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# Short-Term exposure to ambient air pollution and onset of work incapacity related to mental health conditions

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ABSTRACT

The OECD estimates that greater work absenteeism is one of the main drivers behind the impact of air pollution on gross domestic product loss, but research linking air pollution with work absenteeism is scarce. With air pollution increasingly being linked to poor mental health, and poor mental health having become one of the main reasons for work absenteeism, we examined whether the onset of work incapacity related to mental health conditions is associated with short-term fluctuations in ambient black carbon (BC), nitrogen dioxide ($NO_2$), ozone ($O_3$), and particulate matter 2.5 ($PM_{2.5}$), estimating the contributions of these pollutants jointly, while accounting for relative humidity, total solar radiation and temperature. We conducted a bidirectional time-stratified case-crossover study with daily air pollution estimates by municipality linked with 12 270 events of work incapacity related to mental health conditions in 2019 in Belgium. We ran single- and multi-pollutant conditional logistic regression models for three different exposure windows (lag 0, 0–1 and 0–2), considering potential confounding by relative humidity and total solar radiation. We observed positive associations between work incapacity related to mental health conditions and BC, $NO_2$, and $O_3$ exposure, but findings for $PM_{2.5}$ were inconsistent. Results from multi-pollutant models showed a 12% higher risk of work incapacity for an IQR increase in $NO_2$ and $O_3$ at the day of the event (lag 0), with estimates increasing to about 26% for average concentrations up to two days before the event (lag 0–2). We found evidence for effect modification by age and season in the association with $NO_2$, with highest effect estimates in the age group 40–49 years and in spring and summer. For $O_3$, we observed effect modification by type of mental health problem. This country-wide study suggests that air pollution aggravates within 48 h a likely existing propensity to enter work incapacity because of mental health conditions.

## 1. Background and objective

Traditionally, the effect of short or long-term exposure to air pollution used to be mainly studied in association with risk for physical health conditions like cardiovascular and respiratory illnesses. Emerging evidence suggests a close link between air pollution and poor mental health as well. Recent meta-analyses concluded that long-term particulate matter (PM) exposure is associated with depression and anxiety, while short-term exposure is associated with suicide (Braithwaite et al., 2019; Liu et al., 2021). For symptoms of anxiety, however, a landmark study found that short-term higher exposure to $PM_{2.5}$ (PM with a diameter of <2.5 μm) is more relevant than long-term exposure (Power et al., 2015). Also for depression, both short and long-term exposure to black carbon (BC), a crucial component of PM, play a role in its development (Shen et al., 2021). Increases in PM and nitrogen dioxide ($NO_2$) have been found to be associated with community mental health service events, among others (Newbury et al., 2021). While a systematic review concluded that evidence for an association between ambient ozone ($O_3$)

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exposure and mental health outcomes is inconclusive (Zhao et al., 2018), a recently published study observed significant same-day and cumulative 7-day associations between $PM_{2.5}$ and $O_3$ and mental health related emergency department visits (Nguyen et al., 2021).

Harmful levels of air pollutants thus remain a significant health concern worldwide, and the economic burden of air pollution amounts to trillions of dollars annually (World Bank, 2020). The Organisation for Economic Co-operation and Development (Dechezleprêtre et al., 2020) estimates that ninety-five per cent of the impact of air pollution on gross domestic product loss is due to reductions in output per worker, which can occur through greater absenteeism at work or reduced labour productivity. Nevertheless, a recent systematic review on the economic effects of air pollution (Lu, 2020) confirms that research linking air pollution to work productivity is limited. An early study in Norway using data on sick leaves from one company in the 1990 s found that an increase in $PM_{10}$ (PM with a diameter of$<$10 μm) is associated with an increase in the number of sick-leaves (Hansen and Selte, 2000). Similar findings were reported in a country-wide Spanish study (Holub et al., 2020). Strong associations were found for air pollution and sick leaves related to mental disorders, among others. Last, Aragón et al., 2017 showed that even moderate air pollution reduces hours worked, and that this effect was concentrated among households with dependents more susceptible to pollution, i.e., small children and elderly adults.

In Belgium, mental health conditions over the past few years have become the biggest driver of the increase in work incapacity benefit payments. About one in four new entrances in work incapacity are related to mental health conditions, and burnout and depression each mount to about 9% of all new entrances (Bruyneel et al., 2020). In addition, 37% of persons in long-term (greater than12 months) work incapacity find themselves in that situation because of mental health conditions, with an annual cost of about 1.5 billion euros in benefit payments alone (National Institute for Health and Disability Insurance, 2021). With about half a million people in work incapacity at any given time and another half a million in long-term work incapacity, on a working population of about 5.5 million, work incapacity is perceived as a major threat to the sustainability of the social security system.

Environmental epidemiologic research into the impact of air pollution on work incapacity related to mental health conditions may provide new insights and directions for future research in a field that is currently dominated by a focus on understanding the role of job demands and attitudes. Here, we present a time-stratified case-crossover study to quantify the association of BC, $NO_2$, $O_3$ and $PM_{2.5}$ with the onset of work incapacity related to mental health conditions, using single- as well as multi-pollutant models accounting for temperature. We considered potential confounding by total solar radiation and relative humidity and assessed potential effect modification by type of mental health condition, sex, age group, type of worker, region, and season.

## 2. Methods

### 2.1. Study population

The study population comprised members of the Independent Health Insurance Funds (Onafhankelijke Ziekenfondsen / Mutualités Libres). Being one of the seven recognized health insurance funds in Belgium, it serves approximately two million members. It thereby covers nearly 19% of the Belgian population. The study period ran from January 1, 2019 to December 31, 2019. Our analysis was limited to members for whom the home address did not change during the study period, according to our administrative records.

### 2.2. Exposure measures

Daily average concentrations of BC, $NO_2$, $O_3$ and $PM_{2.5}$ at the level of the municipality were provided by the Belgian Interregional Environment Agency (Irceline). Irceline gathers the air pollutant monitoring data from the Belgian regional telemetric air quality networks of the Brussels Capital, Flemish and Walloon Regions. These networks continuously measure the concentrations of several air pollutants, including 33 stations for BC, 91 for $NO_2$, 41 for $O_3$, and 73 for $PM_{2.5}$. The highest temporal resolution available is for hourly values. In a validated spatial–temporal interpolation model, data collected by the monitoring stations are combined with land cover data from satellite images to account for the local variations of pollutant concentrations at locations where no monitoring stations are available (Janssen et al., 2008). This provides air pollution estimates on a 4x4 km grid, which are then used to calculate population-weighted averages per municipality. The overall model performance was assessed by leave-one-out cross-validation, including 14 monitoring stations for black carbon, 44 for $NO_2$, and 34 for $PM_{2.5}$. The validation statistics of the interpolation tool explained more than 74% of the temporal and spatial variability in Flanders for black carbon, 78% for $NO_2$, and 80% for $PM_{2.5}$ (Lefebvre et al., 2011). More detailed information on air quality in Belgium during the study period is available elsewhere (http://www.irceline.be/en).

To adjust for potential confounding by meteorological variables, Irceline also provided daily data on mean ambient temperature, total solar radiation, and relative humidity. Data for temperature were at the level of the municipality, but solar radiation and relative humidity data were only available for one measurement station in the city of Antwerp. Total solar radiation was expressed as the sum of all half hour average solar radiation measurements in a day. Relative humidity was expressed as a percentage that represents the amount of water vapor in the air at a given temperature compared to the max possible water vapor amount at that same temperature. These measures were only available from one measurement station in the city of Antwerp, but can be used as a proxy for total daily sunlight or relative humidity for the whole country. For example, relative humidity measured in Antwerp shows correlations of 0.95, 0.81 and 0.73 with measuring stations in Ghent, Liège and Veurne, respectively.

### 2.3. Outcome measure: Work incapacity related to mental health

In Belgium, the employees, unemployed, self-employed and miners who are no longer able to work due to an illness or an accident, may benefit from work incapacity benefit payments by the health insurance funds. For white-collar workers, there first is a period of guaranteed salary paid by the employer for the first 30 days. Blue-collar workers receive a guaranteed salary for the first 7 days, 85.9% of their normal gross salary for the next 7 days, and from day 15 to 30 they are partly paid by the employer (25.9%) and the health insurance funds (60%). Afterwards, the health insurance funds take over full responsibility for the benefit payments, which correspond to 60% of the salary at daily capped amounts.

Only work incapacity events that involve payment by the health insurance funds are included in this study. Self-employed workers can claim benefits from the first day of work incapacity, provided that they remain incapacitated for at least 8 consecutive days. Blue- and white-collar workers, however, only receive payments from the health insurance funds after 14 days and after 30 days of work incapacity, respectively (the period before they get (partly) paid by the employer).

The person's attending physician completes the work incapacity certificate, which includes a start and end date of work incapacity. This start date is used to indicate the case event in the case-crossover analysis. The certificate also includes a diagnosis or symptomatology and/or functional disorders. Unique to the Belgian situation, the Independent Health Insurance Funds use this information to assign a pathology label and derive a diagnosis using the International Classification of Diseases, Tenth Revision (ICD-10). We retained three major ICD-10 blocks reflecting mental health conditions i.e. 'Problems related to life-management difficulty (Z73)', 'Neurotic, stress-related and somatoform disorders (F40-F48)' and 'Mood [affective] disorders (F30-F39)'. Details on the specific diagnoses that these blocks entail are presented in

**Table 1**
Number of cases of work incapacity related to mental health conditions included in the analysis with control days within 2 °C from that of the case day and distribution across categories of potential effect modifiers.

| | Number of cases (%) |
|---|---|
| Overall | 12 270 |
| Mental health condition | |
| Neurotic, stress-related and somatoform disorders | 1461 (11.9%) |
| Problems related to life-management difficulty | 5442 (44.4%) |
| Mood [affective] disorders | 5367 (43.7%) |
| Age | |
| 18–29 | 1854 (15.1%) |
| 30–39 | 3692 (30.1%) |
| 40–49 | 3596 (29.3%) |
| 50–64 | 3128 (25.5%) |
| Sex | |
| Female | 7687 (62.7%) |
| Male | 4583 (37.3%) |
| Type of worker | |
| Blue-collar | 4483 (36.6%) |
| Independent | 740 (6.0%) |
| White-collar | 7047 (57.4%) |
| Region | |
| Brussels | 1865 (15.2%) |
| Flanders | 5573 (45.4%) |
| Wallonia | 4832 (39.4%) |
| Season | |
| Spring | 3375 (27.5%) |
| Summer | 2173 (17.7%) |
| Autumn | 3721 (30.3%) |
| Winter | 3001 (24.5%) |
| Cold versus warm months | |
| Cold | 6115 (49.8%) |
| Warm | 6155 (50.2%) |

the results section.

