Happiness, Behavioral Economics, and Public Policy

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Abstract

The economics of "happiness" shares a feature with behavioral economics that raises questions about its usefulness in public policy analysis. What happiness economists call "habituation" refers to the fact that people's reported well-being reverts to a base level, even after major life events such as a disabling injury or winning the lottery. What behavioral economists call "projection bias" refers to the fact that people systematically mistake current circumstances for permanence, buying too much food if shopping while hungry for example. Habituation means happiness does not react to long-term changes, and projection bias means happiness over-reacts to temporary changes. I demonstrate this outcome by combining responses to happiness questions with information about air quality and weather on the day and in the place where those questions were asked. The current day's air quality affects happiness while the local annual average does not. Interpreted literally, either the value of air quality is not measurable using the happiness approach or air quality has no value. Interpreted more generously, projection bias saves happiness economics from habituation, enabling its use in public policy.

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Happiness, Behavioral Economics, and Public Policy

How is "happiness" economics related to behavioral economics, and what does that relationship have to do with using happiness as a public policy tool? Although the two new fields of happiness economics and behavioral economics are distinct, they share multiple traits. Behavioral economists develop non-standard utility functions in an attempt to formally model and explain seemingly irrational human choices. Happiness economists take survey respondents' statements about their happiness as a proxy for conventional concepts of utility. Along the way, both weave insights from psychology into standard economic theory. Both confront the standard theory's fundamental assumption that humans make choices as if they are maximizing a well-defined utility function. Both use tools that can circumvent problems posed by neoclassical economics in ways that have important public policy applications. Behavioral economists have proposed policies that capitalize on behavior that appears irrational under conventional utility functions in order to improve outcomes.[1] Similarly, measures of happiness have recently been used to assess costs and benefits of public policy outcomes that are difficult to value using traditional economics tools – intangibles such as the psychic costs of unemployment and inflation, airport noise, and air pollution. And, providing important motivation for this paper, both new fields have enjoyed astonishing growth in the past ten years.

From 2001 to 2011, while the total number of peer-reviewed journal articles indexed by EconLit doubled, the number of those articles referencing happiness or one of its close relatives – well-being or life satisfaction – quadrupled from 153 to 651, and the number referencing behavioral economics quintupled from 113 to 611. For comparison, consider another innovative and controversial economics application that looked promising in 2001: contingent valuation, or stated preferences. There were the same number of papers referencing those terms as behavioral economics in 2001, but since then contingent valuation papers have less than doubled, shrinking as a proportion of all economics papers. One question scholars in all these fields must confront is whether their areas are passing academic fads, interesting for a few years but not ultimately influential, or whether they amount to revolutions in the way economists approach problems.[2]

Links between behavioral and happiness economics are numerous. Here's one example. Gruber and Mullainathan (2005) assess the behavioral claim that cigarette taxes make smokers better off by forcing them to smoke fewer cigarettes. In a standard neoclassical setting, higher prices reduce consumer surplus and make consumers unequivocally worse off. But this is a behavioral setting, smoking is irrational, and smokers' addictions prevent them from being able to quit themselves. Gruber and Mullainathan cannot use conventional welfare measures such as consumer surplus, and instead turn to happiness. They use the General Social Survey (GSS),

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[1] Thaler and Sunstein (2008) have written a book-long compendium of such suggestions.
[2] Frey's book, *Happiness: A Revolution in Economics* (2008), makes the case that studies of happiness are "likely to change economics substantially in the future" (p. ix).

which annually asks 1,500 to 2,000 U.S. respondents "would you say that you are very happy, pretty happy, or not too happy?" They show that in states that increased their cigarette excise taxes, smokers exhibited a corresponding increase in happiness, holding other respondent characteristics equal. By marrying behavioral and happiness economics, this result comes to the exact opposite public policy conclusion from standard economics. The standard view would say that narrowly focused excise taxes have large deadweight losses, reducing the welfare of taxed consumers. Measuring welfare using happiness responses, this paper shows that the opposite can be true, and the authors have a behavioral explanation: smokers have time-inconsistent behavior and taxes substitute for self-control.

Are there other links between happiness, behavioral economics, and public policy? The rest of this paper answers that question.

Valuing Public Goods

One of the most important challenges facing applied economics is valuing public goods. How much parkland should a city provide? Is it worth investing public resources in sports teams? Do the benefits of increased police patrols outweigh the costs? How stringent should air pollution regulations be? None of these important questions can be answered without valuing the public goods involved: recreational space, local city pride, public safety, and air quality. What we want to know is the rate at which a representative person would be willing to trade money for the public good: formally, the marginal rate of substitution between the public good and all other goods valued in dollars. This is just the slope of the indifference curve depicted in Figure 1. If policymakers knew that slope at various levels of the public good, they could choose to provide the amount of the public good where that slope just corresponds to its marginal cost. The result would be efficient. For private goods and services exchanged on free markets there is no problem. Market prices reflect people's willingness to pay for goods and services. For public goods there are no private markets and hence no market prices, and estimating people's willingness to pay is a challenge.

