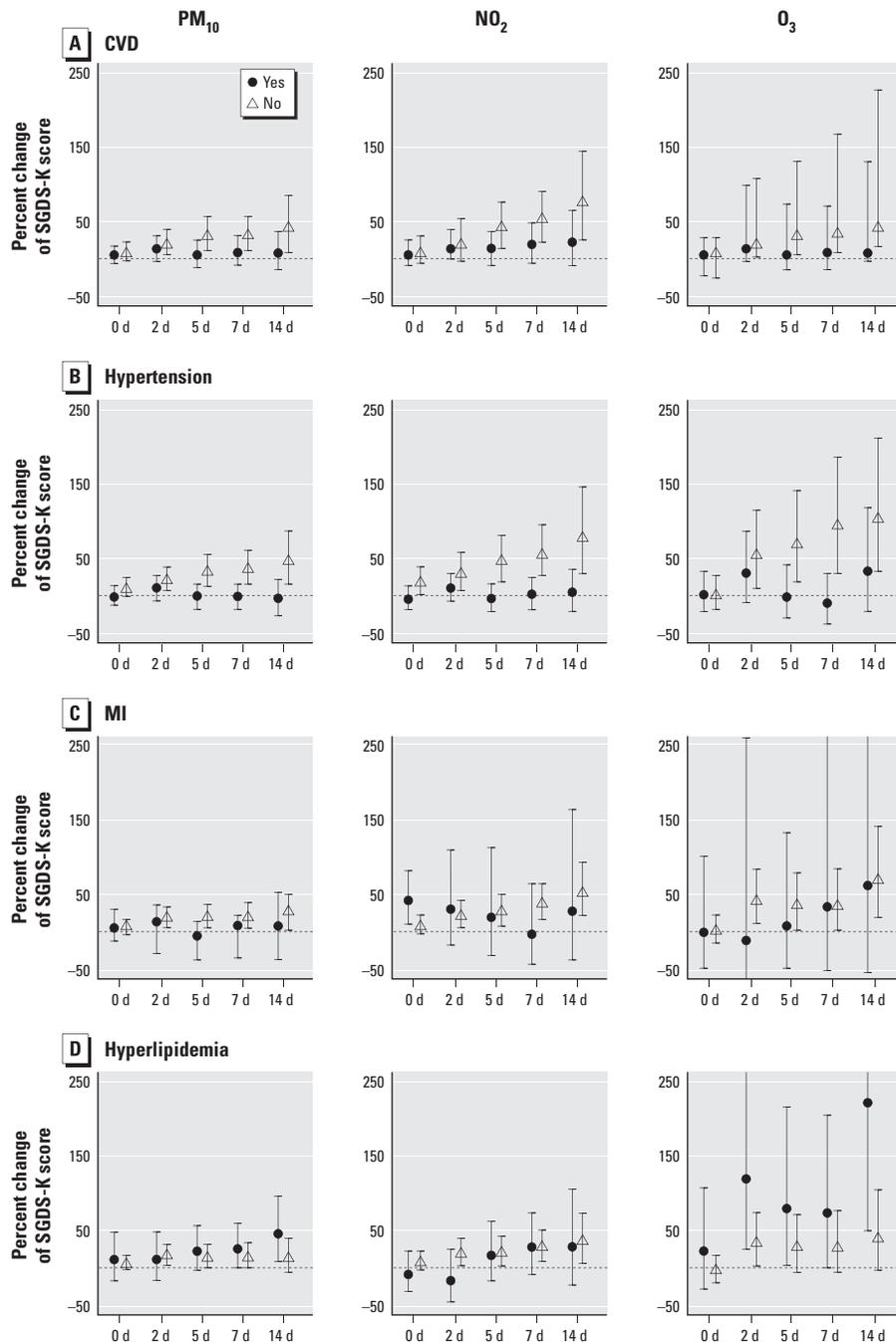
increases in SO<sub>2</sub> apparently had a marginally protective effect at lag 0–21 days [–20.0% (95% CI: –36.6%, 0.9%)] and null effects at other lag days. Increases in CO showed positive associations at lag days 0–5, 0–7, and 0–14, and null associations at other lag days [see Supplemental Material, Figure S2 (<http://dx.doi.org/10.1289/ehp.1104100>)]. When

we performed cross-sectional analysis using data from the first visit only, estimated effects of PM<sub>10</sub> and NO<sub>2</sub> on depressive symptoms were slightly attenuated but similar to associations based on the repeated measures analysis, although the magnitude of estimated effects of O<sub>3</sub> were not statistically significant for any lag days and were considerably lower (see Supplemental Material, Figure S3).

