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The Local Environment and Subjective Well-being

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JEL classification: I31, Q51

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The Local Environment and Subjective Well-being

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This paper explores whether it is possible to use the well-being data collected in the survey *Understanding Society* to produce estimates of the cost put on local air pollution or proximity to a main road and the value placed on proximity to green space. The conclusions are rather negative. Calculations based on the 2012/13 wave point and the 2016/17 wave give very different answers, and a differences in differences approach shows no significant environmental effect. In the near term it seems unlikely that this approach could form a basis for the inclusion of environmental influences in measures of local well-being.

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This work was undertaken in the Office for National Statistics Secure Research Service using data from ONS and other owners and does not imply the endorsement of the ONS or other data owners.

1 Introduction

This paper reports on an attempt to use data on well-being from the UK Survey *Understanding Society* to value key features of the local environment and to incorporate them into local measures of well-being. The aim was to build on the measures of well-being produced by Aitken and Weale (2023) for lower-tier local authorities in England using subjective prices put on adverse features of the local environment such as air pollution, noise and remoteness from green space.

The intended approach is largely distinct from that adopted by the UK Natural Capital Accounts (ONS, 2024) which are designed to show the value of natural capital rather than measures of well-being. The well-being estimates in Aitken and Weale (2023) reflected consumption, health status and life expectancy, on the basis of residency while the Natural Capital Accounts show the value of services generated by environmental capital based on type of capital which reflects location[1], and not the use made of it by people living in the relevant localities[2]. There is nevertheless some overlap with the UK Natural Capital Accounts (ONS, 2024) and the use that might be made of the data underlying these in future work is discussed in section 6.

The approach followed in this paper is, by now, fairly standard. A measure of subjective well-being collected by the survey is regressed onto a range of explanatory variables. These include household income, the environmental features in question and a number of control variables. With suitable parameter estimates it is possible to calculate the trade-off between income and the environmental features needed to deliver a constant level of well-being. And a price for the environmental feature can be inferred from that. H.M. Treasury (2021) provides a good survey of estimates of the relationship between income and well-being. These are discussed further in the literature review which follows this section. We then discuss approaches to modelling before presenting the data and our results which suggested the approach was not successful. A discussion of the way in which the building blocks for the Natural Capital Accounts might be helpful in future work is followed by our conclusions.

[1] As defined by type of land.

[2] The Natural Capital Accounts do show some recreational use, however

2 Literature Review

Over the last twenty years there has been a considerable number of studies attempting to price atmospheric pollution or other environmental influences using life-satisfaction data. If it is possible to see how life satisfaction depends on consumption or income and on environmental effects, it is then possible to work out the increase in income needed to compensate an individual for an adverse environment. van Praag and Barrsma (2005) studied the effects of airport noise using this technique. Luechinger (2009) examined the consequences of sulphur dioxide pollution in Germany and Luechinger and Raschky (2009) put a subjective cost on flood disasters in Europe. Ambrey, Fleming, and Chan (2014) were able to value the effects of particulate pollution in Queensland, while Sarmiento, Wägner, and Zaklan (2023) concluded that the introduction of low emission zones improves air quality but nevertheless results in long-lasting reduction in life satisfaction. They attributed this to the impact of restrictions on mobility. This points to the care needed in making any particular interpretation of results.

For those studies that relate well-being to household income, there is a concern that the impact of income on well-being is rather low, implying a high price for other factors such as the environment which may also influence well-being. To the extent that this arises from endogenity of income or measurement error, the problem can in principle be resolved by looking at influences clearly identified as exogenous, or by using a suitable instrument.

The first approach is illustrated by Frijters, Haisken-DeNew, and Shields (2004). They look at the implications of German re-unification, an exogenous shock, which led to large increases in real household incomes in East Germany. They find that a 41 % increase in household income was associated with increases in self-reported well-being measured on a scale from 1 to 10 of about 0.26 for both men and women, implying roughly speaking that a 1% increase in income raises well-being by 0.0063 units.

Howley (2017) is also concerned about weak income effects and attributes these to endogeneity which he attempts to resolve by the use of parental education as an instrument. The issue of instrumentation is discussed further in section 3.

