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ORIGINAL PAPER

Health status and willingness-to-pay estimates for the benefits of improved recycling rates: evidence from Great Britain

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Abstract

Waste management is a challenging task around the globe. Waste disposal and recycling have important implications, not only for environmental preservation, but also for the public health, well-being, the economy and sustainable development. However, little is known about the impact of the recycling rates on public health and the willingness to pay to increase recycling. The aim of this study was to examine the relationship among household income, recycling rates and health status and to estimate the marginal willingness-to-pay (MWTP) in Great Britain. The empirical analysis relied on data from the British Household Panel Survey (BHPS) over the period 1999–2009. We estimated the impact of recycling rates and income on health status and we calculated the monetary value for a unit increase in recycling. To solve for the endogeneity issues, coming from possible reverse causality and omitted-variable bias, we implemented two instrumental variables (IV) approaches. First, we applied the Two-Stage Least Squares (2SLS) and second, we estimated a Pooled Ordered Probit model. We found that for one percent increase in recycling rates, the average MWTP was estimated between £290 and £340 per annum. Furthermore, our results show that other determinants play an additional significant role on health status, such as the employment and marital status, the age, education level and meteorological conditions. While the study provides insights about the MWTP, future studies regarding the costs of providing recycling services may offer additional useful information to help the policy makers in the decision-making process.

Keywords Environmental valuation · Instrumental variables · Marginal willingness to pay · Panel data · Recycling · Self-reported health status

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Introduction

Solid waste disposal is a stinging and widespread worldwide problem in both urban and rural areas in many developed and developing countries. Solid waste generation when is not recycled affects the climate, causing changes in temperature and rainfall patterns. However, the effect on climate change is only one of a number of environmental impacts that derive from solid waste management options. Other impacts include the contamination of water and emission of various air pollutants, including Sulfur Dioxide (SO_2), Hydrocarbons (HC), Particulate Matter (PM), Carbon Monoxide and Dioxide (CO, CO_2) and Nitrogen Oxides (NOx) that have a detrimental effect on health. The groups that are in particular risk are those living close to landfill sites and waste dumps, and also those whose water supply has been contaminated due to leakage from the landfills. Hazardous waste is also very risky, especially for children who are more vulnerable, leading to diseases through their exposure to dust and chemicals emitted from waste dumps.

Recycling is one of the tools that could potentially cut down the air pollution emissions. Traditionally, recycling was occurred because it was seen as an economically viable way to reduce the costs of new goods production. However, over the recent years with the increased volume of waste generation, and in particular plastic, the perception is changed in a way that recycling should be applied in a large scale. According to the Institute of Scrap Recycling Industries, recycling of ferrous metals instead of using virgin ore to produce new steel, can save energy up to 74% and reduce air pollution by 86%. Aluminium recycling may reduce water pollution even up to 97% compared to the extraction of new ore to make new aluminium (Gerbrandt 2002; Can manufacturers Institute 2006). Furthermore, it is found that recycling is associated with lower level of air pollution in the USA (Giovanis 2015).

Apart from the potential environmental benefits, recycling process is associated with activities related to composting, curbside collection, sorting and reprocessing of recyclables that create more jobs than collecting the waste to landfills or to incineration facilities (Renner 1991; Gray et al. 2004). Recycling overall can have a large contribution to economic growth. A study by European Commission (EC) has shown that the full implementation of the European Union Waste legislation would increase the annual turnover of the European Union (EU) recycling and waste management sector by €42 billion, would save €72 billion a year and create over 400,000 jobs by 2020. Unfortunately, according to the same report, illegal waste operations are still causing these missing opportunities for economic growth and this is also confirmed and backed up by several other studies (BIO Intelligence Service 2011; EC 2012).

On the other, hand, recycling is also associated with energy costs required for the recycling process, including collection, transportation, separation, labouring and others, which considerably increases with the volume of the waste. However, the cost can be lower compared with the energy used to extract, manufacture, produce and transport new materials or the energy spent for waste incineration (Lea

1996; Genc et al. 2019). Furthermore, a degree of pollution is emitted by the heat generated to melt various materials, such as metal and glass. Nevertheless, the air pollution effect on health is limited to the workplaces, while the air pollution emissions from landfills can be channeled with relative ease to the atmosphere, causing health problems to human and animals, and damage to the environment.

The motivation of the paper lies in the potential benefits of recycling on public health and the adverse health effects of waste generation. Numerous studies found that waste disposal sites are potential sources of hazard to public health. A study by Dolk et al. (1998) found that pregnant women located within 3 km of a waste landfill site in five European countries, are more likely to present terminations of pregnancy with non-chromosomal congenital anomalies or have a higher likelihood to give births with high risk of congenital anomaly. Several other studies found similar concluding remarks (Hu and Shy 2001; Rushton 2003; Dolk and Vrijheid 2003; DEFRA 2004; WHO Regional Office for Europe 2007; Russi et al. 2008; Giusti 2009; Porta et al. 2009; Mattiello et al. 2013).

The study intents to inform how recycling may reduce air pollution and therefore, protect and improve public health. The main objective is to estimate the Marginal Willingness-to-Pay (MWTP) for one percent increase in recycling rates to improve the general health status. To accomplish this, we aim to establish a causal link between recycling rates, household income and health status.

The previous literature has employed two main methods to estimate the MWTP; the revealed preferences and stated preferences. The first method relies on the popular travel cost approach and hedonic price analysis, while the second method is based on contingent valuation surveys, whose main purpose is to explicate the environmental value from questions asked to the respondents. These approaches are very popular and well documented in practice (Carson et al. 2003; Carson and Louviere 2011; Johnston et al. 2017). However, their implications are associated with some drawbacks. More specifically, the revealed preference approaches are based on binding assumptions about the markets functioning and the rationality of the agents. More precisely, if the housing markets are not in equilibrium, the estimates will be biased and they can underestimate the benefits of the clean air (Bayer et al. 2009). This is because decisions in private goods markets may not accurately reveal people's hedonic experience from the consumption of public goods (Rabin 1998).

Regarding the stated preference approaches, the results can be unreliable and associated with strategic behaviour, since they use hypothetical scenarios. More specifically, this hypothetical nature of the surveys can allow for superficial answers and strategic behaviour (Kahneman et al. 1999). Overall, the problem of both revealed preference and stated preference approaches is that they mainly value the public goods of which individuals are aware of.

Instead this paper relies on an approach similar to the life satisfaction evaluation, where people are asked about their health status. This is associated with the advantage that the assumption of housing market equilibrium is not required and it does not ask directly people to evaluate the public good, which in our case is recycling. But apart from the benefits, this approach has also drawbacks. One main problem is the endogeneity issue coming from the reverse causality between health status and household income. Another major drawback is the residential sorting problem,

where people choose where they reside. For instance, risk averted people may prefer to live in low polluted and greener areas, given the fact that they can afford the housing prices. For this reason, we control also for socio-economic characteristics, including education, marital and employment status. Nevertheless, this would bias the coefficient of the recycling rate, and therefore, the monetary value upwards, as those least resilient to air pollution coming from waste dumps would choose to reside in areas with cleaner air. Additionally, less risk averted people may not consider the possible negative effects of the air pollution, neglecting the positive effects of clean air and thus, will be indifferent whether they reside in areas with high pollution. Even though the latter can be less likely, given always the income, education level, wealth and employment status, we examine non-movers to reduce the endogeneity.

