

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

Arik Levinson  
Georgetown University and NBER  
*aml6@georgetown.edu*

September 2011

## Abstract

This paper describes and implements a method for valuing a time-varying local public good: air quality. It matches U.S. survey and air quality data to model respondents' self-reported happiness as a function of their demographic characteristics, incomes, and the air pollution on the date and in the place they were surveyed. People with higher incomes report higher levels of happiness, and people interviewed on days with worse local air pollution 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

## Acknowledgments

This research is part of a project funded by the National Science Foundation grant #0617839. I am grateful to Resources for the Future for its hospitality during part of the time I worked on the paper, to Emma Nicholson for superb research assistance, to the research staff at the General Social Survey for assisting me with matching confidential aspects of their data to geographic information, to Sarah Aldy for editorial help, and to Chris Barrington-Leigh, Paul Frijters, Carol Graham, John Helliwell, Simon Luechinger, Erzo Luttmer, David Maddison, George MacKerron, Robert Metcalfe, Yew-Kwang Ng, Andrew Oswald, Nick Powdthavee, Karl Scholz, Russell Smyth, Betsey Stevenson, Heinz Welsch and Justin Wolfers for helpful suggestions.

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

## 1. Introduction

Valuing local public amenities and other non-market goods is one of the greatest challenges facing applied economics. 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. In this paper, 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, air quality, 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 air quality and weather at the date and place they were surveyed. I then use the estimated function to calculate a compensating differential for air pollution: the average marginal rate of substitution between annual household income and air quality that leaves respondents equally happy.

This happiness-based methodology has a number of advantages over existing tools for valuing environmental quality. The people most averse to air pollution choose to visit and live in clean locales; as a result, travel-cost and many hedonic models may underestimate the value of air quality. But 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 these sorting biases. Because I estimate marginal rates of substitution between income and pollution directly, income effects do not confound the approach, nor do large gaps between measures of willingness to pay and willingness to accept. And because I do not rely on asking people directly about environmental issues, the methodology is not susceptible to the strategic biases and framing problems of the contingent valuation approach.

Furthermore, although happiness studies have recently been used to estimate tradeoffs made by public policies, including valuations of public goods and bads, all of the previous work has relied on annual average values across regions or countries.<sup>1</sup> If the public goods are endogenously determined by regional characteristics also associated with happiness, or if people

---

<sup>1</sup> Public policy issues studies have included 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 Metcalfe 2008), terrorism (Frey et al. 2009), and even air pollution (Welsch 2007; Di Tella and MacCulloch 2008; Ferreira et al. 2006; Luechinger 2009).

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 a vague question about how "things are these days." It identifies the relevant compensating differential based on trade-offs 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 attractive 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 uses the estimates from the first part to calculate marginal rates of substitution between pollution and income, and then computes the respondents' implicit willingness to pay for improved air quality. This step does involve several strong assumptions, but I describe those in detail and argue they are no stronger than the assumptions underlying travel cost, hedonic, or contingent valuation estimates of willingness to pay for air quality. Moreover, because the assumptions I make differ entirely from the standard set, at a minimum, the results serve as an alternative to the usual approaches.

Using my preferred specification, I show that people appear willing to sacrifice about \$40 for an improvement of one standard deviation in air quality for one day, a figure considerably

higher than typical hedonic valuations of air quality and double the value the U.S. Environmental Protection Agency (EPA) attributes to the economic benefits of the 1970 and 1977 Clean Air Acts (EPA 1999). One explanation for the large difference is that unlike the EPA approach, the happiness measure captures aesthetics, lost recreation, and benefits from other pollutants correlated with particulates.

My analysis yields two 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 from economists. 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 it does increase with income across individuals within a country at any given point in time. Some recent work challenges the first part 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 the second part remains unchallenged: stated happiness 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.<sup>2</sup> 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.<sup>3</sup>

---

<sup>2</sup> 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 that people become habituated to crime, corruption, democracy, and health.

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

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.<sup>4</sup> 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.<sup>5</sup> Recent work uses happiness surveys to evaluate people's willingness to trade unemployment for inflation and argue that central bankers place too much emphasis on combating inflation (Di Tella et al. 2001), examine the welfare consequences of German reunification on different groups (Frijters et al. 2004), assess the degree to which state cigarette taxes make smokers better off by helping them quit (Gruber and Mullainathan 2005), and estimate the degree to which the marginal utility of consumption increases or decreases 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). All use annual average measures of the public good (or bad), raising the possibility that endogeneity or habituation biases their answers.

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

---

<sup>4</sup> As one reviewer has noted, this issue should also be a concern for hedonic estimates of compensating differentials. If owners of homes in polluted regions become habituated to their circumstances, those houses may have smaller measured compensating differentials.

