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The air pollution effects on children's health in Great Britain

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Abstract

This study explores the relationship between air pollution, children's health status and the parents' willingness to pay for improving the air quality in Great Britain. The estimates are based on cross-sectional data from the General Lifestyle Survey over the period 2000-2010. Ground-level ozone (O_3) and nitrogen oxides (NO_X) are the two main air pollutants examined. The findings rely on regression estimates and the average marginal willingness to pay obtained using the samples derived under specific assumptions. The results show the annual average marginal willingness to pay for O_3 and NO_X range between £2,263-£3,108 and £520-£1,121 for one unit reduction in standard deviation. Furthermore, the results show that the cost of planned-inpatient hospital stay is more than 1.2 times of marginal willingness to pay for non-movers during the sample period in the case of O_3.

Key words: Air pollution, environmental valuation, health status, pseudo-panel Data
JEL codes: I31, Q51, Q53, Q54

1. Introduction

A great social concern is the exposure of children to air pollution, since their immune system is not fully developed resulting to different responses than those observed in adults. The purpose of this study is to examine the effects of air pollution on children's health status and medical care. Two major air pollutants are explored,

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ozone (O_3) and nitrogen oxides (NO_X). The approach followed in this study has the strength that the individuals are not asked to value the environmental good directly, but to evaluate their general health status. Therefore, this approach does not require awareness of cause-effects relationships. The analysis is based on detailed micro-level data and local authority districts, while other studies employed disaggregated data on county or country level (Ferreira et al., 2006; Luechinger, 2009; Ferreira et al., 2013). Moreover, the analysis is limited to the non-movers sample which allows us to reduce the endogeneity derived by the sorting issue of individuals and plausible reverse causality as the individuals may choose to reside or decide to move in areas with better air quality. The findings support that both air pollutants have negative effects on child's health and according to the regression analysis the average simulated MWTP for a drop of one standard deviation for the air pollutants examined range between £520-2,263 for non-movers.

The paper is organized as follows. Section 2 presents a short literature review. In section 3 the theoretical and econometric framework is provided. In section 4 the data and the research sample design are described. In section 5 the results of estimating various versions of a health status function, including air pollutants are reported. Furthermore, the effects of air pollution on health status and their monetary values are discussed. In section 6 the concluding remarks are presented.

2. Literature review

In this section we present previous studies about the association among income, air quality and children's health and we discuss the contribution of this study to the earlier literature. Family income is positively associated with the development of children and youth, as previous studies have demonstrated (Haveman et al., 1991; Huston et al., 1994; Brooks-Gunn and Duncan, 1997; Maurin, 2002; Morris et al., 2002; Morris and Gennetian, 2003). These studies show that the association is larger in early childhood. In a study by Currie and Moretti (2003), the expansion of the higher education which took place in the decades of 1960s and 1970s in the USA is considered, which increased the education levels of women resulting in infants' health improvement expressed by the gestational age and birth weight. Berger et al. (2006) found that income has a significant effect on the child's mental health. However, this effect is weakened when the regressions control for additional factors, including the home environment and the skills of parents. These studies show that the income on child's health has relatively little effect, but it seems that income matters more in a developing country context (Currie and Moretti, 2003; Orr et al., 2003; Berger et al., 2006). A study by Duflo (2003) shows that African girls increased their height, when their grandmothers started receiving old-age pensions, suggesting that they invested on girls' nutrition. Furthermore, the state of the economy may impact child's health. The study by Van den Berg et al. (2006) found that children who are born in Netherlands during recessions have higher mortality rates at all ages compared to those who were born just prior to the recession.

While the majority of the studies explored the relationship between income and child's health, as well the association between health and other socio-economic status (SES) factors, including education, marital status among others, a number of other studies explored the impact of air pollution on health. One of the first applications on MWTP of air pollution and health is by Gerking and Stanley (1986). The authors suggest that the marginal willingness to pay for a 30 per cent reduction in ozone levels, ranges between 18-25$ per year. Overall, previous studies explored the impact of air pollution on various child's outcomes, including mortality rates, adverse pregnancy and adverse respiratory heath outcomes, increased risk of birth defects and school absenteeism among others.

Air pollution is linked to increased mortality rates in children and adults (Wong et al., 2002; Ha et al., 2003; Glinianaia et al., 2004). A leading cause of post-neonatal mortality and sudden infant death syndrome in developed countries has been associated with exposure to air pollution (Rusen et al., 2004; Dales et al., 2004; Malloy and MacDorman, 2005). Also the air pollution has a larger effect on mortality in children younger than five years old (Conceicao et al., 2001). The effects of PM_{10} on infant mortality have been explored by Knittel et al. (2011) in a study in Southern California and in California Central Valley over the period 2002-2007. The authors employed an instrumental variables approach exploiting the relationship between traffic, weather conditions, and various pollutants and they found that particulate matter has large effects on weekly infant mortality rates.

Earlier literature also shows that air pollutants are associated with adverse pregnancy outcomes, including low birth weight, abnormal birth, premature birth and small size for gestational age (Liu et al., 2003; Jedrychowski et al., 2004; Parker et al., 2005). Currie and Neidell (2005) using pollution levels within-zip code-month variation found that the low birth probability occurrence is weakly associated with the prenatal pollution exposure of the mother. School absenteeism is another result of child's exposure to air pollution. Daily changes in the levels of air pollutants have been linked with illness-related absenteeism, while short term changes in sulphur dioxide (SO_2) and ground-level ozone (O_3) have been associated to respiratory illness-related absenteeism in elementary school (Hwang et al., 2000; Gilland et al., 2001; Park et al., 2002; Rondeau et al., 2005). However, these studies found also mixed results.

The majority of the earlier studies explored the association between air pollution and adverse health outcomes, such as chronic respiratory and acute health effects. The impact is significant in both asthmatic and non-asthmatic children, although asthmatic children are more vulnerable and receptive. Several studies provide evidence of the adverse health effects of air pollution exposure, including increased incidence and prevalence of childhood asthma increased asthma emergency department visits and hospitalization admissions due to asthma and lung function (Aekplakorn et al., 2003; Gent et al., 2003; Lin et al., 2004; Kim et al., 2005; Peled et al., 2005; Narang and Bush, 2012; Goldizen et al., 2016). Dickie and Messman (2004) explored the preferences of parents for their health and for the acute health status of their children. They found that the parents behave altruistically and this is reflected to the willingness to pay (WTP) values for their children, which are almost doubled than the WTP values for improvement of their health. Differently from the previous literature, the effects air pollution and meteorological variables are included further into the analysis with other possible determinants of child's health status. This is important because air pollution may have negative effects on the health status, causing many extra admissions to hospitals, and damaging the natural environment (DEFRA, 2010). Therefore, the consideration of the environment and air pollution is very important to the child's health development. Furthermore, we consider the parents' willingness to pay for reduction on air pollution to improve the children's health, while the majority of the earlier studies explored only the impact of air pollution on child's health.

