Indoor Particulate Air Pollution from Open Fires and the Cognitive Function of Older People.

Professor Barbara A. Maher[a,1], Dr. Vincent O'Sullivan[b,1], Dr. Joanne Feeney[c,2], Mr Tomasz Gonet[a,2] and Professor Rose Anne Kenny[c]

[a]Lancaster Environment Centre, Lancaster University, Farrer Avenue, Lancaster, LA1 4YQ, U.K.
[b]Department of Economics, Lancaster University Management School, Lancaster University, LA1 4YX, UK.
[c]The Irish Longitudinal Study on Ageing (TILDA), Trinity College Dublin, Ireland

[1]Professor Maher and Dr. O'Sullivan are joint first authors.
[2]Dr. Feeney and Mr. Gonet are joint second authors.

Corresponding Author: *Dr Vincent O'Sullivan, Lancaster University Management School.*

Email: v.osullivan@lancaster.ac.uk Tel: 00 44 1 5245 93174.

Acknowledgements: Thanks to Clare Benskin, Yani Najman, Brian Davison and Rodney Teck for assistance with sampling indoor fire emissions. Special thanks to Likun Mao for assistance with Stata coding. Mr Gonet gratefully acknowledges PhD funding from Jaguar Land Rover. There was no funding for this project.

Abstract

Exposure to indoor air pollution is known to affect respiratory and cardiovascular health, but little is known about its effects on cognitive function. We measured the concentrations and magnetite content of airborne particulate matter (PM) in the indoor environment arising from burning peat, wood or coal in residential open fires. Highest indoor $PM_{2.5}$ concentrations (60 µg/m^3, i.e. 2.4 times the WHO-recommended 24-hour mean) occurred when peat was burned, followed by burning of coal (30 µg/m^3) and wood (17 µg/m^3). Conversely, highest concentrations of coarser PM ($PM_{10\text{-}2.5}$) were associated with coal burning (20 µg/m^3), with lower concentrations emitted during burning of wood (10 µg/m^3) and peat (8 µg/m^3). The magnetic content of the emitted PM, greatest (for both PM size fractions) when coal was burned, is similar to that of roadside airborne PM. Exposure to PM, and to strongly magnetic airborne PM, can be greater for individuals spending ~5 hours/day indoors with a coal-burning open fire for 6 months/year compared to those commuting via heavily-trafficked roads for 1 hour/day for 12 months/year. Given these high indoor PM and magnetite concentrations, and the reported associations between (outdoor) PM and impaired neurological health, we used individual-level data from The Irish Longitudinal Study on Ageing (TILDA) to examine the association between the usage of open fires and the cognitive function of older people. Using a sample of nearly seven thousand older people, we estimated multi-variate models of the association between cognitive function and open fire usage, in order to account for relevant confounders such as socio-economic status. We found a negative association between open fire usage and cognitive function as measured by widely-used cognitive tests such as word recall and verbal fluency tests. The negative association was largest and statistically strongest among women, a finding explained by the greater exposure of women to open fires in the home because they spent more time at home than men. Our findings were also robust to stratifying the sample between old and young, rich and poor, and urban and rural.

Keywords: indoor air pollution; particulate matter (PM); neurodegeneration; open fires; magnetite particles.

1. Introduction

A growing body of evidence indicates that exposure to airborne particulate matter (PM) is linked with damage to neurodevelopment and cognitive function, thus contributing to neurodegenerative diseases globally. Increasingly, a robust correlation has been found between PM concentrations in the outdoor environment and reduced brain function, both in different geographic settings and among different age groups. For example, in relation to younger people, long-term exposure to fine PM ($PM_{2.5}$, < 2.5 μm) has been linked with increased delinquency of urban-dwelling adolescents in Southern California, USA (Younan et al., 2018). Children attending schools in areas with high levels of particulate air pollution had deficits in cognitive development compared with children attending schools in low-particulate pollution areas in Barcelona, Spain (Sunyer, 2015). Other epidemiological studies, from the USA and Mexico, indicate that both young and old people living in areas with high airborne PM concentrations have cognitive deficits (e.g. Suglia et al., 2008; Ailshire & Crimmins, 2014). Furthermore, for an elderly cohort (the Women's Health Initiative Memory Study, aged 71 to 89 years), magnetic resonance imaging showed that loss of white matter increased by 1% per 3 $\mu g/m^3$ of $PM_{2.5}$ (Chen et al., 2015). At the large population-scale, in Canada, living close (< 50 m) to heavily-trafficked roads was found to be associated with increased incidence of dementia, Alzheimer's disease, Parkinson's disease and multiple sclerosis (Chen et al., 2017; Yuchi et al., 2020).

The specific components of airborne PM which cause these neurological effects are yet to be precisely identified. However, exposure to ultrafine particles (UFPs; < 0.1 μm) provides a major potential pathway for ingress of highly reactive and often metal-rich particles, which can access all major organs of the body (e.g. Miller et al., 2017; Bové et al., 2019; Calderón-Garcidueñas et al., 2019), including the brain (Maher et al., 2016; Maher, 2019). In animal studies, mice exposed to urban ultrafine air pollution for just four months showed reduced cognitive function and inflammatory responses in major brain regions (Cheng et al., 2016). Particles <~150 nm can access the brain directly, bypassing the blood−brain barrier, via transport through the neurons of the olfactory and/or trigeminal nerves (Oberdörster et al., 2004; Maher et al., 2016). Chronic exposure to such UFPs may result in neuroinflammation and oxidative stress (Maher, 2019), arising from generation of reactive oxygen species (ROS), a process catalysed by metal-bearing particles, such as iron, copper, zinc (Gilmour et al., 1996; Li et al., 1996; Shuster-Meiseles et al., 2016; Zhang et al., 2019). Exposure to bioreactive airborne UFPs may occur throughout the entire lifespan, from foetal development in the womb (Barosová et al., 2015; Pinkerton & Joad, 2006; Bové et al., 2019), through infancy and childhood, and subsequent adult lifespan. Early exposures may initiate and/or predispose damage to the brain, manifested most clearly when widespread and irreparable during later middle and/or old age.

The major sources of airborne PM include traffic, industry, and residential heating. Combustion- and friction-derived UFPs (< 0.1μm) are abundant at the roadside, arising from various sources, e.g. exhaust emissions, tyre wear and vehicle brake wear (Kumar et al., 2010, 2013; Sanderson et al., 2014; Thorpe & Harrison, 2008; Gonet & Maher, 2019). In the indoor environment, biomass burning results in emission of PM, especially hazardous to health at high indoor concentrations, such as when cooking and heating occur indoors without chimneys and/or adequate ventilation (Naeher et al., 2007; Chafe et al., 2014). Biomass burning emits health-damaging pollutants, associated with a range of adverse health outcomes including hypertension (Dutta & Ray, 2013), impaired respiratory health (Rivera et al., 2008), increased artery intima media thickness and prevalence of atherosclerotic plaques (Painschab et al., 2013), and lung cancer (Zhang & Smith, 2007). Indoor wood smoke at high doses is thus a well-established cause of morbidity and mortality. However, relatively little is known about the health effects at lower doses.

Where high concentrations of residential stoves are used locally, in high-income countries, for home heating, ultrafine PM emissions can additionally contribute to outdoor PM levels, especially during winter (Alfarra et al., 2007; Gelencser et al., 2007; Sandradewi et al., 2007; Szidat et al., 2007; Reche et al., 2012; Squizzato et al., 2016). In London, U.K., for example, recent rapid take-up of wood-burning stoves contributes an average ~1 μg/m^3 PM mass during the winter season (Crilley et al., 2017). Another study in Northern Italy showed that biomass burning is responsible for up to 33% of PM_1 (PM of aerodynamic diameter smaller than 1 μm) during winter (Squizzato et al., 2016). In small towns of northern Sweden, the contribution of domestic wood stoves produces PM concentrations comparable to busy street canyons in major cities (Krecl et al., 2008). A recent study (Oudin et al., 2019), based on modelled stove emissions to the outdoor environment, identifies an association between the emission of $PM_{2.5}$ from local residential wood burning and increased dementia incidence, with a hazard ratio of 1.55 for a 1 μg/m^3 increase in $PM_{2.5}$ (95% Confidence Interval (CI): 1.00–2.41, p-value 0.05).

Critically, the studies which have sought to examine links between PM emissions from residential heating and cognitive performance have so far focused on PM concentrations in the outdoor environment. Most people, however, spend the majority of their time indoors, not outdoors. Recent measurements of indoor PM associated with the cleaning, lighting and burning of wood-burning open fires in the home have identified $PM_{2.5}$ concentrations as high as 30 to 50 $\mu g/m^3$ (Castro et al., 2018).

Ubiquitous and abundant among the mix of components – solid and gaseous - which make up airborne PM are strongly magnetic, iron-rich UFPs, produced by wood-burning (McClean & Kean, 1993), other types of fossil fuel combustion, and vehicle- and industry-related sources (Gonet & Maher, 2019). In urban environments, such iron-rich UFPs are usually a mixture of magnetite (Fe_3O_4), maghemite (γ-Fe_2O_3) and haematite (α-Fe_2O_3), with smaller proportions of metallic iron (α-Fe) (e.g. Muxworthy et al., 2002; Halsall et al., 2008; Sanderson et al., 2016). Magnetite (a strongly magnetic mixed Fe^{2+}/Fe^{3+} oxide) has been found in human brains, directly associated with Alzheimer's disease (AD) amyloid plaques (Collingwood & Dobson, 2006; Quintana et al., 2006; Plascencia-Villa et al., 2016) and with excess generation of ROS, a key feature of AD (Castellani et al., 2007; Allsop et al., 2008; Tabner et al., 2011). Magnetite and other co-associated metal-bearing air pollution UFPs have been identified in the frontal cortex of human brains (Maher et al., 2016). Exposure to magnetite and other iron- and metal-rich air pollution particles has thus been suggested as a possible environmental risk factor for ROS-induced neurodegenerative diseases, including Alzheimer's disease (Maher et al., 2016; Maher, 2019); and home heating by open fires/stoves a potentially substantial exposure route (Maher et al., 2016).

In this study, we measured the concentrations, and magnetite content, of airborne particulate matter (PM) in the indoor environment arising from burning peat, wood or coal in residential open fires, and examined the association between cognitive function and open fire usage among older people living in Ireland.

Ireland, unusually for a Western European country, has a relatively high proportion of open fire users. According to the 2011 Census of Ireland, about one in ten Irish households use open fires as their main source of heating (Central Statistics Office, 2012), a proportion much higher than other Western European countries. Of those who use open fires, in 2011 there was roughly an even split between those who burned coal and those who burned peat (44% each of the total); the remaining 12% burned wood pellets. Furthermore, in our sample of older people, life-time exposure to open fires in the home has been high. For example, in the 1981 Census of Ireland, around 70% of households used open fires as their main source of heating (Central Statistics Office, 1986). Before then, when the people examined in our study were younger, open fires were near-ubiquitous in Ireland as a source of heating.

Here, we first quantify the concentrations of airborne PM and of strongly magnetic PM associated with residential open fires (for peat, wood and coal burning), and estimate the doses of $PM_{2.5}$ and of magnetite-rich PM which arise from exposure in the home compared with at the urban roadside. We then examine the association between home heating by open fires and cognitive performance in an existing longitudinal population study. We find that older people who used open fires as a source of heating have lower levels of cognitive function as measured by a number of widely used cognitive tests. Furthermore, the size of the negative association is larger and more statistically significant among women, a finding explained by their greater exposure to open fires in the home.

