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Willingness to Pay for Clean Air: Evidence from the UK

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Willingness to Pay for Clean Air: Evidence from the UK

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ABSTRACT: This paper uses life satisfaction data to help the design of climate mitigation policies in the United Kingdom. We assess the effects of the exposure to ambient pollutants on long-term life satisfaction and short-term mental health in the UK. We estimate augmented Cobb-Douglas utility functions using pooled and random effects ordinal logit models. Results show that increases in NO2, PM10 and PM2.5 significantly decrease the odds of long-term happiness and short-term mental health in the UK. The willingness to pay for clean air is also significant and increases with level of education. These measurements derived can be used as benchmarks for pollution abatement subsidies or pollution taxes and can help in projecting a more comprehensive assessment of costs and benefits.

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1. Introduction

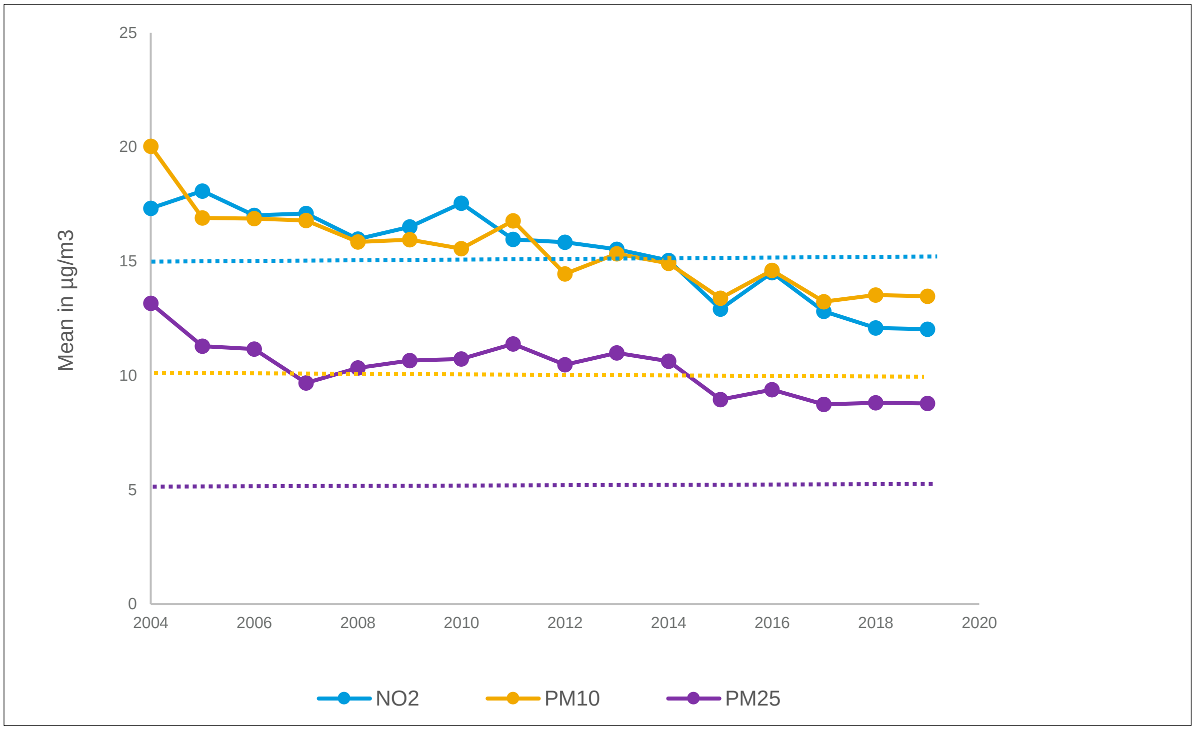
1.1 Background and Motivation

This paper uses life satisfaction data to help the design of climate mitigation policies in the United Kingdom It estimates the willingness to pay of UK citizens to abate air pollution. Abating air pollution is not a new issue in the UK. Ever since the industrial revolution took its toll across the globe, the UK has been increasingly shedding the light on and taking measures to combat air pollution (Environmental Protection UK, 2021). The major local pollutants in the UK include Nitrogen Dioxide (NO_2) and both kinds of Particulate Matter ($PM_{2.5}$ and PM_{10})[1]. The levels of these three pollutants have been significantly higher than the targets set both nationally by the UK government and internationally through the EU Ambient Air Quality Directive. Not surprisingly, the high levels of air pollution impose severe repercussions on residents' health (Harrison, 2018). In fact, the Environmental Audit Committee in the UK estimates the value of these health costs to range between £8.5 billion and £20.2 billion every year. Not only does air pollution incur health costs on the economy, but it also decreases productivity of the labor force. For instance, air contamination with pollutants resulted in approximately a £2.7 billion loss to the UK economy due to declines in productivity (DEFRA, 2015). Recognizing that the costs for air pollution are substantial, and upon exiting the EU, the UK government is currently en route to draft and enforce the Environment Bill (2021). The Environment Bill (2021) seeks to set targets, action plans, measures, and deadlines to improve the air quality along with other environmental problems in line with the Clean Air Strategy and the World Health Organization guidelines (DEFRA, 2021).

As emphasized by the ongoing Environmental Bill (2021) and the 2008 Climate Change Act, the significant costs of air pollution on productivity and health are tremendous and work towards cleaner air is now crucial. Debates to agree on an optimal level of air pollution abatement within the environment-economy tradeoff nexus have been ongoing. The inability to precisely estimate all costs and benefits associated with air pollution abatement has indeed been a hurdle in policy decision making in the UK. Looking at Figure 1, we can see that the trend of the three main pollutants (NO_2, $PM_{2.5}$ and PM_{10}) has been decreasing in the past decade, however their mean levels are still above the World Health Organization (WHO) recommended guidelines. As for Figure 2, it is reflecting a negative relationship between pollution levels and life satisfaction ranking after a certain threshold. For this matter, the output of this paper is of considerable importance to researchers and policymakers seeking to appropriately capture and factor in all benefits and costs of pollution abatement in the decision-making process.

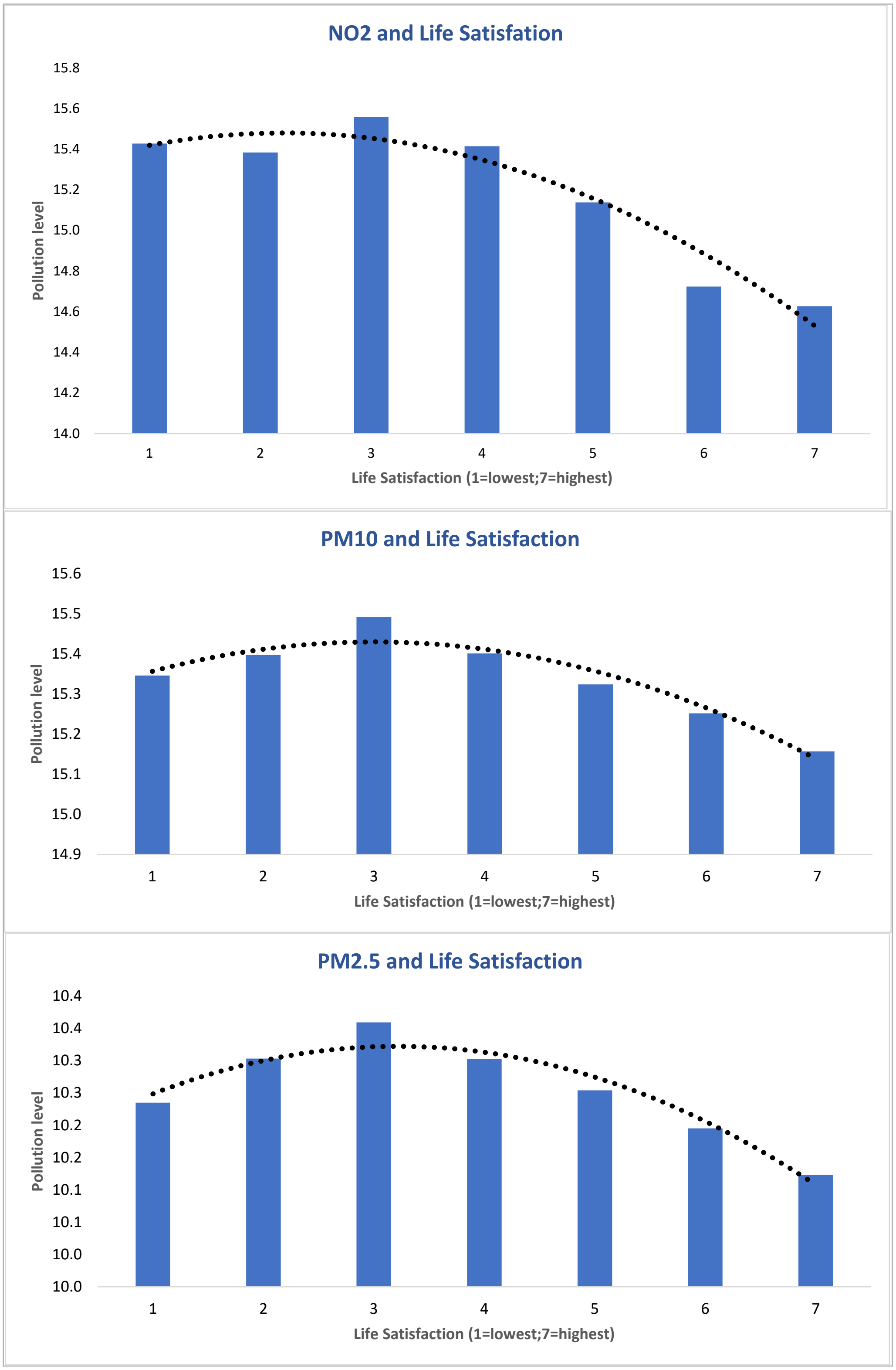
[1] According to the United States Environmental Protection Agency, particulate matter is made of small, microscopic solids that can be inhaled and lead to detrimental health problems, especially those particles with less than 10 micrometers in diameter like the $PM_{2.5}$, which can be absorbed by the lungs and the bloodstream.

Figure 1: Trend mean pollutants level 2010-2019



Source: Based on authors' own calculations by relying on data from BHPS and UKHLS years 2004 – 2019. The straight lines show the WHO updated guidelines levels of each pollutant.

Figure 2: Mean of pollutants by life satisfaction rank



Source: Based on authors' own calculations by relying on data from BHPS and UKHLS years 2004 – 2019.

1.2 Objective of the Study

The objective of this study is to estimate the UK residents' valuation of air quality in terms of NO_2, $PM_{2.5}$, and PM_{10} abatement by tapping into their short-term and long-term happiness. A natural starting point in policy design after recognizing the problem of air pollution is to decide on the amount of ambient pollutants required to be abated i.e. the pollution target. Unfortunately, to date, while many of the costs associated with air pollution have been quantified, some others are yet to be precisely calculated. This problem particularly arises as air quality is a public good, which de-incentivizes individuals from revealing their willingness to pay for it and creates a free-ridership problem. Once all costs of air pollution are made explicit, policy makers can proceed and decide on the optimal level of pollution required, and the instruments required to achieve this.

Estimating the marginal willingness to pay for environmental quality allows to determine the marginal private benefits – and the total benefits – from abating a particular level of a pollutant, in other words, the demand for environmental quality. Compared against the costs of pollution abatement, this monetary value could be put in direct use in a cost-benefit analysis study to evaluate the different environmental proposals currently under discussion (Srinivasan and Stewart, 2004). For example, our estimation provides a clearer insight for policymakers drafting the Environmental Bill (2021) in the House of Commons, amongst others. Additionally, as the willingness to pay is not revealed in the market, its estimation could be used in designing and deciding on any green tax schemes[2] to be set for households in efforts to correct for air pollution externalities (Marrouch and Sinclair-Desgagné, 2012).

The effect of environmental quality on well-being can be divided into three channels. The first channel postulates that different forms of pollution can cause deteriorations in physical health, which would consequently lead to decreased self-evaluation of psychic well-being. The effect of pollution on health has been well documented in the epidemiological literature: living in environments contaminated with pollutants increases risks and occurrences of cardiovascular diseases and respiratory diseases, including bronchitis, rhinitis, and chronic obstructive pulmonary disease (COPD) (Sørensen et al., 2014; Babisch et al., 2014). Additionally, particulates in the air may produce unfavorable conditions for newborns, including abnormal weights at conception and respiratory diseases (WHO, 2013). The second channel is an indirect one whereby lower health levels as a result of environmental pollution may also affect productivity levels, and thus income and eventually happiness (Ostblom and Samakovlis, 2004). The third channel relates to the field of neuropsychology: exposure to air pollution may subject the individual to "environmental stress", which distorts operations of the sympathetic and parasympathetic autonomous nervous system (Evans and Cohen, 2004). These would perturbate brain activity, causing infuriation and frustration, and by definition, lower levels of emotional happiness (Stenlund et al., 2009). Exposure to air pollution is also directly affiliated with increased negative feelings and psychological states, including disgust, or even

[2] An estimate of the tax generated from the marginal willingness to pay is often referred to in the literature as a Lindahl tax.

depression (Ferreira et al, 2013)[3]. In this study we focus on the third channel exclusively as the first two have been well documented in the literature[4]. This is done by controlling for health and income.