Himmler et al. (2020) draw attention to the sensitivity of estimated money values to the specification used. Thus they suggest a value for a quality-adjusted life year ranging from €20,000 to €60,000. They also draw attention to the possibility that the coefficient may depend on the health state of the individual.

Cai and Park (2016) observe that income effects are stronger in cross-sectional models than in panel data or data in differences, as we also find subsequently. They suggest that this may be because consumption rather than income influences well being; this reflects permanent rather than transitory income, and in panel models permanent income effects are absorbed into fixed effects. But even in cross-section models the noise from transitory income will result in parameter attenuation. Barrington-Leigh (2024) suggests that the low effects seen from income arise because many respondents consider only a subset of the possible ordinal responses. It seems unlikely that this problem can be resolved by means of a suitable instrument.

3 Modelling

3.1 Estimation from Cross-sectional Data

The basic approach adopted when using a well-being survey to value some non-market circumstance, such as health or the effects of pollution, is to estimate a regression equation of the following form:

$$y_{i,t} = \alpha + \beta log(x_{i,t}) + \sum_j \gamma_j z_{i,t,j} + \delta \mathbf{s_{i,t}} + \epsilon_{\mathbf{i,t}} \quad (1)$$

Here $y_{i,t}$ is the reported life satisfaction of individual i in period t. This is, in the *Understanding Society* data a score between 1 and 10 given as the answer to the question "Overall, how satisfied are you with your life nowadays?" with scores increasing in life satisfaction. $x_{i,t}$ is the equivalised income of the household in which the individual lives. $z_{i,t,j}$ is the observed magnitude of the effect j it is intended to value, and $\mathbf{s}_{i,t}$ is a vector of control variables.

The ratio $p_j = -\gamma_j/\beta$ then shows the increase in log income needed to offset a unit increase in effect z_j. The fact that the model is estimated in the log of income rather than the level of income needs to be addressed. Ferreira and Moro (2010) show how to do this. The marginal rate of substitution between income and environmental effect j estimated at income level x is given as

$$MRS_j(x) = x\gamma_j/\beta. \quad (2)$$

This can of course be evaluated at any level of income; it is generally evaluated when income takes its mean value, $\bar{x}$. So we may set a price p_j on effect j given by

$$p_j = \bar{x}\gamma_j/\beta. \quad (3)$$

although in some circumstances the variation in the marginal rate of substitution with income may be important. It is also worth mentioning that this approach has the implication that people with low incomes tend to put low prices on adverse environmental effects. Such a feature will not surprise most economists but may seem anomalous to others. It should also be noted that this gives an average price for pollution and not a marginal price.

Where discrete effects are considered, it does not make any sense to talk about the marginal rate of substitution, and it is instead necessary to estimate the compensating or equivalent variation, with the first showing the amount of money needed to restore the initial level of well-being after the discrete change has happened and the second showing the amount of income needed to have an effect on well-being equal to that arising from the discrete change.

A key feature of equation (3) is that the price derived is likely to be very sensitive to the value of β. In particular, if this is under-estimated then the price will be over-estimated. Even if the point estimate of the price is thought to be plausible, uncertainty needs to be considered. There is a substantial literature on the estimation of β which is discussed below but rather less on its distribution. Leitner (2024) discusses the problems in estimating this. There is no guarantee that p_j will be statistically different from zero just because β and γ_j are found to be so.

An additional issue arises when environmental data are the focus of interest. It might be expected that the effects of an adverse residential environment would be fully offset by lower rental values on property. If this were the case, then the direct impact of the environment on well-being would be offset by changes to house prices or rental rates (see section 6). Houses backing on to a park are typically more expensive than those which back on to other houses. That would suggest extending equation (1) to

$$y_{i,t} = \alpha + \beta_x log(x_{i,t}) + \beta_h log(h_{i,t}) + \sum_j \gamma_j z_{i,t,j} + \delta \mathbf{s_{i,t}} + \mathbf{\epsilon_{i,t}} \tag{4}$$

where $h_{i,t}$ is the price of the house inhabited by the members of household i, after adjusting for features such as house size. In practice of course, it is unlikely to be possible to observe this. There may, however, be estimates of average house prices to the same geography as that for which the environmental data are available.

