**Long-term traffic-related air pollutant exposure and amyotrophic lateral sclerosis diagnosis in Denmark: a Bayesian hierarchical analysis**

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**Key Points**

**Question:** How are traffic-related pollutants, individually and combined, associated with diagnosis of amyotrophic lateral sclerosis (ALS)?

**Findings:** In this large population-based case-control study of ALS diagnosis in Denmark, including 3,939 cases, we observed that a 5-year concentration of traffic-related pollutants was associated with a non-significant increase in odds of ALS diagnosis, but with a high posterior probability of a positive association for elemental carbon.

**Meaning:** Our results indicate a potential positive association between ALS diagnosis and traffic-related pollutants. Further work is needed to understand the role of air pollution on ALS pathogenesis and timing of onset.

**Abstract**

**Importance:** Amyotrophic lateral sclerosis (ALS) is a devastating and fatal neurodegenerative disease. There is some limited evidence to suggest ALS onset is associated with exposure to air pollution and specifically to traffic-related pollutants.

**Objective:** To determine whether exposure to traffic-related pollutants is associated with ALS diagnosis.

**Design, Setting, and Participants:** We used prospectively collected data from the Danish National Registers system from 3,939 ALS cases diagnosed between 1989 – 2013 and matched on age, sex, date of birth and vital status to 19,298 population-based controls. We used predictions from validated spatio-temporal models to assign 5-year average exposures prior to ALS diagnosis at residential addresses of study participants, specifically nitrogen oxides (NOx), carbon monoxide (CO), elemental carbon (EC), and fine particles (PM2*.*5). In this population-based case-control study, we used a Bayesian hierarchical conditional logistic model and adjusted for potential confounders to estimate the overall traffic association, the joint association with the 3 traffic-related pollutants (NOx, CO, and EC), as well as pollutant-specific associations.

**Main Outcome Measure:** Adjusted odds ratio for ALS diagnosis associated with 5-year average overall traffic and specific traffic-related pollutant exposure.

**Results:** We found that for a standard deviation (SD) increase in 5-year average concentrations, the total association of included traffic-related pollutants (NOx, CO, EC) was associated with an increase in odds of ALS diagnosis (1.9%; 95% credible interval [CrI]: -5.3%, 9.0%), with EC (SD=0.42 µg/m3) individually associated with an increase in odds (11.5%; 95%CrI: -1.6%, 26.2%), with small decreases individually for NOx and CO. Overall, there was a 69.3% posterior probability of a positive association between the total effect of included traffic-related pollutants and ALS diagnosis, 95.5% for EC, 23.5% for NOx and 30.6% for CO.

**Conclusion:** Our results indicate a potential positive association between ALS diagnosis and traffic-related pollutants, and particularly for elemental carbon. Further work is needed to understand the role of air pollution on ALS pathogenesis and timing of onset.

**Introduction**

Amyotrophic lateral sclerosis (ALS) is a devastating and fatal neurodegenerative disease,1 with approximately half of the patients dying within three years of symptom onset.2 There is currently no cure for ALS.3 Annually, there are nearly 30,000 cases of ALS in Europe and over 200,000 worldwide, with the number projected to increase nearly 70% by 2040.4 Though great advances in our understanding of genetics have been made, known inherited mutated genes only account for 5–10% of ALS cases.5,6 Environmental factors therefore likely play an important role in ALS pathogenesis.7 However, because the disease is relatively rare, it is difficult to conduct large-scale prospective studies. The lack of and the need for more and better epidemiologic studies of the etiology of ALS has been recognized and highlighted.5,8

Although air pollution is most commonly studied in association with respiratory- and cardiovascular-related outcomes,9–14 epidemiological and toxicological studies support several plausible biological mechanisms in association of the nervous system and neurodegeneration.15–34 Ambient air pollution, and especially urban air pollution, is a ubiquitous exposure that has been associated with several other neurodegenerative disorders,16–21 and consistently linked to systemic inflammation,22–24 oxidative stress,25–28 and neuroinflammation,15,29 all of which, in turn, have been reported as key pathways to ALS pathogenesis.30–34