Furthermore, we apply the 2SLS method and Pooled Ordered Probit Regressions with instrumental variables to reduce the endogeneity coming from the reverse causality between income and health status and the omitted variable bias. In particular, we use the following variables as instruments for the household income: whether the household has won the lottery; the council tax band and a categorical variable indicating if the respondent has shown the payslip to the interviewers, which contains information about the income and related taxes. Based on the Ordered Probit and Probit-FE estimates, the results show that the average MWTP values range between £780-£800 per year. On the other hand, the MWTP values found by the IV approaches, range between £290 and £340.

The structure of the paper is the following: In Sect. 2, we briefly discuss the literature review. Section 3 describes the conceptual and empirical framework, while in Sect. 4 we present the data employed in the empirical work. In Sect. 5 we report the MWTP values and in Sect. 6 we discuss the concluding remarks.

Literature review

There have been concerns about the potential adverse health effects of waste dumps and landfill sites (Institute for Environment and Health 1997; Vrijheid 2000; DEFRA 2000). Furthermore, dumping large amounts of waste—due to urbanisation, increase of population and consumption, due to improvements in income and living standards—is very likely to be unsustainable in the long term. According to the European Union (EU) Landfill Directive (1999), a considerable volume of waste is required to be diverted away from waste disposal sites. Among others, recycling is one of the main waste management options that can reduce waste disposal and protect public health. Empirical evidence found that there are toxicological effects on human and animal health caused from waste generation and disposal (Institute for Environment and Health 1997; Vrijheid 2000; DEFRA 2004). Public authorities in Ireland have recognised the importance of recycling as a way to reduce the waste disposal for the protection of public health. One of these actions include the first sustainable development strategy implemented in 1997, which is focused on strategies and policies that promote recycling (DOELG 1997; Wilde et al. 2006).

Next we discuss earlier research studies that have examined the effects of air pollution on health. The study by Gerking and Stanley (1986) was one of the first empirical applications on the relationship between air pollution and health and one of the first attempts to derive the MWTP. The analysis relied on the St. Louis survey over the period 1977–1980 and the main findings show that the annual willingness to pay for a 30% reduction in ambient mean ozone concentrations ranges between $18.45 and $24.48. In another study, Chay and Greenstone (2003) exploited the Clean Air Act Amendments (CAAAs) of 1970 to examine its association to air quality improvement and to identify the impact of pollution on infant mortality during the period 1971–1972. The study reveals a positive impact of the Clean Air Act resulting to a 0.5% reduction in the mortality rates. Numerous recent studies confirm the findings of the detrimental effects of air pollution on health, focusing on both short-term (acute) and long-term (chronic) exposures to air pollutants (Manisalidis et al. 2020). Previous studies suggest that air pollution has long-term effects on health, including cardiovascular diseases and mortality, chronic asthma and diabetes (Hou et al. 2010; Kan et al. 2012; Eze et al. 2014; Pena and Rollins 2017; Manisalidis et al. 2020). Moreover, air pollution is found to have various malign health effects in early human life, such as mental disorders, respiratory and cardiovascular diseases that lead to infant mortality or chronic diseases in adult age (Bellinger 2008; Dherani et al. 2008; Kelishadi and Poursafa 2010).

Instead of exploring the above-mentioned outcomes, we focus on the self-reported health status. Numerous studies have explored the Self-Assessed Health (SAH) and its association with socio-economic characteristics and lifestyle attitudes (Kenkel 1995; Benzeval et al. 2000; Frijters et al. 2003; Contoyannis and Jones 2004; Mackenbach 2008, 2012; Kaikkonen 2009). There is a considerable and well-documented evidence suggesting that people belonging to the lower levels of the socio-economic status (SES) report a poor self-perceived health, higher prevalence of chronic diseases and unhealthy behaviours, such as alcohol use, smoking, inadequate diet and lack of physical exercise (Contoyannis and Jones 2004; De Looper and Lafortune 2009; Jovanovic and Jakovljevic 2011; Dorjdagva et al. 2015). The findings from these studies suggest that unemployed people are more likely to report low health status levels, while health is monotonically improved with educational attainment levels. Wealthier and more educated individuals are more likely to believe that a healthy lifestyle is result of personal responsibility and attitude, such as taking care of their diet. Furthermore, these groups are more likely to participate in sports and other related activities compared to those belonging to low SES classes, who believe that a good health status is result of pure luck (Wardle and Steptoe 2003). Thus, following the earlier literature we control for the standard SES characteristics, such as education and employment status. Furthermore, we control for those factors to improve the robustness of the instrumental variables used, as we discuss in more details in the next section.

This paper differs from previous studies, as it aims to estimate the average MWTP for one percent increase in recycling rates to improve the health status. To accomplish this objective, we examine the relationship between recycling rates and the self-reported health status using data from the BHPS, accounting for various individual-household characteristics and meteorological conditions. Second, we employ

a set of instrumental variables to income, to reduce the possible degree of reverse causality between the health status and income.

We present two main sets of panel data analyses. First, we apply an individual level fixed effects model, and then we estimate a random effects ordered Probit model. The second set of estimates includes IV approaches, and in particular, the first method is the Two-Stage Least Squares-Fixed Effects (2SLS-FE), while the second model is a Pooled Ordered Probit model. As instruments for the household income we use the council tax band; whether the household has won the lottery and if the interviewer has seen the respondent's payslip.

There are several key advantages of using these methods. First, employing fixed effects models, we can control for the local authority district-specific time invariant characteristics. The IV approaches and the instrumental variables methods, allow us to reduce the endogeneity coming from the possible degree of reverse causality between health status and household income. More specifically, a higher income may imply higher levels of physical and mental health status. On the other hand, people who report higher levels of health status, can be more productive and able to work harder, which may consequently lead to higher income. This is crucial, since the MWTP values are based on the effect of income on health status, as we describe in more details in the methodology section. Accounting for endogeneity, we may infer causality, which eventually allow us to estimate more precisely the MWTP values.

Methodology

Conceptual framework

Following the discussion in the previous section, earlier studies provide evidence that demographic and socio-economic characteristics affect both household income and our main outcome of interest; the health status (Kenkel 1995; Benzeval et al. 2000; Frijters et al. 2003; Contoyannis and Jones 2004; Mackenbach 2008; De Looper and Lafortune 2009; Kaikkonen 2009; Jovanovic and Jakovljevic 2011; Dorjdagva et al. 2015; Giovanis and Ozdamar 2014, 2016, 2018). More specifically, these studies suggest that middle aged high educated people are more likely to have better labour opportunities and earning potential, leading consequently to higher household income and living standards and thus, resulting in improvement of their health status. Moreover, previous studies provide evidence that recycling behaviour can be influenced by socio-economic characteristics. In particular, studies found that family size and employed people contribute more to waste generation, while more educated people may recycle more (Bandara et al. 2007; Khan et al. 2016; Vieira 2018). A study by Emery et al. (2003) explored the role of three dwelling types, and more specifically, the semi-detached, terraced and council houses, in a unitary authority in Wales, to investigate the impact on waste recycling behaviour. The authors found different patterns among the households living in different dwelling types. Even though, the aim of this study is not to identify the factors of waste generation and recycling behaviour, our MWTP estimates may provide insights about the implementation of relevant tax schemes that could "punish" more the polluters

or to tax additionally those who contribute more to waste generation. However, one limitation of this study is that it does not account for the supply of recycling services. More precisely, recycling does not depend only on the households' demand and behaviour, but also on supply and availability of recycling policies and practices. Nevertheless, the estimation of the MWTP could be derived as a guide for policy implementation and establishment of relevant recycling services that otherwise could be absent.