This study focuses on a micro-econometric life satisfaction regression. This methodology consists of starting from a sensible indirect utility function for the common consumer, whereby the arguments of the function include income, the air pollutant, and other "personal life" covariates. After estimating the function, the marginal rate of substitution between income and the air pollutant is calculated to determine how much the consumer is willing to give up from their income to abate a unit of pollution. As a proxy for the willingness to pay, this estimate may complement the aforementioned valuation methods for policy decision making. Moreover, conditional on appropriately specifying the functional form and econometric model, this method has been deemed more robust and has been gaining much more popularity across social sciences due to its practicality and accuracy (Oswald and Wu, 2010). We formally present and defend the model in Section 5.

2. Literature Review

2.1 Previous Literature

As previously established, the first step in estimating the benefits of pollution abatement within a life satisfaction micro-econometric regression framework is to compute the estimate of additional units of pollution on happiness. In this section, we discuss publications pertaining to this strand of literature. A summary of the literature is provided in Table 1 of the Appendix.

2.1.1 Negative Effects

A significant proportion of the literature has found that there exists a negative relationship between the different air pollutants and life satisfaction.

Most studies have made use of either cross sectional or pooled cross-sectional data. For instance, Luechinger (2010) makes use of the EU Eurobarometer survey and finds that (aggregated) SO_2 negatively impacts happiness. In their study, the author first makes use of Ordinary Least Squares (OLS), but then instruments local air pollution with foreign sources of pollution to account for endogeneity using a 2-Stage Least Squares model. After controlling for endogeneity, the author finds higher impacts; individuals are willing to pay approximately 1.1 percent of their income to abate a unit of the pollutant (compared to 0.6 percent using OLS).

[3] For a more detailed analysis concerning the physiological and psychological processes relating air pollution to individual well-being, see Lin et al. (2019).

[4] This study has examined the impact of pollution on health. Results are well aligned with the existing literature. We can see that there is a negative effect running from pollution to the odds ratios of satisfaction with health. The coefficients are significant for the 3 pollutants (using random effects ordinal logit). Further, the effect is strongest for PM2.5, as it is the most harmful pollutant among the three.

Cuñado and Pérez de Gracia (2012) finds similar results. Their paper extracts data for Spain from the European Social Survey (ESS) for the year 2008 in efforts of assessing whether there exists any relationship between each of NO_2, CO_2, and PM_{10} on one hand and life satisfaction on the other hand. The data is cross sectional, the empirical model used is OLS, and the spatial modelling is done at the regional level. The authors find a negative association between the two and conclude that the citizen with the mean income would be (implicitly) willing to pay 1.4 percent of their (yearly) salary to decrease the number of days in which PM_{10} exceeds a limit of 50 micrograms per cubic meter (μgm^{-3}) by 1 percent.

Using the Chinese General Social Survey in 2010 to test the effect NO_2 (varying at the city level) plays on happiness in China, Jidong and Yiran (2015) find similar results. Precisely, by estimating with an Ordered Probit model, the authors find that there is a significant negative association whereby an individual values a one μgm^{-3} decline in the pollutant at approximately US$189. While significant, this estimate is considerably lower than estimates in the literature for Europe. While this deviation could arise due to empirical differences and to the fact that standards of living of China are considerably lower relative to Europe, another possibility could stem from the Environmental Kuznets Curve theory. Precisely in this context, the theory would predict that in more advanced economies with higher income per capita (i.e. Europe, compared to China), demand (and consequently valuation) of clean air is higher. This is called the technique effect (Copeland and Taylor, 2004).

Ferreira et al. (2013) combines three ESS waves for several countries and uses data at the regional level (up to NUTS-3) to understand the relationship between Sulfur Dioxide (SO_2) concentrations and life satisfaction. Using an OLS model, their study finds that a one μgm^{-3} increase in SO_2 decreases life satisfaction by a range of 0.016-0.030 points on an 11-point scale.

In an attempt to relate air pollution to the willingness of citizens to pay for taxes, Liu et al. (2018) extract pooled cross-sectional data for China from the World Values Survey for the years 2001, 2007, and 2012. The modelling was done at the regional level. Using an Ordered Probit as well as a Feasible Generalized Least Squares models, the authors confirm the existence of the negative relationship between each of NO_2 and PM_{10} on one hand and life satisfaction on the other hand. Moreover, they conclude that individuals are willing to pay US$130 every year in terms of taxes in order to decrease NO_2 by one μgm^{-3}.

Some studies improve on the modelling of the abovementioned papers by geo-matching pollution with the happiness data at a more finely tuned level of spatial disaggregation.

For example, Ambrey et al. (2014) use the Household, Income, and Labor Dynamics in Australia survey to test the effect of PM_{10} exceeding its advised limit on life satisfaction in Australia. The study geo-matches pollution at the Collection District level. Using an Ordered Probit on cross sectional data and a specification similar to the aforementioned papers, this study also concludes the presence of a negative relationship.

In addition, using the ESS but making use of a fine-tuned level of spatial disaggregation (1x1 km^2 grid), Orru et al. (2016) undertake Estonia in the years 2010 and 2012 to study the effect of PM_{10} on life satisfaction. They confirm the existence of a negative association between the two by using an OLS model.

Finally, a narrow strand of the literature takes the analysis one step further by making use of panel data to account for unobserved heterogeneity. Modelling at the country level, Welsch (2003) uses aggregated life satisfaction data for 10 European countries from the World Database of Happiness for the years 1990-1997 to test the same relationship between NO_2, suspended particulate concentration, and lead and life satisfaction. The empirical methodology used is panel data fixed effects (FE) Generalized Least Squares. Their study concludes that on average across all countries and the period of study, an individual would value abating NO_2 levels by a standard deviation at US$900. The figure for lead is US$1400.

Zhang et al. (2017) use data from the China Family Panel Studies in an effort of testing whether the Air Pollution Index (API) has an effect on overall life satisfaction, short-term hedonic happiness, and on mental health by using panel data with fixed effects. The modelling was done at the city level. While the results of the study do not find a negative relationship between air quality and happiness, the study finds a significant negative relationship with mental health and short-term hedonic happiness. Furthermore, the authors conclude that the effect is asymmetric amongst the sample surveyed in that it affects more some groups such as individuals who work outdoors, have lower salaries, or live in more polluted areas.

Finally, Knight and Howley (2017) use the Understanding Society dataset for the years 2002-2014 in order to examine whether Nitrogen Dioxide (NO_2) plays a role in determining variation in the life satisfaction of UK residents. The empirical model used is also a panel data with fixed effects. Although a regional pollutant, NO_2 is modelled at the Lower Layer Super Output Area (LSOA) level. The study concludes that there is a significant negative effect, whereby a standard deviation increase in the ambient level of the pollutant negatively affects happiness by approximately 0.015 standard deviations. The authors also compare this estimate with coefficients of other regressors in the life satisfaction regression in order to conduct comparisons.

2.1.2 Neutral/Indeterminate Effects

While the majority of the literature has found a significant negative relationship between pollution and happiness, a portion has found different conclusions.

Some studies have found that there are no significant effects. For instance, Lin et al. (2019) examine the relationship between NO_2, $PM_{2.5}$, and PM_{10} on one hand and happiness on the other hand in Taiwan. The authors use a multilevel latent growth modeling (LGM) approach and extract data from the Institute of Sociology in Taiwan before geo-matching it with pollution data at the city level. The authors conclude that the variation in happiness is not significantly explained by exposure to any of the three pollutants.

Other studies have shown that the association suffers from endogeneity bias. For example, Goetzke and Rave (2015) use an IV-probit model in studying the effects of perceptions of NO_2, PM_{10}, and SO_2 play on happiness in Germany using the German Socioeconomic Panel Data dataset. Despite including a similar set of covariates as the aforementioned papers in the literature, the authors find that endogeneity arising from reverse causality biases the results. Nevertheless, it is worthy to note that this endogeneity arises because the authors implement a subjective rather than objective measure of pollution.

2.2 Contribution to the Literature

As can be inferred from the previous subsection, there are potentially several gaps in the literature that this paper seeks to address. First, not many studies have considered assessing the valuation for the UK, and most of the data seems to cover outdated periods. Recognizing that results cannot be generalized across countries, this study aims at providing fresh insights into UK air pollution valuation for the period 2004 – 2019. Second, this study targets three main pollutants. These are NO_2, PM_{10}, and $PM_{2.5}$, with the latter severely lacking in the literature. Although under-researched, $PM_{2.5}$ is one of the most dangerous air pollutants due to its size (European Environmental Agency, 2009) and therefore merits more attention. Third, most of the literature has worked with cross sectional data, which is prone to estimation biases due to its inability to control for unobserved time-invariant characteristics affecting life satisfaction. Panel data methods employed in this paper thus provide a considerable improvement on these grounds. Fourth, most of the studies fail to model air pollution at extensive levels of disaggregated geographic precision. This leads to aggregation bias and to the ecological fallacy error. Simply put, these errors mean that researchers are attributing certain group effects to individuals. This leads to biased results and wrong conclusions (Zhang et. Al, 2017). This paper models data at the LSOA level in efforts of reducing this bias. Fifth, most of the literature seems to confound life satisfaction, which is an overall evaluation of one's happiness, with hedonic happiness, which is a momentarily assessment of mental health linked to the current internal status quo of the individuals. In this paper, we model both as these two measures ought to be different (Deaton and Stone, 2013), with short term happiness hypothesized to be more elastic to current pollution. Finally, this paper seeks to assess whether the effects are uniform across the entire population or if there exist heterogenous effects across the different sub-groups. This could be essential for policymakers.

3. Theoretical Model

We begin by assuming that the life satisfaction function takes a Cobb-Douglas form (Nicholson and Snyder, 2012), as shown in (1)

$$LS_{it} = \prod_{c=1}^{C} D_{itc}^{\beta_c} \qquad (1)$$

Where LS_{it} stands for Life Satisfaction of individual *i* at time *t*, D_{itc} stands for the value of a determinant *c* for individual *i* at time *t*, and β_c represents the elasticity of Life Satisfaction with respect to determinant *c*. We assume a Cobb-Douglas form for two reasons as this allows for some degree of substitutability between the different components of life satisfaction and because it assumes that all determinants are essential. Taking logs on both sides of (1) yields (2)

$$lLS_{it} = \sum_{c=1}^{C} \beta_c lD_{itc} \qquad (2)$$

Where $lLS_{it} = \ln(LS_{it})$ and $lD_{itc} = \ln(D_{itc})$.

It has been reported in multi-disciplinary studies that measures for "life satisfaction" are reliable and objective representations of a person's well-being or satisfaction (Diener et al., 1999 and DiTella et al., 2003).This is indeed the case as (i) different measurements of happiness are highly correlated with each other and with well-being and (ii) individuals reporting higher levels of happiness are found to display both physiological characteristics (lower blood pressure, higher smiling frequency) and mental characteristics (less depression, stress, and likelihood to commit suicide) pertaining to happiness (Diener et al., 1999 and DiTella et al., 2003). Therefore, this study will consider happiness measures to be proxied with the so-called "utility" in economics. As a result, one could compute the Marginal Rate of Substitution (*MRS*) between any two components *c* of (2). As we proceed to show in Section 5, the two main components we consider are the ambient level of a pollutant, and the income of a person *i*. *MRS* between pollution and income is a measure indicating how much an individual *i* is willing to pay (forgo of their income) to abate an additional percent of the pollutant while remain equally happy. The measure refers to the maximum willingness to pay and is derived by first considering the total differential of (2) and then setting it equal to 0. Doing so yields the equation for *MRS* in (3)

$$MRS = -\frac{\partial lLS_{it}/\partial D_{itp}}{\partial lLS_{it}/\partial D_{itI}} \quad (3)$$

Where D_{itp} is the ambient level of the pollutant and D_{itI} is income.

In cost-benefit analyses as well as other decision-making methodologies, environmental economists compare costs and benefits of different potential environmental projects or proposals in order to assist policymakers in making their decisions. This *MRS* provides yet another measure of welfare cost (or benefit[5]) that is not easily quantifiable. It could also aid in constructing a marginal benefit curve for the abatement of a pollutant. The intersection of marginal benefit and marginal cost could allow for the determination of the optimal level of pollution abatement in the UK, shown as $Q*$ in Figure 1 of the Appendix.

Finally, computing the *MRS* could be useful for designing market instruments to abate pollution, by for instance providing an estimate or aid in estimating the value of a pollution externality generated from production. Briefly, a profit-maximizing firm produces a level of output whereby its marginal revenues are equal to its marginal (private) costs. Governments nevertheless acknowledge that pollution from firm production imposes an undesirable effect (externality) on a third party (in this case, the citizens). In order to correct for this externality, the government may impose a Pigouvian tax equal to this external cost (*MEC*) at the optimum level where the marginal social costs (*MSC*) (rather than private (*MPC*)) intersect marginal benefits (*MB*). In this study, we seek to calculate, at least partially, this externality. A sketch diagram of this is represented in Figure 2 in the Appendix. Figure 2 displays the profit maximizing output for the firm (*Qp*), which is the intersection between *MPC* and *MB*, as well as the socially optimal level of output (*Qs*), which happens at the intersection between *MSC* and *MB*. In order to move from *Qp* to *Qs*, the government ought to provide a tax equal to *MEC* at *Qs* (the Pigouvian tax). As mentioned above, this MEC could be partially derived from our *MRS*. It is worthy to note that some other estimates remain unknown to the government, such as the *MPC* and *MB* of the firm. Nevertheless, the willingness to pay remains helpful (Callan and Thomas, 2013).