3. Methodology

3.1. Theoretical framework

It is assumed that the production of the child health in a family requires additional time to spend for childrearing or childbearing activities like a usual work, but at the same time it can be enjoyed by both partners in the family while spending time with the child. The general framework for estimating the determinants of child health starts up with a health utility function where the representative family gets satisfaction from the health status of child H as much as it gets from other consumption goods X. Let the utility function for the child be:

$$U = U(X, H, M, E) \tag{1}$$

where X is a bundle of consumption goods, H is the health production function, M denotes the mitigating behaviour, such as visits to doctors and medical care and E is the air pollution. In this case it is $U_M>0$ and $U_E<0$. The health production is defined as:

$$H = H(M, E; A, K, D) \tag{2}$$

Where A is the averting behavior ie. moving to other locations with better air quality or outdoor activities avoidance, K is health capital and D denotes the human capital. Substitution of health production function (2) into the utility function (1) yields the utility function expressed in composite commodity, leisure, averting behavior, and pollution.

$$U = U(X, H(M, E), M, E) \tag{3}$$

The income and cost functions are

$$I = w(T - H) = wT - wH(M, E) \tag{4}$$

$$C = X + P_M M \tag{5}$$

where w is the wage, T is the total time available, P_x is the price is composite commodity normalized to one and P_M is the market price of mitigating strategy. The full income budget constraint can be derived by equating (4) and (5).

$$wT = wH(M, E) + X + P_M M \tag{6}$$

The maximization problem is expressed by the following Lagrangian function:

$$L = U(X, H(M, E), M, E) + \lambda[wT - wH(M, E) + X + P_M M] \tag{7}$$

First-order conditions for utility maximization need to be satisfied, in which the first partial derivative with respect to M is:

$$\frac{\partial L}{\partial M} = U_{\mathrm{H}} H_M + U_M - \lambda(P_M + wH_M) = 0 \tag{8}$$

After some simple manipulations relation (8) becomes:

$$(U_{\mathrm{H}} + U_M) / \lambda - w = P_M / H_M \tag{9}$$

Relation (9) indicates that the marginal benefit of mitigating behaviour, which includes the marginal value of mitigating behaviour and the opportunity cost of health time, on the left hand side (LHS) equals the marginal cost of mitigating behaviour, which refers to the market cost, time cost on the right hand side (RHS). Individuals or consumers will pursue averting behavior until the value of LHS equals RHS. Similarly, the first order condition for air pollution will be:

$$\frac{\partial L}{\partial E} = U_{\mathrm{H}} H_E + U_E - \lambda w H_E = 0 \tag{10}$$

After some manipulations, which are fully presented in the appendix, relation (10) becomes:

$$(U_{\mathrm{H}} H_E + U_E) / \lambda - wH_E = 0 \tag{11}$$

Relation (11) shows that the individuals or the consumers would avoid pollution until the total of the marginal value of healthy time, the marginal value of quality and the opportunity cost of health time on the LHS equals zero. The indirect utility function is formed by substituting the optimal values of mitigating behaviour, averting behaviour into utility function as:

$$V = V(P_M, P_A, w, E) \tag{12}$$

By totally differentiating the indirect utility function (12) yields:

$$dV = V_M dP_M + V_A dP_A + Vwd_w + V_E d_E) \tag{13}$$

The total derivative of air pollution is:

$$dV / dE = V_w (dw / dE) + V_E \tag{14}$$

The WTP will be:

$$WTP_E = dw / dE = - V_E / \lambda \tag{15}$$

By plugging the optimum values M* into health production function and totally differentiating yields:

$$dH = H_E dE + H_M dM^* \tag{16}$$

And dividing by *dE* it will be:

$$dH / dE = H_E + H_M (dM^* / dE) \tag{17}$$

The function (17) indicates that the total effect on LHS is the sum of a direct effect (the marginal product of pollution on health) and indirect effect (the marginal product of mitigating behaviour on health time and the marginal effect of pollution on mitigating behaviour) on the RHS. Next by multiplying function (17) with *w* and (9) it yields:

$$\begin{aligned}&[dH / dE - H_M (dM^* / dE)][(U_H + U_M) / \lambda - w] \\ &= P_M (H_E / H_M)\end{aligned} \tag{18}$$

$$P_M = H_M (dM^* / dE)[(U_H + U_M) / \lambda - w] \tag{19}$$

Then the WTP_E will be:

$$\begin{aligned}&WTP_E = -P_M (H_E / H_M) = -(dH / dE)(U_H + U_M) / \lambda + w(dH / dE) \\ &+ P_M (dM^* / dE)\end{aligned} \tag{20}$$

Relation (20) is broken into four components; the first shows the disutility associated with illness symptoms, the second shows the incurred medical expenses due to health effect from exposure to pollution, the third shows the lost wages or hours of work due to health effect on child from exposure to pollution and the last term shows the expenditure on mitigating actions taken to prevent negative health effects (see appendix for more details on the theoretical framework derivations).

3.2. *Econometric framework*

3.3. *Pooled ordered probit and logit models*

The first part of this section describes the methodology applied for health status. The following model of health status for individual *i*, in region *j* at time *t* is estimated:

$$HS_{i,k,j,t} = \beta_0 + \beta_1 e_{j,t} + \beta_2 \log(y_{k,t}) + \beta' \mathbf{z}_{i,k,j,t} + \gamma \mathbf{W}_{j,t} + l_j + \theta_t + l_j T + \varepsilon_{i,k,j,t} \quad (21)$$

$HS_{i,,k,j,t}$ is the health status or child i in household k located in area j and time t. The vector $e_{j,t}$ is the measured air pollution in location j and in time t, $log(y_{k,t})$ denotes the logarithm of the household income and **z** is a vector of household and demographic factors, discussed in the next section. **W** is a vector of meteorological variables, set l_j is the location (local authority) effects, θ_t is a time-specific vector of indicators for the month and the year the interview took place, while l_jT is a set of area-specific time trends. The last term is taken to account for unobservables that are likely to be correlated with both health status and pollution level. Finally, $\varepsilon_{i,k,j,t}$ expresses the error term which we assume to be *iid*. Standard errors are clustered at the local authority level. The pooled ordered Probit and Logit models are applied. The marginal willingness-to-pay (MWTP) can be derived from differentiating (21) and setting dHS=0. Thus, the MWTP can be computed as:

$$MWTP = -\frac{dHS}{de} = -\frac{\partial f}{\partial e} / \frac{\partial f}{\partial y} \quad (22)$$

3.4. Pseudo panel fixed effects models

The analysis relies on cross-sectional data where the main issue is that the history of the individuals is unknown since the same individuals are not observed or followed over time. This does not allow us to estimate fixed effects models or to employ any kind of panel data analysis method. On the contrary, cross-sectional data do not suffer from two main problems that panel data face; the non-response and the attrition. One solution proposed by Deaton (1985) is to use cohorts in order to estimate fixed effects models which data are called pseudo-panel. More specifically, in this approach individuals are grouped into cohorts that share some common characteristics, most commonly the age. The analysis also follows the process developed by Verbeek (2008) for linear models with fixed individual effects and discrete choice models. The observations are aggregated in age and region cohorts and the estimated model (21) can be written as:

$$\overline{H}_{c,t} = \bar{a}_{ct} + \beta_1 \bar{e}_{jt} + \beta_2 \log(\bar{y}_{ct}) + \beta' \bar{z}_{ct} + \gamma \overline{W}_{j,t} + \mu_c + l_j + \theta_t + l_j T + \varepsilon_{c,j,t} \quad (23)$$

The variables in (23) are defined as in (21) for cohorts c and time t. The model (23) is estimated with fixed effects and it thus accounts for one form of endogeneity that results from time-invariant omitted variables. Furthermore, the analysis is based on the non-movers sample. In this way it is possible to capture unobservable factors of the area which are fixed over time and that may be correlated with air pollution and health status and which are fixed over time. However, our assumption about reducing the endogeneity issue coming from the "sorting" issue is very strong, because the location can be also a choice. This because there are people less risk averted to air pollution, and those who in the first place chose the area because it's "clean" and the air quality may continue to improve or remain clean. The movers in our analysis are defined according on whether they have changed residence or not over the last five years. The information is available about the number of movements. Those who never moved are considered as the non-movers sample, while those who have moved at least once over the last five years are included in the movers sample. In our case, we have information on whether the households moved to the same authority district or not. While the air pollution mapping is assigned on the specific geographical level, still we consider those individuals as movers for the reason that they may have decided to move for other reasons, such as employment, facilities, housing, but also including unobserved ones.

In the case we could not control for unobserved spatial-area heterogeneity that can be correlated with the air pollution, the cross-sectional estimates would be much more prone to omitted variables bias. Nevertheless, our analysis includes dummies for local authority districts. On the other hand, the data are cross-sectional regarding the individuals-households. Thus, this type of heterogeneity is less important for the estimation of the pollution effect, while it becomes much more crucial for the estimation of the personal characteristics on health status (Ferrer-i-Carbonell and Frijters 2004), including also the income. Controlling for unobserved individual-child and household heterogeneity is crucial to estimate the benefits in terms of monetary values and calculate the MWTP. In this case, an instrumental variables (IV) approach would be necessary to evaluate the causal effect of income on health status.

