International Journal of Epidemiology, 2020, 1899–1908
doi: 10.1093/ije/dyaa074
Advance Access Publication Date: 31 May 2020
Original article

Determinants of Asthma

Local NO_2 concentrations and asthma among over-50s in Ireland: A microdata analysis

Philip Carthy,[1,2] Aonghus Ó Domhnaill,[3] Margaret O'Mahony,[3] Anne Nolan,[1,2,4] Frank Moriarty,[4,5] Brian Broderick,[3] Martina Hennessy,[6] Aoife Donnelly,[7] Owen Naughton[8] and Sean Lyons [1,2]*

[1]Economic and Social Research Institute, Dublin, Ireland, [2]Department of Economics, Trinity College Dublin, Dublin, Ireland, [3]Department of Civil, Structural and Environmental Engineering, Trinity College Dublin, Dublin, Ireland, [4]The Irish Longitudinal Study on Ageing, Trinity College Dublin, Dublin, Ireland, [5]Royal College of Surgeons in Ireland, Dublin, Ireland, [6]School of Medicine, Trinity College Dublin, Dublin, Ireland, [7]Department of Civil and Structural Engineering, Technological University Dublin, Dublin, Ireland and [8]Department of Built Environment, Institute of Technology Carlow, Carlow, Ireland

*Corresponding author. Economic and Social Research Institute, Whitaker Square, Sir John Rogerson's Quay, Dublin 2, Ireland. E-mail: sean.lyons@esri.ie

Editorial decision 1 April 2020; Accepted 6 April 2020

Abstract

Background: Links between air pollution and asthma are less well established for older adults than some younger groups. Nitrogen dioxide (NO_2) concentrations are widely used as an indicator of transport-related air pollution, and some literature suggests NO_2 may directly affect asthma.

Methods: This study used data on 8162 adults >50 years old in the Republic of Ireland to model associations between estimated annual outdoor concentration of NO_2 and the probability of having asthma. Individual-level geo-coded survey data from The Irish Longitudinal Study on Ageing (TILDA) were linked to model-based estimates of annual average NO_2 at 50 m resolution. Asthma was identified using two methods: self-reported diagnoses and respondents' use of medications related to obstructive airway diseases. Logistic regressions were used to model the relationships.

Results: NO_2 concentrations were positively associated with the probability of asthma [marginal effect (ME) per 1 ppb of airborne NO_2 = 0.24 percentage points asthma self-report, 95% confidence interval (CI) 0.06–0.42, mean asthma prevalence 0.09; for use of relevant medications ME = 0.21 percentage points, 95% CI 0.049–0.37, mean prevalence 0.069]. Results were robust to varying model specification and time period. Respondents in the top fifth percentile of NO_2 exposure had a larger effect size but also greater standard error (ME = 2.4 percentage points asthma self-report, 95% CI −0. 49 to 5.3).

Conclusions: Associations between local air pollution and asthma among older adults were found at relatively low concentrations. To illustrate this, the marginal effect of an increase in annual average NO_2 concentration from sample minimum to median (2.5 ppb) represented about 7–8% of the sample average prevalence of asthma.

Key words: Asthma, nitrogen dioxide, older adults, Ireland

Key Messages

- Regressions on individual-level data for a large sample of older people in Ireland showed a strong association between asthma risk and local annual average nitrogen dioxide (NO_2) concentrations.
- Models using self-reported and medication-based identification of asthma gave consistent results.
- Associations are present at lower levels of pollutant exposure than current regulatory thresholds imply.
- Further research is needed into the effects of pollution on asthma in older populations.

Introduction

Asthma is the most prevalent chronic respiratory condition worldwide, affecting over 300 million people.[1] Although the exact causes of the condition are not fully understood,[2] a growing body of evidence suggests that environmental factors, in particular ambient air pollution, are involved. The possibility that sustained exposure to air pollution affects the onset and exacerbation of asthma cases is biologically plausible. Indeed, the UK Committee on the Medical Effects of Air Pollution has proposed a set of pathways through which such effects may operate.[3] Potential mechanisms include oxidative stress and damage, airway remodelling, inflammatory pathways and immunological effects, and enhancing respiratory sensitization to allergens.[4] Although it is likely that individual pollutants bear some direct responsibility in the operation of these mechanistic pathways, it remains methodologically challenging to separate independent effects from those caused by other constituents of air pollution which may be contemporaneously emitted.[3] Nonetheless, nitrogen dioxide (NO_2) concentration is often used as a marker for local transport-related air pollution in epidemiological studies.[5]

Much of the existing observational evidence linking various pollutants to cases of asthma focuses on paediatric cases. A recent survey by Bowatte *et al.*[6] suggests that early childhood exposure to traffic-related air pollution is related to increased incidence of asthma and indeed that some of this effect is directly attributable to NO_2. Globally, effects of NO_2 exposure on asthma are sizeable, with Achakulwisut *et al.*[5] estimating that 4 million new paediatric cases could be attributable to the pollutant annually. Whereas the biological framework above does not preclude an effect on asthma onset or exacerbation later in life, findings from the literature on adult populations remain inconsistent.[7–11]

