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The effect of "smoky" coal bans on chronic lung disease among older people in Ireland

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A B S T R A C T

Globally, coal is still widely used for heating. However, there are concerns about its effect on ambient air quality and health. We estimated the effect of bans prohibiting the sale and use of so-called "smoky coal" on the prevalence of chronic lung disease in older people. Our identification strategy relied on the phased extension of smoky coal bans to Irish towns after 2010. We examined five waves of The Irish Longitudinal Study on Ageing (TILDA), a large nationally representative survey containing detailed information on health, housing, and socio-economic status. Controlling for relevant factors, smoky coal bans reduced the probability that an older person reports being diagnosed with chronic lung disease by between three and five percentage points. In models where we estimated the effect of the ban on the incidence of new cases of chronic lung disease, rather than existing cases, we found the effect was between -0.96 and -2.5 percentage points. Our findings were robust to estimating the model using different sub-samples and control variables. Furthermore, to address potential endogeneity of the ban, we examined subsamples defined by whether participants lived in towns within a range of the population threshold at which the ban was imposed. Estimating our model using these subsamples showed a consistently negative effect of the ban. We also showed parallel trends in health outcomes before the treatment, and that the treatment did not affect attrition from the sample.

1. Introduction

Chronic lung disease (often referred to as chronic obstructive pulmonary disease (COPD), chronic bronchitis or chronic emphysema) is a major component of global morbidity and mortality. It is the third most common cause of death worldwide, with only heart disease and stroke being more common (WHO, 2020), and is the 6th highest cause of disability-adjusted life years (DALYs) worldwide (Vos et al., 2020). Chronic lung disease involves progressive limitation of the airway and is associated with an abnormal inflammatory response of the lungs to noxious particles or gases (Huertas and Palange, 2011). It is primarily a disease of old age (Safiri et al., 2022). Genetic factors and infections can lead to chronic lung disease (Deolmi et al., 2023; Huertas and Palange, 2011; Raherison and Girodet, 2009), and there is an emerging evidence base on the conditions in early life that may predispose an individual to chronic lung disease in later life (Deolmi et al., 2023; Duijts et al., 2014; Postma et al., 2015). The three main risk factors for chronic lung disease are smoking, pollution from ambient (outdoor) particulate matter, and occupational exposure to particulate matter, gases and fumes, accounting for 46%, 21% and 16% of global DALYs respectively (Safiri et al., 2022).

The World Health Organisation (WHO) estimates that three million deaths every year are a result of ambient air pollution (WHO, 2016). In the European Union, during 2018, depending on the method of estimation, between 168,000 and 346,000 premature deaths could be attributed to exposure to outdoor air pollution in the form of fine particulate matter ($PM_{2.5}$) alone (OECD, 2021).[1] To put these estimates in perspective, these premature deaths were between 4 and 7 per cent of all deaths in 2018. Although air pollution has decreased in most European countries over the past two decades, levels of air pollution remain above

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[1] OECD (2021) provides an overview of the data and methods underlying the different estimates.

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WHO guidelines, particularly in central and eastern European cities (OECD, 2021). Not surprisingly, given the substantial toll of air pollution on human life, the economic costs are also substantial. For example, in the EU for 2011, the direct and indirect costs of COPD were estimated to be €48.4 billion (Gibson et al., 2013).

Thus, it is important for policymakers to know the efficacy of policies designed to reduce air pollution on chronic lung disease. In this study, we estimate the effect of one such policy, a ban on smoky coals, on the prevalence of chronic lung disease among older people in Ireland. The legislation bans the sale of "smoky" solid fuels defined as any containing bituminous coal, having a smoke emission rate of more than 10 g per hour, or with a sulphur content greater than 2% by weight on a dry ash-free basis.[2]

We examined five waves of The Irish Longitudinal Study on Ageing (TILDA), a large nationally representative survey that contains detailed health, housing, and socio-economic information on the population aged 50 + . While the data were being collected (2010–2018), smoky coal bans were implemented in an increasing number of towns across Ireland. This temporal and spatial variation in the rollout of the smoky coal bans allows us to examine the effect of smoky coal bans on the probability of chronic lung disease among people living in those areas. The extension of the policy was based on the population of the area reaching a threshold. Controlling for relevant factors, we found that smoky coal bans reduced the probability of chronic lung disease by between three and five percentage points. In models where we estimated the effect of the ban on the incidence of new cases of chronic lung disease, rather than existing cases, we found an effect of between -0.96 – 2.5 percentage points. Our finding was robust to estimating the models on different subsamples and to including different control variables.

The present study contributes to the growing literature on the effects of air pollution on mortality and morbidity among old people by examining longitudinal data from a large representative sample of older people. There are two main advantages of our study. First, we exploit the staggered implementation of coal bans in Ireland across time and geography to identify the causal impact of these regulations on chronic lung disease. Many studies examine the statistical associations between environmental regulations and health, but it can be difficult to rule out reverse causation and influences from other factors correlated with the regulatory "treatment". We also take account of the latest developments in the methodological literature on two-way fixed effects models to generate robust estimates of the effects. Second, the study is carried out in Ireland, a high-income developed country with relatively low levels of ambient air pollution. Over time, a growing body of research findings on health effects from ambient air pollution has led to increasing concern among policymakers about harms at relatively low levels of exposure. This is reflected in sharply reduced thresholds for assessing safe exposures published by the World Health Organization (World Health Organization, 2021). Many areas in Ireland have pollution exposures at levels where this change in focus is relevant.

In Section 2, we discuss the literature on the effects of coal-based air pollution on health. In Section 3, we provide further details about the Irish smoky coal bans. In Section 4, we discuss our data and our model. In Section 5, we present our results, which we discuss further in Section 6. Finally, in Section 7, we summarise and conclude.

2. Literature review

The greatest damage to health from air pollution is caused by chronic exposure to particulate matter, especially fine particulate matter ($PM_{2.5}$) which increases the risk of heart disease, stroke, lung cancer, and respiratory diseases including asthma, bronchitis, respiratory infections, and chronic obstructive pulmonary disease (COPD) (OECD, 2021). PM emissions primarily result from the combustion of fuels, such as for power generation, domestic heating and in vehicle engines. However, combustion is not the only source; for example, they can also arise from animal waste emissions and dust from construction, road traffic and agricultural practices. Small particulates of less than 10 μm in diameter (PM_{10}) are capable of penetrating deep into the respiratory tract and causing significant health damage. Fine particulates smaller than 2.5 μm in diameter ($PM_{2.5}$) cause even more severe health effects because they penetrate deeper into the respiratory tract and are potentially more toxic (OECD, 2021).

By far, the most common outcome examined in the literature on the health effects of ambient (outdoor) air pollution is mortality. Examples of such studies include (Almond et al., 2009; Anderson, 2020; Barreca et al., 2014; Beach and Hanlon, 2018; Cesur et al., 2018; Chen et al., 2013; Currie et al., 2009; Deryugina et al., 2019; Dockery et al., 1993; Fan et al., 2020; Jayachandran, 2009; Laden et al., 2006; Luechinger, 2014; Pope, and et al., 2002, 2004; Tanaka, 2015). While the present study examines mortality as a secondary outcome, the present study focuses on morbidity in the form of chronic lung disease. Examining the preventable morbidity caused by air pollution is important because people can suffer from diseases like chronic lung disease for many years before finally succumbing to it or dying from some other cause.

Some groups are particularly vulnerable to the effects of air pollution. For example, older people, children, and those with chronic diseases are typically more vulnerable to the effects of air pollution than the general population. In addition, lower socioeconomic groups are often more exposed to environments in which air pollution is worse (OECD, 2021). There is an extensive literature examining the impact of air pollution on early life outcomes including infant and child mortality, low birth weight, etc. (see for example Balsa et al., 2016; Chay and Greenstone, 2003; Currie et al., 2009; Currie and Neidell, 2005; Jayachandran, 2009; Luechinger, 2014). For the older population, in addition to research examining mortality and health outcomes related to air pollution such as cardiovascular and respiratory disease diagnoses (for example, see Evans and Smith, 2005 and Gan et al., 2013), there is a growing body of evidence suggesting detrimental effects of air pollution on cognition (e.g., Ailshire et al., 2017; Ailshire and Crimmins, 2014; Weuve et al., 2012).

For policy makers to be well informed about their options, they need good quality evidence that identifies causal effects of policies on health. However, identifying a causal effect of air pollution on health is complicated by non-random exposure across the population to air pollution (for a discussion, see Zivin and Neidell, 2013). For example, property and rental prices might reflect air quality (for recent studies, see Ou et al., 2022 and Borja-Urbano et al., 2021), so poorer people, who typically have worse health, might live in places with worse air pollution.

To identify causal effects, quasi-experimental research designs have been adopted. For example, focusing on the impact of coal-based air pollution, a series of studies have examined variation across time and space in exposure to a heating policy in China that provides free or heavily subsidised residential heating to households north of the Huai River in the winter months. A recent analysis by Fan et al. (2020) used a regression discontinuity design that exploited variation in the exact starting dates of winter heating across 114 northern Chinese cities to estimate the effect of winter heating on contemporaneous air pollution and health. They found that switching on the winter heating system (which is largely coal-based) led to a 36 per cent deterioration in the Air Quality Index and a 14 per cent increase in weekly mortality, mostly from cardiorespiratory diseases. Those that were older, poorer, and living in rural areas were particularly affected. Earlier papers by Chen et al. (2013) and Almond et al. (2009) found similar effects on mortality, although their research designs were different in that they exploited variation in distance to the Huai River to identify exposure to the winter heating policy.

