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Using geographically referenced data on environmental exposures for public health research: a feasibility study based on the German Socio-Economic Panel Study (SOEP)

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Abstract

Background

In panel datasets information on environmental exposures is scarce. Thus, our goal was to probe the use of area-wide geographically referenced data for air pollution from an external data source in the analysis of physical health.

Methods

The study population comprised SOEP respondents in 2004 merged with exposures for NO_2, PM_{10} and O_3 based on a multi-year reanalysis of the EURopean Air pollution Dispersion-Inverse Model (EURAD-IM). Apart from bivariate analyses with subjective air pollution we estimated cross-sectional multilevel regression models for physical health as assessed by the SF-12.

Results

The variation of average exposure to NO_2, PM_{10} and O_3 was small with the interquartile range being less than 10µg/m^3 for all pollutants. There was no correlation between subjective air pollution and average exposure to PM_{10} and O_3, while there was a small positive correlation between the first and NO_2. Inclusion of objective air pollution in regression models did not improve the model fit.

Conclusions

It is feasible to merge environmental exposures to a nationally representative panel study like the SOEP. However, in our study the spatial resolution of the specific air pollutants has been too little, yet.

Keywords

SOEP, geographically referenced data, feasibility study, air pollution, EURAD-IM, physical health

Introduction

Panel studies like the German Socio-Economic Panel (SOEP) allow for a longitudinal analysis of individual characteristics including health [1,2]. In the use of this data, however, researchers usually face a scarcity of information if they want to study the impact of environmental exposures on individual health and its changes. Taking the case of the SOEP there are several reasons for that. First, information on environmental exposures such as air pollution and crime is collected on the basis of a household questionnaire. This questionnaire is completed by the head of household who rates, for instance, the degree of his or her subjective disturbance by air pollution. In a recent study on the impact of neighbourhood deprivation on physical health by two of the authors we did use this information and found that increases in the subjective disturbance by air pollution are associated with worsening physical health [3]. However, our estimates are likely to be biased because an exposure that is self-rated is liable to individual characteristics such as knowledge, perception as well as socially patterned expectations [4].

Second, the subjective degree of disturbance by air pollution in general is not very informative in regard to which specific air pollutant is possibly causing the difference in individual health. To know this would require information on specific air pollutants like oxides of nitrogen, particulate matter and ozone that constitute overall air pollution. Such information would also support health promotion agencies as well as policy makers identifying specific air pollutant exposures that cause health disparities and that should consequently be modified [5,6].

Third, information regarding self-rated air pollution as well as other environmental exposures is collected in a five year interval. This means exposure data is lacking for the years in between the interval. Of course, one can perform cross-sectional analyses for the years with available exposure data but has to put up with the limitations of such analyses, e.g. reverse causality and unobserved heterogeneity [cf. 7]. For longitudinal analyses, however, one would need at least annual data that allows estimating associations between annual changes in environmental exposures and annual changes in health. Some researchers may try to overcome this limitation by making assumptions for the exposure based on the subjective exposure that is available every five years but the validity of an assumed exposure is highly questionable.

To overcome the problem of self-rated and rather unspecific data on environmental exposures within panel studies researchers have to integrate data from external sources. This issue of integrating data from external sources in cohort, panel and other studies will be one of the major challenges for epidemiology in the coming years. For instance, on its biennial conference in 2011 the German Data Forum (German: Rat für Sozial- und WirtschaftsDaten, RatSWD) invited speakers that explored the issue of multiple data sources (e.g. environmental exposure data, cancer registry data, health insurance data, occupational data) and related problems of data protection and data access (Link: http://ratswd.de/5kswd/konferenz.html).

In the study presented here we probe the use of geographically referenced data on specific ambient air pollutants in the panel study SOEP to analyse physical health. The effects of specific air pollutants on morbidity and mortality have been documented in numerous publications including meta-analyses [8-17]. Further reductions in the levels of pollutants like particulate matter and ozone in Northern America as well as in Europe are expected to result in substantial health benefits [9,18,19]. Using the EURopean Air pollution Dispersion-Inverse Model (EURAD-IM) [20,21] we merge objective exposures for nitrogen dioxide (NO_2), particulate matter less than 10µm in aerodynamical diameter (PM_{10}), and ozone (O_3) to the geographically referenced SOEP households. Based on this dataset we calculate individual mean values for the time between the current wave and the previous wave while accounting for individual moves of place of residence. We then explore the association between the specific exposure to air pollutants and the subjective disturbance by air pollution in the year 2004 before we estimate a cross-sectional regression model for physical health in 2004.