<sup>5</sup> These practical applications raise concerns among critics. Smith (2008) writes, "[T]he [happiness economics] train is precipitously close to leaving the station and heading for use in full-scale policy evaluation."

cross-sections and panels of country-level data. The 2006 paper, for example, estimates that the reductions in nitrogen dioxide and lead pollution in Europe from 1990 to 1997 were worth \$1,200 per capita and \$2,200 per capita, respectively, in 2008 dollars. Di Tella and MacCulloch (2008) regress happiness on income and the national, annual, per capita emissions of sulfur dioxide (SO<sub>2</sub>), and show that an increase of one standard deviation in SO<sub>2</sub> 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 share a drawback common to this literature—they use average annual national measures of air quality. Aggregating environmental quality across entire countries masks much of its heterogeneity. The standard deviation of particulate air pollution in the U.S. is twice as large if we look at daily observations within states instead of averages across states or years.

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 SO<sub>2</sub> 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 SO<sub>2</sub> emissions control equipment. Luechinger finds a marginal willingness to pay of \$232 for a one microgram per cubic meter (µg/m<sup>3</sup>) reduction in SO<sub>2</sub>, while average SO<sub>2</sub> concentrations fell by 38 µg/m<sup>3</sup> over the time period.<sup>6</sup>

In theory, all 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 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.

Two final issues contrast most prior attempts to value air quality using happiness data. First, work based on cross-country pollution differences faces the problem that it compares survey questions asked in various languages and cultures, where notions of happiness may differ. Second, air pollution and weather are highly correlated. Studies of happiness and weather omit pollution (Rehdanz and Maddison 2005; Barrington-Leigh 2008), while studies of happiness and

---

<sup>6</sup> €183 in 2002, converted to 2008 dollars using the average 2002 exchange rate and the CPI-U-RS.

pollution omit weather (Welsch 2007; Luechinger 2007; Di Tella and MacCulloch 2008). To date, none have included both, a potentially important source of omitted variable bias.

This paper solves these problems. It focuses entirely on the United States, so fewer language and cultural differences complicate the responses to questions about happiness. It controls for the current local temperature and precipitation, both of which are likely to be correlated with happiness and pollution. 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. 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 the National Opinion Research Center conducts annually.<sup>7</sup> Several thousand U.S. 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, including age, household income, race, education, sex, marital status.<sup>8</sup>

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. Knowing the date and place allows me to 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

---

<sup>7</sup> More information about the GSS can be found at <http://www.norc.org/GSS+Website/> (accessed July 26, 2010).

<sup>8</sup> The GSS income variable is categorical, and the categories change periodically. But the GSS includes numerous categories each year (21 in 1993) and converts these into real values by taking the midpoints of the ranges and adjusting for inflation and top coding. I use the GSS reported real income (Ligon 1989). I also test an instrument for income using the reported incomes of randomly selected Current Population Survey participants with similar characteristics.

throughout the United States. The data include the geographic location of each monitor, the types of pollutants monitored, and the hourly observations.<sup>9</sup> For current local weather conditions, I use data from the National Climate Data Center, which reports daily temperature and rainfall at each of the thousands of weather monitoring stations throughout the United States.

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 circle, where the weights are equal to the inverse of the square root of their distance to the population-weighted centroids.<sup>10</sup>

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.

For particulates, monitoring stations only record ambient concentrations every six days. As a result, 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 use as many of the happiness survey responses as possible, I interpolate between six-day observations for each monitoring station. In the robustness checks below, I also report results for the subset of monitoring stations with actual, 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.

---

<sup>9</sup> 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 <http://www.epa.gov/ttn/airs/airsaqs> (accessed July 26, 2010).

<sup>10</sup> Other weights, such as a simple average of all the monitors in a county, yield similar results. 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. The GSS geographic codes sometimes correspond to individual cities, sometimes to counties, and occasionally to multi-county areas. (This last group is dropped). I first translated the GSS place names to Census county codes by hand, then assigned each county its population centroid, and merged those with the data from the weather and pollution stations within 25 miles.



(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, age, employment and unemployment, race, education, and health.

### *Methodology*

I estimate versions of the following function:

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

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 ( $\ln Y_i$ ) conveniently captures the 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).<sup>11</sup> Below I show that the estimated trade-offs between pollution and income are unchanged if I substitute the log of pollution, the level of income, or ordered probit versions of those; include multiple interactions; or estimate a binomial probability that  $H_{ijt} > H^*$  for an arbitrary  $H^*$ . This robustness to empirical specification is especially important given the limited reporting categories for the happiness variable in the GSS. The vector  $X_i$  contains a set of other socioeconomic characteristics of respondent  $i$ ,  $\delta_j$  is a location-specific fixed effect, and  $\eta_m$  is a month 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,  $\partial Y/\partial P$ :

$$\frac{\partial Y}{\partial P} \Big|_{dH=0} = -Y \frac{\hat{\alpha}}{\hat{\gamma}} , \quad (2)$$

the amount of annual income necessary to compensate for a one-unit increase in air pollution.<sup>12</sup> To avoid the cumbersome phrase "average marginal rate of substitution," henceforth I will use

---

<sup>11</sup> If happiness successfully proxies for utility, we would expect diminishing marginal happiness/utility. Happiness as reported to the GSS, in three discrete categories, may not follow the same distribution. In what follows I show that the estimates are robust to a variety of functional form assumptions for equation (1). Using the log of income also avoids the unattractive feature of exponential functional forms in that the marginal rate of substitution does not become undefined in the middle of the relevant range. See Layard et al. (2008) for alternatives.