2. Methods

2.1. Estimation of indoor exposure to airborne particulate matter.

Samples of $PM_{2.5}$ and $PM_{10-2.5}$ emitted by burning of peat, wood and coal in residential open fires were collected on PTFE ($PM_{2.5}$) and polycarbonate ($PM_{10-2.5}$) filters, using a vacuum pump, operating at a flow rate of ~2 litres/min. The samples emitted by peat burning were collected for ~48 h. The samples emitted by wood and coal burning were collected for ~20 h. The inlet of the pump was placed close (~0.5 – 1.0 m) to the open fire, simulating the situation of a person sitting in a fireside chair.

PTFE and polycarbonate filters were first dried for 24h in a room with controlled temperature (20^{o}C) and humidity (50%) and subsequently weighed, with a Mettler AT250 balance (with accuracy of 0.00001 g). The filters were weighed before and after the PM collection, and the difference attributed to the collected PM mass. Each measurement was repeated three times. No metal tools were used during the laboratory work, to avoid potential contamination of the samples.

To quantify the amount of strongly magnetic, iron-rich PM present in each type of fuel emission, magnetic remanence measurements were performed at the Centre for Environmental Magnetism and Palaeomagnetism, Lancaster University, UK. Saturation isothermal remanent magnetisation (SIRM) was imparted to all the samples at 1 Tesla at room temperature, using a Newport Instruments electromagnet, and measured with a 2G RAPID cryogenic magnetometer (noise level of ~10^{-11} Am^2). Magnetite concentrations in the airborne PM were estimated based on Maher (1988), using the SIRM values for sized synthetic magnetite powders in the size range <2.5 µm.

2.2. Association between open fire usage and cognitive function in older people.

We examined data from Wave 2 of The Irish Longitudinal Study on Ageing (TILDA), collected between April 2012 and January 2013.[1] TILDA is a nationally representative sample of people aged fifty and older living in Ireland. The TILDA sample were asked a range of questions about aspects of their lives such as their health, living conditions, economic circumstances, and social engagement. Trinity College Dublin Health Research Ethics Committee granted ethical approval for the study. Each participant provided written informed consent prior to enrolment in the study. To eliminate potential bias due to differential participation in TILDA by certain groups of people, weights derived from the Irish Central Statistics Office's Quarterly National Household Survey were used in our analysis to maintain a nationally representative sample in terms of gender, age, and educational attainment. Whelan and Savva (2013) give a detailed description of the survey methodology and the weighting scheme for TILDA.[2]

TILDA field workers interviewed respondents face-to-face in their homes. In Wave 2 of TILDA, respondents were asked how they heated their home during winter. The respondents had to choose one of the following options: central heating only; portable heaters only; closed solid fuel appliance only; a combination of closed solid fuel appliances and portable heaters; open fire only; and a combination of open fires and portable heaters. For this study, we categorised respondents as users of open fires if they used open fires only or used a combination of open fires and portable heaters. Although TILDA is a longitudinal dataset, we did not use longitudinal analysis methods because there is very little variation in open fire usage between waves. For example, between Wave 2 and Wave 3 of TILDA, the percentage of open fire users was essentially unchanged.[3]

In the TILDA sample, 9.84% of respondents used open fires. The percentage of open fire users in the TILDA sample tallies with the Irish Census. According to both the 2011 and 2016 Censuses of Ireland, around 10% of households used open fires for heating. While now

[1] We used the Wave 2 of TILDA because that was when heating questions were first included in the survey questionnaire.
[2] A set of estimates using the unweighted sample are discussed in the robustness section that follow.
[3] 9.84% of respondents were open fire users in Wave 2, whereas 9.06% of respondents were open fire users in Wave 3.

only a minority of households use open fires, the decline in their usage has been much more recent than in other European countries. For example, as recently as the 1991 Census of Ireland, 39% of households reported using open fires. Despite the decline in use of open fires, Ireland still uses this form of heating far more than other European countries. For example, in the UK in 2011, only 2% of households reported using solid fuels for central heating (Palmer and Cooper, 2013).

During their face-to-face home interview with TILDA field workers, usually lasting about two hours, respondents had to complete a number of cognitive tests. Our measures of cognitive function were the Immediate Word Recall, Delayed Word Recall, Animal Naming, and the Mini–Mental State Examination (MMSE). In the Immediate Word Recall test, participants were told a list of ten words and were then asked to recall the words immediately. Shortly afterwards, the same list of words was then read out again, and the respondents were again asked to recall the words immediately. The word lists used were from the same task used in the Health and Retirement Study in the U.S. (Blankson & McArdle, 2014). The score for the Immediate Word Recall test was the total number of words recalled by the respondents in these two iterations. In the Delayed Word Recall test, respondents were asked to recall the words again after an average delay of about twelve minutes. In the Animal Naming test, participants were asked to name as many animals as possible within one minute. The Animal Naming test is a measure of semantic knowledge and executive function (Gordon et al. 2018). Successful performance on this test requires word knowledge, self-initiated activity, organisation and abstraction (e.g. categorising animals into groups such as domestic, wild, birds, dogs), and mental flexibility (e.g. moving to a new category when no more animals come to mind from a previous category). Lastly, the MMSE is a brief 30-point test that is used to screen for cognitive impairment (Folstein, Folstein, & McHugh, 1975).

3. Results

3.1. Indoor PM and magnetite concentrations, and exposure estimates

Highest indoor $PM_{2.5}$ concentrations (60 μg/m^3) occurred when peat was burned in an open fire, followed by burning of coal (30 μg/m^3) and of wood (17 μg/m^3) (Fig. 1; Table 1). For comparison, the WHO outdoor air quality guidelines identify a 24-hour mean $PM_{2.5}$ limit value of 25 μg/m^3 (WHO, 2016). Conversely, for coarser PM ($PM_{10\text{-}2.5}$), highest concentrations were measured for coal burning (20 μg/m^3), with lower concentrations emitted during burning of wood (10 μg/m^3) and peat (8 μg/m^3) (Table 1).

The total magnetic content of the emitted PM, as measured by its saturation remanent magnetisation (SIRM), was highest when coal was the fuel used, both for $PM_{2.5}$ ($8.9·10^{-3}$ Am^2/kg) and $PM_{10-2.5}$ ($19.1·10^{-3}$ Am^2/kg) (Fig. 1; Table 1). Lower SIRM values were observed for the PM derived from wood-burning ($7.8·10^{-3}$ Am^2/kg for $PM_{2.5}$ and $6.2·10^{-3}$ Am^2/kg for $PM_{10-2.5}$) and peat-burning ($3.8·10^{-3}$ Am^2/kg for both PM_{10} and $PM_{10-2.5}$). For comparison, these measured SIRM values for PM emissions from indoor open fires are similar to those for vehicle exhaust emissions and roadside airborne PM (Fig. 2). SIRM values for roadside PM (in Lancaster, U.K.) collected on filters ranges between $7·10^{-3}$ Am^2/kg and $167·10^{-3}$ Am^2/kg (Halsall et al., 2008). For exhaust emissions, SIRM reaches $\sim5·10^{-3}$ Am^2/kg and $\sim9·10^{-3}$ Am^2/kg for petrol and diesel emissions, respectively (Gonet et al. 2020a; Fig. 2).

The highest SIRMs, observed for the PM from coal burning, correspond to the highest concentrations of the strongly-magnetic minerals, magnetite and/or its oxidised counterpart, maghemite (Fig. 3; Table 1). In PM_{10} ($PM_{2.5}$ + $PM_{10-2.5}$), the SIRM values measured here indicate a magnetite concentration in the coal emissions of between 3700 mg/kg and 4600 mg/kg. For the wood-burning emissions, the magnetite concentrations are estimated at between 530 mg/kg and 1150 mg/kg, and in the peat emissions, between 550 mg/kg and 690 mg/kg (Fig. 3; Table 1).

In the outdoor, roadside environment, strongly magnetic, iron-rich PM contains a mixture of exhaust-derived emissions (both petrol and diesel) and highly magnetic brake wear (Fig. 2). Although the magnetic content (SIRM) of roadside PM reaches higher values than those for PM emissions from open fires (Fig. 2), people spend more time indoors than outdoors. Thus, the exposure to PM, and to iron-rich and magnetite particles in PM, is likely to be greater inside houses, compared to outdoor environments. Magnetite and co-associated metal-bearing pollution particles $< \sim150$ nm appear to enter the brain directly, via olfactory and trigeminal nerves, bypassing the blood-brain barrier (Maher et al. 2016), and potentially contribute to the oxidative stress and neurological damage associated with Alzheimer's disease (Smith et al. 1997; Castellani et al. 2007; Coccini et al. 2017; Maher 2019).

Based on the PM and magnetic data, it is possible to estimate the PM and magnetite exposure arising from open fire use through the heating season in the indoor environment, compared with a commuter's exposure in the outdoor urban environment (Table 2). Assuming a breathing rate of 0.54 m^3/h (Zhou & Levy 2008) and a roadside $PM_{2.5}$ level of 25 $\mu g/m^3$, a person commuting for ~1 hour/day, 5 days/week, 12 months/year (scenario A) inhales ~3.5 mg of $PM_{2.5}$ per year from outdoor sources. A person at home, using an open fire for ~4.5 h/day, 7 days/week, 6 months/year (scenario B) inhales ~26.5 mg (if burning peat), ~7.5 mg (if burning wood) and ~13.3 mg (if burning coal) (Table 2). The inhaled dose of $PM_{2.5}$ from open fires (burning any fuel) thus exceeds that from roadside airborne sources.

Mass concentrations of PM are usually used as air quality guidelines (e.g. by WHO). However, UFPs contribute very little to the particle *mass*, while contributing most to the particle *number* concentrations. Indeed, UFPs very often dominate number-normalised particle size distributions of PM emitted from various sources (Gonet & Maher, 2019). Among various compounds contained in UFPs which people are exposed to, magnetite and co-associated metal-bearing UFPs might be of particular importance due to their potential link with oxidative stress, and their reported association with Alzheimer-like pathology in the human brain. Assuming that ~0.1% of airborne UFPs can be deposited in the human olfactory bulb (Garcia et al. 2015), we estimated the number of magnetite UFPs that can be deposited in the olfactory bulb. We assumed a particle diameter of 20 nm, the magnetite roadside concentration of 0.20 – 0.95 wt.% (Hansard et al. 2011; Gonet et al. 2020a) and magnetite indoor concentrations from Table 1. Considering the same scenarios as above, a commuter (scenario A) is exposed to $\sim 18.7 \cdot 10^8$ magnetite particles per year from outdoor sources. A person at home, using an open fire (scenario B) is exposed to $\sim 1.6 \cdot 10^8$ magnetite particles per year from the open fire (if burning peat), $\sim 2.1 \cdot 10^8$ (if burning wood) and $\sim 19.2 \cdot 10^8$ (if burning coal). Thus, the exposure to magnetite particles originating from open coal-burning fires exceeds that from roadside sources, especially for those stay and/or work from home.