Economists have confronted this dilemma in a variety of ways. One of the earliest is Harold Hotelling's 1947 letter to the National Park Service suggesting a methodology for valuing their unpriced resources. He suggested drawing concentric zones around each park, with farther zones having higher costs of traveling to visit the park. A graph of the proportion of the population in each zone that chooses to visit plotted against the travel cost from that zone can be converted into a demand curve, the area under which represents the consumer surplus from the park's existence. This travel cost model of valuing public goods has evolved considerably, and now includes structural models of discrete choices over numerous recreational sites (Hausman, et al., 1995). But these models are not without shortcomings. They have difficulty valuing the time people spend en route and on site. For example, is a longer trip better or more costly? By relying on interviews with respondents at the sites, they incur sample selection biases. They typically ignore the problems associated with multiple-stop trips. If people visit Yellowstone and the

Grand Tetons, how can we value them separately? And most importantly, travel cost models are only useful for valuing public goods that people travel to visit. They are useless for assessing the benefits of open space, lower crime, or clean air enjoyed by a city's residents at home.

A second standard approach makes use of the fact that if a location's public goods are valued, that should drive up the demand for houses at that location. So-called "hedonic" regressions of house prices on housing characteristics, including local public goods such as crime rates, air quality, and open space, have become the work-horse of this area of applied microeconomics. See Bahari, et al. (2012) for a recent example. But again, this approach has some severe shortcomings. For one, people sort themselves according to their preferences, with those most attracted to the amenity being most likely to live in its nearby neighborhoods. For another, where amenities are paid for by local funds, homebuyers will both enjoy the amenities and pay the taxes, so that if people can move around sufficiently (and local politicians do their job exactly right), the amenity's benefits should be exactly offset by the corresponding higher taxes and have no effect on house prices. But the biggest problem facing hedonic valuation of public goods is that it is hard to believe that a regression of house prices on local amenities does not omit at least one important local characteristic correlated with both prices and amenities. Regressions of house prices on local amenities will spuriously attribute effects of the omitted characteristics to the measured amenities.

Finally, both travel cost and hedonic techniques value public goods for which people purchase complementary goods at market prices. The whole point of these two techniques is to convert the prices in the associated markets – travel or housing – into implicit prices for the public goods. But what about goods that do not have associated market activities: price inflation, climate change, or biodiversity? For that purpose, researchers have turned to contingent valuation or stated preferences – a fancy way of saying that researchers simply ask respondents their willingness to pay (WTP) for a public good.

To many economists this contingent valuation (CV) approach is an anathema. Conventional economics is about revealed preferences, not surveyed preferences. Hausman (2012) writes that CV respondents are "essentially inventing their answers on the fly, in a way which makes the resulting data useless for serious analysis." Even CV supporters have come up with a taxonomy of biases associated with the practice. Hypothetical bias refers to the fact that respondents don't actually have to pay for the good in question and do not face tangible budget constraints. Embedding refers to the fact that respondents may answer a question about willingness to pay to clean up one river by answering with the value they place on clean water everywhere. Some responses appear strategic: environmentalists claim implausibly high WTP in the hopes of influencing policy, or zero WTP on the grounds that polluters should be responsible for cleanup costs. To some, these biases call into question the legitimacy of contingent valuation.

The best-financed, highest-profile CV study to date was conducted after the Exxon Valdez oil spill. Its central findings, reproduced in Table 1, illustrate CV's biases. After describing the accident and the policy to prevent another, surveyors randomly assigned respondents to one of four versions of the questionnaire. In version A, respondents were first asked if they would support the policy if it cost them $10. If they said yes, the follow-up asked if they would support the policy if it cost $30. If instead they said no, the follow-up asked if they would support the policy at $5. Version B started at $30 and asked follow-ups at $10 and $60, and so on. Here's the problem. Suppose we want to estimate the fraction of the population willing to pay between $30 and $60 for the policy. There are multiple equally valid ways to calculate that number. Those who answered yes to the first question of version B but no to the follow-up have expressed willingness to pay at least $30 but not $60. They represent 26 percent of the randomly chosen respondents given version B of the survey. People who answered no to the first question of version C but yes to the follow-up are not willing to pay $60 and are willing to pay $30. They represent 10 percent of version C recipients. Or here's a third way. Of those given version B, 52 percent answered yes to the first question, and are willing to pay at least $30. Of those given version C, 50 percent answered no to the first question, and are unwilling to pay $60. The difference suggests only 2 percent were willing to pay between $30 and $60. So which is it, 26 percent, 10 percent, or 2 percent? The answer clearly depends on the sequence with which questions are asked. Something distinctly behavioral is biasing the respondents' answers.

Table 1. Willingness to Pay to Prevent Another Exxon Valdez Oil Spill:
Table IV in Carson et al. (2003).

Questionnaire version	Yes, Yes	Yes, No	No, Yes	No, No
A ($10, $30, $5)	*45%*	*22%*	*3%*	*30%*
B ($30, $60, $10)	*26%*	*26%*	*11%*	*37%*
C ($60, $120, $30)	*22%*	*29%*	*10%*	*40%*
D ($120, $250, $60)	*14%*	*21%*	*12%*	*54%*

The new happiness economics literature suggests a possible fourth approach. If happiness can be interpreted as a proxy for utility, then we can directly measure the slope of an indifference curve like that in Figure 1. Alternatively, if we want policymakers to consider policymakers as maximizing happiness rather than utility, we can relabel the Figure 1 curve an "iso-happiness" curve. Either way, we may be able to use surveyed happiness to value public goods.

