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Abstract

Making use of data from the Household, Income and Labour Dynamics in Australia (HILDA) survey coupled with air pollution data generated by The Air Pollution Model (TAPM), this paper employs the life satisfaction approach to estimate the cost of air pollution from human activities in South East Queensland. This paper offers at least three improvements over much of the existing literature: (1) within- (as opposed to cross-) country variations in air pollution are considered; (2) very high resolution air pollution data is employed; and (3) weather variables are included as controls within the life satisfaction function. A negative relationship is found between life satisfaction and the number of days ambient concentrations of PM_{10} exceed health guidelines. This yields an implicit willingness-to-pay, in terms of annual household income, for pollution reduction of approximately AUD 6,000. This result is robust to a number of model specifications and controls.

Keywords: Air Pollution; Happiness; Household, Income and Labour Dynamics in Australia (HILDA); Geographic Information Systems (GIS); Life Satisfaction

JEL Classification: C21; Q51; Q53

This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. The HILDA project was initiated and is funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the authors and should not be attributed to either FaHCSIA or the Melbourne Institute.

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1. Introduction

The negative effects of air pollution are substantial and wide-ranging. While health effects are of most concern, air pollution can also lead to loss of visibility for residents and recreationists, reduced agricultural and forest productivity, damage to buildings and structural materials, and stress on ecosystems. Together these effects impose significant economic costs on governments, businesses and households. Accurately estimating these costs is an important component of the development of efficient pollution reduction policies (United States Environmental Protection Agency, 2011).

Extending 240 km from Noosa in the north to the Gold Coast / New South Wales border in the south and 140 km west to Toowoomba, South East Queensland (SEQ) is one of Australia's fastest growing and most densely populated regions. The region faces increasing air quality issues and ambient concentrations of PM_{10} have exceeded national guidelines on multiple occasions.[2] Addressing these pollutant exceedences is a priority for public policy (Brisbane City Council, 2009) and a number of existing studies clearly demonstrate a link between the region's air quality and residents' health and well-being (cf. Chen et al., 2007; McCrea et al., 2005; Petroeschevsky et al., 2001; Rutherford et al., 2000; Simpson et al., 1997). However, to the best of our knowledge, there are no publicly available monetary estimates of the cost of air pollution in the region. The purpose of this paper is to fill this knowledge gap and estimate the cost of air pollution from anthropogenic activities in SEQ. The chosen valuation method is the life satisfaction approach.

This paper proceeds as follows. The remainder of this section discusses the life satisfaction approach to valuing non-market goods and services. Method and data form the subject of Section 2. Results are presented in Section 3 and discussed in Section 4.

1.1 The life satisfaction approach

The method and practise of placing monetary values on environmental goods and services for which a conventional market price is otherwise unobservable is one of the most fertile areas of research in the field of natural resource and environmental economics. Initially motivated by the need to include environmental values in benefit–cost analyses, practitioners of non-market valuation have since found further motivation in national account augmentation and environmental damage litigation. An

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[2] PM_{10} is particulate matter with an aerodynamic diameter of less than 10 microns. National guidelines state that average ambient concentrations of PM_{10} should not exceed 50 micrograms per cubic metre over a 24 hour period. Australian Government Department of Sustainability Environment Water Population and Communities, 2012. Air quality standards. Available http://www.environment.gov.au/atmosphere/airquality/standards.html, accessed: 20 January 2013.

extensive review of the theory, methods and literature across a range of non-market valuation techniques and applications can be found in Freeman (2003).

Despite hundreds of applications and many decades of refinement, shortcomings in all of the techniques remain and no single technique is considered superior to the others in all respects. Thus, techniques that expand the suite of options available to the non-market valuation practitioner have the potential to represent a genuine contribution to the field.

One technique to recently emerge is the 'life satisfaction approach'. Simply, this approach entails the inclusion of non-market goods as explanatory variables within micro-econometric functions of life satisfaction along with income and other covariates. The estimated coefficient for the non-market good yields first, a direct valuation in terms of life satisfaction, and second, when compared to the estimated coefficient for income, the implicit willingness-to-pay for the non-market good (or in this case, bad) in monetary terms (Frey et al., 2010). The approach therefore reveals *ex-post* experienced utility rather than the *ex-ante* decision utility typically revealed by other non-market valuation techniques (Kahneman and Sugden, 2005).

A number of studies have used this approach to estimate the cost of air pollution. This paper however, offers at least three advantages over much of the existing literature. First, unlike most studies that rely on cross-country variations in air pollution (cf. Luechinger, 2010; Menz, 2011; Menz and Welsch, 2010, 2012; Welsch, 2002, 2006, 2007) this paper considers within-country variations. This is advantageous in that the use of within-country data reduces imprecision in the measurement of an individual's exposure to air pollution, which may lead to an underestimation of the effect of air pollution on life satisfaction (Levinson, 2012). As noted by Welsch (2006), using within-country, region or local area variation in air pollution has the potential to paint a clearer picture of the link between air pollution and life satisfaction.[3] Second, the quality of the air pollution data employed in this study is very high. This is by no means a minor issue; the limited reliability and availabilty of air pollution data has led Moro et al. (2008) to omit air quality from their development of indices ranking quality of life. Third, weather variables are included in model estimation. Recent evidence suggests that weather matters to life satisfaction (cf. Feddersen et al., 2012) and omitting weather variables from the life satisfaction function may, therefore, introduce omitted variable bias. The omission of weather variables also risks confounding the impact of air pollution (Levinson, 2012).