Methods

Data

We used data from the SOEP, version 25 [22], which is a longitudinal nationally representative annual survey of private households in Germany that was started in 1984. Wagner et al. provide further information on the methodology of the survey [1]. In the analysis we included all respondents aged 18 and above who took part in the survey in 2004 and who were living in a geographically referenced private household, i.e. a survey household for which the address could be geocoded with block-level geographic precision (while preventing identification of individuals by name and guaranteeing their complete anonymity). The geocoding of the addresses has been done via the field work agency (TNS Infratest) and the original coordinates cannot be used together with any survey information [cf. 23].

Data on specific air pollutants we obtained from the reanalysis study Air Quality Records which has been accomplished for the Global Monitoring for Environment and Security (GMES) Service Element PROMOTE (Link: http://www.gse-promote.org). For the reanalysis period from January 2002 to December 2008, observations of various trace gases have been assimilated into EURAD-IM on a European grid domain with a horizontal resolution of 45x45 km^2 [20,21]. The measurements comprised hourly observations from routinely operated European networks (AirBase, European Environment Agency), air-borne data from the MOZAIC project and NO_2, carbon monoxide (CO) and O_3 retrievals from satellite based sensors (GOME, SCIAMACHY, OMI, GOME-2 and MOPITT). Based on three hourly analyses inferred with the three dimensional variational data assimilation technique (3d-var) and short-term forecasts, hourly values of a set of chemical constituents are provided from which NO_2, O_3 and PM_{10} have been selected for this study.

The socio-economic data and datasets of air pollutants have been merged using the statistical software R [24] as described in the following. The spatial extension of the individual grid-cells of the EURAD-IM data sets was interpolated from 45x45km^2 to a grid-size of 5x5km^2. For the interpolation we used the utility gdalwarp, which is an image reprojection and warping utility [25], with a bilinear interpolation. Via the geographic location of the households, we matched air pollutant data to each single household. Finally, we calculated the average exposure for the time between the previous interview in 2003 and the current interview in 2004 (on average one year). In case a respondent had moved his or her place of residence we calculated the weighted average based on the number of months the respondent spent at different places.

To control for regional as well as neighbourhood confounders we merged additional data to the SOEP. Regional information at the level of the 413 German counties (German: "Kreise & kreisfreie Städte") was used from the regional INKAR data base of the Federal Institute for Research on Building, Urban Affairs and Spatial Development (German: Bundesinstitut für Bau-, Stadt- und Raumforschung, BBSR). Neighbourhood information was matched to the households on the basis of data from the commercial data provider microm GmbH which is available within the SOEP research data center [26].

Variables

Air pollution

We assessed air pollution by both objective and subjective measures. Our objective measures comprised simulated ambient air concentrations of NO_2 as proxy for total nitrogen oxide (NO_x), PM_{10} as well as O_3. Due to their health damaging effects the European Commission has set air quality standards (amended in 2008 with Directive 2008/50/EC) that are effective in German legislation, too [27]. For each pollutant we calculated the average exposure of a respondent in $\mu g/m^3$. Information on subjective air pollution is based on the household questionnaire that is completed by the head of household and gathers perceived disturbance by air pollution (graded on a five-point Likert scale from "none" to "very strong").

Physical Health

We used the physical component score (PCS) as our health outcome because among all health outcomes provided by the SOEP this is most sensitive regarding potential health effects of air pollution. The PCS is based on the short form 12 health questionnaire (SF-12) that measures health-related quality of life and comprises 12 items. Using principal component analysis these items are aggregated to two summary measures: a physical component score (PCS) and a mental component score (MCS). Both of them are standardized to a mean of 50 and a standard deviation of 10 whereas higher values indicate better health. Further details on the computation of the PCS are provided elsewhere [28].

