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ABSTRACT

Using Life Satisfaction and Happiness Data for Environmental Valuation: An Experienced Preference Approach

A growing literature in economics uses subjective well-being data collected in surveys as a proxy for utility. Environmental economists have combined these data with the public goods experienced by respondents using a novel non-market valuation approach: the experienced preference approach. In this review, we take stock of what we know, including recent developments, and what we still need to learn about this new approach. We first present a conceptual framework that clarifies the relationship between experienced preference and conventional valuation approaches. We then discuss key challenges for its empirical application and identify areas where additional research would be fruitful.

JEL Classification: Q51, I31, H41

Keywords: subjective well-being, life-satisfaction, happiness, experienced utility, non-market valuation, willingness to pay, public goods

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1. Introduction

The experienced preference (EP) approach to environmental valuation is the newest addition to the economist's toolkit for the valuation of non-market goods and services such as environmental amenities or public goods for which we do not observe market prices. From early applications to value climatic conditions (Frijters and van Praag 1998) and air pollution (Welsch 2002), the EP approach (or "life satisfaction" approach) has developed in parallel with the growth of subjective well-being research in economics and has been applied to the valuation of a wide range of intangibles including noise (van Praag and Baarsma 2005), air pollution (Welsch 2006, Luechinger 2009 and 2010, Levinson 2012), green space (Bertram and Rehdanz 2015), scenic beauty (Ambrey and Fleming 2015), natural disasters (Luechinger and Raschky 2009, Ahmadiani and Ferreira 2021), crime (Manning et al. 2016), corruption (Welsch 2008a), civil conflict (Welsch 2008b) or terrorism (Frey et al. 2009).

The term subjective well-being (SWB) refers to individuals' assessments of their own subjective experience of their lives (e.g., Diener and Suh 1997).[1] The basic idea of the EP method is intuitive, and its application is straightforward: survey data on self-reported SWB (typically happiness or life-satisfaction scores) are modeled as a function of respondents' income and sociodemographic controls as well as the environmental conditions experienced by the respondents. Assuming that self-reported SWB is a good empirical approximation to individual welfare or utility, then in an estimated SWB regression a) the coefficient on the environmental amenity of interest measures its direct contribution to welfare; and b) the ratio between the coefficients of the environmental amenity and income captures the average marginal rate of substitution (MRS) between income and the environmental amenity that keeps utility constant, i.e., the average marginal willingness to pay (MWTP).

A common problem for the valuation of public goods is that individuals do not choose their personal level of consumption directly except by relocating or voting. Conventional non-market valuation methods overcome this problem by cleverly exploiting the information conveyed by individuals' location or voting *choices* to recover the implicit MWTP for those public goods. For example, hedonic pricing (HP), a prominent revealed preference (RP) valuation method, examines housing price differentials to estimate the MWTP for non-market amenities embedded in houses such as airport noise (Nelson 2004, Pope 2008). In many applications of contingent valuation, a stated preference (SP) method, survey respondents are asked to "vote" for a scenario describing a hypothetical market that would provide the good being valued (Carson 2012). In contrast to RP and SP, the EP approach does not rely on choices because utility is observed directly and therefore the trade-offs between income and the public good that would keep utility constant can be estimated (Layard 2010, Levinson 2013). This is the key conceptual distinction between the EP approach and the RP or SP approaches. SP and RP methods are based on decision utility while EP has its conceptual underpinnings in the notion of "experienced utility" (Welsch and Ferreira 2014). Decision utility is an *ex ante* concept, understood in terms of humans making choices so as to prospectively maximize "something" (their utility in economic terms). Experienced utility is an *ex post* concept,

[1] SWB is a multidimensional concept that involves components such as pleasant affect, unpleasant affect, life satisfaction, fulfillment, and more specific states such as stress, affection, trust, and joy (Diener 2000), but the various specific components can be grouped into affective and cognitive dimensions, that is, emotional states and evaluations of life, respectively (Diener 1984). While *happiness*, in the narrow sense, refers to the affective (emotional) component, the cognitive (evaluative) component is usually referred to as *life satisfaction*.

reflecting the hedonic experiences resulting from acts of choice (Kahneman et al. 1997, Kahneman and Sugden 2005).

The EP approach is taking root in public policy as “a promising new approach of valuing non-market goods” (OECD 2018 p. 73). Conventional valuation methods based on individuals’ choices lose their appeal in areas of public policy where little individual choice is involved. In these areas, the EP approach could offer alternative measures of the benefits of a policy change through direct measures of SWB (Layard 2010). Another argument often advanced in favor of the application of EP along with mainstream RP and SP methods is that because it relies on such different assumptions, its strengths and weaknesses are different and even complementary to the strengths and weaknesses of RP and SP, and can offer corroboration (or otherwise) of the results from these approaches or be applied where these methods’ assumptions are plainly inapplicable (Welsch and Kühling 2009, MacKerron 2012, Levinson 2013). Despite there being at least four reviews of the EP approach (Welsch and Kühling 2009, Frey et al. 2010, Welsch and Ferreira 2014, Fleming and Ambrey 2017), “[m]uch less is known about the strengths and limitations/open questions of this nascent non-market valuation approach compared to well established revealed and stated preference methods” (OECD 2018 p. 73).[2]

In this chapter, we take stock of what we know, including recent developments, and what we still do not know about the EP approach. In section 2 we present a conceptual framework based on Ferreira and Moro (2010) and Welsch and Ferreira (2014) that clarifies the relationship between the EP and conventional valuation approaches, in particular HP. In section 3, we discuss the empirical application and elaborate on the key assumptions of the EP approach. Section 4 points at areas where additional research could help address outstanding challenges to causal identification using the EP approach, and Section 5 concludes.

2. Conceptual framework

This section presents a simple theoretical model inspired in Roback (1982) that serves as the basis for comparison of EP with HP. The theoretical model shows that both approaches are closely related and clarifies that their relationship depends on whether hedonic markets are in equilibrium or not, and on the econometric specification of the happiness function. For simplicity, in the model individuals are assumed to be rational, perfectly informed, and able to accurately predict the utility they will derive from their choices, i.e., there is no distinction between decision and experienced utility. In the second part of the section, this assumption is relaxed to offer a fuller comparison between EP and standard valuation methods.

2.1. Theoretical model

Consider an economy where individuals derive utility from environmental amenities, housing, and a composite commodity, which we take as the numeraire. The representative agent in this economy then faces the following problem:

$$Max\ U(x, l; a) \ \text{ subject to } \ w = x + rl \qquad (1)$$

where *w* is income, which we assume to be derived from wages, *r* is the rental price of residential land, *l*, *a* is a local amenity, and *x* is the numeraire. Associated with equation (1) is

[2] For surveys on the study of SWB in economics see Frey and Stutzer (2002), Layard (2005), Di Tella and MacCulloch (2006), Clark et al. (2008), van Praag and Ferreir-i-Carbonell (2008), MacKerron (2012), or Clark (2018).

the indirect utility function $v = v(w, r, a)$, with the usual properties: it increases in income $\partial v/\partial w > 0$, and decreases in rents $\partial v/\partial r < 0$. The effect on utility of a change in local amenity *a* depends on whether *a* is a consumption amenity ($\partial v/\partial a > 0$, e.g., clean air) or a disamenity ($\partial v/\partial a < 0$, e.g., noise).

