Relationship between health status and recycling rates: Evidence from Great Britain

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This study explores the relationship between self-reported health status and recycling rates in Great Britain. The estimates are based on the data from the British Household Panel Survey (BHPS). The effects of recycling rates on individuals' health status with a scale from 1-excellent- to 5-very poor- are estimated and their monetary values are calculated. In addition, the non-movers sample is considered in order to reduce endogeneity. Three approaches are followed. The first approach refers to the panel Probit-OLS, while the second approach is the ordered Probit model with random effects. The third approach refers to a dynamic panel regression estimated with the system Generalized Methods of Moments (GMM). The average marginal willingness-to-pay (MWTP) for a one per cent increase in recycling rates ranges between is £470-£800 per year. Moreover, other determinants play significant role on health status such as education, marital status, age, job status, age and weather conditions among others. The originality of this paper is that the relationship between self-reported health status and recycling rates using micro-level panel data is explored. Moreover, the reression analysis controls for various demographic, regional and meteorological factors. Finally, this is the first study presenting three different panel estimates to deal with the potential endogeneity of the pollution measure which is derived from recycling. Using fixed effects the regional time invariant characteristics are controlled, while the dynamic model allows controlling for time varying unobservables.

Key words: Environmental valuation; Panel data; Recycling; Self-reported health status

JEL Classification: I31, Q51, Q53, Q54

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1. Introduction

Recycling has traditionally occurred because it has been economically viable. From the 1970s onwards, however, the perception in modern rich societies has been that we should recycle even more, something that is expressed by existing or proposed solid waste legislation. Solid wastes facilities and landfill fires emit air pollutants, when waste is not recycled. Recycling can potentially cut down these emissions. Additionally, based on Institute of Scrap Recycling Industries (http://www.isri.org) recycled ferrous metals instead of virgin ore to make new steel leads to a reduction in air pollution by 86 per cent, while save energy up to 74 per cent. Also recycling aluminium creates up to 97 per cent less water pollution than using metal from ore in order to make a new one (Gerbrandt, 2002; Can manufacturers Institute, 2006). Solid wastes facilities and landfill fires emit air pollutants, when waste is not recycled, including Carbon Monoxide (CO), Carbon Dioxide (CO_2) Hydrocarbons (HC), Particulate Matter (PM), Nitrogen Oxides (NO_x) and Sulfur Dioxide (SO_2). Recycling can potentially cut down these emissions. Most of the UK's waste is currently buried in landfill sites, which release climate change gases and pollute the soil and water. Additionally, the process of recycling and composting, from kerbside collection to the sorting and reprocessing of recyclables, creates more jobs than incineration and landfill (Renner 1991; Gray et al., 2004). On the other hand there is an energy cost for recycling many materials, and some degree of pollution is created by the heat generated to melt for example glass or metal. Therefore, is important to examine the effects of recycling rate on health status.

This paper proposes an econometric model to understand and describe how the recycling rate is associated to self-reported health status. Unfortunately, because of the recycling prices data unavailability, only the recycling rates are included in the analysis. It should be noticed that council taxes in Great Britain cover the cost of the collection, recycling and disposing household waste. Therefore, future research suggests the inclusion of prices and costs.

To value public goods, two popular methods exist: revealed preference and stated preference. The first method relies on hedonic price analysis or the travel cost approach while the stated preference approach, based on contingent valuation surveys, directly elucidate the environmental value from question. Both methods have been widely used in practice (Carson et al. 2003). However there are some weaknesses. Revealed preference approaches are based on stringent assumptions concerning the rationality of agents and the functioning of markets. More specifically, the results yielded following this approach can be biased, if the housing markets are not in equilibrium, maybe because individuals are not fully informed. Moreover, using the hedonic method the results can be underestimations of the clean air benefits (Bayer et al. 2006). More specifically, decisions in markets for private goods may not accurately reveal people's hedonic experience from the consumption of public goods (Rabin, 1998).

In the stated preference approach, hypothetical scenarios are used, which may entail unreliable results and strategic behaviour. In particular, the hypothetical nature of the surveys allow for strategic behaviour and superficial answers (Kahneman et al., 1999). Overall, the problem of both approaches is that they only value the public goods of which individuals are aware of.