Based on this discussion, we develop the framework of our empirical analysis illustrated in Fig. 1. The arrows point out the direction of the potential relationships and we observe that socio-economic characteristics may influence both household income and recycling rates, but also they can affect health status according to the studies we have presented in the previous section. For instance, more educated, employed, married, wealthier and young people are more likely to report higher levels of health status compared to older, widowed, unemployed and poor households. This relationship is represented by an arrow showing the link from those characteristics to health status. Hence, there could be a direct link between socio-economic characteristics and health status, but also an indirect effect from those factors to health status, through the household income and recycling rates, may exist. This is known as confounding control and it is important to establish causal links, as the absence of a factor may distort the effect of our main variables of interest, which is the household income and recycling rates, required for the estimation of the MWTP. For instance, in the absence of major factors, mentioned above, that affect both income and health status, may overestimate or underestimate the estimated coefficient of the household income. Nonetheless, controlling for confounding variables in the absence of a randomised controlled trial (RCT) and using observational data, as the BHPS we employ in this study, might not be adequate. In particular, there might be a strong degree of reverse causality between health status and income and thus, we will apply IV approaches to reduce this source of endogeneity, which is discussed in the nest sections.

The discussion so far implies that we aim to evaluate the average MWTP for one percent increase in the recycling rates to improve the health status, due to improvement in air quality, since recycling reduces the solid landfill waste and thus, the air pollution emitted from them. To achieve this, we estimate the simultaneous impacts of recycling rates and household income on health status. The average MWTP refers to the household income, and therefore, the recycling tax could be implemented according to this income. Furthermore, council taxes in the UK include waste disposal and recycling services, and the MWTP may serve as a guide for a cost–benefit analysis and for implementing recycling policies.

Our empirical work relies on quantitative methods and more specifically, is based on regression models that we discuss in the next parts of this section. Our underlying justification on implementing quantitative techniques—apart from the availability of data derived from the British Household Panel Survey (BHPS)—are several. First, quantitative studies can be more empirical, faster, more objective and focused and thus, be more scientific. More specifically, employing large amount of observations and individuals, which is also our case, we can derive objective estimates that can be replicated. Hence, the analysis can be specific and unbiased, since we have
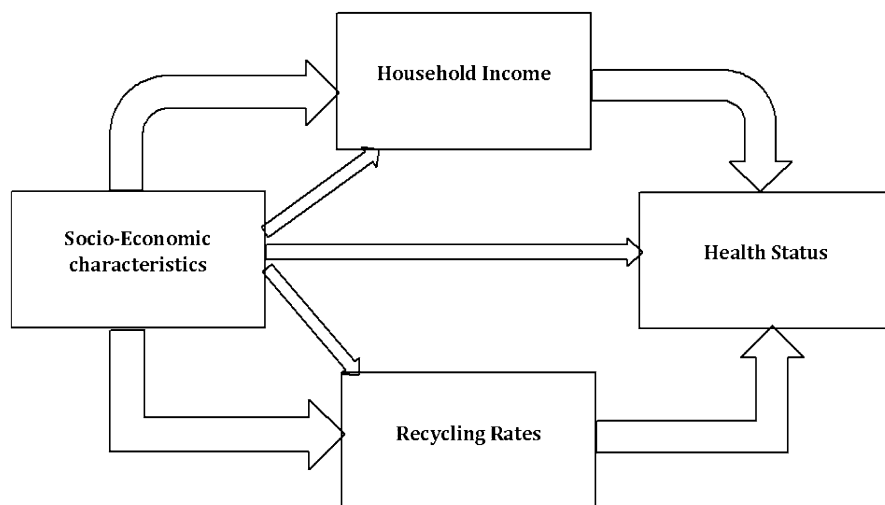
Fig. 1 Conceptual framework

identified our research questions to be explored. Moreover, using large-scale secondary data, we can derive more accurate estimates, as typically these surveys are representative of the total population (Kaplan 2004). Additionally, we can generalise the findings at the national level, which is further supported by the fact that we use a panel dataset, following the same person across the period we explore. This implies that the analysis is dynamic rather than static, which the latter is typically the case in the qualitative studies. Thus, the findings derived may provide insights to policy makers and propose further policy recommendations.

The first part of the research design is based on correlational research and regression models. The aim is to estimate the coefficients of recycling rates and household income that will be used to calculate the average MWTP as we present in more details in the next section. Correlational research is a non-experimental study, where we aim to investigate the direction of the relationships between recycling rates and health status, as well as, between household income and health status. However, the main key drawback of correlational research design that is based on observational-survey data, as the BHPS we employ in this study, is the lack of sufficient evidence to infer causality. This is crucial to the purpose of this study, because to get accurate MWTP estimates, we need to find the effects of recycling rates and household income on health status, which implies causal inference (Pokropek 2016). For this reason, in the second part of our research design we implement causal methods in non-experimental settings and in particular, we apply IV approaches.

Granger causality

In this section we describe the Granger causality test, which is applied to examine whether a reverse causality between recycling rates and health status is present,

which may cause endogeneity bias. Following Holtz-Eakin et al. (1988) we estimate a time-stationary panel Vector Autoregression (VAR) model.

$$\text{HS}_{ijt} = \alpha + \sum_{\kappa=1}^{p} \beta_{jk}\text{rec\_rate}_{jt-k} + \sum_{\kappa=1}^{p} \gamma_{ijk}\text{HS}_{ijt-k} + \mu_i + l_j + \theta_t + v_{ijt} \qquad (1)$$

Using Regression (1) we examine whether recycling has an impact on health status. However, following studies on Granger causality, it is typical to test whether causation runs in both directions, and therefore, we estimate regression (2):

$$\text{rec\_rate}_{jt} = \alpha + \sum_{\kappa=1}^{p} \beta_{jk}\text{rec\_rate}_{jt-k} + \sum_{\kappa=1}^{p} \gamma_{ijk}\text{HS}_{ijt-k} + \mu_i + l_j + \theta_t + u_{ijt} \qquad (2)$$

Based on regression (2), we also explore whether the direction of the causality runs from health status to recycling rates. The optimum length of lags in recycling and health status is chosen according to the Akaike (AIC) and Schwarz (SC) information criteria and whether the coefficients are significant. We employ the Generalised Methods of Moments (GMM) proposed by Blundell and Bond (1998) to estimate regressions (1)–(2). The estimated regressions are reported in Table 1. We conclude that the recycling rates with 1-year-lag have a significant impact on health. On the contrary, we found the estimated coefficient of the health status in regression (2) insignificant, implying as a first test that health does not cause recycling. This is also expected, because health status is measured at the individual level, while recycling is mapped at the local authority district level. Based on the Sargan test, we conclude that the GMM model meets the over-identifying restrictions. We should notice that a negative sign of recycling on health implies a positive impact, since health status is measured on a scale from 1 (excellent health) to 5 (very poor health). Furthermore, the estimated magnitude of the recycling rates coefficient in column (1) of Table 1 is rather overestimated, since the regressions do no control for other characteristics.

Fixed effects panel model

The study explores the self-reported health, which has been served empirically in earlier studies as a valid well-being measure. Moreover, we aim to measure the marginal utility of the public good, which is the recycling rates in our case. The regression for individual i, in area-local authority district-j at time-year t is:

$$\text{HS}_{i,j,t} = \beta_0 + \beta_1\text{rec}_{j,t} + \beta_2 \log(y_{i,j,t}) + \beta'z_{i,j,t} + \gamma W_{j,t} + \mu_i + l_j + \theta_t + l_jT + \varepsilon_{i,j,t} \qquad (3)$$

$\text{HS}_{i,j,t}$ denotes the health status, $\text{rec}_{j,t}$ is the recycling rate expressed in linear term[1] in location j and in time t, $\log(y_{i,t})$ indicates the logarithm of the household income.