3.2 Endogeneity of house prices and incomes

Equation (4) suffers from the problem that house prices are endogenous, compounding the problems created by the fact that income and happiness may be jointly determined. One may of course estimate an equation in which house prices are the dependent variable and use that to value the characteristics of the local environment directly. Luechinger (2009) looks at rents rather than house prices and compares the results obtained for the value put on reducing sulphur dioxide pollution from power stations with those found using the happiness approach. He finds much smaller values from the rental approach and argues that mobility costs mean the adjustment process of rents to changes in the local environment is likely to be very slow.

But even without the problems of trying to integrate the effects of rents or house prices into the analysis, there remains the question of how to deal with the possible endogeneity of income. The approach generally adopted is to use some form of instrumental variable, but, in the absence of being able to conduct a properly-designed experiment, there is no real consensus on appropriate instruments. On the other hand the differences between OLS and instrumental variable estimates are very substantial. Thus Luttmer (2005), in a study of the effects of neighbours' incomes on well-being in the United States, finds an IV estimate for the impact of log income on wellbeing almost three times as large as that generated by OLS. He uses as an instrument for employment income, the mean pay of someone working in the same industry as the subject in question, but in all states except where the subject works, arguing that this makes it exogenous.

Howley (2017) relies on parental education arguing that this is unlikely to have a direct influence on adult children's well-being, a claim which is at least open to question. Looking at the cost of chronic diseases, he finds a factor of about 3.5 for the ratio of the ILS to OLS parameter estimates. Asgeirsdottir, Hardardottir, and Jonbjarnardottir (2023) do not explore possible instruments in their study but simply multiply the OLS result they find by the factor of 2.93 taken from Luttmer (2005). On the other hand Pischke and Schwandt (2012) cast doubt on the exogeneity of Luttmer's instrument. They find that industry affiliations and thus industry wages, the instrument used by Luttmer, are correlated with individual characteristics such as parental education and own height.

This issue matters a great deal if the aim of the work is to produce an indicator of well-being on a regular basis. The coefficient on log income feeds directly into the valuation put on the local environment as equation (3) shows. The uncertainty arising from the uncertain suitability of an instrument used comes, of course, on top of any statistical uncertainty associated with the parameter values. Certainly, the implied costs Howley (2017) derives for chronic medical conditions seem to be on the high side, even with the use of instruments. Thus, for example, high blood pressure, asymptomatic and easily treated by drugs, is given a cost of £6786 p.a., suggesting that the coefficient on log income, 0.49, generated in his IV regression, may still be suffering from downward bias.

H.M. Treasury (2021) certainly suggests that to be a possibility. They quote a range for the coefficient of log income on well-being of 0.35 to 1.96, varying by a factor of six, but they also argue that the range of 0.35 to 0.5 tends to be robust. On the other hand the high values are more consistent with the value of £60,000 put on a quality-adjusted life year when the government conducts welfare analysis. H.M. Treasury (2021) also suggests a linear relationship between income and well-being years. They quote Frijters and Krekel (2021) who identify the range between a level of well-being at which life is not worth living, and the usual maximum score for someone in excellent health, and use this to calibrate the interval between these two scores (2 and 8 on the 10-point scale used in the UK) by valuing the interval at the £60,000 put on the value of a quality-adjusted life year.

In our case it is worth remembering that income would need to be uncorrelated with other control variables for the coefficients on these to be unaffected by an imposed value for the coefficient on income. But at the same time it would be possible to impose a restricted value on the income term and estimate the remainder of the parameters subject to this exogenous value of the income effect. Even then, however, the results would depend on whether estimation took place by ordinary least squares or by instrumental variables.

3.3 Estimation in Differences

One feature of equation 4 is that the error term $\epsilon_{i,t}$ may be correlated with one or more of the explanatory variables. If a panel survey is available, and if data on the environmental effects also take an appropriate panel form, then equation (4) can be estimated using a fixed-effects panel technique. The issue of income endogeneity remains to be resolved, of course; the implicit assumption is that the endogenous influence of well-being on income is a fixed effect which is removed by differencing. We have, however, noted the point made by Cai and Park (2016) that the fixed effect may be rather important.