1.2 Strengths of the life satisfaction approach

The life satisfaction approach offers several advantages over more conventional non-market valuation techniques. For example, the approach does not rely on the

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[3] Using within-country data has the additional advantage of not requiring interpersonal comparison of responses to questions asked in diverse languages and cultures.

assumption of weak complementarity between the non-market good and consumption expenditure (an assumption underpinning the travel cost method), nor does it rely on housing markets being in equilibrium (an assumption underpinning the hedonic property pricing method). The life satisfaction approach also avoids the issues of incomplete information and mistaken perceptions of pollution levels or risks that may otherwise lead to hedonic property pricing estimates understating the cost of pollution. Unlike using healthcare expenditure as a proxy for the cost of air pollution (or other environmental bads), the life satisfaction approach does not understate the amount individuals are willing-to-pay to avoid being sick in the first place (Levinson, 2012).

Further, unlike the contingent valuation method, the life satisfaction approach does not ask individuals to value the non-market good directly. Instead, individuals are asked to evaluate their general life satisfaction. This is perceived to be less cognitively demanding as specific knowledge of the good in question is not required, nor are respondents asked to perform the unfamiliar task of placing a monetary value on a non-market good. This addresses many of the concerns surrounding the hypothetical bias that may arise from the lack of real monetary incentives, credible policy mechanisms, or convincing changes in policy or environmental condition. It also avoids the problem of protest responses. Strategic behaviour (e.g. free riding) and social desirability bias (where an individual responds to a contingent valuation question in what they perceive to be a socially desirable way) are avoided (Welsch and Kuhling, 2009). The life satisfaction approach also avoids the problem of lexicographic preferences, where respondents to contingent valuation or choice modelling questionnaires demonstrate an unwillingness to trade off the non-market good (or bad) for income (Spash and Hanley, 1995). From a non-market valuation practitioner's perspective, the life satisfaction approach avoids the problem of how to make the environmental issue understandable to the population of interest; a task that can be particularly difficult when valuing complex environmental goods such as biodiversity (cf. Christie et al., 2006). In the context of air pollution, the life satisfaction approach avoids problems associated with attempting to define the issue in terms of mortality or morbidity (cf. Dziegielewska and Mendelsohn, 2005).

1.3 Weaknesses or limitations of the life satisfaction approach

The life satisfaction approach however, is not without its weaknesses. While there is growing evidence to support the suitability of individual's responses to life satisfaction questions for the purpose of estimating non-market values (Frey et al., 2010), some potential limitations remain. Crucially, self-reported life satisfaction must be regarded as a good proxy for an individual's utility. Evidence in support of the use of this proxy is provided by Frey and Stutzer (2002) and Krueger and Schkade (2008). Furthermore, in order to yield reliable non-market valuation estimates, self-reported life satisfaction measures must: (1) contain information on respondents' global evaluation of their life; (2) reflect not only stable inner states of respondents, but also current affects; (3) refer to respondents' present life; and (4) be comparable across groups of individuals under different circumstances (Luechinger and Raschky, 2009).

In applying the life satisfaction approach there is another limitation to consider; estimation of the income coefficient. While Pischke (2011) finds evidence to suggest that the direction of the income-life satisfaction relationship is mostly causal, there is some evidence to suggest that people who are more satisfied with their lives earn more (that is, there is a degree of reverse causality). For example, extraverted people are more likely to report higher levels of life satisfaction and be more productive in the labour market (Powdthavee, 2010). Including an instrumental variable for income in life satisfaction regressions is often put forward as a solution (cf. Ferreira and Moro, 2010; Luechinger, 2009) but may not address this issue. Stutzer and Frey (2012) observe, given that almost any factor can be considered to determine an individual's life satisfaction, instrumental variable approaches are difficult to convincingly apply.

There is also a large literature showing that individuals compare current income with past situations and/or the income of their peers. That is, both relative *and* absolute income matter (Clark et al., 2008; Ferrer-i-Carbonell, 2005). As a result, when absolute income is included as an explanatory variable in life satisfaction regressions, small estimated income coefficients are common.

Similar to a limitation of the hedonic property pricing method, it is possible that people self-select where they reside. This would bias the air pollution variable's coefficient (and monetary estimate) downwards, as those least resilient to air pollution would choose to reside in areas with cleaner air. The magnitude of this effect is uncertain, however some authors (cf. Chay and Greenstone, 2005) suggest that the bias is small.

Finally, it is important to acknowledge that there is some debate in the literature about the nature of the relationship between the hedonic property pricing and life satisfaction approaches. Some authors take the view that the life satisfaction approach values only the residual benefits (or costs) of the non-market good not captured in housing markets (Luechinger, 2009; van Praag and Baarsma, 2005). Ferreira and Moro (2010) suggest that the relationship depends on whether the hedonic markets are in equilibrium or disequilibrium, as well as on the econometric specification of the life satisfaction function. If the assumption of equilibrium in the housing market holds, then no relationship should exist between the intangible good and life satisfaction, because housing costs and wages would fully adjust to compensate. If however a significant relationship is found, then residual benefits or costs must remain. Very few life satisfaction functions are specified to incorporate housing markets. Nevertheless, residual benefits or costs are frequently captured; providing further doubt on this assumption.

