Valuing Public Goods Using Happiness Data: The Case of Air Quality

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Abstract

This paper describes and implements a method for estimating the average marginal value of a time-varying local public good: air quality. It uses the General Social Survey (GSS), which asks thousands of people in various U.S. locations how happy they are, along with other demographic and attitude questions. These data are matched with the Environmental Protection Agency's Air Quality System (AQS) to find the level of pollution in those locations on the dates the survey questions were asked. People with higher incomes in any given year and location report higher levels of happiness, and people interviewed on days when air pollution was worse than the local seasonal average report lower levels of happiness. Combining these two concepts, I derive the average marginal rate of substitution between income and air quality – a compensating differential for air pollution.

JEL codes: Q51, Q53, H41

Key words: willingness to pay, stated well-being, pollution, compensating differential.

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1. Introduction

One of the great challenges facing applied economics involves valuing non-market goods such as local public amenities. Existing methods, often applied to environmental quality, include travel-cost models, hedonic regressions of property values, and contingent valuation surveys in which people are asked directly their willingness to pay for public goods. Here I describe and test an alternative method for estimating the economic benefit of a local public good. The fundamental idea is extraordinarily simple. I combine survey data, air quality data, and weather data to model individuals' self-reported levels of "happiness," or "subjective well-being," as a function of their demographic characteristics, incomes, and the current air quality and weather at the date and place they were surveyed. I then use the estimated function to calculate the average marginal rate of substitution between annual household income and air quality that leaves respondents equally happy – a compensating differential for air pollution.

This happiness-based methodology has a number of advantages over existing tools for valuing environmental quality. Because I include county and year fixed effects, coefficients are identified from daily fluctuations in pollution within a U.S. county, and are not subject to the sorting biases associated with travel cost or hedonic models. (The people most averse to air pollution choose to visit and live in clean locales, leading to underestimates of the value of air quality.) Because I estimate marginal rates of substitution between income and pollution directly, the approach is not confounded by income effects, or large gaps between measures of willingness to pay and willingness to accept. And because I do not rely on questions asking people directly about environmental issues, the methodology is not susceptible to the strategic biases and framing problems of the contingent valuation approach.

Furthermore, while happiness studies have recently been used to estimate the value of public goods and bads, including price inflation (Di Tella et al., 2001), state cigarette taxes (Gruber and Mullainathan, 2005), airport noise (van Praag and Baarsma, 2005), inequality (Alesina et al., 2004), urban regeneration (Dolan and Metcalf, 2008), terrorism (Frey et al., 2009), and even air pollution (Welsch, 2007; Di Tella and MacCulloch, 2008; Ferreira et al., 2006; Luechinger, 2009), all of this previous work relies on annual average values of these public goods across regions or countries. If the public goods are endogenously determined by regional characteristics also associated with happiness, or if people become habituated to levels of public goods, these studies using annual regional differences in public goods will yield biased estimates of their value. Air quality, on the other hand, varies daily within each location, for reasons exogenous to any particular respondent, and presumably more quickly than people can become habituated.

Naturally, this approach also has disadvantages. It treats responses to questions about happiness as a proxy for utility, and then makes interpersonal comparisons among respondents. It relies on an oddly vague question about how "things are these days." It identifies the relevant compensating differential based on tradeoffs between fluctuations in *daily* pollution and differences among respondents' *annual* incomes. And it takes household income to be an exogenous determinant of happiness, rather than potentially determined by happiness. The reason to pursue this line of research, therefore, is not that it is without shortcomings. Instead, the nice feature of this approach is that its shortcomings differ so markedly from those of standard approaches to valuing public goods, and therefore it serves as a useful point of comparison.

I present two main results. First, I show that happiness is related in sensible ways to daily local air pollution. After accounting for respondents' demographics, daily local weather conditions, as well as local, year, and even month fixed effects, individuals surveyed when the current local levels of airborne particulates are higher report lower levels of happiness. This first step is a straightforward empirical exercise. It requires no strong assumptions except the empirical specification, and I show that the results are robust to a variety of those. I also show that reported happiness is *not* sensitive to local levels of undetectable pollutants, such as carbon monoxide.

The second result involves using the estimates to calculate marginal rates of substitution between pollution and income, and then backing out the respondents' implicit willingness to pay for improved air quality. This step does involve several strong assumptions, but I describe those assumptions in detail and argue that they are no stronger than the assumptions underlying travel cost, hedonic or stated-preference estimates of willingness to pay for air quality. Moreover, the assumptions I make differ entirely from the standard set, and so at a minimum the results here serve as an alternative to the usual approaches.

Using my preferred specification, I show that people appear willing to sacrifice about $40 for a one-standard-deviation improvement in air quality for one day. If these are interpreted as daily values (and there is some ambiguity about tradeoffs between daily air quality and annual income), then $40 per day is considerably higher than typical hedonic valuations of air quality, and almost double the value attributed by the EPA to the economic benefits of the 1970 and 1977 Clean Air Acts. Of course, in some ways the usual hedonic estimates seem implausibly small, and this happiness measure includes benefits not captured by the EPA approach – aesthetics, lost recreation, and benefits from other pollutants correlated with particulates.

In the end, this exercise probably will not serve as a useful tool for widespread use in cost-benefit analyses. The information requirements are too large, and the approach cannot be applied to pollutants that are imperceptible, though they may be equally damaging. However, the analysis conducted here does yield several important lessons. For environmentalists and environmental economists, the results provide evidence that air pollution, in addition to detrimentally affecting health and property, has a direct negative effect on people's stated well-being, as well as evidence that the monetary value of that effect may be quite large. For the growing literature on happiness and economics, the results provide yet another piece of evidence that subjective well-being varies in sensible ways with respondents' observable characteristics and circumstances.

2. Happiness in economics

Happiness has enjoyed a recent surge of serious attention by economists.[1] Much of the academic and popular happiness literature addresses the decades-old findings of Easterlin (1974): stated happiness does not increase with income across countries, or within a country over time, but does increase with income across individuals within a country at any given point in time. Some recent work refutes the first half of this "Easterlin Paradox," showing that happiness increases with GDP per capita across countries in expected ways (Stevenson and Wolfers, 2008; Deaton, 2008; Helliwell et al., 2009). But support for the second half remains: stated happiness

[1] Articles have appeared in top academic journals, and as cover stories for *The Economist* and *Time* magazines. The *Journal of Economic Literature* and *Journal of Economic Perspectives* have both published recent surveys of happiness research, articles have appeared in the top general interest economics journals, a special issue of the *Journal of Public Economics* was devoted to the issue, and there is even now a "Handbook" on the economics of happiness (Bruni and Porta, 2007).

has not increased over time as per capita incomes have increased (Oswald,1997; Layard, 2006). This paradox has two obvious interpretations. One is that people become habituated to their situations and change their reference level of well-being.[2] Another is that happiness depends on relative income – the richest man in a poor town may be happier than the poorest man in a rich town, even if the rich man is poorer in absolute terms.[3]

Under either interpretation, the Easterlin paradox has implications for using happiness to measure willingness to pay for public goods. If happiness does not increase with income across regions or over time, it would seem unlikely to vary with the level of any particular public good. For income, happiness increases relative to other people in the same locale at the same time. The analog for pollution is that happiness will increase with air quality relative to the current regional norm, but not relative to other regions or within regions over long periods of time. That is why a key feature of this analysis identifies happiness as a function of the place-specific, date-specific air quality, at the place and date where the happiness question was asked. In other words, I compare stated happiness by statistically similar respondents, at the same locale, during the same season of the same year, who just happen to have been surveyed on days when the air quality differed.

While much of the economics literature on happiness focuses on deep questions about the rationality of economic actors, interpersonal comparisons of ordinal utility functions, and links between economics and psychology, economists are also attempting practical, policy-relevant applications.[4] Recent work uses happiness surveys to evaluate people's willingness to trade off unemployment for inflation and argue that central bankers place too much emphasis on combating inflation (Di Tella et al., 2001), to examine the welfare consequences of German reunification on different groups (Frijters et al., 2004), to assess the degree to which state cigarette taxes make smokers better off by helping them quit (Gruber and Mullainathan, 2005), and to estimate the degree to which the marginal utility of consumption increases or decreases

[2] Kahneman (2000) writes about individuals having a base level of stated well-being, which major life events (divorce, injury) perturb at most for a few years. Others, such as Oswald and Powdthavee (2008), show incomplete recovery of happiness after such events. Graham (2009) provides evidence about adaptation to crime, corruption, democracy, and health.

[3] See Luttmer (2005). Also, recent work suggests this relative interpretation may be optimal from an evolutionary standpoint (Rayo and Becker, 2007).