Instead this paper relies on a similar approach to the life satisfaction evaluation (LSE). This approach offers several advantages over other valuation techniques. For example, the approach does not rely on housing markets being in equilibrium- an assumption underpinning the hedonic property pricing method- nor does it ask individuals to directly value the public good or bad in question, as is the case in contingent valuation. However, this approach also has some drawbacks, including that it is simplistic, is determined by expectations and there are response biases, like cultural. Another drawback of this method is the sorting problem, where it is possible that people choose where they reside. This would bias the air pollution variable's coefficient- and therefore the monetary value- downwards as those least resilient to air pollution would choose to reside in areas with cleaner air. Nevertheless, both non-movers and movers sample are examined in order to reduce endogeneity. Therefore, the population of interest in estimates, including robustness checks, is limited to non-movers, similarly to the study by Luechinger (2009), who excludes the individuals moving across county boundaries, thus county specific effects are absorbed by the individual specific fixed effects. Another limitation of the approach followed in this study is the functional form of income and its consequences in monetary valuation. However, also quadratic terms on income are explored too.

The contribution of this paper is the examination of the relationship between self-reported health status and recycling rates using micro-level panel data controlling for various factors, as demographic, regional and meteorological. In addition, the population interest is limited to non-movers sample in order to reduce the endogeneity as it is discussed in more details in the methodology part. This is the first study presenting three different panel estimates to deal with the potential endogeneity of the pollution measure. Initially, an individual level fixed effect model is applied and we then estimate a dynamic panel model. There are several key advantages of using these estimators. Firstly it is possible to control for the local authority district-specific, time invariant characteristics. The dynamic models allow controlling for time varying unobservables. The results show that the average marginal willingness to pay ranges between £470-£800 per year.

The paper is organized as follows. Section 2 presents a short literature review. Sections 3 and 4 describe respectively the theoretical and econometric framework. In section 5 the data and the research sample design are provided. In section 6 the effects of recycling on health status and their monetary values are presented and discussed. In section 7 the concluding remarks are presented.

2. Literature review

One of the first applications on MWTP of air pollution and health is by Gerking and Stanley (1986). The authors used the St. Louis survey, which was conducted over the period 1977-1980 and the individuals whose major activity was recorded as employed were used in this study. The findings show that a 30% reduction in ambient mean ozone concentrations, the annual willingness to pay estimates range from \$18.45 to \$24.48. Chay and Greenstone (2003a) examined the air quality improvements induced by the Clean Air Act Amendments (CAAAs) of 1970 to estimate the impact of particulates pollution on infant mortality during period 1971-1972. The federal air pollution regulations are associated with sharp reductions in both total suspended particulates (TSPs) pollution and infant mortality rates in the first year that the 1970 CAAAs were in force. The authors find that one per cent decline in TSP results in 0.5 per cent decline in the infant mortality rate. Chay and Greenstone (2003b) used substantial differences in air pollution reductions across sites to estimate the impact of TSPs on infant mortality. The authors establish that most of the 1980-82 declining in TSPs was attributable to the differential impacts of the 1981-82 recession across counties. The authors find that a one percent reduction in TSPs results in a 0.35 percent decline in the infant mortality rate at the county level.

The Self-Assessed Health (SAH) has been used widely in previous studies of the relationship between health and socioeconomic status using British data (Benzeval et al., 2000; Frijters et al., 2003; Contoyannis et al., 2004) and of the relationship between health and lifestyles (Kenkel, 1995; Contoyannis and Jones, 2004). The results are various. For example regarding educational attainment a movement from unhealthy to a completely healthy lifestyle the proportions of individuals with higher levels of education gradually increases, while those that are unemployed are more likely to report a poor health status. Wardle and Steptoe (2003) using data from the Health and Behaviours in Teenagers Study (HABITS), which is a school-based study set in 36 schools in London, education, health consciousness, health locus of control, future salience, expectations of longevity and stress are important factors of health behaviour.

Wardle and Steptoe (2003) found that low Socioeconomic Status (SES) participants were less likely than high SES participants to think about the future and more likely to believe that good health was the result of luck rather than the result of personality responsibility as taking care of their diet, the health status and exercise among others. Following the previous literature the regression analysis considers various SES determinants, such as education, marital status and job status among others.

