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ORIGINAL ARTICLE

Pollution risk and life insurance decisions: Microgeographic evidence from the United Kingdom

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Abstract

Recent research documents that exposure to air pollution can trigger various behavioral reactions. This article presents novel empirical evidence on the causal effect of pollution risk on life insurance decisions. We create a unique dataset by linking microgeographic air quality information to the confidential UK Wealth and Assets Survey. We identify an inverse N-shape relationship between pollution risk and life insurance adoption by exploiting the orthogonal variations in meteorological conditions. Over a given range above a threshold of exposure, rising pollution is associated with rising demand for life insurance, whereas at lower than the threshold levels of pollution, higher exposure risk reduces demand for insurance. Our findings indicate—for the first time—a nonlinear relationship between local pollution risk and life insurance demand.

KEYWORDS
air pollution, life insurance, modeled microgeographic data, N-shaped relationship, United Kingdom

1 | INTRODUCTION

Environmental pollution—the classic negative externality—poses a considerable risk to human well-being and economic livelihoods. Air pollution leads to poor health (Chen et al., 2013; Dockery et al., 1993; Pope et al., 2002; Seaton et al., 1995) and adverse economic outcomes such as reduced worker productivity, lower income, higher conflict incidence, and criminal activity (Adetutu et al., 2023; Binder & Neumayer, 2005; Herrnstadt et al., 2021; Maddison, 2005; Samakovlis et al., 2005; Zivin & Neidell, 2012).

Beyond academic research, the knowledge about pollution risk is also well-established within public domains.[1] Meanwhile, the growing awareness of air pollution risk evokes wide-ranging behavioral responses. For instance, some individuals adopt the preventive response of avoiding outdoor activities (Bresnahan et al., 1997) or relocating to areas with better air quality (Banzhaf & Walsh, 2008). Additionally, exposure to pollution risk can elicit defensive responses such as the use of medication (Peters et al., 1997) and particulate-filtering facemasks (Zhang & Mu, 2018). More recently, a stream of studies suggests that exposure to pollutants can trigger more severe behavioral outcomes such as suicide (Chen & Samet, 2017).

One behavioral reaction to risk, widespread in the face of probable loss, is the decision to purchase insurance coverage. Recent developments in insurance research highlight the limited understanding of the behavioral drivers of demand for insurance, especially in the context of environmental and climate risks (Corcos et al., 2020). Although there is a strand of the literature providing evidence on the management of environmental risk through insurance, it often focuses on natural disasters[2] (Botzen & van den Bergh, 2012; Nguyen & Noy, 2020; Raschky et al., 2013) and pollution liability insurance in the context of the polluter (Boomhower, 2019; Katzman, 1988). However, a few studies have emerged on how pollution risk affects the purchase of insurance products (e.g., Chang et al., 2018; Chen & Chen, 2020). Such literature, as it does exist, suffers from two main drawbacks.

[1] For instance, see Maione et al. (2021). See also a recent global Pew Research survey https://www.pewresearch.org/fact-tank/2019/04/18/a-look-at-how-people-around-the-world-view-climate-change/.

[2] For instance, earthquakes, flooding, and hurricanes.

First, it tends to focus on health insurance, with little work investigating whether/the extent to which life insurance demand responds to changes in pollution exposure. However, we note the economic differences between health and life insurance. Compared to life insurance which mainly pertains to insuring the quantity of life, health insurance covers treatments that enhance well-being (quality of life) and life expectancy (quantity). By implication, subscribers to these products face distinct benefit–cost trade-offs that may inform varying behavioral and demand decisions across both products (see Koijen & Van Nieuwerburgh, 2020). This distinction is consistent with the notion that health insurance may be more sensitive to pollution risk than life insurance, reflecting the palpable (direct) effect of pollution on well-being, which ultimately affects mortality outcomes[3] (Zhao, 2020).

We depart from the above literature by focusing on the impact of local pollution on life insurance. A key thesis underlying our focus is the well-grounded economic reasoning that households often choose to maintain and transfer significant fractions of their wealth in bequeathable forms through life insurance coverage (Bernheim, 1991; Yuji & Ventura, 2022). Moreover, academics and policymakers[4] are starting to recognize air pollution as an emerging risk factor for life insurance decisions: long-term exposure to pollution drives mortality. Although a large body of research links mortality and life expectancy to life insurance demand (e.g., Gaganis et al., 2020; He, 2009; Koijen & Yogo, 2015; Lewis, 1989), neither the causal effect of air pollution on life insurance decisions nor the mechanisms via which this effect manifests have been studied in the literature.

Second, the limited focus on life insurance may be due to the lack of appropriate microdata to implement a clear identification strategy to investigate the pollution-life insurance relationship. For instance, although the few existing studies[5] have provided helpful insight into the pollution-insurance demand nexus, they suffer from a common fundamental problem in measuring and specifying pollution risk. Specifically, the use of aggregate (country, city, or province level) proxies for pollution risk raises the issue of a compelling identification strategy through which we can causally interpret the effect of pollution on life insurance. A key novelty of our approach is that we address the measurement issues arising from aggregate pollution measures, which make it difficult to disentangle the impact of pollution exposure and other unobserved aggregate shocks. Research shows that regional covariates, such as aggregate income growth and cohort/network effects, shape the demand for private insurance.[6] Furthermore, such aggregate air pollution measures are inadequate for capturing the variation in pollution concentration, considering that a significant gradient of pollutants can exist within short distances and small spatial dimensions (Borck & Tabuchi, 2019; Herrnstadt et al., 2021; Zhou & Levy, 2007).

In this study, we examine how local exposure to pollution affects the demand for life insurance and make two contributions to the literature. First, we measure air pollution risk at the individual level using a measure of air quality around the sampled individuals' residential location. In essence, we exploit the microgeography of local pollution risk and household life insurance decisions by linking a 1 km-by-1 km grid-level (modeled) pollution data to the nationally representative United Kingdom (UK) Wealth and Asset Survey (WAS) during the period 2006–2018. This approach allows us to compare changes in life insurance decisions over time and between households facing different pollution risks, but at a hitherto unexplored spatial granularity, while also controlling for various factors that shape insurance demand.

Furthermore, we tackle the endogeneity of pollution risk arising from individuals' residential choices by similarly exploiting the variation in 1 km-by-1 km wind and precipitation to instrument for variation in local pollution levels. Following recent studies (Herrnstadt et al., 2021; Schlenker & Walker, 2016), our identification strategy exploits how the spatial diffusion of environmental pollutants is driven mainly by meteorological processes such as wind velocity and wet deposition (e.g., precipitation) over a given location. This approach enables us to address the panel identification issues relating to omitted variables correlated with pollution risk and insurance demand. Consequently, we can interpret our results as the causal impact of pollution risk on life insurance decisions.

Second, our article adds a new dimension to the pollution risk-insurance literature by exploring the effects of environmental pollution on individuals' risk decision-making, that is, the acquisition of life insurance. To date, the pollution-life insurance nexus is a priori unclear, given that there is only scant empirical evidence regarding the extent to which life insurance demand responds to changes in pollution risk. For instance, although some studies suggest a positive relationship between the likelihood of death and life insurance demand (Beck & Webb, 2003; Levy et al., 1988; Lewis, 1989), others contrastingly find a negative relationship (Browne & Kim, 1993; Outreville, 1996). Consequently, we explore—for the first time—the nonlinearity between pollution risk and life insurance decisions.

Our empirical analysis is informed by a theoretical framework that draws on the seminal work by Friedman and Savage (1948) and suggests a nonlinear relationship between pollution and life insurance demand. Hence, our article highlights a novel behavioral response to environmental pollution risk that advances the discourse around the impact and implications of air pollution on life insurance decisions.

[3] According to the World Health Organisation (WHO) (2011), air pollution accounts for several millions of global premature deaths every year. In the same vein, around 9 million annual excess deaths have been linked to outdoor air pollution (Burnett et al., 2018). These estimates are consistent with a recent study by Lelieveld et al. (2020) which indicates that the loss of life expectancy arising from air pollution is around 2.9 years on average, bigger than losses from smoking tobacco (2.2 years), violence (0.3 years lost), and HIV/Aids (0.7 years lost). In short, outdoor air pollution is the leading environmental risk factor for all-cause mortality (Cohen et al., 2017).

[4] See Zhao (2020) and https://www.partnerre.com/opinions_research/poor-air-quality-an-emerging-risk-factor-for-life-insurance-underwriting-and-pricing/.

[5] See Chang et al. (2018) and Chen and Chen (2020)

[6] See Townsend (1994) and Propper et al. (2001).

Finally, our study embodies clear policy implications. Our work underscores the potential demand for new environmental-related insurance products and the liability risk arising from environmental pollution—made even more critical by the emerging public policy drive to engender accountability regarding pollution-related risks across financial markets.[7] The remainder of the article is as follows. In Section 2, we critique the existing literature on the effect of pollution on health, human capital, and life insurance. Section 3 sets out the theoretical framework, whereas Section 4 describes our data and empirical strategy. Section 5 discusses the empirical findings, and Section 6 concludes.

2 | RELATED LITERATURE

We review the literature on the adverse effects of air pollution first and, subsequently, the literature on the uptake of life insurance products. The former spotlights the range of adverse effects of air pollution, whereas the latter examines the antecedents of their adoption. In the following, we provide an illustrative overview focusing on the most relevant research in these categories and discuss how our research contributes to the current literature.

2.1 | The adverse effects of air pollution

Research investigating the adverse effects of air pollution on health is omnipresent in different disciplines. For instance, the impact of pollution on infant health dates back to the 19th century. Using a novel wind pattern for identification, Beach and Hanlon (2018) showed that Britain's heavy reliance on coal had significant infant mortality effects. More recently, economic factors such as the recession-induced reduction in air pollution in the United States (Chay & Greenstone, 2003) and China's increased export intensity have also driven infant mortality (Bombardini & Li, 2020). Similarly, Arceo et al. (2016) showed that the negative effect of pollution on infant mortality holds in both developing and developed country contexts. A significant body of knowledge shows that high-volume exposure to city-level pollution from automobiles has profound adverse effects on infant health (Currie et al., 2015). In turn, several scholars (e.g., DeCicca & Malak, 2020) argue that regulation can significantly mitigate the effect of city-level air pollution on infant health.

Moreover, increased exposure to air pollution can have wide-ranging effects on adults, such as increased hospitalizations (Schlenker & Walker, 2016), high mortality rates (Anderson, 2020; Deschênes & Greenstone, 2011), mental health challenges (Samakovlis et al., 2005), reduced productivity (Zivin & Neidell, 2012), and broader societal impacts such as aggressive behaviors and violent crime (Herrnstadt et al., 2021).

In response to the adverse effects of air pollution, individuals often adopt a range of short- and long-term decisions. For the former, studies find that individuals avoid outdoor activities (Bresnahan et al., 1997; Zivin & Neidell, 2012), use medication (Peters et al., 1997), and adopt defensive measures such as using particulate-filtering facemasks (Zhang & Mu, 2018) to mitigate the effects of air pollution. For the latter, optimization behaviors such as residential sorting, that is, residential choices and relocation to areas with better air quality (Banzhaf & Walsh, 2008; Chen & Chen, 2020), have been observed in extant literature.