The market equilibrium condition in interurban HP models (e.g., Roback 1982, Blomquist et al. 1988) is that utility is equalized across locations:

$$v(w, r, a) = c, \tag{2}$$

where *c* is a constant. In this framework, wages and rents are a function of the local amenity ($w(a)$ and $r(a)$), and must adjust for condition (2) to hold. Otherwise, some individuals would have an incentive to move to locations where they could attain a higher utility.

Taking the total derivative of (2) yields the following expression:

$$\frac{dv}{da} = \frac{\partial v}{\partial w}\frac{dw}{da} + \frac{\partial v}{\partial r}\frac{dr}{da} + \frac{\partial v}{\partial a} = 0, \tag{3}$$

Which after rearranging, dividing by the marginal utility of income $\partial v/\partial w$, and applying Roy's identity to equalize the term $-\frac{\partial v}{\partial r}/\frac{\partial v}{\partial w}$ to the amount of residential land consumed, *l*, results in the implicit price of amenity *a*, or MWTP, expressed as

$$\frac{\partial v}{\partial a}/\frac{\partial v}{\partial w} = -\frac{dr}{da}\frac{\partial v}{\partial r}/\frac{\partial v}{\partial w} - \frac{dw}{da} = -\frac{dr}{da}l - \frac{dw}{da}. \tag{4}$$

Equation (4) illustrates two radically different ways of pricing amenity *a*. One way of approximating the MWTP for amenity *a*, the one followed by HP, calculates the right-hand side of equation (4) using housing and wage regressions to estimate $\frac{dr}{da}$ and $\frac{dw}{da}$, respectively. A second way of estimating the MWTP for amenity *a*, calculates its direct contribution to utility and the trade-offs with income that would keep utility constant. This is what the EP approach does. It produces direct estimates of the left-hand side: $\frac{\partial v}{\partial a}/\frac{\partial v}{\partial w}$, the marginal rate of substitution, or the ratio of marginal utilities depicted in Figure 1 as the slope of the indifference curve at point A for $a = a_0$ at the prices and income compatible with the dashed budget line.

An important additional, practical observation is that for the EP approach to provide an estimate of the marginal utility of the amenity (that is, the partial derivative $\frac{\partial v}{\partial a}$, as opposed to the overall effect of a change in the amenity on utility – the total derivative $\frac{dv}{da}$, which in equilibrium, according to (3) should be zero), other factors that compensate for changes in the amenity and that affect utility, in particular rents or housing prices, should be included in the regression (Ferreira and Moro 2010, MacKerron 2012).

Equation (4) shows the conceptual equivalence between HP and the EP approach when the equilibrium condition holds. In disequilibrium, however, $\frac{dv}{da} \neq 0$, and equation (4) becomes

$$\frac{\partial v}{\partial a}/\frac{\partial v}{\partial w} = -\frac{dr}{da}l - \frac{dw}{da} + \frac{dv}{da}/\frac{\partial v}{\partial w}. \tag{5}$$

The EP approach can continue to yield an estimate of the left-hand side in (5). HP, on the other hand, would miss the residual term $\frac{dv}{da}/\frac{\partial v}{\partial w}$ in the right-hand side, and yield biased estimates of the MWTP for the amenity. Proponents of the EP approach often point at the strong assumptions of rationality, perfect information and costless mobility implicit in the equilibrium condition that HP requires but that the EP method does not. They also note that in disequilibrium, the EP and HP could still be complementary approaches since the EP approach can be applied to estimate the "residual" term $\frac{dv}{da}/\frac{\partial v}{\partial w}$ in a property specified regression (van Praag and Baarsma 2005, Luechinger 2009). This residual term is the part of the externality that is not compensated for in housing and labor markets. Note that, as a special case, if the amenity were not capitalized in markets at all, that is if $\frac{dr}{da} = \frac{dw}{da} = 0$, HP would be inappropriate, while the EP method could yield an estimate of the term $\frac{\partial v}{\partial a}$, which would equal $\frac{dv}{da}$ in this case.

In addition to the MWTP, which is appropriate to value marginal changes in the provision of amenity *a*, two additional monetary measures can be used to calculate the welfare effects of non-marginal changes in *a*, for example, an increase from a_0 to a_1 depicted in Figure 1. The compensating variation (CV) is the amount of money that would keep the individual at the original level of utility, U_0, when a change in the provision of the amenity has occurred. That is, $v(w - CV, r, a_1) = v(w, r, a_0)$. In Figure 1, it is the distance E-F. The equivalent variation (EV) is the amount of money that would move the individual to the new level of utility, U_1, when a change in the provision of the amenity has not occurred. That is $v(w + EV, r, a_0) = v(w, r, a_1)$. In Figure 1 it corresponds to the distance G-E.

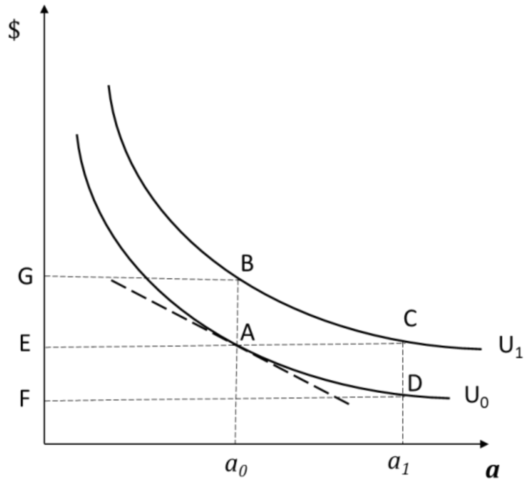

Figure 1: Measures of welfare change

The analysis in this section is based on a highly stylized model that has not explicitly distinguished between decision utility and experienced utility. That is, the model implicitly assumed that individuals are rational, perfectly informed, and that they can accurately predict the utility they will derive from their choices. In reality, divergences between choice and experienced SWB trade-offs are well documented and are often attributed to imperfect information at the time of choice. This could be because individuals lack full information on the characteristics of the choices or due to a lack of accurate affective forecasting whereby individuals mis-predict the utility consequences of their choices (e.g. Loewenstein et al. 2003, Gilbert 2006). It is in this context that SWB measures are described as measures of experienced utility in contrast to the expected or decision utility yielded by the preference satisfaction approach implicit in RP (or SP) methods.

2.2. Relationship to other non-market valuation methods

Table 1 shows the classification of valuation methods according to two criteria: (a) whether they are based on hypothetical or on real situations and (b) whether they are based on choices (*ex ante*) or on experiences (*ex post*). The table illustrates that EP and SP differ on both accounts, while EP and RP differ only on one.

Table 1: Non-market valuation frameworks

	Actual situations	**Hypothetical situations**
Choices (*ex ante*)	Revealed Preference (RP)	Stated Preference (SP)
Experiences (*ex post*)	Experienced Preference (EP)	

Both RP and EP show up on the left column of the table as they refer to actual situations. In contrast to EP, however, RP is based on ex-ante decisions and assumes equilibrium (optimal) adjustment of market behavior to environmental conditions. That is, RP neglects bounded rationality, information asymmetries as well as any other market imperfections such as transaction or moving costs which may prevent optimal adjustment, and absence of regulation, while in fact regulation is a characteristic of housing and labor markets in many countries (van Praag and Baarsma 2005, Welsch and Ferreira 2014).[3] As the theoretical model in the previous subsection indicates, in the absence of market equilibrium, HP would yield biased estimates of the MWTP for environmental amenities, while the EP approach does not assume that agents are rational nor that markets are in equilibrium. This does not mean that EP is without problems, however. In the next section we discuss the (completely different set of) assumptions implicit in empirical applications of the EP approach.