Despite the compelling plausibility, few studies to datehave evaluated the association between traffic-related air pollutants and ALS,35–38 and none has attempted to understand the combined and individual associations of traffic-related pollutants in a single model. Traffic-related pollutants have been consistently associated with adverse health, primarily in single pollutant analyses.13,17,39–41 However, they are highly correlated with one another.39 It is therefore a mixture modelling challenge to infer the association of traffic-related pollutants and health outcomes, and analyses should depend on the research question of interest.42 Using three air pollutants commonly used in health studies as traffic-related emissions tracers, namely nitrogen oxides (NOx), carbon monoxide (CO), and elemental carbon (EC), we aimed to assess whether exposure to each individual traffic-related pollutant is independently associated with ALS diagnosis, and estimate their joint and the average overall traffic emissions associations.

**Methods**

*Study Population and Outcome Assessment*

We used data from the Danish National Registers system during 1989 – 2013, through which details on demographic characteristics and certain health outcomes of all Danish residents can be linked based on a 10-digit unique personal identifier.43 The Danish National Registers system was established in 1977 and is a comprehensive patient register, including nationwide clinical and administrative records for all somatic inpatient data. Outpatient data have also been included in the Danish National Registers system since 1995.

We identified ALS cases based on their International Classification of Diseases (ICD) discharge diagnoses, i.e., ICD-8 code 348.0 (ALS) until 1993 and ICD-10 code G12.2 (motor neuron disease) thereafter. For the diagnosis date, we used the date of the first relevant code. We only included patients who were at least 20 years old when diagnosed. In a previous validation study, Danish National Registers system data for ALS ascertainment were found to be highly reliable.44

We obtained controls through the Danish Civil Registration System, which was established in 1968 and includes administrative records (e.g., date and place of birth, vital status, and history of civil status and addresses) on all persons living in Denmark; records are kept even when a person dies or emigrates.45 We identified as potential controls any person with no mention of ICD-8 code 348.0 or ICD-10 G12.2 in the Danish National Registers system. We randomly matched five controls per case by age, sex, date of birth, and vital status. Controls were alive in the Danish National Registers system at the ALS diagnosis date of the matched case (index date).

We obtained all addresses of cases and controls from January 1st 1979 onwards from the Danish Civil Registration System,45 including the dates of moving to and leaving from each address, prior to the index date. We then obtained the geographical co-ordinates at the door of each house of the residential history of the participants, with previous evidence of the high accuracy of this method of geocoding of addresses in Denmark.17

This study was approved by the Institutional Review Board at the Columbia University.

*Exposure data*

We obtained predictions on monthly concentrations of nitrogen oxides (NOx), carbon monoxide (CO), elemental carbon (EC; of which black carbon is a constituent), ozone (O3), and fine particles (PM2*.*5) at residential addresses of study participants from validated spatio-temporal models with full space and time coverage over our study period, described in detail elsewhere.46,47 We used the O3 concentrations for sensitivity analyses. These predicted pollutant concentrations have been extensively used in previous air pollution epidemiologic studies in Denmark.17,48–50 The models have good predicted accuracy, with average monthly correlations between measured and modelled results of 0.84 for NOx,46 0.8 for CO,46 XX for O3,46 and XX for EC,47 and 0.91 for annual concentrations of PM2.5.51. Based on the residential history of each case or control, we then calculated 1-, 5-, and 10-year average exposure to each pollutant ending at one year before the index date, as diagnosis has been shown previously to occur at a median of 12 months after onset.52 A small number of people in the Danish Civil Registration System lack a complete address history (typically 1.7% from a lack of house number). To ensure we were including participants with adequately complete exposure records, we set the following criteria for including cases and controls across the length of exposure averages: (i) 1-year averages: 9 out of 12 months with complete exposure records, and at least one measurement in each season; (ii) 5-year averages (main exposure): at least 30 out of 60 months with complete exposure records; and (iii) 10-year averages: at least 60 out of 120 months with complete exposure records.