2. Method and data

The first step is to estimate a micro-econometric life satisfaction model, where life satisfaction is a function of socio-economic and demographic characteristics, the level of air pollution in the local area, and other control variables. The model takes the form of an indirect utility function for individual i, in location k, as follows:

$$U_{i,k} = \omega + \beta \ln\left(y_{i,k}\right) + \gamma'^{x_{i,k}} + \delta \alpha_{i,k} + \theta'^{b_{i,k}} + \kappa_k + i_i + \varepsilon_{i,k} \qquad (1)$$

Where: $U_{i,k}$ stands for the utility of individual i, in location k; $\ln\left(y_{i,k}\right)$ is the natural log of disposable household income; $x_{i,k}$ is a vector of socio-economic and demographic characteristics including marital status, employment status, education, time-invariant personality traits and so forth; $\alpha_{i,k}$ is the spatially weighted average of the mean level of air pollution (number of days PM_{10} has exceeded national health guidelines) within the individual's collection district (CD)[4] over the previous 12 months; $b_{i,k}$ is a vector of controls for location effects, some of which vary at the individual level. κ_k; i_i; and $\varepsilon_{i.k}$ are random error terms. In the model, the individual's true utility is unobservable; hence self-reported life satisfaction is used as a proxy.

As shown by Ferreira and Moro (2010) and Welsch (2006), it is possible to estimate the implicit willingness-to-pay (denoted WTP) for a marginal change in air pollution in a local area by taking the partial derivative of air pollution and the partial derivative of household income, as follows:

$$WTP = \frac{\frac{\partial U_{i,k}}{\partial a_{i,k}}}{\frac{\partial U_{i,k}}{\partial y_{i,k}}} = \frac{\partial y_{i,k}}{\partial a_{i,k}}$$
$$= -\bar{y}\frac{\hat{\delta}}{\hat{\beta}} \qquad (2)$$

Where $\bar{y}$ is the mean value of household income.

2.1 Estimation strategy

Similar to the estimation strategies employed elsewhere in the literature (cf. Ambrey and Fleming, 2011a; Brereton et al., 2008; Smyth et al., 2008) an ordered probit model is estimated by maximum likelihood estimation. Note that while the estimated coefficients from an ordered probit model have no meaningful interpretation (as they refer to an underlying latent variable), ratios between any two coefficients can be interpreted (Frey et al., 2010). We are therefore able to use the coefficients for air pollution and income to calculate marginal rates of substitution or willingness-to-pay.

[4] The CD is the smallest spatial unit in the Australian Standard Geographical Classification: Australian Bureau of Statistics, 2010. Australian Standard Geographical Classification, Catalogue No. 1216.0, Canberra.

Identification of the effect of air pollution is achieved through the inclusion of spatial controls at the local government area while allowing the air pollution measure to vary at the CD (the lowest level of spatial disaggregation available). Like other studies (cf. MacKerron and Mourato, 2009), a key assumption, and potential limitation, of this study is that individuals experience the level of air pollution that exists in their local area.

To ameliorate potential rural versus regional effects that might otherwise bias the results (cf. Luechinger, 2009), we include a dummy variable indicating whether or not the individual lives in a major city. We also condition on other spatial variables derived from GIS such as public greenspace, proximity to the coastline and proximity to an international airport. Further, we control for the relative socio-economic disadvantage of the area and, following Shields et al. (2009), a range of observed neighbourhood characteristics. Weather variables are also included. Finally, as we include explanatory variables at different spatial levels, standard errors are adjusted for clustering (Moulton, 1990).

2.2 Household, Income and Labour Dynamics in Australia (HILDA) survey

The measure of self-reported life satisfaction and the socio-economic and demographic characteristics of respondents are obtained from Wave 1 (2001) of the Household, Income and Labour Dynamics in Australia (HILDA) survey. By international standards the HILDA survey is a relatively new nationally representative sample and owes much to other household panel studies conducted elsewhere in the world; particularly the German Socio-Economic Panel and the British Household Panel Survey. See Watson and Wooden (2012) for a recent review of progress and future developments of the HILDA survey.

The life satisfaction variable is obtained from individuals' responses to the question: *'All things considered, how satisfied are you with your life?'* The life satisfaction variable is an ordinal variable, the individual choosing a number between 0 (totally dissatisfied with life) and 10 (totally satisfied with life).

2.3 Air pollution data

The air pollution data employed in this study allows the investigation of intra-regional variation in air pollution, as opposed to the inter-regional, inter-state or inter-country variations usually found in the literature. The data employed compares favourably with other studies that purport to employ spatially disaggregated data and yet often rely on a sparse coverage of monitoring stations and thus require substantial extrapolation (cf. Levinson, 2012; Luechinger, 2009).