The end date of work incapacity can be overruled by the advisory physician of the sickness fund based on a medical examination. A complex interplay of diagnosis, gender, age, type of worker, loss of income, return to work initiatives, and employer characteristics may determine the duration of work incapacity (Bogaerts et al., 2009; Bruyneel et al., 2020), hence the focus of this study was on entrance in work incapacity.

### 2.4. Statistical analysis

Correlations between pollutant concentrations and meteorological

**Table 2**
Spearman correlations between black carbon (BC), nitrogen dioxide ($NO_2$), ozone ($O_3$) and particulate matter 2.5 ($PM_{2.5}$) concentrations as well as total solar radiation (TSR) and relative humidity (RH) in 2019.

| | BC | $NO_2$ | $O_3$ | $PM_{2.5}$ | TSR | RH |
|---|---|---|---|---|---|---|
| BC | 1.00 | | | | | |
| $NO_2$ | 0.90 $P < 0.001$ | 1.00 | | | | |
| $O_3$ | −0.16 $P = 0.0098$ | −0.10 $P = 0.1036$ | 1.00 | | | |
| $PM_{2.5}$ | 0.66 $P < 0.001$ | 0.59 $P < 0.001$ | 0.12 $P = 0.0546$ | 1.00 | | |
| TSR | −0.29 $P < 0.001$ | −0.30 $P < 0.001$ | 0.59 $P < 0.001$ | −0.16 $P = 0.0107$ | 1.00 | |
| RH | 0.21 $P = 0.0004$ | 0.18 $P = 0.0028$ | −0.60 $P < 0.001$ | 0.20 $P = 0.0012$ | −0.70 $P < 0.001$ | 1.00 |

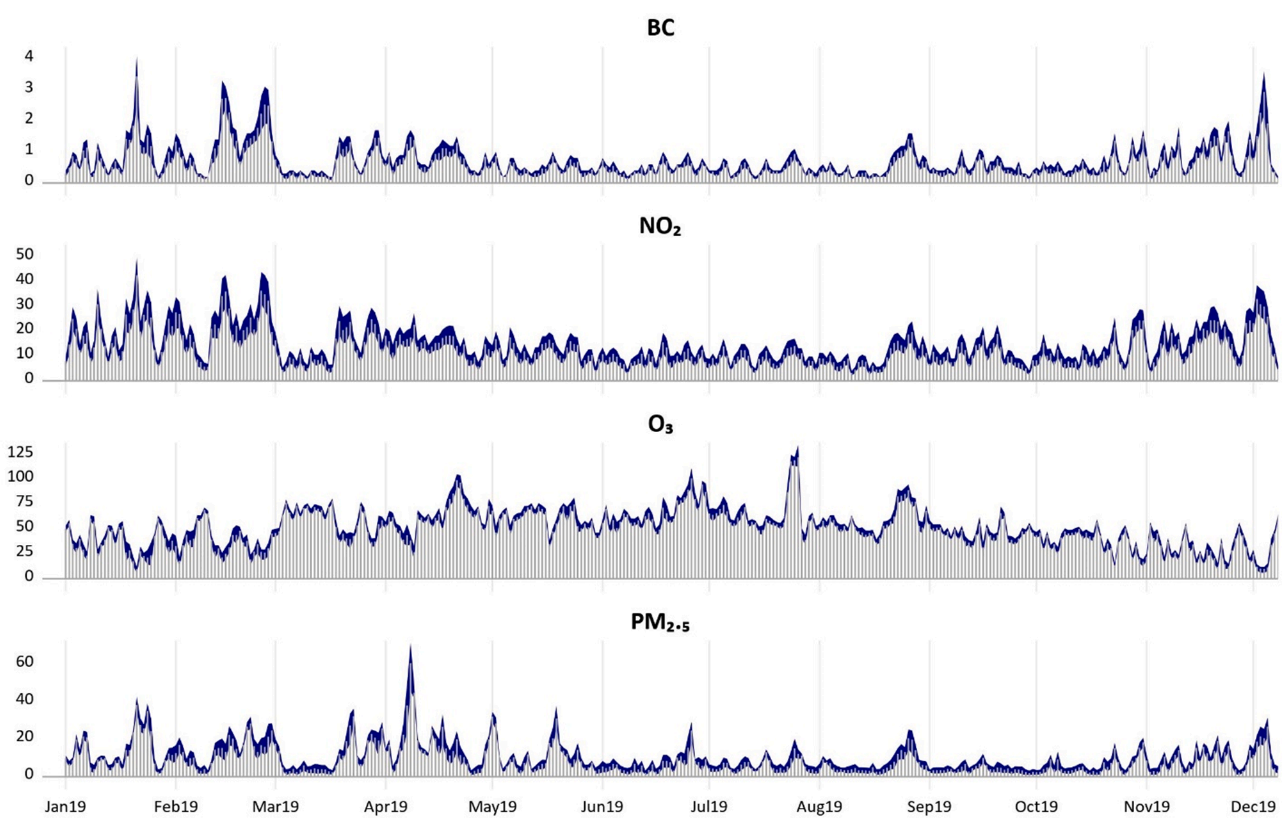


**Fig. 1.** Daily evolution (grey needles) and variation across municipalities (blue band representing the interquartile range) of black carbon (BC), nitrogen dioxide ($NO_2$), ozone ($O_3$) and particulate matter 2.5 ($PM_{2.5}$) concentrations in 2019.

**Table 3**
Associations between work incapacity related to mental health conditions and average nitrogen dioxide ($NO_2$), ozone ($O_3$), particulate matter 2.5 ($PM_{2.5}$), relative humidity (RH) and total solar radiation (TSR) at the day of the event (lag 0) and up to 2 days before (lag 0–2), estimated by three-pollutant models with and without adjustment for RH and TSR and using 3 different scenarios for temperature matching Estimates represent hazard ratios (with 95% confidence intervals) for an IQR increase in exposures.[a]

| | Temperature matching within 1 °C | | | Temperature matching within 2 °C | | | Temperature matching within 3 °C | | |
|---|---|---|---|---|---|---|---|---|---|
| | Unadjusted models | Models adjusted for RH | Models adjusted for TSR | Unadjusted models | Models adjusted for RH | Models adjusted for TSR | Unadjusted models | Models adjusted for RH | Models adjusted for TSR |
| $NO_2$ | | | | | | | | | |
| Lag 0 | 1.14 (1.09–1.20) | 1.16 (1.10–1.22) | 1.20 (1.14–1.26) | 1.12 (1.08–1.16) | 1.13 (1.08–1.18) | 1.15 (1.11–1.20) | 1.08 (1.04–1.12) | 1.13 (1.09–1.17) | 1.13 (1.09–1.17) |
| Lag 0–1 | 1.19 (1.12–1.25) | 1.24 (1.16–1.31) | 1.26 (1.19–1.34) | 1.19 (1.14–1.24) | 1.20 (1.14–1.26) | 1.22 (1.16–1.28) | 1.12 (1.07–1.16) | 1.16 (1.11–1.22) | 1.16 (1.11–1.22) |
| Lag 0–2 | 1.24 (1.16–1.32) | 1.31 (1.23–1.41) | 1.34 (1.24–1.43) | 1.26 (1.20–1.32) | 1.28 (1.21–1.36) | 1.29 (1.22–1.37) | 1.16 (1.11–1.22) | 1.22 (1.16–1.28) | 1.22 (1.16–1.29) |
| $O_3$ | | | | | | | | | |
| Lag 0 | 1.27 (1.17–1.38) | 1.30 (1.20–1.41) | 1.37 (1.25–1.49) | 1.12 (1.05–1.20) | 1.14 (1.06–1.22) | 1.18 (1.10–1.26) | 1.15 (1.08–1.22) | 1.21 (1.14–1.29) | 1.23 (1.15–1.31) |
| Lag 0–1 | 1.42 (1.28–1.56) | 1.50 (1.35–1.66) | 1.53 (1.38–1.70) | 1.23 (1.15–1.33) | 1.25 (1.15–1.35) | 1.27 (1.17–1.38) | 1.26 (1.18–1.34) | 1.32 (1.23–1.42) | 1.33 (1.24–1.43) |
| Lag 0–2 | 1.41 (1.27–1.56) | 1.53 (1.37–1.71) | 1.53 (1.37–1.71) | 1.27 (1.18–1.37) | 1.31 (1.20–1.42) | 1.32 (1.21–1.43) | 1.28 (1.20–1.36) | 1.37 (1.27–1.48) | 1.37 (1.27–1.48) |
| $PM_{2.5}$ | | | | | | | | | |
| Lag 0 | 0.97 (0.93–1.00) | 0.96 (0.93–0.99) | 0.96 (0.92–0.99) | 1.01 (0.98–1.04) | 1.01 (0.98–1.04) | 1.01 (0.98–1.04) | 1.03 (1.00–1.06) | 1.01 (0.99–1.04) | 1.03 (0.99–1.05) |
| Lag 0–1 | 0.97 (0.94–1.01) | 0.96 (0.92–0.99) | 0.96 (0.92–0.99) | 1.02 (0.99–1.05) | 1.02 (0.98–1.05) | 1.02 (0.98–1.05) | 1.05 (1.01–1.08) | 1.03 (1.00–1.07) | 1.04 (1.01–1.07) |
| Lag 0–2 | 0.95 (0.91–1.00) | 0.94 (0.89–0.98) | 0.94 (0.89–0.98) | 0.98 (0.95–1.02) | 0.98 (0.94–1.02) | 0.98 (0.95–1.02) | 1.02 (0.98–1.06) | 1.01 (0.97–1.04) | 1.01 (0.98–1.05) |
| RH | | | | | | | | | |
| Lag 0 | – | 1.07 (0.99–1.16) | – | – | 1.03 (0.97–1.10) | – | – | 1.15 (1.08–1.22) | – |
| Lag 0–1 | – | 1.21 (1.11–1.32) | – | – | 1.02 (0.95–1.10) | – | – | 1.14 (1.06–1.22) | – |
| Lag 0–2 | – | 1.30 (1.17–1.45) | – | – | 1.06 (0.97–1.16) | – | – | 1.16 (1.08–1.26) | – |
| TSR | | | | | | | | | |
| Lag 0 | – | – | 0.80 (0.73–0.88) | – | – | 0.87 (0.81–0.95) | – | – | 0.84 (0.78–0.89) |
| Lag 0–1 | – | – | 0.76 (0.68–0.86) | – | – | 0.92 (0.84–1.01) | – | – | 0.85 (0.78–0.92) |
| Lag 0–2 | – | – | 0.72 (0.62–0.82) | – | – | 0.92 (0.83–1.02) | – | – | 0.83 (0.75–0.91) |