The above studies on the effects of air pollution on a range of behavioral outcomes are closely aligned with our analysis but with a few limitations. First, they focus more on avoidance behaviors in response to air pollution. Second, with some exceptions (Chang et al., 2018; Chen & Chen, 2020; Zhao, 2020), few studies investigate how air pollution affects the demand for insurance products. Of this, existing insights focus on limited contexts, and not all the studies inform a causal relationship between pollution and life insurance decisions (Chang et al., 2018; Chen & Chen, 2020). Although some studies observe insurance decisions at the individual level, these are matched with air quality data at a more aggerate level. To address this issue, we use a microgeographic approach that combines UK microdata with 1 km-by-1 km grid-level modeled data on air pollution. Thus, our analysis is timely in responding to the recent calls for more research to understand the behavioral responses to air pollution better (Corcos et al., 2020).

2.2 | Behavioral responses to the demand for life insurance

Life insurance has long been a hedge against mortality risk (Chen et al., 2006). It captures the source of uncertainty derived from wage earners' preretirement death and the associated loss of labor income to the surviving dependents of the household (Campbell, 1980) and is grounded in the altruistic bequest motive (Barro, 1974; Becker, 1974). The theoretical foundations for the demand for life insurance are rooted in the lifetime consumer allocation theory, whereby consumer preferences depend on consumption and wealth (Yaari, 1964, 1965). Compared to other policies, death is an eventual certainty, which air pollution expectedly exacerbates.

In the literature, Pratt (1964) was one of the first scholars to derive absolute and relative risk aversion. However, Karni and Zilcha (1986) did not find that higher risk aversion stimulates life insurance demand. Some researchers use education as a proxy for risk aversion and find positive and negative associations, raising questions about causality (Outreville, 2015). Recently, research has found risk perceptions as an essential optimization behavior that informs the demand for insurance products such as index-based insurance (Belissa et al., 2020; Visser et al., 2020). Compared to avoidance behaviors, insurance optimization behaviors broadly aim to recognize how individuals internalize the trade-offs associated with the

[7] For instance, see https://www.bankofengland.co.uk/-/media/boe/files/prudential-regulation/publication/impact-of-climate-change-on-the-uk-insurance-sector.pdf.

adverse effects of air pollution. Furthermore, studying optimization behaviors in greater detail can thus offer a more comprehensive understanding of the mechanisms that inform longer term strategies adopted in response to air pollution. To date, aside from some of the studies mentioned above, understanding the behavioral mechanisms of the pollution-life insurance nexus has received limited attention in the literature.

Consequently, our study makes two significant contributions to this literature. First, we estimate the effect of risk perceptions as a novel optimization behavior shaping the demand for life insurance products in response to the adverse effects of air pollution. Second, we contribute to the literature on the consequences of air pollution by studying its causal impact on the demand for life insurance products. Life insurance is a unique product and evokes special considerations so far as the demand is concerned. Recent figures for life insurance products show that the UK ranks as the fourth largest market in the world and the largest life insurance market in Europe, followed by Germany and France (Statista, 2020). By 2024, it is estimated that life insurance gross written premiums will be £195.8 billion. Thus, our focus on the UK context is relevant and timely.

3 | THEORETICAL FRAMEWORK

In this section, we present a simple theoretical framework to inform our empirical analysis. As households recognize risks, they are motivated to purchase insurance; hence, we are interested in the optimal level of life insurance.

Consider the head of a household who faces the possibility of consuming C_0 with probability p and C_1 with probability $1-p$ where p is the probability of death of the head of the household and $C_1 > C_0$, and who is averse,[8] that is, in maximizing expected utility, certainty is preferred over a gamble with the same actuarial value as the certain consumption level.

In this model, we consider pollution and, in particular, the exposure of the individual to pollution, and we assume that the probability of death p is a function of exposure to pollution $\lambda > 0$, where $p(\lambda)$ is increasing in exposure to pollution, $p'(\lambda) > 0$.

We also assume that the head of household has a bequest motive, that is, he gets utility from providing consumption for some purpose after death. In other words, there is a desire to maintain a consumption level for his dependents beyond death. Intuitively, this assumption explains life insurance demand as without the need to provide for dependents after death, which would not be rational to purchase life insurance.

We can derive the household's demand for life insurance following the seminal work by Friedman and Savage (1948).[9] In particular, the decision-maker/head of household would purchase life insurance that maximizes the following expected utility function:

$$max\ EU(I) = pV(C_0 + I - prem) + (1-p)\,U(C_1 - prem),$$

where V is the bequest function (the utility of the household's future consumption after the death of the decision-maker), C_0 is the expected consumption level of the household after the death of the head of household in the future, I denotes the face value of the insurance policy, U denotes the utility of the household's future consumption if the head of household is alive, the strictly concave function, C_1 denotes the expected consumption level of the household if the head is alive in the future, and $prem$ is the premium on insurance which can be expressed as $apI + L$ where $a \geq 1$ is the variable loading factor of the insurance and $L \geq 0$ the fixed loading factor of the insurance.

The bequest function V can be rewritten as β U where $\beta \geq 0$ is the bequest parameter, and U is the utility of consumption function given that the head of the household is still alive. We assume $U = \frac{1}{1-\gamma}C^{1-\gamma}$ which describes a broad class of functions and is commonly used in the literature, and γ, $0 < \gamma < 1$, denotes the risk aversion parameter. For $\beta = 0$, the decision-maker has no bequest motive, whereas for $\beta = 1$, he receives equal utility from consumption during his life as from wealth passed on to their dependents. Hence, to purchase life insurance, we assume that $\beta > 0$.

We can then rewrite the expected utility function that the head of household maximizes as follows:

$$max\ EU(I) = p(\lambda)\,\beta\frac{(C_0 + I - ap(\lambda)\,I - L)^{1-\gamma}}{1-\gamma} + (1-p(\lambda))\,\frac{(C_1 - ap(\lambda)\,I - L)^{1-\gamma}}{1-\gamma}. \quad (1)$$

The first order condition of Equation (1) with respect to I gives us

$$\frac{\partial EU(I)}{\partial I} = p(\lambda)\,\beta(C_0 + I - ap(\lambda)\,I - L)^{-\gamma}(1 - ap(\lambda)) + (1-p(\lambda))\,(C_1 - ap(\lambda)\,I - L)^{-\gamma}(-ap(\lambda)) = 0.$$
$$\Rightarrow \left[\frac{\beta(1-ap(\lambda))}{a(1-p(\lambda))}\right]^{1/\gamma} = \frac{C_0+I-ap(\lambda)I-L}{C_1-ap(\lambda)I-L} \quad (2)$$

[8] The risk aversion assumption means that the decision-maker desires to eliminate uncertainty and diversify against risk through purchasing life insurance.

[9] Although here we follow the standard expected utility model, our results do not change qualitatively if we assume a prospect theory model with the value function being characterized by loss aversion and the value of each outcome being multiplied by a decision weight (not a probability itself, but a function of the probability). We can still show that there is a nonlinear relationship between insurance demand and exposure to pollution. Please see further discussion in Appendix A.

Solving for the I and denoting $[\frac{\beta(1-ap(\lambda))}{a(1-p(\lambda))}] = A$ gives us the optimal level of life insurance demanded[10]:

$$I^* = \frac{A^{1/\gamma}(C_1 - L) - C_0 + L}{1 - ap(\lambda)\left(1 - A^{1/\gamma}\right)}. \quad (3)$$

Examining I^* to understand our finding, we can see that the effect of C_1 is positive as $\frac{\partial I^*}{\partial C_1} > 0$; hence, as the given consumption, if the head of the household is alive, increases, the higher the demand for life insurance, whereas the effect of C_0 is negative as $\frac{\partial I^*}{\partial C_0} < 0$, and hence, as the amount of the current consumption increases, less insurance is demanded as the higher the current consumption, the gap in future consumption if the head of the household dies declines. Additionally, we can see that the effect of the bequest parameter β is positive as $\frac{\partial I^*}{\partial \beta} > 0$ as long as $C_0 \geq L$ (please see Appendix A), which is an intuitive assumption that the level of future consumption, if the head of the household dies, would be higher than the fixed loading costs for the insurance. This supports the altruistic bequest motive as life insurance is used to hedge against the household head's death for the dependents in the household.

More importantly, looking at the effect of exposure to pollution, we can see that taking the derivative of Equation (3) with respect to λ, the sign of the numerator is ambiguous, that is,

$$\frac{\partial I^*}{\partial \lambda} = \frac{\frac{1}{\gamma}A^{\frac{1}{\gamma}-1}\frac{\partial A}{\partial \lambda}(C_1 - L)(1 - ap(\lambda))}{(1 + Aap(\lambda))^2},$$

$$-\frac{\left[\left(A^{\frac{1}{\gamma}}(C_1 - L)\right)\left(-ap'(\lambda)\left(1 - A^{\frac{1}{\gamma}}\right)\right) + (-C_0 + L)\left(-ap'(\lambda)\left(1 - A^{\frac{1}{\gamma}}\right) + \frac{1}{\gamma}A^{\frac{1}{\gamma}-1}\frac{\partial A}{\partial \lambda}ap(\lambda)\right)\right]}{(1 + Aap(\lambda))^2},$$

where $\frac{\partial A}{\partial \lambda} = -\frac{\beta ap'(\lambda)a(1-p) + [\beta(1-ap(\lambda(\theta)))ap'(\lambda)]}{[1-ap(1-A^{\frac{1}{\gamma}})]^2} < 0$.

Hence, the relationship between exposure to pollution and the demand for life insurance is not linear. Consequently, one could argue that the relationship between pollution and insurance is highly complex and may be shaped by several factors. In particular, depending on the parameter values and functional form used, it can take different forms. In Appendix A, we demonstrate that this relationship can take various shapes based on simulations according to certain parameters.[11] Therefore, the intuitively complex relationship between pollution and insurance informs our analysis in the empirical part of the article where we look at the case of the UK and explore the particular shape of the air pollution exposure-life insurance demand nexus in that market.

4 | DATA AND EMPIRICAL STRATEGY

In this section, we discuss the data used in our empirical analysis, along with their sources. Furthermore, we describe the construction of our key variables of interest. Our air quality information is modeled on pollution data from the UK Air Information database, maintained by the Department for Environment, Food & Rural Affairs (DEFRA).[12] This air quality database provides modeled background pollution maps of the annual concentration of different pollutants at 1 km × 1 km resolution. We focus on fine particulates, namely, $PM_{2.5}$ (i.e., particles with diameters of 2.5 μm or less) for two main reasons. First, from a broad methodological point of view, it is generally recognized that particulate matter emissions are a good proxy for many pollutants (Herrnstadt et al., 2021). Empirical economics and epidemiological research link fine particulate matter pollution to mortality and adverse health conditions (Adhvaryu et al., 2019; Dockery et al., 1993; Miller et al., 2007; Pope et al., 2009). In essence, particles with a diameter of 2.5 μm or less can penetrate the lungs and blood system, raising the risk of respiratory and cardiovascular diseases and lung cancer.[13]

Second, particulate matter emission has become the focus of air and environmental quality regulation in advanced countries[14] (Anderson, 2020). Thus, our focus on $PM_{2.5}$ has both methodological and practical policy advantages. Nevertheless, we include estimates relying on the second most concerning UK pollutant, nitrogen dioxide NO_2, as a

[10] The second derivative of the expected utility with respect to I^* is negative, $\frac{\partial^2 EU(I)}{\partial I^2} < 0$, ensuring that the optimal solution is maximizing $EU(I)$ (see Appendix A).