The data is modelled using The Air Pollution Model (TAPM) 4.0 developed by the Commonwealth Scientific and Industrial Organisation (CSIRO) Marine and Atmospheric Research Group (Hurley, 2008). This is an airshed model commonly used for modelling the dispersion of emissions from anthropogenic sources.[5] The modelled period is month-by-month from February 2000 to December 2001. The pollution output is extracted for a 170 km x 206 km grid, with grid cell sizes of 2 km. The modelled results of meteorology (average temperature, minimum temperature, maximum temperature, temperature range and average rainfall) and air quality (average and maximum concentrations and number of exceedences of health guidelines) for each month are then combined with those of the 11 previous months to generate the 12 month average air pollution levels for that month.

A number of life satisfaction models were estimated and compared in order to identify the most appropriate measure of air pollution. Frequency of exceedences of health guidelines is found to outperform average and maximum ambient concentrations. Of the air pollutants considered, PM_{10} is the pollutant that most frequently exceeds health guidelines in SEQ and has the most significant effect on life satisfaction. PM_{10} is thus the air pollutant included in the model presented in the following section. Figure 1 indicates the extent of spatial heterogeneity in PM_{10} exceedences of health guidelines by CD for 2001. Table 1 provides a description of all variables employed.

[5] Insufficient data on emissions from natural sources coupled with the fact that natural contributions such as storm dust and smoke from bushfires tend to increase air pollution levels uniformly across the region led to these sources being excluded from the modelling.