Because the data are pseudo-panel it is not feasible to employ the ordered Probit or Logit models using fixed effects, since these methods are estimated only under the random effects framework. The first option is to apply the method introduced by van Praag and Ferrer-i-Carbonell (2004) which converts the ordered dependent variable into a continuous one. The second method is the "Blow-Up and Cluster" (BUC) estimator developed by Baetschmann et al. (2015), which groups the ordered variable into a binary and then the conditional fixed effects Logit model is applied (see Geishecker and Rield, 2012 and Baetschmann et al., 2015 for more technical details and working example).

Overall, the self-reporting bias is a major concern for our setting. As we mentioned, Logit and Probit cannot be implemented within a fixed effects model. Another possible way to change the grouping of the ordinal variable is to create a dummy taking value 1 if the actual value of the ordinal variable is equal or higher than its average value and 0 otherwise (lower than its average value). However, this approach and other similar ones, are subject of criticism, since the convert the ordered variable to a binary choice variable, which corresponds to using only one transformation. Furthermore, these methods are less efficient for the estimated coefficient and do not provide an estimate of the cut-point differences (Chamberlain, 1980; Baetschmann et al., 2015).

Another method is the FCF developed by Ferrer-i-Carbonell and Frijters (2004). Compared to the simple binary case, the estimation strategy of FCF makes use much more of the variation in the ordinal dependent variable. However, since this procedure requires calculation of the individual Hessian for each binary recoding possibility, is computationally very expensive, especially in our case where our sample is large. Furthermore, Baetschmann et al. (2015) have shown that the estimation strategy of the FCF method produces biased parameter estimates. In both theoretical and empirical evidence the authors show that the individual-mean recoding may result in inconsistent estimates. The reason behind this is the endogeneity problem of the individual threshold, which is by itself a function of the original ordered variable. Since there are cases where the individual-mean and the FCF have the same recoded binary variable, they postulate that the FCF estimator must be inconsistent as well. The second issue associated with the FCF method, is that it uses only individuals who move across the cut-off point resulting in a large loss of data. According to the developers of this method, the large loss of data further leads to measurement errors as they well become a large source of residual variation (Ferrer-i-Carbonell and Frijters, 2004; Riedl and Geishecker, 2012). This is also not appropriate for our analysis because the purpose of this study is to examine additional factors that can be associated with the child's health status. Another possible grouping could be an ordinal variable of 3 categories; however, we do not implement anything like that in the study as there is no formal and robust way and criterion to follow. Therefore, we will use the BUC method as a robustness check.

As we described earlier the pseudo-panel approach is an instrumental variables (IV) approach in which the cohort dummies are used in the first stage. In the absence of panel data, especially surveys for child health, repeated cross-sectional surveys are often implemented for a longer time-period and pseudo-panel method allow us to estimate regressions over a longer time-span. Furthermore, averaging within the cohorts the measurement error at individual-level can be removed (Antman and McKenzie, 2007). One issue we face with the pseudo-panel is the trade-off between the number of cohorts and the number of individuals within those cohorts, where a small number of individuals is allocated into a large number of cohorts. This will result to biased estimators, as there will be few observations in each cohort. On the other hand, a small number of cohorts that contain a large number of observations and as individuals within a cohort are likely to be heterogeneous, then this issue would cause inefficiency. Therefore the optimum choice will be the one that minimizes the heterogeneity within each cohort, but maximizes the heterogeneity among them. The majority of the previous studies, used a sample divided into a small number of cohorts with a large number of observations in each of them (Browning et al., 1985; Blundell et al., 1994; Propper et al., 2001). Overall, if cohorts contain at least 100 individuals and there is sufficient variation in the cohort means, then the measurement error bias would be small and can be ignored (Verbeek and Nijman, 1992). Regarding the region cohort, the minimum and maximum number of observations observed, range between 5,000 and 30,000 respectively. In the pseudo-panel approach cohorts can be constructed based on a single characteristic or multiple characteristics which is our case. More specifically, we construct our pseudo-panel data based on age and region as we mentioned earlier. Cohorts are defined by the interaction of five age groups as: 0-2, 3-5, 6-8, 9-11 and 12-15 years old and 18 regions. Therefore, for example children 0-2 years old in the inner London form one cohort, while children of the same age group- 0-2 years old- in the the outer London form another cohort and so on. The resulting pseudo-panel consists of roughly 35,800 observations over 90 cohorts, which on average is more than 100 individuals per cohort.

While the range of age cohorts is rather small, we still assume that the age groups 0-6 will be mostly likely differ from the age group of 7-15 in terms of consumption needs and exposure to air pollution. More specifically, while infants and children 0-6 years old can be much more sensitive and vulnerable to air pollution, children aged 7-15 are much more likely to spend more time outdoor, including school and sport activities, and therefore be more exposed on air pollution. In addition, there are also differences across regions in terms of air quality, prices, consumer demographics, health services and other patterns which would change over time because of migration and local policy development among others. Nevertheless, the indoor air pollution is another issue for the infants, including also the parents' smoking habits, which we cannot observer in our data. We should notice that decreasing the number of age cohorts by assigning wider age brackets, such as 0-7 and 8-15 years old will not considerably change our estimates, but this will lead to the issue discussed earlier, where the number of individuals in each cohort will be significantly reduced. Also considering for possible confounders, including the employment status and education level of the household head, the marital status and the house tenure, we may control for other characteristics that may affect the child's health status. In particular, even if the children have similar individual characteristics and are affected by the same weather and air pollution conditions, there are household characteristics that may impact their health status.

Overall, using age and region cohorts can be suitable instruments for the child's health. First, as we mentioned earlier, the air pollution effect can be stronger on the younger kids, and especially the infants, since their lings are not yet developed. In this case the air pollution effect can be detrimental for the infants. However, on the other hand, as we discussed, infants are less likely to regularly participate in outdoor activities, such as attending the school or other activities, while kids aged 6-15 have to attend school, increasing their exposure to air pollution. Additionally, the region cohort is important, because the air pollution, weather conditions, and activities that affect the air quality, such as industrial and economic activities, traffic, infrastructure and others, vary and influence in different way the air pollution emissions. Even though we control in our regressions for local authority districts and weather conditions, still we have unobserved heterogeneity in terms of traffic and various economic and industrial activities among other factors. The cohorts-variables employed in the study should satisfy the appropriate conditions for an instrumental variable to be consistent. Therefore they should be valid and uncorrelated to the unobservables of the regression. Also they should be relevant and appropriately correlated to the explanatory variables in the model. As we mentioned earlier we cannot observe the heterogeneity and impact of the traffic and the economic-industrial activities among others. However, we control for the area, considering local authority districts dummies, but also including air pollution, which the latter can be influenced by those activities.

3.5. Binary Logit Model, Visits To General Practitioners and Nights In-patient to Hospital

The next regression takes place whether there is a respiratory related complaint for the child. In this case, model (23) remains the same with the difference that the dependent variable is binary. The respiratory diseases include asthma, emphysema, bronchitis and other categories. The reason why each illness is not examined is because the data availability is not enough to control for additional factors discussed in the next section. However, the air pollutants examined in this study have significant effects in all respiratory diseases. The next model examined is the following Binary Logit Fixed Effects:

$$\overline{GP}_{c,t} = \bar{a}_{ct} + \beta_1 \overline{HS}_{ct} + \beta_2 \log(\bar{y}_{ct}) + \beta' \bar{z}_{ct} + \gamma \overline{W}_{j,t} + \mu_i + h_k + l_j + \theta_t + l_j T + \varepsilon_{c,j,t} \quad (24)$$

where *GP* denotes the person has visited or not a General Practitioner (*GP*) and whether the reason was for respiratory disease. In both models the binary Logit fixed effects is preferred to Probit model, because the latter allows only for random effects. In the next model the effects of health status and other personal and socio-economic characteristics on the number of nights being in-patient in a hospital are estimated.

$$\overline{HD}_{c,t} = \bar{a}_{ct} + \beta_1 \overline{HS}_{ct} + \beta_2 \log(\bar{y}_{ct}) + \beta' \bar{z}_{ct} + \gamma \overline{W}_{j,t} + \mu_i + l_j + \theta_t + l_j T + \varepsilon_{c,j,t} \quad (25)$$

where *Hd* denotes the number of nights the individual was inpatient in hospital. The remained variables are defined as in the previous models. A fixed effects model is implemented in this case. In this case the in-patient nights only for respiratory complaints are examined.