[11] We thank an anonymous referee for their suggestion and guidance on the use of simulations to demonstrate the complexity of the relationship between pollution and insurance.

[12] https://uk-air.defra.gov.uk/data/pcm-data

[13] https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health.

[14] For instance, air quality regulations by the US Environmental Protection Agency (US EPA) (e.g., the Clean Air Act Amendments) embody standards focusing on fine particulates (see US EPA, 2011; Anderson, 2020). Similarly, the UK environmental agencies treat particulate matter as one of the two most concerning pollutants. See report by the Department for Environment and Rural Affairs (DEFRA, 2017) and https://www.london.gov.uk/what-we-do/environment/pollution-and-air-quality/health-and-exposure-pollution.

robustness test of the sensitivity of our results to alternative pollutants' risks. Thus, our two pollution risk measures are the modeled annual means of the pollutants at the 1 km × 1 km grid level, expressed in μg m^{-3}.

Our life insurance data comes from the UK WAS,[15] provided by the Office for National Statistics (ONS). Because the underlying microdata of the WAS is confidential/restricted, it can only be accessed by approved users/researchers through the secure access program of the ONS. The WAS is a biennial longitudinal survey launched in 2006. It contains information[16] about individuals' assets, savings, debt, and other financial products that shape their financial decisions. Using the available six waves (2006–2008, 2008–2010, 2010–2012, 2012–2014, 2014–2016, 2016–2018), we follow the extant literature (e.g., Bauchet & Morduch, 2019; Brown & Goolsbee, 2002) by constructing two measures of the dependent variables as life insurance ownership and the life insurance value. The life insurance ownership variable is a dummy variable that takes the value of 1 if a sampled individual holds a valid life insurance policy, whereas the insurance value is the inflation-adjusted cash (face value) of the life policy.

4.1 | Matching WAS to pollution data

Figure 1 portrays a visual presentation of our spatial data matching exercise, which consists of two crucial stages. First, we collect information on modeled $PM_{2.5}$ concentration (μg m^{-3}) at the 1 km × 1 km grid level. The different color shades in Panel A of Figure 1 depict the spatial variability of pollution concentration. By representing the annual average pollution levels on the map of Great Britain at the local administrative district level, we show air quality ranging from lower pollution levels (lighter shades) to higher pollution levels (darker shades).

The regional distribution of $PM_{2.5}$ pollution is stark. For example, pollution levels are particularly higher in the southern districts relative to their Northern counterparts. This observation is consistent with reports[17] highlighting that over 75% of British districts that exceed the WHO's annual $PM_{2.5}$ limit of 10 μg m^{-3} are in the Southern part of the country (46% in London and 33% in the Southeast). Hence, it is unsurprising that these districts have become the target of a renewed public policy drive to expand low or clean emission zones at the local level (see Adcock & Smith, 2020). To further shed light on the pollution distribution depicted in Figure 1, we note that the higher levels of pollution in London and the Southern regions reflect some composition and scale effects underpinning UK pollution distribution. First, we highlight that $PM_{2.5}$ pollution across the UK is mainly from industrial, domestic, and road transport sectors.[18] Second, further geographical investigations indicate that London and the Southern regions jointly account for 36% of the total UK population[19] and have the most road vehicles (33% of the total UK).[20] Furthermore, available data from the UK pollution inventory[21] shows that 20% of the plants and production units responsible for mass releases of air pollutants across the UK are also located across these regions.

Given the granular (grid-level) pollution data from the UK air quality database, we require microgeographic information on individual locations to match pollution risks at the micro-level. Ideally, we need an accurate data matching scheme driven by a spatial granularity of household location information, that is, as close as possible (in local precision) to the grid-level pollution data. As a result, we use confidential micro-neighborhood data on household output areas (OAs) in the WAS data, the lowest spatial unit available within the UK census geography.[22] OA sizes range from a minimum of 40 resident households to around 125 households, with an average of about 100 resident households.

To create a microgeographic measure of air pollution, we match the geo-coded grid-level pollution data to the WAS OAs. Essentially, this allows us to calculate the average pollution level across the 1 km grids covering each OA. Given that the WAS data is stratified by NUTS level 2 regions, we make point plots in Panel B of Figure 1 using the centroid of the local authority districts of all sampled OAs within the WAS. These point plots depict the nationally representative nature of the survey, showing that it covers most of the UK districts, except for the northernmost parts of Scotland (north of the Caledonian Canal), the Scottish Islands, and the Isles of Scilly.

As the modeled pollution data is not available at 1 km × 1 km resolution, such granular air monitoring data has been calibrated using a network[23] of around 300 Environment Agency-managed monitoring sites. The air quality monitoring process is underpinned by an external certification process (i.e., the MCERTS[24] performance standards for ambient monitoring) that embodies rigorous performance requirements, standards, and testing regimes for measuring air pollutant concentrations.[25] Thus, it is unsurprising that the high-impact analysis of pollution and meteorological

[15] https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/debt/methodologies/wealthandassetssurveyqmi
[16] See Vermeulen (2018) for a comprehensive technical description of the WAS dataset.
[17] https://www.lgcplus.com/services/health-and-care/revealed-more-than-70-areas-have-dangerous-levels-of-pm2-5-air-pollution-06-12-2019/ and https://www.centreforcities.org/reader/cities-outlook-2020/air-quality-cities/
[18] https://www.gov.uk/government/statistics/emissions-of-air-pollutants/emissions-of-air-pollutants-in-the-uk-particulate-matter-pm10-and-pm25
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[23] https://uk-air.defra.gov.uk/networks/
[24] https://www.gov.uk/government/publications/mcerts-performance-standards-for-ambient-monitoring-equipment/mcerts-performance-standards-for-ambient-monitoring-equipment
[25] https://uk-air.defra.gov.uk/networks/monitoring-methods?view=PM-Environment-Act-MonitoringMethods

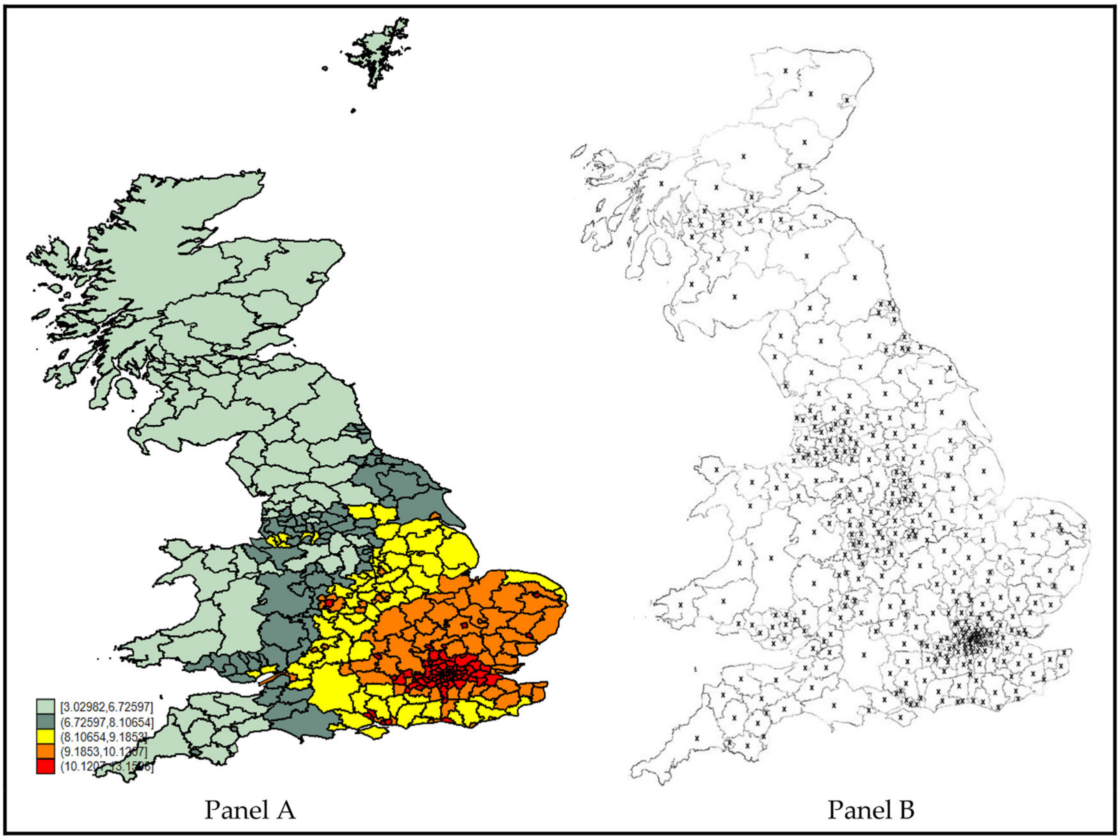

FIGURE 1 Spatial concentration of $PM_{2.5}$ and Wealth and Assets Survey (WAS) areas in 2018. *Notes*: Panel A shows the annual average $PM_{2.5}$ (μg m^{-3}) across 1 km × 1 km grids, aggregated to the official local United Kingdom (UK) district levels and plotted in different colors as presented by the legend. Panel B contains small point plots that are WAS survey areas at the district level.

conditions are increasingly relying on these high-resolution data (Adhvaryu et al., 2019; Bruederle & Hodler, 2019; Harari & Ferrara, 2018; Pinchbeck et al., 2023).[26]

Our final data is an unbalanced panel dataset containing observations spanning 12,196 individuals during the 6 time periods/waves covering 2006–2018. Therefore, our unit of analysis is at the individual × wave level. The above sample results from our data matching exercise across the air quality data and WAS. We particularly note an important sampling limitation of the WAS survey. Unlike some financial and wealth surveys, it suffers from low response rates and some households provide incomplete responses (see Alvaredo et al., 2016; Mumtaz & Theophilopoulou, 2020). Further, our sample size was reduced by instances where we dropped some households due to the lack of location information which prevented us from mapping and deriving their pollution risk measures.

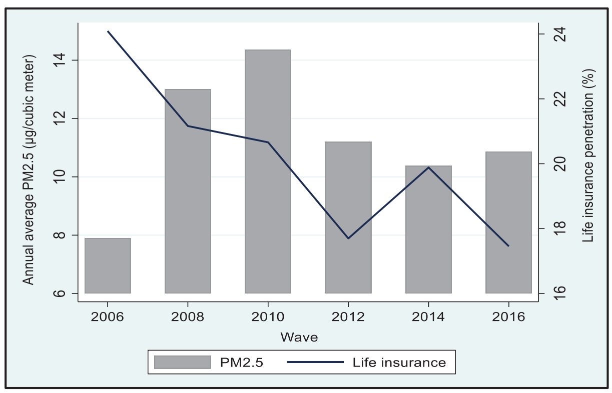

FIGURE 2 Trends in $PM_{2.5}$ concentration and life insurance decisions.

4.2 | Trends and descriptive statistics

Figure 2 displays the overall trend in the average annual concentration of $PM_{2.5}$ and life insurance adoption during our study period. Between 2006 and 2010, the average $PM_{2.5}$ pollution rose by more than 80%, from 7.9 to 14.36 μg m^{-3}. By 2012, the average pollution level spiked by around 22% relative to 2011, stabilizing around 10–11 μg m^{-3} mark. The declining overall trend in $PM_{2.5}$ concentration is due to the significant decrease in coal burning and the higher emission standards for primary sources of particulate matter, such as

[26] We thank an anonymous referee for their guidance on this issue.

TABLE 1 Descriptive statistics.