We examined whether the association between depression and air pollution was modified by a history of CVD. Figure 2B suggests that participants without a history of hypertension may have been more susceptible to air pollution exposures than were those with a history of CVD. However, associations with O<sub>3</sub> were stronger among participants with a history of hyperlipidemia than among those without this history. We observed little difference between participants with and without CVD (Figure 2A) or MI (Figure 2C).

Table 4 depicts the association of each individual item in the SGDS-K with IQR increases in PM<sub>10</sub>, NO<sub>2</sub>, and O<sub>3</sub>. All items in the first factor (emotional symptoms) showed significant associations with some or all of the three pollutants (PM<sub>10</sub>, NO<sub>2</sub>, and O<sub>3</sub>). ORs associated with responding negatively to items related to emotional symptoms (1, 5, 6, 7, 8, and 11) increased significantly with an IQR increase of NO<sub>2</sub>. Some of these items also showed a significant relationship with O<sub>3</sub> and PM<sub>10</sub>. However, in the second and third factors that were related to somatic and affective symptoms, only “life is empty” was associated with three air pollutants, whereas “problems with memory,” “full of energy,” and “others are better off” were associated with one pollutant, and other items were not associated with any pollutants. Similarly, among the factor-specific composite scores (emotional, somatic, and affective symptoms), which were calculated as the loading value–weighted sum of the item responses within each factor structure, we observed that emotional symptom composite scores increased with increasing concentrations of PM<sub>10</sub> [38.2% (95% CI: –3.6%, 98.1%)], NO<sub>2</sub> [118.2% (95% CI: 37.9%, 245.3%)], and O<sub>3</sub> [132.5% (95% CI: 32.0%, 309.3%)]; however, somatic and affective symptoms were associated with an increase of PM<sub>10</sub>, and nonsignificantly but positively associated with increasing NO<sub>2</sub> and O<sub>3</sub>.

In our sensitivity analysis, we compared single- and two-pollutant models using moving average lag 2 days for pollutants. Associations of PM<sub>10</sub> and NO<sub>2</sub> with depression symptoms were attenuated when the model was adjusted for NO<sub>2</sub> [17% (95% CI: 5%, 30%) vs. 9% (95% CI: –8%, 30%)] and for PM<sub>10</sub> [20% (95% CI: 5%, 38%) vs. 11% (95% CI: –10%, 37%)], respectively; however, controlling for other pollutants did not substantially change the risk estimates [see Supplemental



**Figure 2.** Percent change in SGDS-K scores by increasing lag days per IQR of air pollutants with data stratified by responses to a history of CVD [yes (solid circle)] vs. no (triangle) (A), hypertension (B), MI (C), and hyperlipidemia (D). 0 d, concurrent exposure to air pollution; 2 d, moving average lag days from concurrent to the two previous days; 5 d, 0–5 lag days of moving average; 7 d, 0–7 lag days; and 14 d, 0–14 lag days. The model for each lag structure included the following variables: age, sex, number of years of school, BMI, alcohol consumption, regular exercise, creatinine-adjusted urine cotinine level, SBP, triglyceride, daily mean temperature, follow-up time, and day of the week.

Material, Figure S4 (<http://dx.doi.org/10.1289/ehp.1104100>]). In an additional sensitivity analysis, we compared estimates in a full model with unweighted or unadjusted estimates. We found that weighted or unweighted estimates were similar, whereas crude effects of PM<sub>10</sub> and NO<sub>2</sub> were substantially different from adjusted estimates, although no such difference was evident for O<sub>3</sub> (see Supplemental Material, Figure S5). The significant confounders in the association with PM<sub>10</sub> and NO<sub>2</sub> were age, sex, number of years of school, day of week, and follow-up time.