Covariates

Similar to a recent paper by two of the authors [3] we controlled for a number of individual, household as well as contextual risk factors that may be correlated with air pollution. The individual and household risk factors include age, gender, education, unemployment and income. We measured education by the classification "Comparative Analyses of Social Mobility in Industrial Nations" (CASMIN) with the categories "still in school", "low" (German: "bis Hauptschule"), "intermediate" (German: "Abitur/ Realschulabschluss"), "high" (German: "Hochschulabschluss") and "not specified" [29]; unemployment based on the employment status at the day of interview; and income using the annual net household income from the previous year weighted by the modified equivalence scale of the Organisation for Economic Co-operation and Development (OECD) that we additionally log-transformed to achieve a symmetric distribution [30,31]. To perform stratified analyses (outlined below) we classified age into "18 to 39 years", "40 to 59 years" and "60 years and above". In addition we controlled for individual health-related factors such as smoking with the categories "never smoker", "ex-smoker" "current smoker"; sports participation with the categories "every week", "every month", "less than every month" and "never"; as well as Body Mass Index (BMI) with the categories "less than 25 kg/m^2", "25 to 30 kg/m^2" and "above 30 kg/m^2".

The selected contextual risk factors comprise the unemployment quota of the respondent's county as well as the average purchasing power of the respondent's street section. The unemployment quota describes the number of unemployed inhabitants as a proportion of the labour force. The average purchasing power of a respondent's street section is provided by the microm GmbH. The latter divided Germany in approximately 1.5 million street sections with an average of 27 households for which they calculate average (household) purchasing powers based on official revenue statistics [26]. microm GmbH does not publish further information on this variable [32].

Statistical analyses

Data analysis was done in several steps. First, we explored the distribution of the three objective air pollutions measures in boxplots. Second, we calculated bivariate Spearman rank correlation coefficients stratified by age groups and sex to examine the relationship of the subjective and the objective measures of air pollution.

Third, we re-estimated a multilevel linear regression model from a previous publication [3] to analyse the effect of air pollution measured by objective measures on physical health (PCS) while controlling for other individual and contextual factors. In this earlier model we used a three-level-hierarchy (individuals nested in households nested in counties) and estimated the association between subjective air pollution and PCS while controlling for covariates (Model 1). For this article we estimated the same model but substituted subjective air pollution by the three selected ambient air pollutants (Model 2). In a third model we included both, subjective as well as objective air pollution measures, while controlling for the above-mentioned covariates (Model 2). The models for PCS can be written as follows:

$$\begin{aligned}\mathrm{PCS}_i &= \beta_0 + \beta_{i1}x_{i1} + \ldots + \beta_{h1}z_{h1} + \ldots + \beta_{c1}w_{c1} + \ldots \\ &\quad + u_c + v_h + \varepsilon_i\end{aligned}$$

where x_{i1} ,… denote characteristics at the individual level (level 1), e.g. age, sex and average exposure to NO_2, PM_{10} and O_3, with the corresponding model coefficients β_{i1}, …. z_{h1} ,… denote factors measured at the household level (level 2), i.e. income (log-transformed), purchasing power as well as subjective disturbance by air pollution, with the corresponding model coefficients β_{h1}, …. And w_{1s} denotes the factor at the county level (level 3), i.e. county unemployment quota, with its corresponding model coefficient β_{c1}. In the multilevel model there is random variation on each level, mirrored by the random effects, which are assumed to be independently normally distributed with mean 0. Here, u_c is the random effect of the county level (level 3) with variance σ^2_c, i.e. u_c,~$N(0,\sigma^2_c)$, v_h is the random effect of the household level (level 2) with variance σ^2_h, i.e. v_h,~$N(0,\sigma^2_h)$, and ε_i on the individual level (level 1) are the model residuals with the residual variance σ^2_i, i.e. ε_i,~$N(0,\sigma^2_i)$.

Modelling was done with MLwiN 2.22 [33]. All model parameters were estimated using the iterative generalised least squares (IGLS) procedure [34]. Goodness of fit was assessed by the likelihood ratio test.

Results

Fig. 1 provides an example of the bilinear interpolation that we used to reduce the spatial extension of the individual grid-cells of the EURAD-IM data sets. The map on the left shows the distribution of PM_{10} (daily average) across Germany for 3rd June 2004 based on the initial grid size of 45x45km^2. The map on the right shows the distribution of PM_{10} (daily average) across Germany for 3rd June 2004 after interpolating the grid size to 5x5km^2. For this specific day maximum and minimum were 42.0µg/m^3 and 3.4µg/m^3, respectively.