The steps are straightforward. First, use one of the existing surveys, such as the GSS, to gather information about a respondent's happiness (H), income (Y), and other characteristics. From other sources, collect data on the quantity of the public good available to the respondent (G). This could be local crime rates, park land, air pollution, income inequality, etc. Then, econometrically predict happiness as a function of every other conceivable characteristic of the respondent and the locality, including G and Y.

$$H = f(G, Y, \mathbf{X}, \varepsilon) \tag{1}$$

where **X** is a vector of respondent and local characteristics, and ε is an error term. Finally, totally differentiate the estimate of equation (1), set dH=0, and solve for ∂Y/∂G.

$$\left.\frac{\partial Y}{\partial G}\right|_{dH\equiv 0} = \text{MWTP} \,. \qquad (2)$$

This is the tradeoff between income (Y) and the public good (G) that makes the average respondent equally happy. Equation (2) measures people's average marginal willingness to pay (MWTP) for the public good.

In a sense, measuring MWTP this way turns standard economics upside down. We typically estimate preference parameters by observing market prices and the choices people make, and infer from those choices the parameters of their utility functions, such as risk aversion, impatience, and altruism. In other words, we see real-world prices and budgets, and estimate utility functions. But with public goods, we do not observe market prices or choices. Individuals do not choose their personal consumption of public goods directly except by voting or relocating. So instead, the happiness approach reverses the typical economics by observing utility, or happiness, and estimating what tradeoffs would keep happiness unchanged and therefore what prices and quantities would be optimal.

The happiness approach to valuing public goods has a number of advantages over existing tools. It does not rely on people traveling to locations with different amounts of the public good, so there are no issues involving multiple site visits or valuing travel time, both of which may bias the travel cost approach. It does not ask people directly about their willingness to pay, and so does not suffer from the hypothetical, embedding, or strategic biases of the CV approach.

As with the hedonic approach, a key issue with the happiness approach is whether the variation in the public good can be considered exogenous with respect to people's incomes and happiness. If people who dislike noise choose not to live near airports, then neither a regression of house prices on airport noise *nor* a regression of happiness on airport noise can tell us how much the average person would be willing to pay to have less noise. With the happiness approach, however, there is a possible solution. Some public goods vary regularly for reasons exogenous to any particular survey respondent. Airport noise, inflation, unemployment, crime rates, and pollution vary over time at any given location. Residents who have chosen to live in any given city will still experience variations in the level of some public goods, regardless of their location choice. If that daily local variation can be used to identify equation (1), then estimates of equation (2) may be unbiased. By contrast, daily local variation should not affect the prices people pay for homes, and therefore cannot be used by the hedonic method to address the endogeneity of house prices and public good levels.

Of course, the happiness approach also has its own shortcomings. For one, happiness as recorded by questions on surveys is not utility. Utility is the hypothetical construct economists assume humans behave as if they are maximizing. Kahneman (2000) calls this "decision utility." By contrast, happiness is an emotion, a state of mind as represented by an answer to a survey question. Kahneman equates happiness to "experience utility." Still, one way to think about using happiness for policymaking is to treat happiness, or experience utility, as an observable manifestation of underlying unobserved decision utility. If respondents with higher unobserved decision utility are more likely to say they are happier, this approach is consistent with a wide variety of discrete choice econometric models.

Even if happiness can be taken as a proxy for utility, a problem with this approach is that economists normally assume utility is ordinal rather than cardinal, and that interpersonal comparisons based on stated happiness are impossible. If having more public goods moves one person from "not happy" to "pretty happy" and an otherwise identical neighbor from "not happy" to "very happy," that does not mean that the first person gets less utility from the public good or would be willing to pay less for it. Some economists, like Ng (1997), claim that there is ample evidence showing that people's utilities are both interpersonally comparable and cardinal, justifying regressions of happiness on respondents' characteristics. Others assume that happiness is ordinal but interpersonally comparable, allowing researchers to estimate equation (1) using ordered logits or probits (Alesina et al., 2004; Blanchflower and Oswald, 2004; Finkelstein et al., 2012). Most researchers have found little difference between the results of a linear regression and an ordered discrete choice model (Ferrer-i-Carbonell and Frijters, 2004). For valuing public goods, since we are not interested in the marginal utility of income or the public good separately, but only the ratio of the two as in equation (2), the analysis is less sensitive to these issues.

Another problem with the strategy outlined by equations (1) and (2) is that happiness and income may be simultaneous. We need to know the effect of income on happiness, but inherently happier people may earn higher incomes. Luttmer (2005) estimates versions of (1) where he instruments for household income using interactions between the respondents' and spouses' industry, occupation, and location. Powdthavee (2009) instruments for income using the number of household members working.[3] Both find that the income coefficient in instrumental-variables specifications is larger than in OLS specifications, suggesting that equation (2) would otherwise overstate the marginal MWTP.

But the biggest potential problem with this happiness approach involves what happiness economists call "habituation."

Habituation , Projection Bias, and the Nature of Happiness

One of the earliest and most widely noted findings in happiness economics is Easterlin (1974): self-reported 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

[3] Gardner and Oswald (2007) avoid the simultaneity of income by examining the happiness of lottery winners.

given point in time.[4] If true, this "Easterlin paradox" has two obvious interpretations. One is that happiness responds to relative income – being poorer than one's neighbors makes people unhappy, even if the whole neighborhood is rich in in absolute terms.[5] Another is that people become habituated to their circumstances. Once we are used to having material possessions, those items no longer make us happy.