## Discussion

Our study found that increasing concentrations of PM<sub>10</sub>, NO<sub>2</sub>, and O<sub>3</sub> were significantly associated with depressive symptoms measured repeatedly among an elderly population in Korea. Individual test items related to emotional symptoms were more likely to be associated with these three pollutants than were items related to somatic or affective symptoms.

Previous studies showed similar results. Welsch (2006) reported that air pollution was a significant predictor of subjective well-being or happiness, and Szyszkowicz et al. (2009b) reported that air pollution from combustion of fossil fuels in motor vehicles was associated with depressive disorders and suicide attempts (Szyszkowicz et al. 2010). Air pollution was associated with headache and migraine symptoms (Szyszkowicz 2008a, 2008b; Szyszkowicz et al. 2009a, 2009c, 2009d). In contrast with previous study results, we found that SO<sub>2</sub> and CO did not show significant associations with depression symptoms (negative or null

associations, and positive or null associations, respectively). For example, Bullinger (1989) reported that increasing SO<sub>2</sub> concentrations (measured daily at the monitoring sites) were associated with adverse mood and stress. Szyszkowicz (2007a) reported that SO<sub>2</sub> and CO, as well as NO<sub>2</sub> and O<sub>3</sub>, were associated with increased emergency department visits due to depression in warm seasons. It is not clear why the results for SO<sub>2</sub> and CO in our study were not concordant with other studies, although PM<sub>10</sub>, NO<sub>2</sub>, and O<sub>3</sub> showed similar results. One possible explanation is that oxidant-producing pollutants such as PM<sub>10</sub>, NO<sub>2</sub>, and O<sub>3</sub> are more likely to affect depressive symptoms than are SO<sub>2</sub> and CO because oxidative stress is known to be one of the pathogenetic mechanisms of depression (Maes et al. 2011; Wolkowitz et al. 2011). Other plausible explanations for the discrepancies may be different study populations, exposure levels, measurement errors, adjustment of confounding variables, differences in outcome definitions, and sample sizes used in the studies.

Although mechanistic studies linking air pollution to depression are lacking, Block et al. (2004) demonstrated in a study of cell cultures that diesel-exhaust particles activated microglia and induced dopaminergic neurotoxicity by production of proinflammatory factors and reactive oxygen species. Evidence of interdependent relationships between oxidative pathways and neurotransmitters, hormones, and inflammatory mediators involved in the pathogenesis enhance the plausibility of the oxidative stress hypothesis in relation

to depression (Ng et al. 2008). Because airborne particles, nitrogen oxides, and ozone are potent oxidants, air pollution may affect depressive moods by inducing oxidative stress.

Studies have shown that estimated effects of air pollution based on single pollutant models may be different from those estimated using multipollutant models (Bell et al. 2007; Rojas-Martinez et al. 2007; Yang et al. 2005). The results of our sensitivity analysis indicated that associations of PM<sub>10</sub> and NO<sub>2</sub> with depression symptoms in two-pollutant models were attenuated, compared with single-pollutant models; however, controlling for other pollutants did not substantially change the risk estimates. Although there was no clear explanation for dependency of PM<sub>10</sub> with NO<sub>2</sub> in this study area, we can speculate that NO<sub>2</sub> from vehicular combustion emissions may be related to traffic particles such as tire wear, road bitumen, sand traction, and pavement aggregates that may increase concentrations of PM<sub>10</sub> (Kupiainen et al. 2005).

This study examined which items combined were associated with air pollutants. A factor analysis clustered 15 items into three groups (emotional, somatic, and affective symptoms). Responses related to emotional symptoms were increasingly negative as air pollution increased. However, responses related to somatic and affective symptoms were not significantly associated with increases in air pollution.