[Include Fig. 1 here]

Based on the year 2004 the SOEP comprised 21,521 respondents that were living in private households and were aged 18 and above (Tab. 1). Of all the sample members 92.0% were living in a household with a valid geocode for the previous as well as the current interview month. The remaining 8% did either not participate in the SOEP in 2003 or they were living in a private household without a valid geocode for 2003 or 2004. The respondents' average exposure to ambient air concentrations was 21.6µg/m^3 (Standard deviation (SD)=4.6) for NO_2, 19.8µg/m^3 (SD=2.2) for PM_{10} and 50.7µg/m^3 (SD=5.3) for O_3. Fig. 2 shows the pollutants' boxplots. While the interquartile range for NO_2 and O_3 is 7.0µg/m^3 and 6.4µg/m^3, respectively, it is less than 3.0µg/m^3 for PM_{10}. Furthermore, the range is highest for O_3 with a maximum at 94.6µg/m^3. Regarding subjective air pollution 47.0% of the respondents live in a household that is not disturbed by air pollution whereas disturbance is little (39.0%), tolerable (9.6%), strong (3.1%) and very strong (0.7%) for the remaining respondents (Tab. 1).

[Include Tab. 1 here]

[Include Fig. 2 here]

Spearman correlation coefficients between subjective air pollution and specific air pollutants, stratified by age groups and sex, are shown in Tab. 2. For both men and women in all age groups there is no correlation between subjective air pollution and PM_{10} as well as between subjective air pollution and O_3. For NO_2 there is a small positive correlation with subjective air pollution that is significantly different from non-correlation for both sexes and all age groups (e.g. r_s=0.09 for men between 40 and 59 years of age).

[Include Tab. 2 here]

Tab. 3 presents the results of the cross-sectional multilevel air pollution models that were nesting individuals in households in counties. Model 1 with subjective disturbance by air pollution as the only air pollution measure is a re-estimated cross-sectional multilevel model from a previous publication [cf. 3]. According to this model, air pollution is negatively associated with physical health and all categories show a significantly negative coefficient compared to the reference category "None". For instance, the beta coefficients for a strong and very strong disturbance by air pollution are -2.16 (Standard error (SE)=0.38) and -3.01(SE=0.77), respectively. In Model 2 we substitute subjective disturbance by air pollution by objective exposure to air pollutants. For all pollutants the beta coefficients for an increase of 10µg/m^3 are very small and due their standard errors not significantly different from 0 while the coefficients for all other covariates remain the same as in Model 1. Model 3 analyses subjective and objective air pollution measures in the same model. The coefficients of both air pollution measures are similar to Model 1 and Model 2, i.e. a physical health gradient for subjective air pollution and very small coefficients for the specific air pollutants that are not significantly different from 0. The likelihood ratio test of Model 3 and Model 1 results in a p-value of 0.39 meaning that the inclusion of specific air pollutants did not improve the model fit.

[Include Tab. 3 here]

Discussion

This study shows that it is possible to merge objective air pollution data from an external source to a large and representative panel study and thus enrich the initial data set. However, we find little variation in the average exposure to nitrogen dioxide (NO_2), particulate matter less than 10µm in diameter (PM_{10}) as well as ozone (O_3); the interquartile range being less than 10µg/m^3 for all of the pollutants. There is a small positive correlation between the average exposure to NO_2 and the respondents' subjective disturbance by air pollution and none between the latter and PM_{10} as well as O_3. Furthermore, the effects of the specific pollutants on physical health are very small and insignificant and their inclusion does not improve the fit of the explanatory model, i.e. beside the subjective disturbance by air pollution the objective exposure measures do not provide additional information when explaining health inequalities. All other things being equal ('ceteris paribus') the beta coefficients of the specific air pollutants are implausible.