Habituation has important consequences for the happiness approach to valuing public goods. If people become habituated to income, and the corresponding ability to buy private goods, then surely they also become habituated to public goods. Graham (2009) provides evidence that people become habituated to crime, corruption, democracy, and their own health. After a while, airport noise does not bother residents of houses near airports, but does bother their occasional guests. Or consider pollution. People in Los Angeles may not be any less happy than people in Portland, even though the air pollution is worse in Los Angeles. Similarly, Los Angelenos today may not be any happier than their counterparts 40 years ago when the city's air was dirtier. Current Los Angelenos are habituated to worse air quality than Portland today, and better air quality than Los Angeles in the past. But, on days when the air quality in LA is worse than the current norm, residents may be less happy than usual. This suggests that if we run a version of equation (1) in which the public good, G, is measured as the annual average level of that good, and identified via cross-location differences or via within-location differences over many years, the apparent effect on happiness will be smaller than if G is measured using daily fluctuations within a location within a year. This is precisely the exercise I conduct in Levinson (2012) and in the last part of this paper.

The issue of habituation brings up a second, closely related issue regarding the nature of happiness: whether survey is asking about momentary happiness, something like experience utility, or respondents' overall satisfaction with their lives, something closer to Kahneman's decision utility. Some surveys clearly ask about one or the other; some surveys are ambiguous, asking only how things are "these days." Respondent's momentary happiness, or experience utility, could easily be affected by day-to-day changes in circumstances, including the level of some fluctuating public goods. Life satisfaction, on the other hand, should not be affected by the fact that today's noise level is higher than average, but should be the target of public policy.

When it comes to using happiness for public policy, there is conflict between these two central issues: habituation and the nature of the happiness question. It seems intuitive that life satisfaction should be the goal of policy, not momentary happiness. That suggests we want to identify equation (1) based on average difference between locations over many years, not daily fluctions in G that would affect experience utility. But habituation suggests people's reported

[4] Recent work challenges half of this, showing that happiness does increase with GDP per capita across countries (Stevenson and Wolfers 2008; Deaton 2008; Helliwell et al. 2010). But other recent work confirms the paradox (Oswald 1997; Layard 2006). Either way, most seem to agree that stated happiness appears unchanged over time within any country even as per capita incomes have increased.
[5] See Luttmer (2005).

happiness may be a poor indicator of those long-term differences in life satisfaction. Moreover, if the goal of public policy is long-term assessments of welfare, we should identify equation (1) using life-satisfaction rather than momentary happiness to measure H. But daily fluctuations in a public good like air pollution should not, in theory, affect people's overall assessment of their entire lives. Why would a person's life satisfaction be worse just because they are asked about it on a smoggy day?

In fact, evidence abounds that responses to questions of overall life satisfaction can be significantly altered by even the most trivial transient circumstances. Schwarz and Clore (1983) provide a direct and stark example. They telephoned people randomly on rainy and sunny days and asked them two questions: a momentary happiness question, "how happy do you feel at this moment?" and a life-satisfaction question, "how happy do you feel about your life as a whole?" Those called on sunny days reported higher levels on a scale from 1 to 10 in response to *both* questions. The effect disappeared when the interviewer called attention to the weather, either by asking "By the way, how's the weather down there?" or by explicitly saying "we are interested in how the weather affects a person's mood." Table 2 reproduces their key results, which have two notable features. One is that the current weather has a statistically significant effect on overall life satisfaction. This is a puzzle. If people are making true assessments about their satisfaction with their entire lives, the weather on the survey date should be immaterial. Second, the effect of weather is larger on momentary happiness. This suggests that versions of equation (1) will generate different answers depending on the question asked. Which is the right question? That's hard to say. Life satisfaction and long-term public good differences seem like more appropriate policy considerations, but if people become habituated then equation (1) may only be identified based on short term local variations, like the daily weather.

Table 2. Weather, Happiness, and Life Satisfaction:
Table 3 from Schwarz and Clore (1983)

	No prompt	Respondents asked "how's the weather"	Respondents told study about mood and weather
Happiness (1-10)			
Sunny	7.43*	7.29	7.79
Rainy	5.00	7.00	6.93
Life Satisfaction (1-10)			
Sunny	6.57*	6.79	7.21
Rainy	4.86	6.71	7.07

*Statistically different at 5 percent. N=14 observations per cell.

Schwarz and Strack (1991) describe an even more trivial effect on life satisfaction. They randomly placed a dime on a photocopy machine before asking people to make copies, and then interviewed those people about their life satisfaction. Those that found a dime were significantly more satisfied with their lives. One could imagine estimating a version of equation (1) in which G is an indicator for whether or not people have just found a dime and then using equation (2) to place a value on the dime. The Schwarz and Strack result implies people would be willing to give up a significant amount of annual income in exchange for finding ten cents. So it seems as though temporary circumstances, even seemingly inconsequential ones, have significant effects on how people self-report their overall well-being. Transitory phenomena appear to affect people's assessment of permanent conditions. Today's level of a fluctuating public good may affect both momentary happiness and life satisfaction.

This type of behavioral incongruity also appears in real decision-making, aside from inconsequential statements about happiness or satisfaction. Behavioral economists refer to the real-world equivalent as "projection bias." People misestimate their future desires based on current circumstances. One example we are all familiar with involves grocery shopping while hungry. Empirical support for a similar example is in Conlin et al. (2007), who show that cold-weather clothing purchases are more likely to be returned if the purchase orders were placed on colder-than-average days. People overestimate their future demand for parkas based on the current low temperature.

This misjudgment of preferences, as represented by projection bias or people's conflation of momentary happiness and life satisfaction, has profound implications for valuing intangible public goods. Consider hedonic regressions of house prices on local amenities. Suppose people overbid for homes they see on sunny or unpolluted days. Then hedonic regressions of house prices on average local weather or pollution may be biased if they omit the weather or pollution on the day of sale. If a house is shown on several subsequent weekends and sells to the highest bidder, who is also likely to have seen the house on the nicest day, then the variance of local weather and pollution may be more important to predicting sales than their averages.