3.2. Association between open fires and cognitive function among older people in Ireland.

Table 3 presents the means of the measures of cognitive function according to whether a person in the TILDA sample uses open fires. One can see that users of open fires had lower cognitive function as measured by each test. The differences in test scores are statistically significant at the 1% level. Furthermore, the magnitude of the differences is large. For example, for Immediate Word Recall, there is a 0.85 unit difference between open fire users and non-open fire users, a difference equal to about a quarter of standard deviation of the overall distribution of scores in the Immediate Word Recall test.

Table 3 also presents the means and proportions of the covariates included in this analysis. One can see from Table 3 that there was no statistical difference in age and gender between those who used open fires and those who did not. However, users of open fires were more likely to live in rural areas compared to those who do not use open fires (59.8% versus 45.7%). Furthermore, very few users of open fires lived in Dublin when compared to those to do not use fires (6.3% versus 26.5%).

Furthermore, there was a clear socio-economic gradient by open fire usage. Users of open fires were less likely to be university graduates (20.2% versus 35.8%), less likely to be in the top quintile of the income distribution (10.6% versus 21.1%), and less likely to be in the professional or managerial social class groups as measured by their current or pre-retirement occupation (1.9% versus 4.9%). Furthermore, users of open fires were more likely to qualify for free or subsidized healthcare (65.2% versus 46.5%). For the under 70s, this qualification is based on a means-test or on having a long-standing illness. For the over 70s, qualification is based on a much less stringent means-test, and nearly all over 70s qualify. Finally, users of open fire were more likely to have grown up in a poor household (24.5% versus 19.8%).

Additionally, users of open fires had worse health behaviours. Users of open fires were more likely to smoke at the time of the survey (21.5% versus 13.4%) and they were less likely to have never smoked (37.6% versus 46.3%). Furthermore, users of open fires had lower social connectedness as measured using the Berkman-Syme Social Network Index (SNI) (Berkman and Syme, 1979). This index is a composite measure of four types of social connections: marital status (0=not married, 1=married); number of contacts with children, relatives, and friends (0=few, 1=many); church group membership (0=no, 1=yes); and membership of other voluntary organisations (0=no, 1=yes). Scores from each social connection type were combined to create four levels of social connection or engagement: most isolated (0-1); moderately isolated (2); moderately integrated (3); and most integrated (4). All of these observed differences motivated our multivariate analysis as described in the Results section.

Using Ordinary Least Squares, we estimated the following linear model (Equation 1):

$$y_i = \alpha + \beta * OpenFire_i + X'\Gamma + \varepsilon_i \qquad (1)$$

where y_i are the ith person's score from the Immediate Word Recall test, Delayed Word Recall test, or the Animal Naming test. $OpenFire_i$ indicates whether a person uses open fires (or a combination of open fires and portable heaters) as their main source of heating as opposed to some other type of heating. X is a vector of relevant control variables, and ε_i is an error term. Unless otherwise stated, all of the samples used in the analysis were weighted to maintain a nationally representative sample. Furthermore, standard errors were clustered at the household level to allow for within-in household correlation.

Because the MMSE scores have a highly skewed distribution, a negative binomial model was estimated instead of a linear regression. The maximum score in the MMSE is thirty. The residuals (thirty minus the MMSE score), follow a negative binomial distribution. Thus, in relation to the reported coefficients from the negative binomial model of MMSE, a positive coefficient for a variable should be interpreted as that variable being associated with worse cognitive function.[4]

In Table 4, we present our estimates of the association of open fires with different measures of cognitive function. For each of these measures of cognitive function, open fire users had worse cognition. In the Immediate Word Recall test, users of open fires recalled 0.305 fewer words from a possible total of twenty words compared to those who did not use open fires. This difference was statistically significant at the 5% level. On the Delayed Word Recall test, open fire users recalled 0.162 fewer words, but this difference was not statistically significant. On the Animal Naming test, open fire users named about 0.356 fewer animals than those who did not use an open fire, but again the difference was not statistically significant.

The other covariates had associations with cognitive function in the direction one would expect. For example, age had a negative association with each measure of cognitive function. Furthermore, for each measure of cognitive function, the negative association with age was significant at the 1% level. To put the size of the association of heating and cognitive

[4] Specifically, for a one unit change in the predictor variable, the difference in the logs of the expected counts of the outcome will change by the respective coefficient.

function into perspective, one should consider that the coefficient of open fire usage ranges from between 1.8 and 3.3 times the size of the age coefficient.

Another key covariate is gender. In Table 4, one can see that gender had a significant association with cognitive function, but the direction of the association varied depending on the measure of cognitive function being analysed. Specifically, women had better word recall scores, yet they had worse scores on the Animal Naming test.

Those who lived in rural areas had lower cognition compared to those living in more urbanised areas. This lower cognition among rural dwellers is consistent with the finding of Cassarino et al (2018). A possible mechanism for this finding is through lower levels of mental stimulation in rural areas. In our robustness section that follows below, we present results of the models when estimated separately for urban and rural dwellers.

In general, the other covariates revealed a socio-economic gradient in cognitive function. For example, better-educated respondents performed better in all tests. A university graduate's performance on the tests was between one and a half times and twice as good as that of a high school graduate. In relation to income, those in the bottom quartile performed worse in the recall tests. However, there was less strong statistical evidence of income gradient in relation to the Animal Naming test. In relation to occupation, or the former occupations of retirees, respondents in lower social class groups performed worse in the tests relative to those in the Professional class social group. Furthermore, respondents who qualified for free or government-subsidized healthcare performed worse on these tests, but the level of statistical significance varied across cognitive test. Lastly, those who recall being poor during childhood had worse cognitive function, but the effect was significant at the 5% level for only the recall tests.

In relation to health and health behaviours, some of the associations with cognitive function were not statistically significant. For example, being a smoker at the time of the survey was associated with worse cognitive function, but the association was significant only for the Immediate Word Recall test. Furthermore, there was an association between social connection and cognitive function. Those who were more socially integrated had better scores in all of the tests, and this association was significant at the 5% level for the Delayed Word Recall test and the Animal Naming test and at the 1% level for the Immediate Word Recall test and the MMSE.

3.3. Robustness checks

In Table 5, one can see the estimated effect of using open fires on cognitive function when analysing sub-samples separately. The first panel of Table 5 shows the results when different samples were analysed according to the location of the respondents' homes. In the models estimated in Table 4, although we controlled for location, a concern is that the estimated effect of using open fires is biased because of correlation between open fire usage and unobserved factors related to the location of respondents' homes. In particular, we were concerned that differences in cognition might be correlated with the level of urbanization of the respondents' residences which in turn might be correlated with the usage of open fires. Open fires are less common in urban areas because of the availability of alternative sources of heating (e.g. connectivity to the national gas network) and because more densely constructed housing is more unsuitable for open fires (e.g. apartment blocks). Furthermore, open fires are less common in urban areas because of a ban on the sale, but not the use of, smoky coal in all cities and many towns in Ireland. However, people living in areas covered by the ban are allowed to purchase and burn both peat and wood in addition to smokeless coals.

However, in Table 5, when we split the sample according to location, the effect of burning open fires is very similar regardless of sample used. In relation to the Immediate Word Recall test, the estimated effect ranges from -0.23 to -0.344, although none of the effects were statistically significant in the specific samples possibly due to the reduced sample sizes. On the other hand, in relation to the Delayed Word Recall test, the negative association of burning open fires is largest in rural areas where it was significant at the 10% level. However, the effects of burning open fires were smaller and not significant in Dublin, and they were essentially zero in urban areas outside Dublin. The results from the negative binomial model of the MMSE show that the detrimental effect of burning open fires is largest for urban dwellers outside Dublin. However, in relation to MMSE the estimated coefficients were not statistically significant. Again, this lack of significance is most likely due to reduced sample size.

In the second panel of Table 5, one can see the estimates when analysing men and women separately. The negative effect of burning open fires on cognition is much larger for women than for men. The effect is statistically significant at the 5% level when estimated using the women-only sample. The difference in magnitude and statistical significance in effects could be due to life-time exposure to open fires within the home. The women in TILDA sample lived much of their potential working lives during a time when there were social and institutional pressures not to work and to instead stay at home. For example, until 1973 in the public sector, and until 1977 in the private sector, Irish women could be fired from their jobs when they married (for a discussion see Mosca, O'Sullivan & Wright, 2020). Thus, about 11% of women in the TILDA sample never worked outside the home. Of those who did work outside the home, about half spent at least ten years looking after family members on a full-time basis. Thus, the women in the sample were likely to have had greater exposure to the source of home heating than men.

Next, the models were estimated separately for different age groups. Although, as one can see from Table 3, there was no difference in the average age of open fire users, a concern is that the association between open fires and cognition might be due to a correlation between age and open fire usage. However, as one can see from the third panel of Table 5, the association between open fire usage and cognition is of a similar magnitude for different age groups. An exception is that the effect of open fire usage on the Delayed Word Recall test for those aged 65-74 is much smaller when compared to other age groups. Furthermore, the negative association between open fire usage and the Animal Naming test and the MMSE is larger for those older than 74.

We also split the sample by income between the first two quintiles of the income distribution and the top three quintiles of the income distribution. Again, the level of statistical significance of the coefficients falls, most likely because of the smaller sample sizes. However, the coefficients are roughly of the same magnitude when estimated using either the poorer or richer sub-sample.

In the penultimate panel of Table 5, we present the same models when estimated without using sampling weights. In general, one can see that the size of the coefficients is very similar to that of the main estimates which used sampling weights. An exception is that the coefficient relating to open fire usage in the Animal Naming test regression is -0.554 in the unweighted sample, whereas it is -0.356 in the weighted sample. However, the main difference between the weighted and unweighted samples is that, in the unweighted sample, the association between open fire usage is statistically significant at the 5% level for the Immediate Recall test, the Animal Naming test, and the MMSE, whereas in the weighted sample, the association is only significant at the 5% level for the Immediate Recall test.

Another concern is that causality is bi-directional or that there is feedback/ reinforcement between open fire usage and cognitive function. For example, people with lower levels of cognitive function might be less likely to change their heating source or move to housing without open fires. In the absence of random allocation of open fires, it is impossible to rule out the concern of bi-directional causality or feedback/reinforcement. However, to partially address this concern, we present the estimates from an alternative model where we conditioned on cognitive function recorded two years prior (i.e. we estimated a model with a lagged dependent variable). Thus, we estimated the following linear model (Equation 2):

$$y_{it} = \alpha + \delta * y_{it-1} + \beta * OpenFire_{it} + X'\Gamma + \varepsilon_{it} \quad (2)$$

where y_{it} are the i^{th} person's score from the Immediate Word Recall test, Delayed Word Recall test, or the Animal Naming test in Wave 2 of TILDA (between 2012-2013) and where y_{it-1} is the same test score recorded in Wave 1 of TILDA (between 2009 and 2011). A similar Negative Bionomial model was estimated with respect to the MMSE. As we can see from the bottom panel in Table 5, when one includes a lagged dependent variable, the estimated association between open fire usage and the Immediate Word Recall test is slightly more negative and statistically significant than the corresponding estimate in the baseline model without the lagged dependent variable. The other estimates, when one includes a lagged dependent variable, are around the same magnitude as the baseline model without the lagged dependent variable. Further extending the models to control for changes in open fire usage between waves of TILDA was not feasible because open fire usage was not recorded in Wave 1, and very few people changed their open fire usage after Wave 2.