[a] Estimated by conditional logistic regression using a bidirectional time-stratified case-crossover design with controls selected from the same calendar month as the case events and additionally matched by day of the week.

factors were assessed using Spearman correlation coefficients. We used a bidirectional time-stratified case-crossover study design to quantify the association between air pollution and work incapacity. This design was proposed by Janes (2005) to study the effects of transient, short-term exposures on the risk of acute events. The design uses a within-subject comparison, meaning each subject serves as his/her own control. That is, it compares each subject's exposure to air pollution, within his/her municipality of residence, in a time period just before a case event (i.e. the onset of work incapacity) with that subject's exposure on other days. Time-stratification (Levy et al., 2001; Lumley and Levy, 2000) was conducted by taking control days from the same calendar month as the case event, both before and after the event, and events and controls were matched by day of the week to control for any weekly patterns in air pollution or work incapacity. Lumley and Levy (2000) showed that, even when cases are no longer at risk after an event (such as in the case of work incapacity), bidirectional sampling is preferred to unidirectional because the bias in coefficient estimation will be smaller. Mittleman and Mostofsky (2014) stated that individual events do not affect the distribution of future exposure in the overall study population, hence selecting post-event control times is acceptable.

In a first set of conditional logistic regression models, we only included single pollutants. Then we entered relative humidity and total solar radiation in separate models, given the high correlation between these two. Finally, we ran multi-pollutant models including only pollutants with a correlation below 0.6 to avoid multicollinearity which may result in unstable coefficients (Tolbert et al., 2007). We present unadjusted two- and three-pollutant models as well as models adjusted for relative humidity and total solar radiation. To adjust for temperature, only control days with a daily average temperature within 2 °C from that of the event day were included in single and two-pollutant models (Casas et al., 2017; Scheers et al., 2020). For the three-pollutant models, we estimated the coefficients under scenarios with control days with a daily average temperature within either 1, 2 or 3 °C from that of the event day.

We ran separate models for each exposure window: single-day exposure on the day of the event (lag 0) and average exposures up to two days before the event (lag 0–1, lag 0–2). The hazard ratios (HR; equivalent to odds ratio for the conditional logistic regression model) and 95% confidence intervals (CIs) were estimated for an interquartile range (IQR) increase in pollutant concentrations or meteorological factors. Using the three-pollutant model, we examined effect modification by type of mental health condition (problems related to life-management difficulty, mood disorder or neurotic disorder), age group (18–29 years, 30–39 years, 40–49 years, 50–65 years), sex (male, female), type of worker (blue-collar, white-collar, self-employed), region (Brussels Capital Region, Flanders, Wallonia), season (spring: March-May; summer: June-August; autumn: September-November; winter: December-February) and cold versus warm months

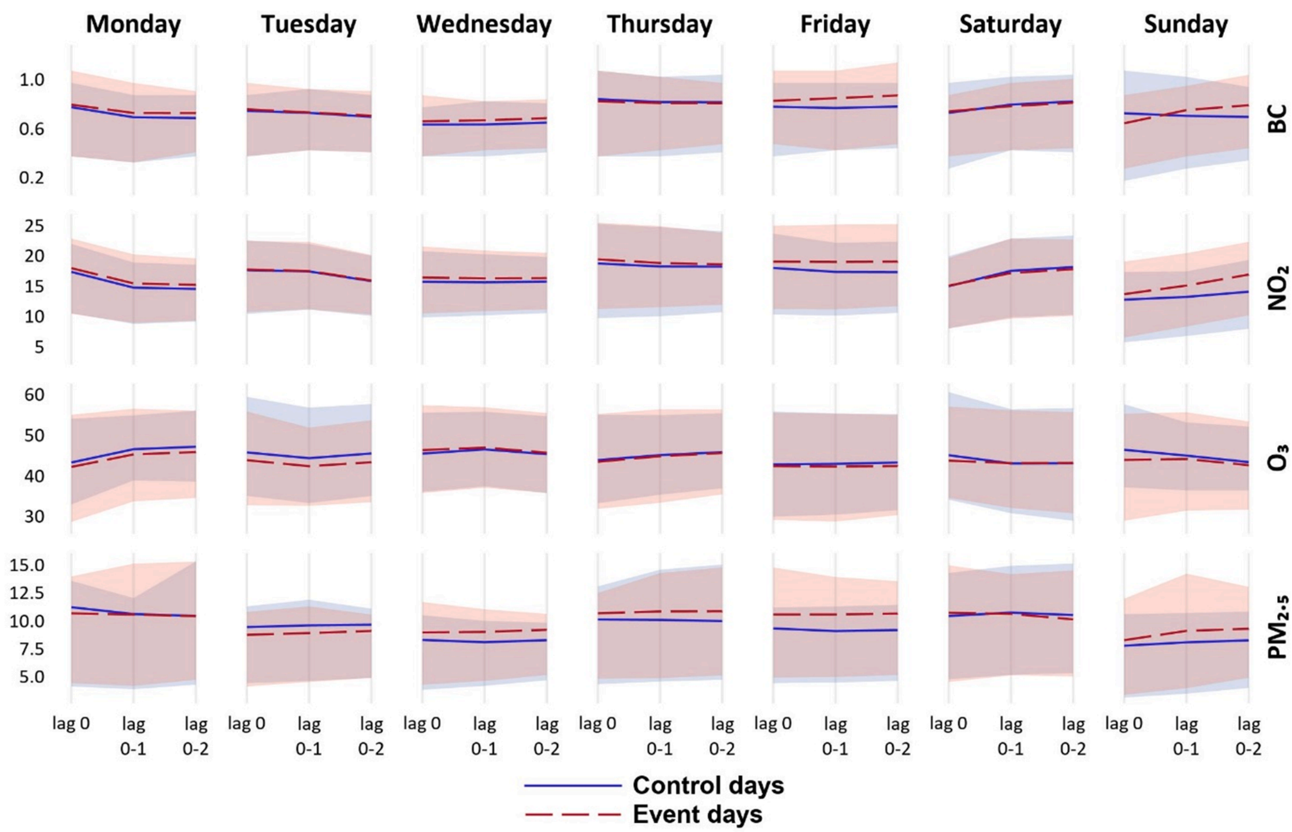


**Fig. 2.** Black carbon (BC), nitrogen dioxide ($NO_2$), ozone ($O_3$) and particulate matter 2.5 ($PM_{2.5}$) concentrations (μg/$m^3$) on event (onset of work incapacity related to mental health conditions) days (red) and on control days (blue), by day of week. Lines represent average values and bands interquartile ranges.

**Table A1**
Single-pollutant models showing the associations between work incapacity related to mental health conditions and average air pollution exposure at the day of the event (lag 0) and up to 2 days before (lag 0–2). Estimates represent hazard ratios (with 95% confidence intervals) for an IQR increase in black carbon (BC), nitrogen dioxide ($NO_2$), ozone ($O_3$), particulate matter 2.5 ($PM_{2.5}$), relative humidity (RH) and total solar radiation (TSR).[a]