4. Data

The data used in this study has been derived by the General Household Survey (GHS) which was renamed as General Lifestyle Survey (GLS) in 2008. This survey is a continuous national survey of people living in private households conducted on an annual basis by the Social Survey Division of the Office for National Statistics (ONS) in England, Wales and Scotland. The main aim of the survey is to collect data on a range of core topics, covering household, family and individual information. The interview consists of questions relating to the household, answered by a reference person or spouse, and an individual questionnaire, asked to all resident adults aged 16 and over. For the children younger than 16 years old, the questions are answered by them, accompanied by an adult, while the parents answer the questions for the children aged 0-7 years old. The period covered for this study is 2000-2010. The children's age range explored is 0-15.

The demographic and household variables include the household income, parent's and child's age, family size, labour force status and education level of the family unit head, house tenure, marital status, education and local authority districts. The income is measured in pounds and is converted to 2010 British pounds using the Consumer Price Index (CPI). Additionally, the regressions control for the month and the year of the survey. The principal health outcome is self-assessed health (SAH) defined by a response to the question "How is your health in general; very good/good/fair/bad/very bad?". Even though we have access to daily pollution level data, the monthly averages before the time of the interview are obtained, since there are daily missing values. The average monthly values can be proper implying an accumulative air pollution effect on health.

In this study we explore the Ground-level Ozone (O_3) and Nitrogen Oxides (NO_X). There are also other major pollutants, including Sulphur Dioxide (SO_2), Particulate Matter ($PM_{2.5}$ and PM_{10}) and Carbon Monoxide (CO). The reason why O_3 and NO_X are examined is because the remained air pollutants have shown improvements during the period 2000-2013. Moreover, some exceedences of the annual average objectives and limit values for NO_X remained between 2005-2010. Even if these exceedences are less widespread than before 2005 they are still appreciable. If the volume of traffic in the future is higher than expected, or if technology to reduce levels of pollutants does not have the expected effects, exceedences will be more widespread than predicted (DEFRA, 2014). Regarding O_3, the urban background ozone pollution has shown a long-term increase, while rural background pollution has shown no clear long-term trend (DEFRA, 2014). Therefore, O_3 is considered still a crucial air pollutant as it is influenced and formed by high temperatures, solar radiation, volcanic compounds (VOC) and NO_X. Therefore, it is important to control in regressions for NO_X and weather data.

Moreover, serious respiratory tract responses are induced by ozone, including asthma and increases in daily hospital admissions.

The air pollutants are collected daily and measured in μg/m^3. The following steps are followed in order to match the air pollution levels with the individuals in the sample. First, the grid points of air monitoring stations expressed in easting and northing are obtained and these can be found on DEFRA website (http://uk-air.defra.gov.uk/). In the second step the grid points of the individuals' local authority district (LAD) level is taken and these are provided from the Office for National Statistics (ONS). Then the inverse distance weighting (IDW) a GIS-based interpolation methods is applied. Then the centroid of each LAD is calculated and the distance between the air pollution monitor and the centre of the LAD is measured. For more details on the formula see Franke and Nielson (1980). The radius is based on 10 km and we use also 5 and 20 km as robustness checks. As we mentioned earlier, we obtain the monthly averages of air pollutants, to assign them on the month of the interview.

In table 1 the summary statistics for the household income expressed in monthly values and the air pollutants, averaged on monthly basis, are reported. In the panel B, where we report the categorical variables, we observe that the majority of the parent's marital status is married at 66.50 per cent and living together as a couple at 11.27 per cent followed by divorced and widowed at 9 and 7.44 per cent respectively. The majority of the family unit heads have completed a GCSE or O level at 48 per cent followed by those with no qualification or with a first or higher university degree. The majority of the sample states that it owns the house either by outright or mortgage at almost 77 per cent. About the ethnicity that used in the regressions we do not report its summary statistics and proportions in table 1 for the reason that the majority of the children are white British or of any other white background at 83 per cent followed by Indian at 2.85 and Pakistani at 2.53, Bangladesh at 1.02, Chinese at 0.21 and the remained 10.39 consist of other races. The majority of the family unit head's employment status is working at 89 per cent, while almost 5 per cent is unemployed. The 3.30 per cent of the sample states that is retired or permanent unable to work due to disability at the same percentage.

In table 2 we present the correlation matrix between air pollutants, health status and household income. As it was expected the correlation between household income and health status is negative indicating that income has positive effects on health. Similarly the household income is negatively correlated with the respiratory illness complaints. Furthemore, the association between both air pollutants and health status and respiratory complaints is positive indicating that air pollution has negative effects on child's health. Moreover, the air pollutants are negatively associated with household income. This most probably indicates that richer families choose to reside in low pollution areas.

Table 1
Summary Statistics

Variables				
Panel A: Continuous Variables				
	Mean	Standard Deviation	Minimum	Maximum
Household Income	1,647.654	913.221	0	55,090.85
Nitrogen Oxides (NO_X)	82.456	49.997	7.268	265.629
Ground Level Ozone (O_3)	61.862	18.442	15.380	81.464
Child's age	9.003	5.251	0	17
Mother's age	38.470	8.084	19	56
Father's age	41.458	8.109	19	59
Household Size	3.8161	0.8991	2	7
Panel B: Categorical Variables				
Parents' marital status	Married 66.50%		Cohabiting 11.27%	
	Single 2.88%		Widowed 7.44%	
	Divorced 9.02%		Separated 2.89%	
Family unit head education level	First and higher Degree 18.21%		Teaching qualification 6.32%	
	Other higher qualification 8.60%		GCSE/O level 48.03%	
			No qualification 18.84%	
House Tenure	Owns outright 28.21%		Mortgage 49.00%	
	Rents from Local Authority 12.88%		Rents from HA/ Regional Social Landlord 6.95%	
	Rents partially furnished 2.96%			
Family unit head job status	Employed 88.66%		Unemployed 4.75%	
	Permanent unable to work 3.30%		Retired 3.29%	
Sample Size	191,531			

* The air pollutants are measured in micrograms per cubic meter ($\mu g/m^3$), while the temperature is measured in

Table 2
Correlation Between Air Pollutants, Household Income, Health Status and Respiratory Illnesses Complaints

	Health Status	Household Income	Ozone	Nitrogen Oxides
Household Income	-0.1639			
	(0.000)***			
Ozone	0.0530***	-0.0048**		
	(0.000)	(0.0232)		
Nitrogen Oxides	0.0263***	-0.0179***	-0.1689***	
	(0.000)	(0.000)	(0.000)	
Respiratory Complaints	0.0827***	-0.0290***	0.0137**	0.0057**
	(0.000)	(0.000)	(0.0304)	(0.0115)

p-values are reported between brackets, *** and ** indicate significance at 1% and 5% level.

5. Empirical results

In table 3 the Adapted Probit- Fixed Effects (FE) results are reported. The estimates take place for three samples; total sample in columns 1 and 4, non-movers sample in columns 2 and 5 and movers sample reported in columns 3 and 6. The household income has the expected negative and significant sign, implying that the health status is improved, because it is scaled from 1 (very good) to 5 (very bad) as it was described in the data section. Moreover, the health status does not include only statements on physical health, but also on mental health. Generally, the results are consistent with the study by Currie et al. (2007), who found that the household income is not the only important factor. Our analysis shows that income has the strongest effects on child health followed by the education level and job status of the family unit head.

Regarding the air pollutants we interpret the coefficients by saying that an increase of a standard deviation in O_3 and NO_X, results on average, in an increase of $\beta_1 * s_y$ in the dependent variable. The parameter β_1 denotes the standardised coefficient of the air pollutant in equation (23), while s_y denotes the standard deviation of the dependent variable. Hence, based on the estimates of table 3, increasing O_3 and NO_X by one standard deviation, health status is deteriorated by 0.0261, and 0.0035 units respectively for the total sample. The respective values for the non-movers are 0.0281, and 0.0061, while for the movers sample are 0.0326 and 0.0065. The meteorological coefficients have the expected signs. More specifically, precipitation, and the difference between minimum and maximum temperature on health status are negative, while average temperature has a positive impact on child's health. Precipitation has a negative effect on health status, which might come from the fact that rainfall and acid rain include chemical compounds and air pollutants. Similarly, the effects of the difference between maximum and minimum temperature on health status are negative and significant, indicating that the extreme weather can be dangerous for child's health.

