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

Arik Levinson
Georgetown University and NBER
aml6@georgetown.edu

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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) and the National Survey of Families and Households (NSFH), which ask 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 variation for air pollution.

JEL codes: Q51, Q53, H41

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

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1. Introduction

A central goal of environmental economics is to place a monetary value on a pure public good: environmental quality. Existing methods include travel cost models, hedonic regressions of property values, and contingent valuation surveys in which people are asked directly their willingness to pay for improvements in the environment. In these pages I describe and test an alternative methodology for estimating the economic benefit of improving air quality, or equivalently, the economic cost of air pollution. The fundamental idea is extraordinarily simple. I combine publicly available 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 circumstances, incomes, and the air quality at the date and place they were surveyed. Then I use the estimated function to calculate the average marginal rate of substitution between annual household income and air quality that leaves respondents equally happy, and use this to calculate respondents' marginal willingness to pay for improved air quality.

This happiness-based methodology has a number of advantages over existing tools for valuing environmental quality. Because I include region and year-specific fixed effects, coefficients are identified from daily fluctuations in pollution within a county or zip code, 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 willingness to pay for 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*., 2000), terrorism (Frey et al., 2009), and even air pollution (Welsch, 2007; Di

Tella and MacCulloch, 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 willingness to pay. Air quality, on the other hand, varies daily within each location, for reasons exogenous to any particular respondent's circumstances.

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." And it identifies willingness to pay based on tradeoffs between fluctuations in *daily* pollution and differences among respondents' *annual* income. 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 air quality, 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 current local air pollution. After accounting for respondents' demographics, current local weather conditions, as well as local, year, and even month fixed effects, individuals surveyed when the current local levels of airborne particulates (PM10) are higher are less likely to report high levels of happiness. This first step is a straightforward empirical exercise. It requires no strong assumptions except the empirical specification, and I show 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 (CO).

The second result involves using the estimates to calculate marginal rates of substitution between pollution and income, and to use that to back 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 a benchmark for the usual approaches.

In my preferred specification, I show that people appear willing to sacrifice about $25 for a one-standard-deviation improvement in air quality. If these are interpreted as daily values (and there is some ambiguity about tradeoffs between daily air quality and annual income), then $25 is considerably higher than typical hedonic estimates of willingness to pay, and almost double the value attributed by the EPA to the economic benefits of the 1970 and 1977 Clean Air Acts. Of course, this happiness measure includes some benefits not captured by the EPA approach -- aesthetics, lost recreation, and benefits from other pollutants correlated with particulates.

In the end, this exercise probably does not serve as a useful tool for widespread use in cost-benefit analyses. The information requirements are too large. But 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. 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. 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, and there is even now a "Handbook" on the economics of happiness (Bruni and Porta, 2007).

Much of this academic and popular 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 has refuted 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 has not increased over time as per capita incomes have increased (Oswald,1997; Layard, 2008). This paradox has two obvious interpretations. One is that people become habituated to their circumstances, relatively quickly becoming accustomed to new circumstances and changing their reference level of well being.[1] Another interpretation is that happiness relates to 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.[2]

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 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.[3] 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 East German unification on different groups (Frijters, *et al.*, 2004), to assess the degree to which state cigarette taxes make smokers better off by helping them cut back (Gruber and Mullainathan, 2005), and to 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, 2009).

[1] 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 (2007), show incomplete recovery of happiness after such events.

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

[3] These practical applications raise concern among critics of this literature on "happiness economics". Smith (2008) writes that "the [happiness economics] train is precipitously close to leaving the station and heading for use in full-scale policy evaluation." I suspect he would view this paper as a catastrophic derailment.

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 (2006) regress happiness on income and the national, annual, per-capita emissions of 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 a first use 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.

Luechinger (2009) avoids the problems associated with inter-country comparisons of happiness, using annual mean concentrations of sulfur dioxide (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 wind patterns relative to large power plants that installed SO2 emissions control equipment. Luechinger finds a marginal willingness to pay of €183 for a one $\mu g/m^2$ reduction in SO2, while average SO2 concentrations fell by 38 $\mu g/m^2$ over the time period he examines.

In theory, all of the prior work using happiness to value public goods, air quality included, could suffer from an 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. In that case, it seems unlikely that tradeoffs between aggregate yearly or national levels of pollution and income can be interpreted as a willingness to pay for air quality.