4. Data

A summary of all the variables used in this study is found in Table 2 of the Appendix.

4.1 Household Data

4.1.1 Dataset Description

The dataset covers the years 2004 – 2019 inclusive in a panel form of yearly frequency. The main source of data are two merged datasets: the British Household Panel Survey (BHPS) and the United Kingdom Household Longitudinal Survey (UKHLS), also known as Understanding Society. BHPS covers the period 1991 to 2008 (18 waves) which encompasses 10,000 individuals, whereas the UKHLS started 2009 and is still ongoing, covering approximately 50,000 individuals. Due

[5] In this framework, the welfare cost of increasing pollution is assumed to be equivalent to the welfare benefit of abating the same amount of pollution.

to limited pollutants' data availability, discussed in subsection 4.2.2, the final dataset extends over the period 2004 – 2019. These datasets are complementary in the sense that the UKHLS implements an overlapping design in such a way that both surveys can be easily merged generating a longer period. The sampling framework calls for interviewing the same samples of individuals across multiple years to obtain household-based panel data. These surveys mainly focus on understanding the drivers behind and the consequences of different social and economic changes of individuals in the UK. To do so, the questionnaire covers an extensive range of households' socioeconomic conditions, including levels of education, levels of income and compensations, health, values, housing conditions, well-being, and attitudes towards the environment. It also covers different questions that are asked less frequently than on an annual basis, depending on exogenous policy shocks and for different research interests. These surveys are nationally representative of the UK population. Besides their panel advantage of controlling for unobserved heterogeneity, they permit analyzing how the different individuals' living conditions, lifestyle values, and behaviors interact and affect one another in dynamic settings. In each wave, there is a fixed set of questions asked in addition to some other questions exclusive to the wave. In general, the questions asked cover all aspects of life: educational, socioeconomic, cultural, political, environmental, mental, health, etc.

The (merged) dataset identifies in which LSOA each individual lives in a particular wave. Simply put, an LSOA is a disaggregated geographical area in the UK with a range of 1,000 to 3,000 residents in each. They are designed for small area statistics, and although they do not have consistent physical size, they are not subject to boundary changes such as wards or postcodes. As of 2011, there are 34,753 LSOAs in England and Wales. This study is restricted to England and Wales as Scotland and Northern Ireland geographically stratify using different units.

4.1.2 Sampling Design

In both the BHPS and UKHLS approximately 20 percent of the entire sample receives face-to-face interviews, whereas the remainder is surveyed by other methods, including telephone calls. The purposes of the sample design are to a build a sample in the UK that is characteristic of the entire population and to permit analyzing differences between different subgroups. The BHPS began in 1991-1992 with only respondents from England and ended in 2008-2009 with samples from Wales and Scotland being introduced in 1999 and Northern Ireland in 2000. Once BHPS ended, the UKHLS was launched (2009 – Present) by continuing and expanding the work done on the BHPS. The BHPS thus became one out of the four sections in the UKHLS (Lynn, 2009). The central section of the UKHLS survey is the General Population Sample (GPS), which consists of approximately 25,000 households during the first wave. It is demonstrative of the entire population and has a large sample size, thus allowing analysis of different subpopulations. The GPS sample consists of a uniform design of addresses in England, Scotland, and Wales chosen based on a proportionally stratified and clustered sample (Lynn, 2009). The second section is the Ethnic Minority Boost Sample (EMBS), designed specifically to create an oversampling of five key ethnic groups[6] by focusing only on areas dense with these groups. The third section is composed of the General Population

[6] The EMBS has at least 1,000 surveyed adults per ethnic group.

Comparison Sample (GPCS), which is a subsample of the GPS whose interviews consist of, in addition to the normal GPS questions, all questions asked in the EMBS. This allows comparative analysis of the general population and specific minority groups to be made. The fourth and final section is the British Household Panel Survey Sample (ex-BHPS). Prior to the UKHLS, the BHPS was introduced in 1991 and was designed to represent all British residents. With the added geographical extensions (Wales and Scotland in 1999 and Northern Ireland in 2001), the BHPS ended with over 8,000 households. The BHPS sample is, like the GPS, a stratified clustered design extracted from postcode sectors. These were first grouped based on addresses, then stratified through a list of characteristics[7].

4.1.3 Variables used

The first dependent variable in this study is "Life Satisfaction", which is an ordinal variable asking respondents how satisfied are they with their lives in the overall. Respondents may answer with a number between 1 (least satisfied) and 7 (most satisfied). However, the dynamics of the effects running from air pollution to long-term happiness (life satisfaction) could be different than those running from air pollution to momentary short-term happiness (hedonic happiness). While life satisfaction consists of an overall evaluation of an individual's happiness across the course of their lifetime, hedonic happiness is linked to the current emotions and feelings. Consequently, changes in air quality might induce asymmetric effects on these two different measures (Deaton and Stone, 2013). This therefore brings us to our second dependent variable, which is hedonic happiness. Hedonic happiness is an ordinal variable taking possible values 0 to 36. It is the sum of 12 mental health covariates, each of which is ordinally scaled from 0 (never) to 3 (most of the time). Examples of these questions include feeling worthless, feeling under strain, lacking sleep, not being confident, feeling incapable of solving problems, feeling incapable of making decisions, and not enjoying daily activities. Therefore, as opposed to life satisfaction, the higher the score, the more distressed the individual is.

Following the literature (see for instance Zhang et al., 2017), we seek to include a vector of covariates that may explain happiness: age, gender, marital status, level of education, labor force status, state of employment, income, and health status.

Age: Much of the literature has found the relationship between age and well-being to be U-shaped: As an individual grows older, her subjective well-being declines up to a turning point (usually between the early 30s and late 40s) where it starts increasing (for example: Blanchflower and Oswald, 2004a). This suggests the necessity of including a squared value of this variable.

Gender: Whether gender (male/female) plays a role in happiness has long been a controversial topic. While some report that gender plays a significant role (e.g., Alesinaet al., 2004), others used the same datasets and found that the differences are not explained by gender (Louis and Zhao, 2002). The effect might differ based on the control variables, and whether some of these are gender related. We include gender in this study as the control variables do not generally proxy for any gender related differences.

[7] The characteristics include region, the percentage of pensionable age, the percentage of agriculturally employed individuals (in urban regions), and the percentage of single households with no pensions (in non-urban regions).

Marital status: Most of the literature has concluded that being in a caring relationship represents the highest level of life satisfaction, whereas being separated represents the lowest, even less than being widowed or divorced (e.g., Helliwell, 2003).

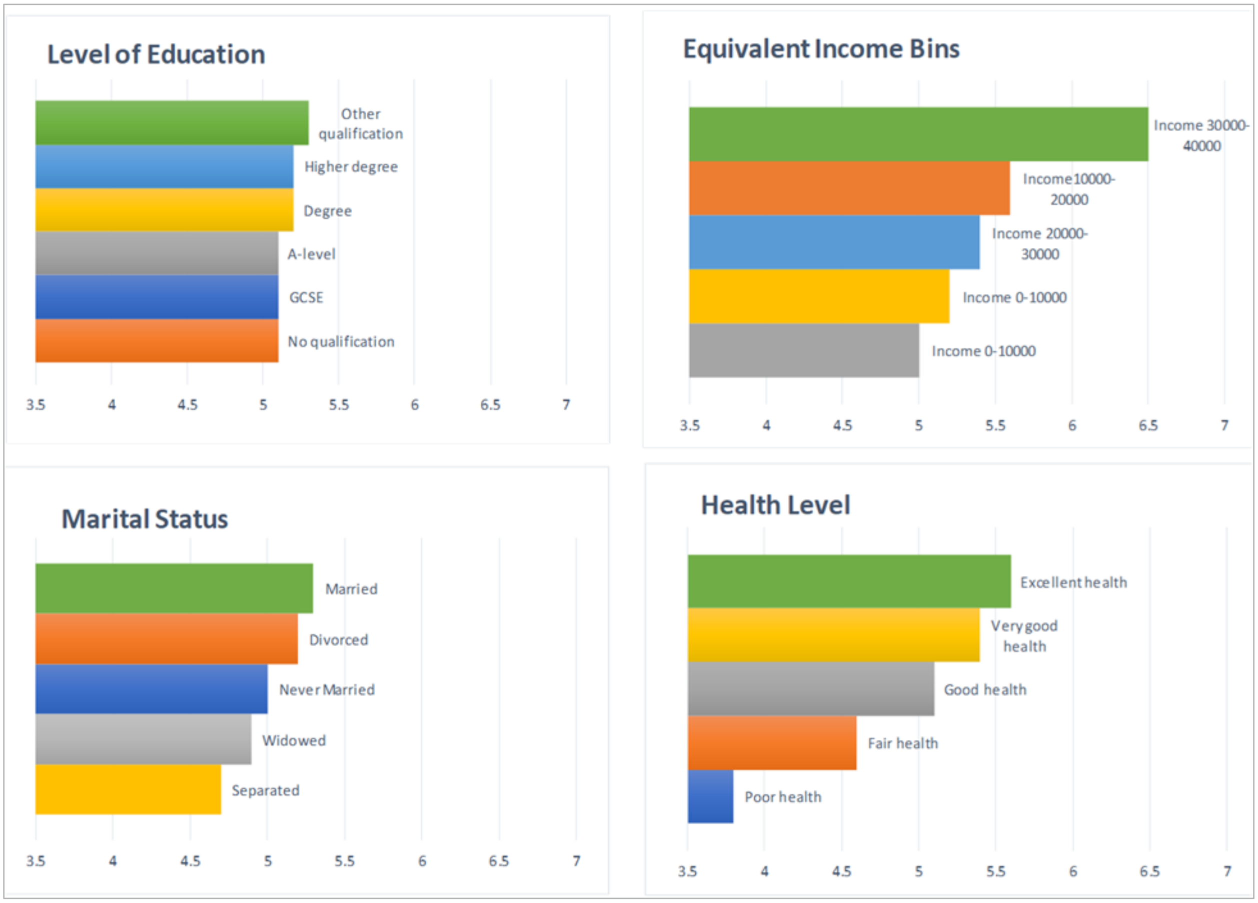
Level of education: The effect of education on happiness is controversial. Some found the relationship to be positive (e.g., Blanchflower and Oswald, 2004b), insignificant (Flouri, 2004), negative (Clark, 2003), or positive in relative rather than absolute terms (Graham and Pettinato, 2001). It is important to note that failure to include income and health might result in overestimating the effect of education on happiness, since these are positively related to education. This presents one additional rationale to include health and income.

Labor force status: The difference between the effects of being employed and self-employed on well-being has been controversial in the literature. While some have concluded that self-employed individuals are on average happier than employees (Blanchflower and Oswald, 1998), others have concluded that this effect is limited to the well-off (Alesina et al. 2004). Nevertheless, it has found generally that unemployment reduces well-being, and that this reduction differs across age groups and genders (Dolan et al., 2008).

Absolute household income, equivalized to adjust for household size, and deflated: The empirical literature has been inconclusive about the positive relationship between income and happiness (Dolan et al., 2008). While some have shown this relationship to be positive solely due to reverse causation (e.g., Graham et al., 2004), others have concluded that there indeed exists a positive and significant effect running from income to happiness (Pischke, 2011). We divide gross household monthly income by the OECD scale. The OECD scale adjusts income to consider the number of adults and children in the household. We then deflate the variable according to the official inflation rates reported by the Office of National Statistics (ONS) and include the logged value as income may be more precisely modelled in percentage terms rather than level terms (Kahneman and Deaton, 2010). Following the literature, we also include a squared logged value to allow for nonconstant marginal utility effects of income changes.

Health satisfaction: A large proportion of the literature shows that severe health problems and disabilities negatively affect subjective well-being (Shields & Wheatley Price, 2005). Many studies show that in regressions with fixed effects, subjective health still negatively affects happiness (Dolan et al., 2008). In this study, we use health satisfaction as a proxy for subjective health assessment.

Figure 3: Mean of Life Satisfaction across different groups



Source: Based on authors' own calculations by relying on data from BHPS and UKHLS years 2004 – 2019.