Figure 1: Geographical distribution of PM_{10} exceedences throughout SEQ

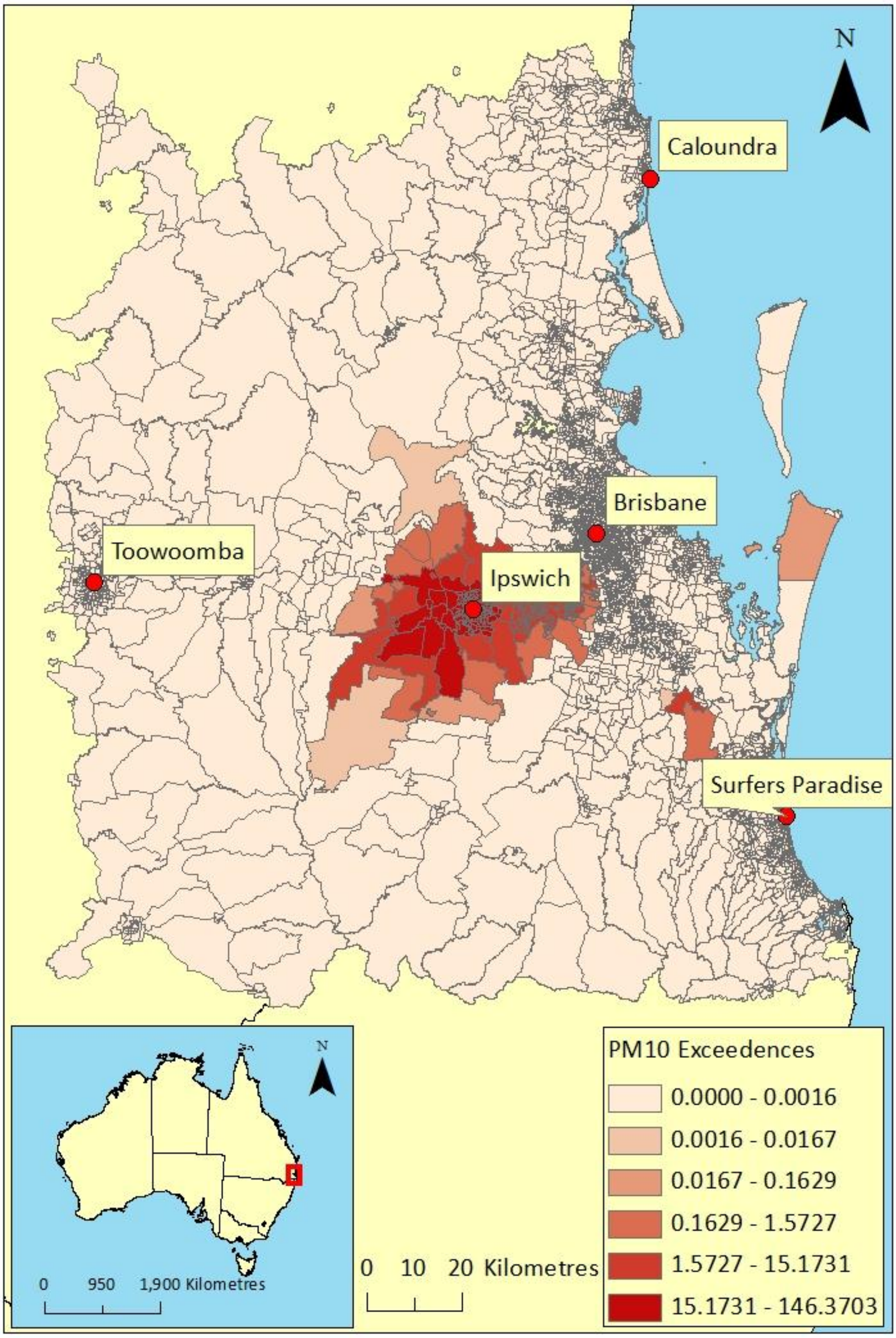


Table 1: Model variables

Variable name	Definition	Mean (std. dev.)	% value 1 (DV)
Life satisfaction	Respondent's self-reported life satisfaction (scale 0 to 10)	7.9097 (1.6025)	
Age (15-19)	Respondent is between 15 and 19 years of age		5.8%
Age (20-29)	Respondent is between 20 and 29 years of age		14.6%
Age (40-49)	Respondent is between 40 and 49 years of age		22.9%
Age (50-59)	Respondent is between 50 and 59 years of age		15.9%
Age (60 or greater)	Respondent is 60 years of age or greater		17.3%
Male	Respondent is male		46.8%
ATSI	Respondent is of Aboriginal and/or Torres Strait Islander origin		1.5%
Immigrant English	Respondent is born in a Main English Speaking country (Main English speaking countries are: United Kingdom; New Zealand; Canada; USA; Ireland; and South Africa)		13.3%
Immigrant non-English	Respondent is not born in Australia or a Main English Speaking country		6.8%
Married	Respondent is legally married		57.2%
Defacto	Respondent is in a defacto relationship		11.2%
Separated	Respondent is separated		2.7%
Divorced	Respondent is divorced		9.5%
Widow	Respondent is a widow		2.8%
Lone parent	Respondent is a lone parent		0.9%
Number of children	Number of respondent's own resident children in respondent's household at least 50 per cent of the time and number of own children who usually live in a non-private dwelling but spend the rest of the time mainly with the respondent	0.8422 (1.2019)	
Long-term health condition	Respondent has a long-term health condition, that is a condition that has lasted or is likely to last for more than six months		22.1%
Year 12	Respondent's highest level of education is Year 12		2.0%
Certificate or diploma	Respondent's highest level of education is a certificate or diploma		28.9%
Bachelors degree	Respondent's highest level of education is a		19.4%

or higher	Bachelors degree or higher		
Employed part-time	Respondent is employed and works less than 35 hours per week		19.4%
Self-employed	Respondent is self-employed.		8.1%
Unemployed	Respondent is not employed but is looking for work		5.0%
Non-participant	Respondent falls into the other non-participant category		31.2%
Household income (ln)	Natural log of disposable household income	10.5984 (0.8011)	
Importance of religion	Respondent's self-report of the importance of religion to them (scale 0 to 10)	4.5617 (3.4709)	
Others present	Someone was present during the interview		36.6%
Extraversion	Degree of extraversion (scale 1 to 7)	4.4193 (1.0472)	
Agreeableness	Degree of agreeableness (scale 1 to 7)	5.4023 (0.9250)	
Conscientiousness	Degree of conscientiousness (scale 1 to 7)	5.2035 (1.0255)	
Emotional stability	Degree of emotional stability (scale 1 to 7)	5.1598 (1.0920)	
Openness to experience	Degree of openness to experience (scale 1 to 7)	4.2404 (1.0621)	
Major city	Respondent is considered to reside in a major city region as defined by the Australian Bureau of Statistics' Accessibility/Remoteness Index of Australia		74.7%
SEIFA index	The Australian Bureau of Statistics' (ABS) Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socio-economic Disadvantage for the CD in which the respondent resides	5.4081 (2.8103)	
Local interaction	Respondent observes neighbourly interaction and support	6.6213 (2.0093)	
Local disamenity	Respondent observes local disamenity	10.5201 (2.8452)	
Local insecurity	Respondent observes insecurity in the neighbourhood	10.0784 (3.5465)	
Proximity to coast	Respondent resides within 3 km of the coastline		20.0%
Proximity to airport	Respondent resides within 5 km of an international airport		1.3%
Public greenspace	Percentage of public greenspace in the respondent's CD		7.7%

PM_{10} exceedences (days)	Average annual number of days that the PM_{10} concentration level has exceeded 24 hour health guidelines for the CD in which the respondent resides	0.4291 (3.0931)
Humidity (%)	Average annual humidity for the CD in which the respondent resides	73.6156 (2.0270)
Rainfall (mm)	Average annual rainfall for the CD in which the respondent resides	116.7853 (109.1752)
Temperature (°C)	Average annual temperature for the CD in which the respondent resides	20.1097 (0.8980)
Wind speed (metres/second)	Average annual wind speed for the CD in which the respondent resides	2.4975 (0.5315)

Note 1: Personality trait variables (extraversion; agreeableness; conscientiousness; emotional stability; and openness to experience) are derived from individual's responses to Waves 5 or 9.

Note 2: Details behind the derivation of observed neighbourhood characteristics variables (neighbourly interaction and support; local disamenity; insecurity in the neighbourhood) can be found in Shields et al. (2009).

3. Results

Model results are reported in Table 2. In regards to socio-economic and demographic characteristics, the results largely support the existing literature and *a priori* expectations. Life satisfaction is found to be U-shaped in age, reaching a minimum at 45 years of age. Once personality traits are controlled for, males are more satisfied with their lives than females, although, on average, males report lower levels of life satisfaction. Being married or widowed is associated with higher levels of life satisfaction, poor health with lower levels. Being a part-time employee or non-participant in the labour force (for example, a student or retired) is, *ceteris paribus*, associated with higher levels of life satisfaction than being employed full-time. Being unemployed is found to have no statistically significant effect on life satisfaction. Income is associated with higher levels of life satisfaction, although, as discussed above, the magnitude of the effect is likely to be understated. We find evidence of social desirability bias, with others present during the interview being associated with higher levels of life satisfaction. Higher levels of life satisfaction are also reported by those who view religion as being important to their lives. Four of the Big Five personality traits (extraversion, agreeableness, emotional stability and openness to experience) (Saucier, 1994) are statistically significant and take the expected signs (DeNeve and Cooper, 1998).