One appeal of using happiness responses to daily changes in a public good like air pollution is that the survey responses do not depend on people assessing their future preferences based on current circumstances, as they might when deciding where to live. Instead the happiness approach measures willingness to pay using current tradeoffs based on current circumstances. Whether that tradeoff is a legitimate basis for public policy remains an open question. In the application at the end of this paper I test the approach using both the local annual average level of air quality and the air quality on the day the survey was administered.

In brief, the happiness approach to evaluating policy has shortcomings. Like the hedonic approach, happiness applications must be careful to ensure that the variation in the public good is exogenous. One solution, using daily fluctuations, is problematic if public policy is aimed at long-term changes in public good levels. But if people become habituated to long-term average levels, the happiness approach may be useless except as identified by short-term fluctuations. For these reasons, many economists view this new happiness economics as just as much an anathema as CV. Smith (2008), for example, asks economists to look as skeptically at happiness as at they have at CV and worries that "the [happiness economics] train is precipitously close to leaving the station and heading for use in full-scale policy evaluation." By now that train has left, and policy evaluations are forming a growing part of the literature documented in Figure 1.

Examples of Policy Applications of Happiness Economics

One of the first high-profile policy applications of happiness analysis involves the unemployment-inflation tradeoff. Many countries' central banks, including the U.S. Federal Reserve Bank, have two competing goals: maintaining full employment and stable prices. But economists have only a mixed understanding of the relative costs of price inflation and unemployment. Di Tella et al. (2001) use responses to a life satisfaction question in the Euro-Barometer survey across 12 European countries from 1975 to 1991, and show that both inflation and unemployment adversely affect stated well-being. More importantly, the effect of a percentage-point increase in unemployment reduces life-satisfaction by 1.7 times as much as a percentage-point increase in the inflation rate. If we knew the rate at which these central banks were able to trade off unemployment and inflation, we could use this result to say whether their focus in those years was lopsided towards one goal or the other.

A second example of happiness data being used to assess otherwise unmeasurable policy parameters comes from health economics. Finkelstein et al. (2012) note that health status may affect the marginal utility of income. If sick people get more utility from a dollar of income than healthy people, less health insurance is necessary to fully compensate people who fall ill, but if sick people have lower marginal utility the opposite is true. The authors use panel data from the Health and Retirement survey, which asked for a yes-or-no response to the statement "Much of the time the past week I was happy." Finkelstein et al. regress the answer on the log of income, poor health status, and the interaction between the two. They find robust evidence that the interaction is negative: "a deterioration in health is associated with a statistically significant decline in the marginal utility of consumption." Their estimates suggest we should lower the share of medical expenditures reimbursed by insurance by 20 to 45 percentage points, and lower the fraction of our earnings we save for retirement by 3 to 5 percentage points.

A number of studies have used the methodology described by equations (1) and (2) to value public goods. Studying airport noise in Amsterdam, van Praag and Baarsma (2005) find that on average a 50 percent increase in noise reduces well-being by as much as a 2.2 percent drop in income. Studying flood disasters, Luechinger and Raschky (2009) conclude that reducing the probability of a flood by 2.6 percent would be worth 0.7 percent of household income. Studying terrorism, Frey et al. (2009) use this approach to show that residents of Paris, London, and Northern Ireland would be willing to pay 14 percent, 32 percent, and 41 percent of annual income, respectively, in exchange for a reduction in terrorism to the levels prevalent in more peaceful parts of their countries.

Several papers have used this happiness-data approach to assess the social costs of pollution. Welsch (2002, 2006, 2007) pioneered this approach. His 2006 paper, for example, estimates that the reductions in lead pollution and nitrogen dioxide in Europe during the 1990s made people there happier by an amount equivalent to an increase in per capita income of $1,200 and $2,200, respectively, in 2008 dollars. Di Tella and MacCulloch (2008) estimate that a one-standard-deviation increase in sulfur dioxide reduces happiness by an amount equivalent to a 17 percent reduction in income. Luechinger (2009) finds a marginal willingness to pay of $232 for a one microgram per cubic meter ($\mu g/m^3$) reduction in SO_2, while average SO_2 concentrations fell by 38 $\mu g/m^3$ over the time period.[6] And Menz (2011) finds that including lagged values of air pollution more than doubles the estimated social cost of pollution.

All of these studies – air quality, terrorism, flood risk, inflation and unemployment –share common drawback: they use average annual regional measures of the intangible good being valued. If people become habituated to their current level of public goods, cross-region or cross-year comparisons of annual average levels may misrepresent willingness to pay for changes. This suggests that we might expand on these studies by estimating versions of equation (1) where the public good is identified based on daily differences. Just as Schwarz and Clore (1983) found that people surveyed on rainy days reported lower life satisfaction, perhaps people surveyed on polluted days report lower life satisfaction. And perhaps this result is stronger for daily public good fluctuations than for annual averages because people become habituated to annual averages. And perhaps when both daily *and* annual average public good levels are included at the same time in equation (1), the results will tell us something about habituation and the use of happiness as tool for valuing public goods.[7] The next section conducts just such an experiment.