4.1.4 Descriptive Statistics

Table 3 represents summary statistics for all variables listed in Table 2. The sample is composed of respondents aged 15 and over, with the average age being 47. The ratio of males to females is 46:54. In the sample, a little more than half of the respondents are married and almost one-third have never been married. The average number of individuals in a household is three. Of the respondents, 75 percent have at least completed their high school education with almost one third having a university degree. In the sample, approximately 5 percent are unemployed, 55 percent are employed, and 40 percent are not part of the labor force (disabled, full-time student, retired, on government training scheme, etc.). After factoring in the OECD scale, which considers family sizes and ages, the average monthly deflated income in the sample is 2,086 British Pounds (£). Without factoring in the OECD scale or inflation, the average monthly income per household rises to £3,679, while the median stands at £3,035. Together with the percentage of unemployed, the figure for median monthly gross household income concurs well with official figures from the UK Office of National Statistics (ONS, 2020). On a scale from 1 (the lowest) to 7 (the highest), the median ratings of the sample for satisfaction with life overall and health are 5 and 6 respectively. Finally, roughly 80 percent of the individuals live in urban areas.

4.2 Pollutants Data

4.2.1 Dataset Description and Variables Used

The second dataset we intend to use is the UK's Department of Environment, Food, and Rural Affairs (DEFRA) pollution data. We extract data for the period 2004 – 2019 for NO_2, $PM_{2.5}$, and PM_{10}, all of which are the main regressors in the study. We consider all three pollutants as they have differing characteristics. In terms of sources, NO_2 is mostly emitted from transportation, electricity, and industrial production, whereas PM sources include transportation, fires, and powerplants. Annually, the maximum safe level in the atmosphere for NO_2 and PM_{10} is 40 μgm^{-3} and for $PM_{2.5}$ is 25 μgm^{-3} (Environmental Protection Agency, 2016). A summary of the pollutants, their sources and their upper limit atmospheric acceptable concentration, and human-health risks is extracted from the U.S. Environmental Protection Agency and DEFRA and presented in Table 4 of the Appendix. These are all local pollutants and are measured in microgram per cubic meter ($\mu g/m^3$). The literature has not reached a consensus as to which air pollutant is the most damaging for human health. Some researchers report that NO_2 causes smog and low-level ozone, which is detrimental to human health (Brunekreef et al., 2015 and Shah et al., 2015). Additionally, NO_2 may cause chronic poisoning, has greater likelihoods of being absorbed, may deeply infiltrate lungs, cause pulmonary alveolar diseases (Jidong and Yiran, 2015), and cause bronchitis (Cuñado and Pérez de Gracia, 2012). According to other studies however, particulate matter ($PM_{2.5}$ and PM_{10}) has more severe effects on health, causing problems within the cardiovascular and respiratory systems (European Environmental Agency, 2009).

The data reported is modelled for 1x1 km^2 grids. As the household dataset contains information on each household's LSOA, we aggregate the pollutants from 1x1 km^2 to the LSOA level by selecting for each pollutant the level that is closest (in Euclidean distance) to the LSOA's population-weighted centroid. A population-weighted centroid denotes the dimensional dispersion of the population in each LSOA layout as one point on the ground, denoted with an ordinate and abscissa point (ONS, 2017). This is done using the Spatial Join Tool from the Environmental Systems Research Institute's Geographic Information System (ESRI ArcGIS).

4.2.2 Descriptive Statistics and Stylized Facts

This study covers three different local pollutants, NO_2, $PM_{2.5}$, PM_{10}, all measured in $\mu g/m^3$ for the time period 2004 – 2019. It is apparent that these have considerably different ranges and variations from their means. The lowest recorded levels of NO_2, PM_{10}, and $PM_{2.5}$ were in the South East of England (registered in 2018, 2017, and 2017 respectively). The highest recorded levels for these pollutants were all registered in London, as expected (recorded in 2005, 2004, and 2004 respectively). Additionally, several lower layer regions have surpassed the UK's legal annual mean ambient levels of the different air pollutions, presented in Table 4. As expected, these include London and areas surrounding the Heathrow airport, Islington, and Westminster and Birmingham, among many others. This is most likely due to the higher level of vehicle traffic and industrial activity in these regions. It has been suggested in the literature that the different pollutants appear to be linked and that their concentration levels move proportionately and concurrently (Liu et al., 2018). This can be clearly seen in Table 5, which represents the matrix correlation among the studied pollutants. For instance, the correlation between $PM_{2.5}$ and PM_{10} is 0.94, whereas the correlation between NO_2 and $PM_{2.5}$ is 0.733. Given the high pairwise correlations, in the subsequent empirical analysis, we consider each pollutant in a separate regression to avoid multicollinearity.

It is also visible from Figure 3 that the LSOA-mean ambient levels have been declining over time for all pollutants. For instance, NO_2 levels were 17.32 μg/m^3 in 2004 and 12.03 μg/m^3 in 2020. Similarly, $PM_{2.5}$ levels were 13.163 μg/m^3 and 8.788 μg/m^3 during the same years. This decline of pollutant levels has partially occurred due to the increased awareness for the need of eco-friendly living to fight climate change in addition to different subnational, national, and international energy policies and acts to fight the phenomenon. These include the Climate Change Act (2008) and Planning and Energy Act (2008).

5. Empirical Model

For purposes of empirical estimation, we expand (2) by the covariates suggested in subsections 4.1.3 and 4.2.1, and augment it by a constant and a set of other covariates as well as error term to get (4)[8]:

$$\begin{aligned} H_{ijt} = \; & \beta_0 + \beta_1 P_{jt} + \beta_2 age_{it} + \beta_3 {age_{it}}^2 + \beta_4 Income_{it} + \beta_5 Income_{it}^2 + \beta_6 sex_{it} + \beta_7 health_{it} + \boldsymbol{\beta_8} educ_{it} + \boldsymbol{\beta_9} emp_{it} \\ & + \boldsymbol{\beta_{10}} marital_{it} + \boldsymbol{\theta_1} GOR_j + \boldsymbol{\theta_2} year_t \\ & + \mu_{ijt} \qquad (4) \end{aligned}$$

where H_{ijt} stands for life satisfaction or hedonic happiness of respondent *i* in LSOA *j* at a time *t*. *P* represents ambient air pollutants, which is NO_2, $PM_{2.5}$, PM_{10} in a specific LSOA *j* to which an individual *i* belongs at time *t*. As mentioned earlier, the pollutants are considered separately to avoid multicollinearity. The regression is therefore run three times per dependent variable, once for each pollutant. *Age* represents the age of individual *i* at time *t*. *Income* represents the equivalent deflated income variables of individual *i* at time *t*. *Gender* represents the gender of the individual *i* at time *t*. *Health* represents the health satisfaction of individual *i* at time *t*. *Educ*, *Emp*, and *Marital* are vectors of dummy variables pertaining to the different possibilities of education, labor force status, and marital status respectively, as defined in Table 2. *GOR* represents the set of Government Office Region dummy variables which are included to capture regional fixed effects[9]. *Year* is the set of year dummy variables, included to capture time fixed effects. β_0 represents the regression intercept, β_1 through β_{10}, θ_1 and θ_2 are the coefficients to be estimated and μ is the error term.

It is worthy to note that (i) the dependent variables and pollutants are in logs, (ii) we include dummy variables for GOR[10] and for the year in order to control for fixed effects over time and across regions, and (iii) we recognize that including a set of weather data in order to segregate effects on happiness derived from pollution with effects derived from weather is

[8] Characters in bold represent vectors of coefficients.

[9] There are nine official GORs in England (North East, North West, Yorkshire and the Humber, West Midlands, East Midlands, South West, South East, East of England, and Greater London) and one GOR in Wales (Wales). Every GOR has its own Enterprise Zone.

[10] The fixed effects are accounted for at the GOR level rather than LSOA due to the high number of LSOA regions.

important to eliminate any possible bias is important (Wolfson, 2013). Nevertheless, we do not proceed with doing so as introducing weather data per LSOA would result in a significant loss of data as well as an aggregation bias.

As the elements of the set of all dependent variables are ordinal in nature, the suggested estimation technique is an ordinal logit model using maximum likelihood with either fixed or random effects (see Jidong and Yiran, 2015 and Liu et al., 2018). In order to determine whether a fixed or a random effects model is to be implemented, econometricians make use of the Hausman test. Nevertheless, in the empirical literature using ordinal logit models, random effects is usually the preferred method as fixed effects could be inconsistent (Baetschmann et al., 2011). We present the results using odds ratios for ease of interpretation. Random effects nevertheless assumes strict exogeneity and that there is no correlation between the unobserved fixed effects and the other covariates of the model. For this matter, we also present results using pooled logit and random effects probit as robustness checks. In our pooled logit model, we cluster standard errors at the LSOA level, since the pollutant varies at the LSOA level whereas happiness varies at the micro-level. This would address the possibility of serial correlation and would inflate standard errors back to their true sizes.

The last estimations we seek to compute are those with standardized (dependent and independent) variables. Standardization facilitates several comparative analyses to be made. First, we would be able to examine whether the effect of the pollutant is stronger on life satisfaction or hedonic happiness. Second, we would be able to inspect the relative importance of pollution to different life factors on life satisfaction and hedonic happiness. Finally, we would be able to examine the relative importance of the different pollutants on life satisfaction and hedonic happiness.

After estimation, we seek to compute the MRS. Applying (3) to (4) yields (5), the estimate of the willingness to pay for pollution abatement for the mean income ($\overline{Income}$) becomes

$$MRS_{ijt} = -\frac{\beta_1}{\beta_4 + 2\beta_5\overline{Income}} \qquad (5)$$

This determines the happiness price (monetary valuation) of pollution, i.e., how much individuals are willing to pay to compensate for a marginal decrease in ambient pollutant levels and remain equally well-off. This method is similar to the Lindahl pricing method. The values obtained for MRS of the different pollutants against income are immune to any monotonically increasing transformations of life satisfaction. Thus, MRS is interpreted as the monetary amount individuals are willing to accept for a marginal increase in the air pollutant while keeping their life satisfaction constant.

We finally repeat the estimation of (4) and the calculations in (5) for different subgroups from the population: (i) individuals with high levels of education, and (ii) urban residents. These could prove to be invaluable for policymakers from both equity and efficiency perspectives.

We also note that reverse causality running from happiness to pollution is highly unlikely and possibly insignificant, particularly since (i) happiness is measured at the individual level while pollution is measured at the LSOA level, (ii) the effect of happiness on pollution is likely to occur with a lag, and (iii) while happiness data is subjective, pollution data is objective. However, one may argue that it is likely that there is reverse causality running from happiness to income (although this could also occur with a lag). In order to test whether endogeneity is a problem in this case, we make use of the methodology employed by Pischke (2011), which calls for restricting the sample to housewives that satisfy the following three conditions: (i) are currently with a partner/husband, (ii) earn a household income, and (iii) are unemployed, study full time, or are unable to work due to sickness. By restricting the sample in this way, we are effectively considering individuals that do not generate an income themselves. Therefore, any effects running from happiness to income would indeed occur due to happiness spillovers from the woman to the man, which is secondary and is assumed to be insignificant. If after the restriction, we still find the effects of the covariates to be roughly the same, we may hypothesize that reverse causality in this case is not too strong. Any conclusions should nevertheless still be taken with a grain of salt.

6. Results and Discussion

6.1 Effects of Local Air Pollutants on Life Satisfaction

The initial results of the regression analysis between the pollutants and life satisfaction are given in Table 6, which reports random effects ordinal logit regressions. The reported coefficients show the odds ratios of a unit increase in each explanatory variable on moving upwards or downwards on the happiness ordinal scale. As mentioned in the previous section, we also conduct the regression using pooled ordinal logit, i.e. without any panel data techniques. Although this does not help account for unobserved heterogeneity, it reduces the risk of biased estimates if fixed effects are correlated with the unobservable. The results are presented in Table 7. As a further robustness check, we report the results using a random effects ordinal probit model in Table 8. As can be seen from all three tables, the results are quite similar. This is an indication that the model used is robust. In the remainder of this subsection, we rely exclusively on the results from Table 6.

When NO_2, PM_{10}, and $PM_{2.5}$ increase by 1 percent, the odds of higher (log) life satisfaction decreases by approximately 9, 9.5, and 10.7 percent[11] holding all other controls constant. These effects are significant, and it is noticeable that $PM_{2.5}$ has the biggest impact on the likelihood of being happy. It is important to note that the regression controls for health assessment; consequently, the effects from the pollutants to happiness should report psychic and psychological changes in happiness without a transmission mechanism from pollution to health and then from health to happiness. If, however, perceptions of health and actual health outcomes do not align, these odds ratios would also report probability changes in happiness levels as a result of changes in health outcomes. The results would therefore concur with the fact that particulate matter of size 2.5 micrometers or less have more severe effects on health than NO_2 or PM_{10}, causing more detrimental problems within the cardiovascular and respiratory systems (European Environmental Agency, 2009). These results confirm those reported in the literature, including Cuñado and Pérez de Gracia (2012), Liu et al. (2018), and Orru et al. (2016), Knight and Howley (2017), Lin et al. (2019), and Jidong and Yiran (2015).

Considering the other covariates, age is shown to have a negative, but diminishing, effect on happiness. Being unemployed, as opposed to being employed or not part of the labor force, also has a negative effect on satisfaction with life. Being married, as opposed to being widowed, divorced or separated, has a positive effect. Income has a non-linear effect on happiness; at first higher income is associated with lower happiness levels. Eventually, higher income becomes associated with higher happiness. This could be attributed to the fact that households with little to no income receive financial assistance through

[11] To calculate these numbers, which represent the odds of marginal changes, we compute the following from the tables' outputs: $100[1 - e^{\beta_1}]$. This is because we report the results as the odds rather than log of odds for easier interpretation.

formal or informal channels. Finally, similar to Clark (2003), higher levels of education are associated with lower odds of having long-term life satisfaction.