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[1] Higher polynomial degrees in recycling rates than linear order have been examined. However, the coefficients are insignificant. In addition, income and age squared are insignificant.

Table 1 Summary Statistics

Variables	Panel A: continuous, ordered and binary individual and household characteristics			
	Average	Standard deviation	Minimum	Maximum
Health status	2.254	0.9798	1	5
Monthly household income	2,643.113	2,089.452	0	86,703.29
Gender (1 for male)	0.4597	0.4983	0	1
Age	45.694	18.739	15	101
Household size	2.822	1.382	1	9
Smoker (1 for smoking)	0.2622	0.4398	0	1

Education level	Panel B: categorical individual and household characteristics			
	Proportion	Marital status	Proportion	
Higher degree	2.39	Married	51.81	
First university degree	10.52	Living as a Couple	12.30	
HND, HNC, teaching	7.13	Widowed	7.76	
A level	19.44	Divorced	5.70	
O level	26.07	Separated	1.57	
CSE	5.04	Single	20.86	
None of these	31.80			

Employment status	Proportion	House tenure	Proportion
Self-employed	6.43	Owned outright	27.33
Employed	50.68	Owned with mortgage	45.77
Unemployed	3.56	Local authority rented	14.34
Retired	21.46	Housing association rented	4.41
Maternity leave	0.42	Rented From employer	0.66
Family care	6.2	Rented private unfurnished	3.95
Student	5.92	Rented private furnished	3.36
Long-term sick-disabled	4.62	Other rented	0.18
Government scheme	0.17		
Other	0.54		

	Panel C: recycling rates and meteorological conditions			
	Average	Standard deviation	Minimum	Maximum
Recycling rates (percent)	17.658	11.484	1	62
Average Temperature	50.754	5.796	23.75	75.80
Minimum temperature	44.798	8.052	4.62	66.70
Maximum temperature	56.255	7.910	23	96.60
Precipitation	38.612	46.815	0	499.72
Wind speed	8.403	3.884	0	33.20

The recycling rates are measured in percent. The average, minimum and maximum temperature are measured in Fahrenheit scale. Precipitation is measured in inches, and the wind speed is measured in Knots per hour

Vector z contains individual and household characteristics, while vector W consists of meteorological conditions, and more specifically, wind speed, precipitation and the average, minimum and maximum temperature values. The underlying justification of adding meteorological conditions in the empirical analysis lies in the fact that an extensive empirical evidence shows that they can have a significant impact on physical and mental health. Furthermore, meteorological conditions can be correlated with air pollution, which is related to our study, as the air pollutants released from landfills can be correlated with the health status. In particular, high temperatures are positively correlated with air pollution deteriorating health, while wind speed is negatively associated with air concentration levels (Statheropoulos et al. 1998; Stafoggia et al. 2008; Bell et al., 2007; Barmpadimos 2012; Lecoeur et al. 2012; Giovanis 2015). However, wind speed can be related with cold temperature and is likely to lead to cold-induced illnesses.

In regression (1) set μ_i indicates the individual-fixed effects, l_j is the location (local authority district) fixed effects, while θ_t is a time-specific vector of indicators for the day, month and year of the interview. l_jT is a set of area-specific time trends, while $\varepsilon_{i,j,t}$ expresses the error term. We cluster standard errors at the area-specific time trends. Next we estimate the marginal willingness to pay (MWTP) for a percentage increase in recycling rates, which is the differentiation of regression (3) and setting dHS = 0. The MWTP can be defined as:

$$\text{MWTP} = \frac{\partial f/\partial \text{rec}}{\partial f/\partial \text{inc}} \tag{4}$$

In relation (4) we denote recycling rates and household income respectively by rec and inc. In the case of ordered dependent variables, which is the self-reported health status in this study, it is common practice to apply ordered discrete choice models, such as Ordered Logit and Probit models. However, ordered discrete choice models for panel data allow only for the estimation of random effects and not fixed, which may rise issues regarding the omitted-variable bias and the differential item functioning (DIF) discussed below. The second option includes the Fixed Effects Ordered Probit method introduced by van Praag and Ferrer-i-Carbonell (2004), where the dependent ordinal health status is converted to a continuous variable (see van Praag and Ferrer-i-Carbonell 2004 and Cornelissen 2006, for an example and more technical details).

The first advantage of this method is that it is straightforward and quick to compute, and second, it allows us to derive fixed effects estimates, controlling for unobserved heterogeneity. Earlier studies and several applications show that the results derived by the fixed effects ordered Probit, and also by the Ordinary Least Squares (OLS) method, are identical or similar to those derived by the ordered Probit method. Hence, these studies suggest that there are no significant differences between the OLS and Ordered Probit for cross-sectional data or between fixed effects and the fixed effects ordered Probit methods for panel data (Van Praag and Ferrer-i-Carbonell 2004, 2006; Van Praag 2007; Luechinger 2009).

Following the discussion so far, we extend the fixed effects ordered Probit method developed by Van Praag and Ferrer-i-Carbonell (2004), where we convert the

ordered health status variable into a continuous one and we apply the 2SLS method. Additionally, we estimate a Pooled Ordered Probit with instrumental variables using the maximum likelihood method. Nevertheless, the main issue of the latter model is that we cannot account for unobserved heterogeneity, as we pool our cross-section observations, which is the respondents in the BHPS.

Moreover, the panel data structure of our analysis is valuable as it allows us to apply the fixed effects method and to identify the model and to explore the impact on health from changes in the air pollution concentrations, coming from the landfills and the air quality improvement due to the recycling process, within the individuals and not between the individuals. This may reduce the possible endogeneity bias in the estimates, since unobservable characteristics of the neighbourhood that may be correlated with pollution- coming from landfills; trash volume and self-reported health status, as well as services related to recycling—are eliminated in a fixed effect model. Thus, the model is identified from changes in the pollution level within individuals and between interviews-waves rather than between individuals across a given year. In other words, we explore the dynamics of health status for the same individual across a period of time and we do not compare the health status levels between two or more individuals in a given year. In particular, according to Kapteyn et al. (2010), we cannot compare the health status between individuals, since it is a self-reported variable. This is known as the differential item functioning (DIF), where the self-reported variables are measured on an arbitrary scale, which makes difficult to compare the health status between individuals. More specifically, DIF refers to the case when individuals or groups by gender, age or education have different probabilities of choosing a given category on a multi-item scale, such as the health status employed in this study, and is measured on a scale from 1 (excellent health) to 5 (very poor health). For instance, the choice 1 (excellent health) by individual A, can be equivalent with the choice 3 (fair health) by individual B. This makes the comparison very difficult, if the equivalence scales between all individuals or groups are unknown beforehand (see for more details Kapteyn et al. 2010). Thus, the within fixed effects estimates rely on inter-temporal comparisons of utility within the same individuals (whose choice of health status is known and consistent since it is measured and answered by the same person) assuming that the question interpretation and the scale of measure remains the same across or between the interviews, reducing in this way the potential bias associated with the DIF.

To further limit the endogeneity issue coming from the residential sorting, the population of interest is split to non-movers and movers. Focussing on non-movers allows us to capture unobservable characteristics of the neighbourhood that may be correlated with recycling and health status that are fixed over time. Therefore, in this case, the area-region fixed effects for the non-movers will be removed, while for movers the error term will include differences in the fixed effects, of the two areas which are likely to be correlated with differences in air pollution, recycling and waste disposal facilities. In other words, using movers is difficult to reduce the selection bias, because of the various reasons that people decide to move, such as family reasons, employment, quality of the areas, including air pollution and crime. Hence, our analysis is limited to non-movers.