Finally, it is worth noting the possibility that some users of open fires are more likely to ventilate their homes by leaving windows and doors open when using an open fire. Thus, some users might avoid the full negative effects of exposure to open fires. Unfortunately, it is not possible to know the ventilation arrangements within the TILDA respondents' homes. However, it should be noted that Ireland has an oceanic climate that can be wet, windy and moderately cold, especially along the western seaboard; thus, opening windows and doors might not be desirable especially during the winter.

4. Discussion

The contribution of this paper is twofold. First, we show that the burning of solid fuels emits similar levels of PM, and of magnetite-rich PM, into the indoor environment of modern homes as do outdoor, traffic-related emissions. We then estimate and compare the exposures to $PM_{2.5}$ and to strongly magnetic, iron-rich PM incurred indoors during the heating season and outdoors annually by daily commuting. Notably, the level of exposure to $PM_{2.5}$, and to magnetite particles, originating from open fires is similar to and indeed might exceed that from roadside sources, especially for those who stay at home during the working day and use coal in their open fires.

Such indoor exposures might cause specific deficits in cognitive function. Given the observed associations between oxidative stress and neurodegeneration, and the presence of ultrafine magnetite particles within plaques of AD brains, indoor exposure to the strongly magnetic, iron-rich particles emitted in abundance by open fires might be causally linked to development of neurological impairment. Magnetite particles < ~150 nm can enter the brain directly (Maher et al. 2016), via olfactory (Oberdorster et al. 2004), and trigeminal nerves, bypassing the blood-brain barrier and potentially contributing to the oxidative stress associated with Alzheimer’s disease (Smith et al. 1997; Castellani et al. 2007; Coccini et al. 2017; Maher 2019).

The inhalation of magnetite particles arising from fossil fuel combustion in residential open fires might be damaging in its own right, through release of free iron and enhanced formation of reactive oxygen species via the Fenton reaction (Maher et al., 2016; Maher, 2019). But airborne magnetite pollution particles are also often co-associated with other toxic species, including other metals (including Ce, Cr, Cu, Mn, Ni, Pb, Ti, Al and Zn) (Spassov et al., 2004; Chen et al., 2006; Kim et al., 2007; Maher et al., 2016, Yang et al., 2016, Hofman et al., 2020) and polyaromatic hydrocarbons (Lehndorff & Schwark, 2004, Halsall et al., 2008), arising from incomplete combustion, which likely bind to the surfaces of magnetite particles (Maher, 2019). Our analysis shows that the dose of inhaled $PM_{2.5}$ from open fires might exceed that at the roadside. A person staying at home and using an open fire to keep their home warm might thus be exposed not only to high concentrations of magnetite, but also to other neurotoxicants contained within $PM_{2.5}$.

Second, we showed that there is a negative statistical association between open fire usage and cognitive function. In relation to the statistical modelling, the negative association must be assessed in the context of potential omitted variable bias, potential measurement error in open fire usage, and potential feedback or reinforcement between open fire usage and cognitive function. In relation to omitted variable bias, we controlled for variables that are likely associated with both open fire usage and cognitive function. Chiefly, these variables were age, socio-economic status, and location. We controlled for these variables, and we also stratified our analysis across these variables. We consistently estimated a negative association between open fire usage and cognition. Further, in relation to measurement error in open fire usage, it is likely that open fire usage at the time of the survey is an understatement of life-time exposure to open fires. The sample comprises older people in Ireland; the youngest people in the sample were born during the late 1950s. Given that open fires were still a very common form of heating until the 1990s, many people not using open fires at the time of the survey previously used open fires for much of their lives. Thus, our estimated association between open fire usage and cognitive function might be an under-estimate of the true association. Lastly, there might be feedback or reinforcement between open fire usage and cognitive function. For example, people with lower levels of cognition might be less likely to change their heating source, or move to housing without open fires. In relation to the latter scenario, our sample excludes people living in care homes. So, we can rule out the situations where an older person with dementia living in a house with an open fire is then institutionalized in a care home. To overcome potential feedback or reinforcement, we estimated models which controlled for prior levels of cognitive function, yet we still found a negative association that was of the same magnitude as our original model.

Our research adds to the body of knowledge about the effects of indoor pollutants. There is a growing body of high quality research demonstrating the negative association between outdoor air pollution and cognitive decline among older people (for a review, see Paul, Haan, Mayeda, & Ritz, 2019). But much less is known about the association between indoor pollution and cognitive decline. However, recently, a few studies have found a negative association between indoor air pollution and cognitive decline. For example, Krishnamoorthy et al (2018) examined a relatively small sample of adults, of all ages, living in a rural and poor area of India. They found, controlling for a limited number of factors, a negative association between MMSE scores and usage of biomass or kerosene as fuel for home cooking. In addition to that study, there are studies in upper-to-middle income countries. For example, using data from the China Health and Retirement Longitudinal Study (CHARLS), Qiu, Yang & Lai (2019) found that usage of solid fuels for cooking or heating, among those older than forty-five, was associated with worse short-term memory and mathematical reasoning. Similarly, Saenz, Wong, & Ailshire (2018) examined data from the Mexican Health and Aging Study (MHAS), and found that, among those older than fifty, usage of wood and coal as a fuel for cooking was negatively associated with verbal learning, verbal fluency, attention, and orientation. Finally, in a study of a high income country, Oudin et. al. (2018), using longitudinal data from Northern Sweden, found a positive association between dementia diagnoses and ownership of wood burners (also conditioning on local levels of wood burner ownership and traffic pollution).

There are similarities in the design of these studies and the present study. For example, TILDA, CHARLS and MHAS are part of the HRS family of studies (see https://hrs.isr.umich.edu/about/international-sister-studies), so there is a degree of harmonisation between the variables in each study. However, there are differences. First, there are differences in the economic settings. Krishnamoorthy et al (2018), Qiu, Yang, & Lai (2019), and Saenz, Wong, & Ailshire (2018) are studies set in poorer or middle income countries, whereas the present study is set in what is now a high income country. The differences in setting are important because of differences in access to, and the quality of, healthcare, as well as the general level of environmental regulations. For example, we find a negative association in spite of the relatively greater level of environmental regulation in Ireland given its membership of the European Union. On the other hand, Oudin et al (2018) is set in the north of Sweden, also a high-income European Union member, but a place where risk of exposure to indoor pollutants through heating might be greater because of much colder winters relative to Ireland.

Secondly, there are differences in the aspect of cognitive function in which an association is found. Although Qiu, Yang & Lai (2019) and Saenz, Wong, & Ailshire (2018) found a negative association between indoor pollution and certain aspects of cognitive function, they did not find a statistical association between indoor pollution and verbal recall. However, in the present study, there was a negative association between indoor pollution and verbal recall. In relation to Oudin et al (2018), that study exclusively examined diagnosis of dementia whereas the present study examined cognitive function more generally.

Lastly, and perhaps most importantly, there were differences in the source of indoor pollution. The exposure to indoor pollution as measured by Krishnamoorthy et al (2018) and Saenz, Wong, & Ailshire (2018) was from cooking and, in the case of Qiu, Yang & Lai (2019) from either cooking or heating (i.e. not separated by source). Arguably, the exposure to pollution from cooking is greater than from heating. Standing directly over a cooker risks greater exposure to pollutants compared to just being in the same room as an open fire. In the present study, open fires were used for heating rather than cooking, yet we still found a negative association between open fire usage and cognitive function.

This present study of older Irish people allows one to speculate about the future health of those currently using open fires. Most of the three billion people estimated by WHO (World Health Organization, 2018a) to be currently using open fires live in rapidly developing countries, many of which will have an economic trajectory during the 21st century similar to Ireland's during the 20th century. Most of the older Irish population lived through the transition of Ireland from a poor rural economy to an urbanized wealth economy which also saw the transition from burning fuel on open fires for heating to using electricity, gas, and other fuels.

For policy makers, the negative association between open fire usage and cognitive function should be seen as further evidence in favour of banning or restricting the usage of open fires. For example, in February 2020, the UK government announced the phasing out of sales of coal (and wet wood) for domestic burning in England between 2021 and 2023 citing health concerns (Department for Environment, Food & Rural Affairs, 2020). The health concerns raised by public health officials in relation to open fires usually relate to the heart and lungs; however, our research demonstrates that cognitive function should also be a health concern to be considered by these policy makers.

Reducing or delaying dementia is a key goal for healthcare systems. The costs of dementia, which include direct medical costs, social care costs, and the costs of informal care, are very large. Wimo et al. (2017) estimated that, in 2015, the worldwide cost of dementia was US $818 billion or 1.1% of World GDP. The 2015 costs were 35% higher than in 2010, and are likely to rise further. Furthermore, dementia is listed as the fifth most common cause of death (WHO, 2018b). Thus, public health policy should aim to reduce exposure to risk factors such as open fires in the home. Arguments against banning or restricting open fires on the grounds of freedom of choice are less compelling in countries where healthcare costs are shared throughout society and are not fully internalized by the individual. However, policy makers need to recognise that heating is a human necessity and that current users of open fires, especially older and poorer users, might need to be subsidised to change to cleaner forms of energy that are less dangerous to their own health and to the health of others.

5. Conclusions

Highest indoor $PM_{2.5}$ concentrations (60 μg/m^3) occurred when peat was burned, followed by burning of coal (30 μg/m^3) and wood (17 μg/m^3). Conversely, highest concentrations of coarser PM ($PM_{10-2.5}$) were associated with burning of coal (20 μg/m^3), with lower concentrations emitted during burning of wood (10 μg/m^3) and peat (8 μg/m^3).

The magnetic content of the emitted PM, greatest (for both PM size fractions) when coal was burned, is similar to that of roadside exhaust emissions.

The level of exposure to $PM_{2.5}$ and to magnetite particles originating from open fires is similar to and indeed might exceed that from roadside sources, especially for those who stay at home during the working day and use coal in their open fires.

A negative association has been found between open fire usage and cognitive function. The negative association was largest and statistically strongest among women, a finding explained by the greater exposure of women to open fires in the home because of societal norms during their lifetimes, which meant they spent more time at home than men.

References:

1986. *Census of Population of Ireland 1981: Volume 8 Housing*. Dublin, Ireland: *Central Statistics Office*

2012. *Census of Ireland 2011 Profile 4 A Roof Over Our Heads* Dublin, Ireland: *Central Statistics Office*.

2016. *Ambient (outdoor) air pollution*. Geneva, Switzerland: World Health Organization.

2018a. "Household air pollution and health." World Health Organization, accessed August 10th 2020. https://www.who.int/en/news-room/fact-sheets/detail/household-air-pollution-and-health.

2018b. *Global Health Estimates 2016: Disease burden by Cause, Age, Sex, by Country and by Region, 2000-2016*. Geneva, Switzerland: World Health Organization.

2020, February 21. Government takes action to cut pollution from household burning: Department for Environment, Food & Rural Affairs.

Ailshire, J. A., and E. M. Crimmins. 2014. "Fine particulate matter air pollution and cognitive function among older US adults." *Am J Epidemiol* 180 (4):359-66. doi: 10.1093/aje/kwu155.