Other studies that have focused on the impact of coal-based air pollution include Barreca et al. (2014) and Beach and Hanlon (2018).

[2] Ireland, Solid Fuel Regulations, S.I. No. 326 of 2012.

Using a triple difference-in-difference methodology to identify causal effects, Barreca et al. (2014) found that reductions in the use of bituminous coal for home heating between 1945 and 1960 in the US led to a 1.25 per cent reduction in winter all-age mortality and a 3.27 per cent reduction in winter infant mortality. Focusing on industrial coal usage at a local level in England and Wales over the period 1851–1960, Beach and Hanlon (2018) found that a one standard deviation increase in local industrial coal usage lowered life expectancy at birth by 0.33–0.56 years or 0.86–1.44 per cent, with larger effects observed for children under five years of age.

In relation to the coal bans in Ireland examined in the present study, Clancy et al. (2002) examined the effect on death rates of the 1990 s ban on coal sales in Dublin. Concentrations of air pollution and standardised non-trauma, respiratory, and cardiovascular death rates were compared for 72 months before and after the ban of coal sales in Dublin, adjusting for weather, respiratory epidemics, and death rates in the rest of Ireland. They found that average black smoke concentrations in Dublin declined by 70 per cent after the ban on coal sales. Adjusted non-trauma death rates decreased by 5.7%, respiratory deaths by 15.5%, and cardiovascular deaths by 10.3%. Respiratory and cardiovascular standardised death rates fell coincident with the ban on coal sales. They estimated that about 116 fewer respiratory deaths and 243 fewer cardiovascular deaths were observed per year in Dublin after the ban.

Examining the same data used in the present study (from The Irish Longitudinal Study on Ageing), Carthy et al. (2020) found a positive association between NO_2 exposure at residential address and diagnoses, and medications for, obstructive airway disease (asthma) in the population aged 50 + . This association between air quality and lung health provides a motivation for the present study to examine the effects of extending smoky coal bans on the lung health of older Irish people.

3. Context

Table 1 shows the timing of the extension of smoky coal bans in Ireland. For each city/town, the effective start date of the ban is shown along with the corresponding population and population density. Initially, the ban was introduced in Dublin during 1990 and in Cork, the second largest city, during 1993. Between 1998 and 2003, the ban was further extended to all cities and larger towns with over 30,000 inhabitants. In general, the sequence of the extension of the ban was based on the order of size of cities/towns, although a few smaller towns were also included in the initial extension of the ban.

In 2011, the ban was extended to all towns with over 15,000 inhabitants. In 2012, the ban was extended to parts of the county of Dublin that were not already covered by the initial ban in the city of Dublin. Likewise, in 2012, the ban was also extended to some small commuter towns near Cork City. In 2013, based on the results of the 2011 Census, the ban was extended to more towns because their populations had grown to over 15,000 inhabitants.[3] In 2020, the ban was extended to all towns with more than 10,000 inhabitants.[4] In 2022, a nation-wide ban was imposed.

It is difficult to know how strictly the ban is enforced and observed. Under the legislation, 'on-the-spot fines' up to €1000 can be issued to any person or organisation who breaches the regulations. A court prosecution can lead to fines of €5000 on summary conviction and €500,000 on conviction by indictment. Unfortunately, there are no comprehensive data relating to the enforcement of the ban, so all of the following analyses should be viewed with that caveat in mind.

Initially, the legislation outlawed only the supply and sale of smoky coal, but in 2011 the legislation was changed to outlaw also the burning

Table 1
Characteristics of cities/towns by year of ban.

City/Town	Year of Ban**	Population (2011)	Density (persons per km^2)	Mean $PM_{2.5}$ 2020–2021 µg/m^3***	Total Days 2020–2021 > 15 µg/m^3***
Dublin*	1990	1110627	3498.1	7.41	40
Cork City	1993	198582	1206.7	7.44	37
Arklow	1998	13009	1924.4		
Drogheda	1998	38578	2529.7		
Dundalk	1998	37816	1029.6		
Limerick City	1998	91454	1609	6.61	6
Wexford	1998	20072	1062.6	9.24	58
Galway City	2000	76778	1437.3		
Waterford City	2000	51519	1161.9	8.91	50
Celbridge	2000	19537	3334	5.09	0
Leixlip	2000	15452	2373.6		
Naas	2000	20713	1135.6		
Bray	2003	31872	3475.7	5.37	10
Kilkenny	2003	24423	1825.3		
Sligo	2003	19452	1260.7	12.22	73
Tralee	2003	23693	1478	11.94	90
Athlone	2011	20153	1162.9	9.09	55
Carlow	2011	23030	1846.8	6.61	26
Clonmel	2011	17908	1088	7.21	36
Ennis	2011	25360	1119.6	13.22	108
Greystones	2013	17468	1748.5		
Letterkenny	2013	19588	820.3	11.23	73
Mullingar	2013	20103	1757.3	4.88	0
Navan	2013	28200	2332		
Portlaoise	2013	20145	2074.7	7.95	42
Wicklow	2013	10356	2092.1		
Maynooth	2015	12510	2433.9		
Ashbourne	2020	11355	3440.9		
Ballina	2020	11086	741	6.04	10
Castlebar	2020	12318	909.7		
Cavan	2020	10205	1109.2	7.33	29
Cobh	2020	12347	2756	7.31	25
Enniscorthy	2020	14219	754.3	9.08	59
Killarney	2020	9601	894.8		
Longford	2020	11605	1384.8	8.21	25
Mallow	2020	12001	1929.4		
Midleton	2020	10838	1228.8		
Tramore	2020	10328	1444.5		
Tullamore	2020	14361	1354.8	4.73	0
Cork City Extension					
Carrigaline	2012	14775	3350.3		
Carrigtwohill	2020	4551	2955.2		
Dublin Extension					
Balbriggan	2012	19960	3006		
Donabate	2012	6778	3548.7		
Lusk	2012	7022	3657.3		
Rush	2012	9231	1580.7		
Skerries	2012	9671	3041.2		

*Initially, the ban covered urban areas administered by Dublin City Council, Dun Laoghaire-Rathdown Council, South Dublin County Council, and the southern part of Fingal County Council. In later years, the ban was extended to all areas governed by these councils. * *Ban implemented for winter heating season starting in a particular year. Legislation for ban enacted at most six months before implementation. However, the extension of 2013 was implemented in May 2013 in accordance with legislation passed in September 2012.
* **Source: https://airquality.ie/readings.

[3] The official government press release can be accessed at: Expansions to Smoky Coal Ban will bring Cleaner Air, Fewer Deaths and can help efficiency – MerrionStreet. https://merrionstreet.ie/en/category-index/environment/climate-change/extensions-to-smoky-coal-ban-will-bring-cleaner-air-fewer-deaths-and-can-help-efficiency.html

[4] The official government press release can be accessed at: gov.ie - Minister Ryan signs Regulations to extend Smoky Coal Ban (www.gov.ie). https://www.gov.ie/en/press-release/f15e2-minister-ryan-signs-regulations-to-extend-smoky-coal-ban/

of smoky coal. Thus, it was legal, before 2011, for people living in areas covered by the ban to purchase banned coal outside their local area and then burn it at home. It is impossible to know exactly how often people circumvented the ban in this way. However, coal is bulky, heavy, and dirty, so it is likely that people were not generally willing to travel outside their local area to purchase it. On the other hand, if people bought banned coal commonly outside their local area, then the estimated effect of the ban is an underestimate of the true effect.

What were the effects of the bans on coal usage? On examination of aggregate data from the Irish Census, we found clear evidence of a decrease in the percentage of households burning solid fuels. Additionally, we found no evidence of households switching from coal to peat or wood. An important aspect of the legislation is that the ban covered a range of smoky coal products, but not wood, peat, or non-smoky coal (e.g., anthracite). Thus, households could still maintain an open fire as their main heating system if they switched to a different type of solid fuel. While data about usage of peat and wood are available, unfortunately, in the TILDA data and, indeed, recent Irish censuses (which collect information on the main fuel used for home heating), no distinction can be made between smoky and non-smoky coal. Therefore, it is not possible to observe directly if households switched from smoky to non-smoky coal. However, the evidence we present below is suggestive that at least some households switched to non-smoky coal.

Over the past few decades, there was a dramatic reduction in solid fire usage in Ireland. According to the 1991 Census, around 60% of households used solid fuels as their main heating source. 20% burned non-smoky coal, 18% burned smoky coals and 23% burned either wood or peat.[5] Yet by the 2011 Census, only around 10.8% of households used solid fuels. However, this percentage increased to 12.4% in 2016. In 2016, 5.1% of households burned coal, 5.3% burned peat, and 2% burned wood. The corresponding percentages for 2011 were 4.8%, 4.8% and 1.3%. This increase in solid fuel usage between 2011 and 2016 was also found by the Sustainable Energy Authority of Ireland (SEAI, 2018) who attributed the increase in solid fuels to the burning of wood pellets but also noted the uncertainty surrounding the data on solid fuel usage.

