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Can clean air make you happy? Examining the effect of nitrogen dioxide (NO_2) on life satisfaction

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Abstract
In order to estimate the welfare effects of exposure to nitrogen dioxide (NO_2), we combine life satsifaction data from the British Household Panel Survey (BHPS) and UK Household Longitudinal Survey (UKHLS) with detailed air quality records held by the UK Department for Environment, Food and Rural Affairs (DEFRA). To address endogeneity concerns, we linked these with a variety of geo-referenced datasets capturing differences in economic, social and environmental conditions across neighbourhoods. We also took advantage of the panel nature of our data by employing individual fixed effects. Our results suggest a significant and negative association between mean annual ambient NO_2 and life satisfaction, and moreover that these effects are substantive and comparable to that of many 'big hitting' life events.

Keywords: NO_2, air pollution, life satisfaction, well-being, environmental quality, Understanding Society, British Household Panel Survey, Geographic Information Systems (GIS), England

JEL classification: Q51, Q53

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Section 1. Introduction

Local environmental amenities such as clean air play a significant role in our quality of life. Much previous research, for instance, has highlighted the importance of proximity/exposure to green space (Pretty *et al.* 2005; Takayama *et al.* 2014) and blue space (Bell *et al.* 2015), climate (Feddersen, Metcalfe & Wooden 2016), biodiversity (Fuller *et al.* 2007; Dallimer *et al.* 2012) and air quality (Welsch 2006; Luechinger 2009; Ambrey & Fleming 2014) for our overall well-being. But how much value do we put on environmental features relative to other factors that affect our utility? Unfortunately environmental amenities often do not have prices and will therefore be typically underprovided by the market. However in order to provide a clear rationale for environmental management and regulation, it is important to calculate how much value people attribute to environmental features (Srinivasan & Stewart 2004; Welsch & Kühling 2009).

Typically economists have relied on stated and revealed preference methods to estimate the utility gains/losses associated with changes in the provision of environmental goods and services (Kuminoff, Parmeter & Pope 2010; Egan, Corrigan & Dwyer 2015). Stated preference studies construct a hypothetical contingent market where the individual is asked to state their willingness to pay for the non-market good in question, whereas revealed preference methods such as Hedonic Pricing try to infer the value of non-market goods by observing the actual behavior of individuals, e.g. their choice of home (Kim, Phipps & Anselin 2003; Chay & Greenstone 2005).

Both methods have their advantages and disadvantages. Revealed preference methods, for instance, reflect real-life decisions that are conducted in actual markets and so avoid the hypothetical bias associated with stated preference methods. One disadvantage with this approach is that consumer decisions are based on perceived rather than objective perceptions of environmental features. If adequate information on the provision of environmental features (e.g. level of air pollution or amount of open space) is missing or at least not readily apparent, an individual's subjective assessment may not correspond with the objective measures. This could lead to biased estimates of an individual's willingness to pay for environmental amenities (Luechinger & Raschky 2009; Frey, Luechinger & Stutzer 2010).

Stated preference methods such as contingent valuation are extremely flexible in that it allows valuation of a wider variety of non-market goods and services than is possible with revealed preferences. A limitation with this methodology is that it is susceptible to hypothetical bias and framing problems (Murphy *et al.* 2005; Lusk & Norwood 2009). More specifically, individuals may find it difficult to provide realistic value estimates due to difficulty evaluating hypothetical choice tasks.

As an alternative to these methods, the use of subjective well-being data has been increasingly used as a mechanism for communicating the welfare effects stemming from exposure to environmental (dis)amenities. With this approach, subjective well-being is used as a proxy for individual utility and indicators of environmental quality are entered as an explanatory variable in a micro-econometric life satisfaction equation. It has been used, for example, to derive a value or, put differently, to illustrate the 'psychological' cost associated with ecosystem diversity (Ambrey & Fleming 2014), airport noise (van Praag & Baarsma 2005), flood disasters (Luechinger & Raschky 2009), climate (Maddison & Rehdanz 2011), scenic amenity (Ambrey & Fleming 2011), green space (Tsurumi & Managi 2015; Krekel, Kolbe & Wüstemann 2016) and air quality (Mackerron & Mourato 2008; Luechinger 2009; Levinson 2012; Ferreira *et al.* 2013; Ambrey, Fleming & Chan 2014; Orru *et al.* 2016).

In this paper, we use subjective well-being data as a means to estimate the welfare losses associated with exposure to nitrogen dioxide (NO_2). We concentrate on NO_2 in this paper as it is a significant gaseous pollutant across the UK, emitted from road traffic and energy production processes. It is a precursor to particulate pollution and low-level ozone and as such highly relevant for human well-being (Brook *et al.* 2010; Brunekreef *et al.* 2015; Shah *et al.* 2015). In addition, UK levels of NO_2 regularly exceed legally enforced EU air quality standards, such as those set out in the EU Ambient Air Quality Directive and the fourth Daughter Directive[1]. Higher levels of NO_2 emissions are largely attributable to increasing numbers of diesel vehicles on the roads. By 2013, diesel cars made up 34.5% of the licensed car total in Great Britain, up from 7.4% in 1994 (Department for Transport 2014). Therefore the study of NO_2 exposure on human well-being also has significant implications for transport policy in the UK.

[1] Air quality management is largely driven by European (EU) legislation which England has passed as law, as part of The Air Quality Standards Regulation 2010. These directives (e.g. EU directives 2008/50/EC, 1996/62/EC, and 1999/30/EC) set out legal daily exceedance and annual mean levels of several ambient outdoor air pollutants, including NO_2, to protect and improve human well-being. The legal NO_2 annual mean 40 $\mu g/m^3$ is exceeded in parts of the UK every year. Details of these directives can be found here: http://ec.europa.eu/environment/air/quality/legislation/existing_leg.htm.

While there has been little previous work examining the role of NO_2 on life satisfaction, there is a growing body of literature which have estimated the relationship between other indicators of air quality, such as particulate matter (PM_{10}) and sulphur dioxide (SO_2) with well-being. For example, Ambrey *et al.* (2014) and Ferreira & Moro (2010) using cross-sectional data find a negative association with PM_{10} and subjective well-being in Australia and Ireland respectively. Levinson (2012) also finds a negative association between PM_{10} and well-being in the United States by using an innovative approach where he was able to match happiness data with air pollution data on the day and place individuals were surveyed. Looking at SO_2, Ferreira *et al.* (2013) conduct a cross-sectional analysis of the European Social Survey and find a negative association between SO_2 and life satisfaction. Luechinger (2009) uses longitudinal panel data and high spatial resolution air pollution data to explore the relationship between SO_2 and life satisfaction in Germany. He uses respondents' locations upwind and downwind of large power plants that installed emissions control equipment as an instrument for SO_2 emissions and similarly to Ferreira *et al.* (2013) observes a significant negative association between SO_2 and life satisfaction.