	Mean	Std. Dev.
Life insurance policy face value (£)	13,686.77	66,939.25
Has a life insurance policy (dummy = 1)	0.129	0.335
Other insurance policies (£)	2656.582	17,970.13
British citizen (dummy = 1)	0.629	0.483
Age (years)	55.90	14.73
Male (dummy = 1)	0.475	0.499
Married (dummy = 1)	0.658	0.474
Degree (dummy = 1)	0.274	0.446
Employed (dummy = 1)	0.434	0.496
Islam (dummy = 1)	0.014	0.115
White (dummy = 1)	0.885	0.319
Household size (persons)	2.151	1.130
Real income (£)	12,976.77	22,537.22
$PM_{2.5}$ (μg m^{-3})	11.630	9.617
Nitrogen oxide (μg m^{-3})	27.848	29.712
Wind speed (miles per second)	5.101	1.307
Precipitation (mm)	1440.87	488.73
Observations	33,454	33,454

industrial processes and transport sectors.[27] Meanwhile, we observe a generally declining trend in adopting life insurance policies within our sample. The adoption rate fell from about 24% in 2006 to 17% in the 2016–2018 wave. The trend in life insurance penetration seems consistent with the overall demand trends in the global and UK life insurance market (McKinsey & Company, 2017). A report by the Association of British Insurers (2019) showed that the UK notably experienced negative growth in the life insurance business due to economic uncertainties and a declining number of firms with authorizations to underwrite insurance risks during our study period.

Table 1 presents the definitions of the variables and their descriptive statistics for our unbalanced panel dataset. The descriptive statistics presented in Table 1 suggest nearly half (48%) of the sample are male, approximately two thirds are married (66%) and British (63%). Twenty-seven percent of the individuals in the sample have a higher degree or above, 43% are employed, and 88% are white. On average, two individuals live in a household with an average health score of 4 and an average age of 56.

In terms of our dependent variables, we note that life insurance ownership is a dummy variable, with a mean of 0.13 over the entire data sampling period. The mean value suggests an average life insurance penetration of 13%, which is higher than most comparable economies, such as the United States, France, and Germany (see Organisation for Economic Cooperation and Development, 2022). However, Figure 2 shows our sample's rapid decline in life insurance ownership. For the insurance face value variable, we deflate the nominal face values of the insurance policies by applying the UK consumer price index. The inflation-adjusted insurance values yield a mean of £13,686.77, which is 1.05 times the average income within the data sample. Turning to the pollution data, we find a sample mean value of 11.63 μg m^{-3} which is bounded by the less stringent annual EU limit[28] of 25 μg m^{-3} and the more stringent WHO limit[29] of 5 μg m^{-3}.

4.3 | Instrumental variables

Our empirical analysis aims to estimate the causal effect of pollution risk on life insurance ownership. However, traditional estimators such as probit and ordinary least squares (OLS) cannot identify the causal impact of exposure to pollution risk on insurance decisions. The reason is twofold. First, pollution risk is possibly a choice variable arising from individual residential location decisions. Such residential choices potentially cause endogeneity issues due to selection bias. Second, there may be unobserved characteristics that drive both insurance and location decisions. For instance, household location decisions may be driven by unobservable family considerations (e.g., care responsibilities and proximity to certain social services such as hospitals), which may also influence insurance decisions. Thus, simultaneity or omitted-variable bias may be present, causing some components of the error term to be correlated with local air pollution.

Thus, our identification strategy must address the possible endogeneity of residential decisions by instrumenting the pollution variable. Selected instruments variables (IVs) have to satisfy two crucial assumptions: (i) that a significant first-stage relationship exists between the IVs and local pollution levels and (ii) that the IVs are random such that they only impact life insurance decisions only through their effect on local pollution risk, that is, there is no correlation between IVs and the error term.

As a result, we instrument for pollution by exploiting the exogenous contribution of atmospheric conditions to the local concentration of pollutants and air quality. Specifically, we employ average wind speed and rainfall as instruments for local pollution levels. In principle, another potentially relevant instrument is inversion temperature pertaining to rising temperature with location height. However, the lack of suitable information on inversion temperature at granular the geographical level employed in this study means that we are unable to call on this IV.

Given that our local pollution variable is computed at the granular 1 km × 1 km grid level, our instruments should reflect this microgeographic level of the pollution variable. As a result, we can exploit the annual HadUK-Grid data from the UK Met Office, which provides 1 km × 1 km modeled

[27] See the national statistics of the Department for Environmental and Rural Affairs (DEFRA, 2022).

[28] https://ec.europa.eu/environment/air/quality/standards.htm

[29] https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health.

climatic data across UK land surfaces using data from meteorological stations (Met Office et al., 2021). Using raw data from the HadUK-Grid database provided by the Centre for Environmental Data Analysis,[30] we compute annual average wind speed (mile per second: m s^{-1}) and precipitation amount (mm) at the 1 km grid level. As with the pollution variable, the modeled meteorological instrumental variables have been calibrated in a similar way to the pollution variables.

Our identifying assumption draws on a robust body of meteorological and geophysical literature, which shows that atmospheric diffusion conditions shape pollution concentration. These conditions include horizontal atmospheric transport (surface wind speed) and wet deposition (precipitation) (Horton et al., 2014; Wang et al., 2016). Thus, the principal determinants of the spatial diffusion of pollutants are the physical processes (e.g., wind velocity and direction) that cause pollution to be dispersed or become more concentrated (see Perman et al., 2011).

Given the above meteorological assumption, the empirical economic literature on pollution dispersion often exploits these physical climatic properties to identify the effects of local pollution conditions (Chen et al., 2020; Herrnstadt et al., 2021; Schlenker & Walker, 2016). Regarding the identifying assumption (i), the above literature documents that these climatic variables are strongly correlated with pollution levels. Given that both the pollution and weather data are captured at the 1 km-by-1 km resolution, along with the above empirical evidence, we expect that the meteorological instruments drive the pollution predictions. We assess this assumption using OLS in the first stage by checking either the statistical significance or explanatory power of the relationship between the IVs and pollution risk. Turning to assumption (ii), our identifying intuition is that the physical processes embodied in our climatic IVs are exogenously determined by nature. This argument would suggest that assumption (ii) seems to be satisfied as households cannot affect the atmospheric conditions of their location. Hence, the IVs should not directly affect life insurance decisions except through their impact on the local pollution risk variable. We, however, note that it is almost impossible to confirm with certainty that our exclusion restrictions hold, considering the potential violation arising from households who may choose to reside in a geographic location due to weather considerations.

Yet, we think that the exclusion restrictions are likely to hold. Even if a household makes location decisions based on weather considerations, the heterogeneity in the IVs at the microgeographic level makes it quite unlikely such weather considerations are boiled down to the grid level. In essence, the sort of variation that we are exploiting for the instrument is at a very fine-grained level, at which variation in weather conditions should not drive household location decisions. This approach is a crucial benefit of our microgeographic identification strategy (see Herrnstadt et al., 2021). Moreover, because we have more IVs than our single endogenous variable, we can at least implement an overidentification test to establish whether the additional instrument is valid.[31]

4.4 | Analytical framework

Figure 3 presents our analytical framework detailing our causal method for identifying the effect of pollution exposure on insurance demand. The empirical framework relies on survey, and pollution as well as weather conditions as data inputs. The survey data is based on information taken from the UK WAS, whereas the pollution information is based on modeled air quality data produced by the DEFRA. Both datasets yield a final database used for conducting our econometric analysis (path 1).

In the econometric component of the framework, we depict the two-stage endogeneity-correction in which we use modeled meteorological variables (wind speed and precipitation) as exogenous instruments to address the endogeneity of the pollution variable (path 2). The relationship between the endogenous pollution variable and the outcome variable (i.e., insurance demand) is captured by the parameter estimate β that measures the direct or causal effect of pollution risk exposure on insurance demand, as depicted by path 3. The bottom arc running from pollution risk to insurance demand portrays the residuals from the first-stage regression of pollution and weather conditions and control variables. Path 3 (the stage-two regression) shows the direct effect of pollution risk on insurance demand, independent of the correlation (*corr*) between the residuals for pollution (u), and the insurance outcome variable (v). The pollution effect is identified by the presence of the weather IVs that are assumed to influence the insurance adoption decision exclusively via its effect on the pollution variable (path 2).

4.5 | Econometric model

The dependent variable that captures an individual's behavior with respect to life insurance demand is nonnegative and characterized by a mass point at zero (78.76% of individuals in the sample do not have life insurance). It also has a long tail on the right-hand side. Such excess zeros are due to "corner-solutions" (Silva et al., 2015), as individuals tend to dismiss low-probability risks. The observed zeros combine two types of individuals: those who would not hold a life insurance policy regardless of the policy price and those who would consider buying a life insurance policy if prices were different. Given these data features, linear estimators such as OLS and 2SLS models are unsuitable for analyzing restricted data (corner solutions) with excess zeros. In essence, our modeling

[30] https://catalogue.ceda.ac.uk/uuid/786b3ce6be54468496a3e11ce2f2669c

[31] Although Hansen-J test cannot be estimated when control function approach is used, 2SLS model is run instead to test the relevance and validity of the selected instruments. Hansen-J test p-value = 0.2664 and statistically significant F-test (96.92, p-value = 0.000) support validity and relevance of the selected instruments, respectively. See Appendix D.

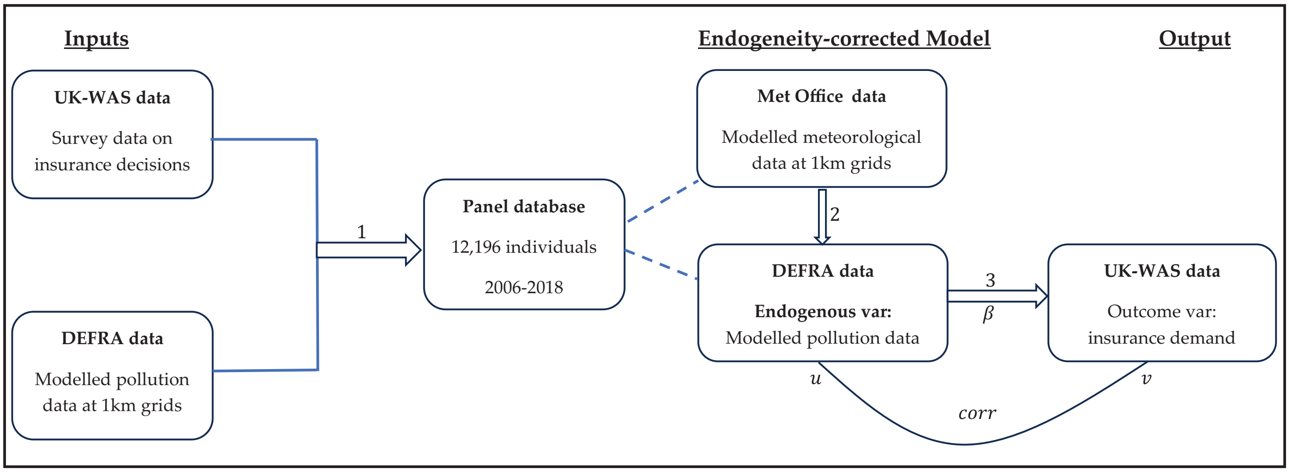

FIGURE 3 Analysis framework.

technique must take cognizance of the above data complications and potential bias arising from using linear models (see King, 1988; Wooldridge, 2010; Silva & Tenreyro, 2006, 2011; Gillingham & Tsvetanov, 2019).