On the other hand many studies examined the waste management expenditures, considering various factors, as collection frequency, recycling rates, the form of service delivery -public or private- among others, finding mixed results. More specifically, Hirsch (1965) found no significant differences in service costs between municipal and private delivery. More interestingly, neither did he find any economies of scale with respect to output in the service. The model proposed by Hirsch (1965) was followed, with slight variations, by Kitchen (1976) in Canada, Kemper and Quigley (1976) and Collins and Downes (1977) in the USA. These studies, with the exception for the study by Collins and Downes (1977), argue that private delivery has significantly lower costs. Callan and Thomas (2001) using a sample of 110 municipalities in Massachusetts of USA , estimated a two-equation model, one for disposal and one for recycling, in which the explained variable was the service cost while the explanatory variables were the amount of waste generated, the population density, the frequency of collection, the form of service delivery-public or contracting out. However, all these studies examine the waste management expenditure, while this paper studies the relationship between recycling rates and health status.

Shen and Saijo (2007) examined the individual environmental concerns about recycling and environmental quality in Shanghai based on a field survey conducted in November 2006. They found that high income and high education classes are significantly more concerned about recycling. Therefore, higher level of environmental quality and recycling could be associated with higher levels of self-reported well-being. Also young people are more concerned with waste and recycling issues and they are willing to sacrifice more life convenience for additional environmental quality including waste management and recycling issues.

Thus, following the previous literature this study tries to combine and explore the effects of recycling on health status considering various SES characteristics and calculating the MWTP.

3. Methodology Framework

3.1 Theoretical Model

In this section a simple theoretical model is presented. Assuming that some individuals may wish to limit the amount of waste generated and sent to a landfills or incinerators the health function is:

$$HS[Z(X), G(S, X), l, M] \tag{1}$$

HS is the health status, *Z* indicates the commodity produced using inputs *X, G* is the amount of garbage for disposal, which is a function of inputs *X, inputs M* expressing medical care and time spent for separating the recyclables, S. In addition, S is a function of labour spent recycling some portion of the waste generated by inputs X and l is the amount of leisure consumed. The marginal utilities are assumed to be U_Z , U_l, $U_M > 0$ and $U_G \leq 0$. Thus, health is increased with leisure and with consumption of products Z including food and others. Also. It is assumed that health is increased with medical care inputs, such as medicine and visits to doctors. The last term U_G is an inequality because garbage generation will impact the utility of some people negatively while it will not affect others. Next the use of inputs X generates trash T and it is a function, $T(X)$, where $T_X > 0$. Trash may be separated into garbage disposal or recycling and the production of recyclables R is a function of the total time spent separating recyclables S and the amount of inputs X available for recycling:

$$R = R(S, X) \tag{2}$$

The amount of garbage is total trash less the recyclables and it is defined as:

$$G(S, X) = T(X) - R(S, X) \tag{3}$$

We assume that the budget constraint is constituted by household's full income consisted of wage and non-wage income and it is:

$$wH + I = P_X X + P_M M + fG(S, X) \tag{4}$$

, where w is the wage, I is the non-wage income, H indicates the total hours worked, p is the price for X and f is the unit cost of garbage disposal. The household's time constraint is:

$$A = H + l + S \tag{5}$$

, where A is the total time available. Substituting (2) and (3) into utility function (1) and the budget constraint (4) the model is formulated in such a way that the variables of interest are S, X and l. The optimization problem becomes:

$$L = HS[Z(X), G(S,X), l, M] + \lambda_1 (wH + I - P_X X + P_M M - f[\mathrm{T}(\mathrm{X}) - \mathrm{P}(S,X)] + \\ \lambda_2 (D - H - l - S) \tag{6}$$