SP methods elicit the WTP or willingness to accept (WTA) for changes in environmental conditions in surveys that present respondents with hypothetical scenarios. Its main appeal is that, in principle, it can be applied to any environmental condition and can capture both use and non-use (including existence) values. In addition, because they are in essence an experimental method, a carefully crafted design of the scenarios allows for causal claims. A key shortcoming of this approach is that to place a monetary value on hypothetical changes may present people, depending on the good or service being valued, with an unfamiliar and cognitively complicated task of affective forecasting which may result in elicitation of attitudes rather than preferences (Kahneman and Sugden 2005). Another challenge of SP methods is that they are subject to framing effects and context effects. In particular, it matters whether valuation questions are formulated in terms of WTP for gains or WTA for losses. While the difference should be small according to standard models of consumer choice, behavioral economics has consistently shown that, due to the so-called endowment effect, the valuation of losses is systematically larger than the valuation of gains (Knetsch 2005). Moreover, strategic responses may further widen the gap.[4]

[3] Bayer et al. (2009) show that controlling for moving costs in a HP framework considerably raises their valuation results for particulate matter.
[4] See Hausman 2012 and Haab et al. 2013 for a taste of the vigorous academic debate surrounding the use of the contingent valuation method, particularly as used in court litigations for natural resource damage assessments.

The EP approach also rests on subjective data from surveys, so similar care is required when designing the questionnaire to avoid that the quality of self-reported data be compromised by question wording, format, or context (Schwarz 1999). Compared to SP methods, however, the EP method is cognitively less demanding because individuals are not requested to directly place monetary values on hypothetical environmental conditions. In addition, less knowledge on the physical effects of those conditions is required than in both SP and RP. In fact, the EP method may capture effects of environmental conditions of which the individual is not consciously aware.

To date, only a few studies have employed the EP approach in combination with SP or RP. Some studies have tested the consistency between decision and experienced utility regarding location decisions (Moro et al. 2008, Ferreira and Moro 2010, Oswald and Wu 2010, Ahmadiani and Ferreira 2019), recreational behavior (Börger et al. 2022), and employment decisions (Ferreira et al. 2023 mimeo). A handful of studies have compared monetary estimates for intangibles derived from EP and conventional approaches. Luechinger (2009) combines the EP method with hedonic housing regressions to value air pollution in Germany and finds that only a small proportion of the overall effects of pollution is capitalized in the housing market whereas the bulk of the effects takes the form of reduced life satisfaction not compensated by lower housing costs. Dolan and Metcalfe (2008) compare the EPM with HP and contingent valuation (CV) for an urban regeneration scheme in the UK and find regeneration not to be positively valued through house sales. From a contingent valuation survey, the WTP is found to amount to about £2,800 over a period of 12 years (the average length of time people live in one house) whereas the value of the regeneration estimated from SWB responses is around £6,400 according to their preferred specification. Similarly, Humphreys et al. (2020) compare contingent valuation and EP estimates of the WTP for medals won by Canadian athletes in the 2010 Vancouver Winter Olympic Games and find EP estimates to be significantly greater than those elicited through contingent valuation.

In addition to empirical concerns pertaining to identification in the context of the EP method (to be discussed in section 4), such divergence between contingent valuation and EP measures may have substantive (psychological) reasons. A chief substantive reason, pertaining to contingent valuation, is projection bias in predicting future utility from both money and the amenity or event to be valued (Loewenstein et al. 2003). Failure in anticipating the impact of (dis)amenities on future utility may, however, also affect the EPM. For instance, Rehdanz et al. (2015) did not find an effect of the level of nuclear radiation on SWB shortly after the Fukushima nuclear disaster, whereas Danzer and Danzer (2016) found even subclinical nuclear radiation doses from the Chernobyl nuclear meltdown to affect SWB twenty years later.[5]

In contrast to SWB, property values around the Fukushima nuclear plant were found to decrease with increasing levels of local nuclear contamination (Yamane et al. 2013), which suggests that well-being and property prices capture different aspects of the disaster in different ways. While SWB effects refer to *actual* (experienced) utility consequences of the disaster to affected individuals, property values seem to capture the *expected* utility consequences not only to currently affected individuals, but also to individuals in the future. Recent evidence suggests, however, that expectations about the future influence SWB.

[5] As suggested by Rehdanz et al. (2015), low-level radiation after Fukushima may not have affected SWB in the short term due to a lack of physical, health effects. People living in a place affected by the tsunami or close to the Fukushima Dai-ichi power plant experienced a drop in life happiness with the effects declining with distance to the plant.

Bartolini and Sarracino (2018) found people's SWB to respond to broad alternative scenarios of the future in terms of whether they expected a "bright" or "bleak" future for humanity.[6]

3. Empirical application of EP to non-market valuation

The EP approach estimates $\frac{\partial v}{\partial a}/\frac{\partial v}{\partial w}$ from equations (4) and (5) in regressions where self-reported SWB, taken to be a proxy of experienced utility, is modelled as a function of the amenity *a*, income *w*, and a vector ***z*** of other determinants of subjective well-being at both the individual (e.g. sex, age, employment status) and macro levels (e.g. rents).

$$SWB = f(a, w, \boldsymbol{z}). \qquad (6)$$

From (6), one can estimate the MWTP for a marginal change in *a* by totally differentiating SWB and setting *dSWB*=0:

$$MWTP \ = -\frac{dw}{da} = \frac{\partial SWB}{\partial a}/\frac{\partial SWB}{\partial w}. \qquad (7)$$

For non-marginal changes in the level of the amenity, the calculation of the CV and EV from (6) would also be straightforward: $SWB(a_1, w - CV, \boldsymbol{z}\,) = SWB(a_0 w, \boldsymbol{z})$ and $SWB(a_0, w + EV, \boldsymbol{z}\,) = SWB(a_1 w, \boldsymbol{z})$.

3.1. On the mapping of utility into self-reported subjective well-being:

A critical assumption of the EP approach is that self-reported SWB is a good proxy for unobservable individual welfare. The indicators of SWB used in most empirical applications of the EP method are based on global evaluations of life satisfaction from large-scale, representative surveys. For example, in the European Social Survey (www.europeansocialsurvey.org) respondents are asked "All things considered, how satisfied are you with your life as a whole nowadays?" and instructed to respond by using a card with numbers 0, 1, 2, …, 10, where 0 is labelled as "extremely dissatisfied" and 10 is labelled as "extremely satisfied". For a description of other publicly available sources of data on SWB, please refer to Appendix A.

The justification for the use of life-satisfaction scores is that the standards underlying people's judgments about their lives reflect their preferences over possible lives (Frey et al. 2010, Kaiser 2022), an assumption supported by studies where anticipated life satisfaction (more so than affective SWB measures) is a strong predictor of people's *ex ante* preferences over life scenarios (Benjamin et al. 2012, 2014). Rayo and Becker (2007, p. 487) "consider that maximizing happiness is closely linked, if not identical, to maximizing utility in the standard economic way", where happiness is understood as hedonic or experienced utility and broadly defined as a synonym for SWB.