If, however, there are, as in our case, just two observations, it is possible to difference out the fixed effect by estimating. Panel methods are not needed. We have

$$\Delta y_i = \alpha + \beta \Delta log(x_i) + \sum_j \gamma_j \Delta z_{i,j} + \delta \mathbf{\Delta s_i} + \epsilon_\mathbf{i} \tag{5}$$

where Δ is the difference operator. A particular appeal of this approach is that, while income and well-being may both be functions of individual characteristics, that is less likely to be true of the terms in differences. Differencing removes individual fixed effects which influence both variables. On the other hand the possibility does remain that an increase in income may be a consequence of an increase in well-being rather than a cause. Differencing probably mitigates rather than completely removes the need to use an instrumental variable for the income term, and it is possible that it accentuates it. It is also possible that happiness does not react instantaneously to income or environmental influences; that may affect the estimated coefficients, particularly if the two sets of observations used to calculate the differences are only a few years apart.

4 Data

The data for this study are drawn from three sources. The survey *Understanding Society* provides information on household structure, household income and the self-reported health and well-being of people from a national sample of about 50,000 households. This survey is an annual panel survey. We work with the waves for 2012/3 and 2016/17 for reasons explained below.

There are two sources of data on air pollution. The data used to compile the Indices of Deprivation (IoD) in 2015 and 2019 include an index of air quality. This is calculated by weighting together atmospheric levels of nitrogen dioxide, benzene, sulphur dioxide and particulates and is available for the 32,844 Lower Layer Super Output Areas[3] (LSOAs) identified in the 2011 Census in England. The component data are also available for 2016 (used in the 2019 Indices of Deprivation) but not for 2012 (used in the 2015 Indices of Deprivation). Given that detailed data are not available for both periods, we work with the composite index of air quality. Across LSOAs it has a correlation with the level of nitrogen dioxide of 0.97, with correlations of 0.88 for benzene and particulates and

[3]LSOAs and Medium Layer Super Output Areas (MSOAs) are small geographic areas defined with reference to a particular census.

0.45 for sulphur dioxide. The index is defined so that an increase in the index represents a decline in air quality.

We also used data showing, for 2018 on a Medium Layer Super Output Area (MSOA) basis, nitrogen dioxide concentrations and three other environmental indicators, the mean distances to green space, to a park or other green space with public access and the mean distance from a main road. 6,791 MSOAs were identified in the 2011 Census. We decided to take advantage of the fact that we have air quality data for 2012 and 2016 on an LSOA basis, and therefore used waves d and h of Understanding Society for 2012/3 and 2016/7.

These are postcode-level environmental exposures aggregated to MSOAs using the 2011 postcode headcount information from the census provided as Office for National Statistics as weights. Annual average concentrations of NO2 for 2015 came from a previously developed Land Use Regression model at 25m x 25m resolution (Wang et al., 2022) which we linked to the 2011 postcode centroids. We calculated the mean distance between postcode centroids to nearest major road (motorway, A road) using Ordnance Survey Open Roads (vector at 1:1,15,000m, 2023 version) as well as nearest green space and, as a subcategory, nearest public park or garden using Ordnance Survey Open Green Space (vector at 1:1,250m, 2018 version).

Summaries of the data for the two years are shown in tables 1 and 2. The mean value of well-being was higher in 2016/17 than in 2012/13 and air quality was better with the IoD measure indicating decreased pollution. Monthly incomes had risen even after taking account of inflation, but hours worked had also increased. The average age of the respondents had also increased but by only $1\frac{1}{2}$ years, as the sample is topped up.

The decline in average air pollution suggests it may be possible to estimate the effects of pollution on wellbeing using a differences in differences approach and we consider that at the end of the next section.