The first order conditions are:

$$\frac{\partial L}{\partial X} = U_Z Z_X + U_G (T_X - R_X) - \lambda_1 [(p + f(T_X - R_X)] \leq 0 \tag{7}$$

$$\frac{\partial L}{\partial S} = -U_G R_S - \lambda_1 f R_S) \leq 0 \tag{8}$$

$$\frac{\partial L}{\partial l} = U_l - \lambda_2 \leq 0 \tag{9}$$

$$\frac{\partial L}{\partial M} = U_M - \lambda_1 \leq 0 \tag{10}$$

, where λ_1 and λ_2 denote the shadow values of income and time respectively. Furthermore, Kuhn-Tucker conditions are required because some consumers do not recycle. Equation (7) shows the optimum input level of X which is affected by the utility of the input and the potential disutility of the garbage produced, in the case that $U_G < 0$. Equation (8) shows the optimum choice for S which is the time spent in recyclables preparation for inputs X. Finally, equation (9) shows the optimum choice for leisure. More specifically, at an interior solution the marginal utility of leisure is equated with the shadow value of time. Similarly, equation (9) expresses the optimum choice for medical care and its marginal utility is equated with the shadow value of income.

3.2 Granger Causality

In this section also the Granger causality methodology test is presented. The main interest here is to examine if an inverse causality between health status and recycling rates is present, which might cause endogeneity bias. A time-stationary VAR model adapted to a panel context as in Holtz-Eakin et al. (1988) of the following form is estimated:

$$HS_{ijt} = \alpha + \sum_{\kappa=1}^{p} \beta_{jk} rec\_rate_{jt-k} + \sum_{\kappa=1}^{p} \gamma_{ijk} HS_{ijt-k} + \mu_i + l_j + \theta_t + v_{ijt} \tag{11}$$

Relation (11) examines if recycling rates cause health status. It is common in Granger-causality studies to test whether causation runs in both directions. So although the main focus of this paper is on testing whether recycling rates cause health status and if so, with which sign, also the following equation is estimated:

$$rec\_rate_{jt} = \alpha + \sum_{\kappa=1}^{p} \beta_{jk} rec\_rate_{jt-k} + \sum_{\kappa=1}^{p} \gamma_{ijk} HS_{ijt-k} + \mu_i + l_j + \theta_t + u_{ijt} \tag{12}$$

Based on relation (12) the causality from health status to recycling rates is explored. Based on Akaike (AIC) and Schwarz (SC) information criteria, as well as, based on the statistical significance of the coefficients, the optimum lag length for (11)-(12) chosen is 1. Equations (11)-(12) are estimated using system GMM proposed by Blundell and Bond (1998). From table 1 it becomes clear that recycling rates with one lag is statistically significant and cause happiness. On the other hand, health status does not cause recycling. Moreover, the Sargan test accepts the over-identifying restrictions in the GMM estimations. In table 1 the Granger causality test results are reported.

4. Econometric Framework

4.1 Static Panel Regressions

Self-assessed health status can serve as an empirically valid and adequate approximation of individual welfare, in a way to evaluate directly the public goods. Additionally, by measuring the marginal utility of public good or recycling rates in that case, the trade-off ratio between income and the recycling rates can be calculated. The following model of health status for individual *i*, in area *j* at time *t* is estimated:

$$HS_{i,j,t} = \beta_0 + \beta_1 rec_{j,t} + \beta_2 \log(y_{i,t}) + \beta' z_{i,j,t} + \gamma W_{j,t} + \mu_i + l_j + \theta_t + l_j T + \varepsilon_{i,j,t} \tag{13}$$

$HS_{i,j,t}$ is the health status, subscript i denotes the individual, $rec_{j,t}$ is the recycling rate expressed in linear term[4] in location j and in time t, $log(y_{i,t})$ denotes the logarithm of household income and z is a vector of household and demographic factors, discussed in the next section. W is a vector of meteorological variables- average, minimum and maximum temperature, wind speed and precipitation. High temperatures can lead to health deterioration, as are positively correlated to air pollution released from landfills and during the recycling process, while wind speed is negatively associated (Statheropoulos, et al., 1998; Lecoeur et al., 2012). However, because of the data unavailability wind direction is not considered. Set μ_i denotes the individual-fixed effects, l_j is a location (local authority) fixed effects; θ_t is a time-specific vector of indicators for the day and month the interview took place and the survey wave, while l_jT is

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

a set of area-specific time trends. Finally, $\varepsilon_{i,j,t}$ expresses the error term which we assume to be *iid*. Standard errors are clustered at the local authority level.