The mother's age is associated positively with the child's health status. This is consistent with the findings of the study by Myrskylä and Fenelon (2012) who found that children who were born from mothers aged between 20-24 are more likely to suffer from more diseases by 5 per cent than those whose mothers' age ranges between 25-34. This value becomes even higher for born to mothers aged 14 to 19 years at approximately 15 percent. Their results remain robust when other confounding factors are considered, including also the mother's education. Sutcliffe et al. (2012) explored children having unintentional injuries and whether the mother's age is associated to children's medical attention or admissions to hospitals. Their results suggest that the probability is decreased to increasing age of mothers.

On the other hand, the results show that paternal age is negatively associated to the child's health; however the coefficient is insignificant. Other researchers found that paternal age is associated negatively with child's health (Gavrilov and Gavrilova, 1997). On the contrary, older fathers are more likely to be educated and aware about the health care and the effects of air pollution on child's health, compensating for the above-mentioned effects. Finally, regarding all the samples, based on the estimates of table 3, the child's age is insignificant.

As we show in table 3, the marital status of the parents or the guardian has significant effects on child's health status. In all samples single parents are associated with lower child's health status. In addition, the association between widowed guardians child's health status is negative concerning the total and mover sample, while in the case of the non-movers sample, only the estimated coefficient of divorced guardians is significant and negative for the child's health. This is consistent with the existing literature, where the children growing in single, divorced and widowed parent families, usually mothers, present significantly lower levels of education, occupational status, and happiness and are more financially stressed. Growing in this type of environment, the child's development can be negative (Biblarz and Gottainer, 2000). Moreover, the data show that almost the 60 per cent of the mothers having children with fair or poor health are singles, widowed or divorced. Regarding the household size, its impact on child's health status is positive in all cases, even though the magnitude of its effects varies among the three samples. The literature provides evidence that family support and size can provide protection to people with a chronic illness (Aldwin and Greenberger, 1987; Doornbos, 2001).

A strong relationship between socio-economic status (SES) and health status has been found in previous researches. On average, the more advantaged individuals are, the better their health, as the social groups are closer to the top of the socio-economic status. Based on the results of table 3, in the case of the family unit heads who do not hold a qualification or they hold only a low education level, the child's health status is lower than the children whose parents hold a higher university degree. Similarly, when the family unit head is unemployed, unable to work and retired, the children present a lower level of health. The ethnic group of the child does not seem to play a significant role on its health status. However, children who are black African British and Pakistani present a lower level of health than white British, while there is no difference between the reference group and the other ethnic groups. The difference of health status of the above mentioned groups can be owed to locations, especially, where the coefficients are only significant for non-movers sample. Therefore, these children might be located in highly deprived areas, such as areas characterized by low income, high unemployment and polluted areas. However, this is out of the scope of the analysis. Finally, the house tenure is not significant in the non-movers sample; however, in the total sample the children belonging in households who rent the house from local authority or social landlord present a lower health status than children in households which own outrightly the house.

The next step is to calculate the MWTP for air pollution reduction. It should be noticed that the MWTP is given in both standardised and non- standardised air pollutants. However, the remained coefficients for the non- standardised air pollutants are not reported, as they are similar. Thus, the MWTP for a one standard deviation drop in O_3 is £2,690, £2,260 and £3,105 for the total, the non-movers and the movers sample, while the respective values for NO_X are £915, £520 and £1,120. Similarly, the MWTP for a one unit of $\mu g/m^3$ for O_3 is £230, £175 and £275 for the total, the non-movers and the movers sample, while the respective values for a one unit drop in NO_X are £80, £65 and £95.

In table 4 some alternative estimates of the child health status regression are reported. More specifically, the pooled ordered Logit and Probit Models give similar results; however some coefficients of the education level become now significant, such as those who have completed a first degree, teaching and other qualifications, and they have negative effects on child's health. However, the BUC estimates confirm the adapted Probit model's results in table 3. The coefficients have different magnitude as they are based on Logit and Probit estimates, while in table 3 the estimates are based on FE-OLS. BUC gives very similar MWTP values with those presented in table 3, while ordered Logit and Probit models give lower MWTP values. These results refer to WTP for changes in standard deviation. More specifically, the WTP for one standard deviation change in O_3, which is equal at 18 and the average value of O_3, which amounts to 62, constitutes a 30 per cent change in O_3. Similarly, the percentage in NO_X is 61 per cent.

Table 3
Adapted Probit Fixed Effects

Variables	**(1)**	**(2)**	**(3)**		**(4)**	**(5)**	**(6)**
Log of Household Income	-0.0166**	-0.0216**	-0.0150**	Family unit head education level (reference higher degree)			
	(0.0073)	(0.0095)	(0.0068)				
O3	0.0261**	0.0281**	0.0326**	First Degree	0.0573	0.1082	0.0559
	(0.0127)	(0.0133)	(0.0145)		(0.0370)	(0.1253)	(0.0552)
NOX	0.0035**	0.0061**	0.0065**	Teaching qualification	-0.0523	-0.1151	-0.0354
	(0.0017)	(0.0026)	(0.0022)		(0.0870)	(0.3085)	(0.1158)
Average Temperature	-0.0098***	-0.0084**	-0.0145***	Other higher qualification	0.0537	-0.0321	0.0381
	(0.0035)	(0.0034)	(0.0048)		(0.0399)	(0.1318)	(0.0576)
Maximum -Minimum Temperature	0.0076**	0.0064*	0.0097**	GCSE/O level	0.2043***	0.4119*	0.2479**
	(0.0037)	(0.0034)	(0.0047)		(0.0713)	(0.2397)	(0.1030)
Precipitation	0.0180*	0.0058*	0.1479	No qualification	0.0976**	0.2476**	0.0911*
	(0.0097)	(0.0033)	(0.0663)		(0.0397)	(0.1111)	(0.0538)
Wind Speed	0.0107	0.0252	0.0083	Ethnic group of child (reference white British)			
	(0.0142)	(0.0181)	(0.0048)				
Child's age	0.0025	0.0012	0.0072	Any other White background	-0.0147	0.2835	-0.0635
	(0.0018)	(0.0017)	(0.0059)		(0.0632)	(0.2315)	(0.0924)
Mother's age	-0.0035**	-0.0079**	-0.0051**	Mixed White and Black African	0.0175	0.1638	-0.1725
	(0.0016)	(0.0037)	(0.0025)		(0.0966)	(0.8902)	(0.2213)
Father's age	0.0013	0.0091	0.0024	Indian	-0.0625	-0.7002	0.1877
	(0.0010)	(0.0064)	(0.0020)		(0.1535)	(0.4874)	(0.2221)
Parents' marital status (reference married)				Pakistani	0.1445	0.5537***	-0.2310
					(0.1678)	(0.2021)	(0.2757)
Cohabiting	0.0071	0.0202	0.0496	Bangladeshi	0.3146*	0.6179	0.2012
	(0.0234)	(0.0727)	(0.0373)		(0.1898)	(0.4517)	(0.2789)
Single	0.0496*	0.0347*	0.0605**	Black or Black British – African	0.2006	0.4164*	0.2993
	(0.0280)	(0.0187)	(0.0305)		(0.2061)	(0.2289)	(0.2888)