There are relatively few past studies focusing on the potential health effects of ambient pollution on the older population. Yet co-morbidities in older groups make management of asthma more difficult, and about two-thirds of asthma-related deaths occur among people >65 years old.[12] Our study is probably most similar to research by Lindgren *et al.*[13] of adults aged 18–77 in southern Sweden. However, the present study focuses on over-50 year olds and introduces a medication-based indicator of asthma in addition to self-reported diagnoses. We use rich survey microdata that allows us to relate estimated levels of ambient pollution at each respondent's residential address to asthma, as well as a range of potentially confounding socioeconomic and health-related factors. The ability to observe such variables at individual respondent level is particularly valuable, because exposure to pollutants and any associated health impacts may be affected by socioeconomic characteristics and individual behaviours.[14] Studies using area-based averages find it difficult to examine such relationships.

The present study was carried out using data from the Republic of Ireland, where the national ambient air quality is relatively high. The EU Directive that governs the legal limits above which ambient air pollutants should not rise (2008/50/EC) limits annual mean concentrations of NO_2 at 40 μg/mg [21 parts per billion (ppb)]. An exceedance in this dimension of the directive has only been observed once in Ireland (in 2009) between the years 2007–2017.[15] Although longitudinal data on health outcomes and many socioeconomic characteristics are available in the dataset, longitudinal pollution exposure data are not yet available for the relevant years. In addition, changes in the structure of questions across survey waves made it difficult to reliably identify the timing of asthma incidence. These data limitations meant that this study estimated cross-sectional models of asthma prevalence rather than the incidence of asthma among older age groups and prevented us from examining causal mechanisms.

Methods

Health information was drawn from The Irish Longitudinal Study on Ageing (TILDA) and linked to estimates of local NO_2 concentrations from Naughton *et al.*[16]