To examine the effects of the extension of smoky coal bans during the 2010 s on solid fuel usage, we examined Census data from 2011 and 2016 at the level of household aggregates in each electoral division (ED). EDs are the smallest legally defined administrative areas in the Republic of Ireland. There are 3440 EDs in Ireland, and the average size is around 25 km^2. The legislation concerning smoky coal bans defines the area covered by the ban in terms of EDs. Unfortunately, these data are unavailable prior to 2011. We combined the electoral divisions to the level of the towns/cities. Using these data, we estimated the effect of extending smoky coal bans on the proportion of households in a town/city using solid fuels as their main source of heating as per the following linear equation:

$$\text{Proportion Using Solid Fuel}_{tk} = \rho I_{t=2016} + \pi_k + \sigma \text{Ban}_{tk} + \zeta_{tk}$$

where Proportion Using Solid Fuel_{tk} is the proportion of households burning solid fuels in area k during year t. With these data, t is either 2011 or 2016. In this case, ρ is the coefficient for a variable indicating the observed usage of solid fuels was from the 2016 Census, thus ρ is the time trend affecting the entire country. π_k is the fixed association between an area and solid fuel usage. Ban_{tk} indicates whether the smoky coal ban was in effect in year t in area k. ζ_{tk} represents unobserved time-varying factors specific to a given area.

In Table 2, we present the difference-in-difference estimate of the effect of the ban on specific types of solid fuel usage. We also present the coefficient for the overall trend in solid fuel usage. This trend is positive and significant albeit small in magnitude. The estimated equations also included fixed effects for each city/town, but these are not displayed in the table for the sake of brevity.

Table 2
Difference-in-difference estimates of effect of ban on solid fuel usage.

	(1)	(2)	(3)
	Proportion Using Coal	Proportion Using Wood	Proportion Using Peat
2016 (ref. cat. 2011)	0.00719 * **	0.00477 * **	0.00338 * *
	(0.00200)	(0.000738)	(0.00127)
Difference-in-difference estimate of effect of ban	-0.00728 * *	0.000698	-0.000179
	(0.00319)	(0.00117)	(0.00202)

Source data are electoral division household aggregates from Census 2011 & 2016.
N = 96 = 48 cities/towns observed twice.
Fixed effects for each city/town were included in the regression but are not displayed for brevity.
Standard errors in parentheses.
* ** p < 0.01, * * p < 0.05, * p < 0.1.

In the first column of Table 2, we can see that there was a negative effect of the ban of about 0.728 percentage points. This coefficient is small in absolute terms, but it should be seen context that only about 5% of households burned coal, so the estimated effect represents a 14.5% reduction in coal usage. The timing of the bans was associated with a positive effect on the usage of wood and a negative effect on the usage of peat, but these effects were not statistically significant and were much smaller than the estimated effect on coal usage. So while households switched away from coal, they did not tend to switch to peat or wood. Thus, the coal users in 2011 either moved to a non-solid fuel or, assuming that the ban on smoky coal was adhered to, switched to non-smoky coal.

What were the effects of the bans on the actual levels of $PM_{2.5}$? The final two columns of Table 1 provide recent data on $PM_{2.5}$ in Ireland. In 2021, the Environmental Protection Agency, the Irish government agency responsible for monitoring pollution, had a network of 96 air monitoring stations which collected hourly data. Over one third of the stations were located in cities. The remainder were located in the towns listed in Table 1, but not all of them collected data on $PM_{2.5}$; hence, there are missing values for $PM_{2.5}$ levels for some cities/towns in Table 1.

However, the data collected at the available stations can be used to assess concentrations of $PM_{2.5}$ in Ireland during 2020 and 2021. The World Health Organizations updated guidelines state that annual average concentrations of $PM_{2.5}$ should not exceed 5 μg/m3, while 24-hour average exposures should not exceed 15 μg/m3 more than 3–4 days per year (WHO, 2021). First, one can see in the second last column that nearly all cities/towns have annual average daily $PM_{2.5}$ concentrations above the recently revised WHO guideline of 5 μg/m^3 (WHO, 2021). Second, from the final column, one can see that nearly all cities and towns are far in excess of the maximum number of days when the 24-hour limit of 15 μg/m^3 was exceeded. However, especially in the cities and larger towns, the levels of $PM_{2.5}$ were generally below the former WHO guideline annual average daily level of 10 μg/m^3. The cities of Dublin, Cork, Limerick, and Waterford, while having $PM_{2.5}$ levels in excess of the new WHO guidelines, had lower $PM_{2.5}$ levels compared to many towns with much smaller populations. Not shown in the table is the level of $PM_{2.5}$ in small towns (with fewer than 10,000 inhabitants), villages and rural areas. From the stations located in these areas, the average $PM_{2.5}$ was 6.89 μg/m^3 between August 2020 and

[5] https://www.cso.ie/en/media/csoie/census/census1991results/volume10/C1991_Vol_10_T15.pdf

November 2021.[6]

To what extent did the ban on smoky coal reduce $PM_{2.5}$ concentrations? While the data do not allow us to draw definitive conclusions, they suggest that the ban may have led to large reductions in $PM_{2.5}$. While the final two columns of Table 1 show the recent pattern of $PM_{2.5}$ concentrations in Ireland, they do not show the effect of the smoky coal ban on $PM_{2.5}$. Unfortunately, daily $PM_{2.5}$ measurements prior to 2020 are available only for a small number of cities/towns. In only three towns can we observe $PM_{2.5}$ levels before and after smoky coal was banned. Analysing archive data from the Environmental Protection Agency,[7] we observed that for the town of Ennis, the $PM_{2.5}$ level during the winter heating season fell from 27.04 just before the ban (Winter 2010/11) to 12.88 just after the ban (Winter 2011/12). In the town of Enniscorthy, the corresponding reduction was from 12.89 just before the ban (Winter 2019/20) to 10.12 just after the ban (Winter 2020/21). The town of Cobh experienced a decline from 8.85 to 7.79. Thus, the reduction in $PM_{2.5}$ associated with the smoky coal ban ranges from around 12–52% from one winter to the next. However, it would be naive to attribute all of the observed decline in $PM_{2.5}$ entirely to the extension of the smoky coal ban. Ideally, one would need to adjust for the severity of the weather during different winters by comparing the towns where the ban was extended to other similar towns unaffected by the ban. However, because of a lack of EPA monitor data on $PM_{2.5}$ concentrations prior to 2020, it is impossible to construct a suitable sample of control towns (in terms of size, location, etc) to provide counterfactual data.[8] However, it is still plausible that extending the smoky coal ban resulted in a large reduction in $PM_{2.5}$.

To evaluate the effect of smoky coal bans on PM levels, in addition to analysing PM readings from EPA monitoring stations throughout Ireland, we examined satellite-based estimates of PM concentrations created by van Donkelaar et al. (2021). To map the satellite-based estimates to Irish electoral divisions, we assigned the satellite estimate of $PM_{2.5}$ exposure for a given year to every building in the Irish Geodirectory (the sampling frame for the TILDA data used in our main analysis that follows), and then calculated the average exposure in each ED weighted by the number of addresses in each building. In this way, using satellite-based estimates of $PM_{2.5}$, we constructed a panel dataset of annual $PM_{2.5}$ exposure for Irish cities/towns from 1998 to 2019.

Using this panel dataset, we estimated the effect of extending smoky coal bans on $PM_{2.5}$ exposure based on a difference-in-difference model with year and town/city fixed effects. We see in Table 3 that the estimated effect of the ban was between − 0.07 and − 0.14 on the annual level of $PM_{2.5}$ exposure or a reduction of 1.77–1.97% in log-linear models. The columns of Table 3 show how the results vary by changing the definition of the sample and control variables, e.g. by excluding cities, controlling for local population and population density, and controlling for the lag of the year of extension of the ban.

Apart from the first column, which is based on a sample including cities, the estimated effects were statistically significant at the 5% level.[9] However, the estimated effect is small and most likely a lower bound of the true effect. That the estimated effect is downward biased could be explained by the satellite-based estimates of $PM_{2.5}$ understating variation in $PM_{2.5}$ between areas.

We compared the satellite-based data estimated by van Donkelaar et al. (2021) to the data collected by the Irish Environmental Protection Agency monitors, the latter being much more limited before 2020. The $PM_{2.5}$ levels are quite similar for the cities of Cork and Dublin. However, in towns (pre-2020, we only have consistent EPA monitor readings for four towns), the van Donkelaar et al. (2021) estimates of $PM_{2.5}$ are consistently lower than the EPA monitor readings (on average, just above half of the EPA readings). An explanation to reconcile the differences between the data sources is that the satellite-based estimates have smoothed variation in $PM_{2.5}$ levels between towns and their rural hinterlands, whereas within cities, neighbouring areas would have similar levels of $PM_{2.5}$. For a discussion of comparing satellite estimates and monitor readings in the USA, see Fowlie et al. (2019).

4. Data

The data examined in this study were five waves of The Irish Longitudinal Study on Ageing (TILDA). TILDA is a large nationally representative sample of people aged 50 and older living in Ireland. For more information about the design of TILDA, see Whelan and Savva (2013). The data contain information about the health, housing, demographics, and socio-economic status of the participants. The first wave of TILDA was collected between late 2009 and early 2011. Participants were interviewed approximately every two years. Attrition of participants from the sample between waves is shown in Table 4. Attrition occurred because participants either died, moved home, or withdrew from the study. We restricted our main analysis to participants present (and who remained at the same home) in all five waves; but in the robustness checks that follow, we examined the effect of non-random attrition on our estimates and found that attrition does not affect our results.