This paper solves these problems. It focuses entirely on the U.S., so there are fewer language and cultural differences. 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.[4] Time and place-specific 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 year, but happen to have been interviewed on a day when the air quality differed.

3. Data and methodology

For happiness measures, I rely on two surveys. The first is the General Social Survey (GSS), which has been conducted annually since 1972 by the National Opinion Research Center (NORC).[5] Over 38,000 respondents were interviewed in person over 30 years.[6] 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.

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 in which each respondent was surveyed. These two pieces of information (date and place) allow me to match the GSS to the particular air quality on the day and in the place the survey was administered.

As a check of the GSS data, I also use the National Survey of Families and Households (NSFH), wave 1, which surveyed 13007 respondents in 1987 and 1988.[7] The key NSFH question asks "taking things all together, how would you say things are these days?" Responses range from "1-very unhappy" to "7-very happy." As with the GSS, NSFH staff assisted me by merging data on local air quality data with individual observations, so that I can estimate happiness as a function of current local air quality and weather conditions. Although the NSFH has a limited time dimension, it does have some advantages over the GSS. It has many more observations in a single period, its happiness question has seven response categories instead of

[4] Barrington-Leigh (2008) does use time and place-varying weather conditions, and finds results similar to those found here for pollution conditions: current weather affects stated well being.
[5] Surveys were not conducted in 1979, 1981, and 1992 due to funding shortfalls.
[6] More information about the GSS can be found at http://webapp.icpsr.umich.edu/GSS.
[7] There are two follow-up waves of the NSFH: wave 2 in 1992-94 and wave 3 in 2001-02. The wave 2 data can be matched to weather and air quality data, raising the intriguing possibility of including individual fixed effects, but for now I have only relied on the first wave.

just three, and the zip code of the respondent is identified, not just the county, making possible an even more precise measure of the current local environment.

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, from 1971 to the present. The data include the geographic location of each monitor, the types of pollutants monitored, and the hourly observations. I have obtained the 1994-2000 data from the EPA web site, and the earlier years by special request to the EPA.[8]

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 levels. 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, 2006). 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 respondent's county or zip code 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.[9]

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 lots of locations going back to the early 1970s. But 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.

[8] More information about the AQS can be found at http://www.epa.gov/ttn/airs/airsaqs.
[9] 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. And, it means that 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. 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, health, and (curiously!) being the type of person who reads a daily newspaper.

Methodology

I estimate versions of the following function:

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

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*, Y_i is respondent *i*'s household income, X_i is 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. As written here, equation (1) imposes linearity, but below I show the estimated tradeoffs between pollution and income are unchanged if I substitute the log of pollution, the log of income, ordered probits versions of those, include multiple interactions, or estimate a binomial probability that $H_{ijt} > H^*$ for an arbitrary H^*.

Once estimated, I can totally differentiate the function, set dH=0, and solve for the average marginal rate of substitution between pollution and income, dY/dP:

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

the amount of annual income necessary to compensate for a one-unit increase in air pollution.[10] In other words, using this methodology, I will be able to estimate the tradeoffs people are willing to make between income and air quality that leave them equally happy according to the GSS or NSFH questionnaires.

Some Theoretical and Practical Concerns

Using equation (2) to measure marginal rates of substitution involves placing some strong assumptions on the underlying utility functions. Economists use utility functions to characterize preferences. We typically assume individuals make choices as though they are maximizing some unobserved utility function. We 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 problem 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 air 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 by 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 don't observe either type of utility directly, and in fact the survey questions are not clear about which they seek, asking only "how happy are you 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.

[10]The linearity of (1) means that, conveniently, WTP can simply be expressed as the ratio of the coefficients on pollution and income. Naturally, alternative formulations of (1) lead to different expressions for WTP in (2). For example, using the log of income instead of its level, $\partial Y / \partial P = -Y\,\hat{\alpha} / \hat{\gamma}$, which has the nice feature that WTP increases with income.

Another potential concern about the approach proposed here is that the GSS and NSFH ask about how "things are these days?" The question not only may confound experience and decision utility, but is also 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 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 and NSFH 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. But given that the surveys only ask the vague "these days" questions, it is fortunate that people seem to respond as if they had been asked the momentary happiness questions, 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. This means that happiness can be used to rank choices for each person separately, but that interpersonal comparisons based on stated happiness are not possible. 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 even 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 OLS estimates.