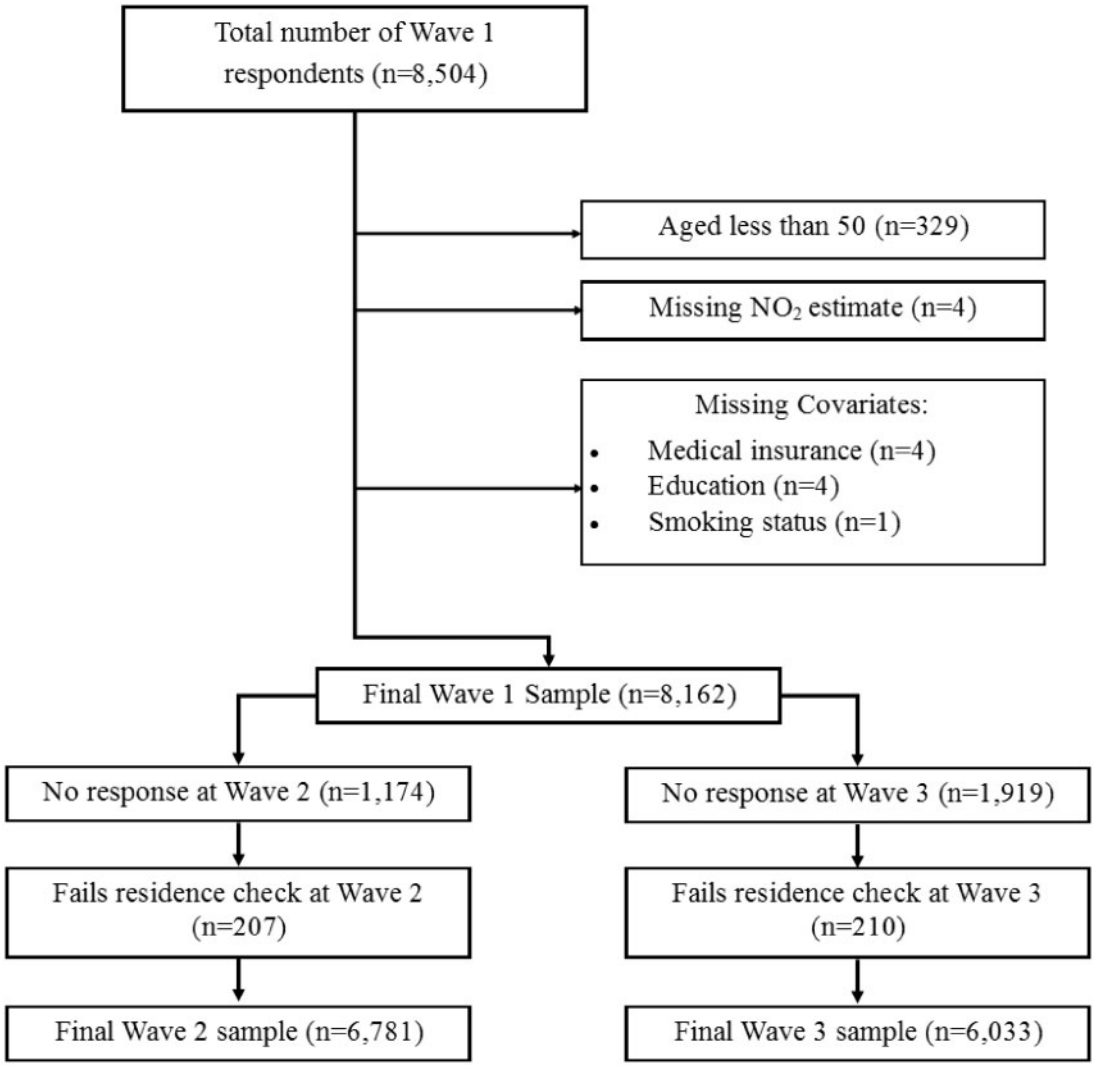

Figure 1 Construction of the final sample.

Sample

TILDA is a nationally representative study of those aged >50 years in the Republic of Ireland. Data collection for Wave 1 (W1) of the study occurred between October 2009 and July 2011, and follow-up data has been subsequently collected at 2-year intervals: Wave 2 (W2) in 2012 and Wave 3 (W3) in 2014–15.[17,18] In W1, 8175 individuals over the age of 50 from a sample of 6279 households participated in the study. Including some spouses and partners of respondents, the total W1 sample size was 8504. Figure 1 shows how our final sample for each wave of the TILDA data was constructed.

The TILDA data used in this study were collected using Computer Assisted Personal Interviewing (CAPI) carried out by trained interviewers, face-to-face at each individual's home. Sensitive questions were included in a supplemental self-completed questionnaire (SCQ), which the respondents returned by mail, and a nurse-administered health assessment was collected in every second wave. However, SCQ and health assessment data were not used in the current study.

The TILDA sample was recruited using the RANSAM protocol,[19] which samples households from the population of residential addresses in the Republic of Ireland. As a result, the residential geo-location of each household is known.

Ethical approval was not required for this secondary data analysis. Ethical approval for each wave of TILDA data collection was obtained from the Trinity College Dublin Faculty of Health Sciences Research Ethics Committee.

Measures

Outcome variables: self-report of asthma diagnosis and use of relevant medications

We identified respondents with asthma in two ways. First, we used self-reported doctor diagnoses of the condition

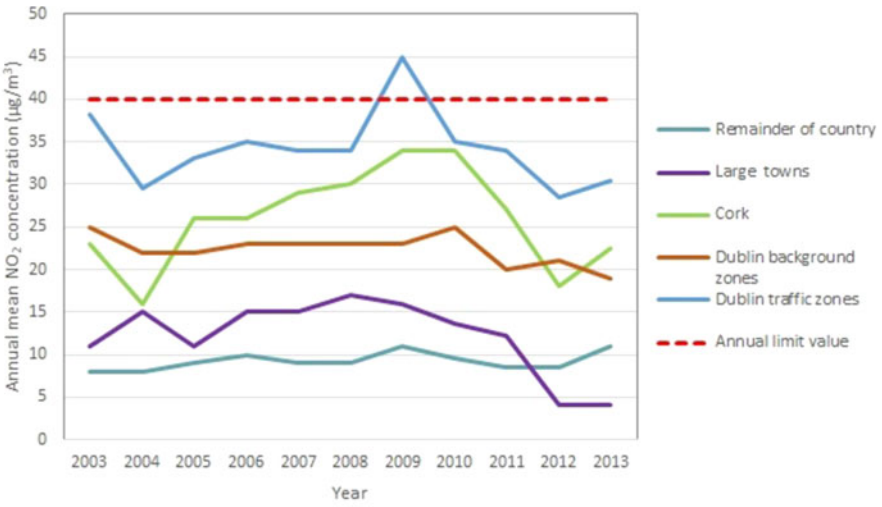

Figure 2 Trend in NO_2 concentrations for zones in Ireland from 2003–2013.[20]

('asthma'). As part of the CAPI interview, respondents were shown a card with a list of various chronic conditions, one of which is asthma, and were asked: 'Has your doctor ever told you that you have any of the following conditions?' The binary responses to this question were used as a dependent variable in the econometric models in this study. However, since self-reported data can be subject to recall bias, we also used an alternative identification method based on whether respondents regularly used medications with a therapeutic purpose in the management of respiratory conditions ('medications'). The set of medications used by each respondent was recorded by interviewers at the CAPI interview. These medications were subsequently classified by their World Health Organisation Anatomical Therapeutic Chemical Classification System codes. Class R03 in this system comprises medications for use in the treatment of obstructive airway diseases (OAD), including adrenergic agents such as salbutamol, inhaled corticosteroids, anticholinergics and leukotriene receptor antagonists. A binary indicator of whether or not respondents were taking any such medications was used in our analysis as a second indicator for asthma.