CVD is also known to affect depressive symptoms (Musselman et al. 1998) and air pollution has been reported to increase the risk of CVD (Bateson and Schwartz 2004; Stieb

**Table 4.** Estimated effects<sup>a</sup> of responding negatively to each SGDS-K item<sup>b</sup> and composite scores<sup>c</sup> per IQR of air pollutants (95% CI).

Factor/Item	PM <sub>10</sub> (IQR = 24 µg/m <sup>3</sup> )		NO <sub>2</sub> (IQR = 15 ppb)		O <sub>3</sub> (IQR = 37 ppb)	
	Estimates (95% CI)	Lag day	Estimates (95% CI)	Lag day	Estimates (95% CI)	Lag day
<b>Factor 1 (emotional symptoms)</b>						
1. Satisfied with life	1.01 (1.00, 1.03)*	0–5	1.04 (1.01, 1.07)*	0–7	1.03 (1.01, 1.06)*	0–28
5. In good spirits	1.01 (1.00, 1.02)	0–2	1.03 (1.01, 1.06)*	0–2	1.01 (0.98, 1.04)	0–28
6. Fear bad things	1.03 (1.01, 1.06)*	0–28	1.10 (1.03, 1.17)*	0–28	1.04 (1.01, 1.08)*	0–28
7. Happy most of the time	1.01 (1.00, 1.03)	0–2	1.11 (1.04, 1.18)*	0–28	1.03 (1.00, 1.06)	0–28
8. Often feel helpless	1.05 (1.02, 1.09)*	0–28	1.11 (1.04, 1.18)*	0–21	1.06 (1.02, 1.1)*	0–28
11. Wonderful to be alive	1.02 (1.00, 1.03)*	0–5	1.05 (1.02, 1.08)*	0–7	0.99 (0.96, 1.02)	0–28
Composite score of factor 1 <sup>c</sup>	38.2% (–3.6, 98.1)**	0–28	118.2% (37.9, 245.3)*	0–28	132.5% (32.0, 309.3)*	0–28
<b>Factor 2 (somatic symptoms)</b>						
9. Prefer to stay home	1.02 (0.99, 1.05)	0–14	1.02 (0.96, 1.09)	0–14	1.03 (1.00, 1.06)	0–28
10. Problems with memory	1.04 (1.02, 1.06)	0–14	1.07 (1.02, 1.12)*	0–14	1.01 (0.99, 1.04)	0–28
13. Full of energy	1.02 (1.00, 1.03)*	0–2	1.03 (1.00, 1.05)	0–5	1.00 (0.98, 1.03)	0–28
Composite score of factor 2 <sup>c</sup>	38.9% (0.7, 91.7)*	0–21	36% (–8.8, 102.9)	0–21	51.9% (–17.4, 179.3)	0–28
<b>Factor 3 (affective symptoms)</b>						
2. Dropped activities/interests	0.98 (0.97, 1.00)	0–21	0.98 (0.94, 1.01)	0–21	0.99 (0.97, 1.01)	0–28
3. Life is empty	1.02 (1.00, 1.03)*	0–7	1.10 (1.04, 1.15)*	0–21	1.04 (1.01, 1.07)*	0–28
4. Often get bored	0.99 (0.97, 1.01)	0–21	1.02 (0.99, 1.05)	0–7	1.01 (0.98, 1.03)	0–28
12. Feel pretty worthless	0.98 (0.96, 1.01)	0–21	1.01 (1.00, 1.03)	0	1.00 (0.97, 1.03)	0–28
14. Situation is hopeless	1.00 (0.99, 1.01)	0	1.03 (0.99, 1.09)	0–21	1.02 (0.98, 1.05)	0–28
15. Others are better off	1.02 (1.00, 1.03)*	0–2	1.05 (1.00, 1.11)	0–14	1.00 (0.96, 1.04)	0–28
Composite score of factor 3 <sup>c</sup>	11.5% (–1.4, 26.1)**	0–2	13.1% (–2.7, 31.4)	0–2	13.0% (–29.5, 81.0)	0–28