There are several reasons for the implausible estimates of which we want to discuss the most important ones. First, the original grid size of 45x45km^2 was rather large and implies little spatial variation in the exposure to specific air pollutants. The aim of the EURAD-IM reanalysis study was to provide air pollution analyses for a large entity such as Europe as well as for a long period and therefore it uses a rather coarse grid size. Although exposure to air pollution is usually confined to a much smaller area, so-called hotspots [35-38], a certain air quality situation or such a hotspot (e.g., an ambient air monitoring site dominated by urban traffic emissions) has a limited representative-ness for the model based analyses on the large grid size. We tried to compensate for that by interpolating the data to a grid size of 5x5km^2 but this grid size would still not be sufficient to measure an extreme exposure to air pollutants and the bilinear spatial interpolation method does not necessarily improve the informational content of the source data. Second, our physical health measure might not have been sensitive enough to reflect health effects from air pollution that are linked to respiratory and cardiovascular disease. Third, we did not use information regarding the composition of PM_{10} or the exposure to particulate matter less than 2.5µm in diameter ($PM_{2.5}$). The latter is supposed to have stronger health effects [9,17]. Fourth, our research design is not able to measure short-term health effects of air pollution. For this, we would need to use detailed exposure data for the few weeks or days before the interview took place.

For future studies it is, based on our results, necessary to use specific air pollutants data with a higher spatial resolution. Integrating data concerning the exposure to $PM_{2.5}$ would very likely provide more valid beta coefficients for health outcomes. Regarding the latter, future waves of the SOEP may provide information on more sensitive health outcomes like respiratory or cardiovascular symptoms so that the association between air pollution and health can be measured more accurately. Thus it will also be possible to estimate the degree of subjectivity in the respondents' assessment of their disturbance by air pollution.

Conclusions

It is possible to enrich a large and representative datasets like the SOEP with external and area-wide geographically referenced data for air pollution. This can potentially be done with other environmental exposures, too. Although the presented data on the exposure to specific air pollutants is so far of limited use (e.g. large grid size) this should not be discouraging because there may be solutions to these problems [e.g. 36]. Integrating data from external sources in cohort, panel and other studies will probably be one of the major challenges for epidemiology in the coming years as it helps to make better use of existing datasets that by nature comprise a limited number of health-related exposures.