An Application: Valuing Air Quality Using Daily Variation

In Levinson (2012) I use the GSS three-category happiness measure to estimate versions of equation (1) and show that people surveyed on days when local air pollution is bad are less likely to report high levels of happiness. Furthermore, I use equation (2) to show that people appear willing to give up about $35 for an improvement of one standard deviation in air quality for one day, a figure about twice as large as the highest recent hedonic valuations of air quality (Bayer et al., 2009) or the U.S. Environmental Protection Agency's (EPA) assessment of the economic benefits of the 1970 and 1977 Clean Air Act Amendments (EPA 1999, 2011).

To explore this issue further, as a replication of that earlier work, and in particular to address issues of habituation, here I use the National Survey of Families and Households (NSFH), wave 1, which surveyed 11,645 respondents in 1987.[8] 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." Staff at the NSFH assisted me by merging data on local air

[6] €183 in 2002, converted using the average 2002 exchange rate and the CPI-U-RS.
[7] Menz (2011), titled "Do people habituate to air pollution?", finds that people do not habituate to air pollution, though they do habituate to income. But he accounts for habituation by including current and lagged values of average national air pollution levels. Country-specific trends correlated with both pollution and happiness may confound both coefficients.
[8] 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 also be matched to weather and air quality data, raising the intriguing possibility of including individual fixed effects, but here I rely on the first wave alone.

quality with individual observations, so that I can estimate happiness as a function of current local air quality and weather conditions in each respondent's zip code on the day the happiness question was asked.

The public good being measured here is air quality, measured as the lack of pollution. In particular, I focus on airborne particulates smaller than 10 microns (PM10). PM10 causes physical discomfort and forms a haze that reduces visibility and may affect people aesthetically. The EPA's Air Quality System (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.[9]

Finally, it is important to control for the current local weather, specifically temperature and precipitation, both of which are likely to be correlated with happiness and pollution levels. Several 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 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.

Column (1) of Table 3 contains descriptive statistics for the 4,654 observations with complete matched data on pollution, weather, and NSFH respondent characteristics. All of the other columns contain estimates of

$$H_{ijt} = \alpha P_{jt} + \gamma \ln Y_{\mathrm{i}} + X'_{ijt}\beta + \varepsilon_{ijt} \,, \tag{3}$$

where H_{ijt} is an indicator for the stated happiness of respondent i in zip code j, surveyed on date t. The variable P_{jt} is the air pollution at location j at date t.[10] Y_i is respondent i's household income, X_i is a set of other socio-economic characteristics of respondent i and region j, including day-of-week, month, and holiday fixed effects.

Examine column (2) of Table 3, for example. This is a simple linear regression of an indicator for whether reported happiness on a 7-point scale is larger than the median (greater than 5) on two variables: the log of the respondent's income, in thousands of dollars, and the

[9] More information about the AQS can be found at http://www.epa.gov/ttn/airs/airsaqs/.
[10] Particulates are monitored every six days, and so here for local monitors without readings on the day of a respondent's interview, I interpolate linearly between the most recent and next subsequent readings.

annual average pollution in the respondent's zip code. The income coefficient is positive and statistically significant. This is consistent with Easterlin's (1974) findings, as all of the variation in income comes from within the U.S. during one year. The coefficient on average pollution is negative, but small and statistically indistinguishable from zero. To calculate willingness to pay for clean air, taking the point estimates as given, apply a version of equation (2):

$$\left.\frac{\partial Y}{\partial P}\right|_{dH\equiv 0} = -\mathrm{Y}\frac{\hat{\alpha}}{\hat{\gamma}}\,. \tag{4}$$

Plugging in -0.00044 for $\hat{\alpha}$ and 0.052 for $\hat{\gamma}$, we get that the average marginal rate of substitution is $\partial Y/\partial P$=\$307, as reported in the bottom row of the table. This means that a one $\mu g/m^3$ increase in average annual local PM10 reduces people's stated happiness by an amount equal to a \$307 decline in annual income. For context, note that annual local pollution averages 38 $\mu g/m^3$, with a standard deviation of 12, so a one-standard-deviation increase would be valued at \$3,500. Though not small, it is also not statistically significant.

Column (3) estimates the same equation but substitutes the local daily pollution level. Here the income coefficient $\hat{\gamma}$ remains unchanged, but the pollution coefficient $\hat{\alpha}$ doubles and is now statistically significant. Applying equation (4), the marginal rate of substitution is now \$630 and is also statistically significant. Clearly the two pollution measures are correlated, and if people's happiness does depend on both, both should be included. Column (4) runs that regression including both. Now the coefficient on annual local pollution is statistically insignificant and even has the wrong (positive) sign. But daily pollution coefficient is again significant, suggesting a marginal WTP (based only on the daily coefficient) of \$929.

Columns (5) through (7) of Table 3 run these same three regressions but include demographic characteristics of the respondent, the local rainfall and temperature, and fixed effects for each day of the week, month of the year, and holidays. Happiness decreases with age until about age 43 when it starts increasing. Respondents who are married, employed, college graduates, and healthy are more likely to indicate high levels of happiness. The weather variables are not statistically significant, partly because so many correlated measures are included. From the point estimates, happiness declines with rainfall and increases with temperature until about 75° Fahrenheit after which it too declines, and happiness increases with the difference between the daily maximum and minimum temperatures, which is a proxy for lack of clouds.

The most important results in columns (5) through (7) are in the first three rows. The inclusion of all of the household demographic variables and weather variable do not alter the fundamental result that air quality affects happiness. The coefficients on daily and annual air pollution are almost identical to those without the other covariates. Annual pollution does not seem to affect happiness, and even has the wrong sign once daily pollution is included. But the inclusion of other respondent characteristics cuts the household income coefficient in half, doubling the estimate of marginal willingness to pay calculated from equation (4).