Air pollution proxy variable: local NO_2 concentration

Estimates of NO_2 exposure were obtained from Naughton *et al.*,[16] who used a wind-sector land use regression (WS-LUR) to produce a high-resolution map from which estimated mean annual NO_2 concentrations at any given location across the Republic of Ireland can be extracted. A spatial join in QGIS 2.18 was used to assign the estimated local pollutant concentration to each TILDA residence. The map used monitoring data from the Environmental Protection Agency's (EPA) national ambient air quality network, which records hourly NO_2 concentrations at various fixed locations throughout the state. The underlying model used air pollution data from 2010 to 2012, when the network consisted of 15 monitoring stations. There is a small offset between the timeline of the two datasets but insufficient local air pollution data were available for years prior to 2010. Figure 2 shows that national NO_2 trends were reasonably static from 2009 to 2013.[20] These data were linked with hourly wind speed and wind direction data for each monitoring station as recorded by Met Éireann (the Irish meteorological service). The spatial variation in NO_2 was explained as a function of various land use and traffic-related variables. NO_2 model validation revealed a good explanation of variation at all sites. Following the approach taken by Beelen *et al.*,[21] a leave-one-out cross validation method was employed in which the final model was fitted to $N-1$ sites and the predicted concentration compared with the actual concentration at the omitted site. This was repeated for all N sites and the overall level of fit between the predicted and measured concentration assessed. The final model explained >78% of the spatial variability in NO_2, whereas the cross validation R^2 was found to be slightly lower at 77.4%. The spread of data was well captured and the relationship between modelled and measured values close to linear.[16] The model was subsequently employed to predict NO_2 concentrations in other locations. More details of the methodology are included in Supplementary Appendix A, available as Supplementary data at *IJE* online.

Since there are very few observations at the upper end of the observed NO_2 distribution, some top-coding is necessary to protect the anonymity of individual TILDA respondents. All respondents for whom the observed concentration is above the 95th percentile of the NO_2 distribution are assigned to a single 'high exposure' category. To further

protect participant anonymity, NO_2 concentration estimates for all other respondents were rounded to the nearest integer ppb. Setting up the data in this way means that we have two variables that together capture the full range of NO_2 exposures in the sample: an ordinal variable rounded to integer level that contains the exposures for each respondent whose exposure was below a ceiling of 13.1 ppb and a second categorical variable set to 1 for all respondents with values >13.1 ppb and zero for those with lower values. Including both of these variables in regression models allows us to observe a linear relationship between exposures and outcomes for most respondents and an average marginal effect for those with exposures above the ceiling.

Other explanatory variables

Asthma risk may be associated with socioeconomic characteristics. The environmental quality around each respondent's residence could also be associated with his or her economic circumstances, with better-off households able to self-select into more attractive and potentially healthier neighbourhoods. While it is not possible to be certain all such factors were captured in our modelling, the TILDA dataset allowed us to control for many socioeconomic, demographic and health-related variables that may jointly affect exposure to NO_2 and the probability of suffering from asthma. In particular, we controlled for age, gender, income category, employment status, educational attainment, marital status, whether or not a respondent has medical insurance, whether or not they were (or had ever been) a smoker and, as a proxy for mobility limitations, whether or not they reported having difficulty walking 100 m

Analysis

Both of our outcome variables of interest are binary: $asthma_i$ takes on a value of 1 if a respondent reports ever having been diagnosed with asthma and is 0 otherwise. Similarly, $medications_i$ takes on a value of 1 if a respondent is found to be taking medications for obstructive airway diseases. Logistic regressions were used to model the factors associated with asthma. Specifically, we estimated:

$$\mathbf{P}(asthma_i = 1|NO_2, \mathbf{X}) = \Lambda(\alpha + \beta_0 NO_{2_i} + \beta_1 HighNO_{2_i} + \sum \beta_k \mathbf{X}_{ki}) + \epsilon_i \quad (1)$$

$$\mathbf{P}(medications_i = 1|NO_2, \mathbf{X}) = \Lambda\left(\alpha + \beta_0 NO_{2_i} + \beta_1 HighNO_{2_i} + \sum \beta_k \mathbf{X}_{ki}\right) + \epsilon_i \quad (2)$$

where $\Lambda(z) = \frac{e^z}{1+e^z}$, the cumulative distribution of the logistic function, NO_{2_i} is the estimated concentration of NO_2 at the residential address of each TILDA respondent rounded to the nearest integer value (or zero for those in the high NO_2 category), $HighNO_{2_i}$ is the dummy variable indicating those whose estimated NO_2 exposure is greater than the 95th percentile, $\mathbf{X}_{ki}$ is a matrix of individual level explanatory variables and ϵ_i is an error term such that $\epsilon_i \sim IID(0,\ \sigma_\epsilon^2)$.

We also conducted several robustness checks aimed at testing the stability of the observed association between NO_2 and the prevalence of asthma under various model specifications. To see if the observed associations are sensitive to the timing of the TILDA survey, we repeated the analysis using data from W2 and W3 of the TILDA data. This was done both for prevalence of self-reported asthma [Model 1 (equation (1))] and for the medication use outcome [Model 2 (equation (2))]. In addition, we tested a combined outcome variable requiring that respondents both self-report asthma and use relevant medication before being classified as having asthma. Finally, we checked the effect of dropping the explanatory variable for mobility limitation, i.e. whether or not respondents report having difficulty walking 100 m. This might be seen as an outcome of ill health, and thus arguably should be omitted as an explanatory variable.