<sup>12</sup> Naturally, alternative formulations of (1) lead to different expressions for willingness to pay in (2). For example, using the level of income instead of its log means that, conveniently,  $\partial Y/\partial P$  is simply the ratio of the coefficients on pollution and income,  $\hat{\alpha}/\hat{\gamma}$ .

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 trade-offs between income and air quality that will leave people, on average, equally happy.

### *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. Public goods such as air quality have no markets, 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; 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 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 proposed approach is that the question the GSS asks is unclear about 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 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. Clark and Georgellis (2004) test whether reported "job satisfaction" proxies for "experience utility." They find that current and lagged values of reported job satisfaction predict the likelihood British laborers will quit, suggesting that reported satisfaction has a current component.

In other words, people who are 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. The second question would identify the effect of contemporaneous local pollution. Given that the survey only asks how things are "these days," 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 would yield the same rank ordering of outcomes for each individual. It would 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 ample evidence shows people's utilities are interpersonally comparable and cardinal. Others have implicitly assumed that happiness is ordinal but 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).<sup>13</sup> 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), my analysis 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.<sup>14</sup> Both find that the income coefficient in IV specifications is much larger than in OLS specifications—three times larger in Luttmer's case. This suggests that equation (2) will overstate the marginal WTP for air quality. Unfortunately, the GSS is not a panel, so I cannot employ either author's IV strategy. Instead, I try one specification where I instrument for income using randomly-selected Current Population Survey incomes for respondents from the same year and state and of the same age, sex, education, and marital status, yielding slightly smaller estimates of WTP.

In the end, my focus 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 WTP. All I can do is remain cognizant of these strong assumptions, remind readers that standard approaches to valuing environmental quality—travel costs, hedonics, contingent valuation—have their own sets of strong assumptions, and demonstrate that the robust results obtained from this approach 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  $10 \mu\text{g}/\text{m}^3$  increase in local daily particulates is

---

<sup>13</sup> One key advantage of the regression approach over the ordered probit is that the former can include fixed effects, so any individual or region-specific norms for happiness can be differenced out.

<sup>14</sup> Gardner and Oswald cleverly circumvent the endogeneity by examining the mental wellbeing of lottery winners.

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 overemphasize the absolute magnitudes. More important is the ratio of the two coefficients, or the trade-off 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 \$1,000s), the WTP is  $\partial Y/\partial P = \$459$ , as reported at the bottom of Table 2.<sup>15</sup> In other words, a one  $\mu\text{g}/\text{m}^3$  increase in PM10, on the day of the interview, reduces an average person's stated happiness by an amount equal to a \$459 decline in annual income. What does this mean? This is where some ambiguity arises.

The \$459 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  $\mu\text{g}/\text{m}^3$  reduction in PM10 pollution, but the PM10 coefficient is identified from *daily* fluctuations in air quality. If we divide the \$459 by 365 days, we get an estimate of \$1.26 per day. To put this into context, note that the standard deviation of PM10 is  $14.4 \mu\text{g}/\text{m}^3$ . Our estimate, then, corresponds to a WTP of \$18 ( $14.4 \times \$1.26$ ) for a one-standard-deviation improvement in air quality, for one day.

Column (2) of Table 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 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.<sup>16</sup> The daily coefficient increases, suggesting a WTP of \$21 rather than \$18. Column (3) adds year, month, and county fixed effects.<sup>17</sup> These do not

---

<sup>15</sup> The mean real (2008) household income for the 6,035 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.

<sup>16</sup> 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.

<sup>17</sup> Note that this standard deviation of  $14.4 \mu\text{g}/\text{m}^3$  represents variation both across and within year-month-county "cells." The average standard deviation within cells is  $5.7 \mu\text{g}/\text{m}^3$ . The sample includes an average of 774 observations per year, 2,298 per month, and 142 per county. The average year-month-county cell has 10 observations, ranging from 1 to 59.

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 maximum and minimum, which proxies for cloud cover or humidity. All these results conform with standard findings 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 \$38 for a change of one standard deviation in PM10.

Table 3 presents a sample of some alternative specifications. Column (1) uses the level of income rather than its log. Nothing changes except the formula for calculating WTP (See footnote 12). Column (2) uses both the log of income and the log of PM10, again with no meaningful change in the calculated WTP. Column (3) estimates equation (1) as an ordered probit. Column (4) estimates a probit where the dependent variable is an indicator for the highest happiness response, with little change to the measured trade-off between pollution and income, though the estimated WTP is somewhat higher at \$65.<sup>18</sup> Table 3 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 addresses some deeper issues with the approach. Column (1) includes a control variable for the PM10 count the previous day, to account for the possibility that the effects of pollution on happiness may be cumulative. The coefficient on yesterday's pollution is positive and insignificant, but its inclusion increases the negative effect of the current day's air pollution on happiness, resulting in a larger measured WTP. However, given the high degree of correlation between the two air quality measures, the point estimate of WTP over the two-day period is about the same as for the basic specification in Table 2.