We are aware of two prior studies that have examined the relationship between NO_2 and subjective well-being (Welsch 2002, 2007; Mackerron & Mourato 2008). The analysis by MacKerron and Mourato (2009) relies on a cross-sectional analysis of approximately 400 Londoners and finds a 10 $\mu g/m^3$ increase in NO_2 is associated with an average decrease of 0.5 across an 11 point scale of life satisfaction. Welsch (2002, 2007) considers the relationship between NO_2 and average self-reported happiness using cross-sectional data for 54 countries and finds a 1 kiloton increase in urban NO_2 is associated with a 0.003 decrease in average population happiness across a 4 point scale.

While both of these studies have made an important contribution to the subjective well-being literature, their estimates are potentially affected by various sources of endogeneity bias. For instance, Welsch relies on relatively large geographical units of analysis (e.g. country-level) as well as uses average reported well-being across countries as opposed to well-being reported at the individual level Second, both of these studies are at risk of confounding the effects of air quality with the effects of unobserved factors, such as differences in economic, social and environmental conditions across neighbourhoods which may be related to both air pollution and individuals' subjective well-being.

To the best of our knowledge, this study is the first analysis of the relationship between NO_2 and subjective well-being that takes account of these endogeneity issues. First, to help isolate the effect of NO_2 from other confounding variables, we link our survey and environmental datasets recording individual's well-being and exposure to NO_2 with a variety of external geo-referenced datasets capturing differences in economic, social and environmental conditions across neighbourhoods. The datasets include the English Indices of Deprivation available from the Department for Communities and Local Government (DCLG) which record relative levels of deprivation in 32,482 small areas or neighbourhoods, called Lower-layer Super Output Areas (LSOA) in England, and estimates of population density available from the Office for National Statistics (ONS). Second, we use estimates of green and blue space available from the Generalised Land Use Database (GLUD), available from DCLG also at the LSOA level. To account for other sources of unobserved time-invariant heterogeneity (e.g. personality traits), we take advantage of the panel nature of our dataset by adopting a fixed effects regression approach. Finally, as a robustness check we instrument NO_2 with annual average daily traffic flow (AADF) counts and road density. Traffic flow and road density are significantly related with NO_2 levels but we argue exogenous to subjective well-being after conditioning on a wide set of control varibables such as economic and social deprivation, population density and commuting patterns.

We find that NO_2 is significantly related with subjective well-being, albeit much smaller in magnitude than previous estimates after controlling for a variety of important spatial controls. That being said, the effect size is substantive and comparable to that of many other widely studied determinants of subjective well-being. For example, our standardised coefficients suggest that the effect of NO_2 on life satisfaction is equivalent to approximately half that of unemployment, and equivalent to that of marital separation and widowhood, factors commonly associated with some of the largest well-being reductions in the literature to date. Given that the effect of NO_2 is, to some extent, experienced by everyone (i.e. not everyone is unemployed but everyone is subject to a certain level of NO_2 exposure) this suggests that the welfare gains to society from reductions in exposure to NO_2 can be substantive.

Section 2: Subjective measures of well-being

One of the central assumptions underpinning neo-classical economics is that utility is formed based on the consumption of goods, and that individuals will always make decisions that maximise their individual utility. There is much research to suggest, however, that individuals may make sub-optimal decisions due to cognitive biases and inadequate information (Sen 1977; McFadden 1999; Rieskamp, Busemeyer & Mellers 2006). In other words, behaviour may not always be reflective of rational self-interest. This has led to an emerging body of research seeking to base assessments of welfare on experience utility (i.e. happiness data) rather than choice based methods such as revealed preferences (Clark, Frijters & Shields 2006; Krueger & Schkade 2008). Proponents behind the use of experience utility as a welfare criterion for public policy seek to explore what factors affect people's subjective well-being and use such information to inform economic and social policy (e.g. Donovan & Halpern 2002; Kahneman & Sugden 2005; Layard 2005; Treasury 2008; Dolan & Metcalfe 2012; OECD 2013). This approach also recognises that while consumers are becoming increasingly satiated with products, this is often not matched by increases in how they rate their quality of life (Forgeard *et al.* 2011; Hirschauer, Lehberger & Musshoff 2015).

Emerging interdisciplinary research has begun to address concerns regarding the reliability of using subjective measures of well-being as an approximation for individually experienced welfare or utility. They have been shown to have a high scientific standard in terms of internal consistency, reliability and validity (Frey *et al.* 2010) and have been shown to be stable over time (Diener *et al.* 1999). They have been found to be consistent with third party respondent evaluations, for example, with those who report high satisfaction with their life also reported as being satisfied by family members, friends and experts (Sandvik, Diener & Seidlitz 1993). Subjective well-being measures have also been shown to be directly associated with physical reactions that can be thought of as describing true internal happiness. For example visible signs of cheerfulness such as smiling have been positively associated with self-reported happiness (Di Tella & Macculloch 2006). Happier nations tend to have lower levels of hypertension (Blanchflower & Oswald 2008) and lower suicide rates (Di Tella, MacCulloch & Oswald 2003), and low levels of subjective well-being have been associated with reported chronic pain and unemployment (Kahneman & Krueger 2006).

When we use subjective measures of well-being (e.g. self-reported life satisfaction) as a valid approximation for individually experienced welfare or utility, we can calculate the welfare effects of environmental goods by estimating a micro-econometric life satisfaction function with the environmental variable(s) of interest (e.g. NO_2) included as an explanatory variable. The coefficients from this equation can then be used to estimate the 'psychological' cost of exposure to an environmental disamenity such as NO_2, relative to other factors that are related with subjective well-being. While not without its own limitations, this approach avoids some of the difficulties inherent with stated and revealed preferences. For example, it is less likely to suffer from hypothetical bias and framing problems associated with stated preference techniques. It is also less cognitively demanding for respondents and there is no reason to expect answers to be affected by strategic behaviour. In fact, people may not even be aware that there is a cause-effect relationship between environmental conditions and their self-reported life satisfaction (Frey *et al.* 2010). Furthermore, in contrast to revealed preference methods, it neither presumes rational agents nor does it need to rely on assumed equilibrium in private market transactions to estimate the value of public goods (Ferreira & Moro 2010; Neuteleers & Engelen 2015).