Instrumental variables (IV) approaches

In this section, we discuss the instrumental variable (IV) approaches and the underlying justification of applying them. More specifically, a strong degree of reverse causality between health status and income is very likely, where income improves health, but on the other hand, healthier individuals can be more productive and earn more. Generally, it is argued that the income and the socio-economic status, such as education and professional class, can have a causal effect. It is reasonable to assume that more educated and wealthier people employed in higher professional and managerial positions, have access to better health care systems, and they follow healthier lifestyles that eventually improve their general health status. However, we can also think of the reverse causality, by arguing that poor health conditions may influence income by reducing the ability to work or reducing the job performance and productivity, which consequently will have a negative impact on the income (Apouey and Clark 2015).

In the literature, pensions and the eligibility retirement age have been implemented as exogenous policies. However, it is difficult to find an instrument for the income across the full adult spectrum of the life course. On the other hand, in the literature review of happiness and life satisfaction economics, the instruments used include wage differentials and interactions between the partner's industry, occupation, and location (Luttmer 2005; Luechinger 2009; Pischke 2011). However, these instruments are not convincible since every factor, including the partner's professional class, wage and industry can determine life satisfaction (Pischke and Schwandt 2012; Stutzer and Frey 2012). In this study, even though we explore the health status, we argue that those instruments are not also convincible, as wage differentials can affect also health status or mental health which is related to happiness. Earlier studies have used various instruments for income to explore its causal impact on health. For instance, Ettner (1996) estimated the impact of income on self-assessed health and daily limitations due to physical and mental difficulties using the work experience, parental education, spousal characteristics and state unemployment rate as instrumental variables for income. Even though the validity of the instruments has been questioned (Kawachi et al. 2010), the study found a significant effect of income on the health outcomes explored.

Thus, in this study we implement three instrumental variables. The first is the council tax band. The argument of using this variable as instrument for income lies in the assumption that is correlated directly with income. In particular, wealthier households prefer to reside in better areas, in terms of safety, and living standards, implying that they rent or purchase more expensive houses, which is associated to higher council taxes. However, even though it is argued that the council tax does not affect the health status, it might be difficult to be a convincible instrument, even if it passes the specification tests. Nonetheless, most importantly, all the household members in the BHPS can be included in the analysis, instead of limiting our analysis only to those who are employed. In particular, as we have discussed before, earlier studies (Luttmer 2005; Pischke 2011; Pischke and Schwandt 2012) consider the industry wage differentials or spouse's wages as instrumental variables, which implies that the empirical analysis is focused only to employed and married

people that is very likely to create an endogenous or selection sample bias, since the remained respondents of the survey are neglected. On the other hand, our instrument refers to all household members, including those who are employed, but single, the unemployed, and also those who do not belong in the labour force, including students, retired, housemakers, sick and disabled.

The second instrument is a dummy indicating whether the household has won the lottery. This instrument has been employed in the earlier literature, including the study by Gardner and Oswald (2007) who used medium-sized lottery wins as instruments to income and they found a positive impact on mental health measured by the General Health Questionnaire (GHQ). Also, apart from the work on well-being and health, lottery wins have been also employed in the empirical labour economics, such as the determinants of labour supply and the decision to become self-employed (Lindh and Ohlsson 1996; Taylor 2001; Henley 2004). We argue that this instrument is valid, since winning the lottery is a random process given that people buy the same number of lottery tickets. The instrument used is a dummy variable taking value 1 if the household won the lottery and 0 otherwise. However, it is impossible to identify in our data the number of times each person had played in the lottery. Nevertheless, many respondents in the BHPS have a financial windfall of some kind. Gardner and Oswald (2007) used the amount of winnings between £1,000 and £120,000 as the treated group, and defined as the control group those with non-lottery winnings, sharing similar characteristics. However, we use the dummy variable indicating whether the household has won the lottery or not, given the fact that also the half of the population in the UK plays the national lottery. Moreover, taking the dummy variable of winning the lottery or not, allows us to keep a significant part of the individuals, and thus, a large part of the number of observations, which avoids the creation of a possible selection bias. In particular, keeping only the households that we have information about the amount won in the lottery we will significantly remove a great number of observations by dropping individuals that have won the lottery, but the exact amount unfortunately is not recorded in the survey.

The third instrument was used in the study by Powdthavee (2010) who explored the impact of income on happiness using the BHPS sample. The instrument illustrates the proportion of the respondents with payslip information. In particular, in each wave the interviewer asks the respondent to show the actual payslip, which is usually issued by the respondent's employer and it contains information about the gross income, taxes and other deductions, including insurance, retirement contributions and others. We assume that when the payslip is shown to the interviewer, the information about the income is likely to be more accurate (Powdthavee 2010). In our case, we argue that the proportion of the household members showing and not showing their payslip to the interviewers is directly correlated to the household income. This is due the fact that the household income is measured more accurately when the proportion of members in a household that have shown their payslips is high. On the other hand, we argue that there is no reason to expect that the health status is affected by whether or not the interviewer has seen the payslip. However, according to Clark (2003), the well-being of the respondent is affected by the unemployment and disability status of the remained household members even if the

household income is not affected. For this reason, we will control in our regressions whether the respondent is disabled, retired or unemployed.

The first method applied is a Pooled Ordered Probit model with instrumental variables. However, as we have discussed in the previous section, implementing this model we cannot control for unobserved heterogeneity. For this reason, we additionally apply the Two Stage Least Squares Fixed Effects (2SLS-FE) method. Furthermore, as we mentioned earlier, the findings derived in previous studies, suggest that the estimates between OLS and Ordered Probit models are very similar.

Data

The empirical work relies on micro-level data derived from the British Household Panel Survey (BHPS). BHPS is an annual survey of each adult member of a nationally representative sample of more than 5,000 households which started in 1991. Based on the data availability and in particular for the recycling rates, we examine the period 1999–2009. Furthermore, we could have employed the understanding society survey using also the BHPS sample included in this survey. While it would be feasible to implement the analysis using the fixed effects model, it is impossible for us to apply the 2SLS, as the instrumental variables used are unavailable.

Following earlier studies, we control for various individual and household characteristics, including age, household income, household size, marital status, education level, employment status, house tenure, and whether the respondent is smoker. Furthermore, we include dummies for local authority districts to control for unobservable characteristics at the area-residence level, such as recycling services provided by the local authority, economic activity and other characteristics that may affect both recycling rates and the health status. We measure the household income in thousands of pounds, which is converted to 2009 British pounds using the Consumer Price Index (CPI). We additionally control, for the day of the week, month of the year and the wave of the survey. The principal health outcome is the self-assessed health (SAH) defined by a response to the question "Please think back over the last 12 months about how your health has been; excellent/good/fair/poor/very poor?". The recycling rates are found in the UK National Statistics, and the meteorological conditions have been derived from the UK Met Office and the National Climatic Data Center (NCDC).