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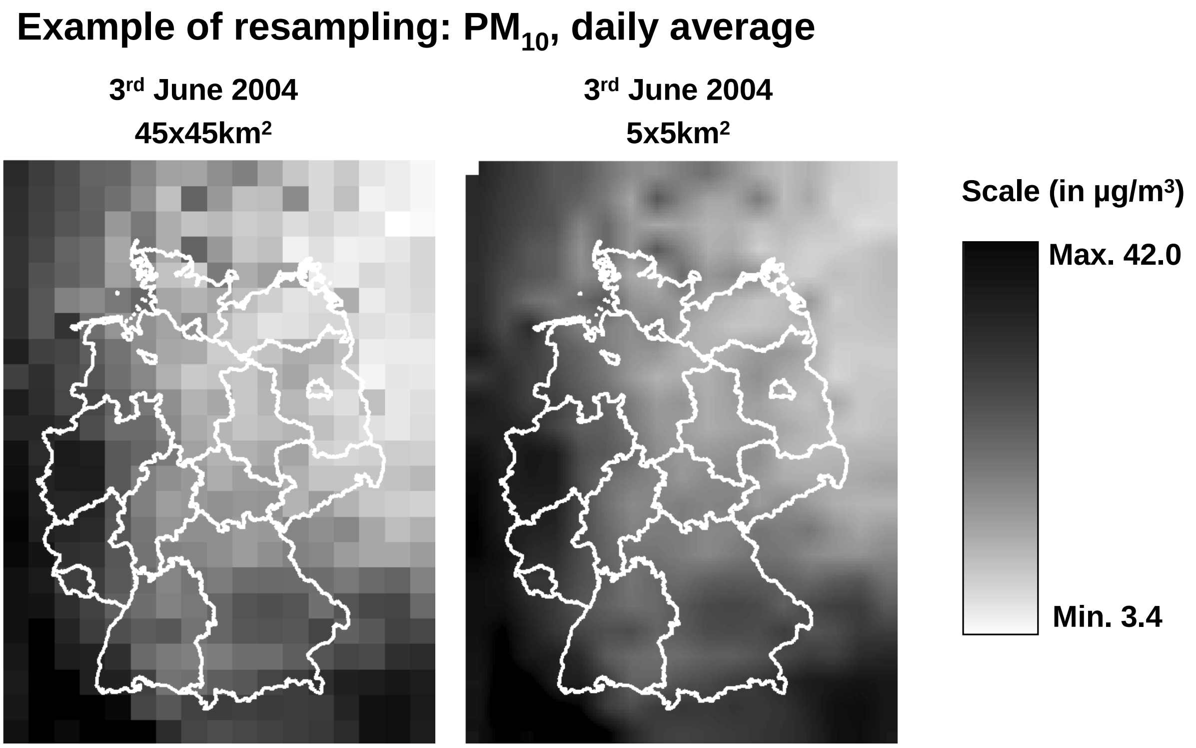
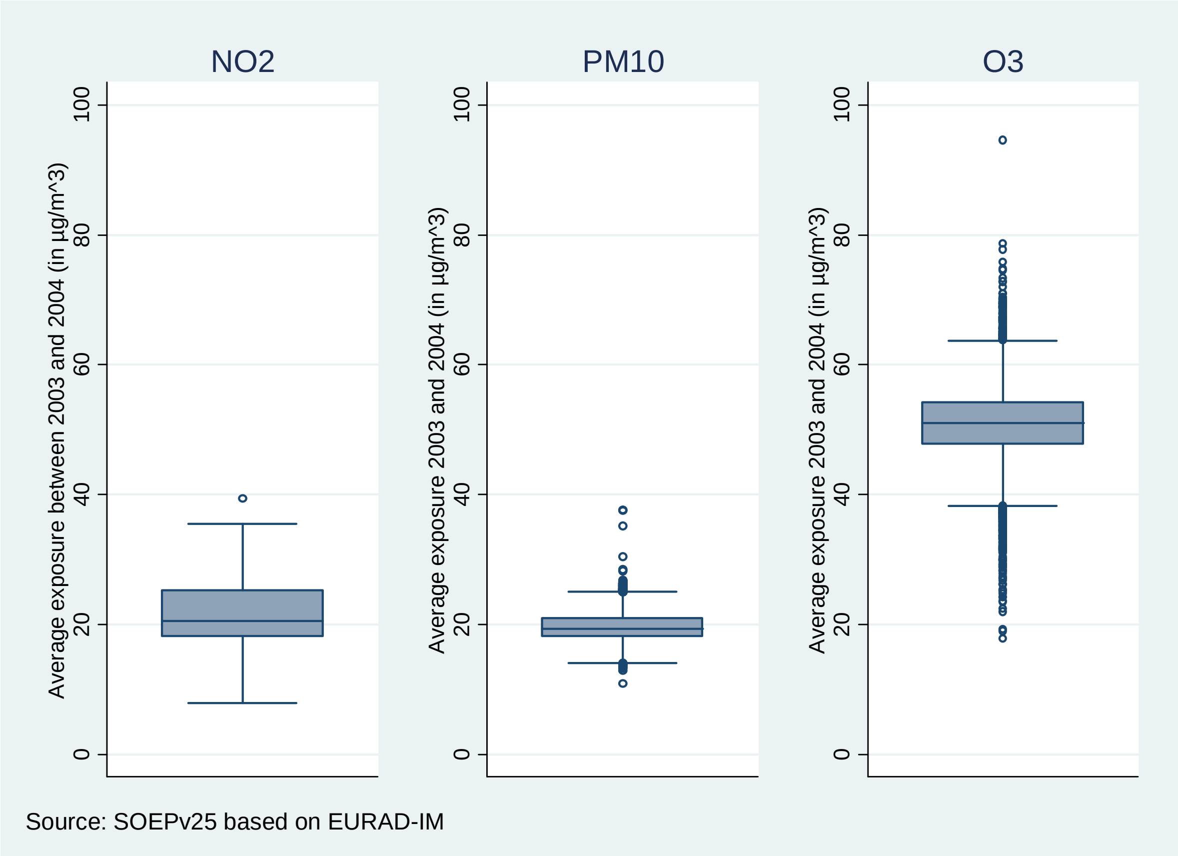
Figures and tables

Figure 1: Bilinear interpolation of the 45x45km^2 grid size provided by the EURopean Air pollution Dispersion-Inverse Model (EURAD-IM)



Notes: The map on the left shows the distribution of particulate matter less than 10µm in aerodynamical diameter (PM_{10}) across Germany for 3rd June 2004 based on the initial grid size of 45x45km^2. The map on the right shows the distribution of PM_{10} across Germany for 3rd June 2004 after interpolating the grid size to 5x5km^2 by using the utility gdalwarp. The white lines represent the borders of Germany and the German Federal States, respectively. Source: EURAD-IM [20,21].