Results

Table 1 provides descriptive statistics for the two primary outcome variables of interest in our analysis. The first shows the prevalence of self-reported asthma. In our sample, 9% of individuals indicated that a doctor had previously diagnosed them with the condition. The share of respondents who were taking medications for the treatment of OAD was smaller, at just 6.9%.

It is helpful to compare the two asthma indicators. If both self-reported and medication-based metrics were fully accurate and referred exclusively to the identical underlying disease process, then respondents taking medications would correspond with those who report having had an asthma diagnosis. Any differences between the two groups

Table 1. Descriptive statistics for dependent variables, TILDA Wave 1

	Frequency	Percent
Self-reported asthma		
No asthma	7424	91.0
Asthma	738	9.0
OAD medications use		
No OAD medications used	7601	93.1
Some OAD medications used	561	6.9
Total	8162	100

would arise only from the subset of diagnosed cases that do not require regular medication (e.g. less severe cases).

There were some differences in what the two metrics measured (see Table 2). Just >51% of those who reported an asthma diagnosis were using OAD medications at the time of interview ($n = 378$). In contrast, 32.6% ($n = 183$) of all those using medications did not report a diagnosis of asthma. It is possible that some respondents made errors when reporting whether they had an asthma diagnosis. In addition, some respondents could have reported accurately that they were not diagnosed with asthma but were taking OAD medications to manage other chronic respiratory conditions such as chronic obstructive pulmonary disease (COPD).

The distribution of estimated exposure to NO_2 among TILDA respondents is illustrated in Figure 3. The figure shows a positive skew in the data. Much of the TILDA sample was exposed to relatively low levels of the pollutant, which is in line with expectations given the overall favourable status of air quality in Ireland.

Supplementary Tables A1 and A2, available as Supplementary data at *IJE* online describe the distribution of NO_2 concentrations among TILDA respondents as used in our analysis. Among those respondents outside the high-exposure category, the mean concentration was 4.8 ppb with a maximum estimated concentration of 13 ppb. This is well below the EU limit for ambient mean annual concentrations of NO_2, which is approximately equivalent to 21 ppb. The high exposure group had a mean concentration of 14.1 ppb.

Table 3 presents descriptive statistics for other explanatory variables in our sample. Of our sample, 54% were female and 46% were male. This is consistent with the full TILDA cohort at W1.[22] For a sample of older people the observed sample was relatively young, with 57% in the 50–64 age bracket. This age profile was also reflected in the employment status variable, which indicated that 36% of the sample were in employment. The sample covers a broad spectrum of educational attainment. Whereas 29% had attained a third-level qualification, 31% had either no formal education or primary level only. The remaining 40% reported having a secondary-level education. Smoking was quite prevalent in the sample, with 56% of respondents reporting having smoked at some point in their lives. Since the relationship between smoking habits and asthma may be different between past and current smokers, we further subdivided this group: 18% reported being current smokers. Mobility-limiting disability appeared relatively uncommon in the sample with just >7% reporting difficulty walking 100 m due to some physical or mental health condition.

Table 4 presents the logistic regression results for the NO_2 variables. Full regression results are provided in Supplementary Table A3, available as Supplementary data at *IJE* online. The numbers reported are average marginal effects of a given variable on the probability of suffering from asthma. Marginal effects show the variation in the dependent variable associated with a 1 unit change in each explanatory variable. This way of expressing the strength of association can be especially useful for expressing results

Table 2. Relationship between dependent variables

	Self-reported asthma		
Medication use	Yes	No	Total
Yes	378	183	561
No	360	7241	7601
Total	738	7424	8162

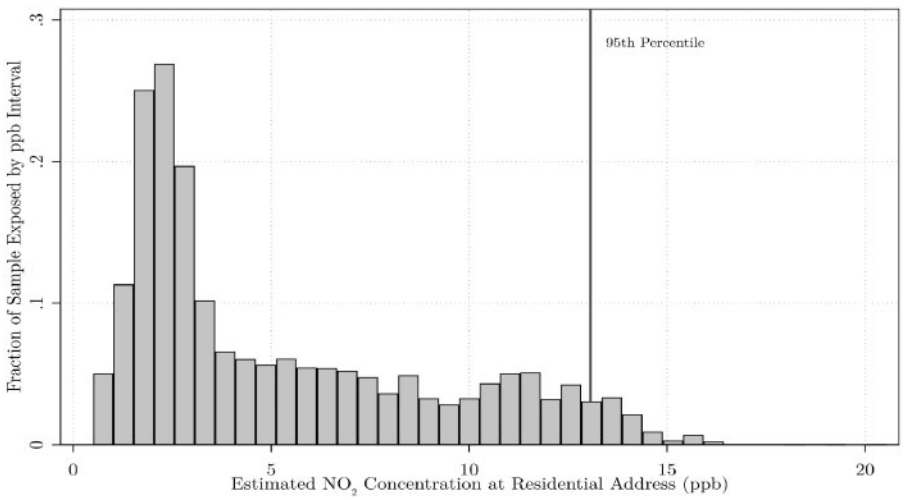

Figure 3 Frequency distribution of NO_2 exposure among respondents to TILDA.