Alfarra, M. R., A. S. Prevot, S. Szidat, J. Sandradewi, S. Weimer, V. A. Lanz, D. Schreiber, M. Mohr, and U. Baltensperger. 2007. "Identification of the mass spectral signature of organic aerosols from wood burning emissions." *Environ Sci Technol* 41 (16):5770-7. doi: 10.1021/es062289b.

Allsop, D., J. Mayes, S. Moore, A. Masad, and B. J. Tabner. 2008. "Metal-dependent generation of reactive oxygen species from amyloid proteins implicated in neurodegenerative disease." *Biochem Soc Trans* 36 (Pt 6):1293-8. doi: 10.1042/BST0361293.

Barošová, H., J. Dvořáčková, O. Motyka, K. M. Kutláková, P. Peikertová, J. Rak, H. Bielniková, and J. Kukutschová. 2015. "Metal-based particles in human amniotic fluids of fetuses with normal karyotype and congenital malformation--a pilot study." *Environ Sci Pollut Res Int* 22 (10):7582-9. doi: 10.1007/s11356-014-3987-0.

Berkman, L. F., and S. L. Syme. 1979. "Social networks, host resistance, and mortality: a nine-year follow-up study of Alameda County residents." *Am J Epidemiol* 109 (2):186-204. doi: 10.1093/oxfordjournals.aje.a112674.

Blankson, A. N., and J. J. McArdle. 2014. "A Brief Report on the Factor Structure of the Cognitive Measures in the HRS/AHEAD Studies." *J Aging Res* 2014:798514. doi: 10.1155/2014/798514.

Bové, H., E. Bongaerts, E. Slenders, E. M. Bijnens, N. D. Saenen, W. Gyselaers, P. Van Eyken, M. Plusquin, M. B. J. Roeffaers, M. Ameloot, and T. S. Nawrot. 2019. "Ambient black carbon particles reach the fetal side of human placenta." *Nat Commun* 10 (1):3866. doi: 10.1038/s41467-019-11654-3.

Calderón-Garcidueñas, L., A. González-Maciel, P. S. Mukherjee, R. Reynoso-Robles, B. Pérez-Guillé, C. Gayosso-Chávez, R. Torres-Jardón, J. V. Cross, I. A. M. Ahmed, V. V. Karloukovski, and B. A. Maher. 2019. "Combustion- and friction-derived magnetic air pollution nanoparticles in human hearts." *Environ Res* 176:108567. doi: 10.1016/j.envres.2019.108567.

Cassarino, M., V. O'Sullivan, R. A. Kenny, and A. Setti. 2018. "Disabilities moderate the association between neighbourhood urbanity and cognitive health: Results from the Irish longitudinal study on ageing." *Disabil Health J* 11 (3):359-366. doi: 10.1016/j.dhjo.2017.12.002.

Castellani, R. J., P. I. Moreira, G. Liu, J. Dobson, G. Perry, M. A. Smith, and X. Zhu. 2007.

"Iron: the Redox-active center of oxidative stress in Alzheimer disease." *Neurochem Res* 32 (10):1640-5. doi: 10.1007/s11064-007-9360-7.
Castro, A., A. I. Calvo, C. Blanco-Alegre, F. Oduber, C. Alves, E. Coz, F. Amato, X. Querol, and R. Fraile. 2018. "Impact of the wood combustion in an open fireplace on the air quality of a living room: Estimation of the respirable fraction." *Sci Total Environ* 628-629:169-176. doi: 10.1016/j.scitotenv.2018.02.001.
Chafe, Z. A., M. Brauer, Z. Klimont, R. Van Dingenen, S. Mehta, S. Rao, K. Riahi, F. Dentener, and K. R. Smith. 2014. "Household cooking with solid fuels contributes to ambient PM2.5 air pollution and the burden of disease." *Environ Health Perspect* 122 (12):1314-20. doi: 10.1289/ehp.1206340.
Chen, H., J. C. Kwong, R. Copes, K. Tu, P. J. Villeneuve, A. van Donkelaar, P. Hystad, R. V. Martin, B. J. Murray, B. Jessiman, A. S. Wilton, A. Kopp, and R. T. Burnett. 2017. "Living near major roads and the incidence of dementia, Parkinson's disease, and multiple sclerosis: a population-based cohort study." *Lancet* 389 (10070):718-726. doi: 10.1016/S0140-6736(16)32399-6.
Chen, J. C., X. Wang, G. A. Wellenius, M. L. Serre, I. Driscoll, R. Casanova, J. J. McArdle, J. E. Manson, H. C. Chui, and M. A. Espeland. 2015. "Ambient air pollution and neurotoxicity on brain structure: Evidence from women's health initiative memory study." *Ann Neurol* 78 (3):466-76. doi: 10.1002/ana.24460.
Chen, Yuanzhi, Naresh Shah, Frank E. Huggins, and Gerald P. Huffman. 2006. "Microanalysis of ambient particles from Lexington, KY, by electron microscopy." *Atmospheric Environment* 40 (4):651-663. doi: https://doi.org/10.1016/j.atmosenv.2005.09.036.
Cheng, H., A. Saffari, C. Sioutas, H. J. Forman, T. E. Morgan, and C. E. Finch. 2016. "Nanoscale Particulate Matter from Urban Traffic Rapidly Induces Oxidative Stress and Inflammation in Olfactory Epithelium with Concomitant Effects on Brain." *Environ Health Perspect* 124 (10):1537-1546. doi: 10.1289/EHP134.
Coccini, T., F. Caloni, L. J. Ramírez Cando, and U. De Simone. 2017. "Cytotoxicity and proliferative capacity impairment induced on human brain cell cultures after short- and long-term exposure to magnetite nanoparticles." *J Appl Toxicol* 37 (3):361-373. doi: 10.1002/jat.3367.
Collingwood, J., and J. Dobson. 2006. "Mapping and characterization of iron compounds in Alzheimer's tissue." *J Alzheimers Dis* 10 (2-3):215-22. doi: 10.3233/jad-2006-102-308.
Crilley, L. R., F. Lucarelli, W. J. Bloss, R. M. Harrison, D. C. Beddows, G. Calzolai, S. Nava, G. Valli, V. Bernardoni, and R. Vecchi. 2017. "Source apportionment of fine and coarse particles at a roadside and urban background site in London during the 2012 summer ClearfLo campaign." *Environ Pollut* 220 (Pt B):766-778. doi: 10.1016/j.envpol.2016.06.002.
Dutta, Anindita, and Manas Ranjan Ray. 2014. "Hypertension and respiratory health in biomass smoke-exposed premenopausal Indian women." *Air Quality, Atmosphere & Health* 7 (2):229-238. doi: 10.1007/s11869-013-0228-5.
Folstein, M. F., S. E. Folstein, and P. R. McHugh. 1975. ""Mini-mental state". A practical method for grading the cognitive state of patients for the clinician." *J Psychiatr Res* 12 (3):189-98. doi: 10.1016/0022-3956(75)90026-6.
Garcia, G. J., J. D. Schroeter, and J. S. Kimbell. 2015. "Olfactory deposition of inhaled nanoparticles in humans." *Inhal Toxicol* 27 (8):394-403. doi: 10.3109/08958378.2015.1066904.
Gelencsér, András, Barbara May, David Simpson, Asunción Sánchez-Ochoa, Anne Kasper-

Giebl, Hans Puxbaum, Alexandre Caseiro, Casimiro Pio, and Michel Legrand. 2007. "Source apportionment of PM2.5 organic aerosol over Europe: Primary/secondary, natural/anthropogenic, and fossil/biogenic origin." *Journal of Geophysical Research: Atmospheres* 112 (D23). doi: 10.1029/2006JD008094.

Gilmour, P. S., D. M. Brown, T. G. Lindsay, P. H. Beswick, W. MacNee, and K. Donaldson. 1996. "Adverse health effects of PM10 particles: involvement of iron in generation of hydroxyl radical." *Occup Environ Med* 53 (12):817-22. doi: 10.1136/oem.53.12.817.

Gonet, Tomasz, Barbara A. Maher, and Jana Kukutschová. 2020a. Source apportionment of magnetite particles in roadside airborne particulate matter.

Gonet, Tomasz, Barbara A. Maher, and Jana Kukutschová. 2020b. Quantitative evaluation of the magnetic mineralogy of airborne brake wear emissions.

Gordon, J. K., M. Young, and C. Garcia. 2018. "Why do older adults have difficulty with semantic fluency?" *Neuropsychol Dev Cogn B Aging Neuropsychol Cogn* 25 (6):803-828. doi: 10.1080/13825585.2017.1374328.

Halsall, C. J., B. A. Maher, V. V. Karloukovski, P. Shah, and S. J. Watkins. 2008. "A novel approach to investigating indoor/outdoor pollution links: Combined magnetic and PAH measurements." *Atmospheric Environment* 42 (39):8902-8909. doi: https://doi.org/10.1016/j.atmosenv.2008.09.001.

Hansard, R., B. A. Maher, and R. Kinnersley. 2011. "Biomagnetic monitoring of industry-derived particulate pollution." *Environ Pollut* 159 (6):1673-81. doi: 10.1016/j.envpol.2011.02.039.

Hofman, J., A. Castanheiro, G. Nuyts, S. Joosen, S. Spassov, R. Blust, K. De Wael, S. Lenaerts, and R. Samson. 2020. "Impact of urban street canyon architecture on local atmospheric pollutant levels and magneto-chemical PM." *Sci Total Environ* 712:135534. doi: 10.1016/j.scitotenv.2019.135534.

Kim, Wonnyon, Seong-Jae Doh, Yong-Hee Park, and Seong-Taek Yun. 2007. "Two-year magnetic monitoring in conjunction with geochemical and electron microscopic data of roadside dust in Seoul, Korea." *Atmospheric Environment* 41 (35):7627-7641. doi: https://doi.org/10.1016/j.atmosenv.2007.05.050.

Krecl, Patricia, Johan Ström, and Christer Johansson. 2008. "Diurnal variation of atmospheric aerosol during the wood combustion season in Northern Sweden." *Atmospheric Environment* 42 (18):4113-4125. doi: https://doi.org/10.1016/j.atmosenv.2008.01.026.

Krishnamoorthy, Y., G. Sarveswaran, K. Sivaranjini, M. Sakthivel, M. G. Majella, and S. G. Kumar. 2018. "Association between Indoor Air Pollution and Cognitive Impairment among Adults in Rural Puducherry, South India." *J Neurosci Rural Pract* 9 (4):529-534. doi: 10.4103/jnrp.jnrp_123_18.

Kumar, Prashant, Liisa Pirjola, Matthias Ketzel, and Roy M. Harrison. 2013. "Nanoparticle emissions from 11 non-vehicle exhaust sources – A review." *Atmospheric Environment* 67:252-277. doi: https://doi.org/10.1016/j.atmosenv.2012.11.011.

Kumar, Prashant, Alan Robins, Sotiris Vardoulakis, and Rex Britter. 2010. "A review of the characteristics of nanoparticles in the urban atmosphere and the prospects for developing regulatory controls." *Atmospheric Environment* 44 (39):5035-5052. doi: https://doi.org/10.1016/j.atmosenv.2010.08.016.