Figure 2: Boxplots for the average exposure to specific air pollutants between 2003 and 2004



Notes: The boxplots present the average exposure of SOEP respondents to nitrogen dioxide (NO_2), particulate matter less than 10µm in aerodynamical diameter (PM_{10}), and ozone (O_3) for the time between previous interview month in 2003 and current interview month in 2004 (on average one year). Source: SOEPv25 [22] based on EURAD-IM [20,21].

Table 1: Description of study sample for 2004 (n=21,521), German Socio-Economic Panel Study (SOEP)

Variable	Mean (SD)	Proportion (number)
Air pollution variables		
Nitrogen dixode, average in μg/m^3 (SD)	21.6 (4.6)	
PM_{10}, average in μg/m^3 (SD)	19.8 (2.2)	
Ozone, average in μg/m^3 (SD)	50.7 (5.3)	
Not geographically referenced, % (number)		8.0 (1,727)
Disturbance by air pollution, % (number)		
None		47.0 (10,112)
Little		39.0 (8,394)
Tolerable		9.6 (2,069)
Strong		3.1 (675)
Very strong		0.7 (156)
Missing		0.5 (115)
Outcome variable		
PCS (SD)	49.9 (10.0)	
No PCS information, % (number)		3.5 (745)
Covariates		
Mean age in years (SD)	47.7 (17.1)	
Sex, % (number)		
Male		48.0 (10,331)
Female		52.0 (11,190)
Education, % (number)		
Still in School		1.6 (355)
Low		38.9 (8,372)
Intermediate		37.1 (7,992)
High		19.5 (4,200)
Not specified		2.8 (602)
Unemployed, % (number)		
Net equivalence income in € (SD)	22,685 (40,335)	7.2 (1,556)
Smoking		
Never smoker		48.6 (10,464)
Ex-smoker		21.6 (4,653)
Current smoker		29.7 (6,398)
Missing		<0.1 (6)
Sports participation		
Every week		34.0 (7,315)
Every month		7.4 (1,599)
Less than every month		18.6 (3,998)
Never		35.8 (7,701)
Missing		4.2 (908)
BMI		
Less than 25 kg/m^2		49.6 (10,673)
25 to 30 kg/m^2		35.6 (7,670)
Above 30 kg/m^2		14.6 (3,139)
Missing		0.2 (39)
Variable	**Min.**	**Max.**
Average purchasing power of street section in €	14,242	121,758
Unemployment quota in % (Min., Max.)	4.4	31.4

Notes: PM_{10}, particulate matter less than 10μm in aerodynamical diameter; PCS, physical component score; SD, standard deviation; BMI, Body Mass Index. Source: SOEPv25 [22] based on EURAD-IM [20,21].

Table 2: Spearman correlation coefficients between subjective and objective air pollution measures, stratified by age groups and sex

Age group	Men		Women	
18 to 39 years		SDAP (r_s)		SDAP(r_s)
	NO_2	0.08*	NO_2	0.10*
	PM_{10}	-0.01	PM_{10}	-0.02
	O_3	<-0.01	O_3	<-0.01
40 to 59 years		SDAP(r_s)		SDAP(r_s)
	NO_2	0.09*	NO_2	0.08*
	PM_{10}	-0.01	PM_{10}	-0.01
	O_3	-0.01	O_3	-0.01
60 years and above		SDAP(r_s)		SDAP(r_s)
	NO_2	0.09*	NO_2	0.10*
	PM_{10}	-0.02	PM_{10}	<0.01
	O_3	0.01	O_3	0.02

Notes: NO_2, average exposure to nitrogen dioxide (in μg/m^3), PM_{10}, average exposure to particulate matter less than 10μm in aerodynamical diameter (in μg/m^3); O_3, average exposure to ozone (in μg/m^3); SDAP, subjective disturbance by air pollution (graded on a five-point Likert scale from “none” to “very strong”); r_s, Spearman’s rank correlation coefficient. * significant at the 5% level. Source: SOEPv25 [22] based on EURAD-IM [20,21].