| | Single-pollutant models | Single-pollutant models adjusted for RH | | Single-pollutant models adjusted for TSR | |
|---|---|---|---|---|---|
| | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | RH HR (95% CI)[a] | Pollutant HR (95% CI)[a] | TSR HR (95% CI)[a] |
| **BC per IQR increase** | | | | | |
| Lag 0 | 1.03 (1.01–1.06) | 1.03 (1.01–1.06) | 0.97 (0.92–1.02) | 1.04 (1.01–1.06) | 0.97 (0.91–1.04) |
| Lag 0–1 | 1.06 (1.03–1.09) | 1.06 (1.03–1.09) | 0.92 (0.86–0.98) | 1.06 (1.03–1.09) | 1.07 (0.99–1.16) |
| Lag 0–2 | 1.08 (1.05–1.12) | 1.07 (1.04–1.11) | 0.88 (0.82–0.94) | 1.07 (1.04–1.11) | 1.15 (1.05–1.25) |
| **$NO_2$ per IQR increase** | | | | | |
| Lag 0 | 1.07 (1.04–1.10) | 1.07 (1.04–1.10) | 0.98 (0.91–1.04) | 1.08 (1.05–1.10) | 0.95 (0.88–1.02) |
| Lag 0–1 | 1.10 (1.07–1.14) | 1.10 (1.06–1.13) | 0.94 (0.88–1.01) | 1.10 (1.06–1.13) | 1.03 (0.95–1.12) |
| Lag 0–2 | 1.13 (1.09–1.17) | 1.12 (1.08–1.16) | 0.91 (0.84–0.98) | 1.12 (1.08–1.16) | 1.10 (1.01–1.20) |
| **$O_3$ per IQR increase** | | | | | |
| Lag 0 | 0.98 (0.94–1.02) | 0.97 (0.93–1.01) | 0.96 (0.90–1.01) | 0.98 (0.94–1.02) | 0.99 (0.92–1.06) |
| Lag 0–1 | 1.00 (0.95–1.05) | 0.98 (0.93–1.04) | 0.91 (0.85–0.97) | 0.99 (0.94–1.04) | 1.10 (1.01–1.19) |
| Lag 0–2 | 1.03 (0.97–1.08) | 0.99 (0.94–1.06) | 0.88 (0.81–0.95) | 1.01 (0.95–1.06) | 1.18 (1.08–1.29) |
| **$PM_{2.5}$ per IQR increase** | | | | | |
| Lag 0 | 1.02 (0.99–1.05) | 1.03 (1.00–1.06) | 0.95 (0.90–1.01) | 1.02 (0.99–1.05) | 0.99 (0.92–1.06) |
| Lag 0–1 | 1.04 (1.01–1.06) | 1.04 (1.01–1.07) | 0.91 (0.86–0.97) | 1.04 (1.01–1.07) | 1.10 (1.02–1.19) |
| Lag 0–2 | 1.03 (0.99–1.06) | 1.03 (1.00–1.06) | 0.87 (0.81–0.93) | 1.02 (0.99–1.05) | 1.18 (1.09–1.29) |

[a] Estimated by conditional logistic regression using a bidirectional time-stratified case-crossover design with controls selected from the same calendar month as the case events and additionally matched by day of the week and temperature (within 2 °C).

(November-April, May-October). Effect modification was assessed by including an interaction term between the air pollutants and the variable of interest in the model.

Some members had more than one case of work incapacity related to mental health conditions during the study period. To test the robustness of the reported results, sensitivity analyses excluding members with repeated cases were conducted for all single-pollutant, two-pollutant and three-pollutant models.

We used a significance criterion of $p < 0.05$. All analyses were performed with SAS version 9.4 (SAS Institute Inc., Cary, NC, USA).

**Table A2**
Two-pollutant models showing the associations between work incapacity related to mental health conditions and average air pollution exposure at the day of the event (lag 0) and up to 2 days before (lag 0–2). Estimates represent hazard ratios (with 95% confidence intervals) for an IQR increase in black carbon (BC), nitrogen dioxide ($NO_2$), ozone ($O_3$) and particulate matter 2.5 ($PM_{2.5}$).[a.]

| | Two-pollutant models including $O_3$ and BC Pollutant HR (95% CI)[a] | Two-pollutant models including $O_3$ and $PM_{2.5}$ Pollutant HR (95% CI)[a] | Two-pollutant models including $O_3$ and $NO_2$ Pollutant HR (95% CI)[a] | Two-pollutant models including $PM_{2.5}$ and $NO_2$ Pollutant HR (95% CI)[a] |
|---|---|---|---|---|
| **BC per IQR increase** | | | | |
| Lag 0 | 1.05 (1.01–1.09) | – | – | – |
| Lag 0–1 | 1.13 (1.08–1.17) | – | – | – |
| Lag 0–2 | 1.16 (1.12–1.22) | – | – | – |
| **$NO_2$ per IQR increase** | | | | |
| Lag 0 | – | – | 1.12 (1.08–1.16) | 1.07 (1.04–1.11) |
| Lag 0–1 | – | – | 1.20 (1.15–1.25) | 1.11 (1.07–1.15) |
| Lag 0–2 | – | – | 1.25 (1.19–1.31) | 1.17 (1.12–1.22) |
| **$O_3$ per IQR increase** | | | | |
| Lag 0 | 1.04 (0.97–1.10) | 0.99 (0.95–1.05) | 1.11 (1.05–1.18) | – |
| Lag 0–1 | 1.15 (1.07–1.24) | 1.05 (0.99–1.11) | 1.22 (1.14–1.31) | – |
| Lag 0–2 | 1.22 (1.13–1.31) | 1.07 (1.01–1.15) | 1.28 (1.19–1.38) | – |
| **$PM_{2.5}$ per IQR increase** | | | | |
| Lag 0 | – | 1.02 (0.95–1.05) | – | 0.99 (0.97–1.02) |
| Lag 0–1 | – | 1.05 (1.02–1.08) | – | 0.99 (0.96–1.02) |
| Lag 0–2 | – | 1.05 (1.01–1.08) | – | 0.96 (0.92–0.99) |

[a] Estimated by conditional logistic regression using a bidirectional time-stratified case-crossover design with controls selected from the same calendar month as the case events and additionally matched by day of the week and temperature (within 2 °C).

## 3. Results

### 3.1. Descriptives

There were 17 338 cases of work incapacity related to mental health conditions, for 16 762 unique health insurance funds members. For a number of members postcode was missing, leaving 16 366 cases for 15 834 unique members. For the scenario in which daily average temperature of control days was within 2 °C from that of the case day, we retained 12 270 cases (11 968 unique members). For a 1 °C difference, the analysis included 8359 cases (8214 unique members). For a 3 °C difference, the analysis included 13 745 cases (13 362 unique members). The descriptives in this section are based on the scenario with a 2 °C difference.

At the time of the data extraction (28 February 2022), 530 work incapacity cases were still open. For the remaining 11 740 cases, the median number of days spent in work incapacity was 120 (25th-75th percentiles: 53–333 days). Most cases concerned problems related to life-management difficulty (n = 5442, 44.4%) and mood disorders (n = 5367, 43.7%), with a smaller amount of cases concerning neurotic, stress-related and somatoform disorders (n = 1461, 11.9%) (Table 1). Problems related to life-management difficulty came largely down to burnout (90.7%). Other diagnoses within this category included stress (6.5%) and social role conflict (2.8%). For mood disorders, 77.7% of cases concerned major depressive disorder and 18.8% dysthymia. Remaining diagnoses within this category were mostly related to bipolar affective disorders. Neurotic, stress-related and somatoform disorders included a wide variety of diagnoses, most frequently other anxiety disorders (28.0%), neurasthenia (17.5%), and reaction to severe stress and post-traumatic stress disorder (8.0%). For the 12 270 cases, 22 781 control days were retained. These were distributed proportionally across categories of the potential effect modifiers.

Most new cases of work incapacity related to mental health conditions took place on Monday (30.5%), followed by a gradual decrease throughout the remainder of the week. Hence the importance of matching event cases and controls by day of the week.

Fig. 1 displays the daily evolution of BC, $NO_2$, $O_3$ and $PM_{2.5}$ concentrations in 2019 and suggests daily fluctuation as well as variation across municipalities. Median values equalled 0.53 μg/$m^3$ for BC (25th-75th percentiles: 0.34–0.85; IQR: 0.51), 11.54 μg/$m^3$ for $NO_2$ (25th-75th percentiles: 8.39–16.74, IQR: 8.35), 50.81 μg/$m^3$ for $O_3$ (25th-75th percentiles: 38.20–62.20, IQR: 24), and 6.88 μg/$m^3$ for $PM_{2.5}$ (25th-75th percentiles: 4.00–13.15, IQR: 9.15). Median values equalled 5023 W/$m^2$ (25th-75th percentiles: 2030–9253, IQR: 7223) for total solar radiation and 79% (25th-75th percentile: 68–88, IQR: 20) for relative humidity.

Spearman coefficients were greater than 0.60 for correlations between BC and $NO_2$ ($\rho = 0.90$), BC and $PM_{2.5}$ ($\rho = 0.66$), and TSR and RH ($\rho = -0.70$). Correlations between $PM_{2.5}$ and $NO_2$ and between TSR and $O_3$ equalled 0.59 (Table 2).

### 3.2. *Association **between air pollution exposure and work incapacity related to mental health conditions***

Fig. 2 describes BC, $NO_2$, $O_3$, and $PM_{2.5}$ concentrations on event (onset of work incapacity related to mental health conditions) and control days from lag 0 up to lag 0–2, by day of the week. BC, $NO_2$ and $PM_{2.5}$ concentrations are generally higher on event days compared to control days, while the inverse can be observed for $O_3$ concentrations.

Findings for single-pollutant and two-pollutant models are presented in Appendix A.

Single-pollutant models suggested statistically significant positive associations between BC and $NO_2$ exposure and work incapacity related to mental health conditions for all studied exposure windows (Table A.1). No overall significant associations were observed for $O_3$, and $PM_{2.5}$ only showed a positive association at lag 0–1. HRs were similar after adjustment for RH and TSR. RH showed a negative association with the outcome at lag 0–1 (with all pollutants except $NO_2$) and lag 0–2 (with all pollutants). TSR showed a positive association with the outcome at lag 0–1 (with $O_3$ and $PM_{2.5}$) and lag 0–2 (with all pollutants).