In the analysis that follows, the outcome of interest is the prevalence of chronic lung disease. Chronic lung disease can be a catch-all term covering asthma, chronic obstructive pulmonary disease, infections like pneumonia and tuberculosis (TB), and even lung cancer. However, in this study, when we use the term “chronic lung disease”, we are following the epidemiological and medical literature and referring to diseases such as chronic obstructive pulmonary disease (COPD), bronchitis and emphysema. In each wave of TILDA, participants were asked if they have ever been diagnosed with chronic lung disease. The probability of an individual reporting chronic lung disease is our dependent variable in our main analysis. In a secondary analysis, discussed in Section 6, we examine the effect on mortality of extensions to the smoky coal ban.

To identify the effect of the extension of the ban to an area, the addresses of the TILDA participants were matched to their Electoral Division (ED). The legislation concerning smoky coal bans defines the area covered by the ban in terms of EDs. Based on this legislation (see notes beneath Table 1), whether and when the smoke coal ban was extended

[6] These locations were Abbeyfeale, Askeaton, Banagher, Birr, Buncranna, Carrick-on-Shannon, Dungarvan, Ennistymon, Macroom, Monaghan, Mountrath, Mungret, Navan, Nenagh, New Ross and Thomastown. The remaining stations in rural areas did not collect $PM_{2.5}$ data.

[7] EPA Ireland Archive of PM 2.5 Monitoring Data. Datasets Available At: Secure Archive For Environmental Research Data managed by Environmental Protection Agency Ireland https://eparesearch.epa.ie/safer/resource?id=0dc73e08–7e15–102b-aa08–55a7497570d3 (Last Accessed: 2021–11–10)

[8] The winter of 2010/2011 was particularly severe by Irish standards, so the large reduction in $PM_{2.5}$ observed for Ennis between 2010 and 2011 might in part be due reduced demand for heating more generally rather than just the banning of smoky coal. However, Cork and Dublin (the only other places for which $PM_{2.5}$ data are available from 2010 and 2011) experienced declines in $PM_{2.5}$ of about 33%.

[9] Another approach to estimating the effect of the smoky coal ban would be to estimate a two-stage model of the effect of $PM_{2.5}$ (based on satellite estimates) on health status using the ban as an instrumental variable for $PM_{2.5}$. However, although the ban’s effect on $PM_{2.5}$ was significant at the 5% level, it would still be a weak instrument in such a two-stage model, thus the resulting estimates would likely be biased. For a discussion of weak instruments, see Andrews et al. (2019).

Table 3
Difference-in-difference estimate of effect of smoky coal ban on $PM_{2.5}$.

	(1)	(2)	(3)	(4)	(5)	(6)
Estimated Effect	-0.0659	-0.130 * *	-0.140 * **	-0.125 * *	-0.0177 * **	-0.0197 * **
(Standard Error)	(0.0448)	(0.0509)	(0.0513)	(0.0520)	(0.00663)	(0.00695)

1. Sample includes both cities and towns.
2. Sample includes towns only.
3. Controlling for log of population of town.
4. Controlling for log of population density of town.
5. Log of $PM_{2.5}$ exposure as outcome variable.
6. Lagged year of implementation of ban.
Source: $PM_{2.5}$ exposure at city/town-level 1998–2019 using the estimates of van Donkelaar et al. (2021)
N = 1078 = 49 towns/cities observed over 22 years.

Table 4
Attrition from TILDA by wave.

Wave	Dates	Useable Responses	Cumulative Withdrawals	Cumulative Deaths	Cumulative Address Changes
1	2009 (Oct) to 2011 (Feb)	8501	0	0	0
2	2012 (Apr-Dec)	7163	899	208	121
3	2014 (Mar) to 2015 (Oct)	6128	1553	519	174
4	2016 (Jan-Dec)	5334	2102	779	218
5	2018 (Jan-Dec)	4551	2636	1051	263

Table 5
Proportion reporting chronic lung disease by area and wave.

	Number of TILDA Participants	Wave 1 2009 Oct to 2011 Feb	Wave 2 2012 Apr to 2012 Dec	Wave 3 2014 Mar to 2015 Oct	Wave 4 2016 Jan to 2016 Dec	Wave 5 2018 Jan to 2018 Dec
Cities with ban before 2009	1412	**<u>0.0377</u>**	**<u>0.0398</u>**	**<u>0.0439</u>**	**<u>0.0460</u>**	**<u>0.0494</u>**
Towns with ban before 2009	183	**<u>0.0174</u>**	**<u>0.0348</u>**	**<u>0.0435</u>**	**<u>0.0391</u>**	**<u>0.0435</u>**
Towns with ban in 2011 *	115	0.0548	**<u>0.0274</u>**	**<u>0.0205</u>**	**<u>0.0274</u>**	**<u>0.0479</u>**
Towns with ban in 2013	85	0.0094	0.0189	**<u>0.0189</u>**	**<u>0.0094</u>**	**<u>0.0094</u>**
Towns with ban in 2020	78	0.0526	0.0737	0.0526	0.0737	0.0842
Towns< 10000 or Rural (No Ban)	2678	0.0318	0.0314	0.0334	0.0342	0.0354

Numbers in bold and underlined indicate that area was subject to smoky coal ban at time of data collection.

to their ED was matched to each participant in the TILDA study.

Table 5 shows the probability of a participant reporting chronic lung disease broken down by the timing of the extension of the ban and collection of TILDA survey waves. The first column also shows the number of participants in each area in the final sample. For example, 1412 and 183 TILDA participants lived in cities and towns where the ban had been in effect before the TILDA survey began. On the other hand, we can see that 2678 TILDA participants lived in towns with fewer than 10,000 inhabitants or in rural areas, both of which were never covered by the ban.

In most areas, the proportion of participants with chronic lung disease rose between Wave 1 and Wave 5, which is not surprising given they aged ten years. For clarity, observations after the ban was extended are shown in bold and underlined. The highest prevalence of lung disease at all waves was found in smaller towns with populations over 10,000 where the ban was imposed in 2020, but which did not have a smoky coal ban when the TILDA data were collected. These towns also experienced the largest increase in lung disease over the five waves. The second highest prevalence was in the cities, which have had bans since the 1990 s and 2000 s, but which also have higher levels of traffic and other forms of air pollution. By contrast, towns with fewer than 10,000 inhabitants and rural areas had relative stable prevalence of lung disease. Interestingly, in medium sized towns, where the ban was extended during 2011, there was an initial decline in the prevalence lung disease once the ban was extended followed by an increase in the final wave, though still below the initial level despite the participants being ten years older. For the towns where the ban was extended in 2013, the prevalence remained very low.

In the main, our analysis concentrates on people living in towns rather than cities or rural areas. A priori, we believed that the characteristics of people living in cities, towns, and rural areas differ both observably and unobservably. For example, in relation to unobservable factors (at least with these data), we expected that city dwellers have much greater exposure to air pollution. For example, Milojevic et al. (2017) show considerable urban-rural differences in $PM_{2.5}$ exposure in England. However, as we saw in Table 1, medium sized towns generally have greater exposure relative to cities.

In relation to observable factors, the average characteristics of city, town, and rural dwellers are shown in Table 6. We can see that the sample is predominantly female, an observation explained by greater female longevity in the context of a study of ageing and that women are more likely to respond to the survey questionnaire. In the second row, we observe that the average age ranges from 63.7 years to 66.5 years. There is no statistically significant difference in age and gender between participants in the cities, towns and rural areas.

However, the other rows of Table 6 reveal differences between the areas and indeed these differences are statistically significant. The

Table 6
Average/proportion in each category by area.

	Initial Ban: Cities	Initial Ban: Towns	2011 Extension Towns	2012/13/15 Extension Towns	2020 Extension Towns	Towns< 10k or Rural Areas
Male	0.443	0.399	0.470	0.402	0.436	0.450
Age	66.280	66.500	64.850	63.730	65.340	66.000
Highest education:						
Primary	0.194	0.209	0.199	0.179	0.168	0.233
Secondary	0.370	0.443	0.473	0.491	0.358	0.452
Post Secondary	0.436	0.348	0.329	0.330	0.474	0.315
Quintile of wealth						
1st	0.091	0.147	0.147	0.132	0.162	0.133
2nd	0.074	0.158	0.193	0.113	0.118	0.165
3rd	0.140	0.171	0.188	0.162	0.154	0.145
4th	0.207	0.186	0.136	0.181	0.152	0.115
5th	0.251	0.103	0.075	0.166	0.103	0.117
Missing wealth	0.236	0.235	0.262	0.245	0.312	0.324
Smoker:						
Never	0.451	0.415	0.473	0.519	0.381	0.488
Past	0.438	0.463	0.381	0.392	0.482	0.393
Current	0.111	0.122	0.147	0.089	0.137	0.119
Health when young:						
Excellent	0.563	0.543	0.596	0.594	0.642	0.573
Very Good	0.252	0.243	0.247	0.255	0.168	0.249
Good	0.120	0.113	0.096	0.104	0.147	0.119
Fair	0.052	0.074	0.034	0.028	0.032	0.045
Poor	0.013	0.026	0.027	0.019	0.011	0.014
Not Always lived in Ireland	0.466	0.383	0.425	0.264	0.284	0.440
Rural when young	0.310	0.439	0.541	0.528	0.568	0.776
Family finances when young:						
Well-off	0.141	0.096	0.089	0.104	0.189	0.105
Average	0.669	0.713	0.705	0.632	0.642	0.703
Poor	0.189	0.187	0.205	0.264	0.158	0.191
Years lived in home	31.04	30.77	27.86	27.15	26.84	31.95
Built before 1940	0.074	0.065	0.082	0.019	0.074	0.161
Built 1941–1960	0.093	0.070	0.055	0.057	0.095	0.076
Built 1961–1970	0.160	0.161	0.151	0.076	0.074	0.079
Built 1971–1980	0.198	0.096	0.110	0.094	0.074	0.078
Built 1981–1990	0.253	0.330	0.192	0.340	0.274	0.207
Built 1991–2000	0.112	0.126	0.247	0.198	0.179	0.179
Built 2001 or later	0.067	0.096	0.075	0.094	0.116	0.098
Built: Don't know	0.023	0.057	0.055	0.066	0.095	0.096
Open fire is main heating	0.037	0.094	0.081	0.098	0.082	0.085
Unknown heating	0.271	0.262	0.290	0.264	0.303	0.298