Reported SWB, however, depends on both (i) a latent (true) level of satisfaction, *h*, which is influenced by observable characteristics, as well as (ii) a reporting function, *R*, that recollects, filters, and aggregates those subjective latent feelings into an objective, discrete number in a satisfaction scale, generally bounded, which individuals report (Oswald 2008, MacKerron 2012). Referring to the conceptual model in the previous section, $h = H(a, w, \boldsymbol{z})$ is the latent level of satisfaction while $SWB = R[H(a, w, \boldsymbol{z})]$ is the self-reported level of life satisfaction, where *R* is the reporting function. In empirical applications using SWB data, because *H* and *R*

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[6] Importantly, their paper controls for endogeneity of expectations by means of instrumental variable techniques.

are unobservable, they are often collapsed into a single function, that in our case would map $(a, w, \boldsymbol{z})$ directly into SWB; i.e. $SWB = f(a, w, \boldsymbol{z})$ or equation (6). In what follows, we elaborate on the assumptions that are required for valid inference using the EP method.

For self-reported SWB to act as a meaningful proxy of experienced utility, one must assume that the reporting function is non-decreasing: higher levels of latent (true) satisfaction cannot lower the reported satisfaction (monotonicity).

To be specific, the relevant empirical model can be stated as follows (Ferrer-i-Carbonell and Fritjers 2004):

$$h = H(a, w, \boldsymbol{z}): \qquad h_{it} = \beta_a a_{it} + \beta_w \log(w_{it}) + \boldsymbol{z}'_{it}\boldsymbol{\beta}_z + \varepsilon_{it} \tag{8}$$

$$SWB = R(h): \qquad SWB_{it} = k \iff \theta_{it,k-1} < h_{it} \leq \theta_{it,k}, k = 0, \dots, K \tag{9}$$

In this formulation, the indices *i* and *t* refer to the individual and time of observation, respectively, and ε is the error term. In equation (8), income is included in log form to account for diminishing marginal utility, in consistency with the concavity of the indifference curve in Fig. 1. Accordingly, the ratio of β_a and β_w times income yields the MRS that the EP method seeks to measure. In equation (9), stating the reporting function, the θs are thresholds that latent satisfaction needs to cross for an individual to start reporting the next category of satisfaction, *k* (where $\theta_{it,0} = -\infty$ and $\theta_{it,K} = \infty$). The reporting function stated in equation (9) clearly satisfies the assumption of monotonicity. While this assumption seems benign, much stronger assumptions are required to recover unbiased estimates of marginal utilities and of marginal rates of substitution. As explained by Ferrer-i-Carbonell and Fritjers (2004), the adequate estimation method depends on the restrictiveness of the assumptions regarding the reporting function.

1. The first key assumption has to do with the ***comparability of reported SWB across individuals and over time*** (interpersonal and intertemporal comparability, respectively). Interpersonal comparability refers to the question whether individuals use a common scale – in terms of the θs – when mapping their latent utility into a satisfaction score. Intuitively, does a “7” in a life satisfaction scale have the same meaning for different individuals? If panel datasets are available, it may not matter very much. Individual fixed effects (or first differencing) can help control not only for individual-specific unobserved heterogeneity of individuals (e.g. due to personality traits) but for differences in reporting styles as long as these are constant over time. The use of “vignettes” has also been proposed to correct for interpersonal differences in reporting scale when longitudinal data on the same individuals are not available.[7] With respect to intertemporal (within-person) comparability – stability of the θs over time – one’s own memories of life satisfaction can help correct for changes in scale for a given individual over time (Kaiser 2022). Reassuringly, although the studies that have used vignettes or people’s memories have found differences in scale across people and over time, the differences are too small to change substantive conclusions (Kaiser and Vendrick 2022). In terms of equation (9), comparability means equality of thresholds across individuals and time: $\theta_{it,k} = \theta_k$.

[7] In this method, vignettes describing imaginary persons’ lives are presented to respondents who are asked to rate the life satisfaction of the people in the vignettes, and can help “anchor” the reporting function (Angelini et al. 2014).

2. The second assumption regards the ***cardinality (linearity) of SWB reports***. That is, $h_i - h_j = g(SWB_i - SWB_j)$ where $g(.)$ is a function known up to a multiplicative constant. Normally equidistance or linearity in reporting scales is assumed so that $h_i - h_j = SWB_i - SWB_j$, that is, the difference between a satisfaction score of a 7 and an 8 is the same as the difference between a 5 and a 6. In terms of equation (9), this assumption means that the difference between any two adjacent θs is the same (which requires that the thresholds are independent of the explanatory variables).

Under this assumption, simple OLS regressions, where responses are labelled in their rank order (i.e., 1, 2, …,K), are appropriate for the estimation of (6), that is, the dependent variable in equation (8), h_{it}, is replaced with SWB_{it}. If, however, we are unwilling to assume cardinality, we can use an ordered probit or logit (which assume only monotonicity and comparability of the reporting function). These models estimate the βs and θs in equations (8) and (9) jointly by the method of maximum likelihood under the assumption of a specific distribution of the error term.[8]

Since the seminal work of Ferrer-i-Carbonell and Frijters (2004), who showed that OLS and ordered probit estimations of SWB equations yielded similar results — in particular with respect to the ratios of coefficients – many papers have replicated their findings and most papers report SWB regression estimates using OLS. Compared to ordered probit, OLS is very attractive because it offers an intuitive, straightforward interpretation of estimated coefficients as marginal utilities and allows for the inclusion of individual fixed effects, which as stated above, help control for individual heterogeneity (among other, in reporting styles).[9]

3.2. Scale use and monetary valuation

While the issue of (non-)cardinality seemed to have been settled by the ability of the ordered probit model to estimate the thresholds of the reporting function, combined with the similarity of results from OLS and ordered probit, recent years have seen a revival of concern about cardinality and linearity based on the fact that the ordered probit (or any other ordinal response regression approach) relies on assuming a specific distribution of the error term. Allowing for possible deviations from the assumed distribution, Bond and Lang (2019) suggest that previous results might be uninformative.

Responding to such renewed concern about non-cardinality and the impossibility to identify the distribution of the error in ordered response models, some recent research has pursued a different approach, by studying the robustness of estimation results to monotonically increasing transformations of the SWB scale (e.g., replacing 1, 2, 3, 4 etc. with 1, 2, 4, 8 etc.). Schröder and Yitzhaki (2017) and Bond and Lang (2019) demonstrated that monotonically increasing transformations of the SWB scale can result in sign reversals on estimates from both, OLS and ordered probit models.

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[8] In the ordered probit approach the error is assumed to be normally distributed. In the ordered logit it is assumed to follow a standard logistic distribution.

[9] In contrast to OLS, controlling for individual fixed effects in ordered probits has been thought to be infeasible (Riedl and Geishecker 2014). Since Ferrer-i-Carbonell and Frijters (2004) found biases from non-comparability to be more serious than biases from non-cardinality, they recommended using OLS with fixed effects (if data availability permits) rather than an ordered probit. This reasoning is losing weight in recent years since van Praag (2015) and Kaiser (2022) have shown that it is possible to make such correction in an ordered probit as well.

Kaiser and Vendrick (2022) argue that the root cause of such findings is that the effect of some independent variable(s) is heterogenous across response categories.[10] They show that, in practice, such reversals are in most cases highly unlikely requiring that respondents interpret SWB scales in a highly non-linear fashion. They also show, however, that ratios of coefficients, such as the MRS in equation (7), which are fundamental for non-market valuation using the EP method, are affected by relatively mild convex or concave transformations. The cause of the sensitivity of ratios to non-linear transformations of the SWB scale is the same as stated above: heterogeneity of effects across response categories.