5 Estimation and Results

Our first examination of the possible connection between well-being and the local environment is carried out by relating the level of self-reported well-being to the explanatory variables shown below it in tables 1 and 2. We adapt the approach suggested by Luttmer (2005) and instrument monthly income with the hourly rate of pay in the industry of the head of the household averaged across all relevant households except the household

	Mean	SD	p25	p75	N
Self-reported well-being	4.90	2.04	4.00	6.00	9906
Air quality(IoD measure)	1.04	0.25	0.87	1.20	9906
Average distance from green space (MSOA)	0.21	0.10	0.15	0.24	9906
Average distance from park (MSOA)	1.19	1.30	0.43	1.38	9906
Average distance from road (MSOA)	0.64	0.66	0.28	0.75	9906
Age of respondent	40.70	13.52	31.00	51.00	9906
Heath status excellent	0.21	0.41	0.00	0.00	9906
Health status very good	0.40	0.49	0.00	1.00	9906
Health status good	0.26	0.44	0.00	1.00	9906
Heath status fair	0.10	0.31	0.00	0.00	9906
Health status poor	0.02	0.15	0.00	0.00	9906
Equivalised monthly net income	1690.90	1179.32	1125.55	1993.82	9906
Equivalised household size	1.93	0.60	1.50	2.30	9906
Hours worked	26.00	17.91	16.00	38.00	9906

Table 1: Data Summary 2012/23

	Mean	SD	p25	p75	N
Self-reported well-being	5.17	1.46	4.00	6.00	8741
Air quality(IoD measure)	0.95	0.24	0.78	1.10	8741
Average distance from green space (MSOA)	0.21	0.10	0.15	0.24	8741
Average distance from park (MSOA)	1.18	1.29	0.43	1.38	8741
Average distance from road (MSOA)	0.64	0.63	0.28	0.74	8741
Age of respondent	42.12	14.01	32.00	53.00	8741
Heath status excellent	0.14	0.35	0.00	0.00	8741
Health status very good	0.38	0.48	0.00	1.00	8741
Health status good	0.34	0.47	0.00	1.00	8741
Heath status fair	0.12	0.32	0.00	0.00	8741
Health status poor	0.02	0.15	0.00	0.00	8741
Equivalised monthly net income	1849.63	979.21	1240.99	2207.74	8741
Equivalised household size	1.94	0.63	1.50	2.30	8741
Hours worked	26.29	17.61	16.00	38.00	8741

Table 2: Data Summary 2016/17

in question. We consider only those heads of households where there are at least ten other people working in the industry in question.

Following authors such as Howley (2017), we do not address the possible interconnection of health status and income. We do, however, look at results both with and without health status as an explanatory variable; we find that effect of income on well-being is considerably higher when health status is omitted than when it is included, pointing to the correlation between health status and income.

Table 3 shows the results of the estimation for 2012/13. The Cragg-Donald statistic suggests that the income instrument is very strong; as noted earlier the concern raised by Pischke and Schwandt (2012) is rather whether it is genuinely exogenous because people's choice of profession may be influenced by their family background. The influence of income on well-being shown in the table is in keeping with other estimates, and we see that pollution, represented by the air quality variable, has a significant adverse effect on well-being. The coefficients on distance from green space are positive but not significant while distance from a park is perversely signed. So too is distance from a main road and here the coefficient is also significant at a 5% level. We therefore also show results omitting this variable; that has little impact on the other coefficients.

The results offer a clear message on the connection between air quality and well-being. We can see from table 1 that the interquartile range for air quality is 0.33 while the coefficient in the first column of table 3 is -0.44 and that on log income is 0.48. So the increase in pollution from the first to the third quartile has the same impact on welfare as a reduction in income of $0.33 \times 0.44/0.48 = 0.30$ log units or about 26%, a figure which seems surprisingly high. When we base our calculations on the model leaving out the health terms, we find moving from the first to the third quartile for pollution is equivalent to an income reduction of 0.23 log units or 21%.