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 lots of 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*. (2001), 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).[11]

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 from this approach are robust to a variety of specifications, 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 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 $10,000 increase in annual income is associated with an increase of happiness of 0.045, on a three point scale. A 10 $\mu g/m^3$ increase in local daily particulates is associated with a decrease in happiness of 0.015, on a three point scale. But happiness being ordinal (or being 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.

[11] One key advantage the regression approach has over the ordered probit is that the former can include fixed effects. So if there are individual-specific or region-specific norms for happiness, those can be differenced out. Allowing for fixed individual 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 (2004), and Ferrer-i-Carbonell and Frijters' (2004) conditional fixed-effect ordered logit.

To place a dollar value on air pollution, we need to calculate equation (2). Plugging in −0.0015 for $\hat{\alpha}$ and 0.0045 for $\hat{\gamma}$, we get that the average marginal rate of substitution is $\partial Y/\partial P$=\$340.[12] This means that a one μg/m^3 increase in PM10, on the day they are interviewed., reduces people's stated happiness by an amount equal to a \$340 decline in annual income. What does this mean? Here's where a bit of ambiguity arises. The \$340 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 μg/m^3 reduction in PM10 pollution. But the PM10 coefficient is identified from *daily* fluctuations in air quality. If we divide the \$340 by 365 days per year, we get an estimate of \$0.93 per day. To try to put this into context, note that the standard deviation of PM10 is 14.4 μg/m^3. Our estimate, then, corresponds to a willingness to pay \$13 for a one-standard-deviation improvement in air quality, for one day. In annual income, this is slightly less than \$5000.

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 difference between air quality on the day of the survey, and the prevailing conditions that month. The monthly coefficient is statistically insignificant, suggesting a degree of habituation to environmental circumstances.[13] The daily coefficient, increases, suggesting a willingness to pay of \$17 rather than \$13. Column (3) adds year, month, and county fixed effects, with no change to the basic findings. 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, employed, and healthy are happier. None of these is surprising and all conform to standard results in this literature. More importantly, none change the basic result that happiness increases with income, and decrease with local daily pollution. If anything, the demographic variables reduce the coefficient on income, thereby increasing the estimate of WTP to \$26 for a one-standard-deviation change in PM10.

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[12] Income is measured in \$1000s. The ratio (0.0015/0.0045) is one-third of \$1000. Rounding differences lead to the \$340 figure reported at the bottom of table 2.

[13] This also accounts for seasonal effects. If people are happier in spring, say, and particulates are lower in the spring, that may bias the results.

Table (3) presents a sample of some of the alternative specifications I have tried. Column (1) uses the log of income, rather than it's level, on the grounds that WTP likely increases with income. (I test this directly later.) Nothing changes, except of course the formula for calculating WTP. (See fn. 10.) Column (2) uses both the log of income and the log of PM10, again with no discernable change on the ratio of the two coefficients. Column (3) estimates equation (1) as an ordered probit, and again the qualitative results are the same, though the estimated WTP is somewhat higher ($32). And column (4) estimates an ordered probit where income and pollution are in logs, again with little change to the measured tradeoff between pollution and income.[14] 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 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. But because the variance across the uninterpolated values is higher, the WTP for a one standard deviation change is slightly higher -- $29.

Columns (2) of Table 4 estimate the same regression for ozone. Here the coefficient on pollution is negative, but statistically insignificant. The point estimate of WTP for a one standard deviation change is $9. My initial expectation was that the ozone coefficient would be significant, since ozone is associated with aesthetically unpleasant brown skies. Perhaps, however, the fact that the GSS is collected only January through June, with almost one third being in March, and that ozone is largely a summer phenomenon, means that I cannot identify an ozone effect.

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 $6. My

[14] I also estimated versions of equation (1) as a both linear probabilities and probits that *H*>1 and *H*>2, respectively, again with the same results.

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 lots of 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 \$10. 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 same range – between \$20 and \$30.

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 the change constitutes a 50 percent increase (or decrease) 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. So the change we discussing amounts to slightly more than a move from an average day in DC to an average day in polluted regions of Southern California.