[4] These practical applications raise concerns among critics of this "happiness economics" literature. Smith (2008) writes that "the [happiness economics] train is precipitously close to leaving the station and heading for use in full-scale policy evaluation."

when people become ill (Finkelstein et al., 2008). Happiness measures have also been used to try to place a monetary value on airport noise (van Praag and Baarsma, 2005), flood disasters (Luechinger and Raschky, 2009), terrorism (Frey et al., 2009), and weather and climate (Rehdanz and Maddison, 2005; Becchetti et al., 2007; Barrington-Leigh, 2008).

Several papers close in spirit to this one use happiness measures to value air quality. Welsch (2002, 2006, 2007) estimates values of willingness to pay for air quality using various cross-sections and panels of country-level data. The 2006 paper, for example, estimates that the reductions in nitrogen dioxide (NO2) and lead pollution in Europe from 1990 to 1997 were worth \$760 per capita and \$1390 per capita, respectively. Di Tella and MacCulloch (2008) regress happiness on income and the national, annual, per-capita emissions of sulfur dioxide (SO2), and show that a one-standard-deviation increase in SO2 correlates with a decline in happiness equivalent to a 17 percent reduction in income. As first uses of happiness data to estimate willingness to pay for air quality, these works break new ground. However, they also face an obstacle common to this literature – using average annual national measures of air quality. Aggregating environmental quality across entire countries masks much of its heterogeneity. I suspect that environmental quality varies more across locations within Germany than between Germany and France. If the Easterlin paradox suggests people become habituated to their material circumstances, they may also become habituated to their environmental circumstances.

Two recent papers avoid the problems associated with inter-country comparisons of happiness by looking across regions within Ireland (Ferreira et al., 2006) and Germany (Luechinger, 2009). Luechinger uses annual mean concentrations of SO2 at 533 monitoring stations in Germany over a 19-year period. To control for sorting by individuals into different locales, he cleverly instruments for air quality using respondents' locations upwind and downwind of large power plants that installed SO2 emissions control equipment. Luechinger finds a marginal willingness to pay of \$232 for a one microgram per cubic meter ($\mu g/m^3$) reduction in SO2, while average SO2 concentrations fell by 38 $\mu g/m^3$ over the time period he examines.[5]

In theory, all of the prior work using happiness to value public goods, air quality included, could suffer from a version of the Easterlin paradox. If happiness does not increase

[5] €183 in 2002, converted to 2008 dollars using the average 2002 exchange rate and the CPI-U-RS.

systematically with income across countries or over time, we should be surprised if it increases with public good levels across countries or over time, perhaps because people become habituated. In that case, it seems unlikely that happiness questions can be used to value public goods using data on aggregate yearly or national public good levels. Furthermore, work based on cross-country differences faces the problem that survey questions are asked in various languages and cultures, where notions of happiness may differ.

This paper solves these problems. It focuses entirely on the U.S., so fewer language and cultural differences complicate the responses to questions about happiness. Instead of aggregate national or yearly measures of pollution, it uses the environmental quality at the time and in the location where the happiness survey question was asked.[6] Time and place fixed effects can account for relative differences in happiness, and the measured effect of pollution on happiness will be relative to similar respondents who were interviewed in the same place during the same month, but happen to have been interviewed on a day when the air quality differed.

3. Data and methodology

For happiness measures, I rely on the General Social Survey (GSS), which is conducted annually by the National Opinion Research Center.[7] Several thousand respondents are interviewed in person each year, usually in March. The key GSS question asks "taken all together, how would you say things are these days? Would you say that you are very happy, pretty happy, or not too happy?" This question forms the basis for the dependent variable. In addition to asking about happiness, the GSS contains the usual demographic information: age, household income, race, education, sex, marital status, etc.[8]

Importantly for this purpose, the GSS contains the date each respondent was questioned. I have obtained from the GSS staff the confidential codes identifying the county or city in which each respondent was surveyed. These two pieces of information (date and place) allow me to

[6] Barrington-Leigh (2008) examines time and place-varying weather conditions, and finds results similar to those found here for pollution conditions: current local weather affects stated well being.
[7] More information about the GSS can be found at www.norc.org/GSS+Website/.
[8] The GSS income variable is categorical, and the categories change periodically. But there are numerous categories each year (21 in 1993), and the GSS has converted these into real values by taking the midpoints of the ranges and adjusting for inflation and topcoding. I use the GSS reported real income (Ligon, 1989).

match the GSS to the particular air quality on the day and in the place where the survey was administered.

For air quality information, I turn to the EPA's Air Quality System (AQS). The AQS contains the raw, hourly and daily data from thousands of ambient air quality monitors throughout the United States. The data include the geographic location of each monitor, the types of pollutants monitored, and the hourly observations.[9]

Finally, I control for the current local weather – specifically temperature and precipitation, both of which are likely to be highly correlated with both happiness and pollution. Previous studies have estimated happiness as a function of annual averages of weather (Rehdanz and Maddison, 2005; Barrington-Leigh, 2008) or pollution (Welsch, 2007; Luechinger, 2007; Di Tella and MacCulloch, 2008). But none have included both, a potentially important source of omitted variable bias. I obtained from the National Climate Data Center the daily weather at each of the thousands of weather monitoring stations throughout the U.S.

To merge the survey data with the weather and air quality data, I take the population-weighted centroid of the GSS respondent's county and draw an imaginary 25-mile circle around it. I then take a weighted average of all the air quality and weather monitors within the 25 mile circle, where the weights are equal to the inverse of the square root of their distance to the population-weighted centroids.[10]

The air quality monitors contain data on ambient concentrations of criteria air pollutants, but not all data are available in all places or during all time periods. Carbon Monoxide (CO), for example, does have consistently measured data in many locations going back to the early 1970s. However, CO is odorless and invisible, and I would not expect it to affect happiness responses in survey data. Airborne particulates, on the other hand, cause physical discomfort, especially particles smaller than 10 micrometers (PM10). In addition, small particles form visible haze that reduces visibility and may affect people aesthetically. The AQS contains PM10 readings beginning in the mid-1980s, so I begin this analysis in 1984.

[9] Recent years are available on the AQS web site, earlier years by special request to the EPA. More information about the AQS can be found at www.epa.gov/ttn/airs/airsaqs.

[10] Other weights, such as a simple average of all the monitors in a county, yield similar results. The process of matching the GSS data to air quality and weather monitors is not simple. The GSS geographic codes sometimes correspond to individual cities, sometimes to counties, and sometimes to multi-county areas. Over the 30 years, the GSS has surveyed about 275 areas, and the names given to these areas do not typically correspond to U.S. Census or U.S. Postal Service names.

For particulates, monitoring stations only record ambient concentrations every six days. That means that many of the happiness survey questions were asked on days when no nearby air quality monitors recorded data. Moreover, in any given location different days may be recorded by different sets of nearby monitoring stations. To smooth out this variation, and to use as much of the happiness survey responses as possible, I interpolate between 6-day observations for each monitoring station. In the robustness checks below, I also report results for the subset of monitoring stations with true, uninterpolated values.

Table 1 presents some descriptive statistics for the GSS, broken out by happiness response. People with larger annual incomes are more likely to have higher levels of happiness. (Asterisks indicate statistically significant differences from the column to the left.) Note that this does not contradict the Easterlin paradox, as most of the income variation is across individuals within years. Other demographic variables correlated with happiness include marital status, employment, race, education, and health.

Methodology

I estimate versions of the following function:

$$H_{ijt} = \alpha P_{jt} + \gamma \ln Y_i + X_i{}'\beta + \delta_j + \eta_t + \varepsilon_{ijt} \qquad (1)$$

where H_{ijt} is the stated happiness of respondent i in location j at date t. The variable P_{jt} is the air pollution at location j at date t. The log of income ($\ln Y_i$) is convenient here because it captures declining marginal effect of income on happiness, consistent with typical papers estimating happiness functions, and it translates directly into an increasing marginal willingness to pay for air quality (which I test explicitly later).[11] Below I show that the estimated tradeoffs between pollution and income are unchanged if I substitute the log of pollution, the log of income, ordered probit versions of those, include multiple interactions, or estimate a binomial probability that $H_{ijt} > H^*$ for an arbitrary H^*. The vector X_i contains a set of other socio-economic characteristics of respondent i, δ_j is a location-specific fixed effect, and η_t is a time fixed effect.