Column (2) of Table 4 addresses two concerns about the measure of respondents' incomes. First, the GSS asks respondents to place their household incomes into categories

---

<sup>18</sup> 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.

representing income ranges, rather than asking them to report their actual incomes, and the income ranges change periodically. The categorical responses were converted by the GSS into intertemporally consistent values by taking the midpoint of each range and adjusting for inflation. However, because there are more than 20 categories, this first concern is not particularly worrisome. A second, deeper issue involves the endogeneity of income. Happiness and household incomes are correlated, but we do not know if that is because income causes happiness, or because happy people earn higher incomes. To address *both* issues, I match each GSS respondent to a randomly selected Current Population Survey respondent from the same state and year and with the same age, sex, education, and marital status as the GSS respondent. The coefficient on this instrumented income variable (0.084), reported in column (2) of Table 4, is larger than in the basic specification in column (4) of table 2 (0.066), consistent with Luttmer (2005) and Powdthavee (2009), resulting in a somewhat smaller WTP for air quality.

Column (3) of Table 4 addresses the concern that 12 percent of the observations are top coded. Dropping those observations with incomes in the top brackets yields estimates nearly identical to the baseline specification in table 2 that includes those observations.

Columns (4) and (5) deal with concerns about the health status variable (four categories ranging from "excellent" to "poor"). If people's self-reported health status varies daily, as a consequence of changes in pollution, then the health and pollution variables in part measure the same thing, and the WTP calculation in equation (2) that omits health will be biased. To check this, in column (4), I estimate a version of equation (1) with health status as the dependent variable, rather than happiness. Here, the coefficient on daily PM10 is small and insignificant, suggesting that people respond to the GSS health question based on their long-term health characteristics, not daily variations. To be certain, in column (5), I estimate a version of equation (1) without the health variables. The pollution coefficient is unaffected, but omitting the health variables, which are negatively correlated with both income and happiness, leads to a higher income coefficient and a correspondingly somewhat smaller estimated WTP.

Table 5 estimates the basic 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 a true uninterpolated reading was available for a nearby station. Those results are summarized in column (1) of Table 5. The effects of pollution and income on happiness are both slightly larger

than in the basic specification, leading on balance to a nearly identical estimate of WTP for a one  $\mu\text{g}/\text{m}^3$  reduction in PM10 (\$969). Because the variance across the uninterpolated values is higher than for the interpolated values ( $18.2 \mu\text{g}/\text{m}^3$  rather than  $14.4 \mu\text{g}/\text{m}^3$ ), the WTP for a change of one standard deviation is slightly higher at \$48.

Column (2) of Table 5 estimates equation (1) for ozone. Here, the coefficient on pollution is negative but statistically insignificant. The point estimate of WTP for a change of one standard deviation is \$11. My initial expectation was that the ozone coefficient would be significant, since ozone is associated with aesthetically unpleasant brown skies. However, because the GSS is collected mostly in March, when ozone is not typically a problem, I may be unable to identify an ozone effect with these data.

Column (3) reports results for  $\text{SO}_2$ . This is the pollutant Luechinger (2009) studied, using annual averages for  $\text{SO}_2$  upwind and downwind from power plants. In my case, the  $\text{SO}_2$  coefficient is statistically insignificant, and the point estimate leads to a WTP of \$9, much less than the WTP for reductions in PM10. The different result may stem from the fact that  $\text{SO}_2$  is less ubiquitous than PM10.  $\text{SO}_2$  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  $\text{SO}_2$  effect. My study covers many areas without significant  $\text{SO}_2$  problems.

Column (4) of Table 5 reports results for carbon monoxide. Again the coefficient on CO is statistically insignificant, and the point estimate, for a change of one standard deviation, is \$13. Because CO 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 5 run the basic specification for PM10, but also include daily measures of Ozone,  $\text{SO}_2$ , 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 change in PM10 stays within the same range—between \$34 and \$49.

### *Magnitudes*

So far, I have been discussing WTP for a one-standard-deviation change in pollution, which amounts to  $14.4 \mu\text{g}/\text{m}^3$  for the interpolated PM10 measurements. How large is this change? The average PM10 reading in the sample is  $30.4 \mu\text{g}/\text{m}^3$ , so one standard deviation constitutes a 50 percent change in pollution.



Perhaps a more relevant benchmark compares the value of air quality from this new estimate to those of the traditional approaches. The EPA (1999) 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 more than 1.6 trillion 2008 dollars, or \$6,880 per capita, or \$19 per day per person.<sup>19</sup> By comparison, the value of \$38 per day in Table 2 does not seem out of the question because the happiness approach incorporates all 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 WTP for a one  $\mu\text{g}/\text{m}^3$  reduction in total suspended particulates of \$226 (in 2008 dollars). A 14.4  $\mu\text{g}/\text{m}^3$  increase would be worth \$3,254, which amortized at 5 percent comes out to \$163 per year, or considerably less than \$1 per day. More recent work by Chay and Greenstone (2005) uses an instrumental variables approach to compare housing values in U.S. counties according to whether they are in compliance with National Ambient Air Quality Standards and finds that housing values in non-compliance counties grew by an average of \$2,774 between 1970 and 1980 (in 2008 dollars) due to the Clean Air Act.<sup>20</sup> Amortized at 5 percent, this amounts to \$137 per year, comparable to the Smith and Huang numbers, but considerably smaller than those in the EPA analysis of the Clean Air Act or these results using happiness data.