Table 3. Descriptive statistics for other explanatory variables

	Frequency	Percent
Gender		
Male	3736	45.77
Female	4426	54.23
Age category, years		
50–64	4662	57.12
65–74	2160	26.46
≥75	1340	16.42
Income category, € per annum		
0–9999	647	7.93
10 000–19 999	1658	20.31
20 000–39 999	2702	33.1
40 000–69 999	1560	19.11
≥70 000	701	8.59
Not reported	894	10.95
Marital status		
Married	5629	68.97
Never married	791	9.69
Separated/divorced	551	6.75
Widowed	1191	14.59
Employment status		
Employed	2930	35.9
Retired	3039	37.23
Other	2193	26.87
Smoking status		
Never	3561	43.63
Past	3112	38.13
Current	1489	18.24
Educational attainment		
Primary/none	2502	30.65
Secondary	3258	39.92
Third-level/higher	2402	29.43
Medical cover		
Not covered	844	10.34
Medical insurance	3282	40.21
Medical card	4036	49.45
Mobility		
No difficulty walking 100 m	7562	92.65
Difficulty walking 100 m	600	7.35
Total	8162	100

from pollution-related models, because regulatory authorities normally express limits on emissions or exposures in absolute terms.

Model 1 suggests that, controlling for a wide range of socioeconomic and health-related factors, a 1 ppb increase in NO_2 concentration was associated with a 0.24 percentage point (95% CI 0.06–0.422) increase in the probability of reporting an asthma diagnosis for those with annual average exposures of <13.1 ppb. The increase in average prevalence of reported asthma for those with exposures in the high NO_2 category has an effect size an order of magnitude higher but also a much larger standard error.

Model 2 explains the probability of taking OAD medications. With this outcome variable, the marginal effect of a 1 ppb increase in local NO_2 concentration was ≈0.21 percentage points [95% confidence interval (CI) 0.0492–0.367]. The marginal effect of being in the high NO_2 category is very imprecisely estimated in this model, which may be due to the limited number of observations in this segment of the NO_2 distribution.

We conducted several robustness checks aimed at testing the stability of the observed association between NO_2 and the prevalence of asthma under various model specifications (see Table 5). In W2 and W3, the associations between the same NO_2 concentrations and asthma were broadly similar to W1 for both the self-report and medication models.

A further robustness check narrowed down the assignment of asthma to cases where a reported diagnosis is corroborated by medication use. The observed association between this definition of asthma and NO_2 was broadly consistent with our previous results for W1 and W2. In W3, there was a smaller effect size that is less precisely estimated. This might reflect a lack of statistical power as attrition reduced the W3 sample size: relatively fewer respondents had asthma under this narrow definition.

As one additional check, we dropped the limited mobility regressor to allow for the possibility that one's perception of having difficulty walking 100 m might be affected by having asthma. If this were the case, including mobility

Table 4. Logistic regressions estimating the relationship between NO_2 and asthma

	Model 1: self-reported asthma			Model 2: OAD medication use		
	$\delta y/\delta x$	95% CI	*P*-value	$\delta y/\delta x$	95% CI	*P*-value
NO_2 Exposure						
NO_2 level (ppb)	0.00241	0.0006, 0.00422	0.009	0.00208	0.000492, 0.00367	0.01
High NO_2 (NO_2 > 95th percentile)	0.0241	−0.00493, 0.0531	0.104	0.000926	−0.0264, 0.0282	0.947
n		8162			8162	
Akaike Information Criterion (AIC)		4898.5			3977.7	
Bayesian Information Criterion (BIC)		5059.7			4138.9	

Table 5. Robustness checks

	NO_2 level			High NO_2 indicator			
	$\delta y/\delta x$	95% CI	*P*-value	$\delta y/\delta x$	95% CI	*P*-value	*n*
Prevalence of self-reported asthma at other waves							
Wave 1	0.00241	0.0006, 0.00422	0.009	0.0241	−0.00493, 0.0531	0.104	8162
Wave 2	0.00191	−0.0000654, 0.00389	0.058	0.0125	−0.0203, 0.0453	0.454	6781
Wave 3	0.00246	0.000464, 0.00446	0.016	0.0204	−0.0139, 0.0548	0.244	6033
Medication use at other waves							
Wave 1	0.00208	0.000492, 0.00367	0.01	0.000926	−0.0264, 0.0282	0.947	8162
Wave 2	0.0019	0.000048, 0.00376	0.044	0.0164	−0.0135, 0.0463	0.282	6781
Wave 3	0.00233	0.000397, 0.00426	0.018	0.0104	−0.0227, 0.0435	0.538	6033
Dependent variable based on both self-reported asthma and medication use							
Wave 1	0.00204	0.000724, 0.00335	0.002	0.0104	−0.0114, 0.0321	0.35	8162
Wave 2	0.0017	0.00016, 0.00323	0.03	0.024	0.000481, 0.0476	0.045	6781
Wave 3	0.00149	−0.0000969, 0.00309	0.066	0.00324	−0.0254, 0.0319	0.825	6033
Drop limited-mobility variable							
Wave 1	0.00248	0.000667, 0.00429	0.007	0.0251	−0.00386, 0.054	0.089	8162
Wave 2	0.00202	0.0000502, 0.004	0.044	0.0134	−0.0194, 0.0462	0.424	6781
Wave 3	0.00254	0.000545, 0.00454	0.013	0.0208	−0.0136, 0.0553	0.237	6033