Once estimated, I can totally differentiate the function, set dH=0, and solve for the average marginal rate of substitution between pollution and income, $\partial Y/\partial P$:

[11] Using the log of income also avoids the unattractive feature of exponential functional forms in that the MRS does not become undefined in the middle of the relevant range. See Layard et al. (2006) for alternatives.

$$\frac{\partial Y}{\partial P}\Big|_{dH\equiv 0} = -Y\frac{\hat{\alpha}}{\hat{\gamma}} \tag{2}$$

the amount of annual income necessary to compensate for a one-unit increase in air pollution. To avoid the cumbersome phrase "average marginal rate of substitution," henceforth I will use the term "willingness to pay" (WTP), fully recognizing that equation (2) represents no one person's stated willingness. Rather, it represents an estimate of the tradeoffs between income and air quality that will leave people, on average, equally happy.[12]

Some Theoretical and Practical Concerns

Using equation (2) to measure marginal rates of substitution involves placing some strong assumptions on the underlying utility functions. We typically assume individuals make choices as though they are maximizing some unobserved utility function, observe market prices and the choices people make, and infer from those prices and choices properties of their underlying utility functions, such as risk aversion, impatience, and altruism. The fundamental challenge facing economists valuing public goods is that we do not observe market prices or choices. There are no markets for public goods such as air quality, and individuals cannot "choose" their own level of public goods directly, except by voting or relocating. So instead, this analysis proposes turning the typical economics around. We will observe utility, or a proxy for utility, and infer what choices people would be willing to make and what prices would therefore be optimal.

The first problem with this approach is that "happiness" as recorded by questions on surveys is not utility. Kahneman (2000) addresses this, distinguishing between "decision utility," which is economists' notion of the underlying individual welfare function that drives economic choices, and "experience utility," something closer to stated happiness, experienced moment-to-moment. We do not observe either type of utility directly, and in fact the survey questions are not clear about which they seek, asking only how happy people are "these days?" Perhaps the easiest way to think about this methodology is that it uses respondents' stated happiness as a proxy for their utility, or as an observable manifestation of latent utility. As long as respondents

[12] Naturally, alternative formulations of (1) lead to different expressions for WTP in (2). For example, using the level of income instead of its log means that, conveniently, WTP can simply be expressed as the ratio of the coefficients on pollution and income, $\hat{\alpha}/\hat{\gamma}$.

with higher latent utility are more likely to say they are happier, this approach is consistent with a wide variety of discrete choice models in economics.

Another potential concern about the approach proposed here is that the GSS asks about how "things are these days?" The question not only may confound experience and decision utility, but also is unclear what length of time "these days" refers to. If the question is about general well-being spanning several months or years, it should not be influenced by temporary changes such as the current daily level of air pollution relative to a regional seasonal norm. Psychologists and economists have found, however, that people tend to respond to these types of questions based on contemporaneous circumstances. Schwarz and Strack (1991) describe how people interviewed after making a photocopy were significantly more satisfied with their lives if they found a dime on top of the copy machine. And Clark and Georgellis (2004) test whether reported "job satisfaction" proxies for "experience utility," meaning something like the instantaneous happiness I would like to use, as opposed to "decision utility." They find the likelihood of quits by British laborers to be predicted by current and lagged values of reported job satisfaction, suggesting that reported satisfaction has a current component.

In other words, people asked about their overall satisfaction with life in general respond in a way that is sensitive to current conditions. I wish, in retrospect, that the GSS had asked people *two* happiness questions: one about their overall life satisfaction, and one about their happiness at the moment the question is asked. I would use the second question to identify the effect of contemporaneous local pollution. Given that the survey only asks the vague "these days" question, it is fortunate that people seem to respond as if they had been asked the momentary happiness question, in a way that is useful for valuing current levels of air quality.

A third likely objection to this approach is that economists normally assume utility is ordinal, rather than cardinal, and that interpersonal comparisons based on stated happiness are impossible. If an unpolluted day moves person #1 from "not happy" to "very happy," and person #2 from "not happy" to "pretty happy," that does not mean that person #1 gets more utility from clean air than person #2, or that person #1 would be willing to pay more for clean air. Put differently, we could alter some people's happiness functions by a positive monotonic transformation, while leaving others' unchanged, and it will yield the same rank ordering of outcomes for each individual. It will not, however, yield the same estimates of equation (1).

Economists studying happiness have responded to this concern in several ways. Some, like Ng (1997), have argued that ordinal utility is an overly restrictive assumption, and that there is ample evidence that people's utilities are interpersonally comparable and cardinal. Others have implicitly assumed that happiness is ordinal, but is interpersonally comparable. In other words, if the latent utility of person #1 is higher than that of person #2, then the stated happiness of person #1 will be higher than that of person #2. This allows researchers to estimate an ordered discrete choice model, such as an ordered logit or probit. Alesina et al. (2004), Blanchflower and Oswald (2000), and Finkelstein et al. (2008) follow this empirical approach. Most researchers who have applied both approaches have found little difference between the results of a linear regression and an ordered logit or probit (Ferrer-i-Carbonell and Frijters, 2004).[13] Since I am not interested in the marginal utility of income or air quality separately, but only the ratio of the two as in equation (2), the analysis here is less sensitive to these issues. I show below that the estimate of equation (2) is robust to a wide variety of empirical specifications.

Finally, economists should be concerned that income is endogenous with respect to happiness. While more income may make people happier, inherently happier people may earn higher incomes. Very few papers address this. Luttmer (2005) instruments for household income using interactions between the respondents' and spouses' industry, occupation, and location. Powdthavee (2009) uses time series data on the number of household members working. Both find that in IV specifications the income coefficient is much larger – three times larger in Luttmer's case. This suggests that equation (2) will overstate the marginal willingness to pay for air quality. Unfortunately, the GSS is not a panel, so I cannot employ either author's IV strategy. Instead, the focus here is on obtaining convincing evidence for the effect of pollution on happiness, based on exogenous daily variation, and then using that cautiously to infer a marginal willingness to pay.

In the end, all I can do is remain cognizant of these strong assumptions, remind readers that standard approaches to valuing environmental quality (travel costs, hedonics, stated preferences) have their own sets of strong assumptions, and demonstrate that the results obtained

[13] One key advantage of the regression approach over the ordered probit is that the former can include fixed effects. So if there are individual or region-specific norms for happiness, those can be differenced out. Allowing for individual fixed effects in an ordered probit generates inconsistent estimates (Cameron and Trivedi, 1998). There have been two recent proposed econometric approaches that deal with this in the context of economics and happiness: Boes and Winkleman's (2004) generalized threshold and sequential models, and Ferrer-i-Carbonell and Frijters' (2004) conditional fixed-effect ordered logit.

from this approach are robust, and yield plausible valuations and sensible differences for various subsets of the sample population.

4. Results

Table 2 begins by estimating versions of equation (1). The first column excludes every right hand side variable except income and daily local pollution, measured using particulates (PM10). Happiness increases with annual income and decreases with pollution on the day of the interview. The coefficients suggest that a 10 $\mu g/m^3$ increase in local daily particulates is associated with a decrease in happiness of 0.014, on a three-point scale. The log income coefficient suggests that a 10 percent increase in annual income is associated with an increase of happiness of 0.013, on a three-point scale. However, since happiness may be regarded as only ordinal (or a proxy for utility which is ordinal), I do not want to make too much of the absolute magnitudes. More important is the ratio of the two coefficients, or the tradeoff between pollution and income that leaves people at the same level of happiness.

To place a dollar value on air pollution, we need to calculate equation (2). Plugging in −0.0014 for $\hat{\alpha}$, 0.132 for $\hat{\gamma}$, and 42.3 for the mean income (in $1000s), we get that the average marginal rate of substitution is $\partial Y/\partial P$=$464.[14] This means that a one $\mu g/m^3$ increase in PM10, on the day of the interview, reduces an average person's stated happiness by an amount equal to a $464 decline in annual income. What does this mean? This is where some ambiguity arises. The $464 figure represents an estimate of the amount of *annual* income that increases happiness (at the mean log income in the sample) by the same amount as a one $\mu g/m^3$ reduction in PM10 pollution, but the PM10 coefficient is identified from *daily* fluctuations in air quality. If we divide the $464 by 365 days per year, we get an estimate of $1.27 per day. A $464 increase in annual income means an extra $1.27 to spend each day. To try to put this into context, note that the standard deviation of PM10 is 14.4 $\mu g/m^3$. Our estimate, then, corresponds to a willingness to pay $18 (14.4×$1.27) for a one-standard-deviation improvement in air quality, for one day.

Column (2) adds the average particulate count for each respondent's location, for the month in which the survey was taken. Now the daily PM10 measure is identified from the

[14] The mean real (2008) household income for the 6052 observations in Table 2 is $62,000. But the mean *log* income, where income is in thousands, is 3.75, which corresponds to $42,000.

difference between air quality on the day of the survey, and the prevailing conditions that month. The monthly coefficient is statistically insignificant. One interpretation is that the monthly values are merely imprecise measures of the daily values, which is what people really care about. Another is that people become habituated to their environmental circumstances, and respond only to daily departures from the local norm.[15] The daily coefficient increases, suggesting a willingness to pay of $23 rather than $18. Column (3) adds year, month, and county fixed effects.[16] These do not change the basic findings, and the year and location fixed effects (unreported) are statistically insignificant, an unsurprising result given the Easterlin paradox.