Section 4: Data and methods

Sample

The British Household Panel Survey (BHPS) and the UK Household Longitudinal Survey (UKHLS) are large multi-year panel surveys collecting individual and household information from a representative UK sample population and are part of the Understanding Society project[2] (University of Essex *et al*., 2014; University of Essex, 2016). Demographic, socio-economic, health and geographic data are collected in both datasets, as well as that pertaining to attitudes, opinions and values. The BHPS runs from 1991 to 2008 (waves 1-18) and collected information from over 10,000 individuals (5000 households). The UKHLS runs from 2009 to present day, with data currently available to 2014 (waves 1-5), collecting information from over 50,000 individuals (40,000 households). Data collection for each wave in the BHPS is undertaken within a single year but the UKHLS uses an overlapping panel design with data collection for a single wave conducted across 24 months. Interviews are typically carried out face-to-face in respondents' homes by trained interviewers. BHPS participants continue to be interviewed as part of the UKHLS and are present from wave 2 onwards. The two datasets were combined to create a longer time series[3].

The measure of subjective well-being used in this study is based on respondents' answer to the following question: 'How dissatisfied or satisfied are you with life overall?' Respondents give a single reply from a likert scale with options ranging from 7 ('completed satisfied') to 1 ('completely unsatisfied'). Life satisfaction is one of the most commonly used subjective well-being measures in the literature to date. Fortunately this life satisfaction question is consistent across both surveys but was not asked in the BHPS wave 11 (relating to the year 2001) so we restricted the analysis to begin in 2002. Based on prior literature, we include a rich set of commonly observed predictors of an individual's subjective well-being in our regression analysis (see Dolan *et al.* (2008) for a review of this literature). These include socio-economic factors such as income, age, gender, relationship

[2] Understanding Society is a longitudinal sample of individuals representing the whole UK population, and interviewed within a household context (www.understandingsociety.ac.uk).

[3] Waves 1-5 of the UKHLS are taken as waves 19-23 of the BHPS, creating a continuous time series. As BHPS waves are collected each calendar year and UKHLS waves over two years, both wave and interview year variables are maintained.

status, health, education, and labour force status (see Table I for a more detailed explanation of all the variables used in the analysis). A year variable was included to account for any natural temporal progression in the data.

Insert table I here

Each individual in the BHPS and UKHLS datasets has a geographic identifier at the LSOA level (32,482 LSOAs in England) for each wave. This geographic identifier allows us to link each individual in the household survey with a number of neighbourhood level datasets, including those recording NO_2 levels. LSOAs are an administrative geography used to describe small area statistics, defined by population size (between 1000-3000) and household count (between 400-1200). As other neighbourhood-level control variables are only available for England we limit our analysis to this extent. The mean area of an English LSOA is 4km^2. Due to population fluctuations approximately 5% of LSOAs changed in 2011 (split, merged or deleted). For consistency across time, any individual who has lived in the LSOAs that changed were removed from this study.

Air pollution

Ambient outdoor NO_2 data were obtained from the UK's Department of Environment, Food and Rural Affairs (DEFRA) as pollution-climate modelled values (DEFRA 2016). These datasets allow the UK Government to report air quality levels to EU Air Quality Directives and allow for us to examine the effects of relatively localised air quality changes. These are outputs based on dispersion modelling using point sources of known emission levels (e.g. monitoring stations, power stations, roadsides) and UK meteorological data, and are available as 1km x 1km grids for the UK as the annual mean NO_2 in µg/m^3. For each year between 2002-2014, a single pollution value was calculated for each LSOA using the NO_2 point closest to each LSOA population-weighted centroid[4]. This was calculated using the Spatial Join tool in ESRI ArcGIS v10.3.1. The pollution values were then attributed to every individual residing in each LSOA using the corresponding LSOA and year variables in Stata 12 (StataCorp, College Station, TX). In Figure 1 we provide a visual illustration of the geographical variation in annual ambient outdoor NO_2 levels across England. The mean value for England in 2014 was 9.95 µg/m^3 and a standard deviation of $\pm$5.03. The overall mean for all years 2002-2014 was 11.6 µg/m^3. As expected the maximum annual ambient level of NO_2 recorded in 2014 occurred in central London (57.68 µg/m^3) and the minimum in Cornwall and Devon (2.83 µg/m^3). In 2014, the locations which exceeded the legal annual ambient level of 40 µg/m^3 were in

[4] Obtained from the Office for National Statistics geography portal.

London, London Heathrow airport, Birmingham, Sheffield and Southampton. This is likely due to relatively high levels of traffic volume and density in these areas.

Insert figure 1 here

Spatial control variables

To obtain measures of deprivation in the respondents' neighbourhood we linked our household survey data (BHPS and UKHLS) with the English Indices of Multiple Deprivation. These are calculated every 2-5 years by the Department for Communities and Local Government (DCLG) and are based on 37 separate indicators, organised across seven distinct domains of deprivation[5] (DCLG 2004, 2007, 2010). Using this data, we are able to match each respondent in our survey datasets with a number of variables reflecting the prevailing economic and social conditions in their neighbourhood. In this analysis we include the Income Deprivation domain and the Geographical Barriers sub-domain (from the Living Environment Deprivation domain) which measure the proportion of the population experiencing deprivation relating to low income and isolation from key local services such as GP surgeries and supermarkets respectively. We also include the Crime Deprivation domain which reflects the risk of personal and material victimisation[6].

Population density measures were calculated for each year using the annual LSOA mid-year population estimate figures obtained from the Office for National Statistics (ONS). These data are calculated from census, natural change and migration figures for each LSOA, and are useful to account for any urbanity effects on life satisfaction. We also added in additional control variables capturing differences in green and blue space across LSOAs as these have been shown to be significantly related with life satisfaction and are also likely to be significantly correlated with NO_2 (McDonald *et al.* 2007; White *et al.* 2013; Jeanjean, Monks & Leigh 2016). We calculated measures of green and blue space using data from the Generalised Land Use Database 2005 (GLUD; DCLG 2005). The GLUD is a dataset providing statistics for nine land use categories for each English LSOA. The dataset is based upon the Ordnance Survey MasterMap January 2005 and is accurate to a spatial

[5] These are Income Deprivation; Employment Deprivation; Health Deprivation and Disability; Education, Skills and Training Deprivation; Crime; Barriers to Housing and Services; and Living Environment Deprivation. Details of these domains and the indicators used to calculate them can be found in https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/464597/English_Indices_of_Deprivation_2015_-_Research_Report.pdf

[6] The data for 2004, 2007 and 2010 were obtained and linearly interpolated/extrapolated to create an annual time series. These domains were selected due to their theoretical significance on life satisfaction. Adding in further domains would increase multicollinearity issues.

resolution of 10 m^2. The proportion of land categorised as green space or domestic garden (we combined these as per White *et al.* (2013)), and surface water, within each LSOA area were used as measures of natural land use.