Consequently, we employ a zero-inflated negative binomial (ZINB) model to handle the right-skewed insurance data with a large proportion of zeros. The details of the ZINB model are given in Appendix B. As the negative binomial overdispersion parameter is larger than one, the negative binomial variance is greater than its mean. By implication, this can be either a consequence of unobserved heterogeneity or excess zeros. However, we note that the ZINB model does not have an analog of the 2SLS that jointly estimates the first and second-stage regressions. Hence, we employ the control function (CF) technique which is also a well-known approach in the literature[32] for addressing endogeneity in nontraditional data settings, as in this study. Under the CF approach, we first obtain the first-stage residuals by regressing the endogenous pollution variable on the instrumental variables and other control variables. The residuals are then included as a regressor in the second stage regression of insurance demand on pollution.

As we observe individuals over multiple periods, we control for the panel data structure by clustering the data at the individual level. We also address the potential endogeneity of pollution by employing a CF approach. To this end, we use wind speed and precipitation as instruments for air pollution. For comparison, we also check the overall consistency of our results by estimating a two-part model that treats the dependent variable as continuous.

Additionally, when the outcome variable is nonnegative and skewed with a mass point at zero, two-part and Tobit models have also been employed in the literature. The Tobit model allows only one type of zero observation (potential participants) and excludes decision-makers who would never participate irrespective of the circumstances (Engel & Moffatt, 2014); for example, some individuals would not buy life insurance regardless of price. The major drawback of the Tobit model is that the probability of a positive outcome and the value of the outcome are driven by the same vector of parameters (Burke, 2009).

On the other hand, two-part models assume that different mechanisms with different densities generate zeros and positive observations. Hence, the censoring mechanism is modeled by a binary estimator and the continuous part by OLS or generalized linear model (GLM). In comparison to two-part models, the negative binomial estimator is remarkably robust to violations in variance assumption as long as the data is overdispersed (Gould, 2011). Nonetheless, we also estimate a two-part model for comparison and robustness checks. The details of the two-part model are given in Appendix C.

5 | FINDINGS AND DISCUSSION

5.1 | Baseline results

Table 2 presents the estimation results from the ZINB model, where columns 1 and 2 contain the estimates for the exogenous specification where we ignore the endogeneity of the pollution variable. However, in columns 3 and 4, we address the endogeneity of air pollution.

In the ZINB model, we can separate the effect of air pollution on the probability of buying life insurance policies (i.e., the binary component) from the value of the policies (i.e., the continuous component). Focusing on the endogeneity-adjusted model, we note the statistical significance of the first-stage residuals in the continuous part, suggesting the presence of endogeneity within the model. The larger coefficient magnitudes of the endogenous model compared to the exogenous specification further underscore the potential endogeneity problem. We also note that the first-stage regression yields statistically significant coefficients on wind speed

[32] For a technical treatment of the CF approach, see Imbens and Wooldridge (2007) and Wooldridge (2010, 2015). For empirical applications, see Aghion et al. (2009), Gillingham and Tsvetanov (2019), Kieschnick and Moussawi (2018).

TABLE 2 The impact of pollution on life insurance decisions-zero-inflated negative binomial (ZINB).

	Exogenous model		Endogenous model	
	Binary	Continuous	Binary	Continuous
	(1)	(2)	(3)	(4)
$PM_{2.5}$	−0.018	−0.090***	−0.015	−0.215***
	(0.011)	(0.016)	(0.027)	(0.036)
$(PM_{2.5})^2$	0.001*	0.002***	0.001*	0.002***
	(0.000)	(0.001)	(0.000)	(0.000)
$(PM_{2.5})^3$	−0.000	−0.000***	−0.000	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
British	0.095***	−0.029	0.131***	−0.153***
	(0.036)	(0.044)	(0.046)	(0.053)
Age	0.018***	−0.0432***	0.022***	−0.061***
	(0.002)	(0.004)	(0.004)	(0.006)
Male	−0.118**	0.297***	−0.141***	0.382***
	(0.050)	(0.066)	(0.054)	(0.066)
Married	−0.571***	0.050	−0.479***	−0.297***
	(0.059)	(0.069)	(0.092)	(0.110)
Degree	−0.152***	0.480***	−0.112*	0.322***
	(0.051)	(0.070)	(0.061)	(0.078)
Employed	0.256**	0.024	0.230**	0.137
	(0.101)	(0.157)	(0.102)	(0.161)
Islam	0.990***	−0.348	0.832**	0.250
	(0.316)	(0.245)	(0.335)	(0.284)
White	0.044	−0.107	0.142	−0.517***
	(0.082)	(0.090)	(0.113)	(0.137)
hh/d size	−0.147***	0.176***	−0.223***	0.474***
	(0.020)	(0.022)	(0.062)	(0.075)
Health	−0.067**	0.154***	−0.049	0.082*
	(0.028)	(0.039)	(0.032)	(0.043)
Income	−0.058***	0.018	−0.058***	0.018
	(0.010)	(0.014)	(0.010)	(0.014)
Other policies	−0.156***	0.003	−0.152***	−0.014*
	(0.006)	(0.006)	(0.006)	(0.007)
First-stage residual			−0.034	0.131***
			(0.026)	(0.033)
Constant	2.399***	5.8363***	1.675***	8.587***
	(0.225)	(0.3461)	(0.611)	(0.804)
N	33,454	33,454	33,454	33,454

Notes: The ZINB model is applied, where the binary process is estimated by the logit model, whereas the continuous part has a negative binomial distribution. We control for our panel data structure by clustering the data at the individual level. Standard errors in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

and wet conditions at the 1% level (see Table D1 in Appendix D). The F-test statistic of 96.92 far exceeds the suggested critical value of 10, whereas the Hansen test p-value of 0.26 indicates that the over-identifying restrictions are valid.

TABLE 3 Joint significance tests.

	ZINB	
	χ^2	p-Value
$PM_{2.5}$	38.11***	0.0000
$(PM_{2.5})^2$	21.80***	0.0000
$(PM_{2.5})^3$	19.55***	0.0001

Notes: As the p-value is less than the significance level of 0.05, we can conclude that $PM_{2.5}$, $(PM_{2.5})^2$, and $(PM_{2.5})^3$ are jointly statistically significant for the two parts of the model.
Abbreviation: ZINB, zero-inflated negative binomial.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The binary parts of both models (columns 1 and 3) indicate weak statistical significance or a lack of it for the effect of $PM_{2.5}$ on the probability of taking out life insurance.[33] However, for the continuous part, the effect of pollution risk is statistically significant at the 1%-level both in the exogenous and endogenous models. Notably, we observe an alternating sign pattern on the level, squared and cube terms of particulate matter, indicating an inverted N-shaped relationship between the value of life insurance policies and pollution.

Given the mixed picture of the statistical significance of air pollution within the two model components, we test for the joint significance across both model components, as presented in Table 3. The test indicates that pollution, its squared, and cubed terms are jointly statistically significant across the two parts of the model, that is, overall, pollution matters for life insurance decisions. We argue that the relationship between local pollution risk and life insurance decisions is nonlinear. This finding chimes with the ambiguous relationship between the probability of death and life insurance demand, as suggested by the broad insurance demand literature (Levy et al., 1988; Lewis, 1989; Outreville, 1996).

Using theory and empirics, we have jointly explored the negative and positive dynamics in the pollution-insurance nexus within a single analytical framework. This approach allows us to show—for the first time—that the relationship between pollution and insurance demand depends on the threshold of pollution concentration. More formally, over a given range above a threshold of exposure, rising pollution magnifies the death probability and is associated with rising demand for life insurance, whereas at lower than the threshold levels of pollution, higher exposure risk reduces demand for insurance. The revealed pattern aligns with the theoretical model's prediction of the nonlinear relationship and is also consistent with medical research[34] that relaxes the assumption of linearity in the relationship between pollution and health outcomes.[35]

Figure 4 provides a diagrammatic depiction of our main empirical finding. Specifically, we plot the predicted average values of insurance coverage from our model against $PM_{2.5}$ across different pollution thresholds. The plot shows

[33] This finding, coupled with the fact that the majority of individuals do not possess life insurance, could be explained by individual's errors in the assessment of life expectancy,

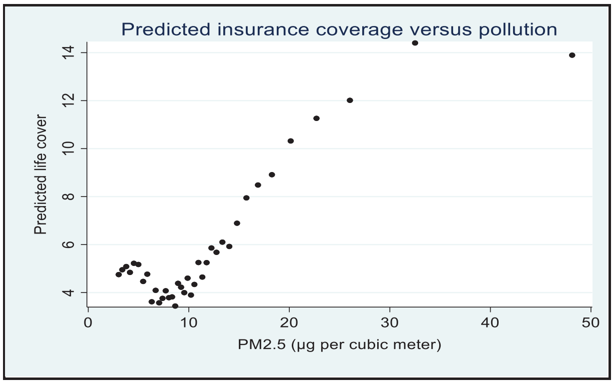

FIGURE 4 Predicted life insurance coverage across $PM_{2.5}$ concentration levels.

that an increase in pollution initially decreases the value and probability of life insurance policy coverage. However, over a certain higher threshold ranging from 10 to 30 μg m^{-3}, the predicted values on the insurance coverage increase, conversely decreasing over the higher threshold. Interestingly, given the WHO's recommended annual $PM_{2.5}$ limit of 10 μg m^{-3}, the plot from our estimated model suggests that individuals exceeding this pollution limit are more likely to purchase a life insurance policy. Beyond the 30 μg m^{-3} threshold insurance demand falls at a much slower rate relative to the initial fall. This inverse N-shape relationship could be supported by studies that show a bimodal response to low-probability risks where either subjects significantly overweight the probability and have a high willingness-to-pay for insurance, or under-weight the probability and consider insurance as unnecessary (Robinson & Botzen, 2019). The latter response may offer an explanation for our finding where initially there is a drop in insurance demand for low-probability risks. As pollution risk increases (above 10 μg m^{-3}), individuals may be able to form a subjective estimate of the true risk probability by using some anchor probability (e.g., an expert guess or publicly available information from reputable institutions such as the WHO's recommended annual limit of 10 μg m^{-3} for $PM_{2.5}$ exposure). Thus, individuals are able to decipher the increased pollution risk and hence demand more insurance.

Furthermore, the empirical results in Table 2 support the altruistic bequest motive as the marginal effects on household size and marital status are positively associated with the probability of taking out life insurance. These findings align with the theoretical model's prediction of the positive impact of the bequest parameter β on the demand for life insurance and are consistent with the notion that life insurance acts as a hedge against mortality risk (Chen et al., 2006). They also

TABLE 4 Results for zero-inflated negative binomial (ZINB) model with interaction terms.

	Coeff. (*p*-value)
$PM_{2.5}$	0.040
	(0.029)
$PM_{2.5} \times married$	−0.016***
	(0.005)
$PM_{2.5} \times income$	−0.000***
	(0.000)
$PM_{2.5} \times other\ policies$	−0.000**
	(0.000)
$PM_{2.5} \times\ health$	0.001
	(0.003)
$PM_{2.5} \times degree$	0.009*
N	33,454

Notes: The same control variables are included as in the main model presented in Table 2. Due to the inclusion of interaction terms, squared and cubed terms of $PM_{2.5}$ are removed from the specification. Standard errors in parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

reflect the implicit uncertainty derived from the wage earners' preretirement death and the associated loss of labor income to the surviving dependents of the household (Campbell, 1980).