characteristics of people living in cities, towns, and rural areas are quite different. But the differences are less stark between towns by date of ban. For example, we observe that city dwellers are wealthier, an unsurprising observation given housing wealth is the main component of wealth and that house prices are highest in cities. Furthermore, city dwellers are less likely to have grown up in the countryside, and less likely to use solid fuels as their main source of heating. Thus, in the main, we concentrate our analysis on people living in towns, although we also estimate our models using the full dataset containing city, town, and rural dwellers. Furthermore, we control for these observable characteristics in the models estimated below.

5. Model and Results

We estimated the probability of a participant having chronic lung disease controlling for the fixed effect of their area (for each particular city/town), year of survey, individual level characteristics and whether the smoky coal ban was in effect in their area at the time of the survey. Thus, we estimated the following equation:

$$P(y_{itk}=1 \mid X_{itk}, Area_k, Year_t, Ban_{t,k}, Z_i)= \alpha_k + \beta_t + \gamma Ban_{itk} + \delta X_{itk} + \theta Z_i + \varepsilon_{itk}$$

where for the i^{th} participant, living in area k and observed in year t, y_{itk} is whether they have chronic lung disease, X_{itk} represents individual time-varying factors (such as wealth and whether they smoked at the time of survey wave), Z_i represents individual fixed characteristics (such as gender and childhood characteristics), and ε_{itk} represents unobserved factors.

In Table 7, we present our results. The first column shows the different samples used with the corresponding sample sizes shown in the second column. One should keep in mind that each TILDA participant appears in the sample in each of the five waves. So the sample of 22,775 represents 4551 TILDA participants observed over the five waves with the normal interval between interviews being about two years.

In the third column, we show the average marginal effect of the ban being in effect in the participants' area based on estimates of a panel random effects model. In the fourth and fifth columns, we display the coefficients from estimated linear models with random effects and fixed effects. For all models, the standard errors were clustered at the level of the locality (i.e., for each particular city/town).

In the first row of Table 7, we display the estimated effect of the ban when using the entire sample. Regardless of the type of model estimated, we found a negative effect of the ban on the probability of lung disease of around 1.67–1.7 percentage points, but this effect was significant at the 10% level in the linear models only.

In the second row of Table 7, we display our estimates when we omitted participants living in rural areas from our sample. On the one hand, rural areas were never covered by the ban, and they had much higher usage of solid fuels (as confirmed by the second last row of Table 3). But rural areas probably had less air pollution from other sources (e.g. traffic or industry) compared to urban areas and, by definition, rural dwellers live further apart from one another, so the burning of solid fuels by one household probably has less of an effect on

Table 7
Effect of living in area with smoky coal ban on probability of lung disease.

	Sample	n	AME Panel Probit Random Effects	Linear Probability Model Random Effects	Linear Probability Model Fixed Effects
(1)	All areas (incl. cities, towns & rural)	22,755	-0.0167	-0.0170 *	-0.0170 *
			(0.0139)	(0.0089)	(0.0089)
(2)	Cities & towns (excl. rural)	9365	-0.0267 *	-0.0198 *	-0.0198 *
			(0.0139)	(0.0103)	(0.0103)
(3)	Towns only	2305	-0.0490 *	-0.0321 * *	-0.0320 * *
			(0.0281)	(0.0140)	(0.0141)
(4)	Towns only and control variables ˆ	2270	-0.0477 * *	-0.0335 * *	-0.0329 * *
			(0.0177)	(0.0156)	(0.0161)
(5)	Towns only, control variables & whether uses open fire in home	2270	-0.0486 * *	-0.0341 * *	-0.0335 * *
			(0.0178)	(0.0157)	(0.0162)

Standard errors (in parentheses) are clustered by electoral division.
Sample comprises only those who remained in the same home between Wave 1 and Wave 5.
ˆControlling for gender, age, education, wealth, smoking, health when young, family finances when young, rural dweller when young, lived away from Ireland, age of building, log population density, years lived in home.
* ** , * *, * corresponds to significance at 1%, 5% and 10% level.
n = number of participants observed across five waves.

neighbouring households than would be the case in an urban area. Indeed, from Table 6, the prevalence of lung disease in rural areas is lower than in towns (marginally so) and cities. Thus, including participants who lived in rural areas might understate the true effect of the ban on lung health. As we can see from the second row of Table 7, the effect of the ban in urban areas ranges from 1.98 to 2.67 percentage points, with the effect being statistically significant at the 10% level in the linear models.

In the model corresponding to the third row of Table 7, we omitted participants who lived in cities, in addition to the previous omission of rural dwellers. That is, we omit those living in the cities of Dublin (covering the entire historic county of Dublin except for the northern part of Fingal County Council where the ban was only extended in 2012), Cork, Limerick, Galway and Waterford. By the time the first wave of TILDA had been collected, during 2009–2011, smoky coal had been banned in Irish cities for 15–20 years. However, the cities likely had worse air pollution than less densely populated areas because of higher traffic levels and industrial production. Indeed, as we can see from Table 6, open fire usage is low in cities compared to towns, yet the prevalence of chronic lung disease is slightly higher. So including cities in the sample likely understates the true effect of the ban on lung health. And as we see from the third row of Table 7, when we excluded the cities, the effect of the ban ranges from 3.2 to 4.9 percentage points, with the effect being statistically significant at the 5% level in the linear models.

In the fourth row of Table 7, we present our estimated results when we controlled for relevant characteristics of participants. From the panel probit model, we can see the average marginal effect of the ban is 4.77 percentage points. This effect is statistically significant at the 5% level. The coefficients from the linear random effects and fixed effects models are − 0.0335 and − 0.0329. These coefficients are significant at the 5% level.

Table 8 presents the full list of estimated average marginal effects

Table 8
Average Marginal Effects of relevant characteristics on probability of lung disease.

	AME	Std. Err.	Significance
Living in area with smoky coal ban	-0.048	0.018	* *
Male	-0.041	0.015	* **
Age	0.002	0.001	* **
Education: (Ref. cat. Primary)			
Secondary	-0.040	0.024	*
Post secondary	-0.016	0.026	
Wealth: (Ref. cat. 1st Quintile)			
2nd Quintile	0.004	0.010	
3rd Quintile	-0.002	0.011	
4th Quintile	-0.046	0.019	* *
5th Quintile	-0.019	0.017	
Refused/Don't Know	0.001	0.011	
Smoker: (Ref. cat. Never)			
Past	0.056	0.013	* **
Current	0.049	0.019	* *
Health when young: (Ref. cat. Excellent)			
Very good	0.018	0.017	
Good	0.013	0.022	
Fair	0.060	0.024	* *
Poor	0.103	0.040	* **
Lived away from Ireland	-0.006	0.015	
Lived in urban area when young	-0.034	0.012	* **
Family finances when young: (Ref. cat. Well-off)			
Average	0.003	0.025	
Poor	0.031	0.026	
Don't Know	-0.016	0.043	
Refused	0.003	0.025	
Log of population density	0.027	0.044	
Years lived in home	-0.002	0.001	* *
Year home built: (Ref. cat. Before 1919)			
1919–1940	-0.044	0.035	
1941–1960	-0.055	0.047	
1961–1970	-0.032	0.046	
1971–1980	-0.053	0.050	
1981–1990	-0.039	0.045	
1991–2000	-0.071	0.063	
2001 or later	-0.077	0.049	
Don't Know	-0.059	0.046	

* ** , * *, * corresponds to significance at 1%, 5% and 10% level.
These estimates correspond to the first column of row (4) of Table 7.

from the panel probit model corresponding to estimates presented in the fourth row of Table 7. Reassuringly, the direction and size of the marginal effects of most of the relevant characteristics are as expected. For example, men were 4.1 percentage points less likely to have lung disease. In the past, chronic lung disease was seen as a disease that affected older men; however, recent studies have shown this is changing (for a discussion, see Barnes, 2016). Age is a risk factor for lung disease; getting older increases the probability of lung disease by 0.2 of a percentage point each year. Furthermore, better educated and wealthier people are less likely to have lung disease.

In Table 8, one can also see the influence of health risk factors on the probability of chronic lung disease. Smoking either in the past or at the time of the survey had a positive effect on the probability of chronic lung disease. Similarly, those who experienced poor health when they were younger (the question asks the participant to recall their health from birth to age 14) were more likely to have chronic lung disease.