In panel A of Table 2, we report the summary statistics for the continuous, ordered and binary variables, while in panel B we present the categorical socio-economic characteristics. We observe that the average value of the main dependent variable of interest-health status-is 2.25. We should note that health status is an ordered variable measured on a scale from 1, implying excellent health status, to 5 indicating very poor health status. The average monthly household income is around 2,600, where the value of 0 refers to the last monthly income and for households that consist of one person and is unemployed. We should make clear that the gender takes value 1 for male and 0 for female, while the variable smoker takes the value 1 if the respondent is a smoker and 0 otherwise. In this case, the average value shows the proportion of males and smokers. In particular, the

Table 2 Granger causality test between health status and recycling rates using the Blundell–Bond system GMM

	DV: hesalth status	DV: recycling rates
Constant	2.9575***	2.811***
	(0.0259)	(0.0592)
Health status with one lag	− 0.2636***	0.0029
	(0.0039)	(0.0153)
Recycling rates with one lag	− 0.0102***	0.5917***
	(0.0015)	(0.0072)
Sargan test	16.25	18.36
	(0.701)	(0.862)
Wald chi square	11,570.92	51,311.17
	[0.000]	[0.000]
No. obs	68,627	66,050

Standard errors between brackets, *p* values between square brackets

***Denotes significance at 1% level

average value of gender is 0.46, which implies that almost the 46% of the sample is males and the remained 56 percent is females. Similarly, the average value for the smoker variable is 0.26, showing that the 26 percent of the sample is smokers and the remained 74% is non-smoker.

Regarding the education level, we observe that the majority of the sample has not completed any of the certificates reported in panel B. Almost the 7% has completed a teaching, HND or HNC certificate. The HNC stands for "Higher national certificate", which is a one year course and is equivalent to the first year of university. The HND stands for the Higher National Diploma that takes two years to complete and is equivalent to the first 2 years of university.

The majority of the sample is married, as it was expected, at 51.81% followed by the singles at 20.86%. Almost the 51% is employed either in private or public sector, while the 6.43% is self-employed. A large proportion of the sample is retired at 21.46%, which is expected given the fact that we include also old aged respondents, which can be seen also by the average and maximum age values in panel A. Finally, in panel B, we observe that almost the 72% of the sample owns the house outright or with mortgage. In Figs. 2, 3, 4, 5, we illustrate the proportions for the health status, education level, marital status and employment status.

In panel C, we report the summary statistics for the recycling rates, and the major meteorological conditions we control for. In Fig. 6, we illustrate the relationship between health status and recycling rates during the period of our analysis. Since, both variables are measured in different scales we have normalised them in such a way that both take value between 0 and 1. It becomes clear that there is a strong negative relationship indicating that increases in recycling rates are associated with improved levels in health status. However, the association illustrated in Fig. 6 does not consider the potential role of other socio-economic characteristics. Therefore, it is important to control for those factors in the regressions to account for confounding.
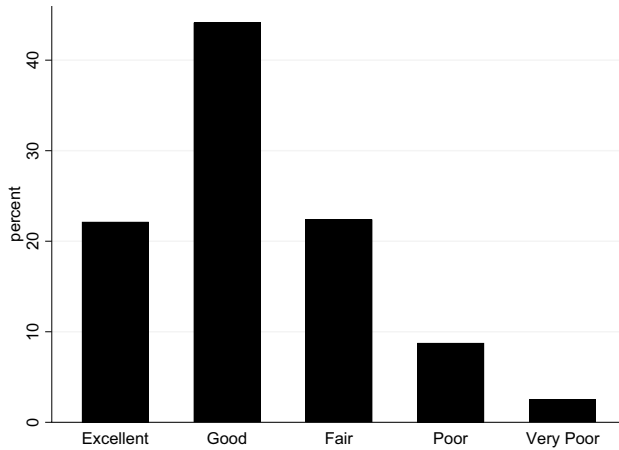
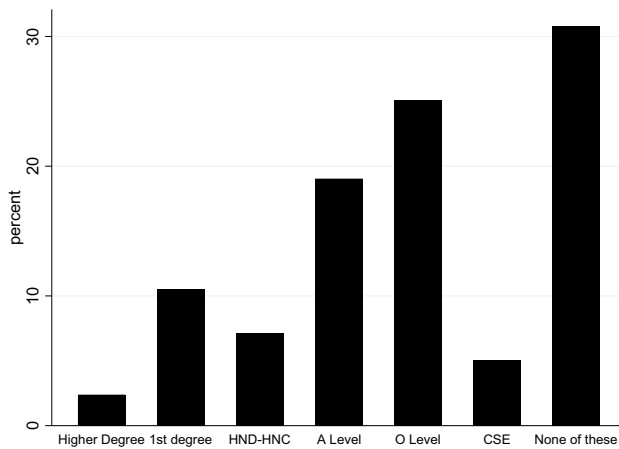**Fig. 2** Bar graph for health status

Fig. 3 Bar graph for educational attainment

Empirical results

In Table 3, we report the Probit-FE and the random effects ordered Probit estimates of regression (3). The results show a significant positive relationship between health status and recycling rates. In particular, the negative sign of the recycling rate shows an improvement in health status, as we have discussed in the previous sections. The relationship between recycling and health found relies on various reasons, such as less mining and energy is required to generate new materials and less air pollution levels are emitted from landfills, because the trash volume is reduced and is used for recycling. Based on the Probit-FE, we find that the average MWTP for a unit
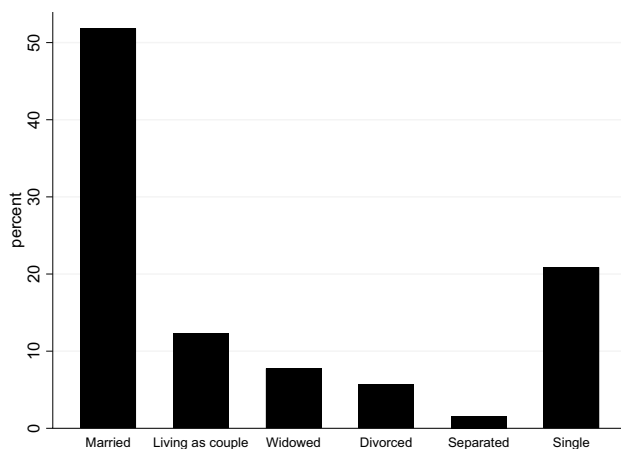
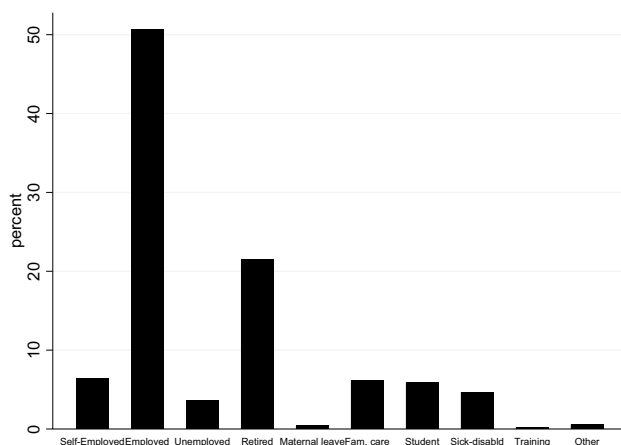**Fig. 4** Bar graph for marital status

Fig. 5 Bar graph for employment status

increase in recycling rates is £587 and £805 per year respectively for the total sample and non-movers, while the respective MWTP values found with the random effects ordered Probit are £557 and £777. Therefore, given these values and considering the costs and other expenditures, the prices of recycling can be adjusted to motivate the people to recycle more. As we have discussed in the methodology section, the MWTP values refer to household income and thus, the tax is implemented at the household level.