Estimation approach

The micro-econometric life satisfaction equation was constructed as follows:

$$LS_{ijt} = \beta_0 + \beta_1 N_{jt} + L_{jt}'\beta_2 + X_{it}'\beta_3 + \beta_4 T_t + \varepsilon_{ijt}$$

Where LS is the dependent variable, life satisfaction, for an individual i, at a given location j and in a given year t. It is a function of the annual ambient outdoor mean value of NO_2 (N_{jt}), a vector of LSOA neighbourhood factors (L_{jt}) and individuals' socio-economic and demographic characteristics (X_{it}), and a year variable (T_t). ε_{ijt} is the error term (all remaining unaccounted for variation). All spatial analysis was carried out in ArcGIS v10.3.1 and regression analysis using the regress and xt suites in Stata 12 software. We first used a pooled cross-sectional approach to estimate the above equation (clustered by LSOA to obtain robust standard errors) and then took advantage of the panel nature of the data by using fixed effects. Fixed effects have a significant advantage over cross-sectional correlations as we will be effectively following the same individuals over time, thereby controlling for time-invariant omitted variables (e.g. personality traits) that could be related with both NO_2 and life satisfaction.

Section 5: Results

Main results

Our main results are summarised in Table II. In our baseline pooled cross-sectional model which includes NO_2 as well as socio-demographic controls (specification 1 in Table II) we find that NO_2 is significantly and negatively related to life satisfaction ($b=-0.007$, $p<0.001$). The coefficient indicates that a 10 $\mu g/m^3$ increase in annual average NO_2 levels in one's LSOA is associated with a 0.07 decrease in life satisfaction (on a 1-7 likert scale). The results relating to the control variables are consistent with existing research in these areas and so for parsimony are not discussed. To control for time-varying local characteristics reflective of economic activity and urbanisation, as well as green and blue space, we added in spatial control variables to our model (specification 2 in Table II). This results in a significant reduction in the size of the NO_2 coefficient relative to that observed under specification 1 (b=-0.004, p<0.001). This highlights the importance of adding in spatial controls to capture differences in economic, social and environmental conditions across neighbourhoods when estimating the relationship between air quality and life satisfaction. In other words, NO_2 is significantly correlated with these factors and in the absence of such controls, the NO_2 coefficient would partially reflect the effect of local socio-economic activity and land use more generally on subjective well-being.

Insert table II here

Despite the inclusion of a wide range of economic and geographic control variables, one may still be concerned that there are other sources of unobserved heterogeneity affecting the model estimates (e.g. personality traits). To address this concern, we take advantage of the panel nature of the dataset by using fixed effects (specification 3 in Table II). The coefficient size for NO_2 from our fixed effects regression analysis falls slightly relative to that from our pooled cross-sectional model in specification 2 (b=-0.003, p<0.05). Here the coefficient indicates that a 10 $\mu g/m^3$ increase in annual average NO_2 levels in one's LSOA is associated with a 0.03 decrease in life satisfaction (on a 1-7 likert scale).

The role of health

It is worth noting that we include a series of dummy variables recording individuals own subjective evaluation of their health status as control variables. This suggests that perceived health status does not mediate the relationship between NO_2 and life satisfaction, i.e. the relationship between NO_2 and life satisfaction is not driven by differences in health. This is also in keeping with findings by Levinson (2012) who also found that his measure of air quality (PM_{10}) had a direct relationship with happiness independent of perceived health status. While perceived health status does not appear to mediate the relationship between NO_2 and life satisfaction, we also examined if it could moderate this relationship, i.e. does the relationship between NO_2 and life satisfaction vary according to health status? We find that NO_2 has a more substantive negative relationship with the life satisfaction of individuals who regard themselves as being in relatively poor health as opposed to those who classify themselves as being relatively satisfied with their health. A graphical representation of this interaction effect in can be seen in Figure 2. It can be seen here that while NO_2 is significantly related with life satisfaction for individuals who perceive themselves as being both relatively healthy and unhealthy, it appears to matter more for those who regard themselves as being in relatively poorer health.

Insert Figure 2 here

How large are these effects?

An increasingly common method for communicating the welfare effects from exposure to air pollution, and indeed other environmental disamenities, when using the life satisfaction approach is to calculate compensating differentials. More specifically, by using the point estimates for income and the environmental variable of interest (e.g. NO_2) we can calculate constant trade-off ratios (Luechinger & Raschky 2009; Levinson 2012). In other words, how much extra income an individual would need to be compensated for the deterioration in air quality. This approach has previously been used to value the welfare losses associated with a diverse range of air pollutants such as PM_{10} (Mackerron & Mourato 2008; Levinson 2012; Ferreira *et al.* 2013; Ambrey *et al.* 2014) and SO_2 (Luechinger 2009). One limitation with this approach is endogeneity in income. That is, the effect of income on life satisfaction is likely to be significantly understated due to measurement error within the income variable. In addition, unobserved heterogeneity, such as working hours, time spent away from family and loved ones, and stress can also result in biased estimates for income (Powdthavee 2010). Failure to account for endogeneity in income would mean that any measures of the extent to which individuals are willing to trade off income for reductions in exposure to environmental disamenities such as NO_2 would likely be significantly biased upwards.

An alternative approach for communicating the 'psychological' cost associated with exposure to environmental disamenities such as NO_2, and one that we employ in this paper, is to compare the relative effects of NO_2 exposure on life satisfaction to that of other predictors of life satisfaction using standardised regression coefficients (z-scores). The results from converting the coefficients into the same standardised units can be seen in Table III. The main advantage of using these standardised units is that it allows us to assess the relative strength of each of the explanatory variables.