Probably the most controversial methodology for valuing environmental quality is contingent valuation, which asks 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

---

<sup>19</sup> 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 U.S. population of 247 million.

<sup>20</sup> Kim et al. (2003) find a nearly identical value (\$2,333) for a 4 percent decline in mean ambient SO<sub>2</sub> concentrations.

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 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. While not directly comparable to the  $14.4 \mu\text{g}/\text{m}^3$  improvements discussed above, the average annual WTP was \$980 in Los Angeles and \$251 in San Francisco (in 2008 dollars), again considerably less than the EPA's values or those in Table 2.

One possible explanation for why the estimates in this analysis are so much larger than typical damage estimates for air pollution is that I treat household income as exogenous. The solution, instrumenting for household income, is conceptually difficult, especially because 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. He 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 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 of \$38 per day by three. The result, \$13 per day, or \$4,750 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  $\alpha_1$  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.

$$H_{ijt} = \alpha_1 P_{jt} + \alpha_2 P_{jt} (\ln Y_i - \overline{\ln Y}) + \gamma \ln Y_i + X_i' \beta + \delta_j + \eta_m + \varepsilon_{ijt}. \quad (3)$$

Results are reported in the first column of Table 6. 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

$$\frac{\partial Y}{\partial P} \Big|_{dH=0} = -Y \frac{[\hat{\alpha}_1 + \hat{\alpha}_2 (\ln Y - \overline{\ln Y})]}{[\hat{\gamma} + \hat{\alpha}_2 P]}. \quad (4)$$

As shown at the bottom of Table 6, the point estimates in column (1) are such that people in the 25th percentile of the GSS income distribution appear willing to pay \$32 for a change of one standard deviation 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 WTP 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  $\mu\text{g}/\text{m}^3$  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. 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 if anything, pollution affects happiness less in polluted areas. The marginal rate of substitution can be calculated as

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

where  $I$  is the interacted variable. WTP appears to fall from \$47 at the 25th percentile of the PM10 distribution to \$40 at the 75th percentile, suggesting that habituation may overcome rising marginal damages.

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. In column (3) of Table 6, I include an interaction between the PM10 count and the indicator for whether a respondent's health status is fair or worse. The interaction term is statistically insignificant and positive, suggesting that people in poor health are not made even worse 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 outdoors and therefore are 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, \$23 and \$45, respectively.

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 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 WTP 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 (4) of Table 6, 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 it does non-environmentalists, but it is statistically insignificant, perhaps due in part to the fact that column (4) has many fewer observations than the other columns.

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 the respondent is older than age 69. The results, in column (5) of Table 6, 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 than younger people.

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 (6), 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.<sup>21</sup>

Column (7) interacts pollution with whether the respondent claims to read a newspaper "every day." This interacted term is statistically significant. In fact, it overwhelms the PM10 coefficient. Taken literally, column (7) means that WTP 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 newspapers report poor air quality.

Perhaps reading a daily newspaper merely signals education. To test this, in column (8), 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 \$19 more per day than those without college degrees for improvements in air quality.

In sum, the interactions in Table 6 do not irrefutably demonstrate the merit of this happiness approach to valuing public goods, nor do they undermine it. Although many of the interactions coefficients are individually statistically insignificant, most are jointly significant with pollution levels. Although some depart from expectations, such as the fact that respondents in poor health and polluted locales appear to value clean air less, those variations do have

---

<sup>21</sup> MacKerron and Mourato (2009) find a similar statistically insignificant result for respondents with children.

theoretically consistent explanations. Moreover, many of the interaction coefficients do make intuitive sense, such as the fact that higher-income, more educated, and environmentally minded respondents value clean air more than others.

## **5. Conclusions: Advantages and disadvantages of the happiness approach**

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 an environmental problem until it is described by the surveyor, the very fact of conducting the survey creates the WTP. Hedonic approaches suffer from Tiebout sorting and omitted variable bias. And using healthcare costs alone to value environmental quality understates the amount people would be willing to pay to avoid being sick in the first place.

The "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 WTP, 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*, avoiding any strategic response bias. As a result, this new approach, if nothing else, serves as a complement to existing approaches.

Second, the proposed happiness approach comes from nationally representative surveys and so can be used to assess how WTP varies over time and by region, age, income, education, current level of pollution, and concern for the environment.

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? This exercise is unlikely to be generally useful as an everyday cost-benefit tool, if only because its data demands are so extensive. It has been feasible in this one special case—a well-monitored, easily observable air pollutant that varies daily. We are not going to be able to use this approach to assess the value of environmental externalities that are imperceptible, such as carcinogens, or that do not vary on a daily basis, such as clean water or accident risk. 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 trade-off between income and environmental quality—a compensating differential for pollution.