In two-pollutant models (Table A.2), BC and $NO_2$ persisted as predictors, with $O_3$ becoming a strong predictor as well. HRs for $PM_{2.5}$ were not significant in combination with $NO_2$, but significant for lag 0–1 and lag 0–2 in combination with $O_3$. The impact from adjusting for RH or

**Table A3**
Two-pollutant models showing the associations between work incapacity related to mental health conditions and average air pollution exposure at the day of the event (lag 0) and up to 2 days before (lag 0–2). Estimates represent hazard ratios (with 95% confidence intervals) for an IQR increase in black carbon (BC), nitrogen dioxide ($NO_2$), ozone ($O_3$), particulate matter 2.5 ($PM_{2.5}$), relative humidity (RH) and total solar radiation (TSR).[a]

| | Two-pollutant models including $O_3$ and BC adjusted for RH (left) or TSR (right) | | Two-pollutant models including $O_3$ and $PM_{2.5}$ adjusted for RH (left) or TSR (right) | | Two-pollutant models including $O_3$ and $NO_2$ adjusted for RH (left) or TSR (right) | | Two-pollutant models including $PM_{2.5}$ and $NO_2$ adjusted for RH (left) or TSR (right) | |
|---|---|---|---|---|---|---|---|---|
| | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] |
| **BC per IQR increase** | | | | | | | | |
| Lag 0 | 1.04 (1.01–1.08) | 1.06 (1.02–1.10) | – | – | – | – | – | – |
| Lag 0–1 | 1.12 (1.07–1.17) | 1.12 (1.07–1.17) | – | – | – | – | – | – |
| Lag 0–2 | 1.16 (1.10–1.21) | 1.15 (1.10–1.21) | – | – | – | – | – | – |
| **$NO_2$ per IQR increase** | | | | | | | | |
| Lag 0 | – | – | – | – | 1.13 (1.09–1.18) | 1.16 (1.10–1.20) | 1.07 (1.04–1.11) | 1.08 (1.05–1.11) |
| Lag 0–1 | – | – | – | – | 1.20 (1.15–1.26) | 1.22 (1.17–1.28) | 1.10 (1.06–1.14) | 1.10 (1.06–1.14) |
| Lag 0–2 | – | – | – | – | 1.27 (1.20–1.34) | 1.28 (1.21–1.35) | 1.15 (1.10–1.20) | 1.15 (1.10–1.20) |
| **$O_3$ per IQR increase** | | | | | | | | |
| Lag 0 | 1.03 (0.96–1.09) | 1.05 (0.99–1.12) | 0.99 (0.95–1.05) | 1.00 (0.95–1.06) | 1.13 (1.06–1.21) | 1.17 (1.10–1.25) | – | – |
| Lag 0–1 | 1.13 (1.05–1.22) | 1.14 (1.06–1.24) | 1.04 (0.98–1.10) | 1.04 (0.98–1.10) | 1.24 (1.15–1.34) | 1.26 (1.17–1.37) | – | – |
| Lag 0–2 | 1.20 (1.10–1.30) | 1.20 (1.10–1.30) | 1.04 (0.97–1.11) | 1.04 (0.97–1.12) | 1.32 (1.21–1.43) | 1.33 (1.22–1.44) | – | – |
| **$PM_{2.5}$ per IQR increase** | | | | | | | | |
| Lag 0 | – | – | 1.03 (0.99–1.06) | 1.02 (0.99–1.05) | – | – | 0.99 (0.97–1.03) | 0.99 (0.96–1.02) |
| Lag 0–1 | – | – | 1.05 (1.02–1.09) | 1.05 (1.02–1.08) | – | – | 1.00 (0.97–1.03) | 1.00 (0.97–1.03) |
| Lag 0–2 | – | – | 1.04 (1.01–1.08) | 1.04 (1.00–1.07) | – | – | 0.96 (0.93–1.01) | 0.96 (0.93–1.00) |
| **RH per IQR increase** | | | | | | | | |
| Lag 0 | 0.98 (0.92–1.03) | – | 0.95 (0.90–1.01) | – | 1.04 (0.98–1.11) | – | 0.99 (0.93–1.05) | – |
| Lag 0–1 | 0.96 (0.89–1.03) | – | 0.90 (0.85–0.97) | – | 1.03 (0.96–1.11) | – | 0.94 (0.88–1.01) | – |
| Lag 0–2 | 0.97 (0.89–1.05) | – | 0.88 (0.81–0.95) | – | 1.05 (0.97–1.15) | – | 0.93 (0.86–1.01) | – |
| **TSR per IQR increase** | | | | | | | | |
| Lag 0 | – | 0.95 (0.88–1.02) | – | 0.99 (0.92–1.06) | – | 0.88 (0.81–0.95) | – | 0.94 (0.88–1.01) |
| Lag 0–1 | – | 1.01 (0.93–1.10) | – | 1.09 (1.01–1.18) | – | 0.92 (0.84–1.00) | – | 1.03 (0.95–1.12) |
| Lag 0–2 | – | 1.05 (0.95–1.15) | – | 1.17 (1.07–1.28) | – | 0.92 (0.83–1.02) | – | 1.08 (0.99–1.18) |

[a] Estimated by conditional logistic regression using a bidirectional time-stratified case-crossover design with controls selected from the same calendar month as the case events and additionally matched by day of the week and temperature (within 2 °C).

TSR was again very limited. In models with $O_3$ and BC or with $PM_{2.5}$ and $NO_3$, RH nor TSR exhibited significant effects. In models with $PM_{2.5}$ and $O_3$, at lags 0–1 and 0–2, RH was negatively associated with the outcome, and TSR was positively associated with the outcome (Table A.3). TSR was, however, negatively associated with the outcome at lag 0 in the model with $O_3$ and $NO_2$. For the same pollutants, HRs for RH reversed to greater than 1, albeit non-significant.

Given the high correlation of BC with both $NO_2$ ($\rho = 0.90$) and $PM_{2.5}$ ($\rho = 0.66$), three-pollutant models included $NO_2$, $PM_{2.5}$ and O (Table 3). For both unadjusted and adjusted models and independent of whether control days were within 1, 2 or 3 °C from that of the event day, $NO_2$ and $O_3$ showed a significant positive association with the outcome at all lags. Estimates were consistently highest for lag 0–2, with HRs for the scenario of temperature matching within 2 °C equal to 1.26 (95% CI 1.20–1.32) and 1.27 (95% CI 1.18–1.37) for IQR increases in $NO_2$ and $O_3$, respectively. Adjusting for RH or TSR consistently resulted in greater HRs. $PM_{2.5}$ only showed small positive associations for temperature matching with 3 °C, no associations for temperature matching within 2 °C, and small negative associations for temperature matching within 1 °C. Similar to findings for two-pollutant models including $O_3$ and $NO_2$, the three-pollutant model indicated that the outcome was positively associated with RH and negatively with TSR. These effects were most pronounced at control days within 1 or 3 °C from that of the event day.

Last, we assessed effect modification for the adjusted three-pollutant models with control days within 2 °C from that of the event day (Fig. 3). Effect estimates for both $NO_2$ and $O_3$ tended to increase with age, but decreased again in the oldest age group (50–65 years), but the interaction term only reached significance for $NO_2$. We also observed significant effect modification by season, and cold/warm months for $NO_2$, with estimates being highest for spring and summer. For $O_3$, we found

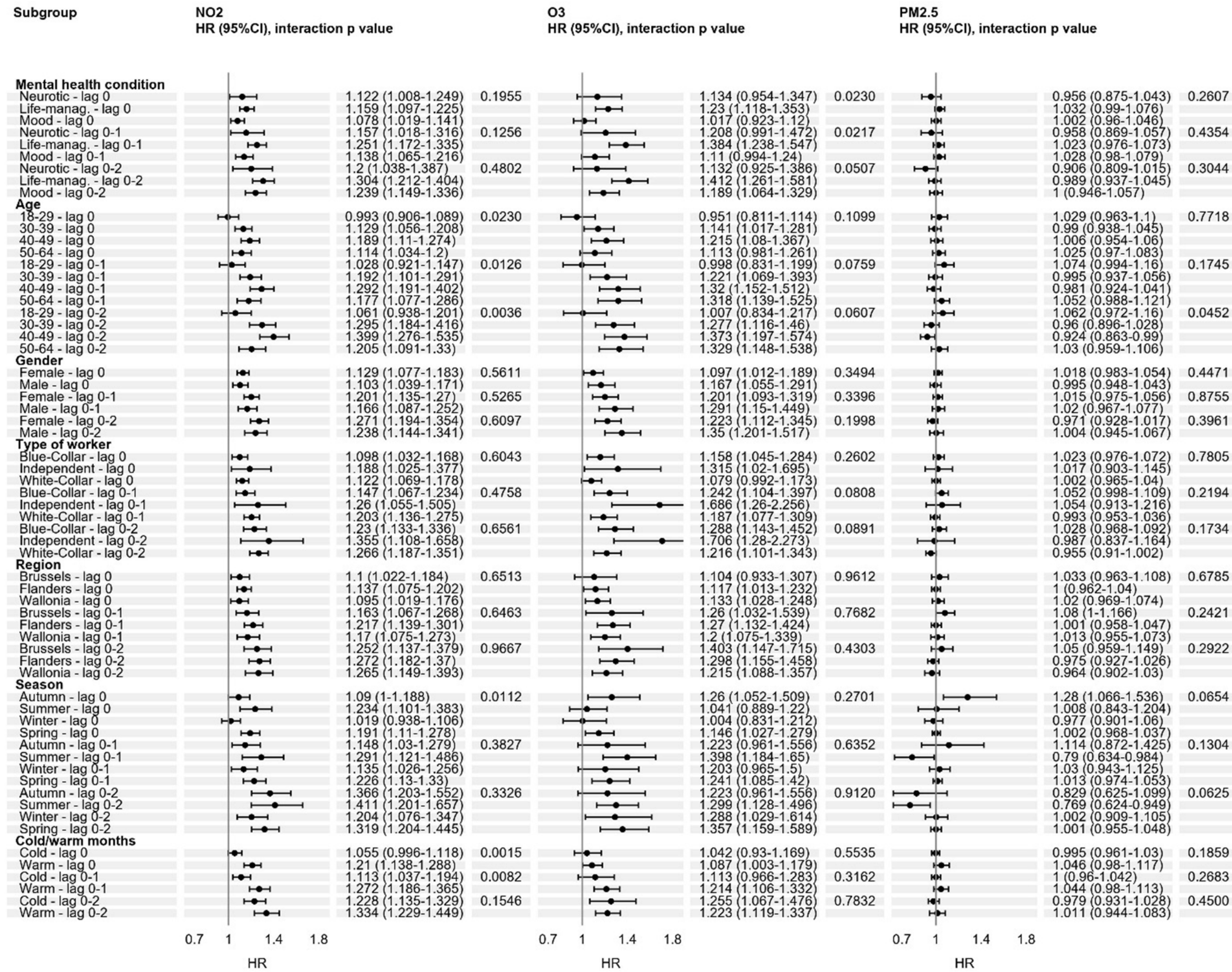


**Fig. 3.** Associations between work incapacity related to mental health conditions and average air pollution exposure at the day of the event (lag 0) and up to 2 days before (lag 0–2) by subgroups, estimated by three-pollutant models including interaction terms between the air pollutants and the variable of interest. Estimates represent hazard ratios (with 95% confidence intervals) for an IQR increase in nitrogen dioxide ($NO_2$), ozone ($O_3$) and particulate matter 2.5 ($PM_{2.5}$).[a]

evidence of effect modification by type of mental health condition, with a stronger association observed for problems related to life-management difficulty.