Insert table III here

We can see, for instance, that a one standard deviation increase in NO_2 is associated with a 0.015 standard deviation decrease in life satisfaction. This is approximately equal to the estimated disutility effect of being separated (β=-0.013) or widowed (β=-0.015) as compared to being single. Unemployment along with health is often associated with the largest reduction in well-being, and we find that the estimated effect of NO_2 on life satisfaction is roughly equal to half the estimated impact from being unemployed relative to being in full time employment (β=-0.031). If we look at variables positively related with subjective well-being, the estimated disutility impact from NO_2 is nearly half that of the utility experienced from being retired as opposed to being in full time employment (β=0.025). Similarly, the estimated effect of NO_2 is nearly a quarter that of being married as opposed to being single (β=0.055). In keeping with the wider economics of happiness literature, we observe that the subjective perception of one's own health status is the most substantive predictor of life satisfaction (Dolan *et al.* 2008). For instance, while broadly comparable to changes in personal circumstances such as unemployment, retirement or widowhood, the estimated effect of NO_2 on life satisfaction is significantly less than that from subjective health status (β=0.279).

Robustness checks

Despite the inclusion of a broad array of time-variant spatial control variables (e.g. economic and social deprivation, population density and greenspace) and our use of fixed effects, (thereby controlling for time-invariant heterogeneity), we recognise that there is still the potential for other sources of endogeneity to affect our regression estimates. For instance, despite our use of a relatively spatially disaggregated dataset, it is possible that measurement error could bias our regression estimates. Such measurement error would bias our estimated effect of NO_2 on life satisfaction downwards. On the other hand, the NO_2 coefficient could partly be capturing the effect of other air pollutants such as PM_{10}. Such omitted variable bias would bias our estimates upwards. To test if endogeneity is affecting our model estimates we adopted an instrumental variables approach. Specifically, we instrument NO_2 with annual average daily traffic flow (AADF) counts and road density per LSOA. We expect that major road traffic flow and road density, both recorded at the LSOA level, will be related to NO_2 levels but not directly related with life satisfaction, after conditioning on our control varibables such as economic and social deprivation, population density and commuting patterns.

AADF counts are maintained by the Department for Transport and measure street-level traffic counts for every A-road and motorway in Great Britain. We calculated average values for each LSOA in England by using the Spatial Join tool in ArcGIS. Road density was calculated using the road layers available in Ordnance Survey's Meridian 2 dataset. This is a vector dataset of Great Britain at a 1:50,000 scale and contains detailed spatial information about motorways, A-roads, B-roads and minor roads. We used the Spatial Join tool in ArcGIS to calculate the length of all roads per LSOA and then divided this by LSOA area to generate a comparable unit across LSOAs[7].

Our instrumented NO_2 coefficient (b=-0.003, p<0.005) was not significantly different from that obtained from our fixed effects model (specification 3 in Table II). All the instruments have the expected positive and statistically significant relationship with NO_2 and in all cases the statistical tests suggest that the instruments are relevant. The Anderson canonical correlations likelihood ratio test, for instance, rejects the null of underidentification and the obtained F statistic (F-statistic =12125) exceeds the conventional minimum standard of power of F = 10 (Stock et al., 2002). We can test the validity of the instruments, conditioning on the assumption that a subset of the instrument is valid, by implementing the standard overidentification test. The resulting Sargan's test statistic was statistically insignificant with a p value of 0.72 and therefore we can be reasonably satisfied that our instruments are consistent in producing robust estimates of the relationship between NO_2 and life satisfaction.

Section 6: Discussion

Policymakers are becoming increasingly supportive of using subjective well-being data for formulating public policy. In 2012, for instance, the UK's Office for National Statistics published its first index of subjective well-being, as part of the government's Measuring National Well-Being project. This index provides evidence for the national state of quality of life and is used across UK government to drive decision-making and policy analysis. Additionally, the UK Department for Environment, Food and Rural Affairs (DEFRA) use well-being data to evaluate the Nature Improvement Areas scheme and the Department for International Development (DFID) leads on how best to use subjective well-being evidence to measure different dimensions of progress[8]. The UK has also officially backed the United Nation's Sustainable Development Goals (SDGs) which, among other things, strive for good health and well-being (SDG 3). The use of well-being measures is therefore used widely across UK government to better understand society's welfare and as such the ability to understand and quantify factors that affect these measures is important.

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[7] We found a significant direct correlation between our instruments and NO_2 (r=0.208 and 0.584) but no significant direct correlation between our instruments and life satisfaction (r=-0.004 and -0.056).

[8] For a review of these schemes see https://www.gov.uk/government/publications/wellbeing-policy-and-analysis

This study focused on ascertaining the disutility effects from NO_2 by matching data on individual well-being from twelve waves of the British Household Panel Survey (BHPS) and the UK Household Longitudinal Survey (UKHLS) with annual ambient air pollution data from DEFRA. To mitigate concerns about unobserved local characteristics correlated with both life satisfaction and NO_2 biasing our fixed effects regression estimates, we matched these data sources with a wide array of external geo-referenced environmental datasets capturing differences in economic, social and environmental conditions across neighbourhoods. To the best of our knowledge it is the first study that couples spatially disaggregated longitudinal household survey and air pollution data with a range of spatial controls when examining the relationship between NO_2 and subjective well-being. Our results serve to highlight how failure to include spatial controls reflective of the wider economic, social and environmental conditions in the neighbourhood could give rise to significant omitted variable bias when examining the relationship between indicators of environmental quality such as NO_2 and life satisfaction.

We find a 10 $\mu g/m^3$ increase in annual average NO_2 levels in one's LSOA is associated with a 0.03 decrease in life satisfaction (on a 1-7 likert scale). To help put these findings into perspective, we compared this effect size to that of many other widely studied determinants of subjective well-being using standardised coefficients. Our standardised coefficients suggest that the substantive magnitude of the relationship between NO_2 and life satisfaction is comparable to that of many 'big hitting' life events. For example, the estimated disutility effect from NO_2 is equivalent to that of being separated or widowed when compared to being single, and approximately half that of being unemployed when compared to being employed.

We observed significant geographic differences in the distribution of NO_2, for example the highest annual levels occurring in London and the lowest in regions of South West England. One avenue for future work would be to go beyond looking at geographic differences and explore if there are any socio-economic or demographic inequalities in exposure, and beyond that, how inequalities in well-being at small-scale geographies are associated with environmental features. Furthermore, the consideration of equity and 'who to prioritise' when using subjective well-being data in public policy-making is out of the scope of this paper, but should be an important consideration when designing intervention strategies (Institute of Economic Affairs 2012).