*Covariate data*

We included a set of covariates to account for potential confounding bias. We used the five-category individual-level socioeconomic status (SES) definitions developed by the Danish Institute of Social Sciences, based on job titles, which have been previously shown as having an association with ALS diagnosis in Denmark,53 and income tax forms. Group 1 (highest status) includes corporate managers and academics; group 2 includes proprietors, managers of small businesses and teachers; group 3 includes technicians and nurses; group 4 includes skilled workers; and group 5 includes unskilled workers. We additionally included a group for unemployed participants (group 9). If a participant were married and information were available, we used the higher of the couple’s individual SES ranks. We also used information on civil status (never married, married, divorced and widowed), place of residence (Greater Copenhagen, big cities of Denmark, rest of Denmark, Greenland) and place of birth (Greater Copenhagen, big cities of Denmark, rest of Denmark, Greenland, foreign, unknown) to adjust for other family-specific, location-specific, and early-life potential confounders. In Denmark, parishes are small administrative units with an average population of ~2,500 residents; as part of the sensitivity analysis, we also the included parish-level SES covariate in the model.

*Statistical analysis*

We analyzed the association between ALS diagnosis (binary outcome; 1 for diagnosed cases and 0 for matched controls) and exposure to traffic-related pollutants by applying a Bayesian formulation of the conditional logistic model, with Bayesian hierarchy on the traffic-related pollutants.54,55 The conditional approach automatically accounts for matching factors (age, sex, date of birth, and vital status) between cases and controls within each matched stratum, i.e., groupings of case and matched controls.54 Bayesian inference allows for full distributional estimation of the parameters of interest.55 We employed a Bayesian hierarchical formulation because it allows us to estimate (a) independent pollutant associations, (b) a joint association of the three pollutants, and (c) an overall average traffic association, while accounting for the variance-covariance structure between the highly correlated exposures and their coefficients.55 We included a linear term for each included pollutant and adjusted for individual- and parish-level SES, civil status, place of residence, and place of birth.

Specifically, via a logit function, we modelled the log-odds of ALS diagnosis, as follows:

where denotes whether there was an ALS diagnosis for subject in matched stratum , i.e., represents a case and its matched controls; the matched stratum-specific intercepts (not estimated in the conditional logistic model); ,,,the pollutant-specific coefficients (log-odds) per standard deviation increase in concentration of , , , respectively, scaled by their respective standard deviations and centered at their means; and the rest as coefficients for subject-specific covariates. If other included sources of air pollution are associated with ALS, then including PM2.5 (an overall air pollution mixture which includes traffic-related pollutants) adjusts for other air pollutants from other sources.56 Therefore,  would be interpreted as the association with non-traffic air pollutants. In a sensitivity analysis, we included to account for exposures in the model, and added to our covariates.

In the above model, the coefficients , , and represent the independent pollutant-specific associations with ALS diagnosis. Additionally, we estimated the joint association between these three pollutants and ALS diagnosis as:

Specifically, this sum quantifies the association (log-odds) with ALS of a one-SD increase in all three traffic-related pollutants simultaneously.

Finally, we assumed that the traffic-related pollutant-specific associations arise from a distribution of the overall traffic association with ALS diagnosis. To estimate this overall traffic effect, we placed a hierarchy on the traffic-specific pollutant terms in the model:

,  
,

where denotes the average overall association of traffic-related pollution with variance . , the estimated variance-covariance matrix among pollutant-specific estimates, was expressed as a decomposition into a positive-definite correlation matrix and scale matrix .57

We used weakly-informative priors so that parameter estimation was driven by the data. Hyper-priors for coefficients on and covariates were N(0,10); for and we used Half-Cauchy(0,10); and was defined by LKJCorr(1).58The exception to this was for the prior on , the average association of traffic-related pollutants, for which estimates became unrealistically high (approaching infinity) with a non-informative prior, and so we used a prior of N(0,0.1), which did not affect estimates of other parameters. We conducted sensitivity analyses to understand the influence of priors and the robustness of the results, as detailed below.