For a marginal change of recycling rate, the marginal willingness-to-pay (MWTP) can be derived from differentiating (13) and setting dHS=0. However, if recycling has a quadratic functional form, more care must be taken. The marginal willingness to pay is the recycling rate change needed to equalise utilities. Generally, the MWTP can be defined as:

$$MWTP = \frac{\partial f / \partial rec}{\partial f / \partial inc} \tag{14}$$

, where *rec* and *inc* denote recycling rates and income respectively. In its current form the model cannot be estimated by ordered probit or logit using fixed effects. Therefore there are two options, either by estimating the model considering the dependent variable as continuous or converting the dependent ordinal variable in continuous variable assigning z-scores. This procedure was introduced by van Praag and Ferrer-i-Carbonell (2004). To compute probit OLS, the categorical dependent variable is rescaled by deriving *Z*-values of the standard normal distribution that correspond to cumulative frequencies of the original categories. More specifically the probit OLS uses a transformation such that the new dependent variable takes the conditional mean-given the original ordinal rating- of a standardised normally-distributed continuous variable, calculated based on the frequencies of the ordinal ratings in the sample (see Cornelissen, 2006, for an example). The advantages of this are that it is quicker to compute, as well as, there is the possibility of applying panel data methods, such as individual fixed effects. Although health status scores are collected on an ordinal scale, assuming cardinality of satisfaction scores makes little difference to the results of regression analysis. Nevertheless, this study uses the Probit –OLS to compare the results derived from OLS; however the results are not presented as are the same. Van Praag and Ferrer-i-Carbonell (2004; 2006) show both heuristically and in several applications that Probit OLS is virtually identical to the traditional ordered probit analysis. Generally, both OLS and Probit-OLS have been compared with the ordered models and no differences have been found among them (Van Praag and Ferrer-i-Carbonell, 2006; Van Praag, 2007; Luechinger, 2009, 2010; Stevenson and Wolfers, 2008; Wunder and Schwarze, 2010). However, in this study both ordered Probit and OLS-Probit estimates are reported. It should be noticed that in the first case ordered Probit with panel data allows only for random effects. The calculation of the dependent ordinal variable can be stated as:

$$HS_{i,j,t} = E(Z \mid \mu_1 < Z < \mu_2) = [\phi(\mu_1) - \phi(\mu_2)]/[\Phi(\mu_2) - \Phi(\mu_1)] \tag{15}$$

, where Z is a standard normal random variable, φ is the standard normal probability density function, and Φ is the standard normal cumulative density function (see Van Praag and Ferrer-i-Carbonell , 2004 for more details).

Having panel data allows us to identify the model from changes in the pollution level, coming from landfills or air pollution reduction as result of recycling process, within individuals rather than between individuals. This reduces 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 are eliminated in a fixed effect model. Thus the model is identified from changes in the pollution level within individuals i.e. between interviews rather than between individuals. To limit endogeneity issue the population of interest is split to non-movers and movers. Focussing on non-movers also allow us to capture unobservable characteristics of the neighbourhood that may be correlated with recycling and health status that are fixed over time.

4.2 Dynamic panel regressions

The second model which can be considered is fixed effects with lagged dependent variable and can be defined as:

$$HS_{i,j,t} = \beta_0 + \beta_1 HS_{i,j,t-1} + \beta_2 rec\_rate_{j,t} + \beta_3 \log(y_{i,t}) + \beta' z_{i,j,t} + \gamma W_{j,t} + \mu_i + l_j + \theta_t + l_j T + \varepsilon_{i,j,t} \quad (16)$$

The dynamic models are useful because the lagged dependent variable control for a dependent variable that follows an autoregressive-AR(1) process. Furthermore, the parameter of the lagged dependent variable shows how an individual changes his or her adaptation level to living conditions represented by the stimulus level in the preceding period. However, the issue with equation (16) is that econometric problems may arise. In particular, causality may run in both directions, from income to health status and vice versa – these regressors may be correlated with the error term. Furthermore, time-invariant fixed effects personal, demographic and geographical characteristics, like local authority districts, may be correlated with the explanatory variables. Moreover, the lagged dependent variable $HS_{,j,t-1}$ gives rise to autocorrelation (Nickell, 1981). On the other hand, inserting a lagged dependent variable might be a dangerous strategy for ridding the residuals of autocorrelation because coefficient estimates can be biased (Achen, 2000). Function (16) presents the mentioned problems when *T*, denoting time, is short. More specifically, the Arellano – Bond estimator was designed for small-*T* and large-*N* panels, where *N* denotes the region or individual effects. Therefore this study examines the Blundell- Bond (1998) system GMM estimator.