Finally, to conclude, our results suggest that the welfare effects, as proxied by subjective well-being, from NO_2 can be substantive. For instance, our analysis suggests that the disutility experienced by

NO_2 may be broadly comparable to that of many major life events such as unemployment, separation and widowhood. Moreover given that the effects of NO_2 on life satisfaction are population-wide (i.e. to some extent everyone is exposed to NO_2, whereas only a fraction of the population are unemployed or separated), this suggests that the benefits to society from any reductions in NO_2 would be substantive.

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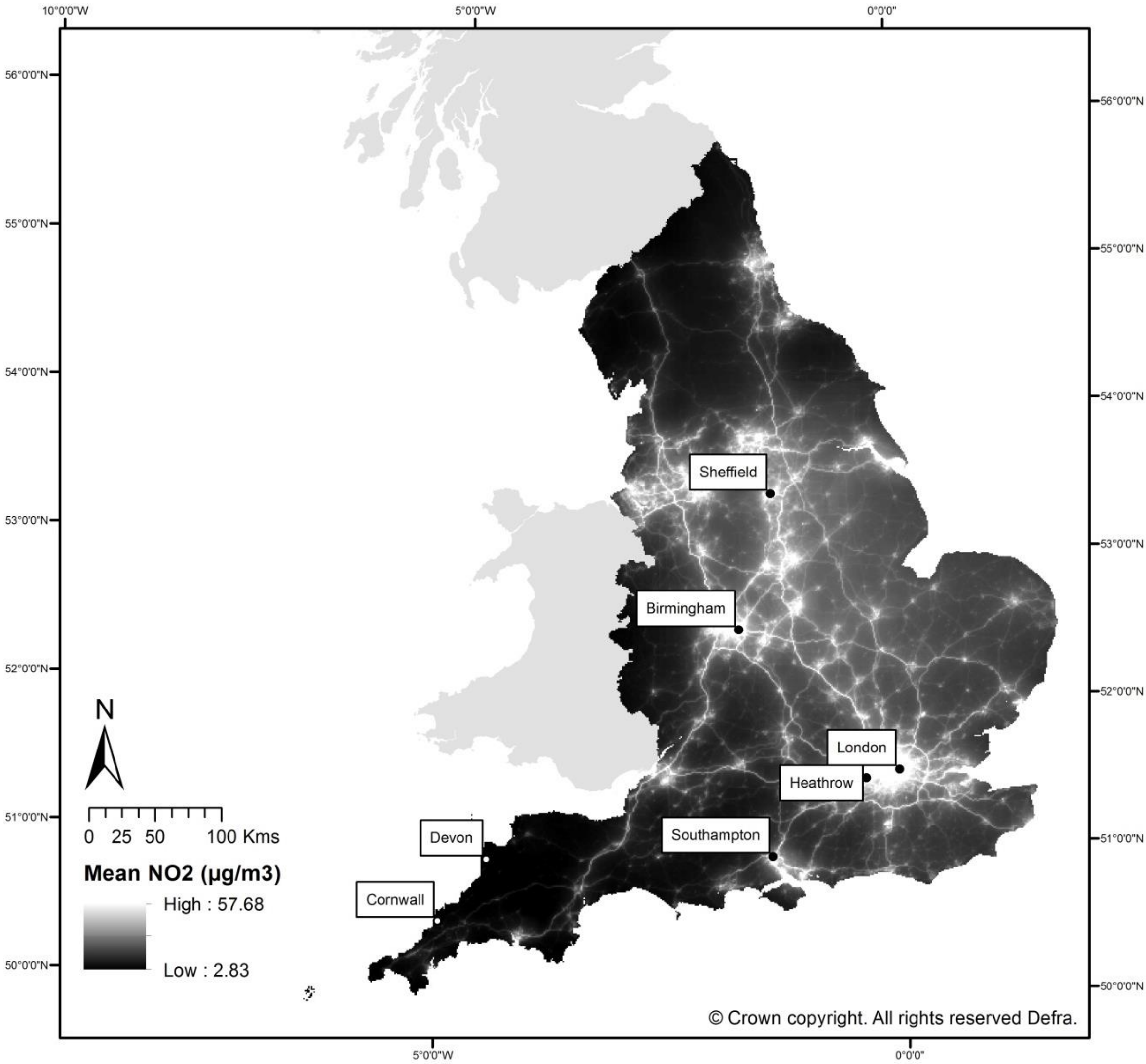

Figure 1. Mean ambient outdoor NO_2 levels in 2014.