In some cases, however, there was no clear association between characteristics of the participants and the probability of chronic lung disease. For example, there was no clear pattern of results in relation to living outside of Ireland (prior to participation in TILDA) or growing up in a poor family. One anomalous finding is that growing up in an urban area was associated with a lower probability of developing chronic lung disease. One might have thought that exposure to air pollution in urban areas during childhood/youth would have a negative association with chronic lung health in later life. However, in Ireland, exposure to indoor pollution in the home might have been greater for rural dwellers who belong to the generations in the TILDA sample because of a lack of electricity in rural areas before the mid-1960 s. In 1946, two thirds of Irish homes, mostly in rural areas, did not have electricity, so both heating and cooking relied on solid fuels. The scheme of rural electrification took place between 1946 and 1964. By 1975, 99% of homes had electricity. For a history of rural electrification, see Shiels (2003). Thus, the negative association between growing up in a rural area and chronic lung disease in later life could be due to greater exposure to harmful indoor pollution.

In relation to the local area characteristics, population density did not have a significant effect on chronic lung disease. However, participants' housing did affect the probability of chronic lung disease. For example, the number of years lived in the home had a negative effect. This negative effect of years lived in the home could represent reverse causality. Perhaps people move home if they are suffering from chronic lung disease, either because they believe that housing conditions (e.g. dampness, etc.) affect their health or because they want to live in home that is easier to live in (e.g. easier mobility within the home or outside the home in the local area). In relation to the age of the home, we found that people who lived in older homes were more likely to develop chronic lung disease, a finding most likely explained by the improvements in building standards having a positive effect on health.

Returning to Table 7, in the final row, we present our estimates from when we included an indicator of whether the participant used an open fire as their main source of heating. On the one hand, controlling for indoor open fire usage is desirable because indoor air pollution likely has a deleterious effect on health, especially lung health. For example, using these same data, Maher et al. (2021) found a negative association between cognitive function and indoor open fire usage.

On the other hand, including open fire usage is problematic, so we did not include this variable in most of our models. First, there is likely a two-way relationship between open fire usage and lung health. For example, a person whose lung health is deteriorating might decide to replace their open fire with a non-solid fuel heating system. Second, open fire usage might be affected by smoky coal bans. Once smoky coal was banned, open fire users were still permitted to burn "smokeless" coal or peat/wood; however, the introduction of the ban might have caused people to replace their open fire with a different heating system. However, as discussed above, the data in Table 3 suggest that most people did not switch to (other) solid fuels in response to the ban being extended to their area.

Lastly, another downside of including an indicator for open fire usage is data availability. The survey question about open fire usage only began to appear in the second wave of TILDA and even then, the question appeared in a self-completion questionnaire that was not part of the main TILDA computer-aided personal interview. This self-completion questionnaire had a lower response rate relative to the main questionnaire because participants had to post their completed questionnaires to the TILDA research centre. Approximately 85% of participants responded to the self-completion questionnaire in addition to the main questionnaire. To address this missing information, the estimates in the final row of Table 7 correspond to a model that controls for indoor open fire usage and an indicator of whether indoor fire usage was unknown. In any case, regardless of these considerations, the estimates in the final row of Table 7 are very similar to those in the preceding rows.

In Table 9, we present estimates of the effect of the ban when excluding those reporting chronic lung disease in Wave 1. The previous models captured a combination of prior prevalence and new incidence of chronic lung disease. By restricting the sample to those who did not have chronic lung disease at Wave 1, we were estimating the effect of the ban on the incidence of new cases. The overall pattern of the results is that the estimates are smaller than the previous estimates. For example, in the linear probability models, the estimates are about one third smaller than those generated using the entire sample which includes those who had lung disease in the first wave. We found a smaller but statistically significant effect of between –0.96% and –2.5 percentage points in the linear probability models depending on the samples used.

Table 9
Effect of living in area with smoky coal ban on probability of lung disease (sample excludes those with lung disease in Wave 1).

	N	AME Panel Probit Random Effects	Linear Probability Model Random Effects	Linear Probability Model Fixed Effects
(1) All	21,990	-0.0116 (0.0223)	-0.0097 ** (0.0046)	-0.0096 ** (0.0046)
(2) Cities and Towns	9040	-0.0130 (0.0248)	-0.0128 ** (0.0057)	-0.0127 ** (0.0058)
(3) Towns only	2235	-0.0277 (0.0431)	-0.0219 ** (0.0093)	-0.0220 ** (0.0093)
(4) Towns only and control variables	2200	-0.0397 (0.0285)	-0.0227 ** (0.0106)	-0.0243 ** (0.0105)
(5) Towns only, control variables and whether uses open fire in home	2200	-0.0403 (0.0298)	-0.0235 ** (0.0108)	-0.0250 ** (0.0107)

Standard errors (in parentheses) are clustered by electoral division.
Sample comprises only those who remained in same home between Wave 1 and Wave 5.
ˆControlling for gender, age, education, wealth, smoking, health when young, family finances when young, rural dweller when young, lived away from Ireland, age of building, log population density, years lived in home.
* ** , * *, * corresponds to significance at 1%, 5% and 10% level.

6. Discussion

6.1. Common trends

The validity of our research design rests on the assumption of parallel trends in health outcomes had the treatment not occurred. This assumption is unprovable, but showing parallel trends for the different areas before the treatment is at least reassuring about the validity of the estimates. To this end, we examined hospital admissions data. The data were from the Hospital In-Patient Enquiry database and generously provided to us by the Healthcare Pricing Office of the Republic of Ireland. We examined aggregate trends, by patients' county of residence, of hospitalisations due to diseases of the respiratory systems as a percentage of total annual hospitalisations.[10] Unfortunately, hospital-level data were not available, which is problematic because it would be better to observe changes in hospitalisation at a particular hospital when the ban was extended to the nearby town(s). Furthermore, data from before 2005 were not available. Lastly, the hospitalisation data refer to the general population and not only the over-50 s as represented in the TILDA dataset.

We categorised the patients' county of residence by timing of extension of smoky coal bans. The first category comprises counties with mostly urban populations where the ban was already in place before

[10] Diagnosis and Procedures are coded using ICD-10-AM/ACHI/ACS (For 2005–2008, coded using 4th edition, for 2009–2010 coded using 6th edition. Diseases of the Respiratory System in the ICD as covered by codes J00-J99.

2005.[11] The second category comprises counties, which have largely rural populations, where either the ban was never introduced or introduced after the TILDA data were collected.[12] The third category comprises mixed urban/rural counties which have at least one town where a smoky coal ban was first introduced before 2005.[13] Finally, the fourth category comprises mixed urban/rural counties which have at least one town where the ban was first introduced during the 2010 s[14]

As one can see from Fig. 1, the percentage of respiratory cases differs according to the category of county. However, broadly speaking, the trends in respiratory hospitalisations were similar and indeed the levels were too. One can see from Fig. 1 that the percentage of respiratory cases fell during the second half of the 2000 s for each category. Furthermore, for all four categories the most significant decline was between 2005 and 2006. There are some minor differences in trends between 2007 and 2010. For example, among the counties to which the ban was never extended and the mixed counties to where the ban was extended after 2010, the downwards trends tended to continue after 2006. For the urban counties and mixed counties to where the ban was extended during the 2000 s, the percentage of respiratory cases increased again slightly after 2006. However, broadly speaking, the assumption of parallel trends between treatment units prior to the collection of the TILDA data seems plausible.

Another approach to investigating the plausibility of assuming parallel trends is to estimate a model with leads and lags of the treatment. For an accessible discussion of this so-called event-study approach, see Cunningham (2021, p.425). Using the TILDA data, we estimated the following model.

$$P(y_{itk} = 1|\text{Area}_k, \text{Year}_t, D_{k,\tau}) = \eta_i + \alpha_k + \beta_t + \sum_{\tau=-5}^{-1} \lambda_\tau D_{k,\tau} + \sum_{\tau=1}^{7} \lambda_\tau D_{k,\tau} + \varepsilon_{itk}$$

Where the λ_τ coefficients are the lead ($\tau < 0$) and lagged ($\tau > 0$) treatment effects with the treatment taking place at $\tau = 0$. Thus, for example, for a respondent i living in an area, k, where the ban was extended during 2013, $D_{k,-1} = 1$ when we observe them in 2012 and $D_{k,-1} = 0$ in all other years. And, for example, for the same respondent, $D_{k,1} = 1$ when we observe them in 2014 and $D_{k,1} = 0$ in all other years. The range of τ from − 5 to –7 was determined by data availability.

Fig. 2, produced using Stata's **eventdd** command (Clarke and Tapia-Schythe, 2021), displays the lead and lag coefficients and their confidence intervals. From Fig. 2, there is a clear downward shift in the estimated treatment effect on the probability of chronic lung disease following the implementation of the ban, although that probability moves towards zero a few years after the ban.

Before the ban was extended, however, the difference in the probability of chronic lung disease between treatment and control is consistently between zero and five percentage points. Thus, compared to the control areas, the treatment areas had consistently higher levels of chronic lung disease prior to the ban being extended. Thus, the estimated effect on chronic lung disease due to extending the ban shown in our main tables of results (Tables 7 and 9) could represent an underestimate of the actual effect.