Finally, column (4) adds a battery of demographic and local covariates. Happiness decreases and then increases with age, falling to a minimum at about age 40. Women, and people who are married, not unemployed, and healthy are happier. Happiness rises with temperature at low temperatures, falls with temperature at high temperatures, and rises in the difference between the daily max and min, which proxies for cloud cover or humidity. None of these are surprising and all conform to standard results in this literature. More importantly, none change the basic result that happiness increases with income and decreases with local daily pollution. If anything, the demographic variables halve the coefficient on income, thereby doubling the estimate of WTP to $41 for a one-standard-deviation change in PM10.

Table 3 presents a sample of some of the alternative specifications I have tried. Column (1) uses the level of income, rather than its log, on the grounds that WTP likely increases with income. Nothing changes, except of course the formula for calculating WTP. (See fn. 12.) Column (2) uses both the log of income and the log of PM10, again with no discernable change in the calculated WTP. Column (3) estimates equation (1) as an ordered probit, and again the qualitative results are the same. Column (4) estimates a probit where the dependent variable is an indicator for the highest happiness response, with little change to the measured tradeoff between pollution and income, though the estimated WTP is somewhat higher ($65).[17] Table 3

[15] The standard errors on the monthly values are large, meaning we cannot differentiate between these interpretations. Monthly fixed effects, added next, also account for seasonal effects. If people are happier in spring, say, and particulates are lower in the spring, that would bias the results absent monthly fixed effects.
[16] Note that this standard deviation of 14.4 $\mu g/m^3$ represents variation both across and within year-month-county "cells." The average standard deviation within cells is 5.7 $\mu g/m^3$. The sample includes an average of 776 observations per year, 2305 per month, and 142 per county. The average year-month-county cell has 10 observations, ranging from 1 to 59.
[17] I also estimated versions of equation (1) as both linear probabilities and probits that H>1 and H>2, respectively, again with the same results.

thus demonstrates that respondents' stated happiness varies systematically with their incomes and the local daily air quality in ways that are robust to a variety of empirical specifications.

Table 4 estimates the basic linear specification from column (4) of Table 2 for alternative measures of air quality. First, the results so far use air quality measures that interpolate between readings that occur every six days. As an alternative, I tried using only those observations where there was a true uninterpolated reading at a nearby station. Those results are summarized in column (1) of Table 4. The effects of pollution and income on happiness are both slightly larger, leading on balance to a smaller estimate of the willingness to pay for a one $\mu g/m^3$ reduction in PM10 ($953). Because the variance across the uninterpolated values is higher (18.2 rather than 14.4), the WTP for a one standard deviation change is slightly higher, $47.

Column (2) of Table 4 estimates equation (1) for ozone. Here the coefficient on pollution is negative, but statistically insignificant. The point estimate of WTP for a one standard deviation change is $13. My initial expectation was that the ozone coefficient would be significant, since ozone is associated with aesthetically unpleasant brown skies. However, the fact that the GSS is collected mostly in March of each year, whereas ozone is largely a summer phenomenon, means that I may be unable to identify an ozone effect with these data.

Column (3) reports results for SO2. This is the pollutant studied by Luechinger (2009), using annual averages for SO2 upwind and downwind from power plants. In my case, the SO2 coefficient is statistically insignificant, though the point estimate leads to a WTP of $10. My guess is that the different result stems from the fact that SO2 is less ubiquitous than PM10. SO2 poses a particular problem downwind of coal-fired electric power plants. By focusing on respondents in the neighborhood of such plants, Luechinger was able to identify an SO2 effect. My study covers many areas without significant SO2 problems.

Column (4) of Table 4 reports results for carbon monoxide (CO). Again the coefficient on CO is statistically insignificant, and the point estimate, for a one standard deviation change, is $14. I am not surprised that daily CO has no effect on happiness, as it is both odorless and colorless – any effect of CO on reported well-being would necessarily be the result of its correlation with omitted covariates.

Finally, columns (5) through (7) of Table 4 run the basic specification for PM10, but also include daily measures of Ozone, SO2, and CO, respectively. In each case, the PM10 coefficient is essentially unaffected, the additional variable is statistically insignificant, and the WTP for a one-standard-deviation in PM10 stays within the same range – between \$30 and \$50.

Magnitudes

So far, I have been discussing willingness to pay for a one-standard-deviation change in pollution, which amounts to 14.4 $\mu g/m^3$ for the interpolated PM10 measurements. How large is this change? The average PM10 reading in the sample is 30.4 $\mu g/m^3$, so one standard deviation constitutes a 50 percent change in pollution. More concretely, the counties of Riverside and San Bernardino, CA, had average readings in this sample of 37 and 38 $\mu g/m^3$, respectively, while Washington, DC's average was 26, slightly cleaner than average. So the change we are discussing amounts to slightly more than a move from an average day in DC to an average day in the most-polluted regions of the U.S.

Perhaps a more relevant benchmark compares the value of air quality from this new estimate to those of the traditional approaches. The 1999 EPA publication *Benefits and Costs of the Clean Air Act*, estimates that the 1970 and 1977 Clean Air Act Amendments reduced ambient particulate matter by an average of 45 percent nationally. This improvement in air quality is predicted to have reduced premature mortality, chronic bronchitis, days with respiratory symptoms, and lost work days, each of which is assigned a monetary value based on the existing economics literature valuing health costs and statistical lives. The total benefit of just those improvements due solely to the reduction in particulate matter is slightly over 1.6 trillion 2008 dollars, or \$6880 per capita, or \$19 per day per person.[18] By comparison, the value of \$41 per day in Table 2 does not seem out of the question. In theory, the happiness approach incorporates all of the effects in the EPA study, as well as aesthetic values, ecological effects, non-monetized health effects, altruism, and any immediately observable consequences of multiple pollutants correlated with PM10.

An alternative to using health and mortality would be the hedonic method. Smith and Huang (1995) conduct a meta-analysis of this literature, and find an average marginal willingness to pay for a one $\mu g/m^3$ reduction in total suspended particulates of \$226 (in 2008 dollars). A 14.4 $\mu g/m^3$ increase would be worth \$3254, which amortized at 5 percent comes out

[18] Calculations based on tables ES-1 and ES-3 in EPA (1999), adjusted for inflation using the CPI-U-RS, and a 1990 48-state US population of 247 million.

to \$163 per year, or considerably less than \$1 per day. More recent work by Chay and Greenstone (2005) compares housing values in U.S. counties according to whether they are in compliance with National Ambient Air Quality Standards, using an instrumental variables approach, and finds that housing values in non-compliance counties grew by an average of \$2774 between 1970 and 1980 (in 2008 dollars) due to the Clean Air Act.[19] Amortized at 5 percent this amounts to \$137 per year, comparable to the Smith and Huang numbers, but again considerably less than the values in EPA (1999) or this study.

Probably the most controversial methodology for valuing environmental quality is contingent valuation – asking respondents directly to place monetary values on environmental changes. The EPA uses a version of this approach in calculating the benefits of the Clean Air Act, in that the monetary benefits of reduced mortality and morbidity come from contingent valuation studies. One could imagine, however, asking directly about air quality. A seminal example of this approach is an EPA-sponsored evaluation of air quality in California (Loehman et al., 1985). They asked respondents whether or not they would vote to improve air quality by 30 percent, along with associated health and visibility, at various costs, and showed them photographs of the sky with clean and dirty air. The average annual willingness to pay was \$980 in Los Angeles and \$251 in San Francisco (in 2008 dollars). While not directly comparable to the 14.4 $\mu g/m^3$ improvements discussed above, these results seem considerably smaller than those in the EPA analysis of the Clean Air Act or these results using happiness data.

One possible explanation for why the estimates here are so much larger than typical damage estimates for air pollution involves my treatment of household income as exogenous. The solution, instrumenting for household income, is conceptually difficult, especially in this context where I have no time-series variation in respondents' incomes. For instruments, we need exogenous changes in income that have no independent effect on happiness. Powdthavee (2009) does have panel data, and he instruments for respondents' household incomes using changes over time in the number of household members working, and finds that the coefficient on household income doubles. Luttmer (2005) instruments for household incomes using the respondents' and spouses' industry, occupation, and location, taking advantage of the fact that he has a panel of respondents over time. Respondents who work in occupations and industries where the average

[19] Kim et al. (2003) find a nearly identical value (\$2333) for a 4 percent decline in mean ambient SO_2 concentrations.

wage grows, or whose spouses work in such occupations and industries, are likely to experience higher household incomes themselves, and are therefore more likely to report higher levels of happiness. Using this instrument, Luttmer finds the coefficient on happiness is three times as large as when he uses household income directly. This suggests I should divide the estimated WTP here ($41 per day) by three. The result, $14 per day, or $5000 per year, is lower than the EPA (1999) estimate, but still considerably higher than the hedonic or contingent valuation estimates.