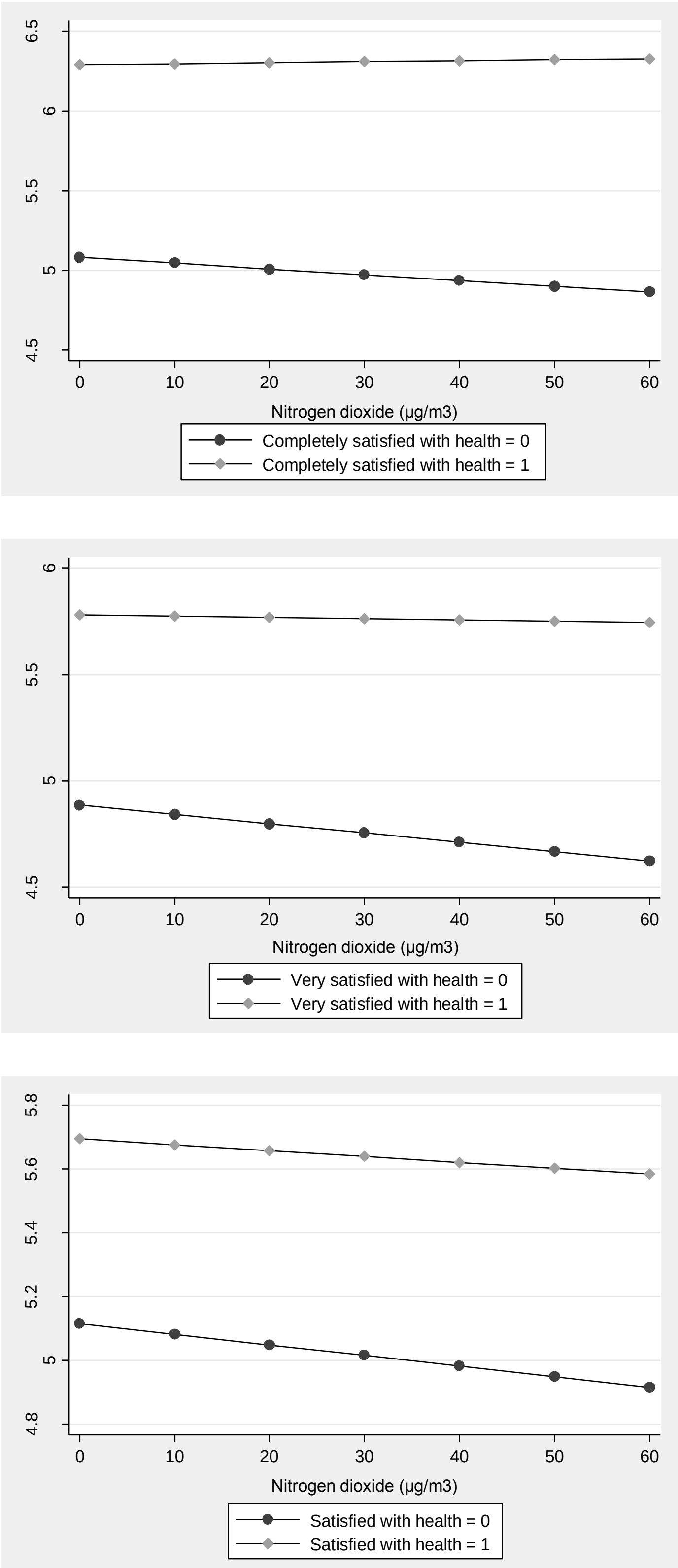

Figure 2. Interaction effects of NO_2 and health satisfaction.

Table I. Descriptive statistics of variables included in analysis.

Variable name		Mean or %	St. dev.	N
Life satisfaction	Respondent's self-reported life satisfaction (scale 1 to 7)	M=5.154	1.437	203426
NO_2	Mean annual ambient nitrogen dioxide (NO_2) in respondent's residential LSOA (μg/m^3)	M=19.668	7.641	244389
Annual household income	Log equivalent annual household income (income divided by square root of household size)	M=7.433	0.725	241299
Age	Respondent's age in years	M=46.279	18.460	244389
Age-squared	Respondent's squared-age in years	M=2482.53	1833.16	244389
Female	Respondent is female (yes/no)	53.38%	0.499	244389
University-level qualification	Respondent has a university-level qualification (yes/no)	29.63%	0.457	244389
Marital status				
Single and never married	Respondent is single and has never been married/civil partnership (yes/no)	22.47%	0.417	244205
Married	Respondent is married (yes/no)	51.87%	0.500	244205
Separated	Respondent is separated but still married/civil partnership (yes/no)	1.71%	0.130	244205
Widowed	Respondent is widowed (yes/no)	5.79%	0.233	244205
Divorced	Respondent is divorced/dissolved civil partnership (yes/no)	6.07%	0.239	244205
Living as couple	Respondent is living as a couple (yes/no)	12.04%	0.325	244205
Employment status				
Employed	Respondent is employed (yes/no)	48.24%	0.500	244389
Self-employed	Respondent is self-employed (yes/no)	7.60%	0.265	244389
Unemployed	Respondent is unemployed (yes/no)	5.07%	0.216	244389
Retired	Respondent is retired (yes/no)	20.98%	0.407	244389
Caring for family	Respondent is caring for family (yes/no)	6.97%	0.255	244389
In training	Respondent is in training (yes/no)	7.09%	0.257	244389
Disabled	Respondent is disabled (yes/no)	3.40%	0.181	244389
Other	Respondent is categorized as other (yes/no)	0.18%	0.042	244389
Health satisfaction				
Completely or very satisfied with health	Respondent is completely satisfied with their health (yes/no)	47.15%	0.499	203797
Less than very satisfied with health	Respondent is less than very satisfied with their health (yes/no)	52.85%	0.499	203797

Commuting time				
Non-commuters	Respondent does not commute (yes/no)	49.22%	0.500	224170
1-15 minutes	Respondent has a commute between 1-15 minutes (yes/no)	21.75%	0.413	224170
16-30 minutes	Respondent has a commute between 16-30 minutes (yes/no)	15.93%	0.366	224170
31-50 minutes	Respondent has a commute between 31-50 minutes (yes/no)	7.12%	0.257	224170
>50 minutes	Respondent has a commute of over 50 minutes (yes/no)	5.98%	0.237	224170
Time variables				
Year	Year of interview			244389
Wave	BHPS or UKHLS wave			244389
Spatial control variables				
Population density	Population of residents per km^2 in respondent's residential LSOA	M=4225.008	4345.957	244389
Crime deprivation	Indices of Multiple Deprivation – risk of personal and material victimisation in the LSOA	M=0.017	1.042	244389
Income deprivation	Indices of Multiple Deprivation – proportion of the population experiencing deprivation relating to low income in the LSOA	M=0.142	0.108	244389
Geographical deprivation	Indices of Multiple Deprivation – proportion of the population experiencing deprivation relating to isolation from key local services	M=37.516	42.962	244389
Area of greenspace	Percentage of LSOA designated as greenspace and/or domestic gardens	M=67.310	20.176	244389
Area of water	Percentage of LSOA designated as surface water	M=1.635	5.886	244389

Table II. Determinants of life satisfaction – unstandardized coefficients and standard errors

Variable name	Model specifications			
	1: OLS - baseline	2: OLS - spatial controls	3: Fixed effects	4: IV
NO_2 ($\mu g/m^3$)	-0.007*** (0.001)	-0.004*** (0.001)	-0.003* (0.001)	-0.003* (0.002)
Annual household income (log equivalence)	0.093*** (0.006)	0.084*** (0.006)	0.024*** (0.006)	0.084*** (0.004)
Age (years)	-0.028*** (0.001)	-0.028*** (0.001)	0.019* (0.010)	-0.028*** (0.001)
Age-squared (years)	0.000*** (0.000)	0.000*** (0.000)	-0.000 (0.000)	0.000*** (0.000)
Female (yes/no)	0.039*** (0.008)	0.038*** (0.008)	0.407 (0.256)	0.038*** (0.006)
University-level qualification (yes/no)	0.039*** (0.009)	0.030*** (0.009)	-0.002 (0.023)	0.030*** (0.006)
Marital status (reference category: single)				
Married (yes/no)	0.276*** (0.013)	0.271*** (0.013)	0.158*** (0.026)	0.271*** (0.009)
Separated (yes/no)	-0.183*** (0.032)	-0.179*** (0.032)	-0.145*** (0.039)	-0.179*** (0.023)
Widowed (yes/no)	0.003 (0.023)	0.002 (0.023)	-0.091* (0.043)	0.002 (0.016)
Divorced (yes/no)	-0.061** (0.021)	-0.059** (0.021)	-0.014 (0.035)	-0.059*** (0.014)
Living as a couple (yes/no)	0.218*** (0.014)	0.217*** (0.014)	0.206*** (0.021)	0.217*** (0.011)
Employment status (reference category: employed)				
Self-employed (yes/no)	0.024 (0.015)	0.021 (0.015)	0.028 (0.019)	0.021 (0.012)
Unemployed (yes/no)	-0.361*** (0.021)	-0.351*** (0.021)	-0.212*** (0.020)	-0.351*** (0.017)