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 trillion 1990 dollars, or \$4300 per capita, or \$12 per day per person.[15] By comparison, the value of \$26 per day using the happiness approach does not seem out of 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 \$110 (in 1982-84 dollars). A 14.4 $\mu g/m^3$ increase would be worth \$1584, which amortized at 5 percent comes out to \$79 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, in an instrumental variables approach, and finds that housing values in non-compliance counties grew by an average of \$1350 between 1970 and 1980 (in 1983 dollars) due to the Clean Air Act.[16] Amortized at 5 percent this amounts to \$67 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 respondent whether or not they would vote to improve air quality, along with associated health and visibility, by 30 percent, at various costs, and showed them photographs of the sky with clean and dirty air. The average annual willingness to pay, in 1978, was \$477 in LA and \$122 in San Francisco (in 1983 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.

[15] Calculations based on tables ES-1 and ES-3 in EPA (1999). The 1990 48-state population was 247 million.
[16] Kim et al., 2003 find a nearly identical value (\$2333) for a 4 percent decline in mean ambient SO_2 concentrations.

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.[17]

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

This is reported in the first column of Table 5. The pollution coefficient is unchanged by the inclusion of the interaction, and although the interaction term is not statistically significant, the two terms together 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 is

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

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 \$17 for a one standard deviation change in air quality, and people in the 75th percentile appear to be willing to pay \$30.

Another variable we might expect to be correlated with willingness to pay for air quality is the local normal air quality. This could go in one of two directions. People could become habituated to poor air quality, and a one $\mu g/m^3$ 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 (3), substituting local monthly pollution for income in the interaction. 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

$$\frac{\partial Y}{\partial P}\Big|_{dH\equiv 0} = -\frac{\left[\hat{\alpha}_1 + \hat{\alpha}_2 I\right]}{\hat{\gamma}} \qquad (5)$$

[17] To ensure that the coefficient α_1 remains comparable to that estimated without the interaction, I interact pollution with the difference between the respondent's income and the mean income in the sample $(Y - \overline{Y})$.

where *I* is the interacted variable. Calculating this at the 25th percentile of the PM10 distribution, WTP is \$30. At the 75th percentile, WTP is \$25.

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 indicator for whether a respondent's health status is fair or worse, and an interaction between that indicator and the PM10 count. The interaction term is statistically significant and positive, suggesting that people in poor health are not made worse-off during high PM10 days than people in good health. This may be an indication that the PM10 variable is measuring some 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 such poor health they remain indoors regardless of pollution levels. To bottom of column (3) reports the point estimates of WTP for people in poor health and those in better health, \$13 and \$39, respectively.

If the health variable captures people likely to remain indoors, perhaps the weekend indicator proxies for time spent outdoors. In column (4) I interact pollution with the weekend indicator. In fact, the interaction variable has the opposite sign, suggesting that people are willing to pay *less* for air quality on the weekends -- \$5 instead of \$35-- 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, some environmentally-minded respondents pose a problem because they will 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 will claim to be willing to pay enormous amounts, perhaps hoping their responses will help determine policy. With this happiness approach, those issues pose no problem, 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 environment 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.

Does ideology matter? Column (6) interacts the PM10 count with a dummy equal to 1 if the respondent's self-reported political view is "liberal." The interaction term is positive but insignificant, suggesting if anything a lower willingness to pay for clean air by liberals.

To examine if older people are willing to pay more for improved air quality, I estimated a version of equation (3), replacing the interaction variable with an indicator for whether or not the respondent is over age 69. The results, in column (7) of Table 5, are largely insignificant, perhaps for the same reasons as 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 surveyed no children, but did ask respondents if they had children. In column (8) 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 $5 more than childless respondents for a one-standard-deviation change in PM10.

African Americans also appear to be willing to pay less for air quality, as shown in column (9) of Table 5. I thought perhaps this might be due to black respondents being more likely to live in polluted areas, but recall that in column (2) the local pollution interaction was insignificant and worked in the opposite direction.

Column (10) 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 (10) 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 (11) 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 $13 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 (12) 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 $1.

In sum, the interactions in Table 5 do not tell a completely convincing story. Many are individually statistically insignificant, though jointly significant with PM10 levels. Many confirm our expectations, such as the fact that higher-income 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.