Local government area and spatial control variables are jointly statistically significant. The level of observed neighbourly interaction and support is found to be positively associated with life satisfaction, as are GIS derived public greenspace and proximity to coast variables. In terms of weather variables, only temperature is found to have a statistically significant association with life satisfaction, a finding that is consistent with existing evidence (cf. Feddersen et al., 2012). Of most relevance to this study, the number of days that PM_{10} concentrations within a respondent's CD exceed health guidelines is negatively associated with life satisfaction, statistically significant at the five per cent level with a coefficient of -0.0177.

Table 2: Ordered probit baseline model results

Variable name	**Coefficient** (standard error)	**Variable name**	**Coefficient** (standard error)
Age (15-19)	0.3921* (0.2291)	Non-participant	0.2236** (0.0996)
Age (20-29)	0.2836*** (0.1078)	Household income (ln)	0.1186* (0.0701)
Age (40-49)	0.0699 (0.1081)	Importance of religion	0.0310*** (0.0109)
Age (50-59)	0.1795 (0.1201)	Others present	0.1558* (0.0824)
Age (60 or greater)	0.3249* (0.1792)	Extraversion	0.1208*** (0.0322)
Male	0.2208*** (0.0866)	Agreeableness	0.1977*** (0.0385)
ATSI	0.3042 (0.2734)	Conscientiousness	0.0243 (0.0397)
Immigrant English	-0.0150 (0.1027)	Emotional stability	0.0852** (0.0340)
Immigrant non-English	-0.0770 (0.1419)	Openness to experience	-0.1111** (0.0480)
Married	0.3343** (0.1306)	Major city	0.0347 (0.0992)
Defacto	0.2060 (0.1518)	SEFIA index	0.0011 (0.0178)
Separated	-0.0565 (0.2240)	Local interaction	0.0668*** (0.0187)
Divorced	-0.1276 (0.1496)	Local disamenity	-0.0168 (0.0173)
Widow	0.8243*** (0.2253)	Local insecurity	-0.0207 (0.0145)
Lone parent	-0.3116 (0.5024)	Proximity to coastline	0.4989** (0.2237)
Number of children	-0.0467 (0.0404)	Proximity to airport	-0.1818 (0.1495)
Long-term health condition	-0.3072*** (0.0911)	Public greenspace	0.0073*** (0.0020)
Year 12	0.4137 (0.2566)	PM_{10} exceedences	-0.0177** (0.0081)
Certificate or diploma	-0.0886 (0.0812)	Humidity	-0.0697 (0.0469)
Bachelors degree or higher	0.0580 (0.1038)	Rainfall	-0.0009 (0.0012)

Employed part-time	0.2374	Temperature	-0.5391**
	(0.1165)		(0.2681)
Self employed	-0.0786	Wind speed	0.1699
	(0.1580)		(0.1878)
Unemployed	-0.0275		
	(0.1814)		
Summary statistics			
Number of observations	919		
Pseudo R^2	0.0766		

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Omitted cases are: Female, Not an Aboriginal and/or Torres Strait Islander, Australian born, Never married and not de facto; Not a lone parent; Does not have a long-term health condition; Year 11 or below; Not self employed; Employed working 35 hours or more per week; No others present during the interview or don't know – telephone interview; Not within 3km of coastline; Not within 5km of an international airport; Not in a major city. LGA dummy variables where the most prevalent is the base case.

Following the procedure described in Equation 2, the average implicit willingness-to-pay in terms of annual household income for a one day decrease in the number of days that the PM_{10} concentration level exceeds health guidelines over a twelve month period in a respondent's CD is $5,987.[6] In per-capita terms, given there are on average 2.95 people living in each household in the sample, this implies a willingness-to-pay of $2,030. These relatively large estimates reflect some of the shortcomings of the life satisfaction approach discussed above.

3.1 Robustness checks

In order to check the robustness of these findings we begin by comparing ordered probit estimates to those obtained using ordinary least squares. The former preserves the ordinal nature of the dependent variable, the latter assumes cardinality. As shown in Table 3, the implicit willingness-to-pay for a decrease in PM_{10} exceedences is $5,508; approximately eight per cent less than the estimate obtained from the ordered probit model. This relatively minor difference lends support to the robustness of the result and is in line with existing evidence (Ferrer-i-Carbonell and Frijters, 2004).

[6] All figures are in AUD. As at 14 February 2013, 1 AUD = 1.04 USD/0.77 EUR.

Table 3: Model specifications and willingness-to-pay

	Ordered probit	Ordered probit	OLS
Variable name	**Coefficient** (standard error)	**Marginal effect** (standard error)	**Coefficient** (standard error)
Household income (ln)	0.1186*	0.0254*	0.1778*
	(0.0701)	(0.0150)	(0.1046)
PM10 exceedences	-0.0177**	-0.0038**	-0.0244*
	(0.0081)	(0.0017)	(0.0127)
WTP	$5,987		$5,508
Summary statistics			
Number of observations	919	919	919
Pseudo R^2	0.0766	0.0766	
Adjusted R^2			0.1911

Marginal effects are interpreted as the likelihood of an individual reporting a life satisfaction score of 10 (totally satisfied with life) for a one unit increase. For example, a one day increase in the number of days PM10 concentrations exceed health guidelines is associated with a 0.38% decrease in the probability of reporting being totally satisfied with one's life. Standard errors are calculated using the Delta Method.