The results of sensitivity analyses excluding members with repeated cases of work incapacity during the study period corresponded with the results of the main analyses (see Appendix B).

Estimated by conditional logistic regression using a bidirectional time-stratified case-crossover design with controls selected from the same calendar month as the case events and additionally matched by day of the week and temperature within 2 °C.

## 4. Discussion

In a population-wide study we show that onset of work incapacity related to mental health conditions may be triggered by ambient levels of air pollution within 48 h of exposure. $NO_2$ and BC emerged as predictors in both single- and multi-pollutant models, whereas $O_3$ only emerged in multi-pollutant models. Findings from the three-pollutant model suggest independent significant effects of $NO_2$ and $O_3$, whereas results for $PM_{2.5}$ were inconsistent.

Although $NO_2$ concentrations are generally higher during winter, the seasonal patterns suggest that these pollutants were most harmful warm months. Stronger effects of air pollution during the warm season than during the cold season have also been reported for outcomes such as mortality (Nawrot et al., 2007), hospital admissions for pneumonia and chronic obstructive pulmonary disease (Medina-Ramón et al., 2006), and suicide (Casas et al., 2017). A possible explanation is that modelled exposures are a better reflection of actual individual exposures during the warm season due to higher ventilation rates, as indicated by higher correlations between indoor and outdoor air pollution concentrations during summer (Meier et al., 2015). Another explanation is a higher amount of time spent outdoors during summer. $NO_2$ was also least harmful in 18–29 year olds, and similar trends were observed for $O_3$. Younger people might in general have a better health status, which reduces the negative effects of air pollution.

Biological mechanisms underlying the association between air pollution and mental health have been revealed in previous research. Air pollutants are directly neurotoxic and associated with structural brain change (Block et al., 2012). Other mechanisms through which these effects potentially occur include oxidative and nitrosative stress, systemic and neuroinflammation, and hormonal dysregulation (Block and Calderón-Garcidueñas, 2009; Calderón-Garcidueñas et al., 2015; Levesque et al., 2011), changes in brain-derived neurotrophic factor (Bos et al., 2011), as well as stress hormone production (Li et al., 2017). We do not claim that short-term ambient air pollution causes the onset of these disorders and the onset of work incapacity. Our findings most likely suggest that when people are to enter work incapacity for reasons of poor mental health, they are more likely to do so when air pollution is higher. In other words, air pollution exerts an influence by advancing the date of the onset of work incapacity. A wide range of factors,

**Table B1**
Single-pollutant models showing the associations between work incapacity related to mental health conditions and average air pollution exposure at the day of the event (lag 0) and up to 2 days before (lag 0–2). Estimates represent hazard ratios (with 95% confidence intervals) for an IQR increase in black carbon (BC), nitrogen dioxide ($NO_2$), ozone ($O_3$), particulate matter 2.5 ($PM_{2.5}$), relative humidity (RH) and total solar radiation (TSR).[a.]

| | Single-pollutant models | Single-pollutant models adjusted for RH | | Single-pollutant models adjusted for TSR | |
|---|---|---|---|---|---|
| | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | RH HR (95% CI)[a] | Pollutant HR (95% CI)[a] | TSR HR (95% CI)[a] |
| **BC per IQR increase** | | | | | |
| Lag 0 | 1.03 (1.01–1.06) | 1.03 (1.01–1.06) | 0.97 (0.92–1.03) | 1.04 (1.01–1.06) | 0.96 (0.89–1.03) |
| Lag 0–1 | 1.06 (1.03–1.10) | 1.06 (1.03–1.09) | 0.91 (0.85–0.98) | 1.06 (1.03–1.09) | 1.07 (0.98–1.16) |
| Lag 0–2 | 1.08 (1.05–1.12) | 1.08 (1.04–1.11) | 0.87 (0.81–0.94) | 1.07 (1.04–1.11) | 1.15 (1.05–1.26) |
| **$NO_2$ per IQR increase** | | | | | |
| Lag 0 | 1.07 (1.04–1.10) | 1.07 (1.04–1.10) | 0.99 (0.93–1.05) | 1.08 (1.05–1.11) | 0.93 (0.87–1.01) |
| Lag 0–1 | 1.10 (1.07–1.14) | 1.09 (1.06–1.13) | 0.94 (0.87–1.01) | 1.10 (1.06–1.13) | 1.03 (0.95–1.12) |
| Lag 0–2 | 1.13 (1.09–1.17) | 1.12 (1.08–1.16) | 0.89 (0.83–0.96) | 1.12 (1.08–1.16) | 1.11 (1.01–1.21) |
| **$O_3$ per IQR increase** | | | | | |
| Lag 0 | 0.98 (0.93–1.02) | 0.97 (0.93–1.01) | 0.96 (0.91–1.02) | 0.98 (0.93–1.02) | 0.98 (0.91–1.05) |
| Lag 0–1 | 1.00 (0.95–1.05) | 0.99 (0.93–1.04) | 0.90 (0.84–0.97) | 0.99 (0.94–1.05) | 1.09 (1.01–1.19) |
| Lag 0–2 | 1.03 (0.97–1.09) | 0.99 (0.94–1.05) | 0.86 (0.79–0.93) | 1.01 (0.95–1.07) | 1.19 (1.09–1.30) |
| **$PM_{2.5}$ per IQR increase** | | | | | |
| Lag 0 | 1.02 (0.99–1.05) | 1.03 (1.00–1.05) | 0.95 (0.90–1.01) | 1.02 (0.99–1.05) | 0.98 (0.91–1.05) |
| Lag 0–1 | 1.04 (1.01–1.07) | 1.04 (1.02–1.07) | 0.89 (0.83–0.95) | 1.04 (1.01–1.07) | 1.09 (1.01–1.19) |
| Lag 0–2 | 1.03 (0.99–1.06) | 1.04 (1.00–1.07) | 0.85 (0.79–0.92) | 1.03 (0.99–1.06) | 1.19 (1.09–1.30) |

[a] Estimated by conditional logistic regression using a bidirectional time-stratified case-crossover design with controls selected from the same calendar month as the case events and additionally matched by day of the week and temperature (within 2 °C), excluding members with repeated cases of work incapacity related to mental health conditions during the study period.

**Table B2**
Two-pollutant models showing the associations between work incapacity related to mental health conditions and average air pollution exposure at the day of the event (lag 0) and up to 2 days before (lag 0–2). Estimates represent hazard ratios (with 95% confidence intervals) for an IQR increase in black carbon (BC), nitrogen dioxide ($NO_2$), ozone ($O_3$) and particulate matter 2.5 ($PM_{2.5}$).[a]

| | Two-pollutant models including $O_3$ and BC Pollutant HR (95% CI)[a] | Two-pollutant models including $O_3$ and $PM_{2.5}$ Pollutant HR (95% CI)[a] | Two-pollutant models including $O_3$ and $NO_2$ Pollutant HR (95% CI)[a] | Two-pollutant models including $PM_{2.5}$ and $NO_2$ Pollutant HR (95% CI)[a] |
|---|---|---|---|---|
| **BC per IQR increase** | | | | |
| Lag 0 | 1.05 (1.01–1.09) | – | – | – |
| Lag 0–1 | 1.13 (1.08–1.18) | – | – | – |
| Lag 0–2 | 1.17 (1.12–1.22) | – | – | – |
| **$NO_2$ per IQR increase** | | | | |
| Lag 0 | – | – | 1.12 (1.08–1.16) | 1.08 (1.04–1.11) |
| Lag 0–1 | – | – | 1.20 (1.15–1.25) | 1.10 (1.06–1.15) |
| Lag 0–2 | – | – | 1.26 (1.20–1.32) | 1.17 (1.12–1.22) |
| **$O_3$ per IQR increase** | | | | |
| Lag 0 | 1.03 (0.97–1.10) | 0.99 (0.94–1.05) | 1.11 (1.04–1.18) | – |
| Lag 0–1 | 1.16 (1.07–1.25) | 1.05 (0.99–1.12) | 1.23 (1.14–1.32) | – |
| Lag 0–2 | 1.23 (1.14–1.32) | 1.08 (1.01–1.15) | 1.29 (1.20–1.39) | – |
| **$PM_{2.5}$ per IQR increase** | | | | |
| Lag 0 | – | 1.02 (0.99–1.05) | – | 0.99 (0.97–1.02) |
| Lag 0–1 | – | 1.05 (1.02–1.08) | – | 0.99 (0.96–1.03) |
| Lag 0–2 | – | 1.05 (1.01–1.09) | – | 0.96 (0.92–0.99) |

[a] Estimated by conditional logistic regression using a bidirectional time-stratified case-crossover design with controls selected from the same calendar month as the case events and additionally matched by day of the week and temperature (within 2 °C), excluding members with repeated cases of work incapacity related to mental health conditions during the study period.

including intrapersonal factors and home/work interference, but particularly work-related psychosocial factors, may lead to work incapacity. In Belgium, between 2009 and 2016, the percentage of employees who regularly experienced stress at an unacceptable level in the last 12 months rose from 26.5% to 30.8%. The stress level was strongly influenced by, among other things, the mental and emotional load of the job and the extent to which the organization is concerned with the well-being of its employees (Sdworx, 2016). According to employers, at least half of the causes of burnout lie in their own organization (Securex, 2015).