There are two questions to be considered with respect to estimates of the MRS. First, how sensitive is the MRS with respect to non-linear transformations, and second, do people use SWB scales in a non-linear fashion?

With respect to the first of these questions, Kaiser and Vendrik (2022) derive bounds on ratios of OLS coefficients. Their proposition 4, applied to the present context can be stated as:

Proposition:

> Let $d_{it,k}$ be dummy variables that take the value 1 if reported SWB_{it} is less than or equal to k for all k = 1, ..., K-1 and zero otherwise. Consider the regression equations (i) $SWB_{it} = \beta_a a_{it} + \beta_w \log(w_{it}) + \boldsymbol{z}'_{it}\boldsymbol{\beta}_z + \varepsilon_{it}$ and (ii) $d_{it,k} = \beta_{a,k} a_{it} + \beta_{w,k} \log(w_{it}) + \boldsymbol{z}'_{it}\boldsymbol{\beta}_{z,k} + \varepsilon_{it,k}$. Then the following holds:
> The ratios of OLS coefficients from (i) vary across all monotonically increasing transformations of the SWB scale within a range given by the smallest and the largest value of the corresponding ratios of OLS coefficients from (ii).

While the robustness checks suggested by this proposition do not seem to have been applied to environmental valuation using the EP method, Kaiser and Vendrik (2022) found, using data from Germany, that the MWTP for being married varies within a relatively small range of 6,748 and 9,590 Euro of equivalized annual net income whereas ranges are much larger for being unemployed or disabled.

To put this line of research in perspective, it is worth noting that it responds to a hypothetical scenario: That people use the SWB scale in a non-linear fashion. This leads us to the second question regarding linearity of SWB scales. A small literature has studied how likely non-linear scale use actually is in practice (van Praag 1991, Layard et al. 2008, Oswald 2008, Kristoffersen 2017). As explained in more detail in Appendix B, these papers have used a variety of strategies and assumptions but conclude that scale use is approximately linear. In addition, the many SWB studies that used ordered response estimation methods (ordered logit or probit) found little evidence of strongly non-linear estimated thresholds of the SWB scale. While the assumptions on the distribution of errors underlying these studies cannot be tested, these

[10] They explain the logic of sign reversals as follows: "when the effect of some variable X is positive in one part of the distribution of reported wellbeing, but negative in another, then the sign of the average effect of X can be flipped by rescaling the different parts of the response scale. For example, if the effect of X were negative at the bottom of the response scale, but positive at the top, we could adopt the assumption that differences between response categories are miniscule at the bottom of the scale and extremely large at the top. With that assumption, we could obtain a positive average effect of X. However, if we were instead to assume that differences between response categories are extremely large at the bottom of the scale, but miniscule at the top, we could obtain a negative average effect of X. Thus, so long as the effect of X is heterogenous across response categories, we can flip the sign of the average effect of X by changing our assumptions about how respondents interpret the meaning of each response category."

results are consistent with those in studies that more formally test non-linear use of scales. In sum, the similarity of conclusions across vastly different approaches suggests convergent evidence for approximately linear scale use (Kaiser and Vendrik 2022).[11]

4. Considerations for causal identification

The main empirical challenges confronting researchers when using the EP method are those common to non-experimental studies in environmental and health economics. One key challenge is to accurately measure and assign environmental amenities to a unit (i.e., the individual respondent) as well as to address the endogeneity bias between the environmental variables and SWB that might arise from, e.g., residential sorting. HP regressions confront similar challenges. Additionally, and specific to the EP approach, empirical researchers need to carefully consider how to deal with the endogeneity of income and its measurement.

<u>4.1 Environmental amenities measurement and sorting</u>

To gauge the impact of environmental factors on SWB, the EP method quantifies and matches "exposure" to, or "experience" of, environmental (dis)amenities to each respondent at the spatial level at which the survey data are available. This has been done by, e.g., calculating the density of such (dis)amenities in the respondent's region or their distance to the region's centroid (see Brereton et al. 2008 for one of the first applications of Geographic Information Systems (GIS) in this context). In the case of assigning air pollution, rather than simply using the measurements from the nearest monitoring station or unweighted regional averages, researchers now can use pollution concentrations from environmental models that incorporate data from multiple stations and weighting techniques to capture exposure more accurately. 3D-GIS models can also be employed to account more accurately for topographic features, such as elevation and spatial barriers that could be combined with spatially detailed information about factors such as the weather and wind direction which interact with pollutants. A more refined level of geographical information, such as the respondent's residential address, offers the potential for enhanced precision in the assignment of each (dis)amenity. However, obtaining such granular data poses ethical and confidentiality concerns and may not be accessible to every researcher. Further, the EP method typically assigns pollution to individuals based on where they live. This is common practice shared in environmental and health economics. However, individuals divide their time across several locations (e.g., work, school) whose environmental conditions may impact SWB in ways not accounted for.

One important consideration in the case of pollution is whether to assess the impact of *daily* or *annual* concentrations. Daily variations are more suitable for capturing acute effects from immediate exposure, while annual concentrations can help detect cumulative or average effects depending on the pollutant. In practice, whether annual concentrations can detect cumulative effects depends on two additional considerations. The first one is habituation

[11] It may also be noted that the way survey respondents use an SWB scale arguably depends on how SWB reports are actually elicited. While respondents to the European Social Survey are presented a card showing the numbers 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, the US General Social Survey includes only three verbally labeled happiness categories: very happy, pretty happy, not too happy. Whether people interpret these verbal categories as equidistant is presumably more ambiguous than in the case of explicitly stated numbers. An approach specifically designed to attenuate scale ambiguity is the so-called Cantril Ladder (Cantril 1961) where respondents are shown a ladder with steps numbered from 0 at the bottom ("worst possible life") to 10 at the top ("best possible life") and asked to indicate the step on which they feel they stand. As the steps are equally high, this is expected to encourage linear scale use.

(Graham 2009) whereby individuals gradually become accustomed to their environment, which may lead to a reduced perception of impacts on well-being. If panel data are available, habituation can be tested explicitly. There is some evidence that people become inured over time (see, e.g., Krekel and Zerahn 2017) but habituation may not be universal in the context of environmental amenities as it may depend on the specific environmental or contextual factor being investigated. For example, while existing evidence suggests that individuals habituate to the presence of windmills (Krekel and Zerahn 2017), they do not habituate to biomass burning for power generation (Von Möllendorff and Welsch 2017). In the case of air pollution, Menz (2011) finds little evidence of habituation to air pollution, but using long-term measures such as annual average concentrations may capture long run effects, after individual adaptation actions have been adopted to cope with potential negative effects.

The second consideration is the endogeneity of pollution arising from residential sorting resulting from preference heterogeneity of the individuals being exposed, which is exacerbated when using annual concentrations rather than random (exogenous) daily fluctuations (Levinson 2020). People (including respondents to SWB surveys) can alter the level of exposure to local amenities including pollution by moving away from sources of contamination (e.g., Banzhaf and Walsh, 2008) or by protecting themselves through the purchase of e.g., bottled water, air purifiers or masks (see, e.g., Graff Zivin et al. 2011).

As such, the EP approach requires researchers to carefully consider the potential endogeneity bias that may arise from residential sorting (or other avoidance behaviors). From this practical point of view then, the EP method shares important similarities with HP.