	Dependent Variable				
	Self-reported Measure of Well-being				
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Log equivalised	0.331**	0.480**	0.679**	0.484**	0.683**
household income	(0.044)	(0.168)	(0.165)	(0.168)	(0.165)
Air quality		-0.440**	-0.484**	-0.404**	-0.447**
		(0.093)	(0.095)	(0.092)	(0.093)
Mean distance		0.297	0.289	0.166	0.151
from Green Space		(0.272)	(0.277)	(0.265)	(0.270)
Mean distance		-0.011	-0.009	-0.021	-0.019
from Park		(0.020)	(0.020)	(0.019)	(0.019)
Mean distance		-0.079*	-0.083*		
from a Main Road		(0.036)	(0.037)		
Age of Respondent		-0.028**	-0.034**	-0.027**	-0.033**
		(0.008)	(0.008)	(0.008)	(0.008)
$Age^2/100$		0.034**	0.035**	0.033**	0.035**
		(0.010)	(0.010)	(0.010)	(0.010)
General Health					
Very Good		-0.266**		-0.269**	
		(0.054)		(0.054)	
Good		-0.561**		-0.561**	
		(0.062)		(0.062)	
Fair		-0.990**		-0.992**	
		(0.084)		(0.084)	
Poor		-1.767**		-1.769**	
		(0.144)		(0.144)	
Intercept	2.479**	2.752*	1.167	2.673*	1.083
	(0.320)	(1.223)	(1.196)	(1.221)	(1.194)
Number of observations	9906	9906	9906	9906	9906
Cragg-Donald		725.4	768.8	726.2	769.7

Table 3: Results: 2012/2013

If these estimates were replicated they might nevertheless be seen as convincing. But when we look at 2016/17, we are unable to reproduce these results; the main problem we have is that the income effects are very weak; they are also statistically insignificant. The air quality terms are also much weaker than before. Nevertheless, if we look at the estimates in the second column, we find a poorly-determined estimate of $0.33 \times 0.187/0.21{=}0.29$ log units or 0.25% as the estimate of the cost of pollution. But if we work with the model where health status is included, the cost is computed as 3.4 log units or 97%, a clear consequence of the very low income term. While this is the main problem we identify with the results, it is also worth noting that in the 2016/17 results we find correctly-signed coefficients on the distance from green space and from a main road.

We were concerned that there could possibly be an error in the programming and, to investigate this, looked at a simple model in which log equivalised income was the only explanatory variable in an OLS regression. The results of this are shown in the first columns of tables 3 and 4, and it is clear that the coefficients are, even when the samples used are those of the other regressions, fairly close.

Even if it had been possible to obtain results for 2016/17 coherent with those for 2012/13, there is a question of the precision with which implied prices could be determined. Leitner (2024) points out that the implied price is given by the ratio of two asymptotically normally distributed variables, the coefficients on the environmental effect and on income respectively. This ratio is likely to be poorly determined and moments of it may not exist; in any case any confidence interval is likely to be poorly determined.

	Dependent Variable				
	Self-reported Measure of Well-being				
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Log equivalised	0.254**	0.018	0.212	0.018	0.212
Household Income	(0.034)	(0.133)	(0.140)	(0.133)	(0.140)
Air quality		-0.148*	-0.187*	-0.158*	-0.202**
		(0.070)	(0.075)	(0.068)	(0.073)
Mean distance		-0.431*	-0.508*	-0.382*	-0.435*
from Green Space		(0.197)	(0.211)	(0.183)	(0.196)
Mean distance		0.010	0.014		
from Park		(0.014)	(0.015)		
Mean distance		0.065*	0.061*	0.068*	0.066*
from Main Road		(0.027)	(0.029)	(0.027)	(0.028)
Age		-0.024**	-0.034**	-0.024**	-0.034**
		(0.006)	(0.006)	(0.006)	(0.006)
$Age^2/100$		0.031**	0.034**	0.031**	0.034**
		(0.007)	(0.007)	(0.007)	(0.007)
General Health					
Very Good		-0.339**		-0.338**	
		(0.045)		(0.045)	
Good		-0.891**		-0.891**	
		(0.047)		(0.047)	
Fair		-1.593**		-1.593**	
		(0.061)		(0.061)	
Poor		-2.461**		-2.460**	
		(0.108)		(0.108)	
Intercept	3.282**	6.270**	4.576**	6.279**	4.587**
	(0.250)	(0.963)	(1.009)	(0.963)	(1.009)
Number of observations	8741	8741	8741	8741	8741
Cragg-Donald Statistic		538.2	552.7	538.2	552.7

Table 4: Results: 2016/2017

Finally we looked at the model in first differences, explaining the change to well-being in terms of changes in log of equivalised income and changes in air quality. As noted earlier the air quality data are available on an LSOA basis, giving a much finer distribution than is possible with the other variables. In estimating this model we are making the assumption that the endogeneity arises from fixed individual effects and that examining the difference between 2012-13 and 2016-17 removes the influence of these. The results are shown in table 5.