6.2 Effects of Local Air Pollutants on Hedonic Happiness

In order to test the effect of pollutants on hedonic happiness, we follow the same strategy as that described in subsection 6.1. Tables 9, 10, and 11 report the estimation results from random effects ordinal logit, pooled ordinal logit, and random effects ordinal probit respectively. The results are again similar across all different models, and we report the random effects ordinal logit model from table 9.

When NO_2, PM_{10}, and $PM_{2.5}$ increase by 1 percent, the odds of higher (log) hedonic unhappiness[12] increase by approximately 7.9, 9.9, and 9.9 percent[13] holding all other controls constant. These effects are significant, and it is noticeable that PM_{10} and $PM_{2.5}$ have the bigger impact on the likelihood of being happy in the short-run. These results are similar to those of Zhang et al. (2017). However, as opposed to this paper, we conclude that there is an effect of pollutants on both short-term hedonic happiness and long-term life satisfaction, with the effect on the latter being slightly higher.

Concerning the other covariates, we find that income only has a positive, non-linear, effect on short-term happiness. This is because an increase in income could provide a short-term morale boost to the individual regardless of their income status. Men have higher odds of being happy in the short-term. As opposed to results for life satisfaction, having some education compared to no education increases the likelihood of being happy in the short-term. This likelihood is stronger for GCSE education compared to A-level education and stronger for A-level education than having a degree education. Being employed, retired, or a student as opposed to being unemployed and being married as opposed to being never married, divorced, retired, or widowed increases the likelihood of being happier in the short-term. Finally, people who believe they are healthier have higher odds of having higher hedonic happiness.

6.3 The Relative Magnitudes of Pollutants on Both Happiness Measures

We now turn to the standardized version of the dependent and explanatory variables: life satisfaction in Table 12 and hedonic happiness in Table 13. We note that in these regressions, the dependent variables and the pollutants are presented in level rather than log form. From Table 12, we find that a one standard deviation increases in NO_2 or $PM_{2.5}$ decreases the odds of a higher standard deviation of life satisfaction by 1.1 percent. For PM_{10}, the odds are 0.9 percent. From Table 13, we find very similar results: a one standard deviation increase in any of the pollutants decreases the odds of a higher standard deviation of hedonic happiness by roughly 1 percent. We therefore conclude that all three pollutants play almost the same role and have the same intensity effects on both happiness measures, although $PM_{2.5}$ has slightly stronger effects. These results are expected especially since the pollutants present high levels of pairwise correlations.

[12] It is worthy to remember that higher values of hedonic happiness represent higher levels of short-term unhappiness (more distress).

[13] To calculate these numbers, which represent the odds of marginal changes, we compute the following from the tables' outputs: $100[1 - e^{\beta_1}]$. This is because we report the results as the odds rather than log of odds for easier interpretation.

6.4 The Relative Magnitudes of Pollutants and Major Life Events on Happiness

The last objective of using the standardized results presented in Tables 12 and 13 is to be able to compare the explanatory power of the different variables despite these being measured in different units. This is important as it facilitates comparison between air pollution, which could be quite unfelt, with major life events that are more "tangible" to human beings. For instance, unemployment (as opposed to being in paid employment), decreases the odds of a 1 standard deviation increase in happiness by approximately 9 percent, whereas for divorce (as compared to marriage), this is 4 percent. It is therefore safe to say that in standard deviation increases, the estimated disutility from unemployment is 9 times as large as that of pollutant disutility. Additionally, divorce disutility is almost 4 times as important as pollutant disutility. While it is expected that major life events have stronger effects on life satisfaction, pollution also plays a significant role. These relative comparisons are similar in direction to those calculated by Knight and Howley (2017), although the importance of the pollutants as compared to those "big life events" is a bit lower in the present study. The conclusion here is that pollution is quite comparable to unemployment and divorce; these life events are between 4 and 9 times as important as pollution[14]. When examining the same effects on hedonic happiness, we find that while unemployment (compared to in-paid employment) is almost 14 times as important as pollution, divorce plays almost the same effect as air pollution. This result is expected as being currently unemployed may cause short-term distress that is stronger than hedonic unhappiness coming from being divorced in the past. This is especially true as coping strategies over time may help divorced individuals who have once been in more distress. Moreover, it has been reported that interpersonal problems may have a stronger effect on hedonic unhappiness rather than divorce itself (Berman and Turk, 1981). However, unemployment is usually a short-term problem and would therefore have strong effects on mood.

6.5 The Happiness Price of Air Pollution

As mentioned earlier, the primary objective of this paper is to estimate the happiness price of pollution through the MRS. The results of this exercise are found in Table 14[15]. The first column reports the results for the entire sample. It follows that a UK household with an average income is willing to pay almost £60 monthly to avoid a one $\mu g/m^3$ increase in PM_{10}, £103 to avoid a one $\mu g/m^3$ increase in $PM_{2.5}$, and £62.5 to avoid a one $\mu g/m^3$ increase in NO_2 and remain equally happy, given that all other factors remain the same. These results are telling. $PM_{2.5}$ are smaller particles and can consequently penetrate the lungs through the nose and mouth and cause lung cancer more swiftly than PM_{10} (or NO_2) can. These estimates are not too different from the literature. Welsch (2003) conducted his study for ten European countries and found that individuals were willing to pay a maximum of US$900 per year to abate one $\mu g/m^3$ of NO_2. Additionally, Ferreira and Modo's (2010) valuation for Ireland shows that for a one $\mu g/m^3$ of PM_{10} abated, individuals were willing to pay US$870 annually.

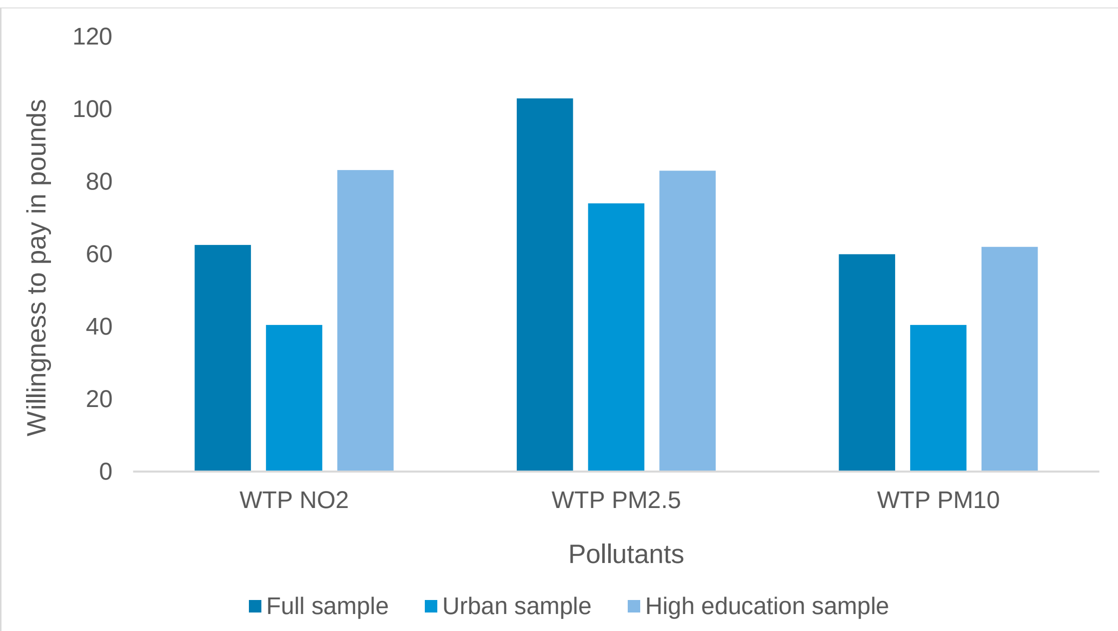
[14] It is worthy to shed the light on the fact that although pollution seems to be less important than these major life events, pollution is irreversible, long-lasting, and mass reaching. These three characteristics are not applicable to the life events and may serve as a means of justifying that the coefficients found are attenuated due to the model's restrictions.

[15] In line with the literature, we focus exclusively on life satisfaction rather than hedonic happiness as the former could better proxy for utility. The latter is more oriented towards short-term mental health and could thus lead to distorted results.

The second and third columns present the same exercise for two different subsamples: the urban dwellers and the individuals with at least a degree level education. It follows that urban citizens are willing to pay less than the overall sample. They are willing to pay around 66 percent of the amount the average household is willing to pay, namely £40.5 for PM_{10} £74 for $PM_{2.5}$ and £40.5 for NO_2. This can stem from the fact that urban dwellers have better access to medical aid as well as better opportunities to earn higher incomes in urban areas (as compared to rural ones.) Additionally, urban dwellers may simply care less about environmental amenities.

The third column shows that the average earners of the more educated subsample are willing to pay more than the whole sample's average earners to abate one $\mu g/m^3$ of PM_{10} (£60.66) or for NO2 (£83.19), but less for $PM_{2.5}$ (£83). The increase definitely partly stems from the fact that highly educated individuals are expected to have higher household income (it is visible in the table that the sample mean income of the educated sample is higher than that of the general sample). However, for NO_2, if we use the income from the entire sample in the calculation, we still see an increase in the valuation to pollution for the highly educated subsample. This could possibly arise from the fact that higher education increases the individuals' awareness concerning the importance of the environment (See for instance Dibeh et al., 2021). Finally, although the payment for $PM_{2.5}$ is lower, the variance in the distribution of payments across pollutants is approximately 3.75 times smaller for the highly educated sample.

Figure 4: Willingness to pay across different groups



Source: Based on authors' own calculations by relying on data from BHPS and UKHLS years 2004 – 2019.

6.6 The Endogeneity of Income

We have previously discussed and argued why we think that endogeneity of pollution is unlikely. Another possible concern – however – is that income is endogenous due to the possibility of reverse causality: while higher income increases happiness, happier people tend to be more productive and generate higher incomes. If reverse causality mediates the reported results, then the regression estimates are biased and the reported MRS results are misleading. For this reason, we follow the methodology of Pischke (2011) and restrict the sample to married housewives and housewives with a partner, who are either unemployed, full-time students, long term sick, or on government training schemes with a household income. In all these cases, it is hypothesized that the majority of the women will not be earning income themselves, but will be receiving income from another family member, such as a husband. With this sample restriction, and with the additional hypothesis that any source of income will affect happiness whereas increased personal happiness will not affect the income of the partner or husband[16], the coefficients would represent exogenous effects, free of reverse causality. It follows[17] that the relationship between income and happiness is still U-shaped and significant. The coefficients are also very comparable to those of the original regressions in Tables 6 to 13. The coefficients for the pollutants are also similar and significant. This shows that there does exist a positive and significant unidirectional causality running from income to happiness.

Having made sure that estimates for pollutants and income are not significantly altered after accounting for endogeneity, there are still concerns about the other variables. Indeed, due to the complex nature of happiness, it can be indeed hypothesized that all other explanatory variables may be endogenous, thereby biasing the estimates. For instance, it can be hypothesized that married people are happier but also that happier people tend to get married. Nevertheless, the literature has not presented instrument selections to consider all of these variables (Van Praag, 2007). Additionally, with the other controls not being of primary importance for this study, this issue was dropped from further consideration.

7. Conclusion

The UK has long been a supporter of the United Nations' 3rd Sustainable Development Goal (UN SDG 3) to achieve overall and health well-beings. With the quality of the environment being one of the primary concerns in the UK, the objective of this study was to assess the effect of air pollution on the happiness of individuals in the UK in order to assess their willingness to pay. Deriving the willingness to pay would be important for policymakers so that they can better determine taxes consumers should pay for clean air, and to develop a more comprehensive idea about the costs and benefits needed for any reform such as the Environmental Bill (2021). This analysis was done by implementing a happiness regression method that relies on survey data of subjective well-being. Our results show that 1 percent higher levels of NO_2, PM_{10} and $PM_{2.5}$ significantly decrease the odds of the log of happiness by 9, 9.5 and 10.7 percent respectively, after controlling for a set of demographic and socioeconomic conditions. The effects on short-term hedonic happiness are almost the same, with the percentages respectively being 7.9, 9.9, and 9.9. We also find that when standardized, all pollutants have roughly the same effect on life satisfaction and hedonic happiness. Further, the event of a 1 $\mu g/m^3$ increase in any of the pollutants generates disutility that is approximately 4 and 9 times less important than divorce (compared to being married) and being unemployed (compared to being in paid employment). In other words, on average, a person transitioning from marriage to divorce would have the same odds of being at a particular level of satisfaction if pollution decreases by approximately 4%. Similarly, on

[16] Unless through second-degree effects such as if happiness spillover effects between the couple exist, and if there is assortative mating, i.e. happier females marrying richer males, both of which we disregard.