Lehndorff, E., and L. Schwark. 2004. "Biomonitoring of air quality in the Cologne Conurbation using pine needles as a passive sampler—Part II: polycyclic aromatic hydrocarbons (PAH)." *Atmospheric Environment* 38 (23):3793-3808. doi: https://doi.org/10.1016/j.atmosenv.2004.03.065.

Li, X. Y., P. S. Gilmour, K. Donaldson, and W. MacNee. 1996. "Free radical activity and pro-inflammatory effects of particulate air pollution (PM10) in vivo and in vitro."

Thorax 51 (12):1216-22. doi: 10.1136/thx.51.12.1216.
Maher, B. A. 2019. "Airborne Magnetite- and Iron-Rich Pollution Nanoparticles: Potential Neurotoxicants and Environmental Risk Factors for Neurodegenerative Disease, Including Alzheimer's Disease." *J Alzheimers Dis* 71 (2):361-375. doi: 10.3233/JAD-190204.
Maher, B. A., I. A. Ahmed, V. Karloukovski, D. A. MacLaren, P. G. Foulds, D. Allsop, D. M. Mann, R. Torres-Jardón, and L. Calderon-Garciduenas. 2016. "Magnetite pollution nanoparticles in the human brain." *Proc Natl Acad Sci U S A* 113 (39):10797-801. doi: 10.1073/pnas.1605941113.
Maher, Barbara A. 1988. "Magnetic properties of some synthetic sub-micron magnetites." *Geophysical Journal International* 94 (1):83-96. doi: 10.1111/j.1365-246X.1988.tb03429.x.
McClean, Richard G., and W. F. Kean. 1993. "Contributions of wood ash magnetism to archaeomagnetic properties of fire pits and hearths." *Earth and Planetary Science Letters* 119 (3):387-394. doi: https://doi.org/10.1016/0012-821X(93)90146-Z.
Miller, M. R., J. B. Raftis, J. P. Langrish, S. G. McLean, P. Samutrtai, S. P. Connell, S. Wilson, A. T. Vesey, P. H. B. Fokkens, A. J. F. Boere, P. Krystek, C. J. Campbell, P. W. F. Hadoke, K. Donaldson, F. R. Cassee, D. E. Newby, R. Duffin, and N. L. Mills. 2017. "Inhaled Nanoparticles Accumulate at Sites of Vascular Disease." *ACS Nano* 11 (5):4542-4552. doi: 10.1021/acsnano.6b08551.
Mosca, I., V. O'Sullivan, and R. Wright. 2020. "The educational attainment of the children of stay-at-home mothers: evidence from the Irish Marriage Bar." *Oxford Economic Papers* In press.
Muxworthy, A. R., E. Schmidbauer, and N. Petersen. 2002. "Magnetic properties and Mössbauer spectra of urban atmospheric particulate matter: a case study from Munich, Germany." *Geophysical Journal International* 150 (2):558-570. doi: 10.1046/j.1365-246X.2002.01725.x.
Naeher, L. P., M. Brauer, M. Lipsett, J. T. Zelikoff, C. D. Simpson, J. Q. Koenig, and K. R. Smith. 2007. "Woodsmoke health effects: a review." *Inhal Toxicol* 19 (1):67-106. doi: 10.1080/08958370600985875.
Oberdörster, G., Z. Sharp, V. Atudorei, A. Elder, R. Gelein, W. Kreyling, and C. Cox. 2004. "Translocation of inhaled ultrafine particles to the brain." *Inhal Toxicol* 16 (6-7):437-45. doi: 10.1080/08958370490439597.
Oudin, A., D. Segersson, R. Adolfsson, and B. Forsberg. 2018. "Association between air pollution from residential wood burning and dementia incidence in a longitudinal study in Northern Sweden." *PLoS One* 13 (6):e0198283. doi: 10.1371/journal.pone.0198283.
Painschab, M. S., V. G. Davila-Roman, R. H. Gilman, A. D. Vasquez-Villar, S. L. Pollard, R. A. Wise, J. J. Miranda, W. Checkley, and CRONICAS Cohort Study Group. 2013. "Chronic exposure to biomass fuel is associated with increased carotid artery intima-media thickness and a higher prevalence of atherosclerotic plaque." *Heart* 99 (14):984-91. doi: 10.1136/heartjnl-2012-303440.
Palmer, Jason, and Ian Cooper. 2013. *United Kingdom Housing Energy Fact File*. Department of Energy and Climate Change.
Paul, K. C., M. Haan, E. R. Mayeda, and B. R. Ritz. 2019. "Ambient Air Pollution, Noise, and Late-Life Cognitive Decline and Dementia Risk." *Annu Rev Public Health* 40:203-220. doi: 10.1146/annurev-publhealth-040218-044058.
Pinkerton, K. E., and J. P. Joad. 2006. "Influence of air pollution on respiratory health during perinatal development." *Clin Exp Pharmacol Physiol* 33 (3):269-72. doi:

10.1111/j.1440-1681.2006.04357.x.
Plascencia-Villa, Germán, Arturo Ponce, Joanna F. Collingwood, M. Josefina Arellano-Jiménez, Xiongwei Zhu, Jack T. Rogers, Israel Betancourt, Miguel José-Yacamán, and George Perry. 2016. "High-resolution analytical imaging and electron holography of magnetite particles in amyloid cores of Alzheimer's disease." *Scientific Reports* 6 (1):24873. doi: 10.1038/srep24873.
Qiu, Yun, Feng-An Yang, and Wangyang Lai. 2019. "The impact of indoor air pollution on health outcomes and cognitive abilities: empirical evidence from China." *Population and Environment* 40 (4):388-410. doi: 10.1007/s11111-019-00317-6.
Quintana, C., S. Bellefqih, J. Y. Laval, J. L. Guerquin-Kern, T. D. Wu, J. Avila, I. Ferrer, R. Arranz, and C. Patiño. 2006. "Study of the localization of iron, ferritin, and hemosiderin in Alzheimer's disease hippocampus by analytical microscopy at the subcellular level." *J Struct Biol* 153 (1):42-54. doi: 10.1016/j.jsb.2005.11.001.
Reche, C., M. Viana, F. Amato, A. Alastuey, T. Moreno, R. Hillamo, K. Teinilä, K. Saarnio, R. Seco, J. Peñuelas, C. Mohr, A. S. Prévôt, and X. Querol. 2012. "Biomass burning contributions to urban aerosols in a coastal Mediterranean city." *Sci Total Environ* 427-428:175-90. doi: 10.1016/j.scitotenv.2012.04.012.
Rivera, R. M., M. G. Cosio, H. Ghezzo, M. Salazar, and R. Pérez-Padilla. 2008. "Comparison of lung morphology in COPD secondary to cigarette and biomass smoke." *Int J Tuberc Lung Dis* 12 (8):972-7.
Saenz, J. L., R. Wong, and J. A. Ailshire. 2018. "Indoor air pollution and cognitive function among older Mexican adults." *J Epidemiol Community Health* 72 (1):21-26. doi: 10.1136/jech-2017-209704.
Sanderson, P., S. S. Su, I. T. H. Chang, J. M. Delgado Saborit, D. M. Kepaptsoglou, R. J. M. Weber, and Roy M. Harrison. 2016. "Characterisation of iron-rich atmospheric submicrometre particles in the roadside environment." *Atmospheric Environment* 140:167-175. doi: https://doi.org/10.1016/j.atmosenv.2016.05.040.
Sanderson, Paul, Juana Maria Delgado-Saborit, and Roy M. Harrison. 2014. "A review of chemical and physical characterisation of atmospheric metallic nanoparticles." *Atmospheric Environment* 94:353-365. doi: https://doi.org/10.1016/j.atmosenv.2014.05.023.
Sandradewi, J., A.S.H. Prévôt, M.R. Alfarra, S. Szidat, M.N. Wehrli, M. Ruff, S. Weimer, V.A. Lanz, E. Weingartner, N. Perron, A Caseiro, A Kasper-Giebl, H Puxbaum, L. Wacker, and U. Baltensperger. 2008. "Comparison of several wood smoke markers and source apportionment methods for wood burning particulate mass." *Atmospheric Chemistry and Physics Discussions* 8:8091-8118.
Shuster-Meiseles, T., M. M. Shafer, J. Heo, M. Pardo, D. S. Antkiewicz, J. J. Schauer, A. Rudich, and Y. Rudich. 2016. "ROS-generating/ARE-activating capacity of metals in roadway particulate matter deposited in urban environment." *Environ Res* 146:252-62. doi: 10.1016/j.envres.2016.01.009.
Smith, M. A., P. L. Harris, L. M. Sayre, and G. Perry. 1997. "Iron accumulation in Alzheimer disease is a source of redox-generated free radicals." *Proc Natl Acad Sci U S A* 94 (18):9866-8. doi: 10.1073/pnas.94.18.9866.
Spassov, S., R. Egli, F. Heller, D. K. Nourgaliev, and J. Hannam. 2004. "Magnetic quantification of urban pollution sources in atmospheric particulate matter." *Geophysical Journal International* 159 (2):555-564. doi: 10.1111/j.1365-246X.2004.02438.x.
Squizzato, Stefania, Mauro Masiol, Chiara Agostini, Flavia Visin, Gianni Formenton, Roy M. Harrison, and Giancarlo Rampazzo. 2016. "Factors, origin and sources affecting PM1