6.2. *Staggered implementation of policy*

Another aspect of the study design is the staggered implementation of the policy in different areas over time. Recently, the appropriate methodology for these types of studies has been discussed (for example, see Cunningham, 2021). Such studies can be seen as an extension of the simple "2 × 2" difference-in-difference design with a treatment and control group observed before and after the introduction of a policy. However, recent methodological research has shown the complexity of extending the difference-in-difference design to situations where a policy is implemented in multiple areas over time, a so-called two-way fixed effects design. For a discussion, see Goodman-Bacon (2021) and de Chaisemartin and D'Haultfœuille (2019). The insight of this recent methodological research is that the estimated difference-in-difference effect from a regression model with fixed effects for each area and time period is a weighted average of each separate average treatment effect from the difference-in-difference observed as the policy is extended to more areas. This weighted average can be a misleading estimate of the causal effect of the policy if there is heterogeneity in the effects. Indeed, in an extreme case, the weighted average could have the opposite sign to each separate average treatment effect.

Table 10 shows the decomposition of Goodman-Bacon (2021) applied to our difference-in-difference estimates. In all cases in the first panel, the average treatment effect is negative, ranging from − 0.011 to − 0.041. When we use the entire sample of people living in cities, towns and rural areas, the greatest weighting, 0.6, corresponds to the estimate when the comparison group are never treated (the smaller towns and the rural areas). The second largest weight, 0.385, corresponds to the estimate when the comparison group are always treated (in this case, the cities and larger towns). Much less weight is given to the estimates that use the medium sized towns that received the treatment earlier or later as the comparison group.

In the second panel of Table 10, we display the decomposition when omitting the rural areas, which were never treated. In this decomposition, the estimate where the areas that have always been treated (cities and large towns) is the comparison group has the largest weighting. Finally, in the third panel, we display the decomposition when omitting both rural areas and cities. In this case, the estimate which uses the already treated (large towns) as a comparison group gets the largest weighting, followed by the estimate that has the never treated (towns smaller than 10,000 inhabitants) as the comparison group. However, regardless of the weighting, the average treatment effects are of a similar magnitude.

6.3. *Effect on mortality and other outcomes*

Another important aspect of the ban on smoky coal is its possible effect on mortality. If the ban affected mortality, and not just morbidity, then we are in a sense understating the effect of the ban by examining only those present in every wave of TILDA. Thus, we examined the possible effect of the ban on mortality by examining TILDA records on participant deaths, which are based on interviews with next of kin. Of the original TILDA participants, 1051 were confirmed as having died, a death rate of around 12% when expressed as a percentage of those present in the first wave of TILDA.

A key finding from Table 11 is that deaths were unrelated to the timing of the extension of the ban. In the left-hand panel of Table 11, we show the estimated effect of the ban in models with death as the outcome variable. As we can see, the coefficients are mostly positive.

[11] These are the counties of Dublin, Cork, Limerick, Galway and Waterford. The cities in these counties introduced bans between 1990 and 2000. Nearly 98% of County Dublin's population (i.e. Fingal, South Dublin, Dublin City and Dun Laoghaire-Rathdown combined) live in urban areas. Unfortunately, our hospital admissions data by county of residence were not disaggregated by county and city for Cork, Limerick, Galway and Waterford. Rural parts of these counties were not covered by the ban, but the majority of people, 57%, living in these counties live in urban areas. We also included County Louth in this category because nearly 70% of its population live in either Dundalk or Drogheda where the ban was extended during 1998.

[12] These were Cavan, Leitrim, Longford, Mayo, Meath, Monaghan, Offaly, and Roscommon.

[13] These were Kerry, Kildare, Kilkenny, Sligo, Wexford, and Wicklow.

[14] These were Carlow, Clare, Donegal, Laois, Tipperary, and Westmeath.

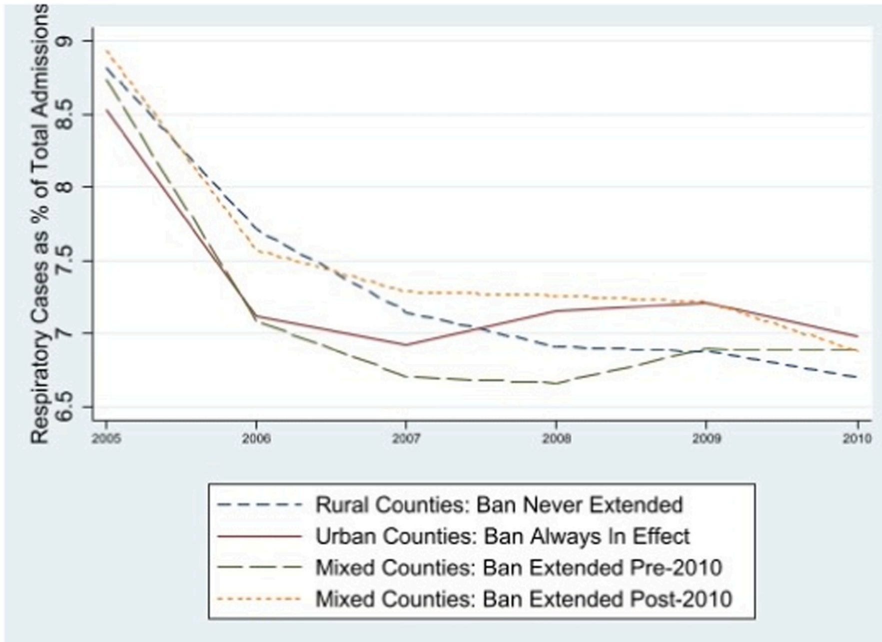

Fig. 1. Hospital admissions due to disease of the respiratory system as a percentage of total admissions by county of residence of patient.
Source: Hospital In-Patient Enquiry database collect by the Healthcare Pricing Office of the Republic of Ireland.

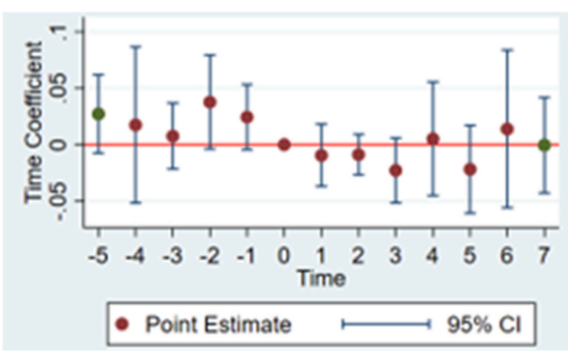

Fig. 2. Leads and lags of effect of smoky coal ban on chronic lung disease.

Table 10
Decomposition of D-i-D estimates by timing of treatment.

	(1)		(2)		(3)	
	Cities, Towns and Rural Areas		Cities & Towns Only		Towns Only	
	Weight	ATT	Weight	ATT	Weight	ATT
Earlier T vs. later C	0.003	-0.041	0.006	-0.052	0.035	-0.052
Later T vs. earlier C	0.009	-0.011	0.017	-0.016	0.098	-0.016
T vs. never treated	0.603	-0.014	0.046	-0.038	0.259	-0.038
T vs. already treated	0.385	-0.021	0.931	-0.019	0.608	-0.031

T = Treatment; C = Comparison
Generated using ddtiming Stata command (Goldring, 2019), which decomposes d-i-d estimates with variation in treatment timing based on Goodman-Bacon (2021).

However, in all cases, the estimated coefficients were not statistically significant.[15] Thus, we can conclude that the ban did not significantly affect mortality among TILDA participants. Perhaps this conclusion is not surprising given that it might take a few years for the bans to affect mortality because people can live with chronic lung disease for some time before passing away. Lastly, in relation to mortality, it was not possible to stratify the analysis according to different causes of death because the numbers in many categories were small and, in some cases, cause of death was unknown.

That we found no evidence that mortality was affected by the extension of the ban contrasts with Clancy et. al. (2002) who found significant reductions in pollution related deaths when comparing death rates before and after the introduction of the ban in Dublin City in 1990. They found non-trauma death rates decreased by 5.7%, respiratory deaths by 15.5%, and cardiovascular deaths by 10.3%. The difference in our findings is not surprising given the context. Levels of air pollution were much higher in the 1980 s, and Dublin, in particular, was highly polluted before the ban. Black soot concentrations (highly correlated with $PM_{2.5}$) fell by 70% after the imposition of the ban. Furthermore, Dublin was and remains much more densely populated than the towns where the ban was extended to, so one would have additional reason not to expect the bans of the 2010 s to have had the same effect on mortality.

More broadly, attrition from the sample occurred not just due to mortality. Another concern one might have is potential non-random withdrawal from the study. For example, people who became unwell, perhaps due to chronic lung disease, might have decided to withdraw from the survey. Thus, participants might withdraw from the study at different rates in different areas affected by the ban and this differential withdrawal might be correlated with health outcomes. For example, suppose people living in remote rural areas (where the ban was never extended) were more likely to withdraw from the study and these people had worse health. In that case, we would be understating the effect of the ban. Thus, it is important to examine withdrawal from the study.

[15] We present the results of only the linear panel models because in some cases the maximum likelihood estimation would not converge for the panel probit models when using Stata 16.1.

Table 11
Effect of living in area with smoky coal ban on probability of attrition from sample.