5 Data

We use the British Household Panel Survey (BHPS) 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 for the recycling rates, the period examined in the current study covers the years 1999-2009. Based on the literature (Giovanis, 2014) the demographic and household variables of interest are household income, gender, age, family size or household size, labour force status, house tenure, marital status, education level, local authority districts, whether the respondent is smoker or not. In addition, the income is measured in thousands of pounds and has been converted to 2009 British pounds using the CPI. Additionally, the regressions control for the day of the week, month of the year and the wave of the survey, and an area-specific trend. The principal health outcome is 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 come from the UK National Statistics, while the weather data have been derived from Met Office and the National Climatic Data Center (NCDC).

In table 1 the summary statistics for recycling rate and income are reported. In table 2 the correlation matrix for income, recycling rates, SO_2, wind speed and temperature is presented. The purpose of this table is to show that there might be a significant relationship between recycling rates, air pollution and weather data. SO_2 has been chosen randomly, as other air pollutants could have been chosen as well, which are emitted from the trash and landfills. The correlation between SO_2 and wind speed is negative. On the other hand, as it was expected, the relationship between SO_2 and temperature is positive (Barmpadimos et al., 2012; Lecoeur et al., 2012). Similarly, the relationship between recycling rates and temperature is negative, while the association of recycling rates and wind speed is positive. This can be explained by the indirect effects of weather data on recycling rates. On the one hand the maximum temperature increases the effects of air emissions, while on the other hand wind speed cleans the air reducing this way the air pollution. The relationship between recycling rates and SO_2 is negative and significant; indicating that recycling might lead to air pollution reduction.

6 Empirical Results

In table 4 the Probit-OLS and random effects ordered Probit regression results of (13) are reported[5]. It is clear that there is a significant positive relationship between recycling rates and health status for the total and non-movers samples. More specifically, the coefficients of recycling rate is negative leading to improvement of health status, as the health status is ranked from 1-excellent health status- to 5 indicating very poor status. Therefore, recycling has a positive impact on health status. To mention some reasons, less mining and energy is needed for generating new materials and less air pollution levels are emitted from landfills because the trash volume is reduced and used for recycling. Based on Probit-OLS estimates the average marginal willingness-to-pay (MWTP) for a unit increase in recycling rates is £587 and £805 per year respectively for the total sample and non-movers, while the respective MWTP values for ordered Probit is £557 and £777 per year respectively for the total sample and non-movers. The results for movers sample are insignificant. Therefore given these values and considering the costs and other expenditures, the prices of recycling can be adjusted in order to motivate the people to recycle more.

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[5] Based on Hausman test fixed effects are preferred.

Regarding the rest of the coefficients and specifically the meteorological data the average temperature is significant and has a positive impact on health status for total and non-movers sample. However, in ordered Probit regressions, average temperature has positive and significant effects on health status for movers sample too. In addition, both minimum and maximum temperatures have negative and significant impact on health, as it is derived by the negative effects of extreme weather conditions.

Age and smoking have a negative effect on health status, while income, married couples and the respondents who own a house present a better health status. Regarding household size its impact on individuals' health status is positive. The literature 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). In addition, the respondents who are unemployed and own the highest degree are more likely to present a worse and better health status respectively; however, the coefficients are insignificant. These findings are consistent with other studies (Benzeval et al., 2000; Prus, 2001; Beckett and Elliott, 2002). Similar conclusions are derived from the system GMM results reported in table 5.