## References

- Alesina, Alberto, Rafael Di Tella, and 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 247.
- Blanchflower, David and Andrew Oswald. 2000. "Well being over time in Britain and the U.S." NBER Working Paper 7487.
- Bruni, Luigino, and Pier Luigi Porta. 2007. *Handbook on the Economics of Happiness*. Northampton, MA: Edward Elgar.
- 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 Mimeo.
- 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. 2008. "Gross National Happiness as an Answer to the Easterlin Paradox?" *Journal of Development Economics*, 86(1): 22–42.
- Dolan, Paul, and Robert Metcalfe. 2008. "Comparing Willingness-To-Pay and Subjective Well-Being in the Context of Non-Market Goods." CEP Discussion Paper 890.
- Easterlin, R. 1974. "Does Economic Growth Improve the Human Lot? Some Empirical Evidence." In *Nations and Households in Economic Growth: Essays in Honour of Moses Abramovitz*, ed. P.A. David and M.W. Reder, 89–125. New York: Academic Press.
- 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. Washington, DC: EPA.



- Ferreira, Susana, Mirko Moro, and Peter Clinch. 2006. "Valuing the Environment Using the Life-Satisfaction Approach." University College Dublin Working Paper.
- 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.
- 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.
- 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.
- Frey, Bruno, Simon Luechinger, and Alois Stutzer. 2009. "The Life Satisfaction Approach to Valuing Public Goods: The Case of Terrorism." *Public Choice*, 138(3–4): 317–345.
- Gardner, Jonathan, and Andrew J. Oswald. 2007. "Money and Mental Wellbeing: A Longitudinal Study of Medium-sized Lottery Wins." *Journal of Health Economics*, 26(1): 49–60.
- Graham, Carol. 2009. "Why Societies Stay Stuck in Bad Equilibrium: Insights from Happiness Studies amidst Prosperity and Adversity." Paper presented to the IZA Conference on Frontiers in Labor Economics: The Economics of Well-Being and Happiness, Washington, DC.
- Gruber, Jonathan, and Sendhil Mullainathan. 2005. "Do Cigarette Taxes Make Smokers Happier?" *Advances in Economic Analysis and Policy*, 5(1): Article 4.
- 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 14720.
- Kahneman, Daniel, Peter P. Wakker, and Rakesh Sarin. 1997. "Back to Bentham? Explorations of Experienced Utility." *Quarterly Journal of Economics*, 112(2): 375–
- Kahneman, Daniel. 2000. "Experienced Utility and Objective Happiness: A Moment-Based Approach." In *Choices, Values and Frames*, ed. D. Kahneman and A. Tversky, 673–692. New York: Cambridge University Press.
- 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. Washington, DC: EPA.
- 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*, 93(3–4): 620–633.
- 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." *Journal of Environmental Economics and Management*, 58(2): 119–128.
- Ng, Yew-Kwang. 1997. "A Case for Happiness, Cardinalism, and Interpersonal Comparability." *The Economic Journal*, 107(445): 1848–1858.
- Oswald, Andrew. 1997. "Happiness and Economic Performance." *The Economic Journal*, 107(445): 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*, 39(1): 77–92.
- 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 *Subjective Well-Being: An Interdisciplinary Perspective*, ed. Fritz Strack, Michael Argyle, and Norbert Schwarz, 27–47. Oxford, UK: 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.
- Stevenson, Betsey, and Justin Wolfers. 2008. "Economic Growth and Subjective Well-Being: Reassessing the Easterlin Paradox." *Brookings Papers on Economic Activity*, Spring: 1–87.
- 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.
- 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.

**Table 1: Descriptive Statistics by Happiness Status**

	Happiness (1–3)		
	"Not too happy" (1)	"Pretty happy" (2)	"Very happy" (3)
Real income (\$1,000 2008)	38.9	55.8*	68.2*
- (std. dev.)	(40.8)	(49.9)	(57.1)
- no. of obs.	4,124	19,877	11,045
Age	46.1	44.5*	46.8*
- (std. dev.)	(17.9)	(17.4)	(17.7)
- no. of obs.	4,607	21,856	12,252
Female	0.58	0.56*	0.57
no. of obs.	4,626	21,918	12,301
Married	0.33	0.50*	0.69*
no. of obs.	4,626	21,914	12,299
Kids	0.74	0.71*	0.74*
no. of obs.	4,611	21,850	12,275
Employed	0.49	0.62*	0.60*
no. of obs.	4,626	21,917	12,300
Unemployed	0.075	0.029*	0.017*
no. of obs.	4,626	21,917	12,300
Black	0.23	0.14*	0.10*
no. of obs.	4,626	21,918	12,301
College graduate	0.12	0.19*	0.24*
no. of obs.	4,615	21,863	12,271
Health fair or worse	0.47	0.24*	0.15*
no. of obs.	3,445	15,667	8,857
Liberal	0.27	0.26	0.23*
no. of obs.	4,626	21,918	12,301
Environmentalist	0.47	0.50	0.54*
no. of obs.	437	2,177	1,155
Read newspaper daily	0.42	0.49*	0.55*
no. of obs.	3,106	15,591	8,475
Weekend	0.31	0.29*	0.28
no. of obs.	4,611	21,841	12,256

Continued ...