<sup>a</sup>The model included the following variables: age, sex, number of years of school, BMI, alcohol consumption, regular exercise, creatinine-adjusted urine cotinine level, SBP, triglyceride, daily mean temperature, follow-up time, and day of the week. Estimated effects were expressed as ORs in each individual item and percent change in the composite scores. <sup>b</sup>Positive symptoms were reverse coded before analysis. ORs > 1 indicate adverse symptoms in every case. <sup>c</sup>Composite scores were calculated as the loading value-weighted sum of binary scores (0 or 1) of each individual item that contributed to the factor. \**p* < 0.05. \*\**p* < 0.1.

et al. 2009; Szyszkowicz 2007b). Therefore, the role of air pollution in relation to the cardiovascular system should be considered when evaluating mechanistic pathways of air pollution effects on depressive symptoms. We examined confounding effects of CVD history on the air pollution–depression relationship. Common CVDs such as hypertension, stroke, MI, and hyperlipidemia were examined as covariates in the model. CVD history did not affect or confound the estimated effects of air pollutants; however, hypertension and hyperlipidemia appeared to modify the depression relationship. Participants without hypertension were at a higher risk for depression in association with air pollution exposure than were those with hypertension, although participants with hyperlipidemia appeared to be at increased risk of depression in association with air pollution, especially in relation to O<sub>3</sub> exposure. However, caution should be used when interpreting the results because we had no clear explanation for the contradictory results between hypertension and hyperlipidemia and limited power to assess differences.

This study has some strengths and limitations. First, since toxicological studies showed that many health effects were delayed (Coffin and Stokinger 1977), we used moving average lag structures of air pollutant concentrations up to 4 weeks. Second, to the best of our knowledge, this is the first study to investigate associations between specific depressive symptoms among the elderly and air pollution after controlling for individual and temporal effects. A big challenge in the present study was the aging of the participants. For example, the elderly participants may have responded incorrectly to questions on the questionnaire, depending on instantaneous memories or health conditions. To validate the instrument to some extent, a test-retest was conducted. The results provided information regarding the reliability of SGDS-K scores over time. Although the number of observations ( $n = 537$ ) was sufficient to estimate effects of air pollution on depression, our findings may not be generalizable to younger populations or those living in different atmospheric conditions. Lag days of air pollution on depression were selected based on the lowest QIC up to 28 lag days. However, there is no clear biological explanation that the selected lags are more appropriate, and a data-driven approach to find the best lag day may be flawed.

## Conclusions

This is the first report to investigate the relationship between depressive symptoms and air pollution in a panel study. Increasing concentrations of PM<sub>10</sub>, NO<sub>2</sub>, and O<sub>3</sub> were significantly associated with depressive symptoms

among an elderly population in Korea. Among depression symptomatology, emotional symptoms were more likely to be associated with the three pollutants evaluated.