To the best of our knowledge, no scientific evidence is available on the association of work absenteeism and meteorological factors such as relative humidity, solar radiation or sunshine duration. The observed associations between work incapacity related to mental health conditions and total solar radiation and relative humidity merit further research. Opposite from the results from single-pollutant models, the three-pollutant model indicated that work incapacity was negatively associated with total solar radiation and positively associated with

**Table B3**

Two-pollutant models showing the associations between work incapacity related to mental health conditions and average air pollution exposure at the day of the event (lag 0) and up to 2 days before (lag 0–2). Estimates represent hazard ratios (with 95% confidence intervals) for an IQR increase in black carbon (BC), nitrogen dioxide ($NO_2$), ozone ($O_3$), particulate matter 2.5 ($PM_{2.5}$), relative humidity (RH) and total solar radiation (TSR).[a]

| | Two-pollutant models including $O_3$ and BC adjusted for RH (left) or TSR (right) | | Two-pollutant models including $O_3$ and $PM_{2.5}$ adjusted for RH (left) or TSR (right) | | Two-pollutant models including $O_3$ and $NO_2$ adjusted for RH (left) or TSR (right) | | Two-pollutant models including $PM_{2.5}$ and $NO_2$ adjusted for RH (left) or TSR (right) | |
|---|---|---|---|---|---|---|---|---|
| | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] | Pollutant HR (95% CI)[a] |
| **BC per IQR increase** | | | | | | | | |
| Lag 0 | 1.04 (1.01–1.08) | 1.06 (1.02–1.10) | – | – | – | – | – | – |
| Lag 0–1 | 1.13 (1.07–1.17) | 1.13 (1.08–1.18) | – | – | – | – | – | – |
| Lag 0–2 | 1.16 (1.10–1.21) | 1.15 (1.10–1.21) | – | – | – | – | – | – |
| **$NO_2$ per IQR increase** | | | | | | | | |
| Lag 0 | – | – | – | – | 1.13 (1.08–1.18) | 1.16 (1.10–1.21) | 1.07 (1.04–1.11) | 1.08 (1.05–1.12) |
| Lag 0–1 | – | – | – | – | 1.20 (1.15–1.26) | 1.23 (1.17–1.29) | 1.09 (1.05–1.14) | 1.10 (1.06–1.14) |
| Lag 0–2 | – | – | – | – | 1.27 (1.20–1.34) | 1.29 (1.22–1.36) | 1.15 (1.10–1.20) | 1.15 (1.10–1.21) |
| **$O_3$ per IQR increase** | | | | | | | | |
| Lag 0 | 1.02 (0.95–1.09) | 1.05 (0.98–1.13) | 0.99 (0.94–1.04) | 1.00 (0.94–1.05) | 1.13 (1.05–1.21) | 1.17 (1.09–1.25) | – | – |
| Lag 0–1 | 1.14 (1.05–1.23) | 1.15 (1.07–1.25) | 1.04 (0.98–1.10) | 1.04 (0.98–1.11) | 1.24 (1.14–1.34) | 1.27 (1.17–1.38) | – | – |
| Lag 0–2 | 1.20 (1.10–1.30) | 1.20 (1.10–1.30) | 1.04 (0.97–1.12) | 1.05 (0.98–1.12) | 1.31 (1.20–1.43) | 1.34 (1.23–1.45) | – | – |
| **$PM_{2.5}$ per IQR increase** | | | | | | | | |
| Lag 0 | – | – | 1.02 (0.99–1.05) | 1.02 (0.99–1.05) | – | – | 0.99 (0.97–1.02) | 0.99 (0.96–1.02) |
| Lag 0–1 | – | – | 1.05 (1.02–1.09) | 1.05 (1.02–1.08) | – | – | 1.00 (0.97–1.04) | 1.00 (0.96–1.03) |
| Lag 0–2 | – | – | 1.05 (1.01–1.08) | 1.04 (1.00–1.08) | – | – | 0.97 (0.93–1.01) | 0.96 (0.93–1.00) |
| **RH per IQR increase** | | | | | | | | |
| Lag 0 | 0.98 (0.92–1.04) | – | 0.95 (0.90–1.01) | – | 1.04 (0.98–1.11) | – | 0.99 (0.93–1.06) | – |
| Lag 0–1 | 0.95 (0.88–1.02) | – | 0.89 (0.84–0.96) | – | 1.02 (0.95–1.10) | – | 0.93 (0.87–1.01) | – |
| Lag 0–2 | 0.95 (0.87–1.03) | – | 0.86 (0.80–0.93) | – | 1.03 (0.95–1.13) | – | 0.91 (0.84–0.98) | – |
| **TSR per IQR increase** | | | | | | | | |
| Lag 0 | – | 0.94 (0.87–1.01) | – | 0.98 (0.91–1.05) | – | 0.86 (0.80–0.94) | – | 0.93 (0.86–1.00) |
| Lag 0–1 | – | 1.01 (0.92–1.10) | – | 1.09 (1.00–1.18) | – | 0.91 (0.83–1.00) | – | 1.03 (0.94–1.12) |
| Lag 0–2 | – | 1.05 (0.95–1.15) | – | 1.17 (1.07–1.28) | – | 0.92 (0.83–1.02) | – | 1.09 (0.99–1.19) |

[a] Estimated by conditional logistic regression using a bidirectional time-stratified case-crossover design with controls selected from the same calendar month as the case events and additionally matched by day of the week and temperature (within 2 °C), excluding members with repeated cases of work incapacity related to mental health conditions during the study period.

relative humidity. Reduced duration of sunshine has previously been associated with an increased risk of depression (Kim et al., 2021). On the other hand, solar radiance during the day before the suicide event has repeatedly been found to be significantly associated with an increased suicide risk (Frangione et al., 2021). In Belgium, the hot summer months in 2018 were accompanied by a sharp increase in short-term absenteeism for any reason (Verlinden, 2019), but effects on long-term absenteeism are not known. Relative humidity has also been shown to be a risk to individuals with mental disorders. Together with an increase in ambient temperature, higher relative humidity was associated with increased use of emergency services for mental and psychosocial problems (Vida et al., 2012).

Strengths of our study include the use of a case-crossover design, its country-wide character and the coverage of a sample representative for the entire population. Only one previous nation-wide study, in Spain, demonstrated an impact of air pollution ($PM_{10}$) on workers' propensity to call in sick (Holub et al., 2020). That study used a linear probability approach to model a workers' weekly share of sick days of in relation to weekly air pollution concentrations, using data from 2005 to 2014. Our results are based on the most recent data available excluding the COVID-19 pandemic. We did not include data of 2020 as such analysis would be complicated by unprecedented drops in work incapacity related to mental health condition that have occurred during the COVID-19 lockdown periods. These are linked with the various government support measures that have been created, such as temporary unemployment because of COVID-19 for employees and the COVID-19 crisis bridging right for self-employed, respectively (Bruyneel et al., 2021).

Our findings should be viewed in light of some limitations. First, this

**Table B4**
Associations between work incapacity related to mental health conditions and average nitrogen dioxide ($NO_2$), ozone ($O_3$), particulate matter 2.5 ($PM_{2.5}$), relative humidity (RH) and total solar radiation (TSR) at the day of the event (lag 0) and up to 2 days before (lag 0–2), estimated by three-pollutant models with and without adjustment for RH and TSR and using 3 different scenarios for temperature matching Estimates represent hazard ratios (with 95% confidence intervals) for an IQR increase in exposures.[a]

| | Temperature matching within 1 °C | | | Temperature matching within 2 °C | | | Temperature matching within 3 °C | | |
|---|---|---|---|---|---|---|---|---|---|
| | Unadjusted models | Models adjusted for RH | Models adjusted for TSR | Unadjusted models | Models adjusted for RH | Models adjusted for TSR | Unadjusted models | Models adjusted for RH | Models adjusted for TSR |
| **$NO_2$** | | | | | | | | | |
| Lag 0 | 1.15 (1.09–1.20) | 1.16 (1.10–1.22) | 1.21 (1.15–1.27) | 1.12 (1.08–1.16) | 1.13 (1.08–1.18) | 1.16 (1.11–1.21) | 1.08 (1.04–1.12) | 1.13 (1.08–1.17) | 1.13 (1.09–1.18) |
| Lag 0–1 | 1.19 (1.13–1.26) | 1.24 (1.16–1.32) | 1.28 (1.20–1.36) | 1.19 (1.14–1.25) | 1.19 (1.13–1.26) | 1.22 (1.16–1.28) | 1.12 (1.08–1.17) | 1.16 (1.11–1.22) | 1.17 (1.12–1.23) |
| Lag 0–2 | 1.24 (1.17–1.33) | 1.32 (1.23–1.41) | 1.35 (1.25–1.45) | 1.26 (1.20–1.33) | 1.28 (1.21–1.36) | 1.30 (1.22–1.38) | 1.17 (1.12–1.23) | 1.22 (1.16–1.29) | 1.24 (1.17–1.30) |
| **$O_3$** | | | | | | | | | |
| Lag 0 | 1.26 (1.16–1.37) | 1.29 (1.18–1.40) | 1.36 (1.25–1.49) | 1.11 (1.04–1.19) | 1.13 (1.05–1.21) | 1.17 (1.09–1.26) | 1.14 (1.07–1.21) | 1.21 (1.13–1.29) | 1.23 (1.15–1.31) |
| Lag 0–1 | 1.42 (1.28–1.58) | 1.50 (1.35–1.67) | 1.54 (1.39–1.72) | 1.24 (1.15–1.34) | 1.25 (1.15–1.35) | 1.28 (1.18–1.39) | 1.27 (1.18–1.36) | 1.32 (1.23–1.42) | 1.34 (1.24–1.44) |
| Lag 0–2 | 1.43 (1.28–1.59) | 1.54 (1.37–1.72) | 1.55 (1.37–1.74) | 1.28 (1.19–1.39) | 1.31 (1.20–1.43) | 1.33 (1.22–1.45) | 1.29 (1.20–1.38) | 1.37 (1.27–1.48) | 1.38 (1.28–1.50) |
| **$PM_{2.5}$** | | | | | | | | | |
| Lag 0 | 0.97 (0.93–1.00) | 0.96 (0.93–0.99) | 0.96 (0.92–0.99) | 1.01 (0.98–1.04) | 1.01 (0.97–1.03) | 1.01 (0.98–1.03) | 1.03 (1.00–1.06) | 1.01 (0.98–1.04) | 1.02 (0.99–1.05) |
| Lag 0–1 | 0.98 (0.94–1.02) | 0.96 (0.92–1.00) | 0.96 (0.92–1.00) | 1.02 (0.99–1.05) | 1.02 (0.99–1.05) | 1.02 (0.98–1.05) | 1.05 (1.02–1.08) | 1.04 (1.00–1.07) | 1.04 (1.01–1.07) |
| Lag 0–2 | 0.96 (0.92–1.01) | 0.95 (0.90–0.99) | 0.95 (0.90–0.99) | 0.99 (0.95–1.02) | 0.98 (0.94–1.02) | 0.99 (0.95–1.02) | 1.02 (0.99–1.06) | 1.01 (0.98–1.05) | 1.02 (0.98–1.06) |
| **RH** | | | | | | | | | |
| Lag 0 | – | 1.07 (0.98–1.16) | – | – | 1.04 (0.97–1.11) | – | – | 1.15 (1.08–1.22) | – |
| Lag 0–1 | – | 1.19 (1.08–1.31) | – | – | 1.01 (0.94–1.09) | – | – | 1.13 (1.05–1.21) | – |
| Lag 0–2 | – | 1.27 (1.14–1.42) | – | – | 1.04 (0.95–1.14) | – | – | 1.14 (1.05–1.24) | – |
| **TSR** | | | | | | | | | |
| Lag 0 | – | – | 0.79 (0.71–0.87) | – | – | 0.86 (0.80–0.94) | – | – | 0.82 (0.77–0.88) |
| Lag 0–1 | – | – | 0.75 (0.66–0.85) | – | – | 0.92 (0.83–1.01) | – | – | 0.84 (0.77–0.92) |
| Lag 0–2 | – | – | 0.71 (0.62–0.82) | – | – | 0.92 (0.83–1.02) | – | – | 0.82 (0.75–0.91) |