Generally, letting the public know about what happens to the materials once after they have been collected also helps to reinforce individual's interest for the public good and encourages participation. Recycling can be the platform from which many people can be educated about their environment and good citizenship. Councils should also promote and support waste minimisation schemes. These include the use of home composting, local bring banks and household amenity sites as well as opportunities to reduce waste and reuse items where possible. For example, this could include preventing food waste and promoting furniture reuse schemes, nappy washing services, local refillable schemes and low packaging shops and markets. Finally, estimating the MWTP the councils could adjust the prices in way that the expenditures are covered, the recycling is increased and air quality is improved.

7 Conclusions

This study proposed a quantification of the relationship between self-reported status and recycling rate in Great Britain. The results showed that the MWTP values, range between £474-£800 per year. The importance of this study comes from the fact that the analysis relies on detailed micro-level data, using relatively highly spatially disaggregated data based on local authority district. This study reveals important points. Firstly, the results showed that recycling has direct effects on individuals' well-being and welfare, in addition through other measured effects, such as the health status, productivity and lost work days among others. Secondly, there is evidence of a substantial compensating differential for recycling. This study seek to assess how the use of environmental quality could advance the empirical literature examining connections between and recycling, weather and other socioeconomic factors and health. Using the detailed geographical level in this study it becomes possible to examine, strengthen and extend existing arguments in favour of policies to increase recycling, reducing indirectly the air pollution.

This study suggests that costs and prices of recycling rate should be examined. Moreover, latent class models, Probit or Logit, are proposed in order to model for slope heterogeneity and calculate the MWTP in each class (see Clark et al., 2005 for more details). Furthermore, future research suggests that additional factors should be examined, as the curbside and drop off services for trash and recycling, the collection frequency, incinerators-combustion, and expenditures among others. In addition, the recycling rates for spate materials, as paper, aluminium and steel among others, could be examined. Finally, disaggregated data of higher spatial frequency, such as ward, neighbourhood or post code level, for more precise estimates, should be applied in the future.

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Table 1. Granger causality test between health status and recycling rates using Blundell-Bond system GMM

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

Standard errors between brackets, p-values between square brackets,
*** denotes significance at 1% level

Table 2. Summary statistics

	Mean	Standard deviation	Minimum	Maximum
Income	3,216.014	2,348.668	0	86,703.29
Recycling rates	36.847	9.567	10.07	90

Table 3. Correlation matrix

	Income	SO_2	Recycling rates	Wind speed
SO_2	-0.0482 (0.000)***			
Recycling rates	0.2514 (0.000)***	-0.4056 (0.000)***		
Wind Speed	0.0039 (0.2023)	-0.0203 (0.0109)*	0.0031 (0.0027)	
Temperature	0.0298 (0.000)***	0.0346 (0.000)***	-0.0696 (0.000)***	-0.0336 (0.000)