Moreover, age is negatively associated with the probability and size of life insurance premiums, as the proportion of insured capital decreases with age (Campbell, 1980). We also find a positive association between income and the probability of taking out life insurance. This finding supports the lifetime consumer allocation theory (Yaari, 1964, 1965), whereby individuals maximize lifetime consumption and bequest upon death. Furthermore, older adults control more financial resources, which might become more complex in the context of age-related decline in cognitive ability (Agarwal et al., 2009).

Possessing a higher degree is positively associated with the probability of taking out life insurance and the insurance premium size, supporting previous findings (Kumar, 2019). Education could also indicate that individuals are more aware of pollution health risks and the availability of various life insurance products. We also find a positive and statistically significant relationship between the possession of other insurance products (a proxy for risk aversion) and the probability of taking out life insurance. The positive relationship indicates that more risk-averse individuals are more likely to take out life insurance.

5.2 | Exploring the channels of impact

Next, we aim to understand better if the pollution-life insurance relationship manifests via different channels. In Table 4, the interaction terms between $PM_{2.5}$ and three variables (i.e., marital status, income, and taking out other insurance products) are negative and statistically significant. The interaction

a strong preference for the present the lack of insurance literacy (Corcos et al., 2020) and time-inconsistent behavior due to its dynamic nature (Tang et al., 2018).

[34] For instance, Schwartz et al. (2001); Zoeller and Vandenberg (2015).

[35] Such health studies have assessed the relationship between pollution and health outcomes, with the majority of nonlinear functions being modeled using cubic splines, where the estimated curve is restricted to be smooth (three times differentiable) with no constraint on the shape (e.g., Powell et al., 2012).

TABLE 5 Estimation results for the two-part model.

	Binary	Continuous
$PM_{2.5}$	−0.024	−0.208***
	(0.027)	(0.035)
$(PM_{2.5})^2$	−0.001	0.002***
	(0.000)	(0.000)
$(PM_{2.5})^3$	0.000	−0.000***
	(0.000)	(0.000)
All controls	Yes	Yes
N	33,454	33,454

Notes: The binary part is modeled using the logit regression, whereas the continuous part is modeled using GLM with the log link and gamma distribution. We control for the panel data structure by clustering the data at the individual level. Standard errors in parentheses.
Abbreviation: GLM, generalized linear model.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

terms with health status and education lack statistical significance. More specifically, $PM_{2.5}$ is positively[36] associated with the probability of taking out life insurance for individuals with higher income, as they possess more resources to buy life insurance coverage; individuals who are married, as married individuals are more likely to have an incentive to protect their partner's income; and those who have other insurance policies, as the possession of other insurance covers might indicate higher risk aversion and, therefore, more willingness to extend such protection across different domains.

5.3 | Alternative estimator

Next, we present the estimation results from an alternative, two-part model estimator. In this specification, the binary component is modeled with the logit estimator, whereas the continuous part is modeled using GLM (i.e., the log link and gamma distributions) (see Table 5). For brevity, we do not report the estimation results on the control variables and only present results for pollution terms. The estimation results mirror the direction and statistical significance of the ZINB model, supporting the nonlinear inverse N-shape relationship between $PM_{2.5}$ and the size of the life insurance premium.

Given the differences in the estimators employed to accommodate the nature of the dependent variable, the magnitudes of estimated coefficients are not comparable across the two models. To aid comparison, we present the joint marginal effects of pollution across the ZINB and two-part models in Table 6. The estimates show that the statistical significance and direction of the estimated coefficients and the magnitudes of the joint marginal effects for ZINB and two-part models are very similar. Thus, our overarching finding of an inverse N-shaped relationship between pollution and life insurance holds.

[36] In the binary part, we are modeling the probability of zero, which means that we need to interpret the signs in the opposite way.

TABLE 6 Joint marginal effects for the zero-inflated negative binomial (ZINB) and generalized linear model (GLM) models.

	ZINB model		Two-part model	
	MA	*t*-Stats	MA	*t*-Stats
$PM_{2.5}$	−3.2586***	−5.37	−3.2378***	−5.20
$(PM_{2.5})^2$	0.0242***	3.05	0.0242***	3.04
$(PM_{2.5})^3$	−0.0002***	−2.91	−0.0002***	−2.96
All controls	Yes	Yes	Yes	Yes

Notes: The marginal effects capture the joint effects of $PM_{2.5}$, $(PM_{2.5})^2$, and $(PM_{2.5})^3$ across the two parts of each model.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 7 Estimation results for the zero-inflated negative binomial (ZINB) and two-part models.

	ZINB		Two-part	
	Binary	Continuous	Binary	Continuous
NO_2	0.005	−0.047***	−0.007	−0.045***
	(0.005)	(0.008)	(0.005)	(0.007)
$(NO_2)^2$	0.000	0.000***	−0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$(NO_2)^3$	−0.000	−0.000***	0.000	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
All controls	Yes	Yes	Yes	Yes
N	33,454	33,454	33,454	33,454

Notes: Standard errors in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.4 | Alternative pollutant

We conduct further robustness tests to check the sensitivity of our results to variations in pollution type. To do this, we study the effects of the UK's second most concerning pollutant, nitrogen dioxide (NO_2) on the purchase of life insurance (DEFRA, 2017). Table 7 presents the NO_2 results across the ZINB and two-part models. Similar to our baseline $PM_{2.5}$ results, we confirm the inverse N-shape relationship between pollution and life insurance decisions, albeit with a lack of statistical significance in the binary part.

5.5 | Accounting for regional effects

Finally, there might be concerns that our empirical work fails to account for regional effects adequately. Although we have attempted to control for the different sources of endogeneity (e.g., residential selection bias) in the estimation process, we carry out further robustness checks to inform whether regional shocks or characteristics may alter our findings. For instance, areas with better air quality might have higher house prices. At the same time, houses in urban areas, where pollution tends to be higher, may also have higher property prices. Concurrently, local house valuations may predict insurance adoption decisions and policy values. Hence, we introduce

TABLE 8 Estimation results for the zero-inflated negative binomial (ZINB) and two-part models including house prices.

	ZINB		Two-part	
	Binary	**Continuous**	**Binary**	**Continuous**
Ln(house price)	−0.068	0.393***	0.082*	0.383***
	(0.046)	(0.061)	(0.045)	(0.060)
$PM_{2.5}$	0.009	−0.163***	−0.015	−0.158***
	(0.028)	(0.033)	(0.027)	(0.032)
$(PM_{2.5})^2$	0.001*	0.002***	−0.001*	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
$(PM_{2.5})^3$	−0.000	−0.000***	0.000	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
All controls	Yes	Yes	Yes	Yes
N	33,454	33,454	33,454	33,454

Notes: Standard errors in parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

the real values of local house prices (£) into our estimations. Ideally, capturing these house price dynamics at our OA level of geographic aggregation is preferable. However, the lack of house price data at the OA level means that we resort to the available information at a higher level of geographical aggregation (i.e., the ONS data on Median house prices by lower layer super output area [LSOA]).[37] Table 8 presents the results from this extended regional analysis for the ZINB and two-part models. In addition to the house price variable being statistically significant for both estimators, the inverse N-shape relationship between pollution and life insurance decisions holds for both estimators.

Further robustness checks are carried out by including the year and regional dummies in the ZINB and a two-part model for both pollutants, namely, $PM_{2.5}$ and NO_2. The estimation results presented in Appendix E show that the inverse N-shape relationship between pollution and life insurance decisions remains for both estimators.

6 | CONCLUSIONS

It is widely acknowledged that air pollution can have devastating health, economic, and behavioral consequences. In this article, we examine how local exposure to pollution affects the demand for life insurance. More specifically, we extend the emerging literature by testing a new hypothesis that suggests a nonlinear relationship between pollution risk and the demand for life insurance coverage. To empirically test this hypothesis, we create a unique dataset by linking microgeographic information on air quality data to a confidential UK individual-level survey from 2006 to 2018. By employing ZINB and two-part models, our estimates account for the skew of the life insurance variable with a mass point at zero.

[37] While an OA typically contains around 100 households, LSOAs could contain from 400 to 1200 households.

Additionally, as we also control for the self-selection bias arising from individuals' choices regarding their residential locations, we interpret our results as the causal effect of the air pollution risk on life insurance decisions. Our main finding is that over a given range above a threshold of exposure, rising pollution magnifies the death probability and is associated with rising demand for life insurance, whereas at lower than the threshold levels of pollution, higher exposure risk reduces demand for insurance. This result suggests that, at very high levels of pollution exposure, the demand for life insurance increases as exposure rises, whereas, for low levels of exposure, the insurance demand reduces.

This assessment of the pollution-life insurance relationship offers three implications for research, practice, and policy. First, our estimated results support the notion that the effect of pollution risk on life insurance demand follows a nonlinear pattern. Therefore, our analysis advocates a research approach that jointly explores the negative and positive dynamics in the pollution-insurance nexus within a single analytical framework. Second, insurance practitioners have a growing consensus[38] that air pollution is an emerging risk factor for life insurance decisions as long-term exposure to pollution drives mortality. Our study constitutes an additional step toward an evidence base that informs practitioners about the different behavioral responses to air pollution that may shape future development and refinement of new pollution-related insurance products.

Finally, it has never been more critical for public policy drive to engender accountability regarding pollution-related risks across financial markets.[39] It seems vital for policymakers to understand better how local pollution sufferers respond to pollution risk. For instance, we note that the nonlinear effect documented in this study is not the entirety of the behavioral mechanisms that may drive the pollution-insurance demand relationship. As microgeographic household datasets become more abundant, we expect future research to explore the role of additional behavioral mechanisms such as individual avoidance behaviors. We also anticipate that researchers will further exploit questions on how regulatory interventions could draw up compensation mechanisms that transfer payments from polluters to sufferers.[40]

6.1 | Disclaimer

This work contains statistical data from ONS, which is crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation

[38] For instance, see https://www.partnerre.com/opinions_research/poor-air-quality-an-emerging-risk-factor-for-life-insurance-underwriting-and-pricing/
[39] For instance, see https://www.bankofengland.co.uk/-/media/boe/files/prudential-regulation/publication/impact-of-climate-change-on-the-uk-insurance-sector.pdf
[40] This compensation idea is theoretically well established in economics under the "Coase theorem" (Coase, 1960).

or analysis of the statistical data. This work uses research datasets, which may not exactly reproduce National Statistics aggregates.

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CONFLICT OF INTEREST STATEMENT

We declare that we have no financial, commercial, legal, or professional relationship with other organizations, or with the people working with them, that may have influenced our research.