## REFERENCES

- Bae JN, Cho MJ. 2004. Development of the Korean version of the Geriatric Depression Scale and its short form among elderly psychiatric patients. *J Psychosom Res* 57(3):297–305.
- Bateson TF, Schwartz J. 2004. Who is sensitive to the effects of particulate air pollution on mortality?: A case-crossover analysis of effect modifiers. *Epidemiology* 15(2):143–149.
- Bell ML, Kim JY, Dominici F. 2007. Potential confounding of particulate matter on the short-term association between ozone and mortality in multisite time-series studies. *Environ Health Perspect* 115:1591–1595.
- Blazer DG, Hybels CF, Pieper CF. 2001. The association of depression and mortality in elderly persons: a case for multiple, independent pathways. *J Gerontol A Biol Sci Med Sci* 56(8):M505–M509.
- Block ML, Wu X, Pei Z, Li G, Wang T, Qin L, et al. 2004. Nanometer size diesel exhaust particles are selectively toxic to dopaminergic neurons: the role of microglia, phagocytosis, and NADPH oxidase. *FASEB J* 18(13):1618–1620.
- Bullinger M. 1989. Psychological effects of air pollution on healthy residents—a time-series approach. *J Environ Psychol* 9(2):103–118.
- Campbell A, Oldham M, Becaria A, Bondy SC, Meacher D, Sioutas C, et al. 2005. Particulate matter in polluted air may increase biomarkers of inflammation in mouse brain. *Neurotoxicology* 26(1):133–140.
- Coffin D, Stokinger H. 1977. *Biological Effects of Air Pollutants*. 3rd ed. Amsterdam:Academic Press.
- Cole MG, Dendukuri N. 2003. Risk factors for depression among elderly community subjects: a systematic review and meta-analysis. *Am J Psychiatry* 160(6):1147–1156.
- Grippo AJ. 2009. Mechanisms underlying altered mood and cardiovascular dysfunction: the value of neurobiological and behavioral research with animal models. *Neurosci Biobehav Rev* 33(2):171–180.
- Hasler G. 2010. Pathophysiology of depression: do we have any solid evidence of interest to clinicians? *World Psychiatry* 9(3):155–161.
- Horsten M, Wamala S, Vingerhoets A, Orth-Gomer K. 1997. Depressive symptoms, social support, and lipid profile in healthy middle-aged women. *Psychosom Med* 59(5):521–528.
- Keatinge WR, Donaldson GC. 2001. Mortality related to cold and air pollution in London after allowance for effects of associated weather patterns. *Environ Res* 86(3):209–216.
- Kim BS, Bae JN, Cho MJ. 2010. Depressive symptoms in elderly adults with hypotension: different associations with positive and negative affect. *J Affect Disord* 127(1–3):359–364.
- Kim Y, Guldman J-M. 2011. Impact of traffic flows and wind directions on air pollution concentrations in Seoul, Korea. *Atmos Environ* 45(16):2803–2810.
- Korea Meteorological Administration. 2012. Korea meteorological administration weather data. Available: <http://web.kma.go.kr/eng/> [accessed June 5 2012].
- Kupiainen KJ, Tervahattu H, Räisänen M, Mäkelä T, Aurela M, Hillamo R. 2005. Size and composition of airborne particles from pavement wear, tires, and traction sanding. *Environ Sci Technol* 39(3):699–706.
- Lyness JM, Heo M, Datto CJ, Ten Have TR, Katz IR, Drayer R, et al. 2006. Outcomes of minor and subsyndromal depression among elderly patients in primary care settings. *Ann Intern Med* 144(7):496–504.
- Maes M, Kubera M, Obuchowiczwa E, Goehler L, Brzeszcz J. 2011. Depression's multiple comorbidities explained by (neuro)inflammatory and oxidative and nitrosative stress pathways. *Neuro Endocrinol Lett* 32(1):7–24.
- McCracken J, Baccarelli A, Hoxha M, Dioni L, Melly S, Coull B, et al. 2010. Annual ambient black carbon associated with shorter telomeres in elderly men: Veterans Affairs Normative Aging Study. *Environ Health Perspect* 118:1564–1570.
- MOE (Ministry of Environment). 2009. Annual report of ambient air quality in Korea, 2008. Gwacheon:Korea Ministry of Environment.
- MOE (Ministry of Environment). 2010. Annual report of ambient air quality in Korea, 2009. Gwacheon:Korea Ministry of Environment.
- MOE (Ministry of Environment). 2011. Annual report of ambient air quality in Korea, 2010. Gwacheon:Korea Ministry of Environment.