The National Survey of Families and Households

The General Social Survey, used in tables 1 through 5, has several disadvantages for this study. It only surveys only one or two thousand respondents per year, and given that PM10 is only sampled once every six days, that leaves few observations directly measured. It also only identifies counties, and so respondents' locations are not precisely identified. To address some of these issues, I turn to an alternative source of happiness data, the National Survey of Families and Households (NSFH).

The NSFH solves some of the shortcomings of the GSS. It surveys over 13,000 people in 1987 and 1988. With the assistance of NSFH staff, researchers can match the data to geographic descriptions at the level of zip codes. The NSFH does, however, have several drawbacks. It does not have the extent of opinion data that the GSS has, such as the self identified "environmentalist" variables. And the NSFH wave 1 is just a snapshot at a single point in time.

Table 6 presents some summary statistics from the NSFH, limited to those observations with nonmissing responses to the income and happiness questions, organized by happiness response, from 1 (very unhappy) to 7 (very happy). In general, happiness increases with income, marital status, having kids under age 5 and *not* having kids between 5 and 18, employment, college completion, and health. Note, however, that there are several odd non-monotonicities. The highest income group, for example, are those in happiness category 6, not category 7. Similarly, employment and college completion peak in happiness category 6. As a consequence, in what follows I show that the qualitative results do not differ by function form (linear regression, ordered probit, linear probability, etc.). But for the main analysis I focus on a simple partition of the happiness response into two categories: less than 6, and greater than 5.

Table 7 presents estimates of happiness as a function of total suspended particulates (TSP) and PM10, income, and other covariates. The TSP coefficient is negative and statistically significant, and the PM10 coefficient is negative and marginally statistically significant. Both yield estimates of WTP for a one-standard deviation reduction in pollution of about $30. This is larger than the estimates from the GSS, perhaps due to the greater geographic accuracy.

5. Conclusions -- Advantages of the happiness approach

Economists estimate the benefits of environmental improvements using several approaches. Each has associated advantages and disadvantages. Travel costs 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 understates the amount people would be willing to pay to avoid being sick in the first place.

This "happiness" approach to measuring willingness to pay has its own set of weaknesses. It makes stronger assumptions about preferences than economists typically need to make, in that it compares stated happiness of different individuals. And 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. Nevertheless, this new approach has a number of key advantages.

First, the drawbacks of this approach are different from the drawbacks of the typically-used approaches. It is much more direct than hedonic studies or travel cost models, in that it relies on surveys of people's well-being. And 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 for 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 approximates the marginal rate of substitution between income and air quality. Thus it does not suffer from the drawback of hedonic studies, in that the coefficient on pollution measures the locus of equilibrium property values in different cities, which may not be the MRS. Nor does the happiness approach 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 these public goods do not vary across individuals in the same location during the same year. It seems only natural, therefore, to use this tool 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 ever 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 analysis here has, however, demonstrated several important points. First, the results add to the evidence demonstrating that self-reported subjective will-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 peoples welfare, at least as self-reported well-being, in addition to any measured effects through health, lost work days, other observable outcomes. And third, whether or not we believe the particular point estimates, the results do support there being a substantial willingness to trade lower income for higher environmental quality.

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Table 1: Descriptive statistics by Happiness Status – GSS

	Happiness (1-3)		
	"not too happy"	"pretty happy"	"very happy"
	(1)	(2)	(3)
Real income ($1000 1986)	20.7	29.2*	35.2*
- (std. dev.)	(20.6)	(25.0)	(28.9)
- number of obs.	*3,530*	*17,153*	*9,594*
Age	45.9	44.2*	46.7*
- (std. dev.)	(18.0)	(17.3)	(17.8)
- number 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	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)
- number 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)
- number 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)
- number of obs.	*763*	*3,561*	*1,898*
TSP	66.82	66.89	67.52
- (std. dev.)	(38.39)	(40.41)	(47.13)
- number of obs.	*641*	*2,691*	*1,573*
CO	1.76	1.64*	1.65
- (std. dev.)	(1.84)	(1.59)	(2.17)
- number of obs.	*2,715*	*12,022*	*6,553*
SO2	3.00	2.95	2.93
- (std. dev.)	(10.10)	(9.15)	(9.07)
- number of obs.	*2,461*	*10,945*	*6,020*
Ozone	7.41	7.79	8.46*
- (std. dev.)	(17.63)	(17.78)	(18.60)
- number of obs.	*2,267*	*9,632*	*5,382*

