APPENDICES FOR

The econometrics of happiness: Are we underestimating the returns to education and income?

C P Barrington-Leigh

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A Model specification

Some details of the cognitive mixture models are spelled out here.

We may motivate the model by conceiving of two latent variables. One, $S^\star$, is the experienced wellbeing we wish to measure. That is, the respondent's internal, weighted evaluation of life has an explicit form, $S^\star$, in the model as a continuous latent variable which depends on life circumstances. I assume that the latent value $S^\star$ is the same for the two numeracy types, i.e., that the internal wellbeing measure for *high* and *low* types exhibits the same dependence on other individual characteristics. Thus, types differ only in their reporting behavior (see Figure A.1).

Another latent variable, $N^\star$, is the continuous measure of numeracy, predicted by education level and possibly other individual characteristics, which determines whether a respondent will project $S^\star$ on to the full scale provided, or simplify it to a 3-point subset (focal values). The response process then occurs in three steps: (i) the respondent carries out all but the last step described in Section 1.1 to arrive at $S^\star$; (ii) the respondent chooses whether or not to simplify the scale, effectively eliminating certain response options; and based on this choice, (iii) the respondent carries out the final cognitive step of projecting $S^\star$ onto their chosen discrete scale, resulting in their observed response, $s \in \mathbb{S}$.

For each type, *high* and *low* numeracy, the possible responses represent an ordered set, and response probabilities can be modeled using an ordered logistic or ordered probit formulation.

Altogether, then, the parameters to be estimated are the coefficients and cutoff value predicting the numeracy classification; the coefficients predicting the latent wellbeing variable $S^\star$, and two sets of thresholds α_i^H and α_i^L used to transform $S^\star$ into discrete values in the focal-value or full-range ordinal scales.

Formally,

$$\begin{aligned} P(s \mid \boldsymbol{x}) =& P(\text{high} \mid \boldsymbol{x})\, P(s \mid \boldsymbol{x}, \text{high}) + [1 - P(\text{high} \mid \boldsymbol{x})]\, P(s \mid \boldsymbol{x}, \text{low}) \\ =& F_N(\boldsymbol{z'}\boldsymbol{\beta}_N)\left[F_S\left(\alpha_s^H - \boldsymbol{x'}\boldsymbol{\beta}_S\right) - F_S\left(\alpha_{s-1}^H - \boldsymbol{x'}\boldsymbol{\beta}_S\right)\right] + \\ & \left[1 - F_N\left(\boldsymbol{z'}\boldsymbol{\beta}_N\right)\right] \times \left[F_S\left(\alpha_s^L - \boldsymbol{x'}\boldsymbol{\beta}_S\right) - F_S\left(\alpha_{s-1}^L - \boldsymbol{x'}\boldsymbol{\beta}_S\right)\right] \end{aligned} \tag{5}$$

for each value $s \in \mathbb{S}$. Here $\boldsymbol{x}$ is the full vector of observed explanatory variables, used to predict wellbeing, while $\boldsymbol{z}$, which possibly overlaps with $\boldsymbol{x}$ and is usually a subset of $\boldsymbol{x}$, is used to predict numeracy. There is a column of constants included in $\boldsymbol{z}$, but none in $\boldsymbol{x}$. That is, an intercept for $N^\star$ is used and the numeracy cutoff is set to 0. Twelve values of α_s^H, with $\alpha_{-1}^H = -\infty$ and $\alpha_{10}^H = +\infty$ and $\alpha_s^H > \alpha_{s-1}^H \forall s \geq 0$, are the thresholds for responses by *high* types; and four distinct values of α_s^L are those for *low* types, with $\alpha_{-1}^L = -\infty$, $\alpha_{10}^L = +\infty$, $\alpha_0^L = \alpha_1^L = \alpha_2^L = \alpha_3^L = \alpha_4^L$, and $\alpha_5^L = \alpha_6^L = \alpha_7^L = \alpha_8^L = \alpha_9^L$.