Robustness and interactions with other demographics

One natural test of whether these results truly measure reactions to air pollution, and not some spurious covariate, is to check whether they vary sensibly with respondents' characteristics. A natural candidate is income. If environmental quality is a normal good, we would expect WTP to increase with income. To test this directly, I include an interaction between the income variable and the daily PM10 count. To ensure that the coefficient α_1 can be interpreted in the same way as previously, at the average income, I interact pollution with the difference between the respondent's log income and the mean log income in the sample. Bars above variables denote means.

$$H_{ijt} = \alpha_1 P_{jt} + \alpha_2 P_{jt}\left(\ln Y_i - \overline{\ln Y}\right) + \gamma \ln Y_i + X_i{}'\beta + \delta_j + \eta_t + \varepsilon_{ijt} \qquad (3)$$

Results are reported in the first column of Table 5. The pollution coefficient is unchanged by the inclusion of the interaction, and although the interaction term's coefficient ($\hat{\alpha}_2$) is not statistically significant, the two terms together ($\hat{\alpha}_1$ and $\hat{\alpha}_2$) are jointly significant and the interaction coefficient is negative, suggesting that higher-income individuals are willing to pay more for clean air.

The marginal rate of substitution between income and air quality in this case, for the average level of pollution and log income, is

$$\frac{\partial Y}{\partial P}\bigg|_{dH=0} = -Y\frac{\left[\hat{\alpha}_1 + \hat{\alpha}_2(\ln Y - \overline{\ln Y})\right]}{\left[\hat{\gamma} + \hat{\alpha}_2 P\right]} \qquad (4)$$

As shown at the bottom of Table 5, the point estimates in column (1) are such that people in the 25th percentile of the GSS income distribution appear willing to pay $33 for a one standard deviation change in air quality, and people in the 75th percentile appear to be willing to pay $51.

Another variable we might expect to be correlated with willingness to pay for air quality is the local average air quality. This could go in one of two directions. People could become habituated to poor air quality, and a one μg/m^3 change could affect people less in polluted areas than in clean areas. Or, if marginal disutility from pollution increases, we could find the opposite. In column (2) of Table 5 I estimate a version of

$$H_{ijt} = \alpha_1 P_{jt} + \gamma \ln Y_i + \alpha_2 P_{jt} I_{ijt} + X_i ' \beta + \delta_j + \eta_t + \varepsilon_{ijt} \quad (5)$$

where I_{ijt} represents the interacted variable, in this case local monthly pollution. Here again the interaction is statistically insignificant, but the interaction and the pollution variables together are jointly significant. The point estimate of the interaction is positive, suggesting the first interpretation – if anything pollution affects happiness less in polluted areas. The marginal rate of substitution can be calculated as

$$\frac{\partial Y}{\partial P}\Big|_{dH \equiv 0} = -Y \frac{\left[\hat{\alpha}_1 + \hat{\alpha}_2 I\right]}{\hat{\gamma}} \quad (6)$$

where I is the interacted variable. Calculating this at the 25th percentile of the PM10 distribution, WTP is \$48. At the 75th percentile, WTP is \$40.

PM10 is especially harmful for people with asthma or other respiratory problems. The GSS does not have data on respiratory problems *per se*, but does have self-reported health status: "fair," "poor," etc. In column (3) of Table 5 I include an interaction between the indicator for whether a respondent's health status is fair or worse and the PM10 count. The interaction term is statistically insignificant and positive, suggesting that people in poor health are not made even more worse-off during high PM10 days than people in good health. This may be an indication that the PM10 variable is measuring a spurious correlation between something unmeasured, air pollution, and happiness. Or, it may be a reflection of the crude nature of the health variable. For example, it could be that people in excellent health are more likely to exercise out-of-doors, and therefore be more affected by PM10 than people in poor health who remain indoors regardless of pollution levels. The bottom of column (3) reports the point estimates of WTP for people in poor health and those in better health, \$25 and \$46, respectively.

If the health variable captures people likely to remain indoors, perhaps weekends can proxy for time spent outdoors. In column (4) I interact pollution with an indicator for whether the respondent was surveyed on a weekend day. In fact, the interaction variable has the opposite sign, suggesting that people are willing to pay *less* for air quality on the weekends – \$9 instead of \$54 – though again the interaction term alone is statistically insignificant.

Another natural candidate to interact with pollution is whether the respondent considers himself an environmentalist. In the contingent valuation approach, environmentally-minded respondents create problems because some claim to be unwilling to pay anything for reduced pollution, out of the belief that environmental quality should be free, or that polluters should be required to pay for cleanup. Others claim to be willing to pay unrealistically large amounts, perhaps hoping their responses will help determine policy. This happiness approach avoids those strategic response problems because respondents are not asked directly about the environment or their willingness to pay to improve it. They are only asked about their happiness, and I use data from other sources to gather information about the air quality where and when the happiness question was asked.

In 1993, the GSS began asking respondents if they are a "member of any group whose main aim is to preserve or protect the environment," or if in the last five years they have "taken part in a protest or demonstration about an environmental issue," "given money to an environmental group," or "signed a petition about an environmental issue." People who respond yes to all four, I label "environmentalists," and in column (5) of Table 5 I include the environmentalist indicator and its interaction with pollution. The interaction is negative, as expected, suggesting pollution reduces the well-being of environmentalists by more than non-environmentalists, but it is statistically insignificant, perhaps due in part to the fact that the environmental questions were asked only on recent surveys, so column (5) has many fewer observations.

To examine if older people are willing to pay more for improved air quality, I estimated a version of equation (5), replacing the interaction variable with an indicator for whether or not the respondent is over age 69. The results, in column (6) of Table 5, are largely insignificant, perhaps for the same reasons as for people in poor health. Old people are more susceptible to respiratory problems associated with high levels of particulates, but may be less likely to be outdoors and exposed to those particulates.

The other group strongly affected by PM10 is children. The GSS did not survey children, but did ask respondents if they had children. In column (7) I interact the PM10 count with a dummy for respondents with kids. The interaction is negative, but statistically insignificant.

Taken literally, the point estimate suggests that respondents with kids were willing to pay $10 more than childless respondents for a one-standard-deviation change in PM10.[20]

Column (8) interacts pollution with whether or not the respondent claims to read a newspaper "every day." This interacted term is statistically significant. In fact, it wipes out the PM10 coefficient. Taken literally, column (8) means that the willingness to pay for clean air comes entirely from newspaper readers, raising the possibility that *reported* air quality may be driving the results, as opposed to *actual* air quality. Neidell and Zivin (2009) show that people do avoid outdoor activities when local newpapers report poor air quality.

Perhaps reading a daily newspaper merely signals education. To test this, in column (9) I interact the PM10 count with the college indicator. That coefficient is statistically insignificant, though again it is jointly significant with daily PM10. The point estimates suggest college graduates are willing to pay $21 more than those without college degrees for improvements in air quality.

Finally, I was curious to see if this measure of WTP has changed over time. We know the Easterlin paradox says happiness does not increase with income over time. And it seems this has an environmental counterpart in that happiness does not change with pollution over time. That would seem to rule out the *ratio* of those two correlations changing over time, but to make sure, in column (10) I interacted the PM10 count with a year trend. The coefficient is not only insignificant but tiny. The difference between measured WTP in 1984 and 1996 amounts to only $7.

In sum, the interactions in Table 5 do not tell a completely convincing story. Many of the interaction coefficients are individually statistically insignificant, though jointly significant with PM10 levels. Many confirm our expectations, such as the fact that higher-income respondents, more educated respondents, and environmentalists appear willing to pay more for clean air. But others do not, such as the fact that those in poor health and those in polluted locales appear willing to pay less.

5. Conclusions – Advantages and disadvantages of the happiness approach

[20] MacKerron and Mourato (2009) find a similar statistically insignificant result for respondents with children.

Economists estimate the benefits of public goods using several approaches. Each has associated advantages and disadvantages. Travel cost models face difficulty valuing time spent en route and on site. Contingent valuation methods are vulnerable to biases due to framing of the question, the monetary starting points used, strategic responses, and the critique that if respondents do not know about the environmental problem until it is described by the surveyor, the very fact of conducting the survey creates the willingness to pay. Hedonic approaches suffer from Tiebout sorting and omitted variable bias. And using health care costs alone to value environmental quality understates the amount people would be willing to pay to avoid being sick in the first place.

This "happiness" approach to valuing public goods has its own set of weaknesses. It makes stronger assumptions about preferences than economists typically make, in that it compares the stated happiness of different individuals. It translates changes in stated happiness in response to temporary changes in pollution into systematic willingness to pay, while at the same time stated happiness does not seem responsive to systematic differences in pollution. And it treats household income as exogenous. Nevertheless, this new approach has a number of notable advantages.