Table 3 (cont.) Adapted Probit Fixed Effects

Variables	(1)	(2)	(3)		(4)	(5)	(6)
Widowed	0.1235*	0.2510	0.2196**	Chinese	-0.1541	-1.1101	-0.0271
	(0.0740)	(0.2846)	(0.1054)		(0.3175)	(0.8226)	(0.4942)
Divorced	0.0112	0.2530*	0.0781	Household Size	-0.0130**	-0.0082**	-0.0155**
	(0.0349)	(0.1497)	(0.0494)		(0.0061)	(0.0036)	(0.0069)
Separated	-0.0327	-0.1286	-0.0361	Family unit head job status (reference Employed)			
	(0.0407)	(0.1445)	(0.0590)				
				Unemployed	0.3996*	0.3161*	0.3595**
					(0.2257)	(0.1687)	(0.1789)
Permanent unable to work	0.0778*	0.0138*	0.1036*				
	(0.0433)	(0.0078)	(0.0615)				
Retired	0.1251*	0.5798**	0.0349	No observations	35,404	12,528	22,876
	(0.0711)	(0.2656)	(0.0259)				
House tenure (reference Owns outright)				R square	0.4591	0.5091	0.4658
Mortgage	-0.0416	0.0211	0.0681	MWTP for a drop of one standard deviation in O_3 per year	£2,690	£2,260	£3,105
	(0.0275)	(0.1117)	(0.0483)				
Rents from Local Authority	0.0668*	0.0656	0.0428	MWTP for a drop of one standard deviation in NO_X per year	£915	£520	£1,120
	(0.0372)	(0.1406)	(0.0229)				
Rents from HA/ Regional Social Landlord	0.0971**	0.1228	0.0640**	MWTP for a drop of one unit O_3 per year	£230	£175	£275
	(0.0410)	(0.1597)	(0.0302)				
Rents partially furnished	0.0502	0.0847	0.0443	MWTP for a drop of one unit NO_X per year	£80	£65	£95
	(0.0602)	(0.2152)	(0.0866)				

Standard errors between brackets, clustered standard errors on local authority districts, ***, ** and * indicate significance at 1%, 5% and 10% level.
Columns (1) and (4) refer to total sample, (2) and (5) to non-mover sample, (3) and (6) to movers

Table 4
Pooled Ordered Probit and Logit Models and BUC Estimates for Non-Movers

Variables	Ordered Logit	Ordered Probit	BUC		Ordered Logit	Ordered Probit	BUC
Log of Household Income	-0.0684***	-0.0381**	-0.1955***	Family unit head education level			
	(0.0161)	(0.0091)	(0.0460)	(reference higher degree)			
O_3	0.0445**	0.0387**	0.2725**	First Degree	0.1055**	0.0612**	0.0727
	(0.0204)	(0.0175)	(0.1338)		(0.0526)	(0.0294)	(0.2139)
NO_X	0.0061*	0.0069*	0.0156*	Teaching qualification	0.2251*	0.1495**	-0.0830
	(0.0032)	(0.0038)	(0.0088)		(0.1296)	(0.0725)	(0.4624)
Average Temperature	0.0098*	-0.0091*	-0.0166**	Other higher qualification	0.1451**	0.0688**	-0.2794
	(0.0057)	(0.0049)	(0.0078)		(0.0587)	(0.0328)	(0.2215)
Maximum -Minimum Temperature	0.0122**	0.0082*	0.0106**	GCSE/Olevel	0.1301**	0.2573***	0.3902*
	(0.0056)	(0.0043)	(0.0052)		(0.0546)	(0.0614)	(0.2103)
Precipitation	0.0845*	0.0357*	0.0331*	No qualification	0.2327***	0.1285***	0.2194**
	(0.0441)	(0.0208)	(0.0176)		(0.0559)	(0.0312)	(0.0994)
Wind Speed	0.0169	0.0101	0.0271	Ethnic group of child (reference white			
	(0.0269)	(0.0150)	(0.0304)	British)			
Child's age	0.0178	0.0096	0.0445	Any other White background	-0.0663	-0.0587	-0.2880
	(0.0128)	(0.0065)	(0.0341)		(0.1141)	(0.0637)	(0.2994)
Mother's age	-0.0062**	-0.0036**	-0.0098**	Mixed White and Black African	0.3321	0.1917	0.5134
	(0.0025)	(0.0014)	(0.0047)		(0.2764)	(0.1560)	(0.6508)
Father's age	0.0021	0.0032	0.0075	Indian	-0.2787	0.1782	-1.404
	(0.0016)	(0.0025)	(0.0056)		(0.2644)	(0.1505)	(0.8728)
Parents' marital status (reference				Pakistani	0.4002*	0.2437*	0.7829**
married)					(0.2321)	(0.1397)	(0.3199)
Cohabiting	0.1368***	0.0726***	0.0165	Bangladeshi	0.2132	0.0933	0.2012
	(0.0369)	(0.0207)	(0.0808)		(0.2827)	(0.1623)	(0.2789)
Single	0.1519**	0.0766*	0.0517**	Black or Black British – African	0.1635	0.0861	0.8705*
	(0.0753)	(0.0421)	(0.0253)		(0.2919)	(0.1682)	(0.5168)

Table 4 (cont.) Pooled Ordered Probit and Logit Models and BUC Estimates for Non-Movers

Variables	Ordered Logit	Ordered Probit	BUC		Ordered Logit	Ordered Probit	BUC
Widowed	0.2385	0.0944	0.2689	Chinese	-1.266**	-0.6710**	-2.111
	(0.1520)	(0.0829)	(0.3192)		(0.5616)	(0.3191)	(1.965)
Divorced	0.1221*	0.0607*	0.2522	Household Size	-0.0268**	-0.0152**	-0.0293**
	(0.0682)	(0.0313)	(0.1347)		(0.0115)	(0.0064)	(0.0144)
Separated	-0.0648	-0.0369	0.0530	Family unit head job status (reference Employed)			
	(0.0848)	(0.0469)	(0.2028)				
				Unemployed	0.1474**	0.1046***	0.3595**
					(0.0693)	(0.0387)	(0.1789)
Permanent unable to work	0.2101**	0.1357***	0.0475*	No observations	12,528	12,528	9,014
	(0.0433)	(0.0389)	(0.0252)				
Retired	0.3021**	0.2385***	0.7743**	LR Chi- square	18,332.42	16,771.79	
	(0.1408)	(0.0481)	(0.3808)		[0.000]	[0.000]	
House tenure (reference Owns outright)				Wald Chi- square			35,414.67 [0.000]
Mortgage	-0.0242	-0.0192	0.0445	MWTP for a drop of one standard deviation in O_3 per year	£2,495	£2,135	£2,320
	(0.0447)	(0.0251)	(0.1496)				
Rents from Local Authority	0.2775***	0.1603***	0.1971	MWTP for a drop of one standard deviation in NO_X per year	£466	£481	£494
	(0.0591)	(0.0331)	(0.1935)				
Rents from HA/ Regional Social Landlord	0.2661***	0.1686***	0.3042	MWTP for a drop of one unit O_3 per year	£156	£163	£169
	(0.0644)	(0.0361)	(0.2095)				
Rents partially furnished	0.0954	0.0511	0.1525	MWTP for a drop of one unit NO_X per year	£52	£61	£68
	(0.1100)	(0.0609)	(0.2248)				

Standard errors between brackets, p-values between square brackets, clustered standard errors on local authority districts, ***, ** and * indicate significance at 1%, 5% and 10% level.

Columns (1) and (4) refer to total sample, (2) and (5) to non-mover sample, (3) and (6) to movers

In table 5 we present two alternative specifications of the main regressions, considering two different radius distances between the local authority district centroid and the air monitoring station. While our main results in the previous tables are based on a 10 km radius, in table 5 we present our estimates using a radius of 5 and 20 km. We observe that the estimated coefficient of income remains almost similar across the different specifications of the air pollution mapping radius, while the air pollutant coefficients vary. More specifically, the air pollution has a stronger negative impact on child' health the closer we assign the air pollution mapping to monitor station and this is defined at 5 km. We observe the opposite situation when the air pollution mapping takes a place within a 20 km radius. This can be concluded also by the MWTP values that are monotonically increasing with decreases in the radius of the air pollution mapping. The estimated coefficients for the rest of the control variables and factors are not reported, since the main concluding remarks remain the same.