One empirical strategy to attenuate this bias is to include a rich set of control variables. This strategy is readily available to happiness researchers given that the surveys that include SWB questions also come with a rich set of individual characteristics, including age, education, and income. If panel data are available, fixed-effects models can control for unobservable time-invariant individual heterogeneity, offering a powerful strategy for identification.[12] However, even the best datasets may fail to capture important but subtle differences across individuals, such as medical pre-existing conditions, that might explain differences in sorting across neighborhoods. These unobservable characteristics are problematic if they are correlated with life satisfaction and the environmental variables. One way to address the endogeneity bias that arises from sorting in the EP approach is to use causal inference methods that exploit natural experiments, such as unanticipated policy shocks, natural disasters, accidents, or arbitrary features of policies.[13]

Within the EP method literature, Luechinger (2009) estimated the effect of improvement in air quality on SWB by using the mandated installation of scrubbers at power plants and wind direction as an instrument for air pollution in German counties. The use of a valid instrumental variable for environmental quality can also attenuate the potential bias arising from measurement error (Wald 1940). Krekel and Zerrahn (2017) and von Möllendorff and Welsch (2017) employ a difference-in-difference design to estimate the (dis)amenity value of wind

[12] For instance, personality traits can be reasonably assumed to correlate to both SWB and environmental conditions and to be stable.

[13] Naturally occurring experiments must divide the population into groups exposed to different levels of an environmental amenity, i.e., into *treatment* and *control* groups. The baseline characteristics must be statistically similar, between treatment and control groups which can be easily tested. Quasi-experiments are typically analyzed by employing methodologies such as the instrumental variable approach, difference-in-differences, or regression discontinuity design.

turbines using a life satisfaction regression. They exploit the spatial and temporal variation in wind turbine construction and assign respondents to the treatment group if a wind turbine is constructed within their neighborhood.

The use of natural experiments and other causal inference methods is very popular in empirical economics and widely adopted in HP (Bishop et al. 2020) and in the environmental and health economics literature (Graff Zivin and Neidell 2013). Causal inference methods, however, have their own limitations, and their assumptions need to be carefully validated within the study.[14]

4.2 Income measurement and endogeneity

The marginal effect of income on SWB, which is necessary to compute the MWTP per equation (7), is also difficult to carefully estimate because of measurement and endogeneity issues. Income is often measured with error in surveys and may affect SWB in nonlinear ways. Happy people tend to be more productive and may earn more (Oswald et al. 2015). Income levels at a point in time may be the resulting outcome of a set of unobservable circumstances and choices that may also influence SWB (see, e.g., Diener et al. 2002). Here we review in detail some of the typical challenges facing researchers.

Concerning the measurement of income, concerns arise when thinking about the following: (a) the appropriate functional form; (b) the appropriate definition of income. Concerning the functional form, it is common practice to incorporate income into SWB regressions using a logarithmic transformation. This approach is widely accepted due to substantial evidence indicating that the association between income and SWB exhibits a steeper gradient at lower income levels, gradually plateauing as income levels rise. Researchers have the option to explore semi-parametric or non-parametric techniques to identify potentially more suitable functional form. However, the potential benefit of adopting a more complex functional form should be balanced against the added complexity in calculating MRS. The logarithmic transformation of income presents a notable advantage in this regard.

There is little discussion about the appropriate measure of income to include in the regressions. It could be *individual* income, *household* income, or *equivalized* household income adjusted for household size and composition. Presumably, the last one allows for analysis at an individual level. Ultimately, though, it is a matter of articulating the results with care: "an individual would be willing to forego a certain amount of individual/household/equivalized income to attain a specified improvement of environmental quality."

Respondents might be hesitant to disclose their exact income, introducing potential measurement error which might bias the estimated income coefficient downwards. Surveys often rely on "income brackets" for measuring income. Income dummies are often transformed into continuous variables, which may exacerbate the attenuation bias from measurement errors. These types of inaccuracies can play a role in the modest income effect observed in conventional SWB regression analyses.

[14] For instance, in the case of instrumental variables, the instrument needs to satisfy the "relevance" condition (the instrument must be a good predictor of environmental variable) and the "exclusion restriction" (the instrument must affect SWB exclusively via its effects on the environmental amenity). While the first condition is usually easier to satisfy, the second one is much harder. For one, the exclusion restriction cannot, in general, be statistically tested. The validity of the instrument must be instead motivated by using social, environmental, or economic arguments to convince the reader that the selected instrument does indeed affect SWB only via the environmental variable (for a recent review of causal inference methods, assumptions and tests, see Cunningham, 2021).

The relatively small effect of income on SWB may be the consequence of additional factors such as habituation, expectations, aspirations, and social comparison. The specifications used in EP analyses frequently overlook the impact of negative aspects associated with the disutility of income (such as working hours, commuting, and stress). Consequently, the EP method may underestimate the marginal effect of income (Stutzer and Frey 2008). Another aspect pertains to the influence of relative income. A substantial body of research indicates that the significance of income on SWB is linked to its relative nature in comparison to one's own past income (aspirations and expectations) and the income of others (social comparison), rather than on absolute income levels (see Clark et al. 2008 for a comprehensive overview).

The findings on relative income effects might suggest including not only current own income but also lagged own income and the income of others in SWB regressions. It is, however, open to debate whether omitting these additional income terms introduces bias or whether different specifications offer valuable yet distinct insights. For example, when controlling for lagged own income and the income of others, the coefficient on current own income may capture the short-term "private" marginal utility of income. On the other hand, when these variables are excluded, the coefficient on current own income internalizes the adverse effects of past income and the negative external impact of others' income, capturing the long-term "social" marginal utility of income (Layard 2005, Welsch and Ferreira 2014). In light of this rationale, standard studies employing the EP method using current own income should be viewed as estimating the value of environmental quality based on the long-term social value of income. Consequently, the larger values of environmental quality obtained by using the EP method may be due to the use of long-term social value of income.

It is also likely that monetary valuation may vary along alternative measures of SWB as income may affect overall life satisfaction more strongly than, say, affective well-being (Kahneman and Deaton, 2010). This discussion links back to how to measure SWB and its time horizon. Experience sampling (ES) and the Day Reconstruction methods (DRM) are believed to be the gold standard for affective well-being, but are seldom used to evaluate environmental quality, given they require *ad hoc* surveys. Future research should focus on constructing a framework for environment valuation using different SWB measures, including ES and DRM (see, e.g., Krekel and MacKerron 2023, for a recent attempt to use these methods to value time).

The choice of how to measure and incorporate income into the SWB regression is key to the income-SWB relationship. Another concern for the empirical analysis is that income levels may be determined by unobservable characteristics that are also correlated with SWB. In other words, income is not randomly assigned to individuals, but it is endogenous. Some papers addressed this challenge directly and provided interesting insights. Gardner and Oswald (2007) studied happiness variation among lottery winners, as a plausible exogenous variation of income, and found that larger windfalls are associated with higher levels of SWB. The use of lottery winnings, or unanticipated income windfalls, may serve as a quasi-random income variation to mitigate the biases outlined here. Nevertheless, these data are not universally available, may only impact a limited portion of respondents, and the magnitude of the windfall may not accurately represent the average income variation encountered by individuals. Another way to overcome the endogeneity of income is by using instrumental variables. Studies have instrumented income using spousal income spouse, industry affiliation, or interactions between occupation and industry affiliation (e.g., Luttmer 2005; Luechinger 2009). Instrumental variable estimations consistently yield effect sizes considerably larger than those derived through OLS methods.