- Mulsant BH, Ganguli M. 1999. Epidemiology and diagnosis of depression in late life. *J Clin Psychiatry* 60(suppl 20):9–15.
- Musselman DL, Evans DL, Nemeroff CB. 1998. The relationship of depression to cardiovascular disease: epidemiology, biology, and treatment. *Arch Gen Psychiatry* 55(7):580–592.
- Ng F, Berk M, Dean O, Bush AI. 2008. Oxidative stress in psychiatric disorders: evidence base and therapeutic implications. *Int J Neuropsychopharmacol* 11(6):851–876.
- Pan W. 2001. Akaike's information criterion in generalized estimating equations. *Biometrics* 57(1):120–125.
- Pope CA III. 2000. Epidemiology of fine particulate air pollution and human health: biologic mechanisms and who's at risk? *Environ Health Perspect* 108 (suppl 4):S713–S723.
- Robins JM, Rotnitzky A, Zhao LP. 1995. Analysis of Semiparametric Regression Models for Repeated Outcomes in the Presence of Missing Data. *J Am Stat Assoc* 90(429):106–121.
- Rojas-Martinez R, Perez-Padilla R, Olaiz-Fernandez G, Mendoza-Alvarado L, Moreno-Macias H, Fortoul T, et al. 2007. Lung function growth in children with long-term exposure to air pollutants in Mexico City. *Am J Respir Crit Care Med* 176(4):377–384.
- Rubin DB. 1976. Inference and missing data. *Biometrika* 63(3):581–592.
- Stieb DM, Szyszkowicz M, Rowe BH, Leech JA. 2009. Air pollution and emergency department visits for cardiac and respiratory conditions: a multicity time-series analysis. *Environ Health* 8:25; doi:10.1186/1476-069X-8-25 [Online 10 June 2009].
- Szyszkowicz M. 2007a. Air pollution and emergency department visits for depression in Edmonton, Canada. *Int J Occup Med Environ Health* 20(3):241–245.
- Szyszkowicz M. 2007b. Air pollution and emergency department visits for ischemic heart disease in Montreal, Canada. *Int J Occup Med Environ Health* 20(2):167–173.
- Szyszkowicz M. 2008a. Air pollution and daily emergency department visits for headache in Montreal, Canada. *Headache* 48(3):417–423.
- Szyszkowicz M. 2008b. Ambient air pollution and daily emergency department visits for headache in Ottawa, Canada. *Headache* 48(7):1076–1081.
- Szyszkowicz M, Kaplan GG, Grafstein E, Rowe BH. 2009a. Emergency department visits for migraine and headache: a multicity study. *Int J Occup Med Environ Health* 22(3):235–242.
- Szyszkowicz M, Rowe BH, Colman I. 2009b. Air pollution and daily emergency department visits for depression. *Int J Occup Med Environ Health* 22(4):355–362.
- Szyszkowicz M, Rowe BH, Kaplan GG. 2009c. Ambient sulphur dioxide exposure and emergency department visits for migraine in Vancouver, Canada. *Int J Occup Med Environ Health* 22(1):7–12.
- Szyszkowicz M, Stieb DM, Rowe BH. 2009d. Air pollution and daily ED visits for migraine and headache in Edmonton, Canada. *Am J Emerg Med* 27(4):391–396.
- Szyszkowicz M, Willey JB, Grafstein E, Rowe BH, Colman I. 2010. Air pollution and emergency department visits for suicide attempts in Vancouver, Canada. *Environ Health Insights* 4:79–86.
- Valvanne J, Juva K, Erkinjuntti T, Tilvis R. 1996. Major depression in the elderly: a population study in Helsinki. *Int Psychogeriatr* 8(3):437–443.
- Veronesi B, Makwana O, Pooler M, Chen LC. 2005. Effects of subchronic exposures to concentrated ambient particles. VII. Degeneration of dopaminergic neurons in Apo E<sup>-/-</sup> mice. *Inhal Toxicol* 17(4–5):235–241.
- Waern M, Rubenowitz E, Wilhelmson K. 2003. Predictors of suicide in the old elderly. *Gerontology* 49(5):328–334.
- Welsch H. 2006. Environment and happiness: valuation of air pollution using life satisfaction data. *Ecol Econ* 58(4):801–813.
- Wolkowitz OM, Reus VI, Mellon SH. 2011. Of sound mind and body: depression, disease, and accelerated aging. *Dialogues Clin Neurosci* 13(1):25–39.
- Yang Q, Chen Y, Krewski D, Burnett RT, Shi Y, McGrail KM. 2005. Effect of short-term exposure to low levels of gaseous pollutants on chronic obstructive pulmonary disease hospitalizations. *Environ Res* 99(1):99–105.