[a] Estimated by conditional logistic regression using a bidirectional time-stratified case-crossover design with controls selected from the same calendar month as the case events and additionally matched by day of the week, excluding members with repeated cases of work incapacity related to mental health conditions during the study period.

study does not include short episodes of work incapacity, as payment by the health insurance funds requires a period of at least 8 consecutive days of work incapacity for self-employed workers, and payment is only activated after a certain period of time for blue-collar workers (after two weeks) and white-collar workers (after one month). Second, we used modelled ambient air pollutants with a resolution of 4x4 km which may lack some precision. Third, whereas we used municipality-level air pollution and temperature data, humidity and solar radiation data were only available for one single measuring station. Last, while the member of the Independent Health Insurance Funds are representative for the Belgian population, the one-country sample possibly limits generalizability of the findings to other countries.

In conclusion, mental health conditions are multifactorial disorders in which, traditionally, work and private factors play a role. Here, we provided evidence of an association between ambient air pollution and work incapacity related to mental health conditions, a link that the sizable literature focusing on mental health conditions had not yet accounted for.

## CRediT authorship contribution statement

**Luk Bruyneel:** Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft, Project administration. **Wies Kestens:** Data curation, Writing – review & editing. **Marc Alberty:** Writing – review & editing. **Güngör Karakaya:** Data curation, Writing – review & editing. **Renata Van Woensel:** Writing – review & editing. **Christian Horemans:** Conceptualization, Writing – review & editing. **Elke Trimpeneers:** Writing – review & editing. **Charlotte Vanpoucke:** Writing – review & editing. **Frans Fierens:** Writing – review & editing. **Tim S Nawrot:** Supervision, Conceptualization, Writing – review & editing. **Bianca Cox:** Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft, Project administration.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix

### *A. Supplementary material for the main analysis*

In this section, we provide the results for single-pollutant models assessing the associations between work incapacity related to mental

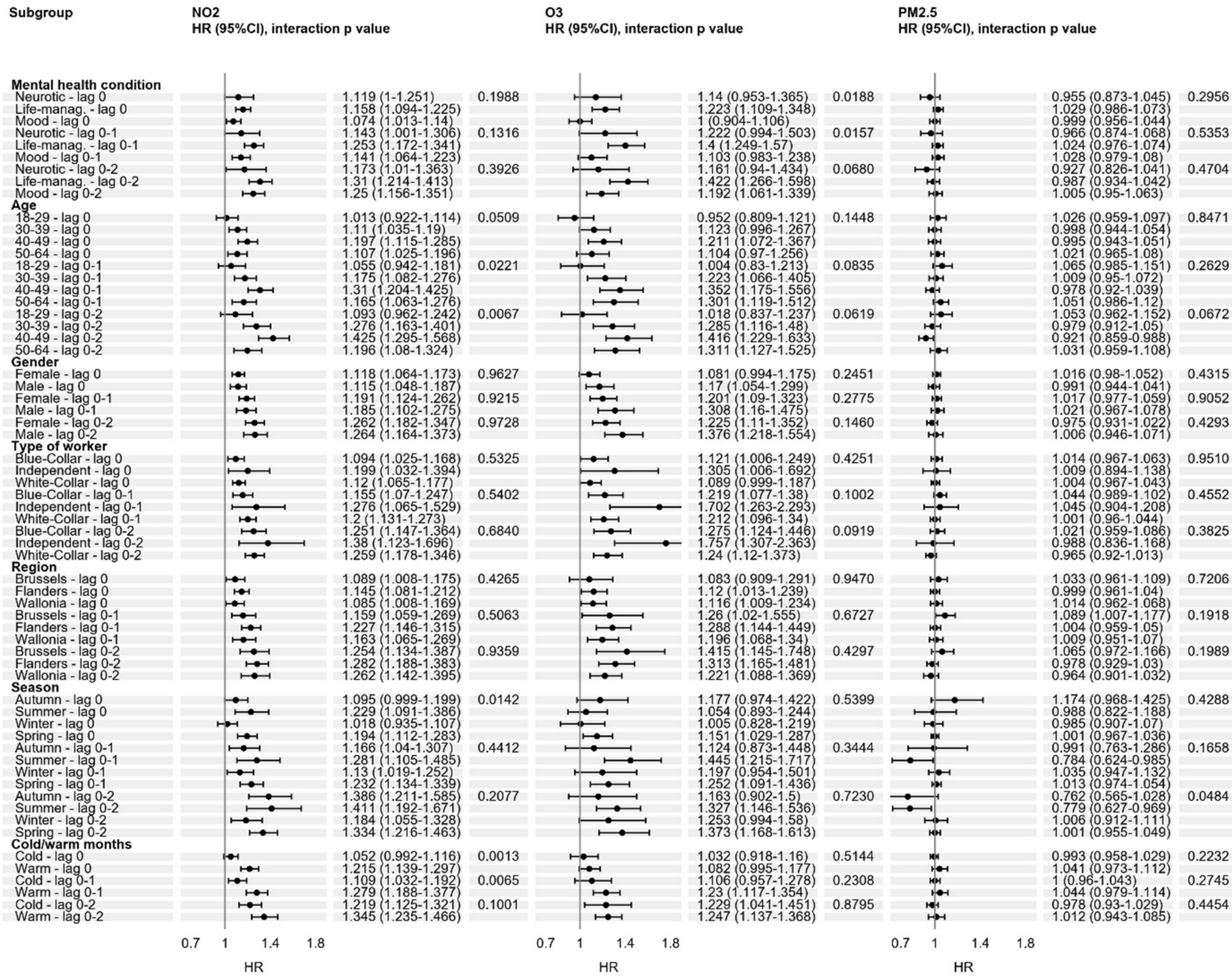


**Fig. B1.** Associations between work incapacity related to mental health conditions and average air pollution exposure at the day of the event (lag 0) and up to 2 days before (lag 0–2) by subgroups, estimated by three-pollutant models including interaction terms between the air pollutants and the variable of interest. Estimates represent hazard ratios (with 95% confidence intervals) for an IQR increase in nitrogen dioxide ($NO_2$), ozone ($O_3$) and particulate matter 2.5 ($PM_{2.5}$).[a]

health conditions and average air pollution exposure at the day of the event (lag 0) and up to 2 days before (lag 0–2) without and with adjustment for RH and TSR (Table A.1), as well as two-pollutant models assessing these associations without (Table A.2) and with (Table A.3) adjustment.

## Appendix B. Sensitivity analyses

In this section, to test the robustness of the reported results in the main analyses, we examine the associations between work incapacity related to mental health conditions and average air pollution exposure at the day of the event (lag 0) and up to 2 days before (lag 0–2), excluding cases of members who had more than one case of work incapacity related to mental health conditions during the study period. Sensitivity analyses were conducted for all previously reported single-pollutant (Table B.1), two-pollutant (Tables B.2 and B.3) and three-pollutant (Table B.4 and Fig. B.1) models.

In the main analysis, for the scenario in which daily average temperature of control days was within 2 °C from that of the case day, we retained 12 270 cases (11 968 unique members). For a 1 °C difference, the analysis included 8359 cases (8214 unique members). For a 3 °C difference, the analysis included 13 745 cases (13 362 unique members). In the sensitivity analyses, for the scenario in which daily average temperature of control days was within 2 °C from that of the case day, we retained 11 675 cases for as many unique members. For a 1 °C difference, the analysis included 8073 cases for as many unique members. For a 3 °C difference, the analysis included 12 991 cases for as many unique members.

Estimated by conditional logistic regression using a bidirectional time-stratified case-crossover design with controls selected from the same calendar month as the case events and additionally matched by day of the week and temperature within 2 °C, excluding members with repeated cases of work incapacity related to mental health conditions during the study period.

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