We present all results as percentage change in odds of ALS diagnosis per standard deviation (SD) increase in pollutant concentration (calculated via e.g., etc. and obtained in the modelling process). We conducted statistical analyses using the R Statistical Software, version 4.1.1 (Foundation for Statistical Computing, Vienna, Austria),59 and R-STAN, version 2.21.2.55 We ran each model with four chains with a sample size of 1,000 each, after a warm-up of 1,000 samples, which resulted in 4,000 total samples. We assessed whether the models converged by checking that the Gelman-Rubin potential scale reduction statistic,60 , was below 1.1 for all estimated model parameters. The reported 95% credible intervals (CrI) are the 2.5th to 97.5th percentiles of each parameter’s posterior marginal distribution. To calculate the probability that an association estimate was greater than null, we used the 4,000 samples of the posterior and took the proportion of samples which were above a null association. All code for analysis, results from analysis and visualization presented in this manuscript will be publicly available via GitHub.

We assessed the sensitivity of our results to hyper-prior adjustment; running more iterations and warm-up per chain; inclusion of O3; single traffic-related pollutant models adjusting for PM2.5; as well as including parish-level SES as a covariate.

**Results**

After filtering the original 4,011 cases and 20,055 controls based on completeness of exposure and covariate records, we used information on 3,934 (98.1%) cases and 19,298 (96.2%) controls for 5-year average exposure. We were also used 3,937 (98.2% of total) cases and 19,333 (96.4% of total) controls for 1-year average exposure and 3,939 (98%) cases and 19,250 (96%) controls for 10-year average exposure. Descriptive statistics of included cases and controls can be found in Table 1.

A summary of mean and standard deviation of 5-year average concentrations for each pollutant included in the analysis are presented in Table 2. The 5-year average traffic-related pollutant concentrations were 27 µg/m3 for NOx (SD=20 µg/m3), 238 µg/m3 for CO (SD=106 µg/m3) and 0.85 µg/m3 for EC (SD=0.42 µg/m3). The Spearman correlation between pollutants for 5-year average exposure is found in Figure 1. In general, traffic-related pollutants (NOx, CO, EC) were highly correlated in cases and controls and overall, ranging from correlations of 0.91 to 0.96. Otherwise, PM2.5 was correlated with CO most highly (0.77 to 0.78), as well as NOx (0.64 to 0.65) and EC (0.67 for each) to a lesser degree. O3 was negatively-correlated with all other included pollutants (-0.67 to -0.88).

We analyzed the association between change in odds of ALS diagnosis per standard deviation increase in individual 5-year average pollutant concentrations, as well as the association with joint exposure to these three pollutants and the average traffic contribution (Figure 2). We observed the largest overall association for the individual standard deviation increase in EC (11.5%; 95% CrI: -1.6%, 26.2%; 95.5% posterior probability of positive association per 0.42 µg/m3). Standard deviation increases were associated with a slight percentage decrease in odds of ALS diagnosis in both NOx (-4.9%%; 95% CrI: -18.3%, 8.7% per 20 µg/m3) and CO (-3.3%; 95% CrI: -15.5%, 9.4% per 106 µg/m3). The joint association (i.e., the percentage change in odds of ALS diagnosis with a standard deviation increase in each of EC, NOx, CO) was 1.9%; (95% CrI: -5.3%, 9.0%), with an 69.3% posterior probability of a positive association. Finally, the average overall traffic association was 0.4%; (95% CrI: -16.9%, 19.8%). PM2.5 (which in this context represented the association of non-traffic-related PM2.5) was associated with an increase in odds of ALS diagnosis (1.3%; 95% CrI: -10.4%, 14.5%). For 1-year average exposure, EC was associated with an increase in odds of ALS diagnosis which was significant at a 95% CrI (12.7 %; 95% CrI: 0.1%, 26.1%) (Figure 2). Single-pollutant models for each traffic-related pollutant adjusting for PM2.5 (eFigure 1) resulted in positive associations for each of EC, NOx, CO, with positive associations for PM2.5 in all but the model with EC. Results from variations of the main model in the sensitivity analyses were robust to prior choices and inclusion of parish-level SES (eFigure 1). In the parish-level SES analysis: (i) 819 participants for the 1-year average exposure, (ii) 826 participants for the 5-year average exposure, and (iii) 838 participants for the 10-year average exposure lived in areas without parish-level SES data, and so were excluded from that sensitivity analysis.