Table 5

Adapted Probit Fixed Effects and Robustness Check using 5 and 20 km Radius

Variables	5 km radius	20 km radius
Log of Household Income	-0.0208**	-0.0213**
	(0.0086)	(0.0902)
O_3	0.0293**	0.0265**
	(0.0141)	(0.0123)
NO_X	0.0068**	0.0049*
	(0.0032)	(0.0026)
MWTP for a drop of one standard deviation in O_3 per year	£2,380	£2,145
MWTP for a drop of one standard deviation in NO_X per year	£565	£495
MWTP for a drop of one unit O_3 per year	£188	£162
MWTP for a drop of one unit NO_X per year	£74	£58
No observations	11,843	13,649
R square	0.4333	0.4043

Standard errors between brackets, clustered standard errors on local authority districts ** and * indicate significance at 5% and 10% level.

In table 6 we present another specification as robustness check. In particular, we estimate three different regressions; the first for households with one child, and two regressions for households with more than one child having different health conditions. The analysis can be expanded in such a way that we can explore the additional health related costs of children. More specifically, to estimate and compare the health associated costs of households with ill or disabled children and those with healthy children as base line. Next using the standard of livings approach (Zaidi and Burchardt, 2005; Cullinan et al., 2011) and various tests, including the independence of base (IB) property, shape invariance, parallel lines, vertical-horizontal distance and Engel curves, we could calculate impact of poor health conditions on household's welfare and the additional income needed to improve it, due to the child's extra health related costs (Pollak and Wales, 1979, 1981; Yatchew, 1999, 2003). The analysis also can be expanded by the number of children with health problems. So, a household with a healthy child can be compared with a household with one ill child and then with another household with two ill children and so on and considering the impact of air pollution. While this is not the purpose of the current study, we suggest it for future research applications.

Table 6
Adapted Probit Fixed Effects and Robustness Check for Household with Different Child Health Status

Variables	Household with 1 child	Household with 2 children (1 with poor health conditions and 1 with no health problems)	Household with 3 children (2 having poor health conditions and 1 with no health problems)
Log of Household Income	-0.0202**	-0.0119*	-0.0105**
	(0.0089)	(0.0066)	(0.0039)
O_3	0.0178*	0.0297**	0.0308**
	(0.0093)	(0.0134)	(0.0147)
NO_X	0.0013*	0.0044**	0.0053*
	(0.0007)	(0.0019)	(0.0045)
MWTP for a drop of one standard deviation in O_3 per year	£1,800	£2,950	£3,320
MWTP for a drop of one standard deviation in NO_X per year	£685	£1,220	£1,450
MWTP for a drop of one unit O_3 per year	£160	£280	£310
MWTP for a drop of one unit NO_X per year	£55	£110	£135
No observations	9,867	4,690	2,293
R square	0.6399	0.6896	0.7295

Standard errors between brackets, clustered standard errors on local authority districts ** and * indicate significance at 5% and 10% level

In table 7 three different estimates are reported, which in combination with the findings from table 3 they can provide calculations for the last term of relation (20). First, in panel A the conditional fixed effects Logit regression results for respiratory illnesses complaints are presented. Household income is significant and decreases the probability occurrence of respiratory illnesses complaint. In this case, the MWTP for a drop of standard deviation is £1,085 and £125 for O_3 and NO_X respectively.

The estimates in panels B and C are quite different. In that case, instead of taking the air pollutants, we consider a dummy variable indicating whether a child has poor health status and 0 otherwise. In panel B the dependent variable is the number of visits to GP for respiratory reasons, while in panel C the dependent variable is the number of inpatient nights in hospital for respiratory illnesses reasons. In all cases, the coefficients present the expected signs and are significant. More specifically, increases in air pollution levels are associated with increased probability of respiratory complaints occurrence. The findings are not in line with the study by Violato et al (2009) who found that household income has insignificant effects on improving child respiratory health.

In panel B we observe that children having poor health visit a GP 1.2 more than their counterparts with good health status, while in panel C the estimates show that on average a child with poor health status stays inpatient in hospital almost 4 nights more than a child with good health status. The last term of (20) is: $P_M(dM^*/dE)$ indicating the mitigating actions. Using panel B, the visits to doctors can be considered as mitigating action. However, P_M is free, therefore zero, because these visits take place in National Health Survey (NHS) of United Kingdom which is free. Nevertheless, two scenarios can be considered. In the first case a P_M equal at three hours can be taken as an example including the transportation time to doctor, waiting and consultation time. This number is totally hypothetical and it depends mainly on the location, the distance between the health centre and the residence and the NHS service. Taking this case and the estimates from table 3 and panel B of table 7 (1.203) then the term $P_M(dM^*/dE)$ is equal at £440 for O_3 and £95 for NO_X for one drop of their standard deviation per year. In the second case, the possible monthly fee of £10 per GP visit proposed by Lord Warner a former Labour health minister Borland (2014) is considered. Using the information provided by UK Government the minimum wage in 2010 was 5.5 (https://www.gov.uk/national-minimum-wage-rates). This is a very simplified example and minimum wage is used as the opportunity cost for being in hospital instead of working. Therefore the fee of £10 is equivalent with almost 2.5 working hours paid in minimum hourly wage plus the three hours scenario which might be necessary for transportation, waiting and consultation time. Thus, term $P_M(dM^*/dE)$ becomes £810 for O_3 and £175 for NO_X.

Based on NHS (2010) the national average cost of an elective (planned) inpatient stay excluding excess bed days is £2,749, while the cost for non-elective (unplanned) is £527 for short stays and £2,197 for long stays. Using the estimates of table 3 and the panel C of table 7 then the planned inpatient cost is £350 and £65 for O_3 and NO_X respectively and children with poor health. Regarding the unplanned short stays the cost becomes £55 and £15 respectively. The respective cost values for unplanned long stays are £235 and £50. Regarding panel A of table 7 then the costs of unplanned short stays due to O_3 and NO_X pollution in respiratory diseases is £27 and £5 respectively, while the cost for planned short and long stays range between £2-6 and £4-27 respectively.

Table 7
Respiratory Diseases Complaints, Visits to GP and Number of Nights in-Patient in Hospital for Non-Movers

Variables	Panel A: Conditional Fixed Effects Binary Logit Estimates for Respiratory Diseases Complaints	Panel B: Fixed Effects Estimates for Visits to GP	Panel C: Fixed Effects Estimates for Number of Nights Inpatient
Poor Health		1.203***	3.805**
		(0.0210)	(1.708)
Log of Household Income	-0.0107**	-0.0186**	-0.0325**
	(0.0050)	(0.0081)	(0.0153)
O_3	0.0033**		
	(0.0015)		
NO_X	0.0005**		
	(0.0002)		
No observations	6,579	4,609	2,845
R Square		0.1354	0.1531
LR Chi-Square	323.51		
	[0.0005]		

Standard errors between brackets, clustered standard errors on local authority districts *** and ** indicate significance at 1% and 5% level.

However, there are major limitations and drawbacks in this study and the results should be interpreted and dealt with caution. First, only the general health status is examined, therefore the results are not so precise. Respiratory diseases and lung functions should be explored in future studies and evaluate the MWTP for reduction on air pollution. Second, this study is using a pseudo-panel data set based on repeated cross-sectional surveys, associated with all the disadvantages that have been discussed previously. However, in our study we control for unobserved spatial heterogeneity that can be correlated with the air pollution and thus, it makes our cross-sectional estimates less prone to omitted variables bias. On the other hand, controlling for individual heterogeneity may be less important to estimate the effect of pollution, but it is crucial for the estimation of the effects of individual and household characteristics, including income (Ferrer-i-Carbonell and Frijters, 2004). This is important as the income is the major component of calculating the MWTP and the benefit estimates in monetary terms. Furthermore, the choice of the household to reside in a specific area or to move to another location cannot be captured by cross-sectional data. Even with the use of panel data we can evaluate the propensity of the movers to change residence and location due to air quality, but it is not possible to explore whether the non-movers, across the time-period of the survey, are less concerned about the air pollution or because the air quality is better.