The observation that strategies addressing endogeneity seem to yield notably greater income effects suggests that conventional SWB regressions might indeed underestimate the impact of income on SWB due to downward biases. Consequently, this could lead to an overestimation of the MRS for environmental valuation.

As with the case of environmental amenities, researchers must handle instrumental variables for income with care. For instance, Pischke and Schwandt (2012) warn that industry affiliation may be an invalid instrument after finding that industry choice is correlated with pre-determined personal characteristics, such as mother's education and respondent's height. These characteristics might, for example, be associated with unmeasured cognitive or non-cognitive skills or personality traits, which, in turn, may also be correlated to SWB.

Measurement issues and endogeneity biases that affect both income and environmental amenities affect estimated marginal effects with consequences for the computation of the MWTP. We encourage researchers to carefully reflect and discuss assumptions and limitations of their SWB regression specifications and the direction of potential biases. Few papers address these issues for both variables directly, which offers opportunities for further research.

5. Conclusions

Data on subjective well-being, in particular life satisfaction, are routinely collected in a large number of countries around the world and increasingly used as an indicator of experienced utility both in research and public policy. A particular use of such data is for non-market valuation through the experienced preference method. This approach involves estimating well-being regressions with (environmental) amenities and income on the right-hand side and computing the marginal rate of substitution between income and the amenity in question, that is, the amount of income an individual is willing to trade off against a change in the level of the amenity at constant utility. The experience preference approach has been around for more than two decades now, and there exist some previous reviews of it. In comparison with the issues discussed in those previous works, this review has highlighted some more recent developments and insights, which we summarize in what follows.

First, there is an improved understanding of the relationship between the experienced preference approach and more conventional approaches to non-market valuation. Conceptually, the experienced preference and revealed preference approaches both refer to *actual situations*, whereas stated preference approaches refer to *hypothetical situations*. In addition, experienced preference focuses on *experiences* regarding amenities, whereas both revealed preference and stated preference approaches focus on *choices*. Results from the latter approaches thus rely on how accurately individuals anticipate the utility consequences of those choices. This circumstance (together with market imperfections in the case of revealed preference) may explain differences in valuation outcomes between the experienced preference method and the conventional methods found in some recent studies. Interestingly, some (albeit scarce) evidence suggests that property prices may capture expected impacts of some (dis)amenities on future well-being which current SWB may not (yet) reflect. In addition, stated preference methods are able to capture existence values which the experienced preference method arguably is less suited to account for. These are important issues given that some of the most important environmental concerns (predominantly) refer to impacts in the future (e.g., climate change) or/and to existence values (e.g., biodiversity). Reassuringly, however, new evidence suggests that people's current SWB does reflect their concern for the fate of future generations. Overall, the empirical literature comparing approaches remains small and insufficient to develop a full picture of which methods are better suited to value which (dis)amenities and their respective features. It may well be that the experienced preference and revealed and stated preference methods are complementary in some regards. More systematically exploring these issues remains an important venue for future research.

A further issue that has received attention in recent literature is how reported SWB relates to the latent (unobservable) utility it is supposed to measure, and what this implies for the robustness of experienced preference valuation results. Technically, the issue refers to the reporting function that respondents to well-being surveys use when translating their experienced utility into SWB scores. Responding to the fact that common approaches in SWB research rely on difficult-to-test assumptions such as linearity of the SWB scale, some recent papers have studied the consequences of respondents using SWB scales in several ways. This research has found that experienced preference valuation results – the marginal rate of substitution between income and amenities – based on assuming linearity of scale use are sensitive to violations of the linearity assumption. An important outcome of this research is a method for calculating the range in which the marginal rate of substitution can vary for all permissible (that is, monotonically increasing) transformations of the linear response scale. While the method has not been applied to environmental amenities as yet, it offers a robustness check to be used in future applications of the experienced preference method. In using this robustness check, it should be noted, however, that it refers to hypothetical scenarios of scale use and that – while linearity cannot be tested in a rigorous way – several pieces of evidence using a variety of different approaches suggest that significant deviations from linearity are unlikely to be the norm. Both, the robustness of experienced preference valuation results to hypothetical variations in scale use and respondents' actual use of the SWB scale are important areas for future research.

In addition to these fundamental issues, the recent literature on the experienced preference approach has made progress with respect to several more specific empirical concerns. These relate to the measurement of both the environmental amenities being valued and income, and to econometric approaches to estimating the SWB function. Some of the measurement issues pertain not only to the experienced preference approach but also to other approaches, in particular revealed preference methods. One of these issues is the mapping of environmental amenities to the individuals affected by them – a problem the experienced preference method shares with hedonic property price regressions. In this regard, tremendous progress has been achieved through the use of GIS and remote sensing. Another issue (also shared with hedonic pricing) is endogeneity of exposure to an amenity due to residential sorting, that is, people who value an amenity more move to the respective locales. This problem is more relevant when the level of an amenity shows little intertemporal variation than when it varies from day to day (say) and the respective data are available with appropriate temporal resolution. An adequate temporal resolution of the data also helps addressing the issue of habituation to (dis)amenities. With individual-level panel data, it is possible to track the dynamics of habituation and to test whether some amenities are more subject to it than others. While many of the measurement issues relating to amenities also pertain to revealed preference methods, issues relating to the marginal utility of income are specific to the experienced preference method. The ubiquitous endogeneity concerns (due to measurement error, simultaneity and omitted variables) can in principle be addressed by means of established econometric methods (e.g., instrumental variables). With the availability of better data, significant progress in using the experience preference method has been made since its early applications. Typically, however, not all empirical concerns have been addressed at the same time. A meta study could help shed light on how assumptions and methods used have shaped the results of valuation using the experienced preference method.

The experienced preference approach has been mainly concerned with global self-reports of SWB as proxies for utility. Another intriguing avenue of research involves the use of measures such as the Day Reconstruction Method whereby participants reconstruct their activities, emotions and experiences in the previous day. Integrating the Day Reconstruction Method into existing surveys would enable the analysis of experiences involving the environment with the potential to unveil nuanced aspects that may not be captured with standard environmental valuation techniques.

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APPENDIX A: Relevant SWB data sources

This Appendix provides a brief description of some of the most notable sources of data used by SWB researchers worldwide. This information is summarized in Table A1, which presents a list of datasets systematically collected through regular, extensive, and nationally representative surveys, conducted at both national and international scales. The table draws heavily from the work of Frijters and Krekel (2021) (see their Appendix A for a more comprehensive list of sources).

At the international scale, SWB data are collected through initiatives such as the World Values Survey, which encompasses over 80 countries worldwide, the Gallup World Poll spanning more than 160 countries, the Eurobarometer Surveys, which cover European Union member states and the European Social Survey spanning more than 30 European nations. At the national level, prominent sources include the German Socio-Economic Panel (GSOEP), the UK Household Longitudinal Study (UKHLS), the General Social Survey (GSS) in the USA, and the Keio Household Panel Survey (KHPS) in Japan.

Table A1 provides web links to facilitate access to each survey and distinguishes between international and national surveys, and provides useful to implement the EP method, namely spatial identifiers, and temporal coverage. Concerning the spatial identifiers, many surveys include variables identifying subnational units such as administrative regions. Some, like GSOEP and UKHLS, offer controlled access to more detailed geographic data, such as anonymized postcodes, under a special license agreement. This additional layer of granularity enhances the accuracy of the spatial linkages, improving the estimation of the relationship between SWB in relation to environmental attributes. Recognizing the empirical issues highlighted in the Chapter, Table A1 provides information into the survey types, specifying whether they are repeated cross-sectional or panel data. Finally, details about the wording of the SWB question are provided to offer a more comprehensive context.