[17] The results from these regressions are not presented in this manuscript but are available upon request.

average, a person transitioning from in paid employment to unemployment will have the same odds of being at a particular level of satisfaction if pollution decreases by approximately 9%. For hedonic happiness, divorce is equally as important as pollution, but unemployment is 14 times more important. Evaluated at the mean income level, households are willing to pay £62.5, £60 and £103 per month to abate 1 μg/m^3 of these pollutants respectively and remain equally happy, with urban dwellers paying less than this amount and highly educated individuals paying more than that (except for $PM_{2.5}$). For example, Knight and Howley (2017) show that the effect of reaching the EU pollution legal limit is 53 percent of the impact of being unemployed on happiness.

The results concerning willingness to pay to abate pollution are in line with Welsch (2003) and Ferreira and Modo (2010), in which individuals were willing to pay a maximum of US$900 per year to abate one μg/m^3 of NO_2 and US$870 to abate a one μg/m^3 of PM_{10} annually, respectively. The magnitudes of the effects are also quite similar. However, unlike Zhang et al. (2017) and Lin et al. (2019), the study finds an effect from pollution on long-term life satisfaction.

Many of the implications of the results can be useful as a primary framework to guide climate change policy in the UK and give policymakers additional insight regarding efficient, effective, and equitable pro-environmental governmental efforts. With air pollution being both a national and a long-lasting problem across generations, especially the emissions of global pollutants, it can be inferred that the welfare increase from pollution control is substantial. This stands in contrast to other problems, including unemployment and divorce: while this study shows that these problems affect well-being significantly more than air pollution, they only affect a fraction of the population, and their effects on future generations may not be too significant. Hence, the efficiency grounds for the policy are set. In terms of equity, the heterogeneity results among different groups highlights the fact that policy interventions should take into consideration equity and heterogeneity issues in addition to efficiency issues. This includes tailoring policies that are education and city specific. It should be noted that a substantive portion of the local air pollutants that we examined are emitted from automobiles and other transportation methods, thus environmental policy needs to be tailored to the transportation sector, which is also a primary contributor to the emission of climate changing greenhouse gases. Policy measures could be set to increase the usage of more environmentally friendly transportation methods that decrease air pollution. Furthermore, with the individuals having a positive marginal willingness to pay for pollution reduction, governments can implement environmental (or green) tax reforms through indirect green consumption taxes based on happiness/utility regression estimates. Some have found that the public's perception of government efforts to fight air pollution also plays an important role in determining the happiness of the individuals (Wang and Cheng, 2015). Thus, mass media apparatuses should enhance their information-delivery regarding the government's efforts to reduce air pollution so that the individuals' perceptions become well-aligned with actual efforts. Additionally, the present study shows the importance of education in encouraging individuals to engage in more environmentally friendly behavior and in increasing the valuation of pollution in monetary terms. This result also highlights the importance of educating the public on the importance of preserving the atmosphere from pollution to alleviate both local and global negative consequences on well-being.

Overall, this paper offers more robust and comprehensive results compared to those in the literature; additionally, it has attempted to test for possible endogeneity. Furthermore, one of the advantages of relying on a life regression equation in this paper (as opposed to stated preferences methods) is that it calculates these valuations without asking individuals how much they would be willing to pay, as these would be governed by biases arising from asymmetric information and undervaluation due to the free rider problem. Nevertheless, possibilities of endogeneity are not null, especially due to the complex nature of the happiness variable, with happiness being both a cause and an effect to all explanatory variables. Dealing with these problems by delving into possible instrumental variables as well as novel empirical strategies will be one of the subjects for future research.

Despite the limitations of this paper and the possible disadvantages of using the happiness regression method, this study consistently found that air pollution does affect happiness significantly. At the least, this study can serve as a complementary method to the standard valuation techniques so that policymakers can make better informed decisions when it comes to drafting policies that tackle climate change in the future.

Appendix I.

Table 1: Summary of the Literature							
Paper	Year	Countries	Pollutants	Nature of Data	Model	Result	Aggregation Level
Luechinger	2010	Europe	SO_2	Pooled	2SLS	Negative	Country
Cuñado and Pérez de Gracia	2012	Spain	NO_2, CO_2, PM_{10}	Cross Section	OLS	Negative	Region
Jidong and Yiran	2015	China	NO_2	Cross Section	Ordered probit	Negative	City
Ferreira et al.	2013	Europe	SO_2	Pooled	OLS	Negative	(Up to) NUTS3
Liu et al.	2018	China	NO_2, PM_{10}	Pooled	Ordered probit	Negative	Region
Ambrey et al.	2014	Australia	PM_{10}	Pooled	Ordered probit	Negative	Collection District
Orru et al.	2016	Estonia	PM_{10}	Pooled	OLS	Negative	1x1 km2 grid
Welsch	2003	Europe	NO_2	Panel	FE GLS	Negative	Country
Zhang et al.	2017	China	API	Panel	FE	Negative	City
Knight and Howley	2017	UK	NO_2	Panel	FE	Negative	LSOA
Lin et al.	2019	Taiwan	NO_2, $PM_{2.5}$, PM_{10}	Panel	Multilevel LGM	No effect	City
Goetzke and Rave	2015	Germany	Subjective Perception	Cross Section	IV probit	Indeterminate	N/A

Figure 5: The Market for Pollution Abatement

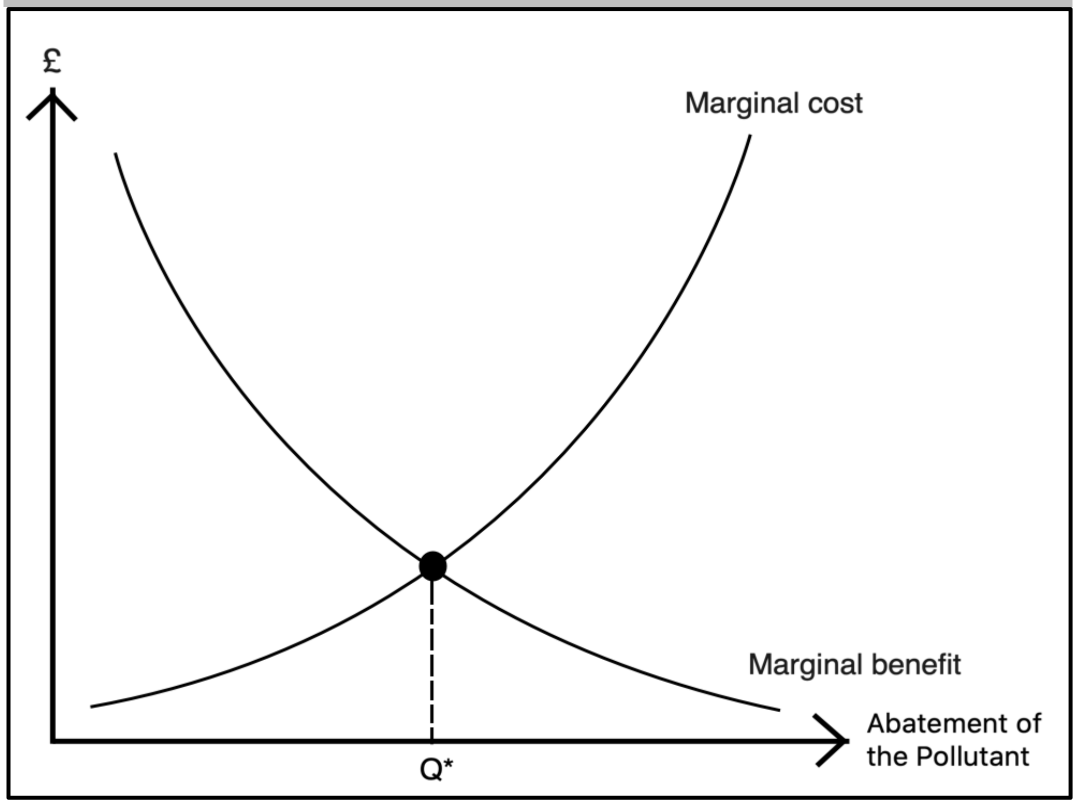


Figure 6: Pigouvian Tax

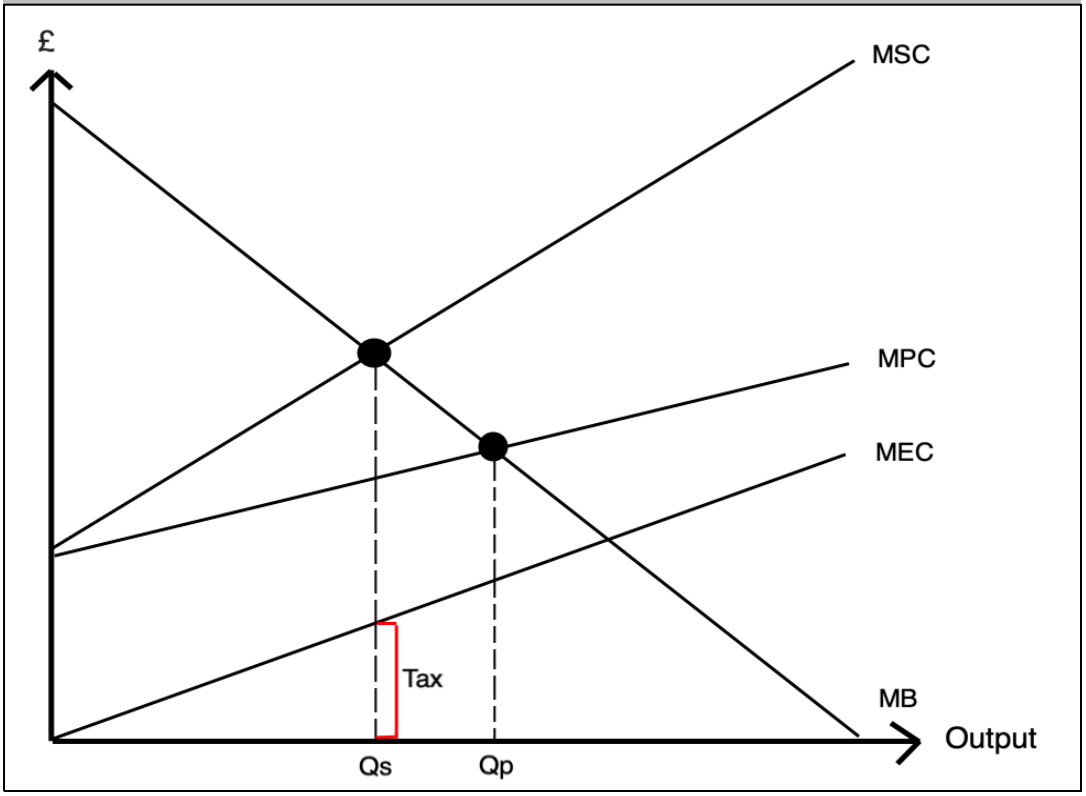


Table 2: Description of Variables

Variable Name	Variable Definition	Variable Values
	Dependent Variables	
Life Satisfaction	Subjective report of individual's life satisfaction.	1 (not satisfied) – 7 (very satisfied)
Hedonic Happiness	How distressed is the individual?	0 (not distressed) – 36 (very distressed)
	Main Regressors	
NO_2	Annual mean concentration of NO_2 for each LSOA.	In µg/m^3
$PM_{2.5}$	Annual mean concentration of $PM_{2.5}$ for each LSOA.	In µg/m^3
PM_{10}	Annual mean concentration of PM_{10} for each LSOA.	In µg/m^3
	Objective Individual Covariates	
Male	Is individual a male?	No (female) – yes (male)
Age	Age of individual	
Urban	Individual lives in an urban area.	No – yes

Labor Force Status[18]		
Unemployed	Is individual unemployed?	No – yes
Self-employed	Is individual self-employed?	No – yes
In paid employment	Is individual in paid employment?	No – yes
Full-time student	Is individual a full-time student?	No – yes
Retired	Is individual retired?	No – yes
On maternity leave	Is individual on maternity leave?	No – yes
Family care /home	Is individual engaged in family care or home?	No – yes
Long term sick or disabled	Is individual long term sick or disabled?	No – yes
Highest level of education[19]		
No qualification	Individual has no educational qualification.	No – yes
GCSE Education	Individual's highest qualification is GCSE education.	No – yes
A-Level Education	Individual's highest qualification is A-level education.	No – yes
Degree	Individual's highest qualification is an undergraduate degree.	No – yes
Higher Degree	Individual's highest qualification is higher than an undergraduate.	No – yes
Other Qualification	Individual has a qualification not listed above.	No – yes
Marital Status[20]		
Married	Individual is married.	No – yes
Never married	Individual has never been married.	No – yes
Separated	Individual is separated but legally married.	No – yes
Widowed	Individual is widowed.	No – yes
Divorced	Individual is divorced from partner.	No – yes
	Subjective Individual Covariates	
Health Satisfaction	Subjective report of individual's life satisfaction.	1 (not satisfied) – 7 (very satisfied)
	Objective Household Covariates	
Household Size	Number of individuals in the household.	
Children	Number of children in the household.	
Equivalent Income	Gross household deflated monthly income divided by the equivalence OECD scale.	
	Geographic Covariates	
GOR	Government Office Region.	
LSOA	Lower Layer Super Output Area.	
	Time Covariates	
Year	Year of interview response.	