concentrations and composition at an urban background site." *Atmospheric Research* 180:262-273. doi: https://doi.org/10.1016/j.atmosres.2016.06.002.
Suglia, S. F., A. Gryparis, R. O. Wright, J. Schwartz, and R. J. Wright. 2008. "Association of black carbon with cognition among children in a prospective birth cohort study." *Am J Epidemiol* 167 (3):280-6. doi: 10.1093/aje/kwm308.
Sunyer, J., M. Esnaola, M. Alvarez-Pedrerol, J. Forns, I. Rivas, M. López-Vicente, E. Suades-González, M. Foraster, R. Garcia-Esteban, X. Basagaña, M. Viana, M. Cirach, T. Moreno, A. Alastuey, N. Sebastian-Galles, M. Nieuwenhuijsen, and X. Querol. 2015. "Association between traffic-related air pollution in schools and cognitive development in primary school children: a prospective cohort study." *PLoS Med* 12 (3):e1001792. doi: 10.1371/journal.pmed.1001792.
Szidat, Sönke, André S. H. Prévôt, Jisca Sandradewi, M. Rami Alfarra, Hans-Arno Synal, Lukas Wacker, and Urs Baltensperger. 2007. "Dominant impact of residential wood burning on particulate matter in Alpine valleys during winter." *Geophysical Research Letters* 34 (5). doi: 10.1029/2006GL028325.
Tabner, B. J., J. Mayes, and D. Allsop. 2010. "Hypothesis: soluble aβ oligomers in association with redox-active metal ions are the optimal generators of reactive oxygen species in Alzheimer's disease." *Int J Alzheimers Dis* 2011:546380. doi: 10.4061/2011/546380.
Thorpe, A., and R. M. Harrison. 2008. "Sources and properties of non-exhaust particulate matter from road traffic: a review." *Sci Total Environ* 400 (1-3):270-82. doi: 10.1016/j.scitotenv.2008.06.007.
Whelan, B. J., and G. M. Savva. 2013. "Design and methodology of the Irish Longitudinal Study on Ageing." *J Am Geriatr Soc* 61 Suppl 2:S265-8. doi: 10.1111/jgs.12199.
Wimo, A., M. Guerchet, G. C. Ali, Y. T. Wu, A. M. Prina, B. Winblad, L. Jönsson, Z. Liu, and M. Prince. 2017. "The worldwide costs of dementia 2015 and comparisons with 2010." *Alzheimers Dement* 13 (1):1-7. doi: 10.1016/j.jalz.2016.07.150.
Yang, Yi, Marina Vance, Feiyun Tou, Andrea Tiwari, Min Liu, and Michael F. Hochella. 2016. "Nanoparticles in road dust from impervious urban surfaces: distribution, identification, and environmental implications." *Environmental Science: Nano* 3 (3):534-544. doi: 10.1039/C6EN00056H.
Younan, D., C. Tuvblad, M. Franklin, F. Lurmann, L. Li, J. Wu, K. Berhane, L. A. Baker, and J. C. Chen. 2018. "Longitudinal Analysis of Particulate Air Pollutants and Adolescent Delinquent Behavior in Southern California." *J Abnorm Child Psychol* 46 (6):1283-1293. doi: 10.1007/s10802-017-0367-5.
Yuchi, W., H. Sbihi, H. Davies, L. Tamburic, and M. Brauer. 2020. "Road proximity, air pollution, noise, green space and neurologic disease incidence: a population-based cohort study." *Environ Health* 19 (1):8. doi: 10.1186/s12940-020-0565-4.
Zhang, Junfeng, and R. Smith Kirk. 2007. "Household Air Pollution from Coal and Biomass Fuels in China: Measurements, Health Impacts, and Interventions." *Environmental Health Perspectives* 115 (6):848-855. doi: 10.1289/ehp.9479.
Zhang, Y., P. Demokritou, D. K. Ryan, and D. Bello. 2019. "Comprehensive Assessment of Short-Lived ROS and H." *Environ Sci Technol* 53 (13):7574-7583. doi: 10.1021/acs.est.8b05677.
Zhou, Ying, and Jonathan I. Levy. 2008. "The impact of urban street canyons on population exposure to traffic-related primary pollutants." *Atmospheric Environment* 42 (13):3087-3098. doi: https://doi.org/10.1016/j.atmosenv.2007.12.037.

Table 1: Mass, Magnetic Remanence (SIRM) and Magnetite Concentration in PM Emitted from Open Fires Burning Peat, Wood, and Coal

Parameter		**$PM_{2.5}$**			**$PM_{10-2.5}$**		
		Peat	**Wood**	**Coal**	**Peat**	**Wood**	**Coal**
PM mass	[µg/m^3]	60	17	30	8	10	20
	[µg/h]	42.5	21.8	27.7	9.5	13.2	18.2
SIRM	per mass [10^{-3} Am^2/kg]	3.79	7.78	8.92	3.83	6.21	19.10
	per time [10^{-10} Am^2/h]	0.16	0.21	2.47	0.22	0.71	3.48
	per volume [10^{-5} Am^2/m^3]	1.1	2.7	44.0	11.2	20.4	94.1
Magnetite concentration	per mass [mg/kg]	50 - 60	100 – 130	1200 – 1500	500 – 630	430 – 1020	2500 - 3100
	per time [ng/h]	2.1 - 2.6	2.7 - 3.4	32.1 - 40.4	2.8 - 3.5	7.1 - 14.2	45.3 - 56.9
	per volume [ng/m^3]	3.0 – 3.7	2.2 – 2.8	34.5 - 43.4	4.0 – 5.0	5.9 - 9.6	48.6 - 61.1

Table 2: Exposure Parameters and Doses for Commuting (Scenario A) and Indoor Use of Open Fires (Scenario B)

Parameter		**Scenario A (outdoors, commuting)**	**Scenario B (indoors, open fires)**		
			Peat	**Wood**	**Coal**
Breathing rate	[m^3/h]	0.54	0.54	0.54	0.54
Exposure time	[h/day]	1	4.5	4.5	4.5
	[days/week]	5	7	7	7
	[months/year]	12	6	6	6
Magnetite dose*	[#/year]	$18.7 \cdot 10^8$	$1.6 \cdot 10^8$	$2.1 \cdot 10^8$	$19.2 \cdot 10^8$
$PM_{2.5}$ dose*	[mg/year]	3.5	26.5	7.5	13.3

**Scenario A* – outdoors, roadside, based on 1 hour of commuting per day: particle diameter of 20 nm; olfactory deposition rate of 0.1% (Garcia et al. 2015); breathing rate of 0.54 m^3/h (Zhou & Levy, 2008); 1 h/day of exposure, 5 days/week, 12 months/year; PM_{10} level of 50 µg/m^3 and $PM_{2.5}$ level of 25 µg/m^3; magnetite roadside concentration of 0.20 – 0.95 wt.% (Hansard et al. 2011; Gonet et al. 2020a); and *Scenario B* – indoors, fireside: particle diameter of 20 nm; olfactory deposition rate of 0.1% (Garcia et al. 2015); breathing rate of 0.54 m^3/h (Zhou & Levy 2008); 4.5 h/day of exposure, 7 days/week, 6 months/year; magnetite concentrations from Table 1.

Table 3: Summary Statistics by Open Fire Usage

	Uses Open Fire (9.84%)	Does Not Use Open Fire (90.16%)	p-value of Difference
Cognitive Outcomes:			
Immediate Recall	13.061	13.911	<0.001
Delayed Recall	5.625	6.171	<0.001
Animal Naming	18.118	19.636	<0.001
MMSE	1.775	1.282	<0.001
Control Variables:			
Age	64.891	64.364	0.205
Female	0.554	0.564	0.632
Resides in Dublin	0.063	0.265	<0.001
Resides in Urban Area (Non-Dublin)	0.338	0.278	0.002
Resides in Rural Area	0.598	0.457	<0.001
Highest Education Level: Primary	0.385	0.237	<0.001
Highest Education Level: Secondary	0.413	0.405	0.734
Highest Education Level: University	0.202	0.358	<0.001
Income Quintile: First	0.212	0.196	0.364
Income Quintile: Second	0.267	0.175	<0.001
Income Quintile: Third	0.224	0.199	0.151
Income Quintile: Fourth	0.191	0.22	0.117
Income Quintile: Fifth	0.106	0.211	<0.001
Social Class: Professional	0.019	0.049	0.001
Social Class: Managerial & Technical	0.159	0.264	<0.001
Social Class: Non-Manual	0.277	0.289	0.555
Social Class: Skilled Manual	0.212	0.15	<0.001
Social Class: Semi-skilled Manual	0.197	0.146	0.001
Social Class: Unskilled	0.044	0.037	0.388
Social Class: Never worked	0.056	0.033	0.003
Social Class: Unknown	0.036	0.032	0.586
Eligible for free/subsidized medical care	0.652	0.465	<0.001
Childhood SES: Well-Off	0.089	0.115	0.064
Childhood SES: Average	0.666	0.687	0.282
Childhood SES: Poor	0.245	0.198	0.007
Smoker: Never	0.376	0.463	<0.001
Smoker: Past	0.409	0.403	0.809
Smoker: Current	0.215	0.134	<0.001
Social Connectedness: Most Isolated	0.109	0.066	<0.001
Social Connectedness: Moderately Isolated	0.287	0.255	0.089
Social Connectedness: Moderately Integrated	0.377	0.401	0.274
Social Connectedness: Most Integrated	0.227	0.279	0.009

n=6977

Table 4: Estimated Association with Cognitive Function

Covariates	(1) Immediate Recall	(2) Delayed Recall	(3) Animal Naming	(4) MMSE
Uses Open Fire	-0.305**	-0.162	-0.356	0.091*
	(0.134)	(0.124)	(0.266)	(0.055)
Age	-0.117***	-0.090***	-0.142***	0.029***
	(0.006)	(0.005)	(0.010)	(0.003)
Female	0.802***	0.687***	-0.630***	-0.180***
	(0.086)	(0.069)	(0.161)	(0.041)
Resides in Urban Area (Non-Dublin)	-0.217*	-0.180	-0.893***	0.041
	(0.131)	(0.118)	(0.271)	(0.057)
Resides in Rural Area	-0.497***	-0.397***	-1.029***	0.103*
	(0.120)	(0.101)	(0.264)	(0.057)
Highest Education Level: Secondary	0.830***	0.515***	1.039***	-0.361***
	(0.114)	(0.092)	(0.209)	(0.048)
Highest Education Level: University	1.295***	0.954***	2.563***	-0.590***
	(0.135)	(0.113)	(0.276)	(0.060)
Income Quintile: Second	0.417***	0.140	0.065	-0.128**
	(0.155)	(0.125)	(0.273)	(0.061)
Income Quintile: Third	0.653***	0.305**	0.151	-0.218***
	(0.140)	(0.119)	(0.261)	(0.060)
Income Quintile: Fourth	0.545***	0.311***	0.161	-0.254***
	(0.143)	(0.112)	(0.276)	(0.060)
Income Quintile: Fifth	0.507***	0.222*	0.551*	-0.326***
	(0.143)	(0.119)	(0.289)	(0.071)
Social Class: Managerial & Technical	0.022	0.007	-0.794*	-0.036
	(0.199)	(0.161)	(0.436)	(0.116)
Social Class: Non-Manual	-0.379*	-0.207	-1.265***	0.015
	(0.211)	(0.168)	(0.430)	(0.115)
Social Class: Skilled Manual	-0.641***	-0.383**	-1.853***	0.275**
	(0.222)	(0.175)	(0.456)	(0.121)
Social Class: Semi-skilled Manual	-0.722***	-0.382**	-1.984***	0.232*
	(0.230)	(0.187)	(0.459)	(0.122)
Social Class: Unskilled	-1.092***	-0.792***	-2.704***	0.377***
	(0.302)	(0.245)	(0.561)	(0.139)
Social Class: Never worked	-0.995***	-0.845***	-2.135***	0.474***
	(0.316)	(0.259)	(0.585)	(0.151)
Social Class: Unknown	-0.415	-0.300	-1.495***	0.221
	(0.288)	(0.240)	(0.575)	(0.147)
Eligible for free/subsidized medical care	-0.377***	-0.163*	-0.314	0.177***
	(0.103)	(0.088)	(0.205)	(0.051)
Childhood SES: Average	-0.227*	-0.322***	-0.214	0.076
	(0.124)	(0.114)	(0.270)	(0.064)
Childhood SES: Poor	-0.334**	-0.324**	-0.365	0.077
	(0.156)	(0.135)	(0.311)	(0.075)
Smoker: Past	0.091	0.039	0.244	-0.084**
	(0.085)	(0.072)	(0.176)	(0.040)
Smoker: Current	-0.411***	-0.110	-0.164	0.047

	(0.125)	(0.106)	(0.254)	(0.053)
Social Connectedness: Moderately Isolated	0.176	0.101	0.717**	-0.070
	(0.207)	(0.162)	(0.328)	(0.073)
Social Connectedness: Moderately Integrated	0.570***	0.324**	0.829**	-0.199***
	(0.196)	(0.159)	(0.324)	(0.075)
Social Connectedness: Most Integrated	0.644***	0.407**	0.766**	-0.245***
	(0.205)	(0.166)	(0.343)	(0.082)

n=6977
Sample weighted according to Whelan & Savva (2013).
Standard errors, clustered at household-level, in parenthesis.
Columns (1), (2) & (3) are OLS coefficients. (4) are coefficients from negative binomial model.
***, **, & * indicates statistical significance at the 1%, 5% and 10% level.