The distinct effects of daily and average annual local air pollution are striking, especially given the vagueness of the NSFH happiness question: "how would you say things are these days?" If "these days" means "recent years," it may be interpreted as life satisfaction; if "these days" means "today and yesterday," it means something more like momentary happiness. Perhaps, given the psychology evidence that life satisfaction responds to obviously temporary changes, the vagueness does not matter.

The troubling aspect of the differential effects of daily and annual pollution is that people respond to the daily measure, but the policy objective should be to target the annual level. Consider, for example, public goods that do not vary daily: open space, crime risk, clean water. If we take the result in Table (3) literally, we must conclude that either those public goods are not measurable using this approach, or that those public goods have no value using this approach.

Conclusions

Happiness economics has been around since Easterlin (1974), but only in the past 10 years has the literature turned to the serious applications of public policy described here. The new happiness approach to policy questions differs fundamentally from standard economics approaches. Standard economics observes people's choices, constrained by prices and budgets, and infers from those choices characteristics of people's preferences. But some policy questions cannot be asked in that way, and so happiness economics reverses the approach. It asks how happy or satisfied people are in different situations and directly infers their preferences over those situations based on their responses. The approach has been used to put a monetary value on situations where there are no market prices: unemployment, inflation, terrorism, noise, health, and in the example here, pollution. The approach is intriguing, maybe even promising, but before happiness studies can be used to make public policy, some difficult issues must be addressed. One of the most difficult, and the one highlighted here, involves habituation and projection bias, two words for essentially the same concept as labeled by happiness economists and behavioral economists, respectively.

Habituation, to happiness economists, refers to the fact that people's happiness seems to revert to a base level, even after being perturbed dramatically by major life events. People adapt to divorce, disability, crime, and bad weather. Interviewed immediately after an injury or on a particularly gloomy day, people will be less happy. But disabled people or residents of cities with gloomy climates are no less happy than able-bodied people in sunny climates. They are habituated to their circumstances. Projection bias, to behavioral economists, refers to the fact that people systematically mistake current circumstances for permanence. They buy too much food if they shop while hungry and too many sweaters on cold days. These two behaviors combine when people's assessments of their overall life-satisfaction responds significantly to trivial changes in circumstances, like sunny weather or finding a dime on a copy machine. At the same time people's happiness or life satisfaction does not respond to even dramatic differences in long-term circumstances to which they have become habituated. Projection bias means people's happiness over-reacts to temporary changes, and habituation means it does not react to long-term changes.

Can we use happiness for public policy anyway? An optimistic, or maybe even Pollyannaish, view would be that we are fortunate that people exhibit *both* behaviors. Habituation without projection bias would mean there would be no way of using happiness to estimate the value of public goods. People would be habituated to long-term changes in public good levels, and would not mistake short-term changes for permanence. There would be no effect on life-satisfaction of either local annual average air pollution levels across regions, thanks to habituation, or to daily fluctuations within regions, thanks to the lack of projection bias. Fortunately, responses to life-satisfaction questions do vary with temporary circumstances, like today's weather or air pollution. Projection bias may partly save this methodology from habituation. On the other hand, there's no guarantee that the valuations of public goods with habituation and projection bias would be the same as the valuations with neither, or that the magnitudes would be comparable.

The pessimistic view was stated by Schwarz and Starck (1999) even before the recent growth of policy applications began: “What is being assessed, and how, seems too context dependent to provide reliable information about a population’s well-being, let alone information that can guide public policy.” If that seems too negative, recall that other methods of valuing public goods are not without their own biases and unaddressed issues. Contingent value responses vary wildly based on the nature of the questions asked, and hedonic regressions may be skewed if home purchasers exhibit projection bias. Although travel cost models, hedonic regressions, and contingent valuations are not without unsolved problems, they have become mainstream tools for cost-benefit analysis and other policy applications. The past 10 years have seen the introduction of happiness economics as a new tool for answering important policy questions, a tool with its own new set of hurdles and biases that must be confronted. Whether in coming years we can learn enough about those biases to make happiness a policy tool on par with the others remains to be seen, but in the meantime there's no doubt the process will be interesting.

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Figure 1. The Econ 101 of Valuing Public Goods.