Table 3: Cross-sectional air pollution model with fixed effects, random effects and standard errors for PCS in 2004

Fixed effects	**Model 1** (subjective air pollution) β (SE)	**Model 2** (objective air pollution) β (SE)	**Model 3** (subjective + objective air pollution) β (SE)
Constant	53.34* (0.21)	52.90* (0.20)	53.351* (0.21)
Level 1 (individuals)			
Nitrogen dixode (in 10 µg/m^3)		0.04 (0.29)	0.41 (0.29)
PM_{10} (in 10 µg/m^3)		-0.14 (0.55)	-0.29 (0.54)
Ozone (in 10 µg/m^3)		0.15 (0.22)	0.25 (0.22)
Age	-0.29* (<0.01)	-0.29* (<0.01)	-0.29* (<0.01)
Male	1.00* (0.12)	1.00* (0.12)	1.00* (0.12)
Education			
High	Ref.	Ref.	Ref.
Intermediate	-1.52* (0.18)	-1.54* (0.18)	-1.51* (0.18)
Low	-2.38* (0.19)	-2.41* (0.19)	-2.37* (0.19)
Still in school	-3.96* (0.62)	-3.91* (0.62)	-3.95* (0.62)
Not specified	-2.69* (0.42)	-2.78* (0.42)	-2.68* (0.42)
Unemployed	-0.50* (0.24)	-0.51* (0.24)	-0.50* (0.24)
Smoking			
Never smoker	Ref.	Ref.	Ref.
Ex-smoker	-0.59* (0.16)	-0.59* (0.16)	-0.59* (0.16)
Current smoker	-0.44* (0.15)	-0.43* (0.15)	-0.44* (0.15)
Sports participation			
Every week	Ref.	Ref.	Ref.
Every month	-0.06 (0.24)	-0.08 (0.24)	-0.06 (0.24)
Less than every month	-1.00* (0.17)	-1.03* (0.17)	-1.00* (0.17)
Never	-1.68* (0.16)	-1.68* (0.16)	-1.68* (0.16)
BMI			
Less than 25 kg/m2	Ref.	Ref.	Ref.
25 to 30 kg/m2	-0.95* (0.14)	-0.96* (0.14)	-0.95* (0.14)
Above 30 kg/m2	-3.50* (0.19)	-3.51* (0.19)	-3.50* (0.19)
Level 2 (households)			
Disturbance by air pollution			
None	Ref.		Ref.
Little	-0.63* (0.14)		-0.65* (0.14)
Tolerable	-1.52* (0.23)		-1.55* (0.23)
Strong	-2.16* (0.38)		-2.20* (0.38)
Very strong	-3.01* (0.77)		-3.06* (0.77)
Net equivalence income (log)	1.08* (0.14)	1.13* (0.14)	1.08* (0.14)
Purchasing power in 1,000€	0.03* (0.01)	0.04* (0.01)	0.03* (0.01)
Level 3 (counties)			
County unemployment quota	-0.02 (0.02)	-0.02 (0.02)	-0.01 (0.02)
Random variation	**σ^2 (SE)**	**σ^2 (SE)**	**σ^2 (SE)**
Level 1 (individuals)	57.2 (0.9)	57.3 (0.9)	57.2 (0.9)
Level 2 (households)	8.7 (0.7)	9.0 (0.7)	8.7 (0.7)
Level 3 (counties)	1.2 (0.2)	1.2 (0.2)	1.2 (0.2)
-2*loglikelihood	130,351	130,432	130,348
(number of cases)	(18,547)	(18,547)	(18,547)

Notes: PM_{10}, particulate matter less than 10µm in aerodynamical diameter; PCS, physical component score; β, beta coefficients; SE, standard errors; σ^2, variance. * significant at the 5% level using the Wald test. Source: SOEPv25 [22] based on EURAD-IM [20,21].