First, the drawbacks of this approach are different from the drawbacks of the typically-used approaches. It is more direct than hedonic or travel cost models, in that it relies on surveys of people's well-being, yet it is not as direct as the contingent valuation approach, in that it does not ask about environmental quality *per se*. Thus this new approach, if nothing else, serves as a complement to existing approaches. Second, the happiness approach proposed here comes from nationally representative surveys, and so can be used to assess how willingness to pay varies over time and by region, age, income, education, current level of pollution, and concern for the environment. Third, the output can be used to estimate the marginal rate of substitution between income and air quality directly, and thus it does not suffer from the contingent valuation problem of large gaps between stated willingness to pay and willingness to accept.

Finally, economists are increasingly interested in using happiness to measure the value of public goods and bads, such as unemployment and inflation, terrorism, airport noise, inequality, and flood control. These all face the obstacle that such public goods do not vary across individuals in the same location during the same year. It seems only natural, therefore, to use this happiness approach to evaluate the economic benefits of the environment, and to take advantage of the fact that air quality changes daily in any given location.

What have we learned from this? The exercise here is unlikely to be generally useful as an everyday cost-benefit tool, if only because its data demands are too extensive. Moreover, the approach only captures one aspect of environmental damages. It cannot, for example, be used to value unnoticeable pollutants with long-term consequences. The exercise has, however, demonstrated several important points. First, the results add to the evidence that self-reported subjective well-being captures something meaningful about people's circumstances – in this case the quality of their environments. Second, the results demonstrate that pollution has a direct effect on people's welfare, at least as self-reported well-being, in addition to any measured effects through health, lost work days, and other observable outcomes. Finally, whether or not we believe the particular point estimates, the results do support a substantial tradeoff between income and environmental quality – a compensating differential for pollution.

References

Alesina, Alberto, Rafael Di Tella, Robert MacCulloch. 2004. "Inequality and Happiness: Are Europeans and Americans Different?" *Journal of Public Economics* 88(9-10): 2009-2042.

Barrington-Leigh, Christopher P. 2008. "Weather as a Transient Influence on Survey-reported Satisfaction with Life" University of British Columbia working paper.

Becchetti, Leonardo, Stefano Castrioto, and Londono Bedoya David Andres. 2007. "Climate, Happiness and the Kyoto Protocol: Someone Does not Like it Hot" Tor Vergata University Working Paper No. 247.

Blanchflower, David and Andrew Oswald. 2000. "Well being over time in Britain and the U.S." NBER Working Paper No. 7487.

Boes, Stefan and Rainer Winkelman. 2004. "Income and Happiness: New Results from Generalized Threshold and Sequential Models" IZA Discussion Paper No. 1175.

Brereton, Finbarr, J. Peter Clinch, and Susana Ferreira. 2008. "Happiness, Geography, and the Environment" *Ecological Economics* vol 65: 386-396.

Bruni, Luigino and Pier Luigi Porta. 2007. *Handbook on the Economics of Happiness*. Northampton, MA: Edward Elgar.

Cameron, A. Colin and Pravin K. Trivedi. 1998. *Regression analysis of count data.* New York: Cambridge University Press.

Chay, Kenneth and Michael Greenstone. 2005. "Does Air Quality Matter? Evidence from the Housing Market" *Journal of Political Economy* 115(2): 376-424.

Clark, Andrew E. and Yannis Georgellis. 2004. "Kahneman Meets the Quitters: Peak-End Behavior in the Labour Market" DELTA working paper.

Clark, Andrew E., Paul Frijters, and Michael A. Shields. 2008. "Relative Income, Happiness, and Utility: An Explanation for the Easterlin Paradox and Other Puzzles" *Journal of Economic Literature* 46(1): 94-144.

Deaton, Angus. 2008. "Income, Aging, Health and Wellbeing Around the World: Evidence from the Gallup World Poll" *Journal of Economic Perspectives* 22(2): 53-72

Di Tella, Rafael, Robert MacCulloch and Andrew Oswald. 2001. "Preferences over Inflation and Unemployment: Evidence from Surveys of Happiness" *American Economic Review* 91(1): 335-341.

Di Tella, Rafael and Robert MacCulloch. 2005. "Partisan Social Happiness" *Review of Economic Studies*, 72(2), 367-393.

Di Tella, Rafael and Robert MacCulloch. 2006. "Some Uses of Happiness Data in Economics" *Journal of Economic Perspectives* 20(1): 25-46.

Dolan, Paul and Robert Metcalfe. 2008. "Comparing Willingness-To-Pay and Subjective Well-Being in the Context of Non-Market Goods" CEP Discussion Paper No 890.

Di Tella, Rafael and Robert MacCulloch. 2008. "Gross National Happiness as an Answer to the Easterlin Paradox?" *Journal of Development Economics* 86(1): 22-42.

Easterlin, R. 1974. "Does Economic Growth Improve the Human Lot? Some Empirical Evidence," in P.A. David and M.W. Reder, eds., *Nations and Households in Economic Growth: Essays in Honour of Moses Abramovitz*. New York: Academic Press: 89-125.

EPA (Environmental Protection Agency). 1999. *Benefits and Costs of the Clean Air Act*: *Final Report to Congress on Benefits and Costs of the Clean Air Act, 1990 to 2010*. EPA 410-R-99-001.

Ferrer-i-Carbonell, Ada and Paul Frijters. 2004. "How Important is Methodology for the Estimates of the Determinants of Happiness?" *The Economic Journal* 114(497): 641-659.

Ferreira, Susana, Mirko Moro, and Peter Clinch. 2006. "Valuing the Environment Using the Life-Satisfaction Approach" University College Dublin working paper.

Finkelstein, Amy, Erzo F.P. Luttmer, and Matthew J. Notowidigdo. 2008. "What Good is Wealth without Health? The Effect of Health on the Marginal Utility of Consumption" NBER working paper 14089, June 2008.

Frijters, Paul, John Haisken-DeNew, and Michael Schields. 2004. "Money Does Matter! Evidence from Increasing Real Income and Life Satisfaction in East Germany Following Reunification" *American Economic Review* 94(3): 730-752.

Frank, Robert H. 1997. "The Frame of Reference as a Public Good" *The Economic Journal* 107: 1832-1847.

Freeman, A. Myrick III. 2003. *The Measurement of Environmental and Resource Values*. Washington, DC: Resources for the Future Press.

Frey, Bruno and Alois Stutzer. 2002. "What Can Economists Learn from Happiness Research?" *Journal of Economic Literature* 40(2): 402-435.

Frey, Bruno, Simon Luechinger and Alois Stutzer. 2009. "The Life Satisfaction Approach to Valuing Public Goods: The Case of Terrorism" *Public Choice*, forthcoming.

Graham, Carol. 2009. "Why Societies Stay Stuck in Bad Equilibrium: Insights from Happiness Studies amidst Prosperity and Adversity" The Brookings Institution.

Gruber, Jonathan and Sendhil Mullainathan. 2005. "Do Cigarette Taxes Make Smokers Happier?" *Advances in Economic Analysis and Policy* 5(1)

Helliwell, John F., Christopher P. Barrington-Leigh, Anthony Harris, and Haifang Huang. 2009. "International Evidence on the Social Context of Well-being" NBER Working Paper No. 14720.

Kahneman, Daniel, Peter P. Wakker, Rakesh Sarin. 1997. "Back to Bentham? Explorations of Experienced Utility" *Quarterly Journal of Economics* 112(2): 375-405.

Kahneman, Daniel. 2000. "Experienced Utility and Objective Happiness: A Moment-Based Approach" in D. Kahneman and A. Tversky, eds., *Choices, Values and Frames*. New York, Cambridge University Press.

Kahneman, Daniel. 2005. "What Were They Thinking?" *Gallup Management Journal*. January 13.

Kim, Chong Won, Tim Phipps, Luc Anselin. 2003. "Measuring the Benefits of Air Quality Improvement: A Spatial Hedonic Approach" *Journal of Environmental Economics and Management* 45(1): 24-39.

Layard, Richard. 2006. "Happiness and Public Policy: A Challenge to the Profession" *The Economic Journal* 116(510): c24-c33.

Layard, R., G. Mayraz, and S. Nickell. 2008. "The Marginal Utility of Income" *Journal of Public Economics* 92(8-9): 1846-1857.

Ligon, Ethan. 1989. "The Development and Use of a Consistent Income Measure for the General Social Survey," GSS Methodological Report No. 64. Chicago: NORC.

Loehman, Edna, David Boldt, and Kathleen Chaikin. 1985. *Measuring the Benefits of Air Quality Improvements in the San Francisco Bay Area: Property Value and Contingent Valuation Studies, Volume IV of Methods Development for Environmental Control Benefits Assessment*, EPA-230-12-85-022.

Luechinger, Simon. 2009. "Valuing Air Quality Using the Life Satisfaction Approach" *Economic Journal* 119(536):482-515.

Luechinger, Simon and Paul A. Raschky. 2009. "Valuing Flood Disasters Using the Life Satisfaction Approach" *Journal of Public Economics*, forthcoming.