p-values between brackets, *** and * denote significance at 1% and 10% level

Table 4. Probit-OLS Regressions

Variables	Total sample	Non-movers	Movers	Total sample	Non-movers	Movers
	Probit-OLS			Ordered Probit		
Recycling Rate	-0.0033 (0.0008)***	-0.0035 (0.0009)***	-0.0028 (0.0032)	-0.0031 (0.0007)***	-0.0034 (0.0008)***	-0.0031 (0.0028)
Household Income	-0.0234 (0.0065)***	-0.0184 (0.0089)**	-0.0026 (0.0389)	-0.0222 (0.0044)***	-0.0176 (0.0052)***	-0.0081 (0.0225)
Age	0.0242 (0.0125)*	0.0231 (0.0109)**	0.294 (0.304)	0.0264 (0.0139)*	0.0249 (0.0113)**	0.229 (0.315)
Average Temperature	-0.0019 (0.0010)*	-0.0015 (0.0007)**	0.0083 (0.0254)	-0.0016 (0.0008)**	-0.0015 (0.0007)**	-0.0120 (0.0044)***
Minimum Temperature	0.0014 (0.0062)	0.0019 (0.0011)*	0.0084 (0.0191)	0.0011 (0.00068)	0.0016 (0.0009)*	0.0090 (0.0443)
Maximum Temperature	0.0035 (0.0015)**	0.0031 (0.0014)**	0.0013 (0.0187)	0.0039 (0.0016)**	0.0044 (0.0019)**	0.0050 (0.0046)
Precipitation	0.0012 (0.0017)	0.0014 (0.0018)	0.0014 (0.0266)	0.0013 (0.0017)	0.0014 (0.0018)	0.0039 (0.0067)
Wind Speed	0.0081 (0.0073)	0.0072 (0.0061)	-0.0045 (0.0260)	0.0093 (0.0076)	0.0072 (0.0062)	-0.0016 (0.0062)
Household Size	-0.0174 (0.0072)**	-0.0219 (0.0104)**	0.0063 (0.0811)	-0.0121 (0.0041)***	-0.0135 (0.0044)***	0.0043 (0.0144)
Smoker (No)	-0.0547 (0.0249)**	-0.0530 (0.0277)*	-0.0681 (0.251)	-0.0533 (0.0117)***	-0.0515 (0.0110)***	-0.0049 (0.0356)
Job status (Unemployed)	0.0939 (0.0414)**	0.1021 (0.0425)**	0.660 (0.487)	0.0912 (0.0401)**	0.0988 (0.0436)**	0.0126 (0.007)*
Marital Status (Living as couple)	-0.270 (0.151)*	-0.352 (0.164)**	-0.600 (0.963)	-0.253 (0.133)*	-0.383 (0.165)**	-0.583 (0.309)*
House tenure (owned house)	-0.387 (0.205)*	-0.470 (0.276)*	-0.679 (0.420)	-0.241 (0.123)*	-0.329 (0.151)**	-0.504 (0.755)
Education level (Highest degree)	-0.0213 (0.0106)**	-0.0228 (0.0110)**	0.413 (0.766)	-0.0225 (0.0108)**	-0.0237 (0.0114)**	0.951 (0.863)
R square	0.2351	0.2426	0.7626			
Wald Chi-Square				1,157.31 [0.000]	1,149.91 [0.000]	319.39 [0.000]
No. Observations	89,971	75,264	7,263	89,971	75,264	7,263
MWTP	£587	£805	£4,221	£557	£777	£1,519

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

Table 5. Blundell-Bond GMM System Estimates

Variables	Total sample	Non-movers	Movers
Health Status with one lag	-0.4040 (0.1726)**	-0.3961 (0.1382)***	-0.4064 (0.1705)**
Recycling Rate	-0.0028 (0.0004)***	-0.0031 (0.0004)***	0.0022 (0.0027)
Household Income	-0.0273 (0.0054)***	-0.0188 (0.0042)***	-0.0069 (0.0256)
Age	0.0260 (0.0138)*	0.0238 (0.0110)**	0.0032 (0.0021)
Average Temperature	-0.0066 (0.0029)**	-0.0068 (0.0028)**	0.0035 (0.0074)
Minimum Temperature	0.0011 (0.0007)	0.0023 (0.0012)*	-0.0017 (0.0049)
Maximum Temperature	0.0031 (0.0016)*	0.0030 (0.0015)**	0.0013 (0.0051)
Precipitation	-0.0022 (0.0023)	-0.0025 (0.0023)	0.0050 (0.0069)
Wind Speed	0.0010 (0.0012)	0.0014 (0.0012)	0.0018 (0.0070)
Household Size	-0.0090 (0.0049)*	-0.0126 (0.0050)**	0.0053 (0.0162)
Smoker (No)	-0.0224 (0.0127)*	-0.0226 (0.0130)*	-0.0049 (0.0040)
Job status (Unemployed)	0.0921 (0.0395)**	0.0958 (0.410)**	-0.176 (0.119)
Marital Status (Living as couple)	-0.218 (0.112)*	-0.323 (0.163)*	-0.0917 (0.115)
House tenure (owned house)	-0.316 (0.158)**	-0.443 (0.248)*	-0.206 (0.722)
Education level (Highest degree)	-0.0230 (0.0111)**	-0.0248 (0.0121)**	-0.0334 (0.118)
Wald Chi-Square	1,269.59 [0.000]	1,232.26 [0.000]	382.71 [0.000]
Sargan Statistic	21.53 [0.607]	25.30 [0.389]	19.23 [0.740]
No. Observations	47,580	41,482	3,520
MWTP	£474	£713	£1,294

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.