Table 2: Happiness, Pollution, and Income – linear regressions and PM10

	(1)	(2)	(3)	(4)
PM10 (μg/m^3)	-0.0015*	-0.0019*	-0.0016*	-0.0016*
	(0.0006)	(0.0007)	(0.0007)	(0.0007)
Real income ($1000 1986)	0.0045*	0.0045*	0.0046*	0.0025*
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Average PM10 by county		0.0018	0.0016	0.0015
and month		(0.0011)	0.0018	(0.0015)
Age (÷10)				-0.112*
				(0.030)
Age (÷10) squared				0.014*
				(0.003)
Female				0.042*
				(0.016)
Married				0.253*
				(0.018)
Kids				-0.113*
				(0.020)
Employed				-0.014
				(0.020)
Unemployed				-0.187*
				(0.054)
College grad				0.023
				(0.019)
Health fair or worse				-0.248*
				(0.022)
Health poor				-0.221*
				(0.041)
Rain (indicator)				-0.014
				(0.018)
Rain (0.01 inches)				0.017
				(0.036)
Temperature mean				0.066*
(10° F)				(0.028)
Temperature squared				-0.0065*
				(0.0033)
Weekend				-0.023
				(0.017)
Constant	2.07*	2.03*	2.25*	2.16*
	(0.02)	(0.03)	(0.27)	(0.27)
Year fixed effects	--	--	yes	yes
Month fixed effects			yes	yes
County fixed effects	--	--	yes	yes
R^2	0.040	0.040	0.043	0.124
No. obs. = 6052				
Years: 1984-1996, skipping 1992, 1995				
WTP to pay for a one μg/m^3 reduction	$340	$418	$337	$646
WTP to pay for a one std. dev. reduction for one day	$13	$17	$13	$26

* Statistically significant at 5 percent. Standard errors adjusted for clustering by county.

Table 3: Happiness, Pollution, and Income – alternative regressions and PM10

	ln(income)	ln(income) ln(PM10)	Ordered Probit: linear	Ordered Probit: log income and pollution
	(1)	(2)	(3)	(4)
PM10 daily (μg/m^3) [α]	-0.0016*	-0.050*	-0.0036*	-0.116*
	(0.0007)	(0.021)	(0.0011)	(0.036)
Income [γ]	0.066*	0.066*	0.0045*	0.122*
	(0.010)	(0.010)	(0.0006)	(0.019)
Average PM10 by county and	0.0015	0.001	0.0021	0.0023
month	(0.0015)	(0.002)	(0.0025)	(0.0025)
Age (÷10)	-0.116*	-0.115*	-0.233*	-0.238*
	(0.030)	(0.030)	(0.058)	(0.058)
Age (÷10) squared	0.015*	0.015*	0.030*	0.030*
	(0.003)	(0.003)	(0.006)	(0.006)
Female	0.042*	0.042*	0.080*	0.078*
	(0.016)	(0.016)	(0.031)	(0.031)
Married	0.250*	0.249*	0.519*	0.510*
	(0.018)	(0.018)	(0.035)	(0.036)
Kids	-0.109*	-0.109*	-0.222*	-0.215
	(0.020)	(0.020)	(0.039)	(0.039)
Employed	-0.027	-0.027	-0.018	-0.048
	(0.020)	(0.020)	(0.039)	(0.040)
Unemployed	-0.186*	-0.186*	-0.410*	-0.411*
	(0.054)	(0.054)	(0.105)	(0.105)
College grad	0.032†	0.032†	0.041	0.058
	(0.019)	(0.019)	(0.038)	(0.037)
Health fair or worse	-0.246*	-0.246*	-0.485*	-0.482*
	(0.022)	(0.022)	(0.043)	(0.043)
Health poor	-0.210*	-0.211*	-0.428*	-0.411*
	(0.041)	(0.041)	(0.081)	(0.082)
Rain (indicator)	-0.011	-0.011	-0.030	-0.028
	(0.018)	(0.018)	(0.034)	(0.034)
Rain (0.01 inches)	0.011	0.011	0.026	0.017
	(0.036)	(0.036)	(0.069)	(0.069)
Temperature mean	0.064*	0.063*	0.084†	0.080
(10° F)	(0.028)	(0.028)	(0.050)	(0.050)
Temperature squared	-0.0063†	-0.0061†	-0.0088	-0.0082
	(0.0033)	0.0033	(0.0058)	(0.0058)
Weekend	-0.022	-0.023	-0.051	-0.051
	(0.017)	(0.017)	(0.033)	(0.033)
Constant	2.05*	2.17*		
	(0.27)	(0.28)		
Year, month, county effects	yes	yes	yes	yes
R^2	0.123	0.123		
No. obs. = 6052				
Years: 1984-1996, skipping 1992, 1995				
WTP to pay for a one μg/m^3 reduction [-α/γ]	$534	$566	$801	$708
WTP to pay for a one std. dev. reduction for one day	$21	$22	$32	$28