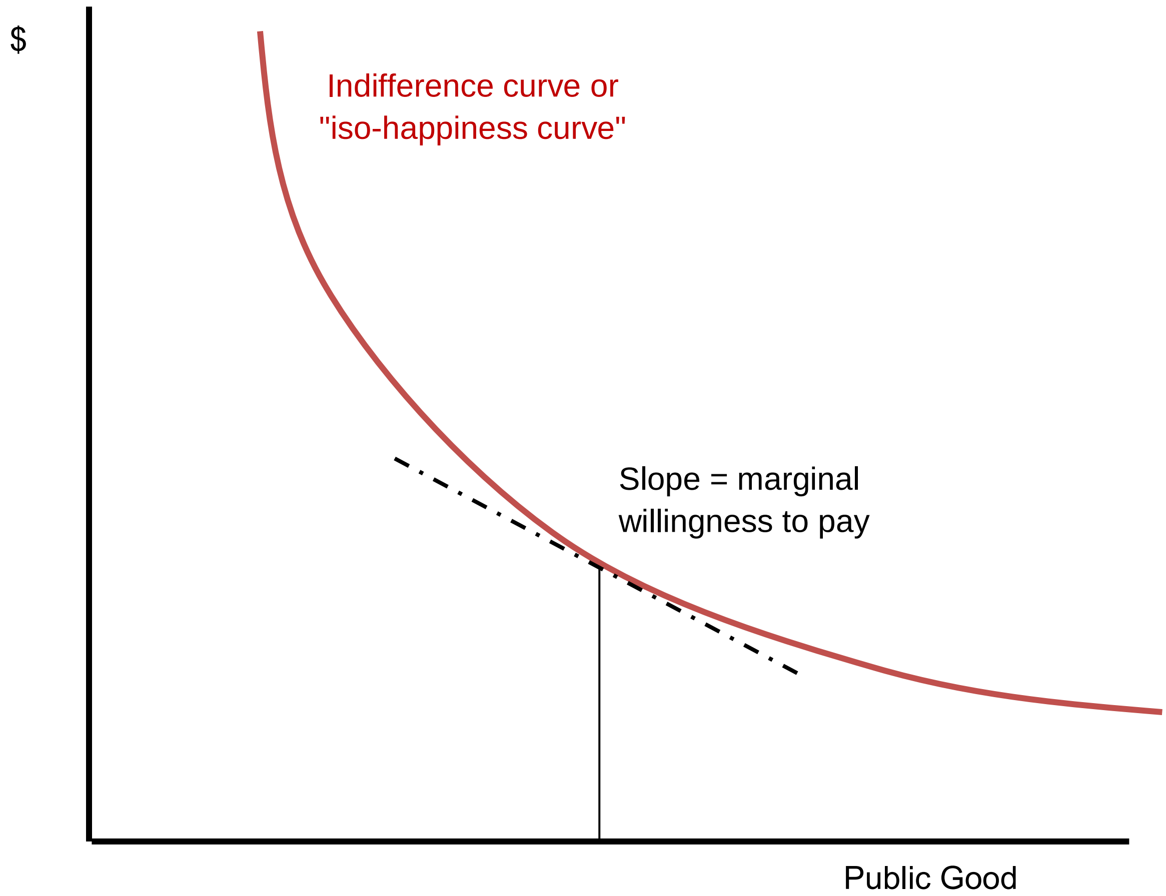

Table 3: Happiness, Air Pollution, and Income

Dependent variable: Happiness >5	**Means**	**Coefficients**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Daily local pollution	37.7		-0.00090*	-0.0013*		-0.0010*	-0.0014*
(100 μg/m^3) [α]	(16.7)		(0.00041)	(0.0006)		(0.0004)	(0.0006)
Annual local pollution	37.7	-0.00044		0.0009	-0.0005		0.0008
	(11.6)	(0.00060)		(0.0009)	(0.0006)		(0.0008)
log(real income	3.59	0.052*	0.052*	0.052*	0.022*	0.022*	0.022*
($1,000 2008)) [γ]	(1.24)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Age (÷10)	4.29				-0.094*	-0.094*	-0.094*
	(1.65)				(0.027)	(0.027)	(0.027)
Age (÷10) squared					0.011*	0.011*	0.011*
					(0.003)	(0.003)	(0.003)
Female	0.603				0.0008	-0.0001	-0.0005
					(0.0151)	(0.0151)	(0.0150)
Married	0.553				0.176*	0.175*	0.175*
					(0.017)	(0.017)	(0.017)
Kids	0.462				-0.0268	-0.0267	-0.026
					(0.017)	(0.017)	(0.017)
Employed	0.650				0.0025	0.0021	0.0014
					(0.0192)	(0.0192)	(0.0192)
Unemployed	0.033				-0.073†	-0.073†	-0.074†
					(0.044)	(0.044)	(0.044)
College graduate	0.218				0.063*	0.062*	0.062*
					(0.019)	(0.019)	(0.019)
Health poor	0.046				-0.207*	-0.207*	-0.207*
					(0.033)	(0.033)	(0.033)
Rain (indicator)	0.486				0.0023	-0.0003	-0.0007
					(0.0167)	(0.0167)	(0.0167)
Rain (0.01 inches)	9.6				-0.00003	-0.00006	-0.00006
	(24.2)				(0.00031)	(0.00031)	(0.00031)
Temperature mean	6.33				0.062	0.060†	0.057†
(10° F)	(1.33)				(0.045)	(0.045)	(0.045)
Temperature squared					-0.0043	-0.0039	-0.0037
					(0.0037)	(0.0037)	(0.0037)

(continued)

(Table 1 continued)

Temp. diff. (daily max–min)	2.28				0.018	0.020	0.021
	(0.74)				(0.012)	(0.012)	(0.012)
Constant		0.340*	0.358*	0.341*	0.321*	0.330*	0.324*
		(0.032)	(0.028)	(0.032)	(0.162)	(0.161)	(0.161)
Day of week, month, holiday fixed effects		no	no	no	yes	yes	yes
R^2		0.017	0.018	0.018	0.062	0.063	0.063
No. of obs. = 4,654							
WTP to pay for a one μg/m^3 reduction		\$307	\$630*	\$929*	\$818	\$1642†	\$2269†
		(417)	(301)	(440)	(1026)	(887)	(1224)

* Statistically significant at 5 percent. † Statistically significant at 10 percent. Std. deviations in column (1). Standard errors in columns (2)-(7) adjusted for clustering by zip code. Standard errors of WTP use the delta method. The dependent variable in columns (2)-(7) is an indicator for whether the happiness response is greater than 5 (the median value), on a 7-point scale.