18 In all regressions, "unemployed" is the base category. A category called "other" is included in the regressions, but omitted from the output tables.
19 In all regressions, "No qualification" is the base category.
20 In all regressions, "married" is the base category.

Table 3: Summary Statistics					
Variable Name	**N**	**Mean**	**Std. Dev**	**Min**	**Max**
Dependent Variables					
Life Satisfaction	341,833	5.173	1.453	1	7
Hedonic Happiness	350,769	11.124	5.517	0	36
Main Regressors					
NO_2	241,000	15.202	6.692	2.409	66.036
$PM_{2.5}$	241,000	15.398	3.015	6.468	33.272
PM_{10}	241,000	10.304	2.102	4.319	24
Objective Individual Covariates					
Male	408,000	0.461	0.498	0	1
Age	410,000	47.359	18.679	15	104
Urban	351,000	0.795	0.404	0	1
Labour Force Status					
Unemployed	409,178	0.047	0.213	0	1
Self-employed	409,178	0.078	0.269	0	1
In paid employment	409,178	0.473	0.499	0	1
Full-time student	409,178	0.069	0.253	0	1
Retired	409,178	0.227	0.419	0	1
On maternity leave	409,178	0.005	0.073	0	1
Family care /home	409,178	0.058	0.234	0	1
Long term sick or disabled	409,178	0.033	0.179	0	1
Highest level of education					
No qualification	402,487	0.140	0.347	0	1
GCSE Education	402,487	0.216	0.412	0	1
A-Level Education	402,487	0.210	0.407	0	1
Degree	402,487	0.226	0.418	0	1
Higher Degree	402,487	0.109	0.312	0	1
Other Qualification	402,487	0.098	0.298	0	1
Marital Status					
Married	387,522	0.532	0.499	0	1
Never married	387,522	0.299	0.458	0	1
Separated	387,522	0.018	0.134	0	1
Widowed	387,522	0.063	0.244	0	1
Divorced	387,522	0.087	0.282	0	1
Subjective Individual Covariates					
Health Satisfaction	342,000	4.791	1.692	1	7
Objective Household Covariates					
Household Size	407,000	2.976	1.534	1	16
Children	407,000	0.595	0.988	0	10
Equivalent Income	395,162	2086.6	1412.155	0	62288

Table 4: Description of Pollutants		
Pollutant	**Nitrogen Dioxide (NO_2)**	**Particulate Matter ($PM_{2.5}$ And PM_{10})**
Source	vehicle emissions, electricity, industrial operations	fires, caliche-topped roads; chemical reactions inside powerplants and vehicles
Maximum Acceptable Concentration	0.053 ppm (1 year)	150 μg/m3 (1 day for particles <10 μm); 35 μg/m3 (1 day for particles <2.5 μm)
Health Risks	inflammation and irritation in respiration system	irritation in respiratory system, asthma, irregular cardiac activity
Maximum Annual Mean Ambient Level for Human Health Protection	40 $\mu g/m^3$	$PM_{2.5}$: 25 $\mu g/m^3$ PM_{10}: 40 $\mu g/m^3$

Source: United States Environmental Protection Agency. (2016). National Ambient Air Quality Standards Table.

Table 5: Pollutants' Correlation			
Variables	NO_2	PM_{10}	$PM_{2.5}$
NO_2	1.000		
PM_{10}	0.691	1.000	
$PM_{2.5}$	0.733	0.940	1.000

Table 6: Pollutants on Life Satisfaction: Random Effects Ordinal Logit			
Log(Life Satisfaction)	NO_2	PM_{10}	$PM_{2.5}$
Log(Pollutant)	-0.094***	-0.099***	-0.113***
	(0.019)	(0.038)	(0.038)
Log(EquivalentIncome)	-0.349***	-0.351***	-0.351***
	(0.052)	(0.052)	(0.052)
Log^2(EquivalentIncome)	0.040***	0.040***	0.040***
	(0.004)	(0.004)	(0.004)
Gender	-0.110***	-0.110***	-0.110***
	(0.017)	(0.017)	(0.017)
Age	-0.046***	-0.046***	-0.046***
	(0.003)	(0.003)	(0.003)
Age^2	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)

GCSE Education	-0.109***	-0.106***	-0.106***
	(0.030)	(0.030)	(0.030)
A-Level Education	-0.117***	-0.114***	-0.115***
	(0.031)	(0.031)	(0.031)
Degree	-0.148***	-0.147***	-0.147***
	(0.032)	(0.032)	(0.032)
Higher Degree	-0.108***	-0.105***	-0.105***
	(0.035)	(0.035)	(0.035)
Other Qualification	-0.096***	-0.095***	-0.095***
	(0.035)	(0.035)	(0.035)
Self-employed	0.519***	0.523***	0.522***
	(0.036)	(0.036)	(0.036)
In Paid Employment	0.430***	0.430***	0.430***
	(0.029)	(0.029)	(0.029)
Retired	0.978***	0.980***	0.979***
	(0.036)	(0.036)	(0.036)
Full-Time Student	0.795***	0.797***	0.796***
	(0.038)	(0.038)	(0.038)
On Maternity Leave	1.055***	1.056***	1.056***
	(0.071)	(0.071)	(0.071)
Family Care or Home	0.495***	0.496***	0.496***
	(0.037)	(0.037)	(0.037)
Long-term Sick or Disabled	-0.064	-0.064	-0.064
	(0.043)	(0.043)	(0.043)
Never Married	-0.345***	-0.346***	-0.346***
	(0.022)	(0.022)	(0.022)
Separated	-0.577***	-0.578***	-0.578***
	(0.045)	(0.045)	(0.045)
Divorced	-0.374***	-0.374***	-0.374***
	(0.026)	(0.026)	(0.026)
Widowed	-0.472***	-0.474***	-0.474***
	(0.034)	(0.034)	(0.034)
Health Satisfaction	0.747***	0.748***	0.748***
	(0.004)	(0.004)	(0.004)
Number of Obs.	201129	201129	201129

Notes: ***, **, * indicate significance at the 1, 5, and 10% levels respectively. Year and regional fixed effects were included across all regressions.

Table 7: Pollutants on Life Satisfaction: Pooled Ordinal Logit			
Log(Life Satisfaction)	NO_2	PM_{10}	$PM_{2.5}$
Log(Pollutant)	-0.056***	-0.108***	-0.124***
	(0.019)	(0.041)	(0.040)
Log(EquivalentIncome)	-0.422***	-0.422***	-0.422***
	(0.052)	(0.052)	(0.052)
Log^2(EquivalentIncome)	0.047***	0.047***	0.047***
	(0.004)	(0.004)	(0.004)
Gender	-0.099***	-0.099***	-0.099***
	(0.013)	(0.013)	(0.013)
Age	-0.037***	-0.037***	-0.037***
	(0.002)	(0.002)	(0.002)
Age^2	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
GCSE Education	-0.117***	-0.117***	-0.117***
	(0.027)	(0.027)	(0.027)
A-Level Education	-0.130***	-0.130***	-0.130***
	(0.028)	(0.027)	(0.027)
Degree	-0.182***	-0.183***	-0.183***
	(0.028)	(0.028)	(0.028)
Higher Degree	-0.109***	-0.108***	-0.108***
	(0.030)	(0.030)	(0.030)
Other Qualification	-0.084***	-0.084***	-0.084***
	(0.031)	(0.031)	(0.031)
Self-employed	0.470***	0.473***	0.472***
	(0.036)	(0.036)	(0.036)
In Paid Employment	0.387***	0.388***	0.388***
	(0.030)	(0.030)	(0.030)
Retired	1.020***	1.022***	1.021***
	(0.037)	(0.037)	(0.037)
Full-Time Student	0.689***	0.690***	0.690***
	(0.038)	(0.038)	(0.038)
On Maternity Leave	0.950***	0.951***	0.951***
	(0.064)	(0.064)	(0.064)
Family Care or Home	0.502***	0.503***	0.503***
	(0.038)	(0.038)	(0.038)
Long-term Sick or Disabled	0.076*	0.078*	0.077*

	(0.045)	(0.045)	(0.045)
Never Married	-0.312***	-0.312***	-0.312***
	(0.020)	(0.020)	(0.020)
Separated	-0.514***	-0.515***	-0.515***
	(0.045)	(0.045)	(0.045)
Divorced	-0.305***	-0.305***	-0.305***
	(0.024)	(0.024)	(0.024)
Widowed	-0.389***	-0.391***	-0.391***
	(0.032)	(0.032)	(0.032)
Health Satisfaction	0.724***	0.724***	0.724***
	(0.005)	(0.005)	(0.005)
Number of Obs.	201129	201129	201129

Notes: ***, **, * indicate significance at the 1, 5, and 10% levels respectively. Year and regional fixed effects were included across all regressions.

Table 8: Pollutants on Life Satisfaction: Random Effects Ordinal Probit

Log(Life Satisfaction)	NO_2	PM_{10}	$PM_{2.5}$
Log(Pollutant)	-0.049***	-0.052**	-0.063***
	(0.011)	(0.021)	(0.021)
Log(EquivalentIncome)	-0.057***	-0.057***	-0.057***
	(0.009)	(0.009)	(0.009)
Log^2(EquivalentIncome)	-0.024***	-0.024***	-0.024***
	(0.001)	(0.001)	(0.001)
Gender	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Age	-0.062***	-0.060***	-0.061***
	(0.016)	(0.016)	(0.016)
Age^2	-0.066***	-0.064***	-0.064***
	(0.017)	(0.017)	(0.017)
GCSE Education	-0.084***	-0.083***	-0.083***
	(0.017)	(0.017)	(0.017)
A-Level Education	-0.062***	-0.061***	-0.061***
	(0.019)	(0.019)	(0.019)
Degree	-0.054***	-0.053***	-0.054***
	(0.019)	(0.019)	(0.019)
Higher Degree	0.285***	0.287***	0.286***
	(0.020)	(0.020)	(0.020)

Other Qualification	0.232***	0.232***	0.232***
	(0.016)	(0.016)	(0.016)
Self-employed	0.537***	0.538***	0.537***
	(0.020)	(0.020)	(0.020)
In Paid Employment	0.432***	0.433***	0.433***
	(0.021)	(0.021)	(0.021)
Retired	0.572***	0.572***	0.572***
	(0.039)	(0.039)	(0.039)
Full-Time Student	0.275***	0.276***	0.276***
	(0.021)	(0.021)	(0.021)
On Maternity Leave	-0.041*	-0.041*	-0.041*
	(0.024)	(0.024)	(0.024)
Family Care or Home	-0.188***	-0.189***	-0.189***
	(0.012)	(0.012)	(0.012)
Long-term Sick or Disabled	-0.314***	-0.314***	-0.314***
	(0.025)	(0.025)	(0.025)
Never Married	-0.197***	-0.197***	-0.197***
	(0.014)	(0.014)	(0.014)
Separated	-0.255***	-0.256***	-0.256***
	(0.019)	(0.019)	(0.019)
Divorced	-0.188***	-0.189***	-0.189***
	(0.029)	(0.029)	(0.029)
Widowed	0.022***	0.022***	0.022***
	(0.002)	(0.002)	(0.002)
Health Satisfaction	0.405***	0.405***	0.405***
	(0.002)	(0.002)	(0.002)
Number of Obs.	201129	201129	201129

Notes: ***, **, * indicate significance at the 1, 5, and 10% levels respectively. Year and regional fixed effects were included across all regressions.

Table 9: Pollutants on Hedonic Happiness: Random Effects Ordinal Logit

Log(Hedonic Happiness)	NO_2	PM_{10}	$PM_{2.5}$
Log(Pollutant)	0.076***	0.094**	0.094***
	(0.020)	(0.037)	(0.036)

Log(EquivalentIncome)	0.06 (0.049)	0.061 (0.049)	0.061 (0.049)
Log^2(EquivalentIncome)	-0.012*** (0.004)	-0.013*** (0.004)	-0.013*** (0.004)
Gender	-0.558*** (0.019)	-0.558*** (0.019)	-0.558*** (0.019)
Age	0.034*** (0.003)	0.034*** (0.003)	0.034*** (0.003)
Age^2	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
GCSE Education	-0.167*** (0.032)	-0.169*** (0.032)	-0.169*** (0.032)
A-Level Education	-0.108*** (0.033)	-0.111*** (0.033)	-0.110*** (0.033)
Degree	-0.083** (0.034)	-0.085** (0.034)	-0.085** (0.034)
Higher Degree	-0.115*** (0.037)	-0.117*** (0.037)	-0.117*** (0.037)
Other Qualification	-0.142*** (0.037)	-0.142*** (0.037)	-0.142*** (0.037)
Self-employed	-0.865*** (0.036)	-0.867*** (0.036)	-0.867*** (0.036)
In Paid Employment	-0.769*** (0.029)	-0.769*** (0.029)	-0.769*** (0.029)
Retired	-0.943*** (0.035)	-0.944*** (0.035)	-0.944*** (0.035)
Full-Time Student	-0.769*** (0.038)	-0.770*** (0.038)	-0.770*** (0.038)
On Maternity Leave	-0.976*** (0.066)	-0.977*** (0.066)	-0.977*** (0.066)
Family Care or Home	-0.507*** (0.036)	-0.507*** (0.036)	-0.507*** (0.036)
Long-term Sick or Disabled	0.547*** (0.044)	0.547*** (0.044)	0.547*** (0.044)
Never Married	0.087*** (0.023)	0.087*** (0.023)	0.087*** (0.023)
Separated	0.439*** (0.045)	0.439*** (0.045)	0.439*** (0.045)

Divorced	0.127***	0.127***	0.128***
	(0.027)	(0.027)	(0.027)
Widowed	0.225***	0.227***	0.227***
	(0.034)	(0.034)	(0.034)
Health Satisfaction	-0.333***	-0.333***	-0.333***
	(0.003)	(0.003)	(0.003)
Number of Obs.	199839	199839	199839

Notes: ***, **, * indicate significance at the 1, 5, and 10% levels respectively. Year and regional fixed effects were included across all regressions.