Luttmer, Erzo F.P. 2005. "Neighbors as Negatives: Relative Earnings and Well-being" *Quarterly Journal of Economics* 120(3): 963-1002.

MacKerron, George and Susana Mourato. 2009. "Life satisfaction and air quality in London" *Ecological Economics* 68(5): 1441-1453.

Neidell, Matthew and Joshua Graff Zivin. 2009. "Days of Haze: Environmental Information Disclosure and Intertemporal Avoidance Behavior" Columbia University working paper.

Ng, Yew-Kwang. 1997. "A Case for Happiness, Cardinalism, and Interpersonal Comparability," *The Economic Journal* 107: 1848-1858.

Oswald, Andrew. 1997. "Happiness and Economic Performance" *The Economic Journal* 107: 1815-1831.

Oswald, Andrew and Nattavudh Powdthavee. 2008. "Does Happiness Adapt? A Longitudinal Study of Disability with Implications for Economists and Judges" *Journal of Public Economics*, 92(5-6): 1061-77.

Powdthavee, Nattavudh. 2009. "How much does money really matter? Estimating the causal effects of income on happiness" *Empirical Economics*, in press.

Rayo, Luis and Gary Becker. 2007. "Evolutionary Efficiency and Happiness" *Journal of Political Economy* 115(2): 302-337.

Rehdanz, Katrin and David Maddison. 2005 "Climate and Happiness" *Ecological Economics* 52(1): 111-125.

Rehdanz, Katrin and David Maddison. 2008. "Local environmental quality and life-satisfaction in Germany" *Ecological Economics*, 64(4): 787-797.

Schwarz, Norbert and Fritz Strack. 1991. "Evaluating One's Life: a Judgment Model of Subjective Well-Being," in Fritz Strack, Michael Argyle, and Norbert Schwarz, eds. *Subjective Well-Being: An Interdisciplinary Perspective*, 27-47. Pergamon Press.

Smith, V. Kerry. 2008. "Reflections on the Literature" *Review of Environmental Economics and Policy* 2(2): 292 - 308.

Smith, V. Kerry and Ju-Chin Huang. 1995. "Can Markets Value Air Quality? A Meta-Analysis of Hedonic Property Value Models" *Journal of Political Economy* 103(1): 209-227.

Smyth, Russell, Vinod Mishra and Xiaolei Qian. 2008. "The Environment and Well-Being in Urban China" *Ecological Economics*, 68(1-2): 547-555.

Stevenson, Betsey and Justin Wolfers. 2008. "Economic Growth and Subjective Well-Being: Reassessing the Easterlin Paradox" *Brookings Papers on Economic Activity*.

van Praag, Bernard M. S. and Barbara E. Baarsma. 2005. "Using Happiness Surveys to Value Intangibles: The Case of Airport Noise" *The Economic Journal* 115(500): 224-246.

van Praag, Bernard M. S. and Ada Ferrer-i-Carbonell. 2004. *Happiness Quantified: A Satisfaction Calculus Approach*. Oxford University Press.

Weinhold, Diana. 2008. "How big a problem is noise pollution? A brief happiness analysis by a perturbable economist" LSE Working Paper.

Welsch, Heinz. 2002. "Preferences over Prosperity and Pollution: Environmental Valuation based on Happiness Surveys." *Kyklos* 55: 473-494.

Welsch, Heinz. 2006. "Environment and Happiness: Valuation of Air Pollution Using Life Satisfaction Data" *Ecological Economics* 58: 801-813.

Welsch, Heinz. 2007. "Environmental Welfare Analysis: A Life Satisfaction Approach" *Ecological Economics* 62: 544-551.

Welsch, Heinz. 2009. "Implications of happiness research for environmental economics" *Ecological Economics*, in press.

Table 1: Descriptive statistics by Happiness Status

	Happiness (1-3)		
	"not too happy"	"pretty happy"	"very happy"
	(1)	(2)	(3)
Real income ($1000 2008)	38.7	54.8*	65.9*
- (std. dev.)	(38.6)	(46.8)	(53.0)
- no. of obs..	*3,530*	*17,153*	*9,594*
Age	45.9	44.2*	46.7*
- (std. dev.)	(18.0)	(17.3)	(17.8)
- no. of obs.	*4,305*	*20,463*	*11,582*
Female	0.58	0.56*	0.57
no. of obs.	*4,323*	*20,516*	*11,625*
Married	0.35	0.52*	0.69*
no. of obs.	*4,323*	*20,516*	*11,625*
Kids	0.74	0.71*	0.75*
no. of obs.	*4,323*	*20,516*	*11,625*
Employed	0.49	0.62*	0.59*
no. of obs.	*4,323*	*20,516*	*11,625*
Unemployed	0.080	0.029*	0.015*
no. of obs.	*4,323*	*20,516*	*11,625*
Black	0.23	0.14*	0.09*
no. of obs.	*4,323*	*20,516*	*11,625*
College grad.	0.12	0.19*	0.23*
no. of obs.	*4,323*	*20,516*	*11,625*
Health fair or worse	0.46	0.24*	0.15*
no. of obs.	*3,344*	*15,207*	*8,587*
Liberal	0.266	0.265	0.237*
no. of obs.	*4,323*	*20,516*	*11,625*
Environmentalist	0.331	0.427*	0.421
no. of obs.	*390*	*1,943*	*1,007*
Read newspaper daily	0.443	0.514*	0.567*
no. of obs.	*2,960*	*14,710*	*8,045*
Vocabulary	0.108	0.143*	0.145
no. of obs.	*2,125*	*10,906*	*6,058*
Weekend	0.310	0.298*	0.290
no. of obs.	*4,323*	*20,516*	*11,625*

Continued ...

Table 1 (continued)

	Happiness (1-3)		
	"not too happy"	**"pretty happy"**	**"very happy"**
	(1)	(2)	(3)
Temperature	44.99	44.39*	44.94*
- (std. dev.)	(14.47)	(15.01)	(14.88)
- no. of obs.	*3,836*	*18,332*	*10,373*
Precipitation (0.01")	10.57	9.78	10.19
- (std. dev.)	(28.31)	(25.44)	(26.66)
- no. of obs.	*3,932*	*18,769*	*10,715*
PM10 (μg/m^3)	29.65	30.62	30.23
- (std. dev.)	(16.67)	(18.47)	(17.96)
- no. of obs.	*763*	*3,561*	*1,898*
TSP	66.82	66.89	67.52
- (std. dev.)	(38.39)	(40.41)	(47.13)
- no. of obs.	*641*	*2,691*	*1,573*
CO	1.76	1.64*	1.65
- (std. dev.)	(1.84)	(1.59)	(2.17)
- no. of obs.	*2,715*	*12,022*	*6,553*
SO2	3.00	2.95	2.93
- (std. dev.)	(10.10)	(9.15)	(9.07)
- no. of obs.	*2,461*	*10,945*	*6,020*
Ozone	7.41	7.79	8.46*
- (std. dev.)	(17.63)	(17.78)	(18.60)
- no. of obs.	*2,267*	*9,632*	*5,382*

*Mean statistically significantly different from mean for category one column to the left, at 5 percent.

Table 2: Happiness, Pollution, and Income:
Linear regressions and PM10

	(1)	(2)	(3)	(4)
PM10 daily (μg/m^3) [α]	-0.0014*	-0.0018*	-0.0015*	-0.0016*
	(0.0006)	(0.0006)	(0.0007)	(0.0007)
log(real income ($1000 2008))	0.132*	0.133*	0.134*	0.066*
[γ]	(0.012)	(0.012)	(0.008)	(0.010)
Average PM10 by county		0.0017	0.0015	0.0015
and month		(0.0011)	(0.0016)	(0.0015)
Age (÷10)				-0.116*
				(0.030)
Age (÷10) squared				0.015*
				(0.003)
Female				0.042*
				(0.016)
Married				0.250*
				(0.018)
Kids				-0.109*
				(0.020)
Employed				-0.027
				(0.020)
Unemployed				-0.187*
				(0.054)
College grad				0.032†
				(0.019)
Health fair or worse				-0.246*
				(0.022)
Health poor				-0.212*
				(0.041)
Rain (indicator)				-0.0055
				(0.0189)
Rain (0.01 inches)				0.015
				(0.036)
Temperature mean				0.064*
(10° F)				(0.028)
Temperature squared				-0.0065*
				(0.0033)
Temp diff (daily max – min)				0.011
(10° F)				(0.013)
Weekend				-0.022
				(0.017)
Constant	1.72*	1.68*	1.90*	1.99*
	(0.04)	(0.05)	(0.27)	(0.27)
Year fixed effects	--	--	yes	yes
Month fixed effects			yes	yes
County fixed effects	--	--	yes	yes
R^2	0.044	0.044	0.050	0.123
No. obs. = 6052				
Years: 1984-1996, skipping 1992, 1995				
WTP to pay for a one μg/m^3 reduction	$464*	$572*	$467*	$1041*
	(188)	(198)	(210)	(450)
WTP to pay for a one std. dev. reduction for one day	$18	$23	$18	$41

* Statistically significant at 5 percent. †10 percent. Standard errors adjusted for clustering by county. Standard errors of WTP use the delta method.