**Table 1 (continued)**

	<b>Happiness (1–3)</b>		
	<b>"Not too happy"</b>	<b>"Pretty happy"</b>	<b>"Very happy"</b>
	(1)	(2)	(3)
Temperature	44.22	43.77	44.31*
- (std. dev.)	(14.54)	(14.94)	(14.82)
- no. of obs.	3,226	15,464	8,731
Precipitation (0.01")	10.19	9.42	9.92
- (std. dev.)	(28.01)	(24.77)	(26.42)
- no. of obs.	3,286	15,800	8,972
PM10 ( $\mu\text{g}/\text{m}^3$ )	30.71	30.54	30.16
- (std. dev.)	(14.51)	(14.26)	(14.54)
- no. of obs.	1,348	6,567	3,470
CO (ppm)	1.71	1.61*	1.59
- (std. dev.)	(1.48)	(1.31)	(1.26)
- no. of obs.	2,244	10,053	5,459
SO <sub>2</sub>	3.30	3.18	3.19
- (std. dev.)	(10.76)	(9.66)	(9.62)
- no. of obs.	2,127	9,524	5,205
Ozone	6.57	7.00	7.74*
- (std. dev.)	(17.56)	(17.69)	(18.79)
- no. of obs.	1,882	8,089	4,488

\*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 ( $\mu\text{g}/\text{m}^3$ ) [ $\alpha$ ]	-0.0014*	-0.0017*	-0.0014*	-0.0015*
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
log(real income (\$1,000 2008))	0.132*	0.133*	0.134*	0.066*
[ $\gamma$ ]	(0.012)	(0.012)	(0.008)	(0.010)
Average PM10 by county and month		0.0018	0.0034	0.0023
		(0.0012)	(0.0032)	(0.0032)
Age ( $\div 10$ )				-0.114*
				(0.030)
Age ( $\div 10$ ) squared				0.014*
				(0.003)
Female				0.042*
				(0.016)
Married				0.250*
				(0.018)
Kids				-0.108*
				(0.020)
Employed				-0.030
				(0.020)
Unemployed				-0.190*
				(0.054)
College graduate				0.034 <sup>†</sup>
				(0.019)
Health fair or worse				-0.247*
				(0.022)
Health poor				-0.211*
				(0.041)
Rain (indicator)				-0.0054
				(0.0190)
Rain (inches)				0.015
				(0.036)
Temperature mean ( $10^\circ$ F)				0.067*
				(0.028)
Temperature squared				-0.0069*
				(0.0033)
Temperature difference (daily maximum–minimum) ( $10^\circ$ F)				0.011
				(0.013)
Weekend				-0.024
				(0.017)
Constant	1.72*	1.67*	1.82*	1.95*
	(0.04)	(0.05)	(0.29)	(0.29)
Year fixed effects	--	--	yes	yes
Month fixed effects			yes	yes
County fixed effects	--	--	yes	yes
$R^2$	0.044	0.044	0.050	0.122
No. of obs. = 6,035				
Years: 1984–1996, skipping 1992, 1995				
WTP to pay for a one $\mu\text{g}/\text{m}^3$ reduction	\$459*	\$541*	\$440*	\$967*
	(188)	(194)	(205)	(442)
WTP to pay for a one std. dev. reduction for one day	\$18	\$21	\$17	\$38

\* Statistically significant at 5 percent. <sup>†</sup> Statistically significant at 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 ( $\mu\text{g}/\text{m}^3$ ) [ $\alpha$ ]	-0.0016* (0.0007)	-0.051* (0.021)	-0.0037* (0.0012)	-0.0039* (0.0014)
Income [ $\gamma$ ]	0.0013* (0.0002)	0.066* (0.010)	0.123* (0.019)	0.101* (0.023)
Average PM10 by county and month	0.0014 (0.0015)	0.001 (0.002)	0.0022 (0.0025)	0.0031 (0.0029)
Other covariates and fixed effects as in column (4) of Table 2				
R <sup>2</sup>	0.125	0.124		
No. obs. = 6,035 Years: 1984–1996, skipping 1992, 1995				
WTP to pay for a one $\mu\text{g}/\text{m}^3$ reduction [ $-\alpha/\gamma$ ]	\$1,228* (527)	\$1,085* (485)	\$1,278* (440)	\$1,647* (679)
WTP to pay for a one std. dev. reduction for one day	\$49	\$43	\$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: Alternative Approaches**

	Lagged environment	Current Population Survey income	Main specification without top code	Health as dependent variable	Main specification without health
	(1)	(2)	(3)	(4)	(5)
PM10 daily ( $\mu\text{g}/\text{m}^3$ ) [ $\alpha$ ]	-0.0032* (0.0015)	-0.0013 <sup>†</sup> (0.0007)	-0.0015* (0.0007)	-0.0004 (0.0008)	-0.0016* (0.0007)
PM10 yesterday	0.0017 (0.0015)	--	--	--	--
log(real income (\$1,000 2008)) [ $\gamma$ ]	0.066* (0.010)	0.084* (0.013)	0.050* (0.012)	0.152* (0.012)	0.091* (0.010)
Other covariates and fixed effects as in column (4) of Table 2					
R <sup>2</sup>	0.123	0.108	0.111	0.165	0.091
No. of obs. Years: 1984–1996, skipping 1992, 1995	5,975	4,985	5,298	6,035	6,035
WTP to pay for a one $\mu\text{g}/\text{m}^3$ reduction	\$2,023* (1,019)	\$812 <sup>†</sup> (452)	\$1,007 (540)	--	\$764 (326)
WTP to pay for a one std. dev. reduction for one day	\$80	\$34	\$40	--	\$30