**Discussion**

In the largest case-control study of ALS and traffic-related air pollution to date, we used 3,939 ALS diagnoses in Denmark, pollutant predictions from well-validated spatio-temporal models, along with a Bayesian hierarchical structure to examine how increases in traffic-related pollutant concentrations, individually and combined, are associated with percentage change in odds of ALS diagnosis. We found that a standard deviation increase of 5-year concentration of traffic-related pollutants was associated with an increase in odds of ALS diagnosis, though not significant at the 95% credible interval level. We found that EC had the largest-in-magnitude independent association with ALS diagnosis, while the non-significant associations with NOx and CO were negative and smaller in magnitude.

Traffic-related pollutants pose great danger to public health in many ways.9–21,39–41 Overall, while not significant at 95% CrI for 5-year averages, our results that indicate that traffic-related pollutants may also be associated with ALS diagnosis. Our finding—that increases in traffic-related pollutants, and specifically elemental carbon, are potentially positively associated with ALS diagnosis—is plausible. A recent case-control study in the Netherlands reported that ultrafine particles, another traffic emissions-related surrogate, were associated with ALS diagnosis.36 Another case-control study in the Netherlands also found a significant association with PM2.5.37 A population-based study in New York State found an association with ALS disease aggravation and PM2.5,38 while another based in Catalonia, Spain found ALS cases clustered around key road infrastructure.61 Although we did not find an association with PM2.5 in our study, our results are not directly comparable to those of the other studies, as our PM2.5 effect estimates capture the non-traffic PM2.5 components.

Our results indicate that EC exposure—a large part of which comes from diesel combustion in European urban centers, where prevalence of diesel cars is high62—has a high probability of a positive association with ALS diagnosis. A previous study of ALS diagnosis and occupational exposures in Denmark found that those working in agriculture and construction, associated with exposure to diesel exhausts, were at higher relative risk than those in other employment.53 Truck drivers, for whom diesel exposure is common, are also at increased risk of sporadic ALS.63 EC has been associated with inflammation,64 mitochondrial dysfunction65 and DNA damage,65,66 all of which are plausible pathways of neurodegeneration in the human body. These factors have also previously been identified as pathways to pathogenesis of ALS.30–34 We did not find a high probability of a positive association with NOx in our analyses, in contrast with a previous study, though that study did not include EC.36 NOx is also highly correlated with EC (0.95 to 0.96 in our study), which is expected given that they are both combustion products commonly associated with traffic-related emissions in urban environments. EC exposure was more strongly associated with 1-year than for 5- or 10-year average concentration, which may indicate that the previous year may be the most relevant exposure window, or also perhaps that we expect less error in 1-year concentrations of EC.

Our study used one the largest number of ALS diagnoses ever included in an environmental health study. Another great strength of our study, further, is that leveraging highly correlated traffic pollutants and Bayesian hierarchical modeling, we were able to estimate independent and joint traffic-related pollutant associations, as well as an overall traffic estimate. Though it is the largest dataset ever used for this purpose, we expect that more cases would further help power future studies. Although we have adjusted implicitly (by matching) and explicitly for many common covariates (age, sex, date of birth, SES, civil status, place of birth), we cannot rule out residual confounding. However, to induce confounding bias, any unaccounted-for variable would have to covary with both ALS diagnosis and air pollution. Body Mass Index (BMI), previously associated with ALS,67,68 would not be a confounder of the association between traffic-related air pollution and ALS;69 concentrations of pollutants from for this study were derived from air pollution models independent from the geographical BMI distribution of the Danish population. BMI could be associated with air pollution in our study would be via SES, which we adjusted at both the individual and parish level. Exposure measurement error is also likely, as any modelled exposure will be inaccurate to some degree. However, any error is not likely correlated with ALS diagnosis, and would therefore be expect any bias to be towards the null.70

Future research should use larger cohort data to understand the importance of each respective pollutant in a single model. The timing of exposure, furthermore, will also be an important study route. ALS is projected to increase in prevalence over the next few decades all over the world, and therefore understanding its pathogenesis and identifying modifiable risk factors is critical for both preventive action, as well as eventually to finding a full cure.