To explore the extent to which our results may be sensitive to model specification, we sequentially omit spatial control variables from the model. Reassuringly, the implicit willingness-to-pay estimates deviate by no more than 24 per cent from the baseline estimate, with an average deviation of less than nine per cent (Table 4). The largest deviation can be attributed to the omission of the annual average temperature variable. Existing studies investigating the effect of air pollution on life satisfaction have largely failed to control for weather, whereas studies investigating the effect of weather have largely failed to control for air pollution. Although there is some degree of collinearity between the two variables,[7] this is an important source of omitted variable bias. In abstracting from the confounding influence of weather we see more clearly the link between air pollution and life satisfaction. Finally, as a further robustness check, we consider alternative transformations of the air pollution variable. Compared to natural logarithm, squared and reciprocal transformations, the linear specification presented in the model above provides the superior (most statistically significant) functional form.

[7] An auxiliary regression of weather variables on air pollution yields an adjusted R^2 of 0.0464 indicating that multicollinearity among these variables is not of great concern.

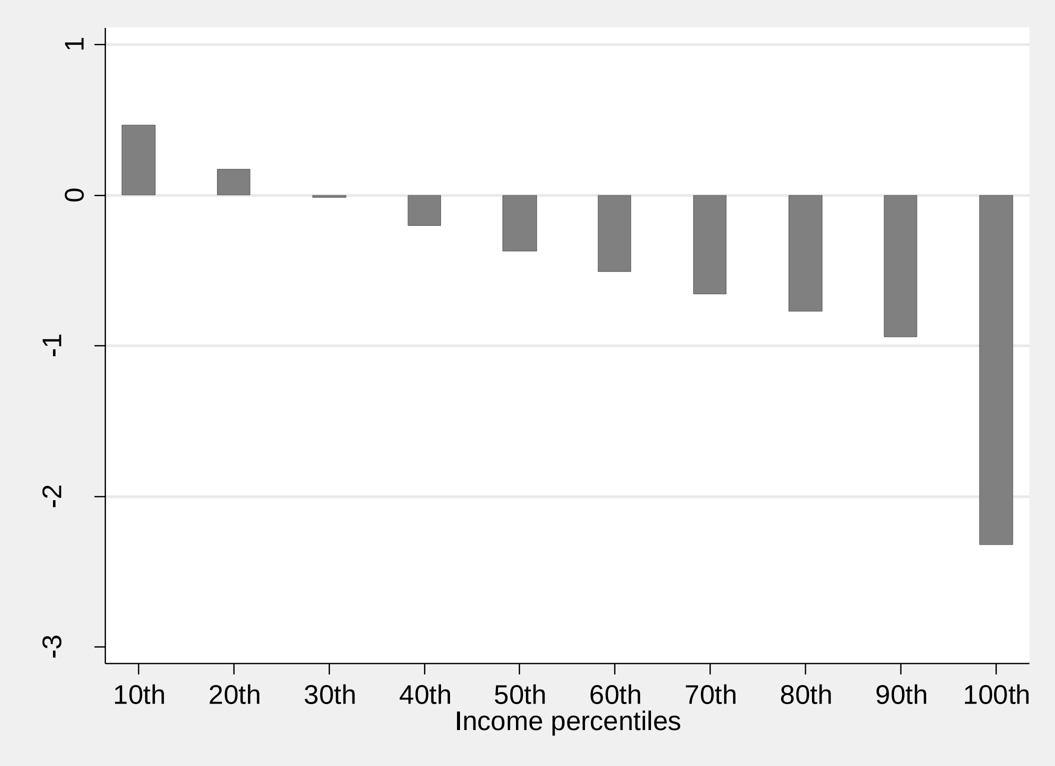
Table 4: Ordered probit model and willingness-to-pay sensitivity to omitted variables

	PM_{10} exceedences	Household income (ln)	WTP	Deviation from mean (%)
Omitted variable name	**Coefficient** (standard error)	**Coefficient** (standard error)		
SEFIA index	-0.0177** (0.0081)	0.1186* (0.0702)	$5,986	0.0%
Major city	-0.0177** (0.0081)	0.1186* (0.0701)	$5,982	0.1%
Local interaction	-0.0150* (0.0078)	0.1191* (0.0702)	$5,057	15.5%
Local disamenity	-0.0182** (0.0084)	0.1188* (0.0700)	$6,135	2.5%
Local insecurity	-0.0160** (0.0077)	0.1280* (0.0674)	$4,997	16.5%
Proximity to coastline	-0.0144* (0.0085)	0.1194* (0.0675)	$4,818	19.5%
Proximity to airport	-0.0179** (0.0080)	0.1205* (0.0701)	$5,961	0.4%
Public greenspace	-0.0167** (0.0083)	0.1243* (0.0713)	$5,385	10.1%
Humidity	-0.0157** (0.0080)	0.1175* (0.0707)	$5,337	10.9%
Rainfall	-0.0169** (0.0082)	0.1168* (0.0692)	$5,782	3.4%
Temperature	-0.0127 (0.0090)	0.1108 (0.0685)	$4,577	23.6%
Wind speed	-0.0173** (0.0081)	0.1155 (0.0709)	$5,992	0.1%