* Statistically significant at 5 percent. Standard errors adjusted for clustering by county.
† Statistically significant at 10 percent.

Table 4: Other pollutants

	PM10 without interpolation	**OZ**	**SO2**	**CO**	**PM10 *and* OZ**	**PM10 *and* SO2**	**PM10 *and* CO**
Dependent variable: Happiness (1-3)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pollution (daily) [α]	-0.0018*	-0.0004	-0.0005	-0.0063	-0.0015†	-0.0020*	-0.0013†
	(0.0008)	(0.0008)	(0.0008)	(0.0072)	(0.0009)	(0.0007)	(0.0007)
Income ($1000 1986) [γ]	0.0030*	0.0022*	0.0023*	0.0024*	0.0020*	0.0024*	0.0023*
	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)
Pollution (monthly county average)	0.0020	0.0012	0.0027	-0.0042	-0.0017	0.0003	0.0010
	(0.0023)	(0.0013)	(0.0018)	(0.0113)	(0.0002)	(0.0017)	(0.0016)
Second pollutant					0.0012	0.0023	-0.0224
					(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 [-α/γ]	$590	$174	$218	$2643	$735	$824	$588
WTP to pay for a one std. dev. reduction for one day	$29	$9	$6	$10	$28	$31	$23

* Statistically significant at 5 percent.
† Statistically significant at 10 percent.

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

Table 5: Interactions

	Income	Polluted month and county	Health fair or worse	Weekend	Environmentalist	Liberal
Dependent variable: Happiness (1-3)	(1)	(2)	(3)	(4)	(5)	(6)
PM10	-0.0016*	-0.0017*	-0.0018*	-0.0021*	-0.0008	-0.0017*
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0023)	(0.0007)
Income ($1000 1986)	0.0034*	0.0025*	0.0025*	0.0025*	0.0022*	0.0025*
	(0.0007)	(0.0003)	(0.0003)	(0.0003)	(0.0008)	(0.0003)
Interaction	-0.000029	0.00003	0.0009	0.0018	-0.0015	0.0004
	(0.000020)	(0.00006)	(0.0013)	(0.0012)	(0.0023)	(0.0012)
Interacted variable		0.0003	-0.276*	-0.0772*	0.0197	0.0066
		(0.0026)	(0.045)	(0.0388)	(0.0701)	(0.0411)
N	6052	6052	6052	6052	1032	6052
R^2	0.12	0.12	0.12	0.12	0.14	0.12
F test that pollution *and* interaction zero	4.06*	3.13*	3.23*	4.15	0.51	3.06*
WTP to pay for a one std. dev. reduction for one day when interaction = 25th percentile	$17	$30				
WTP to pay for a one std. dev. reduction for one day when interaction = 75th percentile	$30	$25				
WTP to pay for a one std. dev. reduction for one day when interaction = 0			$29	$34	$12	$27
WTP to pay for a one std. dev. reduction for one day when interaction = 1			$14	$5	$37	$20

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

Table 5: Interactions (continued)