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



**Table 5: Other Pollutants**

Dependent variable: Happiness (1–3)	PM10 without interpolation	Ozone	SO <sub>2</sub>	CO	PM10 and Ozone	PM10 and SO <sub>2</sub>	PM10 and CO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pollution (daily) [α]	-0.0019* (0.0008)	-0.0003 (0.0008)	-0.00053 (0.00078)	-0.0058 (0.0073)	-0.0015 <sup>†</sup> (0.0009)	-0.0019* (0.0008)	-0.0013 <sup>†</sup> (0.0007)
Income (\$1,000 2008) [γ]	0.082* (0.015)	0.067* (0.009)	0.071* (0.008)	0.067* (0.008)	0.056* (0.012)	0.064* (0.011)	0.063* (0.010)
Pollution (monthly county average)	0.0018 (0.0023)	0.0014 (0.0013)	0.0027 (0.0018)	-0.0048 (0.0113)	-0.0019 (0.0022)	0.0001 (0.0017)	0.0009 (0.0016)
Second pollutant					0.0018 (0.0013)	0.0025 (0.0019)	-0.0237 (0.0149)
R <sup>2</sup>	0.14	0.13	0.13	0.13	0.13	0.13	0.13
No. of obs.	2,567	8,140	9,860	10,081	3,855	4,916	5,439
Years	1984–1996	1975–1996	1975–1996	1975–1996	1984–1996	1984–1996	1985–1996
WTP to pay for a one μg/m <sup>3</sup> reduction	\$969* (456)	\$200 (494)	\$321 (471)	\$3,609 (4539)	\$1,120 (728)	\$1,295* (562)	\$880 <sup>†</sup> (497)
WTP to pay for a one std. dev. reduction for one day	\$48	\$11	\$9	\$13	\$43	\$49	\$34

\* Statistically significant at 5 percent. <sup>†</sup> 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 6: Interactions**

Dependent variable: happiness (1–3)	Income	Local monthly pollution	Health fair or worse	Environmentalist
	(1)	(2)	(3)	(4)
PM10 [ $\alpha_1$ ]	-0.0016* (0.0007)	-0.0018* (0.0007)	-0.0018* (0.0007)	-0.0008 (0.0023)
Income (\$1,000 2008) [ $\gamma$ ]	0.086* (0.020)	0.066* (0.010)	0.066* (0.010)	0.075* (0.026)
Interaction [ $\alpha_2$ ]	-0.00065 (0.00058)	0.00003 (0.00006)	0.0008 (0.0013)	-0.0014 (0.0023)
Interacted variable		0.0003 (0.0026)	-0.274* (0.045)	0.0175 (0.0702)
N	6035	6035	6035	1032
R <sup>2</sup>	0.12	0.12	0.12	0.14
F test that pollution <i>and</i> interaction = zero	3.54*	3.05*	3.13*	0.42
WTP to pay for a one std. dev. reduction for one day when interaction = 25th percentile	\$32	\$47		
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			\$45	\$16
WTP to pay for a one std. dev. reduction for one day when interaction = 1			\$23	\$45
Continued ...				

**Table 6 Interactions (continued)**

<b>Dependent variable: Happiness (1–3)</b>	<b>Age &gt; 69</b>	<b>Kids</b>	<b>Read news</b>	<b>College</b>
	(5)	(6)	(7)	(8)
PM10 [ $\alpha_1$ ]	-0.0016* (0.0007)	-0.0013* (0.0011)	-0.0003 (0.0011)	-0.0015* (0.0007)
Income (\$1,000 2008) [ $\gamma$ ]	0.0066* (0.0010)	0.066* (0.010)	0.062* (0.012)	0.066* (0.010)
Interaction [ $\alpha_2$ ]	0.0002 (0.0017)	-0.0004 (0.0012)	-0.0034* (0.0013)	-0.0007 (0.0013)
Interacted variable	-0.077 (0.072)	-0.096* (0.041)	0.132* (0.047)	0.056 (0.044)
N	6035	6035	3675	6035
R <sup>2</sup>	0.12	0.12	0.13	0.12
F test that pollution <i>and</i> interaction = zero	2.89 <sup>†</sup>	2.97 <sup>†</sup>	6.25*	3.08*
WTP to pay for a one std. dev. reduction for one day when interaction = 0	\$41	\$33	\$7	\$36
WTP to pay for a one std. dev. reduction for one day when interaction = 1	\$35	\$43	\$98	\$55

\* Statistically significant at 5 percent. <sup>†</sup> 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.