**Table 1.** Demographic characteristics of cases and controls.

| Characteristic | Overall, N = 23,2321 | Case, N = 3,9341 | Control, N = 19,2981 |
| --- | --- | --- | --- |
| **Average age (years)** | 66 (12) | 66 (12) | 66 (12) |
| **Sex** |  |  |  |
| Female | 10,973 (47%) | 1,854 (47%) | 9,119 (47%) |
| Male | 12,259 (53%) | 2,080 (53%) | 10,179 (53%) |
| **Family SES** |  |  |  |
| Group 1 (Highest) | 2,337 (10%) | 451 (11%) | 1,886 (9.8%) |
| Group 2 | 2,839 (12%) | 499 (13%) | 2,340 (12%) |
| Group 3 | 4,360 (19%) | 785 (20%) | 3,575 (19%) |
| Group 4 | 6,598 (28%) | 1,076 (27%) | 5,522 (29%) |
| Group 5 (Lowest) | 4,419 (19%) | 717 (18%) | 3,702 (19%) |
| Group 9 (Unemployed) | 2,679 (12%) | 406 (10%) | 2,273 (12%) |
| **Place of birth** |  |  |  |
| Greater Copenhagen | 4,858 (21%) | 831 (21%) | 4,027 (21%) |
| Big cities of Denmark | 7,923 (34%) | 1,357 (34%) | 6,566 (34%) |
| Rest of Denmark | 9,009 (39%) | 1,548 (39%) | 7,461 (39%) |
| Greenland | 243 (1.0%) | 53 (1.3%) | 190 (1.0%) |
| Foreign | 1,065 (4.6%) | 122 (3.1%) | 943 (4.9%) |
| Unknown | 134 (0.6%) | 23 (0.6%) | 111 (0.6%) |
| **Civil status** |  |  |  |
| Married | 14,158 (61%) | 2,411 (61%) | 11,747 (61%) |
| Divorced | 2,703 (12%) | 433 (11%) | 2,270 (12%) |
| Widower | 4,224 (18%) | 726 (18%) | 3,498 (18%) |
| Never married | 2,147 (9.2%) | 364 (9.3%) | 1,783 (9.2%) |
| **Place of residence** |  |  |  |
| Greater Copenhagen | 1,887 (8.1%) | 335 (8.5%) | 1,552 (8.0%) |
| Big cities of Denmark | 9,385 (40%) | 1,590 (40%) | 7,795 (40%) |
| Rest of Denmark | 11,954 (51%) | 2,008 (51%) | 9,946 (52%) |
| Greenland | 6 (<0.1%) | 1 (<0.1%) | 5 (<0.1%) |
| 1Mean (SD); n (%) | | | |

**Table 2.** Summary of 5-year average pollutant concentrations (all in μg/m3).

| Pollutant | Overall, N = 23,2321 | Case, N = 3,9341 | Control, N = 19,2981 |
| --- | --- | --- | --- |
| **NOX** | 27 (20) | 28 (21) | 27 (20) |
| **CO** | 238 (106) | 239 (112) | 237 (105) |
| **EC** | 0.85 (0.42) | 0.86 (0.45) | 0.85 (0.42) |
| **PM2.5** | 12.61 (2.64) | 12.64 (2.68) | 12.60 (2.63) |
| **O3** | 51.9 (6.0) | 51.9 (6.1) | 52.0 (6.0) |
| 1Mean (SD) | | | |

**Figure 1**. Spearmancorrelation of 5-year average pollutant concentrations.

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**Figure 2**. Percentage change in odds of ALS diagnosis per 1-, 5- and 10-year average standard deviation increase for each pollutant.

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**eFigure 1**. Sensitivity of percentage change in odds of ALS diagnosis for non-pollutant parameters.

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**eFigure 2**. Map of pollutants?

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