difficulties as a control variable might obscure the true association between NO_2 and the condition. The results were robust to this exclusion.

Discussion

This study found a positive association between local air pollution and the probability of suffering from asthma for a large representative sample of older adults in Ireland. Specifically, our results indicated that a 1 ppb increase in local NO_2 was associated with a 0.15–0.25 percentage point increase in the probability of suffering from asthma, depending on the metric used to identify asthma, the sample period and the model specification. The magnitude of this association is large. We can illustrate this by observing that the overall observed probability of self-reporting asthma in our data was about 9% and the share of respondents taking relevant medications was 6.9%. Based on the models in Table 4, the marginal effect of a 2.5 ppb increase in annual average NO_2 concentration (equivalent to someone moving from a place with sample minimum NO_2 to the median) represented about 7–8% of the sample average prevalence of asthma.

These results differ from the findings of Lindgren *et al.*,[13] who reported associations between asthma prevalence and living close to a major road (odds ratio = 1.40, 95% CI =1.04–1.89), but found weaker evidence for associations with NO_2 exposure. They refer to effects only in one of the cities within their sample and at exposure levels >19 $\mu g/m^3$ of NO_2.

Our study makes several contributions. First, it found evidence of an association between NO_2 exposure and asthma among older adults, a group that is underrepresented in the literature. Second, it uses both self-reports and use of medication to identify asthma cases, with consistent results. Third, the findings relate to a geographic area where levels of air pollution are relatively low, with exposures for many in the sample below standard regulatory thresholds. Finally, the individual-level data used in this study allowed us to control for a wealth of socioeconomic factors and health-related factors that may confound the relationship between NO_2 and asthma.

The study was subject to limitations. First, since our measure of local NO_2 concentrations was available only for a single point in time, we could not relate changes in exposure to changes in outcomes. In addition, variations in how the health status questions were asked in different survey waves made it hard to be certain about the timing of incidence for some individuals. The number of new cases reported in later waves was also small. Taken together, these problems limited us to analysing associations with the prevalence of asthma rather than its incidence among older people. If longitudinal data on a sufficiently large sample were available, it would allow researchers to control for unobserved individual-level heterogeneity and perhaps to test a possible channel of reverse causation, such as respondents reacting to local air pollution when choosing where to live.[23]

Second, the indicator used for local air pollution, NO_2, is only one of several pollutants implicated in respiratory disease. For policy purposes, it would be useful to examine the

full range of air pollutants (e.g. adding particulates and ozone) simultaneously so that the relative contributions of different pollutants to disease burdens could be measured and any interactions among the pollutants might be identified. As a result of these limitations, it remains for future work to establish whether the association between NO_2 and the incidence of asthma in an older age group can be considered causal.

Data availability

Data may be obtained from a third party and are not publicly available. The linked data file can be accessed on site via the TILDA hot desk system (contact tilda@tcd.ie for details). The unlinked data file can be accessed from the Irish Social Science Data Archive (www.ucd.ie/issda/) and other sources, e.g. the Gateway to Global Aging (www.g2aging.org/) and the Interuniversity Consortium for Political and Social Research (www.icpsr.umich.edu/icpsrweb/).

Supplementary data

Supplementary data are available at *IJE* online.

Funding

This work was supported by the Economic and Social Research Institute's Environment Research Programme, which is funded by Ireland's Environmental Protection Agency (EPA) [to P.C., S.L. and A.N.]; Environmental Protection Agency [grant number 2016-CCRP-MS.42 to A.O'D.]. This project is funded under the EPA Research Programme 2014-2020. The EPA Research Programme is a Government of Ireland initiative funded by the Department of Communications, Climate Action and Environment. It is administered by the Environmental Protection Agency, which has the statutory function of co-ordinating and promoting environmental research.

Acknowledgements

We are grateful for comments from two anonymous reviewers and from participants at the first Irish National Modelling Forum; the Symposium on Linking Air Quality and Health Data in Ireland, Environmental Research Institute, Cork; and the Irish Postgraduate and Early Career Economics Workshop at NUI Galway, 2019.

Disclaimer

Although every effort has been made to ensure the accuracy of the material contained in this paper, complete accuracy cannot be guaranteed. Neither the Environmental Protection Agency nor the authors accept any responsibility whatsoever for loss or damage occasioned or claimed to have been occasioned, in part or in full, as a consequence of any person acting, or refraining from acting, as a result of a matter contained in this paper.