3.2 Income and air pollution

We also explore if the effect of air pollution varies as we would expect with income. We find evidence that the linear (PM_{10} exceedences) and interaction (PM_{10} exceedences x ln(household income)) terms are jointly statistically significant, suggesting individuals residing in households with higher incomes are implicitly willing-to-pay more for a reduction in PM_{10} exceedences than lower income households. This result supports the diminishing marginal utility assumption underlying the natural logarithm transformation of income. This finding also lends confidence to the implicit assumption of increasing willingness-to-pay with income that underlies Equation 2. That is, higher income individuals are more sensitive to air pollution and, as such, higher income individuals are implicitly willing-to-pay more for any given reduction in air pollution exceedences. This is illustrated in Figure 2, where, for a one unit increase in PM_{10} exceedences, individuals at increasingly higher ends of the income distribution are less likely to report being totally satisfied with their lives.

Figure 2: The effect of PM_{10} exceedences on life satisfaction is dependent on household income



Note 1: Marginal effects are interpreted as the likelihood of an individual reporting a life satisfaction score of 10 (totally satisfied with life) for a one unit increase in PM_{10} exceedences. Standard errors are calculated using the Delta Method.

Note 2: 10^{th}, 20^{th}, 30^{th}, 40^{th} and 100^{th} percentiles are not statistically significant.

Source: Derived from HILDA and GIS data

4. Discussion

This paper offers at least three improvements over much of the existing literature employing the life satisfaction approach to estimate the cost of air pollution: (1) the consideration of within-country variations in air pollution; (2) the use of very high resolution air pollution data; and (3) the inclusion of weather variables in the life satisfaction function. We find that air pollution (at least as measured by the number of days that the ambient concentration of PM_{10} from anthropogenic activities exceeds health guidelines) in an individual's local area significantly detracts from that individual's self-reported life satisfaction. The individual is estimated to have an implicit willingness-to-pay of $5,987 in annual household income for a one day decrease in the number of days PM_{10} exceeds health guidelines in their CD.

This estimate is larger than that obtained using conventional techniques (such as the hedonic property pricing technique) and to some extent highlights the difficulty of using the life satisfaction approach to value non-market goods (or bads). In particular, difficulty with estimating the marginal effect of income. While some authors have attempted to address this issue by instrumenting income, this approach has its shortcomings. Even when instrumental variables 'work', they are difficult to convincingly apply; almost any factor can be considered to determine an individual's life satisfaction (Stutzer and Frey, 2012). This is an area worthy of considerable further research.

Despite limitations surrounding the monetary estimates, useful information can still be gleaned from the life satisfaction regressions. For example, we can conclude that residents in SEQ have a preference (inferred through life satisfaction effects) for air pollution abatement. We find this result and the associated implicit willingness-to-pay to be quite robust to a number of model specifications. Furthermore, through the use of spatially disaggregated air pollution data we have been able to capture a link between air pollution and life satisfaction subject to less measurement error than many earlier studies; measurement error which would tend to bias the air pollution coefficient towards zero. Our study also reveals that weather can be an important conditioning factor in life satisfaction regressions investigating air pollution and, in accordance with *a priori* expectations, that individuals residing in higher income households are more adversely affected by air pollution than those in lower income households.

While not the main thrust of this investigation, from a theoretical perspective these value estimates point towards a substantial residual shadow value associated with air pollution that is not captured in housing costs or wages. Echoing earlier life satisfaction valuation literature (cf. Ambrey and Fleming, 2011b), this finding challenges the validity of the assumption of equilibrium in housing and wage markets that underpins many models that rely on choice. In this context, the life satisfaction approach may serve as a useful complement to the hedonic method when attempting to value non-market goods.

From a public policy perspective these findings reaffirm the goals and standards of the National Environment Protection Measure for Ambient Air Quality (Australian Government Department of Sustainability Environment Water Population and Communities, 2012). At a regional level, the SEQ Regional Plan 2009-2031 and regional transport planning initiatives make important contributions to mitigating air pollution emissions, and while the Brisbane City Council Clean Air Strategy (Brisbane City Council, 2009) is a useful initiative, our results provide a strong case for bringing the time frame for 'clean air' forward from the current target date of 2026.

Unfortunately, despite the regional and local efforts to increase the proportion of travel taken by public transport, walking and cycling (and thereby reduce emissions), at a national level the Commonwealth Government has opted to exempt fuel from the carbon tax in order to appease voters. In doing so, the Commonwealth has fostering the use of cars with relatively poor fuel economy and contradicted the efforts of air quality initiatives at other levels of government, as well as the Commonwealth's internal economic advice on the issue (Maher, 2011). Our results point to substantial welfare improvements from air pollution abatement, particularly a reduction in exceedences of health guidelines. Price and tax incentives provide a useful tool to achieve this end, as well as contribute towards a more cohesive set of public policies.

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