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APPENDIX A: COMPARATIVE STATICS

Second derivative of $EU\ (I)$ with respect to I

$$\frac{\partial^2 EU\ (I)}{\partial I^2} = -\frac{\begin{array}{c}(1-ap(\lambda))(C_1 - ap(\lambda) I - L)\\ -[(C_0 + I - ap(\lambda) I - L)(-ap(\lambda))\end{array}}{(C_1 - ap(\lambda) I - L)^2} < 0.$$

Effect of C_1 on I^*

$$\frac{\partial I^*}{\partial C_1} = \frac{A^{1/\gamma}}{1 - ap(\lambda)\left(1 - A^{1/\gamma}\right)} > 0.$$

Effect of C_0 on I^*

$$\frac{\partial I^*}{\partial C_0} = \frac{-1}{1 - ap(\lambda)\left(1 - A^{1/\gamma}\right)} < 0.$$

Effect of β on I^*:

denoting $A^{\frac{1}{\gamma}} = k$

$$\frac{\partial I^*}{\partial \beta} = \frac{\partial I^*}{\partial k}\frac{\partial \mathrm{k}}{\partial \beta},$$

where

$$\frac{\partial I^*}{\partial k} = \frac{\begin{array}{c}1 - ap(\lambda)(1-\mathrm{k})(C_1 - L)\\ -[k((C_1 - L) - C_0 + L)\, ap(\lambda)\end{array}}{1 - ap(\lambda)(1-\mathrm{k})},$$

if $L \le C_0$ then $\frac{\partial I^*}{\partial k} > 0$

and

$$\frac{\partial k}{\partial \beta} = \frac{1}{\gamma}\frac{\beta(1-ap(\lambda))}{a(1-p(\lambda))}^{\frac{1}{\gamma}}\frac{(1-ap(\lambda))}{a(1-p(\lambda))} > 0.$$

Hence,

$$\frac{\partial I^*}{\partial \beta} > 0.$$

PROSPECT THEORY APPROACH

Although we follow an expected utility approach, we can make some remarks regarding using a prospect theory approach with its two prominent features, probability weighting and loss aversion (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992).

In this case, the objective probabilities $p(\lambda)$ and $1 - p(\lambda)$ are replaced by subjective decision weights $\pi(p(\lambda))$ and $\pi(1 - p(\lambda))$, respectively,[41] which can be computed with the help of a weighting function whose argument is an objective probability. The utility function is replaced by a value function, $v(\cdot)$, that is defined over changes in wealth rather than final asset position.

Empirical applications of PT often employ the following functional form of the value function where x_i indicate possible consequences:

$$v(x) = \begin{cases} x^\sigma \text{ if } x \ge 0 \\ -\varphi(-x^\sigma) \text{ if } x < 0 \end{cases}.$$

This value function exhibits diminishing sensitivity for $\sigma < 1$ and loss aversion for $\varphi > 1$.

Hence under PT, Equation (1) can be written as

$$\pi(p(\lambda))\ \beta\ v(I - prem) + \pi(1 - p(\lambda))\ v\ (-prem)$$

Using the functional form of the value function $v(x)$ above, the FOC for the insurance demand I now reads

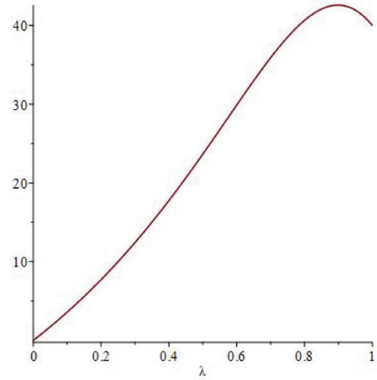
$$\pi\ (p(\lambda))\beta\ \sigma(I - (ap(\lambda) I + L))^{\sigma-1}(1 - ap(\lambda))$$
$$+\pi(1 - p(\lambda))\ \varphi\ \sigma\ (ap(\lambda) I + L)^{\sigma-1}\ \ (-ap(\lambda)) = 0.$$

Solving for I^*, gives us $I^* = (L(B\hat{}(1/\sigma - 1)+1))/(1 - ap(\lambda) - ap(\lambda)B\hat{}(1/\sigma - 1))$ for $B = (\pi(1 - p(\lambda))\varphi(ap(\lambda)))/(\beta\, \pi(p(\lambda))(1 - ap(\lambda)))$. Hence, we find that the effect of λ on the demand for insurance is still ambiguous, and hence, there is a nonlinear effect as also shown in our empirical part.

Thus, as we are interested in the effect of exposure on life insurance demand, the expected utility approach followed allows us to show this effect in a tractable manner along with highlighting the channels (comparative statics) that affect this relationship. It still shows and aligns with the case of underinsuring low-probability events with high losses which is a common in insurance and usually highlighted through prospect theory models (Friedl et al., 2014).

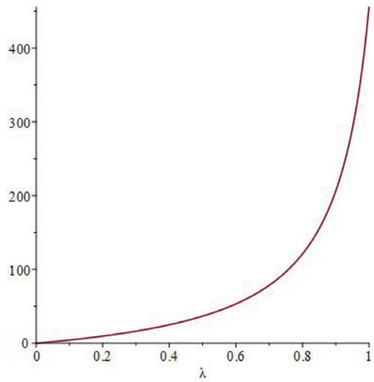
[41] We assume π is increasing in p, as in Prelec (1998) where the probability weighting function takes the form $\exp(-(-\ln(p)^{\delta}))$, $0 < \delta < 1$.

SIMULATIONS



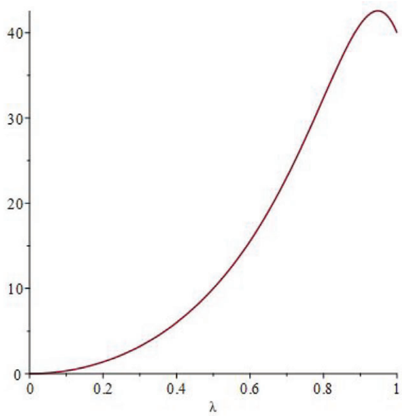
Assuming $p(\lambda) = 1 - \frac{1}{\lambda}$

$C_0 = 40, C_1 = 80, L = 0.6, \alpha = 2, \beta = 2, \gamma = 0.6$



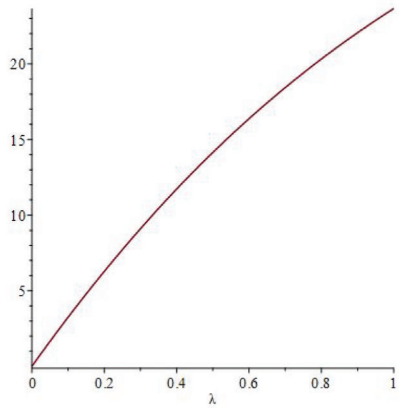
Assuming $p(\lambda) = 1 - \frac{1}{\lambda}$

$C_0 = 40, C_1 = 80, L = 0.6, \alpha = 2, \beta = 6, \gamma = 0.6$



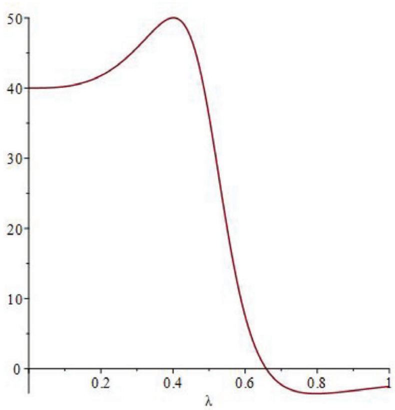
Assuming $p(\lambda) = 1 - \frac{1}{\lambda^2}$

$C_0 = 40, C_1 = 80, L = 0.6, \alpha = 2, \beta = 2, \gamma = 0.6$



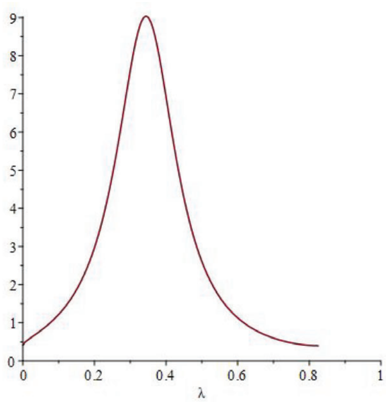
Assuming $p(\lambda) = -\frac{1}{\lambda}$

$C_0 = 40, C_1 = 80, L = 0.6, \alpha = 2, \beta = 2, \gamma = 0.6$



Assuming $p(\lambda) = \lambda^3$

$C_0 = 5, C_1 = 40, L = 25, \alpha = 6, \beta = 8, \gamma = 1$



Assuming $p(\lambda) = \sqrt{\lambda}$

$C_0 = 0.4, C_1 = 0.8, L = 0.8, \alpha = 1.1, \beta = 1.5, \gamma = 0.4$

APPENDIX B: ZERO-INFLATED NEGATIVE BINOMIAL (ZINB) MODEL

Following Greene (1994), we can specify our base model as

$$y_i \sim 0 \quad \textit{with probability} \quad q_i$$

$$y_i \sim \text{negative binomial}\,(\lambda_i, \theta) \quad \textit{with probability} \quad 1 - q_i$$

$$(y_i = 0, 1, 2, 3 \ldots)$$

where $q_i = \frac{e^{z_i\gamma}}{1+e^{z_i\gamma}}$. This splitting mechanism separates individuals into non-holders of life insurance with probability q_i and potential holders of life insurance with probability $1 - q_i$.

Then, the fully observed dependent variable y_i is generated as a product of two latent variables z_i and y_i^*:

$$y_i = z_i y_i^*, \tag{B1}$$

where z_i is a binary variable that takes the values of 0 or 1, and y_i^* is distributed as a negative binomial (λ_i, θ). Therefore,

$$\Pr(y_i = 0) = \Pr(z_i = 0) + \Pr\left(z_i = 1, y_i^* = 0\right) = q_i + (1 - q_i) f(0), \tag{B2}$$

$$\Pr(y_i = k) = (1 - q_i) f(k), \quad k = 1, 2, \ldots,$$

where $f(\cdot)$ is the negative binomial probability distribution for y_i^*. The binary part of the model (the splitting mechanism) is modeled with either binary probit or logit models. If the ZINB model is applied where the binary process is estimated by the logit model and y_i^* has a negative binomial distribution, the variance is as follows:

$$Var(y_i) = \lambda_i (1 - q_i)\left[1 + \lambda_i (q_i - \alpha)\right], \tag{B3}$$

$$\frac{Var(y_i)}{E(y_i)} = 1 + \left[\frac{q_i + \alpha}{1 - q_i}\right] E(y_i), \tag{B4}$$

This shows that the negative binomial overdispersion parameter is larger than one, indicating that the negative binomial variance is greater than its mean.

APPENDIX C: TWO-PART MODEL

Following Belotti et al. (2015), the zeros in two-part models are captured by modeling the probability of a positive outcome:

$$\phi(y > 0) = \Pr(y > 0|x) = F(x\delta), \tag{B5}$$

where x is a vector of explanatory variables, δ is the corresponding vector of parameters to be estimated, and F is a cumulative distribution function of the error term, which is typically either extreme value or normally distributed depending on whether logit or probit estimator is chosen. The continuous part of the model can then be written

$$\phi(y\,|y\rangle\,0, x) = g(x\gamma), \tag{B6}$$

where x is a vector of explanatory variables, γ is the corresponding vector of parameters to be estimated, and g is a density function for $y|y\rangle 0$.

The overall mean is then the product of expectations from both parts, where the joint distribution is decomposed into marginal and conditional distributions:

$$E(y|x) = \Pr(y > 0|x) \times E(y\,|y\rangle\,0, x), \tag{B7}$$

In this article, $\Pr(y > 0|x)$ is modeled using the logit regression, whereas $E(y|y\rangle 0, x)$ is modeled using GLM with the log link and gamma distribution:

$$E(y\,|y\rangle\,0, x) = g^{-1}(x\gamma), \tag{B8}$$

where g is the link function in the GLM. Alternatively, the continuous part of the two-part model is often modeled with OLS regression on $\ln(y)$; therefore, a retransformation of $\widehat{\ln(y)}$ to $\hat{y}$ is required. The retransformation in two-part models is based on homoscedastic and normally distributed errors. If the errors are heteroscedastic, the log-linearization of the model leads to inconsistent estimates as the transformed errors are correlated with the covariates (Silva et al., 2015). The gamma GLM with log link ensures the consistent estimation of coefficients and marginal effects.