6. Conclusions

This study used a set of pseudo panel micro-data on self-reported child health status from General Lifestyle Survey. The findings showed that the MWTP for a one unit drop in O_3 and NO_X per year is £2,263 and £520 respectively for the non-movers sample. Two possible scenarios of visiting a GP have been examined, where the cost of visit associated with the poor health and air pollution ranges between £442-£811 for O_3 and £94-£172 for NO_X. Considering that the inpatient planned stay cost per day is £2,749 the MWTP for non-movers is 0.82 and 0.19 times the inpatient stay cost for a drop reduction in standard deviation of O_3 and NO_X respectively. The approach followed in this study was used to assess how willingness to pay varies over time and by region, age, income, education and level of pollution among others. Additionally, one very strong and useful point of this approach is that the estimated coefficients can be used to calculate the marginal rate of substitution between income and air quality directly.

Appendix A

Theoretical Framework Derivations

Let the utility function for the child be:

$$U = U(X, H, M, E) \tag{A.1}$$

The health production, according to the main text, is defined as:

$$H = H(M, E; A, K, D) \tag{A.2}$$

Where A is the averting behavior ie. moving to other locations with better air quality or outdoor activities avoidance, K is health capital and D denotes the human capital. Substitution of health production function (A.2) into the utility function (A.1) yields the utility function expressed in composite commodity, leisure, averting behavior, and pollution.

$$U = U(X, H(M, E), M, E) \tag{A.3}$$

The income and cost functions are

$$I = w(T - H) = wT - wH(M, E) \tag{A.4}$$

$$C = X + P_M M \tag{A.5}$$

,where w is the wage, T is the total time available, P_x is the price is composite commodity normalized to one and P_M is the market price of mitigating strategy. The full income budget constraint can be derived by equating (A.4) and (A.5).

$$wT = wH(M, E) + X + P_M M \tag{A.6}$$

The maximization problem is expressed by the following Lagrangian function:

$$L = U(X, H(M,E), M, E) + \lambda[wT - wH(M,E) - X - P_M M] \quad \text{(A.7)}$$

First-order conditions for utility maximization need to be satisfied, in which the first partial derivative with respect to *M* is:

$$\frac{\partial L}{\partial M} = U_{\mathrm{H}} H_M + U_M - \lambda(P_M + wH_M) = 0 \quad \text{(A.8)}$$

We will have the following algebraic manipulations:

$$\begin{aligned} &(U_{\mathrm{H}} H_M + U_M)/\lambda = P_M + wH_M \Rightarrow \\ &(U_{\mathrm{H}} H_M + U_M)/\lambda - wH_M = P_M + wt_M \Rightarrow \\ &(U_{\mathrm{H}} H_M + U_M)/\lambda - wH_M = P_M + wt_M \Rightarrow \\ &(U_{\mathrm{H}} + U_M)/\lambda - w = P_M / H_M \end{aligned} \quad \text{(A.9)}$$

Since $P_M = P_M + wt_M$ where P_M is the market price and t_M is the time the individuals conduct the behaviour. Similarly, the first order condition for air pollution will be:

$$\frac{\partial L}{\partial E} = U_{\mathrm{H}} H_E + U_E - \lambda w H_E = 0 \quad \text{(A.10)}$$

$$U_{\mathrm{H}} H_E + U_E = \lambda w H_E \Rightarrow (U_{\mathrm{H}} H_E + U_E)/\lambda = wH_E \Rightarrow \quad \text{(A.11)}$$

And it will become:

$$(U_{\mathrm{H}} H_E + U_E)/\lambda - wH_E = 0 \quad \text{(A.12)}$$

Relation (A12) shows that the individuals or the consumers would avoid pollution until the total of the marginal value of healthy time, the marginal value of quality and the opportunity cost of health time on the LHS equals zero. The indirect utility function is formed by substituting the optimal values of mitigating behaviour, averting behaviour into utility function as:

$$V = V(P_M, P_A, w, E) \quad \text{(A.13)}$$

By totally differentiating the indirect utility function (A.13) yields:

$$dV = V_M dP_M + V_A dP_A + V_w d_w + V_E d_E \quad \text{(A.14)}$$

The total derivative of air pollution is:

$$dV / dE = V_w (dw / dE) + V_E \quad \text{(A.15)}$$

The WTP will be:

$$WTP_E = dw / dE = -V_E / V_w \quad \text{(A.16)}$$

Besides, the marginal utility of pollution from A.10 could be expressed as:

$$V_E = (U_H - \lambda w)\mathrm{H}_{\mathrm{E}} + U_E = 0 \tag{A.17}$$

And re-write equation A.8 as:

$$U_{\mathrm{H}} H_M + U_M - \lambda(P_M + wH_M) = 0 \Leftrightarrow U_{\mathrm{H}} - \lambda w = (\lambda P_M - U_M)/H_M \tag{A.18}$$

And plugging A.17 to A.18 will be:

$$\begin{aligned} V_E &= H_E(\lambda P_M - U_M)/H_M + U_E \Rightarrow \\ V_E/\lambda &= P_M(H_E/H_{\mathrm{M}}) - (U_M/\lambda)(H_E/H_{\mathrm{M}}) + U_E/\lambda \Rightarrow \\ V_E/\lambda &= H_E(P_M - U_M) - (U_M/\lambda)(H_E/H_{\mathrm{M}}) + U_E/\lambda \end{aligned} \tag{A.19}$$

By plugging the optimum values M^* into health production function and totally differentiating yields:

$$dH = H_E dE + H_M dM^* \tag{A.20}$$

Dividing by dE it will be:

$$dH/dE = H_E + H_M(dM^*/dE) \tag{A.21}$$

The function (A.21) indicates that the total effect on LHS is the sum of a direct effect, which is the marginal product of pollution on health and the indirect effect, expressed by the marginal product of mitigating behaviour on health time and the marginal effect of pollution on mitigating behaviour, on the RHS. Next by multiplying function (A.21) with *w* it will be:

$$wdH/dE = w[H_E + H_M(dM^*/dE)] \tag{A.22}$$

And then multiplying A.20 with A.9 it yields:

$$[(U_{\mathrm{H}} + U_M/H_M)/\lambda - w][dH/dE - H_M(dM^*/dE)] = H_E \cdot P_M/H_M \tag{A.23}$$

$$[dH/dE - H_M(dM^*/dE)][(U_{\mathrm{H}} + U_M/H_M)/\lambda - w] = P_M(H_E/H_M) \tag{A.24}$$

Since we found that

$$P_M = H_M(dM^*/dE)[(U_H + U_M/H_M)/\lambda - w] \tag{A.25}$$

Then WTP_E will be:

$$WTP_E = -P_M(H_E/H_M) = -(dH/dE)(U_H + U_M/H_M)/\lambda + w(dH/dE) + P_M(dM^*/dE) \tag{A.26}$$

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Özet

İngiltere'de hava kirliliğinin çocuk sağlığı üzerindeki etkileri

Bu çalışma, hava kirliliği, çocukların sağlık durumu ve ebeveynlerin İngiltere'de hava kalitesini iyileştirmek için gönüllü olarak yaptıkları ödeme miktarı arasındaki ilişkiyi araştırmaktadır. Tahminler, 2000-2010 dönemi boyunca Genel Yaşam Tarzı Araştırması'ndan alınan yatay-kesit verilerine dayanmaktadır. İncelenen iki ana hava kirleticisi zemin seviyesinde ozon (O_3) ve azot oksitlerdir (NO_X). Bulgular, belli varsayımlar altında türetilmiş örneklemlerin kullanımı ile elde edilen regresyon tahminlerine ve gönüllü olarak yapılacak ortalama marjinal ödeme miktarına dayanmaktadır. Sonuçlar, O3 ve NOX için gönüllü olunan yıllık ortalama ödeme miktarının, standart sapmadaki bir birimlik düşüş için £ 2,263- £ 3,108 ve £ 520- £ 1,121 arasında olduğunu göstermektedir. Sonuçlar ayrıca örneklem döneminde adres değişikliği yapmayanların hastanede planlı kalış maliyetinin O3 hava kirleticisi için gönüllü olarak yapacakları ödemeden 1.2 kat daha fazla olduğunu göstermektedir.

Anahtar kelimeler: Hava kirliliği, çevresel değerlendirme, sağlık düzeyi, sözde-panel veri

JEL kodları: I31, Q51, Q53, Q54