Table A1 – Nationally representative surveys of SWB for experienced method

Dataset	Link	Countries' coverage	Spatial coverage	Time coverage	Type	SWB question
World Values Survey	www.wvs.com	International (80+ countries)	Region identifiers within each country not always linked to administrative regions	1981- (multiple rounds)	Cross-sections	*Life satisfaction (1-10)* 'All things considered, how satisfied are you with your life as a whole these days? Using this card on which 1 means you are "completely dissatisfied" and 10 means you are "completely satisfied" where would you put your satisfaction with your life as a whole?'
Gallup World Poll	https://www.gallup.com/ analytics/318875/global-research.aspx	International (160+ countries)	Region identifiers within each country available for some nations	2005- (annual)	Cross-sections	*Life satisfaction (0-10)* 'All things considered, how satisfied are you with your life as a whole these days? Where 0 is dissatisfied and 10 is satisfied.'
European Social Survey	www.eurpeansocialsurvey.org	Europe (36 countries)	Administrative region identifier within each country	2001- (biannual)	Cross-sections	*Life satisfaction (0-10)* 'All things considered, how satisfied are you with your life as a whole nowadays? Please answer using this card, where 0 means extremely dissatisfied and 10 means extremely satisfied.'
Eurobarometer	https://www.gesis.org/en/eurobarometer-data-service/search-data-access/data-access	Europe	Region identifiers within each country not always linked to administrative regions	1980- (annual)	Cross-sections	*Life satisfaction (1-4)* 'On the whole, are you very satisfied, fairly satisfied, not very satisfied or not at all satisfied with the life you lead?"
General Social Survey	https://gss.norc.org/	USA	County identifiers available; In addition, granular spatial information available under special license	1984 (biannual from 1994)	Cross-sections	*Life satisfaction (1-7);* wording of question changed slightly over time From 2018: 'All things considered, how satisfied are you with your life as a whole nowadays?' *Happiness (0-10)* 'On a scale from 0 (Extremely unhappy) to 10 (Extremely happy): Taking all things together, how happy would you say you are?'
Behavioral Risk Factor Surveillance System	https://www.cdc.gov/brfss/index.html	USA	County identifiers available	2005- (annual)	Cross-sections	*Life satisfaction (1-4)* 'How satisfied with life as a whole? 1(Very satisfied); 2 (Satisfied); 3 (Dissatisfied); 4 (Very dissatisfied)'
German Socio-Economic Panel (GSOEP)	https://www.diw.de/en/diw_01.c.601584.en/data_access.html	Germany	Regional identifiers available; In addition, granular spatial information available under special license	1985- (annual)	Panel	*Life satisfaction (0-10)* 'How satisfied are you at present with your life, all things considered? 0

						(completely dissatisfied); 10 (completely satisfied).
British Household Panel Study (BHPS)	https://www.understandingsociety.ac.uk/documentation/access-data	UK	Regional identifiers available; In addition, granular spatial information available under special license	1991-2008 The BHPS sample is included from Wave 2 of the UK Household Longitudinal Study (annual)	Panel	*Life satisfaction (1-7)* 'How dissatisfied or satisfied are you with life overall?'' 1 (completely dissatisfied); (completely satisfied).
UK Household Longitudinal Study (UKHLS; also known as 'Understanding society')	https://www.understandingsociety.ac.uk/documentation/access-data	UK	Regional identifiers available; In addition, granular spatial information available under special license	2009- Successor of the BHPS (annual)	Panel	*Life satisfaction (1-7)* 'How dissatisfied or satisfied are you with life overall?'' 1 (completely dissatisfied); (completely satisfied).
Household, Income Panel and Labour Dynamics (HILDA)	https://dataverse.ada.edu.au/dataverse/hilda	Australia	Regional identifiers available; in addition, granular spatial information available under special license	2001- (annual)	Panel	*Life satisfaction (0-10)* 'All things considered, how satisfied are you with your life? Again, pick a number between 0 and 10 to indicate how satisfied you are.'
Panel Study of Income Dynamics (PSID)	https://simba.isr.umich.edu/data/data.aspx	USA	County identifiers available; in addition, granular spatial information available under special license	2009- (annual)	Panel	*Life satisfaction (1-4)* 'Please think about your life- as-a-whole. How satisfied are you with it? Are you completely satisfied, very satisfied, somewhat satisfied, not very satisfied, or not at all satisfied?'
Keio Household Panel Survey	https://www.pdrc.keio.ac.jp/en/paneldata/datasets/jhpskhps/	Japan	Municipality identifiers available	2004 (annual)	Panel	*Happiness with life over the last year (0-10)* 'Please choose a number on a scale of 0 to 10, where "0" means having no feeling of happiness at all and "10" means having a feeling of complete happiness over the last one year' *Happiness with life overall(0-10)* 'Please choose a number on a scale of 0–10, where "0" means having no feeling of happiness at all and "10" means having a feeling of complete happiness for your whole life up to the present.'

Notes: Table based on Appendix A in Frijters and Krekel (2021)

APPENDIX B: Summary of papers testing non-linearity of scale use in subjective questions

Van Praag (1991) tested how individuals translate five ordered verbal labels (very bad; bad; not bad; not good; good; very good) into cardinal quantities. In a first experiment he asked respondents to assign numbers between 1 and 1,000 to each of the five verbal labels. In a second experiment, he asked respondents to produce lines of certain length corresponding to each of the verbal labels. He found roughly linear scale use across both experiments.

Layard et al. (2008) estimated an OLS regression of rank-order-coded reported life satisfaction on a wide set of explanatory variables and individual fixed effects. Assuming that the error of a similar model with latent (true) life satisfaction as the dependent variable is homoscedastic, any heteroskedasticity in their OLS regression of reported life satisfaction would then indicate a non-linear response scale. They indeed find the residual variance to be larger for low than for high predicted reported satisfaction. Under their assumption of homoscedasticity with respect to true satisfaction, this pattern implies that the response scale is convex. However, the amount of convexity they infer is small.

Oswald (2008) pursued an approach not related to SWB but nevertheless instructive. He asked respondents to report on their height using only a bounded slider. The extremes of the slider were labelled as “very short” and “very tall”. He then regressed these responses on respondents’ actual and squared height. He found a small but statistically significant negative coefficient on the squared term. In turn, when inverting the equation he estimated, this implies a small amount of convexity when transforming subjectively reported height into actual height. However, this estimate is rather close to linearity. Moreover, when distinguishing between genders, the squared term is no longer significant, suggesting that the observed convexity in the pooled sample may have been driven by a reporting difference across genders.

Kristoffersen (2017) used a psychometric index of mental health which she assumed to be a cardinal measure of SWB. She regressed these mental health scores on dummies for each of the 11 response categories of a life satisfaction question and found a largely linear pattern, albeit with the dummy for the lowest satisfaction category being an outlier. Nevertheless, if her assumption of the cardinality of the mental health index holds, her results also suggest that strongly non-linear scales are unlikely to be the norm.

Related to the information content in subjective responses, *Schwarz (1995)* argues that rather than providing superficial and meaningless responses, respondents systematically exploit the information available to them in an attempt to understand their task and to provide a meaningful answer (p. 11).