Conflict of interest

None declared.

References

1. Soriano J, Abajobir B, Abate AA *et al*. Global, regional, and national deaths, prevalence, disability-adjusted life years, and years lived with disability for chronic obstructive pulmonary disease and asthma, 1990–2015: a systematic analysis for the Global Burden of Disease Study 2015. *Lancet Respir Med* 2017;**5**:691–706.
2. World Health Organization. Asthma. http://www.who.int/news-room/fact-sheets/detail/asthma (30 May 2019, date last accessed).
3. Committee on the Medical Effects of Air Pollutants. Statement on the Evidence for the Effects of Nitrogen Dioxide on Health. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/411756/COMEAP_The_evidence_for_the_effects_of_nitrogen_dioxide.pdf (7 June 2019, date last accessed).
4. Gowers AM, Cullinan P, Ayres JG *et al*. Does outdoor air pollution induce new cases of asthma? Biological plausibility and evidence; a review. *Respirology* 2012;**17**:887–98.
5. Achakulwisut P, Brauer M, Hystad P, Anenberg SC. Global, national, and urban burdens of paediatric asthma incidence attributable to ambient NO2 pollution: estimates from global datasets. *Lancet Planet Health* 2019;**3**:e166–178.
6. Bowatte G, Lodge C, Lowe AJ *et al*. The influence of childhood traffic-related air pollution exposure on asthma, allergy and sensitization: a systematic review and a meta-analysis of birth cohort studies. *Allergy* 2015;**70**:245–56.
7. Guarnieri M, Balmes JR. Outdoor air pollution and asthma. *Lancet* 2014;**383**:1581–592.
8. Le Moual N, Jacquemin B, Varraso R, Dumas O, Kauffmann F, Nadif R. Environment and asthma in adults. *Presse Med* 2013;**42**:e317–333.
9. Lazarevic N, Dobson AJ, Barnett AG, Knibbs LD. Long-term ambient air pollution exposure and self reported morbidity in the Australian Longitudinal Study on Women's Health: a cross-sectional study. *BMJ Open* 2015;**5**:e008714.
10. Jacquemin B, Schikowski T, Carsin AE *et al*. The role of air pollution in adult-onset asthma: a review of the current evidence. *Semin Respir Crit Care Med* 2012;**33**:606–19. https://doi.org/10.1055/s-0032-1325191
11. Modig L, Tore K, Janson C, Jarvholm B, Forsberg B. Vehicle exhaust outside the home and onset of asthma among adults. *Eur Respir J* 2009;**33**:1261–267.
12. Gibson P, McDonald V, Marks G. Asthma in older adults. *Lancet* 2010;**376**:803–13.
13. Lindgren A, Stroh E, Montnémery P, Nihlén U, Jakobsson K, Axmon A. Traffic-related air pollution associated with prevalence of asthma and COPD/chronic bronchitis. A cross-sectional study in Southern Sweden. *Int J Health Geogr* 2009;**8**:2–15.
14. Neidell MJ. Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma. *J Health Econ* 2004;**23**:1209–236.
15. Environmental Protection Agency. Air Quality in Ireland, 2017. Johnstown Castle Estate, Co. Wexford: EPA. http://www.epa.ie/pubs/reports/air/quality/epaairqualityreport2017.html.

16. Naughton O, Donnelly A, Nolan P, Pilla F, Misstear BD, Broderick B. A land use regression model for explaining spatial variation in air pollution levels using a wind sector-based approach. *Sci Total Environ* 2018;**630**:1324–334.
17. Donoghue O, McGarrigle C, Foley M, Fagan A, Meaney J, Kenny RA. Cohort profile update: the Irish Longitudinal Study on Ageing (TILDA). *Int J Epidemiol* 2018;**47**:1398–98l.
18. Kearney P, Cronin H, O'Regan C *et al*. Cohort profile: the Irish Longitudinal Study on *ageing*. *Int J Epidemiol* 2011;**40**:877–84.
19. Whelan BJ. RANSAM-random sample design for Ireland. *Econ Soc Rev* 1979;**10**:169–74.
20. O'Dwyer M. Air Quality in Ireland 2013, Key Indicators of Ambient Air Quality. EPA https://www.epa.ie/pubs/reports/air/quality/Air%20Quality%20Report%202013.pdf(22 November 2019, date last accessed).
21. Beelen R, Raaschou-Nielsen O, Stafoggia M *et al*. Effects of long-term exposure to air pollution on natural-cause mortality: an analysis of 22 European cohorts within the multicentre ESCAPE project. *Lancet* 2014;**383**:785–95.
22. Barrett A, Savva G, Timonen V, Kenny RA (eds). *Fifty Plus in Ireland 2011: First Results from the Irish Longitudinal Study on Ageing (TILDA)*. Dublin: Trinity College Dublin, 2011. http://www.tara.tcd.ie/handle/2262/55417 (22 November 2019, date last accessed).
23. Graff Zivin J, Neidell M. Environment, health, and human capital. *J Econ Lit* 2013;**51**:689–730.