Table 5: Associations Between Open Fire Usage and Cognitive Function in Sub-Samples

	Sample Size	(1) Immediate Recall	(2) Delayed Recall	(3) Animal Naming	(4) MMSE
Separate Location Samples:					
Dublin	1649	-0.230	-0.139	-0.535	0.079
		(0.519)	(0.496)	(0.857)	(0.222)
Urban Non-Dublin	1977	-0.344	0.010	0.045	0.131
		(0.228)	(0.211)	(0.475)	(0.085)
Rural	3329	-0.266	-0.279*	-0.611*	0.062
		(0.175)	(0.161)	(0.346)	(0.074)
Separate Gender Samples:					
Men	3163	-0.184	0.071	-0.201	0.049
		(0.190)	(0.163)	(0.385)	(0.072)
Women	3814	-0.411**	-0.401**	-0.558	0.155*
		(0.189)	(0.178)	(0.346)	(0.089)
Separate Age Samples:					
Aged 50-64	3674	-0.265	-0.118	-0.310	0.068
		(0.180)	(0.175)	(0.397)	(0.092)
Aged 65-74	2026	-0.120	-0.013	-0.173	0.050
		(0.226)	(0.198)	(0.474)	(0.079)
Older Than 74	1277	-0.344	-0.199	-0.947*	0.157
		(0.344)	(0.288)	(0.560)	(0.107)
Separate Income Samples:					
Bottom 40% of Income Distribution	2779	-0.233	-0.122	-0.328	0.076
		(0.207)	(0.180)	(0.393)	(0.078)
Top 60% of Income Distribution	4198	-0.350*	-0.193	-0.372	0.090
		(0.185)	(0.170)	(0.347)	(0.082)
Unweighted Sample					
Unweighted estimates	6977	-0.296**	-0.156	-0.554**	0.099**
		(0.119)	(0.101)	(0.249)	(0.050)
Model with Lagged Dependent Variable		-0.363***	-0.182	-0.186	0.078
	6977	(0.128)	(0.115)	(0.234)	(0.060)

Sample weighted according to Whelan & Savva (2013) except for final panel.
Standard errors, clustered at household-level, in parenthesis.
Columns (1), (2) & (3) are OLS coefficients. (4) are coefficients from negative binomial.
***, **, & * indicates statistical significance at the 1%, 5% and 10% level.

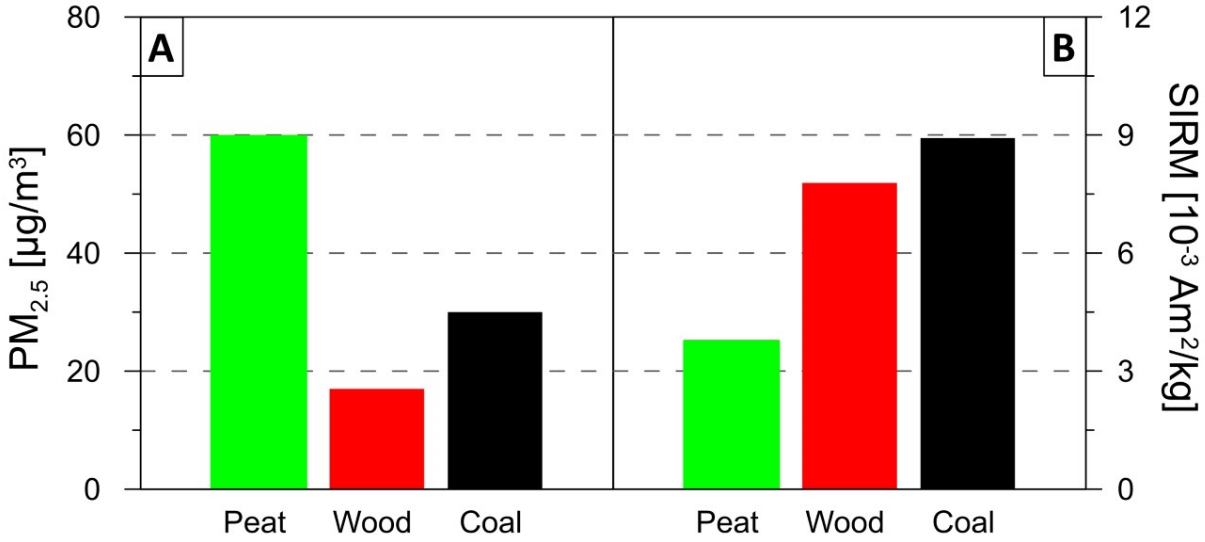

Figure 1: (A) Mass and (B) Magnetic Remanence (SIRM) of $PM_{2.5}$ Emitted by Burning of Peat, Wood and Coal

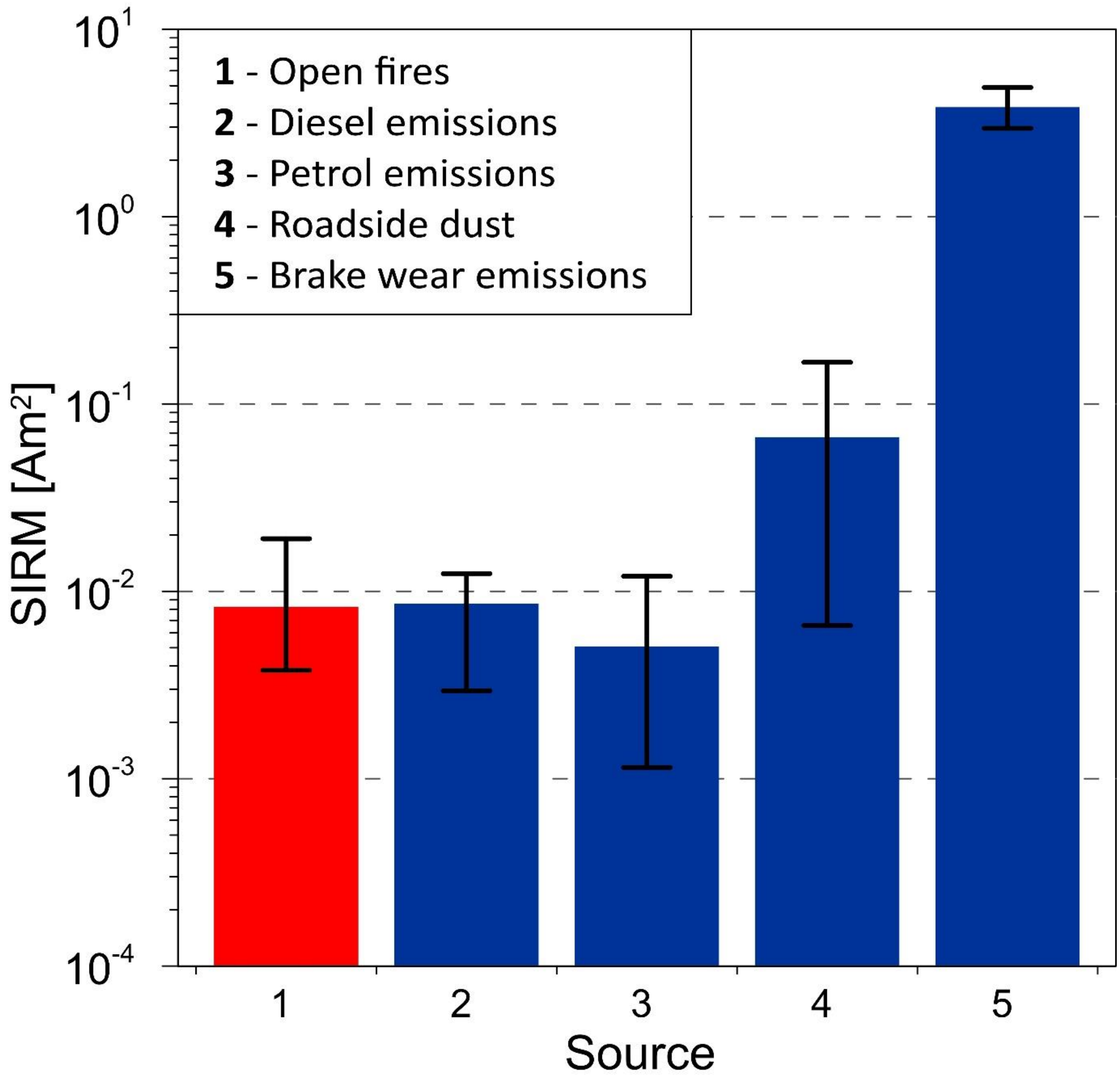

Figure 2: Magnetic Remanence (SIRM) for PM: (1) from Open Fires, (2) from Diesel Engine (Gonet et al. 2020a), (3) from Petrol Engine (Gonet et al., 2020a), (4) Roadside Dust (Halsall et al. 2008) and (5) from Brake Wear (Gonet et al., 2020b)

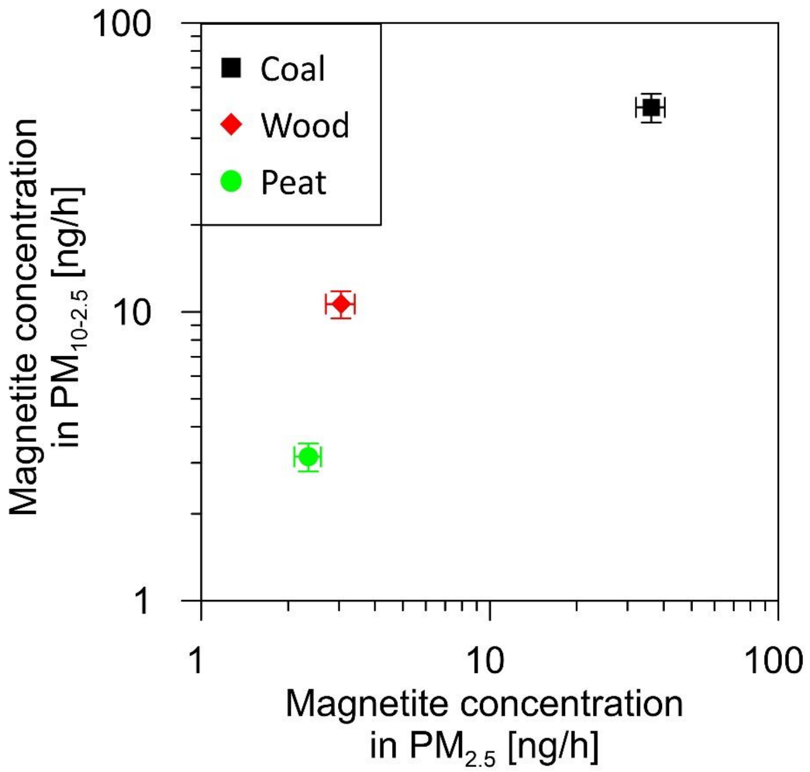

Figure 3: Magnetite Concentration in $PM_{2.5}$ vs $PM_{10-2.5}$ Emitted from Open Fires Burning Peat, Wood and Coal