Table 10: Pollutants on Hedonic Happiness: Pooled Ordinal Logit

Log(Hedonic Happiness)	NO_2	PM_{10}	$PM_{2.5}$
Log(Pollutant)	0.054***	0.136***	0.131***
	(0.019)	(0.041)	(0.041)
Log(EquivalentIncome)	0.115**	0.115**	0.115**
	(0.045)	(0.045)	(0.045)
Log^2(EquivalentIncome)	-0.017***	-0.017***	-0.017***
	(0.003)	(0.003)	(0.003)
Gender	-0.396***	-0.396***	-0.396***
	(0.013)	(0.013)	(0.013)
Age	0.017***	0.017***	0.017***
	(0.003)	(0.003)	(0.003)
Age^2	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
GCSE Education	-0.057**	-0.057**	-0.057**
	(0.027)	(0.027)	(0.027)
A-Level Education	-0.033	-0.033	-0.033
	(0.027)	(0.027)	(0.027)
Degree	0.048*	0.050*	0.049*
	(0.028)	(0.028)	(0.028)
Higher Degree	-0.036	-0.035	-0.036
	(0.031)	(0.031)	(0.031)
Other Qualification	-0.074**	-0.074**	-0.074**
	(0.031)	(0.031)	(0.031)
Self-employed	-0.691***	-0.693***	-0.693***
	(0.037)	(0.037)	(0.037)
In Paid Employment	-0.610***	-0.611***	-0.611***

	(0.032)	(0.032)	(0.032)
Retired	-0.805***	-0.806***	-0.806***
	(0.038)	(0.038)	(0.038)
Full-Time Student	-0.561***	-0.562***	-0.562***
	(0.041)	(0.041)	(0.041)
On Maternity Leave	-0.763***	-0.765***	-0.765***
	(0.065)	(0.065)	(0.065)
Family Care or Home	-0.447***	-0.448***	-0.447***
	(0.039)	(0.039)	(0.039)
Long-term Sick or Disabled	0.538***	0.537***	0.538***
	(0.051)	(0.051)	(0.051)
Never Married	0.025	0.025	0.025
	(0.021)	(0.021)	(0.021)
Separated	0.325***	0.325***	0.326***
	(0.051)	(0.051)	(0.051)
Divorced	0.066***	0.066***	0.066***
	(0.025)	(0.025)	(0.025)
Widowed	0.151***	0.152***	0.152**
	(0.032)	(0.032)	(0.032)
Health Satisfaction	-0.408***	-0.408***	-0.408***
	(0.004)	(0.004)	(0.004)
Number of Obs.	199839	199839	199839

Notes: ***, **, * indicate significance at the 1, 5, and 10% levels respectively. Year and regional fixed effects were included across all regressions.

Table 11: Pollutants on Hedonic Happiness: Random Effects Ordinal Probit			
Log(Hedonic Happiness)	NO_2	PM_{10}	$PM_{2.5}$
Log(Pollutant)	0.042***	0.050**	0.053***
	(0.011)	(0.021)	(0.020)
Log(EquivalentIncome)	0.033	0.034	0.034
	(0.028)	(0.028)	(0.028)
Log^2(EquivalentIncome)	-0.007***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)
Gender	-0.298***	-0.298***	-0.298***
	(0.010)	(0.010)	(0.010)
Age	0.019***	0.019***	0.019***
	(0.002)	(0.002)	(0.002)
Age^2	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
GCSE Education	-0.084***	-0.086***	-0.085***
	(0.017)	(0.017)	(0.017)
A-Level Education	-0.059***	-0.061***	-0.061***
	(0.018)	(0.018)	(0.018)
Degree	-0.041**	-0.042**	-0.042**
	(0.019)	(0.019)	(0.019)
Higher Degree	-0.057***	-0.059***	-0.059***
	(0.020)	(0.020)	(0.020)
Other Qualification	-0.079***	-0.079***	-0.079***
	(0.020)	(0.020)	(0.020)
Self-employed	-0.465***	-0.466***	-0.466***
	(0.019)	(0.019)	(0.019)
In Paid Employment	-0.410***	-0.410***	-0.410***
	(0.016)	(0.016)	(0.016)
Retired	-0.505***	-0.506***	-0.506***
	(0.019)	(0.019)	(0.019)
Full-Time Student	-0.400***	-0.400***	-0.400***
	(0.020)	(0.020)	(0.020)
On Maternity Leave	-0.523***	-0.523***	-0.523***
	(0.036)	(0.036)	(0.036)
Family Care or Home	-0.261***	-0.262***	-0.262***
	(0.020)	(0.020)	(0.020)
Long-term Sick or Disabled	0.322***	0.321***	0.322***
	(0.024)	(0.024)	(0.024)

Never Married	0.043***	0.043***	0.043***
	(0.012)	(0.012)	(0.012)
Separated	0.241***	0.242***	0.242***
	(0.024)	(0.024)	(0.024)
Divorced	0.066***	0.066***	0.066***
	(0.015)	(0.015)	(0.015)
Widowed	0.125***	0.126***	0.125***
	(0.019)	(0.019)	(0.019)
Health Satisfaction	-0.192***	-0.192***	-0.192***
	(0.002)	(0.002)	(0.002)
Number of Obs.	199839	199839	199839

Notes: ***, **, * indicate significance at the 1, 5, and 10% levels respectively. Year and regional fixed effects were included across all regressions.

Table 12: Pollutants on Life Satisfaction: Pooled Ordered Logit (Standardized)

Life Satisfaction	NO_2	PM_{10}	$PM_{2.5}$
Pollutant	-0.011***	-0.009***	-0.011***
	(0.001)	(0.002)	(0.003)
Log(EquivalentIncome)	-0.120***	-0.120***	-0.120***
	(0.044)	(0.044)	(0.044)
Log^2(EquivalentIncome)	0.193***	0.193***	0.193***
	(0.003)	(0.003)	(0.003)
Gender	-0.022***	-0.022***	-0.022***
	(0.009)	(0.009)	(0.009)
Age	-0.305***	-0.305***	-0.305***
	(0.002)	(0.002)	(0.002)
Age^2	0.344***	0.344***	0.344***
	(0.000)	(0.000)	(0.000)
GCSE Education	-0.022***	-0.022***	-0.022***
	(0.016)	(0.016)	(0.016)
A-Level Education	-0.024***	-0.023***	-0.024***
	(0.017)	(0.017)	(0.017)
Degree	-0.034***	-0.034***	-0.034***
	(0.017)	(0.017)	(0.017)
Higher Degree	-0.016***	-0.016***	-0.016***
	(0.018)	(0.018)	(0.018)
Other Qualification	-0.011***	-0.011***	-0.011***

	(0.019)	(0.019)	(0.019)
Self-employed	0.057***	0.057***	0.057***
	(0.027)	(0.027)	(0.027)
In Paid Employment	0.086***	0.086***	0.086***
	(0.024)	(0.024)	(0.024)
Retired	0.199***	0.199***	0.199***
	(0.028)	(0.028)	(0.028)
Full-Time Student	0.07***	0.070***	0.070***
	(0.030)	(0.030)	(0.030)
On Maternity Leave	0.032***	0.032***	0.032***
	(0.061)	(0.061)	(0.061)
Family Care or Home	0.048***	0.048***	0.048***
	(0.029)	(0.029)	(0.029)
Long-term Sick or Disabled	0.006**	0.006**	0.006**
	(0.033)	(0.033)	(0.033)
Never Married	-0.061***	-0.061***	-0.061***
	(0.013)	(0.013)	(0.013)
Separated	-0.029***	-0.029***	-0.029***
	(0.032)	(0.032)	(0.032)
Divorced	-0.039***	-0.039***	-0.039***
	(0.015)	(0.015)	(0.015)
Widowed	-0.042***	-0.042***	-0.042***
	(0.020)	(0.020)	(0.020)
Health Satisfaction	0.541***	0.541***	0.541***
	(0.003)	(0.003)	(0.003)
Number of Obs.	201129	201129	201129

Notes: ***, **, * indicate significance at the 1, 5, and 10% levels respectively. Year and regional fixed effects were included across all regressions.

Table 13: Pollutants on Hedonic Happiness: Pooled Ordered Logit (Standardized)			
Hedonic Happiness	NO_2	PM_{10}	$PM_{2.5}$
Pollutant	0.010***	0.011***	0.011***
	(0.001)	(0.002)	(0.002)
Log(EquivalentIncome)	0.035***	0.035***	0.035***
	(0.040)	(0.040)	(0.040)
Log^2(EquivalentIncome)	-0.076***	-0.076***	-0.076***
	(0.003)	(0.003)	(0.003)
Gender	-0.098***	-0.098***	-0.098***
	(0.008)	(0.008)	(0.008)
Age	0.159***	0.159***	0.159***
	(0.002)	(0.002)	(0.002)
Age^2	-0.186***	-0.186***	-0.186***
	(0.000)	(0.000)	(0.000)
GCSE Education	-0.011***	-0.011***	-0.011***
	(0.015)	(0.015)	(0.015)
A-Level Education	-0.006**	-0.006**	-0.006**
	(0.015)	(0.015)	(0.015)
Degree	0.010***	0.010***	0.010***
	(0.016)	(0.016)	(0.016)
Higher Degree	-0.006**	-0.006**	-0.006**
	(0.017)	(0.017)	(0.017)
Other Qualification	-0.010***	-0.010***	-0.010***
	(0.017)	(0.017)	(0.017)
Self-employed	-0.093***	-0.093***	-0.093***
	(0.026)	(0.026)	(0.026)
In Paid Employment	-0.151***	-0.151***	-0.151***
	(0.023)	(0.023)	(0.023)
Retired	-0.174***	-0.175***	-0.174***
	(0.027)	(0.027)	(0.027)
Full-Time Student	-0.063***	-0.063***	-0.063***
	(0.030)	(0.030)	(0.030)
On Maternity Leave	-0.028***	-0.028***	-0.028***
	(0.057)	(0.057)	(0.057)
Family Care or Home	-0.047***	-0.047***	-0.047***
	(0.029)	(0.029)	(0.029)
Long-term Sick or Disabled	0.046***	0.045***	0.046***

	(0.033)	(0.033)	(0.033)
Never Married	0.005*	0.005*	0.005*
	(0.012)	(0.012)	(0.012)
Separated	0.021***	0.021***	0.021***
	(0.031)	(0.031)	(0.031)
Divorced	0.009***	0.009***	0.009***
	(0.014)	(0.014)	(0.014)
Widowed	0.018***	0.019***	0.018***
	(0.018)	(0.018)	(0.018)
Health Satisfaction	-0.344***	-0.344***	-0.344***
	(0.003)	(0.003)	(0.003)
Number of Obs.	200412	200412	200412

Notes: ***, **, * indicate significance at the 1, 5, and 10% levels respectively. Year and regional fixed effects were included across all regressions.

Table 14: The Marginal Rate of Substitution (MRS) between Happiness and Pollutants: Heterogeneity Differences

	Full Sample	Urban Sample	High Education Sample
PM_{10} β_1	0.0002362	0.0001608	0.0003056
β_4	-4.44E-06	-4.25E-06	-5.92.E-06
β_5	1.15E-10	7.12E-11	1.65E-10
$\overline{Income}$	2079.3	2018.2	2674.3
MRS PM_{10} for Income	59.62	40.58	60.66
$PM_{2.5}$ β_1	0.0004078	0.0002924	0.0004189
β_4	-4.44E-06	-4.25E-06	-5.93E-06
β_5	1.15E-10	7.11E-11	1.65E-10
$\overline{Income}$	2079.3	2018.2	2674.3
MRS $PM_{2.5}$ for Income	102.93	73.78	82.99
NO_2 β_1	0.0002458	0.0001596	0.0004158
β_4	-4.41E-06	-4.23E-06	-6.E-06
β_5	1.14E-10	7.06E-11	1.63E-10
$\overline{Income}$	2079.3	2018.2	2674.3
MRS NO_2 for Income	62.45	40.46	83.19

Source: Based on authors' own calculations by relying on data from BHPS and UKHLS years 2004 – 2019.

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