Table 3: Happiness, Pollution, and Income:
Alternative functional forms and PM10

	linear in income	**ln(income) ln(PM10)**	**Ordered Probit: ln(income)**	**Probit Happy=3 ln(income)**
	(1)	(2)	(3)	(4)
PM10 daily (μg/m^3) [α]	-0.0016*	-0.053*	-0.0037*	-0.0039*
	(0.0007)	(0.021)	(0.0011)	(0.0014)
Income [γ]	0.0013*	0.066*	0.124*	0.101*
	(0.0002)	(0.010)	(0.019)	(0.023)
Average PM10 by county and month	0.0015	0.001	0.0024	0.0032
	(0.0015)	(0.002)	(0.0025)	(0.0029)
Age (÷10)	-0.112*	-0.115*	-0.239*	-0.189*
	(0.030)	(0.030)	(0.058)	(0.069)
Age (÷10) squared	0.014*	0.015*	0.030*	0.027*
	(0.003)	(0.003)	(0.006)	(0.007)
Female	0.042*	0.042*	0.080*	0.081*
	(0.016)	(0.016)	(0.031)	(0.037)
Married	0.253*	0.249*	0.508*	0.523*
	(0.018)	(0.018)	(0.036)	(0.042)
Kids	-0.112*	-0.109*	-0.215*	-0.229*
	(0.020)	(0.020)	(0.039)	(0.045)
Employed	-0.014	-0.027	-0.044	-0.078
	(0.020)	(0.020)	(0.040)	(0.046)
Unemployed	-0.188*	-0.187*	-0.412*	-0.279*
	(0.054)	(0.054)	(0.105)	(0.138)
College grad	0.023	0.032†	0.059	0.028
	(0.019)	(0.019)	(0.038)	(0.043)
Health fair or worse	-0.248*	-0.246*	-0.482*	-0.493*
	(0.022)	(0.022)	(0.043)	(0.055)
Health poor	-0.222*	-0.212*	-0.414*	-0.257*
	(0.041)	(0.041)	(0.082)	(0.115)
Rain (indicator)	-0.008	-0.006	-0.001	-0.010
	(0.019)	(0.019)	(0.035)	(0.042)
Rain (0.01 inches)	0.021	0.015	0.039	0.052
	(0.036)	(0.036)	(0.070)	(0.082)
Temperature mean (10° F)	0.065*	0.062*	0.081	0.067
	(0.028)	(0.028)	(0.050)	(0.060)
Temperature squared	-0.0066*	-0.0062†	-0.0091	-0.0075
	(0.0033)	(0.0033)	(0.0058)	(0.0069)
Temp diff (daily max – min) (10° F)	0.013	0.011	0.050*	0.046†
	(0.013)	(0.013)	(0.022)	(0.025)
Weekend	-0.023	-0.023	-0.049	-0.025
	(0.017)	(0.017)	(0.033)	(0.038)
Constant	2.14*	2.12*		-1.15*
	(0.27)	(0.28)		(0.58)
Year, month, county effects	yes	yes	yes	yes
R^2	0.124	0.123		
No. obs. = 6052				
Years: 1984-1996, skipping 1992, 1995				
WTP to pay for a one μg/m^3 reduction [-α/γ]	$1263*	$1112*	$1282*	$1636*
	(529)	(484)	(438)	(676)
WTP to pay for a one std. dev. reduction for one day	$50	$44	$51	$65

* Statistically significant at 5 percent. † Statistically significant at 10 percent. Standard errors adjusted for clustering by county. Standard errors of WTP use the delta method.

Table 4: Other pollutants

Dependent variable: Happiness (1-3)	PM10 without interpolation	OZ	SO2	CO	PM10 *and* OZ	PM10 *and* SO2	PM10 *and* CO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pollution (daily) [α]	-0.0019*	-0.0004	-0.00053	-0.0064	-0.0015†	-0.0019*	-0.0013†
	(0.0008)	(0.0008)	(0.00078)	(0.0072)	(0.0009)	(0.0007)	(0.0007)
Income ($1000 1986) [γ]	0.083*	0.068*	0.071*	0.068*	0.055*	0.064*	0.063*
	(0.015)	(0.009)	(0.008)	(0.008)	(0.012)	(0.011)	(0.010)
Pollution (monthly county	0.0019	0.0012	-0.0028	-0.0048	-0.0018	0.0003	0.0010
average)	(0.0023)	(0.0013)	(0.0018)	(0.0113)	(0.0022)	(0.0017)	(0.0016)
Second pollutant					0.0012	0.0023	-0.0239
					(0.0013)	(0.0019)	(0.0149)
R^2	0.14	0.13	0.13	0.13	0.13	0.13	0.13
No. obs.	2576	8177	9902	10124	3863	4930	5455
Years	1984-96	1975-96	1975-96	1975-96	1984-96	1984-96	1985-96
WTP to pay for a one μg/m³ reduction	$953*	$243	$318	$3930	$1189	$1322*	$901†
	(443)	(485)	(465)	(4461)	(743)	(561)	(495)
WTP to pay for a one std. dev. reduction for one day	$47	$13	$9	$14	$46	$50	$35

* Statistically significant at 5 percent. † Statistically significant at 10 percent. Standard errors of WTP use the delta method.

All regressions contain the other demographic and local variables, location, year and month fixed effects, as in column (4) of Table 2.

Table 5: Interactions

Dependent variable: Happiness (1-3)	Income	Local monthly pollution	Health fair or worse	Weekend	Environmentalist
	(1)	(2)	(3)	(4)	(5)
PM10 [α_1]	-0.0016*	-0.0018*	-0.0018*	-0.0021*	-0.0008
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0023)
Income ($1000 1986) [$\gamma$]	0.085*	0.066*	0.066*	0.066*	0.075*
	(0.020)	(0.010)	(0.010)	(0.010)	(0.026)
Interaction [α_2]	-0.00063	0.00003	0.0008	0.0018	-0.0014
	(0.00057)	(0.00006)	(0.0013)	(0.0012)	(0.0023)
Interacted variable		0.0004	-0.272*	-0.0755†	0.0175
		(0.0026)	(0.045)	(0.0388)	(0.0702)
N	6052	6052	6052	6052	1032
R^2	0.12	0.12	0.12	0.12	0.14
F test that pollution *and* interaction = zero	3.67*	3.22*	3.23*	4.24*	0.42
WTP to pay for a one std. dev. reduction for one day when interaction = 25th percentile	$33	$48			
WTP to pay for a one std. dev. reduction for one day when interaction = 75th percentile	$51	$40			
WTP to pay for a one std. dev. reduction for one day when interaction = 0			$46	$54	$16
WTP to pay for a one std. dev. reduction for one day when interaction = 1			$25	$9	$45

* Statistically significant at 5 percent.
† Statistically significant at 10 percent.
All regressions contain the other demographic and local variables, location, year and month fixed effects, as in column (4) of Table 2.

Table 5: Interactions (continued)

Dependent variable: Happiness (1-3)	Age > 69	Kids	Read news	College	Trend[a]
	(6)	(7)	(8)	(9)	(10)
PM10 [α_1]	-0.0016*	-0.0014*	-0.0003	-0.0015*	-0.0016*
	(0.0007)	(0.0011)	(0.0011)	(0.0007)	(0.0007)
Income ($1000 1986) [$\gamma$]	0.0066*	0.066*	0.061*	0.066*	0.066*
	(0.0010)	(0.010)	(0.012)	(0.010)	(0.010)
Interaction [α_2]	0.0002	-0.0004	-0.0034*	-0.0008	0.2×10^{-5}
	(0.0017)	(0.0012)	(0.0013)	(0.0013)	(1.7×10^{-5})
Interacted variable	-0.077	-0.097*	0.132*	0.057*	-0.0029
	(0.071)	(0.041)	(0.047)	(0.044)	(0.0080)
N	6052	6052	3688	6052	6052
R^2	0.12	0.12	0.13	0.12	0.12
F test that pollution *and* interaction = zero	3.06*	3.13*	6.44*	3.27*	3.08*
WTP to pay for a one std. dev. reduction for one day when interaction = 0	$41	$34	$9	$37	$45 (year=1984)
WTP to pay for a one std. dev. reduction for one day when interaction = 1	$37	$44	$101	$58	$38 (year=1996)

* Statistically significant at 5 percent.
† Statistically significant at 10 percent.
[a]The variable "trend" takes on the values 0 through 12 for 1984 through 1996.
All regressions contain the other demographic and local variables, location, year and month fixed effects, as in column (4) of Table 2.