The most striking result is that, while the coefficients are not statistically significant, they suggest that an increase in the air quality measure, which is a decline in quality, is associated with an increase in well-being. The change in health status and the change in income, whether estimated symmetrically using the difference between the waves, or from the levels of the two waves separately, have the expected signs, but the income effect is relatively weak, perhaps because differencing magnifies the effects of noise as Cai and Park (2016) suggested. These results again point to the fact that it is not possible to draw robust inferences on the price of atmospheric pollution from this type of analysis.

	Change in self-reported well-being				
	(1)	(2)	(3)	(4)	(5)
Change in air quality	0.074	0.096	0.082	0.102	0.104
	(0.150)	(0.149)	(0.150)	(0.150)	(0.149)
Change in age^2/100	0.048**	0.054**	0.049**	0.055**	0.055**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Change in health status		-0.498**		-0.498**	-0.499**
		(0.035)		(0.035)	(0.035)
Change in equivalised log income			0.062*		0.064*
			(0.026)		(0.026)
Log income in wave h				0.067*	
				(0.029)	
Log income in wave d				-0.062*	
				(0.029)	
Intercept	-0.077	-0.082	-0.088	-0.129	-0.094*
	(0.045)	(0.045)	(0.046)	(0.199)	(0.045)
N	15676	15676	15676	15676	15676

Table 5: Results for the Model in Differences (OLS Estimates)

6 Local Environmental Valuation and the UK Natural Capital Accounts

The study described so far attempted to estimate the costs of remoteness from green space and public green space based on reported well-being; ONS (2024) estimates the effects of remoteness on house prices and provides valuations based on these. These valuations are grossed up from an impact on rental rates and it would be possible to use the effect on annual rental as a measure of the overall benefits of green space; there is nevertheless the risk of double-counting because the rental value can be presumed to reflect health influences while these were embedded directly in the measure of well-being developed by Aitken and Weale (2023).

Secondly, ONS (2024) looks at the benefits urban vegetation provides in screening noise. Our focus on noise was proxied by distance from a main road.

The calculation of the benefits of screening relied on general estimates of the cost of noise taken from DEFRA (2014)[4]. The effects on health are already reflected in health-adjusted life expectancy but the effects of annoyance caused by noise is treated separately and DEFRA (2014) does provide an explicit price for this, albeit one which is measured per household rather than per person. The logic behind working on a household basis is very unclear, since there are fewer people to be annoyed by noise in a small household than in a large one. To make use of the values put on distance from green space and noise annoyance it would of course be necessary to have small area details of these. The Office for National Statistics would need to investigate this if it intended to develop small-area estimates of well-being which took account of environmental effects.

ONS (2024) also show the benefits of vegetation in removing local (and global) atmospheric pollutants. The local pollutants are, however, valued solely in terms of health benefits, which are already reflected in the measures produced by Aitken and Weale (2023). The Natural Capital Accounts do not suggest the existence of any implicit prices for the disamenity of local atmospheric pollution.

[4]The study provides links to the original sources of the relevant prices but these are no longer functional.

7 Conclusions

This paper sets out an unsuccessful attempt to infer a price for the local environment from data on individual well-being. A reasonably coherent price was obtained for 2012-13, but the income effects were found to be much weaker in 2016-17, implying a much higher monetary value for clean air, distance from a main road and distance from green space.

One explanation of this is that the instrument used in this estimation is not exogenous, as Pischke and Schwandt (2012) have suggested. That said, estimation in first differences has the effects of removing individual fixed effects, and should avoid this problem. We found using this approach a wrong sign on the change in air quality.

This work was originally intended to support estimates of well-being at MSOA level, which is why the focus was on road and green space distance effects defined in those terms; the estimates were then to be aggregated to lower tier local authorities, consistent with the approach adopted by Aitken and Weale (2023). Work on atmospheric pollution was carried out at LTLA level but this also failed to deliver usable estimates. In any future work drawing on *Understanding Society* it would probably be necessary to proceed at post-code level, but the problem of finding suitable instrumental variables remains to be solved.

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