APPENDIX D: FIRST-STAGE OLS REGRESSION OF POLLUTANT ON INSTRUMENTS

TABLE D1 First stage of 2SLS test analysis.

Dep var.: PM25	
Wind	0.633***
	(0.170)
Rain	−0.010***
	(0.000)
Constant	72.686***
	(1.386)
R-squared	0.209
All controls	Yes
F-test of excluded instruments	96.92
Hansen-*J* test (*p*-value)	0.266
Obs.	33454

Note: Standard errors in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

APPENDIX E: ESTIMATION RESULTS WITH YEAR AND REGIONAL DUMMIES

TABLE E1 Estimation results for zero-inflated negative binomial (ZINB) model with year and regional dummies.

	(1) Nitrogen	(2) Particulate matter
NO_2	−0.052***	
	(0.008)	
$(NO_2)^2$	0.000***	
	(0.000)	
$(NO_2)^3$	−0.000***	
	(0.000)	
First-stage residual	0.026***	
	(0.007)	
$PM_{2.5}$		−0.233***
		(0.037)
$(PM_{2.5})^2$		0.002***
		(0.000)
$(PM_{2.5})^3$		−0.000***
		(0.000)
First-stage residual		0.141***
		(0.034)
British	−0.016	−0.089
	(0.091)	(0.098)
Age	−0.054***	−0.066***
	(0.005)	(0.007)
Male	0.343***	0.390***
	(0.061)	(0.062)
Married	−0.151*	−0.334***
	(0.088)	(0.113)
Degree	0.394***	0.277***
	(0.069)	(0.073)
Employed	0.115	0.115
	(0.178)	(0.176)
Islam	0.433	0.433
	(0.317)	(0.293)
White	−0.456***	−0.545***
	(0.140)	(0.153)
hh/d size	0.288***	0.476***
	(0.038)	(0.074)
Health	0.086**	0.064
	(0.039)	(0.041)
Income	0.012	0.019
	(0.015)	(0.015)

(Continues)

TABLE E1 (Continued)

	(1) Nitrogen	(2) Particulate matter
Other policy	−0.008	−0.015**
	(0.006)	(0.007)
2006	0.000	0.000
	(.)	(.)
2008	0.094	0.149
	(0.108)	(0.113)
2010	0.064	0.134*
	(0.076)	(0.078)
2012	−0.120	−0.060
	(0.114)	(0.114)
2014	−0.046	0.043
	(0.226)	(0.231)
2016	−0.115	−0.039
	(0.223)	(0.229)
1. region_id	0.000	0.000
	(.)	(.)
2. region_id	−0.040	0.000
	(0.190)	(0.179)
3. region_id	0.494**	0.393**
	(0.204)	(0.195)
4. region_id	−0.478**	−0.529**
	(0.213)	(0.212)
5. region_id	−0.208	−0.337*
	(0.200)	(0.191)
6. region_id	−0.020	0.014
	(0.186)	(0.177)
7. region_id	−0.270	−0.144
	(0.200)	(0.189)
8. region_id	−0.414**	−0.347*
	(0.203)	(0.191)
9. region_id	−0.242	−0.265
	(0.196)	(0.187)
10. region_id	−0.189	−0.233
	(0.185)	(0.177)
Constant	7.490***	9.165***
	(0.576)	(0.856)
Inflate		
NO_2	0.010*	
	(0.006)	
$(NO_2)^2$	0.000	
	(0.000)	

(Continues)

TABLE E1 (Continued)

	(1) Nitrogen	(2) Particulate matter
$(NO_2)^3$	0.000	
	(0.000)	
First-stage residual	−0.008	
	(0.006)	
$PM_{2.5}$		0.037
		(0.029)
$(PM_{2.5})^2$		0.000
		(0.000)
$(PM_{2.5})^3$		−0.000
		(0.000)
First stage residual		−0.048*
		(0.028)
British	0.025	0.050
	(0.109)	(0.110)
Age	0.023***	0.026***
	(0.003)	(0.005)
Male	−0.142***	−0.156***
	(0.052)	(0.054)
Married	−0.510***	−0.452***
	(0.074)	(0.095)
Degree	−0.132**	−0.108*
	(0.054)	(0.062)
Employed	0.144	0.140
	(0.108)	(0.108)
Islam	0.667**	0.661*
	(0.340)	(0.340)
White	0.117	0.151
	(0.133)	(0.142)
hh/d size	−0.177***	−0.243***
	(0.037)	(0.066)
Health	−0.044	−0.038
	(0.031)	(0.032)
Income	−0.050***	−0.051***
	(0.010)	(0.010)
Other policy	−0.152***	−0.149***
	(0.006)	(0.007)

(Continues)

TABLE E1 (Continued)

	(1) Nitrogen	(2) Particulate matter
2006	0.000	0.000
	(.)	(.)
2008	−0.189	−0.164
	(0.115)	(0.116)
2010	−0.165***	−0.142**
	(0.058)	(0.060)
2012	0.041	0.054
	(0.072)	(0.073)
2014	−0.373**	−0.381**
	(0.179)	(0.179)
2016	−0.318*	−0.327*
	(0.176)	(0.176)
1. region_id	0.000	0.000
	(.)	(.)
2. region_id	−0.246**	−0.244**
	(0.100)	(0.101)
3. region_id	−0.038	0.037
	(0.131)	(0.127)
4. region_id	0.059	0.050
	(0.132)	(0.132)
5. region_id	0.095	0.104
	(0.106)	(0.107)
6. region_id	−0.081	−0.080
	(0.098)	(0.098)
7. region_id	0.111	0.100
	(0.110)	(0.110)
8. region_id	0.252*	0.234*
	(0.137)	(0.137)
9. region_id	0.091	0.110
	(0.112)	(0.112)
10. region_id	−0.205*	−0.198*
	(0.107)	(0.107)
Constant	1.772***	1.421**
	(0.418)	(0.653)
N	33454	33454

Note: Standard errors in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE E2 Estimation results for two-part model with year and regional dummies.

	(1) Nitrogen	(2) Particulate matter
NO_2	−0.012**	
	(0.006)	
$(NO_2)^2$	0.000	
	(0.000)	
$(NO_2)^3$	−0.000	
	(0.000)	
First-stage residual	0.009	
	(0.006)	
$PM_{2.5}$		−0.046
		(0.029)
$(PM_{2.5})^2$		−0.000
		(0.000)
$(PM_{2.5})^3$		0.000
		(0.000)
First-stage residual		0.053*
		(0.028)
British	−0.026	−0.053
	(0.108)	(0.110)
Age	−0.025***	−0.028***
	(0.003)	(0.005)
Male	0.154***	0.169***
	(0.051)	(0.053)
Married	0.504***	0.440***
	(0.073)	(0.094)
Degree	0.143***	0.114*
	(0.053)	(0.061)
Employed	−0.138	−0.134
	(0.108)	(0.108)
Islam	−0.646*	−0.642*
	(0.339)	(0.339)
White	−0.131	−0.168
	(0.131)	(0.141)
hh/d size	0.185***	0.256***
	(0.036)	(0.066)
Health	0.047	0.040
	(0.030)	(0.032)
Income	0.050***	0.051***
	(0.010)	(0.010)
Other policy	0.150***	0.147***
	(0.006)	(0.006)
2006	0.000	0.000
	(.)	(.)
2008	0.190*	0.168
	(0.115)	(0.115)

(Continues)

TABLE E2 (Continued)

	(1) Nitrogen	(2) Particulate matter
2010	0.166***	0.147**
	(0.058)	(0.060)
2012	−0.045	−0.055
	(0.071)	(0.072)
2014	0.372**	0.384**
	(0.178)	(0.177)
2016	0.314*	0.327*
	(0.175)	(0.175)
1. region_id	0.000	0.000
	(.)	(.)
2. region_id	0.243**	0.242**
	(0.099)	(0.100)
3. region_id	0.053	−0.024
	(0.131)	(0.127)
4. region_id	−0.074	−0.067
	(0.131)	(0.132)
5. region_id	−0.100	−0.114
	(0.105)	(0.106)
6. region_id	0.078	0.078
	(0.097)	(0.098)
7. region_id	−0.120	−0.104
	(0.110)	(0.109)
8. region_id	−0.266*	−0.245*
	(0.137)	(0.136)
9. region_id	−0.099	−0.118
	(0.111)	(0.111)
10. region_id	0.195*	0.188*
	(0.106)	(0.106)
Constant	−1.697***	−1.286**
	(0.413)	(0.645)
Inflate		
NO_2	−0.050***	
	(0.008)	
$(NO_2)^2$	0.000***	
	(0.000)	
$(NO_2)^3$	−0.000***	
	(0.000)	
First-stage residual	0.025***	
	(0.007)	
$PM_{2.5}$		−0.226***
		(0.036)
$(PM_{2.5})^2$		0.002***
		(0.000)
$(PM_{2.5})^3$		−0.000***
		(0.000)

(Continues)

TABLE E2 (Continued)

	(1) Nitrogen	(2) Particulate matter
First-stage residual		0.137***
		(0.033)
British	−0.017	−0.088
	(0.089)	(0.095)
Age	−0.052***	−0.064***
	(0.005)	(0.006)
Male	0.332***	0.377***
	(0.058)	(0.060)
Married	−0.143*	−0.321***
	(0.085)	(0.110)
Degree	0.382***	0.268***
	(0.067)	(0.071)
Employed	0.106	0.106
	(0.171)	(0.170)
Islam	0.424	0.423
	(0.310)	(0.286)
White	−0.443***	−0.528***
	(0.136)	(0.148)
hh/d size	0.280***	0.462***
	(0.037)	(0.072)
Health	0.084**	0.063
	(0.038)	(0.039)
Income	0.012	0.019
	(0.014)	(0.014)
Other policy	−0.008	−0.015**
	(0.006)	(0.007)
2006	0.000	0.000
	(.)	(.)
2008	0.089	0.143
	(0.105)	(0.109)
2010	0.064	0.131*
	(0.073)	(0.075)

(Continues)

TABLE E2 (Continued)

	(1) Nitrogen	(2) Particulate matter
2012	−0.117	−0.059
	(0.110)	(0.109)
2014	−0.054	0.031
	(0.217)	(0.222)
2016	−0.124	−0.051
	(0.214)	(0.221)
1. region_id	0.000	0.000
	(.)	(.)
2. region_id	−0.037	0.002
	(0.184)	(0.174)
3. region_id	0.480**	0.383**
	(0.199)	(0.190)
4. region_id	−0.466**	−0.516**
	(0.206)	(0.205)
5. region_id	−0.205	−0.330*
	(0.193)	(0.185)
6. region_id	−0.018	0.015
	(0.180)	(0.171)
7. region_id	−0.260	−0.139
	(0.194)	(0.183)
8. region_id	−0.399**	−0.333*
	(0.196)	(0.185)
9. region_id	−0.239	−0.261
	(0.189)	(0.180)
10. region_id	−0.182	−0.224
	(0.179)	(0.171)
Constant	7.414***	9.038***
	(0.556)	(0.827)
N	33454	33454

Note: Standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.