	Age > 69	Kids	Black	Read news	College	Trend[a]
Dependent variable: Happiness (1-3)	(7)	(8)	(9)	(10)	(11)	(12)
PM10	-0.0016*	-0.0013*	-0.0019*	-0.0002	-0.0014*	-0.0016*
	(0.0007)	(0.0010)	(0.0007)	(0.0011)	(0.0007)	(0.0007)
Income ($1000 1986)	0.0025*	0.0025*	0.0023*	0.0022*	0.0025*	0.0025*
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)
Interaction	0.0002	-0.0003	0.0022	-0.0034*	-0.0008	6.1×10^{-6}
	(0.0017)	(0.0012)	(0.0016)	(0.0013)	(0.0013)	(0.0002)
Interacted variable	-0.071	-0.102*	-0.163*	0.134*	0.048*	-0.0024
	(0.071)	(0.040)	(0.054)	(0.046)	(0.044)	(0.0079)
N	6052	6052	6052	3688	6052	6052
R^2	0.12	0.13	0.12	0.13	0.12	0.12
F test that pollution *and* interaction zero	2.97†	3.02*	3.85*	6.21*	3.18*	2.98†
WTP to pay for a one std. dev. reduction for one day when interaction = 0	$26	$22	$32	$4	$23	$26 (year=1984)
WTP to pay for a one std. dev. reduction for one day when interaction = 1	$23	$27	-$6	$65	$36	$25 (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 and year fixed effects, as in column (4) of Table 2.

Table 6: Descriptive statistics by Happiness Status -- NSFH

	Happiness (1-7)						
	1	2	3	4	5	6	7
Number of responses	213	178	463	1653	1385	2739	2380
Income ($1000)	12.8	13.7	15.4	13.7	16.6	18.9	16.0
Age	46.5	43.9	42.0	43.4	39.9	40.4	45.3
Female	0.68	0.63	0.60	0.64	0.57	0.58	0.60
Married	0.36	0.40	0.38	0.42	0.50	0.61	0.64
Kids under 5	0.17	0.24	0.25	0.27	0.29	0.28	0.25
Kids 5-18	0.72	0.75	0.66	0.64	0.65	0.61	0.61
Employed	0.53	0.57	0.56	0.57	0.69	0.70	0.58
Black	0.20	0.20	0.20	0.20	0.17	0.13	0.18
College grad	0.10	0.14	0.13	0.12	0.18	0.25	0.14
Health status poor	0.21	0.15	0.10	0.07	0.04	0.02	0.03
Trouble climbing stairs	0.18	0.16	0.14	0.12	0.07	0.05	0.07
Weekend	0.19	0.31	0.25	0.23	0.24	0.24	0.25
Environment by zip code							
Precipitation	7.0	9.9	8.1	9.4	9.6	8.6	9.2
Temp max	73.9	74.0	73.6	74.1	72.9	72.9	73.8
Temp min	49.9	50.1	50.4	51.1	50.1	49.9	50.7
TSP	62.2	61.9	61.2	61.0	61.6	59.7	60.1
PM10	37.9	38.3	38.2	38.2	38.3	36.8	37.6
CO	1.32	1.27	1.34	1.35	1.29	1.28	1.24
SO2	2.93	3.50	2.90	2.37	2.64	2.50	2.59
Ozone	13.7	14.5	15.9	15.2	14.7	14.4	15.4

Table 7: The Environment and Happiness – by zip code -- NSFH

	Linear probability (Happy > 5)	
	TSP	PM10
	(1)	(2)
Pollution	-0.00112*	-0.00062†
	(0.00057)	(0.00032)
ln(Income ($1000))	0.0175*	0.0140*
	(0.0082)	(0.0069)
Age	-0.104*	-0.081*
	(0.026)	(0.022)
Age squared	0.0123*	0.0098*
	(0.0028)	(0.0023)
Female	0.015*	0.028*
	(0.016)	(0.013)
Married	0.196*	0.196*
	(0.016)	(0.013)
Kids	-0.045*	-0.054*
	(0.017)	(0.014)
Employed	0.0081	0.0005
	(0.0194)	(0.0166)
College grad	0.050*	0.045*
	(0.020)	(0.017)
Health poor	-0.180*	-0.176*
	(0.037)	(0.031)
Trouble climbing stairs	-0.077*	-0.075*
	(0.029)	(0.025)
Max temperature	0.0015	0.0001
	(0.0012)	(0.0010)
Max temperature × summer	-0.00259	-0.00097
	(0.00198)	(0.00165)
Min temperature × winter	0.00014	0.00004
	(0.00180)	(0.00149)
Rain	-0.0091	-0.0103
	(0.0161)	(0.0135)
Weekend	0.028	0.015
	(0.017)	(0.015)
Location fixed effects	yes	yes
Month fixed effects	yes	yes
N	5840	7973
R squared		
WTP for a one standard deviation decline in pollution for one day.	$33.6	$32.2

* Statistically significant at 5 percent.
† Statistically significant at 10 percent.