Retired (yes/no)	0.271*** (0.019)	0.268*** (0.019)	0.090*** (0.021)	0.268*** (0.015)
Caring for family (yes/no)	-0.021 (0.018)	-0.013 (0.018)	0.019 (0.019)	-0.013 (0.015)
In training (yes/no)	0.178*** (0.018)	0.172*** (0.018)	0.126*** (0.022)	0.171*** (0.016)
Disabled (yes/no)	-0.708*** (0.031)	-0.692*** (0.031)	-0.356*** (0.029)	-0.691*** (0.019)
Other (yes/no)	-0.069 (0.070)	-0.068 (0.070)	-0.071 (0.064)	-0.068 (0.064)
Health satisfaction (reference category: neither satisfied/unsatisfied to completely unsatisfied)				
Completely satisfied with health (yes/no)	1.777*** (0.012)	1.777*** (0.012)	1.292*** (0.012)	1.777*** (0.010)
Very satisfied with health (yes/no)	1.323*** (0.009)	1.318*** (0.009)	0.966*** (0.008)	1.318*** (0.007)
Satisfied with health (yes/no)	0.833*** (0.009)	0.831*** (0.009)	0.609*** (0.009)	0.831*** (0.008)
Commuting time (reference category: non-commuters)				
1-15 mins (yes/no)	0.025 (0.013)	0.024 (0.013)	0.017 (0.015)	0.024* (0.011)
16-30 mins (yes/no)	-0.002 (0.013)	-0.004 (0.013)	0.009 (0.015)	-0.004 (0.012)
31-50 mins (yes/no)	-0.004 (0.016)	-0.004 (0.016)	0.023 (0.018)	-0.005 (0.014)
>50 mins (yes/no)	-0.045** (0.017)	-0.046** (0.017)	0.006 (0.019)	-0.047** (0.015)
Time variables				
Year	-0.001 (0.008)	0.002 (0.008)	-0.011 (0.016)	0.002 (0.006)

Wave	-0.014 (0.008)	-0.013 (0.008)	-0.024 (0.018)	-0.013* (0.006)
Spatial control variables				
Population density (people per km^2)		-0.000** (0.000)	0.000 (0.000)	-0.000*** (0.000)
Crime deprivation		-0.008 (0.004)	-0.011 (0.007)	-0.009* (0.004)
Income deprivation		-0.380*** (0.050)	-0.075 (0.085)	-0.382*** (0.032)
Geographical deprivation		-0.000** (0.000)	-0.000** (0.000)	-0.000*** (0.000)
Area of greenspace (% of LSOA)		-0.000 (0.000)	0.001 (0.001)	-0.000 (0.000)
Area of water (% of LSOA)		-0.001 (0.001)	0.001 (0.001)	-0.001 (0.001)
Constant	6.649 (15.761)	-0.152 (15.855)	25.285 (32.675)	-0.043 (11.165)
Observations	199,602	199,602	199,602	199,602
Individuals			54,348	
R^2	0.28	0.28	0.20	0.28
Interaction terms				
NO_2*completely satisfied with health			0.004*** (0.001)	
NO_2*very satisfied with health			0.004*** (0.001)	
NO_2* satisfied with health			0.002 (0.002)	

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table III. Determinants of life satisfaction – standardised coefficients

Variable name	Model specifications			
	1: OLS - baseline	2: OLS - spatial controls	3: Fixed effects	4: IV
NO_2	-0.034***	-0.020***	-0.015*	-0.016*
Annual household income	0.046***	0.042***	0.012***	0.042***
Age	-0.351***	-0.354***	0.246*	-0.354***
Age-squared	0.383***	0.384***	-0.041	0.384***
Female	0.014***	0.013***	0.141	0.013***
University-level qualification	0.012***	0.010***	-0.001	0.010***
Marital status (reference category: single)				
Married	0.096***	0.094***	0.055***	0.094***
Separated	-0.016***	-0.016***	-0.013***	-0.016***
Widowed	0.001	0.000	-0.015*	0.000
Divorced	-0.010**	-0.010**	-0.002	-0.010***
Living as couple	0.050***	0.050***	0.048***	0.050***
Employment status (reference category: employed)				
Self-employed	0.004	0.004	0.005	0.004
Unemployed	-0.054***	-0.052***	-0.031***	-0.052***
Retired	0.077***	0.076***	0.025***	0.076***
Caring for family	-0.004	-0.002	0.003	-0.002
In training	0.031***	0.030***	0.022***	0.030***
Disabled	-0.085***	-0.083***	-0.043***	-0.083***
Other	-0.002	-0.002	-0.002	-0.002
Health satisfaction (reference category: less than very satisfied with health				
Completely satisfied with health	0.384***	0.384***	0.279***	0.384***
Very satisfied with health	0.442***	0.440***	0.323***	0.440***
Satisfied with health	0.215***	0.215***	0.157***	0.215***
Commuting time (reference category: non-commuters)				
1-15 minutes	0.007	0.007	0.005	0.007*
16-30 minutes	-0.001	-0.001	0.002	-0.001
31-50 minutes	-0.001	-0.001	0.004	-0.001
>50 minutes	-0.008**	-0.008**	0.001	-0.008**
Time variables				
Year	-0.003	0.005	-0.024	0.005
Wave	-0.028	-0.027	-0.051	-0.027*
Spatial control variables				
Population density		-0.015**	0.002	-0.016***
Crime deprivation		-0.006	-0.008	-0.006*
Income deprivation		-0.028***	-0.005	-0.028***
Geographical deprivation		-0.010**	-0.014**	-0.010***

Area of greenspace		-0.005	0.007	-0.004
Area of water		-0.002	0.005	-0.002

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$