Regarding the meteorological conditions, we find a positive relationship between health status and the average temperature, while minimum and maximum temperatures have negative and significant impact on health, which is associated with the negative effects that extreme meteorological conditions may have. Old aged people
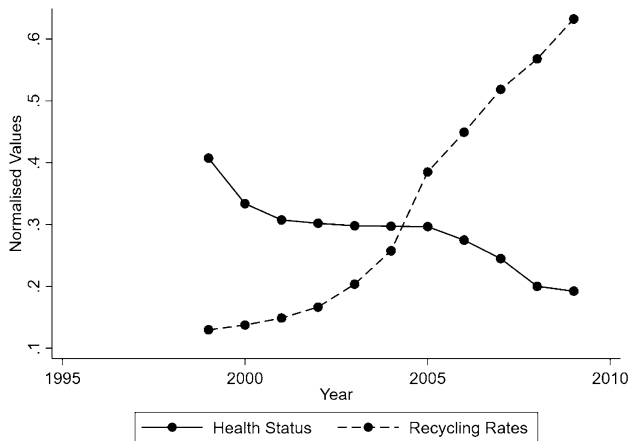
Fig. 6 Relationship between health status and recycling rates

and smokers are more likely to report lower levels of health status, while married couples, wealthier households and respondents who own a house report better health status. Household size is positively correlated with the health status confirmed by earlier literature, which provides evidence that family support and size can be protective and beneficial to people with a chronic illness and health problems (Aldwin and Greenberger 1987; Doornbos 2001; Ferrer et al. 2005; Grinde and Tambs 2016).

In addition, unemployed people report lower levels of health status compared to those who are employed. Even though we do not report the results for the remained categories of the employment and marital status, our results show that those who are unable to work due to disability or other health issues, and the unemployed present the lowest health status levels. Also, widowed are more likely to present lower health levels compared to singles, couples and divorced. Those who have completed a higher education or a university degree present a better health status. These findings are consistent with earlier studies (Benzeval et al. 2000; Prus 2001; Beckett and Elliott 2002; Mackenbach 2008; Kaikkonen 2009; De Looper and Lafortune 2009; Jovanovic and Jakovljevic 2011; Dorjdagva et al. 2015).

In Table 3, we report also the diagnostic tests and in particular, we test for heteroskedasticity and autocorrelation. In all cases, we accept the null hypothesis, concluding that there is no autocorrelation and heteroscedasticity in the residuals. This is expected as we estimate our regression with robust standard errors and more specifically, we cluster the standard errors on area-specific time trends. Furthermore, we report the Wald test for the Proportional Odds–Parallel Lines Assumption. This is one of the key assumptions of the ordered discrete choice models, where the effects of any explanatory variables are proportional or consistent across the different thresholds. In this case, the thresholds are the ordered answers to health status, ranging from excellent to very poor. Hence, the Wald test shows whether the explanatory variables have the same effect on the odds of the health status regardless of the threshold. According to the p values, we accept the null hypothesis, implying that our regression estimates do not violate the proportional parallel lines

Table 3 Probit Regressions

Variables	Ordered probit-FE		Ordered probit random effects	
	Total sample	Non-movers	Total sample	Non-movers
Recycling rate	− 0.0033***	− 0.0035***	− 0.0031***	− 0.0034***
	(0.0008)	(0.0009)	(0.0007)	(0.0008)
Household income	− 0.0234***	− 0.0184**	− 0.0222***	− 0.0176***
	(0.0065)	(0.0089)	(0.0044)	(0.0052)
Age	0.0242*	0.0231**	0.0264*	0.0249**
	(0.0125)	(0.0109)	(0.0139)	(0.0113)
Average temperature	− 0.0019*	− 0.0015**	− 0.0016**	− 0.0015**
	(0.0010)	(0.0007)	(0.0008)	(0.0007)
Minimum temperature	0.0014	0.0019*	0.0011	0.0016*
	(0.0062)	(0.0011)	(0.00068)	(0.0009)
Maximum temperature	0.0035**	0.0031**	0.0039**	0.0044**
	(0.0015)	(0.0014)	(0.0016)	(0.0019)
Precipitation	0.0012	0.0014	0.0013	0.0014
	(0.0017)	(0.0018)	(0.0017)	(0.0018)
Wind speed	0.0062*	0.0072	0.0093	0.0072
	(0.0032)	(0.0061)	(0.0076)	(0.0062)
Household size	− 0.0174**	− 0.0219**	− 0.0121***	− 0.0135***
	(0.0072)	(0.0104)	(0.0041)	(0.0044)
Smoker (no)	− 0.0547**	− 0.0530*	− 0.0533***	− 0.0515***
	(0.0249)	(0.0277)	(0.0117)	(0.0110)
Job status (unemployed)	0.0939**	0.1021**	0.0912**	0.0988**
	(0.0414)	(0.0425)	(0.0401)	(0.0436)
Marital status (married)	− 0.270*	− 0.352**	− 0.253*	− 0.383**
	(0.151)	(0.164)	(0.133)	(0.165)
House tenure (owned house)	− 0.387*	− 0.470*	− 0.241*	− 0.329**
	(0.205)	(0.276)	(0.123)	(0.151)
Education level (highest degree)	− 0.0213**	− 0.0228**	− 0.0225**	− 0.0237**
	(0.0106)	(0.0110)	(0.0108)	(0.0114)
R square	0.2351	0.2426		
Wald Chi-Square			1,157.31	1,149.91
			[0.000]	[0.000]
Breusch–Pagan heteroscedasticity Test	0.582	0.487	0.126	0.408
	[0.8335]	[0.9063]	[0.8992]	[0.5288]
Wooldridge autocorrelation test	0.233	0.904	0.633	.714
	[0.6294]	[0.3418]	[0.4272]	[0.3984]
Wald proportional odds–parallel lines assumption test			5.25	7.42
			[0.9489]	[0.8286]
No. observations	89,971	75,264	9,971	75,264
MWTP	£587	£805	£557	£777

Standard errors between brackets, p values between square brackets, ***, ** and *denote significance at 1%, 5% and 10% level, clustered standard errors on area-specific time trends

Null Hypothesis of the Breusch–Pagan Heteroskedasticity Test is H_o: Homoskedasticity

Null Hypothesis of the Wooldridge Autocorrelation Test is H_o: no autocorrelation

Null Hypothesis of the Wald Proportional Odds–Parallel Lines Assumption Test is H_o: Parallel Lines Assumption Holds