		Probability of Death			Probability of Withdrawal from Study			Probability of Changing Address		
	Sample	n	Linear Model Fixed Effects	Linear Model Random Effects	n	Linear Model Fixed Effects	Linear Model Random Effects	n	Linear Model Fixed Effects	Linear Model Random Effects
(1)	All areas (cities, towns & rural)	28,010	0.0031	0.0062	35,935	-0.0107	-0.0063	24,070	-0.0021	-0.0021
			(0.0193)	(0.0201)		(0.0217)	(0.0217)		(0.0086)	(0.0086)
(2)	Including cities & towns	11,525	0.0044	0.0074	14,675	-0.0041	-0.0005	9895	0.0033	0.0033
			(0.0223)	(0.0231)		(0.0269)	(0.0268)		(0.0098)	(0.0099)
(3)	Towns only	2845	0.0064	0.0114	3695	-0.0143	-0.0087	2480	-0.0106	-0.0106
			(0.0249)	(0.0261)		(0.0292)	(0.0292)		(0.0120)	(0.0121)

Standard errors (in parentheses) are clustered by electoral division.
Reference category for each outcome (i.e., death, withdrawal or changing address) is being in sample used in main analysis (i.e. in all five waves at the same address).

Of the original sample of 8504 participants, 2636 people withdrew from the study (see Table 3). Relative to similar studies, the attrition rate is favourable. For example, in the English Longitudinal Study on Ageing (ELSA), there was a 22% attrition rate from the first to second wave (Steptoe et al., 2013), whereas the TILDA attrition rate was 14%. However, it should be noted that the other studies recruited refreshment samples after their first few waves, whereas the first five waves of TILDA relied on the original sample alone.

In any case, withdrawal from the sample was not correlated with the timing of the extension of the ban. The middle panel of Table 11 shows the results from estimating models when withdrawal from the sample was the outcome variable. While the coefficients are negative, they were not statistically significant.

Finally, a few TILDA participants (262 – as shown in Table 3) were not in our main sample because they moved address. Unfortunately, their new addresses are unavailable to the authors of this study. Even if these addresses were available, using variation in address to identify the effect of the ban might not be valid because not only were there very few changes, but these changes might be due to health shocks. In any case, in the right-hand panel of Table 11, we present estimates of the effect of the policy on changing address. We show that the timing of the policy was not associated with changes of address.

We also conducted the same analysis on the effect of the ban on other aspects of respiratory health. The participants were asked separately about diagnoses of asthma. When we repeated the above analysis with the probability of asthma as our outcome of interest, we did not find any statistically significant effect of smoky coal bans. It is possible we did not find an effect because chronic lung diseases such as chronic bronchitis or emphysema are often more serious conditions than asthma, so perhaps the lack of statistical effect of the ban on asthma is due to a dose-response mechanism. Or perhaps we did not find an effect because asthma is often diagnosed in childhood, in contrast to chronic lung diseases such as chronic bronchitis or emphysema. For the sake of brevity, results of this additional analysis are omitted from this paper. They are available on request from the authors.

A previous analysis of the relationship between NO_2 concentrations and asthma in the TILDA population (Carthy et al., 2020) found that a 1ppb increase in NO_2 concentrations was associated with a 0.24 percentage point increase in the prevalence of doctor-diagnosed asthma (baseline prevalence of 9%. Comparing the magnitude of results of this analysis with that of Carthy et al. (2020) is difficult due to differences in the environmental exposure and health outcomes examined, as well as the relevant population and study design and methodology. The main source of NO_2 is emissions from diesel vehicles, while the smoky coal ban that is examined in this paper was designed to affect emissions from solid fuel burning, primarily $PM_{2.5}$.

6.4. Effect on window around threshold

Next, we examined the potential for endogeneity in relation to the policy. In our estimated models, we controlled for a variety of individual-level factors related to health such as gender, age, education, wealth, smoking behaviour, migration history, and health and socio-economic status when young. Additionally, in relation to the participant's home, we controlled for how long they have lived there and how the age of the building. Furthermore, we also used panel data methods to control for fixed unobservable factors affecting health.

Even after controlling for these observable and fixed unobservable factors, it is possible that those living in the areas where the ban was implemented earlier, areas with larger populations, have different health status and exposure to pollution compared to those who living in areas where the ban was implemented later, areas with smaller populations. For example, it is likely that those living in larger towns are more exposed to pollutants from traffic. In which case, we might be underestimating the true effect of the smoky coal ban, especially if traffic pollution became worse in larger towns relative to smaller towns.

To counter this problem, when estimating our models, we controlled for the log of population density of the town. A reason for doing so is that controlling for population density is arguably a better way to account for exposure to pollutants compared to controlling for population, which was the basis for the assignment of the ban. When the TILDA data were being collected, a cut-off of a population of 15,000 was used to assign the ban to towns (later the cut-off was lowered to a population of 10,000).

However, to explore whether the estimated effect of the ban is affected by the population of the towns where it was implemented, in Table 12 we present estimates when examining only those living in towns with populations of a given range around the cut-off of 15,000.[16] One can see the estimated effect is always negative, but is quite small and not significant for a range of 11,000–19,000 inhabitants. However, as one can see, when the range becomes larger, beginning at 10,000–20,000 inhabitants, the estimated effect of the ban is statistically significant and is around the same magnitude as the effect estimated using the entire sample (around -2.5 to -3 percentage points). The lack of statistical significance for sample living in towns with populations within a range of 11,000–19,000 inhabitants or narrower could be due to lack of statistical power. For those estimates, the number of datapoints is fewer than 1000, representing fewer than 200 people observed longitudinally.

6.5. Early-life risk factors

Finally, while the main risk factor for chronic lung disease is active smoking (followed by exposure to ambient air pollution) (Safiri et al., 2022), there is some evidence to suggest that adult lung disease can have

[16] Again, we present the results of only the linear panel models because in some cases the maximum likelihood estimation would not converge for the panel probit models when using Stata 16.1.

Table 12
Effect of smoky coal ban on lung disease using towns with population within range of threshold of 15,000 inhabitants.

	n	Participants	Linear Model Random Effects	Linear Model Fixed Effects
14,000–16,000 inhabitants	240	48	-0.0038	-0.0041
			(0.0023)	(0.0031)
13,000–17,000 inhabitants	308	92	-0.0027	-0.0033
			(0.0019)	(0.0031)
12,000–18,000 inhabitants	597	141	-0.0079	-0.0082
			(0.0087)	(0.0087)
11,000–19,000 inhabitants	764	163	-0.0087	-0.0089
			(0.0063)	(0.0062)
10,000–20,000 inhabitants	1147	281	-0.0129 * *	-0.0130 * *
			(0.0063)	(0.0064)
9000–21,000 inhabitants	1477	325	-0.0299 *	-0.0300 * *
			(0.0149)	(0.0151)
8000–22,000 inhabitants	1676	346	-0.0279 *	-0.0281 *
			(0.0156)	(0.0159)
7000–23,000 inhabitants	1912	409	-0.0287 *	-0.0288 *
			(0.0146)	(0.0148)
6000–24,000 inhabitants	2133	451	-0.0281 *	-0.0281 *
			(0.0147)	(0.0149)
5,000–25000 inhabitants	2339	489	-0.0245 *	-0.0244 *
			(0.0145)	(0.0147)

* ** , * *, * corresponds to significance at 1%, 5% and 10% level.

its origins in prenatal and early life (Deolmi et al., 2023). Parental history of lung disease, exposure to passive smoking and air pollution during childhood and acute viral infections can predispose an individual to the development and exacerbation of chronic lung disease in later life (Deolmi et al., 2023; Duijts et al., 2014; Postma et al., 2015). TILDA respondents are first surveyed in middle- and older-age, with the result that information on their early life conditions is limited. However, we control for several aspects of early life conditions, such as family socioeconomic background, whether the respondent lived in a rural or urban area growing up and childhood health status. In addition, for our identification strategy to be violated, other unobserved early life conditions linked to the potential development of chronic lung disease (e.g., maternal smoking in pregnancy) would have to vary in accordance with exposure to the policy change (i.e., the smoky coal ban). Given the way in which the smoky coal ban was extended (i.e., over time, based on population size of towns), this is considered unlikely.

7. Summary and Conclusion

We estimated the effect of bans on sale and use of so-called “smoky coal” on the probability of chronic lung disease among older people. To overcome potential sorting of healthy and unhealthy people into areas with better or worse air pollution, our identification strategy relied on the phased extension of smoky coal bans to Irish towns after 2010.

We examined five waves of The Irish Longitudinal Study on Ageing (TILDA), a large nationally representative survey that contains detailed information on health, housing, and socio-economic status. We controlled for relevant factors such as gender, age, education, wealth, smoking history, circumstances in childhood, and housing quality. We found that smoky coal bans reduced the prevalence of chronic lung disease by between three and five percentage points. In models where we estimated the effect of the ban on the incidence of new cases of chronic lung disease, rather than existing cases, we found an effect of between -0.96 and − 2.5 percentage points. Our finding was robust to estimating the model using different sub-samples that differentiated between cities, large towns, small towns, and rural areas. Our estimated effect was about the same across different decompositions of the difference-in-difference design. Furthermore, there was no effect of the policy on mortality or other forms of attrition from the sample. Finally, we estimated a negative effect when examining subsamples within a range of local populations around the threshold for imposing the ban. A limitation of our estimated models is that they do not allow for spatial dependence. For example, $PM_{2.5}$ concentrations in areas close to where the ban extended might have fallen too. Modelling the spatial dispersion of PM as a result of the bans has been left for future work as it likely to be a complex function of seasonal wind patterns.

Based on our results, we suggest policy makers ban smoky coal to protect the lung health of older people, although policy makers would need to consider the wider costs (e.g. replacing heating systems) and distributional effects of such a ban.

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Declaration of Competing Interest

none.

Data Availability

The authors do not have permission to share data.

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