Table 4 Instrumental variables (IV) estimates

Variables	Pooled ordered probit		Ordered probit two-stage least squares fixed effects (2SLS-FE)	
	Total sample	Non-movers	Total sample	Non-movers
Recycling rate	− 0.0035***	− 0.0037***	− 0.0036***	− 0.0039**
	(0.0071)	(0.0076)	(0.0012)	(0.0018)
Household income	− 0.0579***	− 0.0512***	− 0.0582***	− 0.0516**
	(0.0082)	(0.0182)	(0.0187)	(0.0224)
Age	0.0241**	0.0201**	0.0260**	0.0219**
	(0.0118)	(0.0091)	(0.0124)	(0.0103)
Average temperature	− 0.0025*	− 0.0022**	− − 0.0027**	-0.0023**
	(0.0013)	(0.0011)	(0.0012)	(0.0011)
Minimum temperature	0.0029	0.0021*	0.0025	0.0023*
	(0.0019)	(0.0011)	(0.0014)	(0.0012)
Maximum temperature	0.0023*	0.0031*	0.0028*	0.0033**
	(0.0013)	(0.0016)	(0.0015)	(0.0016)
Precipitation	− 0.0046	− 0.0017	− 0.0035	− 0.0019
	(0.0032)	(0.0028)	(0.0023)	(0.0024)
Wind Speed	0.0059*	0.0066	0.0064*	0.0068
	(0.0032)	(0.0047)	(0.0033)	(0.0052)
Household Size	− 0.0103**	− 0.0222***	− 0.0091*	− 0.0228**
	(0.0047)	(0.0082)	(0.0046)	(0.0105)
Smoker (No)	− 0.0424*	− 0.0512**	− 0.0480*	− 0.0539*
	(0.0223)	(0.0241)	(0.0231)	(0.0281)
Job status (Unemployed)	0.0846**	0.1148**	0.0874**	0.1153**
	(0.0352)	(0.0565)	(0.0370)	(0.0561)
Marital status (Married)	− 0.268**	− 0.337*	− 0.276**	− 0.349**
	(0.0127)	(0.182)	(0.0126)	(0.163)
House tenure (owned house)	− 0.304**	− 0.424*	− 0.316**	− 0.432*
	(0.151)	(0.228)	(0.152)	(0.248)
Education level (Highest degree)	− 0.0229**	− 0.0244**	− 0.0238**	− 0.0260**
	(0.0943)	(0.0115)	(0.0114)	(0.0121)
Wald Chi-square	7,764.63	7,006.79		
	[0.000]	[0.000]		
Centered R square			0.1183	0.1415
Durbin–Wu–Hausman test	1.013	1.214		
	[0.8633]	[0.6505]		
Sargan statistic exogeneity test			3.887	4.388
			[0.9523]	[0.9281]
Weak instrument test	25.246	21.471	16.815	12.050
	[0.000]	[0.000]	[0.0003]	[0.0029]
No. observations	4,032	69,065	84,032	69,065
MWTP	£288	£324	£296	£341

Standard errors between brackets, p values between square brackets, ***, ** and *denote significance at 1%, 5% and 10% level, clustered standard errors on area-specific time trends

assumption. We should notice that we report this test only for the Ordered Probit regression, while it is infeasible to implement this in the case of the Ordered Probit Fixed Effects, since our dependent variable is converted to a continuous one, as we have described in the methodology section.

Next in Table 4, we report the 2SLS estimates where we use the following three variables as instruments for the household income: lottery wins; the council tax band and whether the payslip is seen by the interviewer. The MWTP values now become lower, compared with those found in Table 3, as the denominator of relation (4) becomes higher due to the higher effects of income on health status, while the nominator remains the same. In this case, the MWTP in Table 4 for the total sample becomes £288 and £296 derived respectively from the Ordered Probit with Instrumental Variables and the 2SLS, while it was £587 and £557 based on the Probit FE and the random effects ordered Probit, respectively. Regarding the non-movers sample, the MWTP value is equal at £324 using the Ordered Probit model and £341 with 2SLS, while the MWTP derived by the Probit FE and the random effects ordered Probit were found equal at £805 and £777, respectively.

The specification tests confirm the suitability of the instrumental variable methods used and their robustness. More specifically, based on the exogeneity Sargan test and its p value the null hypothesis of no endogeneity is not rejected in the 2SLS regressions. In addition, based on the p value of the weak instrument test, the null hypothesis of weak instrument is rejected in both 2SLS and the Pooled Ordered Probit regressions. In the case of the last method, we implement the Durbin–Wu–Hausman test and we accept again the null hypothesis, concluding that the instruments employed are exogenous to the health status.

Conclusion

This study proposed a quantification of the relationship among the self-reported health status, recycling rates and household income to estimate the MWTP. Based on our favoured instrumental variables estimates, the MWTP values range between £324 and £340 per year. This study reveals several important points. First, the results showed that recycling has direct effects on individuals' health, in addition through other measured effects, such as the marital status, education and employment status. Second, there is evidence of a substantial compensating differential for recycling. Third, the effect of income on health is significantly underestimated using the fixed effects OLS, which consequently overestimate the MWTP values. Fourth, the estimation of MWTP can be used for policy implementation. This study seeks to assess how the use of environmental quality could advance the empirical literature that investigates the associations between recycling and health, considering various socio-economic factors and meteorological conditions. The analysis was based on a high level of geographical aggregation, making possible to identify, examine and strengthen existing arguments in favour of policies that increase recycling, which can indirectly improve the air quality among other potential benefits.

Overall, systematic campaigns providing detailed information and letting know the public what happens to the materials once they have been collected should be

implemented. Furthermore, these campaigns should advertise and promote the potential benefits of recycling which will help to reinforce individual's interest for the public good and to encourage an active participation. Recycling can act as the platform through which people can be educated and informed about their environment and good citizenship. Apart from the campaigns, public local and national authorities and councils should promote and implement waste minimisation schemes, including household amenity sites, home composting, local bring banks opportunities to reduce waste and reuse items wherever possible. This may include among others local refillable, prevention of food waste, promotion of material reuse and low packaging shops.

The study is not without limitations and drawbacks. The most important issue is that our dependent variable is the self-reported health status. Hence, instead of employing self-reported outcomes, "objective" indicators should be used, including respiratory and cardiovascular diseases, as asthma, heart and breathing problems among others. A second drawback is that the analysis was limited only to recycling rates, because of the data unavailability about costs and prices of recycling. Nevertheless, we should notice that the costs of collection and household waste recycling is included in the council taxes. Furthermore, our results report only the average MWTP. Future empirical studies should consider the role of socio-economic and demographic characteristics. In particular, the estimates could take place by gender, age groups, education groups and employment status. In this case, the average MWTP may differ by age and employment status, and hence, policies could be implemented according to the financial situation and needs of the household.

Another major limitation of the study is that the analysis is focused on the UK, which as a developed economy has established a more efficient supply of recycling services compared to those implemented in developing and underdeveloped countries. Therefore, the analysis does not recognise the potential role of inequalities and poverty that could influence the waste generation and recycling behaviour. Earlier studies suggest that low income and poorer households make use of coal and other sources of energy for cooking and heating purpose that damage the environment, because they cannot afford to use other more efficient types of energy sources. Furthermore, they may contribute more to waste generation, because of the unavailability of proper recycling services by the local authorities, especially for those living in more deprived areas (Khan et al. 2016; Vieira et al. 2018). Hence, it is important to incorporate those additional factors in future studies to estimate the MWTP by socio-economic groups, area characteristics and also to consider the role of public national and local authorities on the implementation of recycling policies and supply of relevant services especially in the developing countries.

Moreover, Probit or Logit latent class models are proposed in future applications, to model for slope heterogeneity. In particular, latent class models would provide estimates for each class-category of the health status and we can estimate the MWTP in each class (see Clark et al. 2005 for more details). We further suggest that future studies should explore additional factors and recycling related services, including the collection frequency, the role of incinerators-combustion, expenditures, and

curbside and drop off services for trash and recycling among others. While in this study we have considered the total recycling rates, future research applications may consider the role of recycling on each material separately and to disentangle their effect, such as recycling for steel, plastic, paper, aluminium and glass. Furthermore, a higher disaggregated geographical data level or a higher spatial frequency should be considered in future studies, such as ward or post codes, for more precise estimates. In particular, using the exact location of the respondent's residence and the nearest landfill we will be able to identify in a much higher precision, not only the recycling effect, but also the pollution emitted from the waste dumps, given the area characteristics, such as population, waste generation and other recycling services. This will further improve the estimates of the MWTP values and thus, will provide more accurate information and insights about the development and implementation of policies, including recycling services and environmental taxes.

Availability of data and material The data are confidential and cannot be distributed. These can be requested from the UK Data Archive for research purposes at no cost.

Code availability The STATA files are available upon request from the corresponding author.

Compliance with ethical standards

Conflict of interest The authors declare that have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by the authors.

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