Eq. (5) is a rather flexible specification in that the two sets of cutoff values α^L and α^H for low and high types are determined independently of each other. Rather than allowing for a separate set of two thresholds for the ordinal value cutoffs, a possible simplifying assumption is that the collapsing of the 11-point scale to a 3-point scale occurs precisely where one might expect for rounding behavior. A suitable assignment for an 11-point (0–10) scale would be:

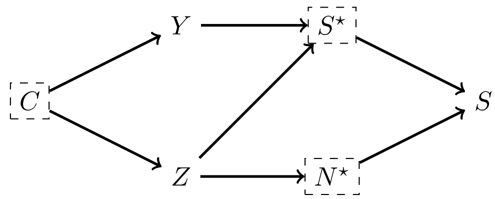


Figure A.1. Directed Acyclic Graph (causal diagram) for the mixture model. Experienced utility $S^\star$ is contemporaneously determined by some life conditions (such as education) Z, which also affect numeracy $N^\star$, and by other life conditions Y. The numerical self-report S is a reflection of $S^\star$ but is influenced by numeracy through FVR. The contemporaneous conditions Y and Z may be codetermined by prior influences C. The boxed variables are not directly observable.

$$\begin{aligned}\alpha_0^L &= \frac{\alpha_2^H + \alpha_3^H}{2} \\ \alpha_5^L &= \frac{\alpha_7^H + \alpha_8^H}{2}\end{aligned} \tag{6}$$

In the case of a ten-point (1–10) SWB scale, there is one fewer distinct α^H value, and the corresponding restriction is:

$$\begin{aligned}\alpha_1^L &= \alpha_3^H \\ \alpha_5^L &= \frac{\alpha_7^H + \alpha_8^H}{2}\end{aligned}$$

B Estimation

The cognitive model Eq. (5) can be estimated using the observed responses S_i and characteristics $\boldsymbol{x}_i$ (assuming all columns of $\boldsymbol{z}_i$ are also in $\boldsymbol{x}_i$) of individuals i. The estimation objective is to find the marginal effects associated with $\boldsymbol{\beta}_S$, and to compare these with those derived from the canonical regressions which are naive to the preferential use of focal values. With or without the constraints on $\{\alpha^L\}$, the unknown parameters can be estimated by the maximum likelihood method, i.e. by maximising

$$\mathcal{L}\left(\boldsymbol{\beta}_N, \boldsymbol{\beta}_S, \boldsymbol{\alpha}^H, \boldsymbol{\alpha}^L \middle| S, \boldsymbol{z}, \boldsymbol{x}\right) = \sum_i \ln P\left(S_i \mid \boldsymbol{x}_i\right) \tag{7}$$

where the first sum is over individuals i with observed response S_i and characteristics $\boldsymbol{x}_i$, and where $\mathbb{1}\left(S_i = s\right) \equiv 1$ when $S_i =$s and 0 otherwise.

Nothing guarantees concavity of the objective function, so a “hopping” algorithm, for instance as implemented in Python’s SciPy suite, can be used to search for a global maximum. Bootstrapping of the data is then used both to assess confidence due to sampling and to ensure that the hopping algorithm is robustly attaining a global optimum. Alternatively, a Markov chain Monte Carlo procedure using a Bayesian estimation framework provides better efficiency and coverage of the sample space. This latter approach was used for all mixture model estimates reported in this paper. Section B.1 provides derivations of gradients and Hessians which may be useful for computation of the log likelihood. Section B.2 outlines the priors used for Bayesian estimates.

B.1 Computation

For computational efficiency, it is useful to compute the gradient and Hessian of the objective function. I use the following shorthand, below:

$$
\begin{aligned}
P_s &\equiv P\left(s \mid \boldsymbol{x}\right) = P_H P_S^H + \left[1 - P_H\right] P_S^L \\
P_s^H &\equiv P\left(s \mid \boldsymbol{x}, \text{high}\right) = \Phi_s^H - \Phi_{s-1}^H \\
P_s^L &\equiv P\left(s \mid \boldsymbol{x}, \text{low}\right) = \Phi_S^L - \Phi_{S-1}^L \\
\Phi(\cdot) &= \Phi_N(\cdot) = \Phi_S(\cdot) \\
\Phi_S^H &\equiv \Phi\left(\alpha_s^H - \boldsymbol{x'}\boldsymbol{\beta}_S\right) \\
\Phi_S^L &\equiv \Phi\left(\alpha_s^L - \boldsymbol{x'}\boldsymbol{\beta}_S\right) \\
P_H = \Phi_N &\equiv \Phi\left(\boldsymbol{z'}\boldsymbol{\beta}_N\right) = 1 - \Phi\left(-\boldsymbol{z'}\boldsymbol{\beta}_N\right) \\
\mathbb{1}_{a,b} &\equiv \begin{cases} 1 & \text{if } a = b \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
$$

and $D(\cdot)$, ∂, ∇ denote total derivative, partial derivative, and gradient operators.

The log likelihood is thus written

$$\mathcal{L} = \sum_i \ln P_s$$

where s refers to S_i, the response of individual i.

Also, note that for the logistic CDF, $\Phi(\xi) = \frac{1}{1+e^{-\xi}}$,we have:

$$D(\log \Phi) = 1 - \Phi$$

and

$$D(\Phi) = \Phi\left[1 - \Phi\right]$$

and

$$D^2(\Phi) = \Phi - 3\Phi^2 + 2\Phi^3$$

Starting with the top level notation, we have the gradient with respect to parameter k

$$\partial_k \mathcal{L} = \sum_i \frac{1}{P_s} \partial_k P_s$$

and thus the Hessian matrix

$$\partial_j \partial_k \mathcal{L} = \sum_i \left[\frac{-1}{P_s^2} \partial_j P_s \partial_k P_s + \frac{1}{P_s} \partial_j \partial_k P_s\right]$$

B.1.1 Gradient

All derivatives below refer to a single respondent. The subscript s refers to the particular value reported by respondent i. The gradient ∂P_s can be expressed in general as

$$\partial P_s = \left[P_s^H - P_s^L\right] \partial P_H + P_H \partial P_s^H + [1 - P_H]\, \partial P_S^L \tag{8}$$

Considering the four groups of parameters in the parameter vector $v = \left[\beta_N' \ \beta_S' \ \alpha_H' \ \alpha_L'\right]$, we can express the components of the gradient (Eq. (8)) separately as follows, based on the limited parameter dependencies $P_H = P_H(\beta_N)$; $P_s^H = P_s^H(\beta_S, \alpha_H)$; and $P_s^L = P_s^L(\beta_S, \alpha_L)$:

$$\begin{aligned}
\nabla_{\boldsymbol{\beta}_N} P_s &= \left[P_s^H - P_s^L\right] \nabla_{\boldsymbol{\beta}_N} P_H && (9)\\
&= \left[P_s^H - P_s^L\right] \Phi_N \left[1 - \Phi_N\right] \boldsymbol{z} && (10)\\
\nabla_{\boldsymbol{\beta}_S} P_s &= P_H \nabla_{\boldsymbol{\beta}_S} P_s^H + [1 - P_H]\, \nabla_{\boldsymbol{\beta}_S} P_S^L && (11)\\
&= && (12)\\
\nabla_{\boldsymbol{\alpha}_H} P_s &= P_H \nabla_{\boldsymbol{\alpha}_H} P_s^H && (13)\\
\nabla_{\boldsymbol{\alpha}_L} P_s &= [1 - P_H]\, \nabla_{\boldsymbol{\alpha}_L} P_S^L && (14)
\end{aligned}$$

In turn:

$$\begin{aligned}
\nabla_{\boldsymbol{\beta}_S} P_s^H =& - \Phi_S^H \left[1 - \Phi_S^H\right] \boldsymbol{x}\\
&+ \Phi_{S-1}^H \left[1 - \Phi_{S-1}^H\right] \boldsymbol{x}\\
=& \boldsymbol{x} \left[-D\left(\Phi_S^H\right) + D\left(\Phi_{S-1}^H\right)\right]
\end{aligned}$$

and similarly for H replaced by L. Elements of $\nabla_{\boldsymbol{\alpha}_H} P_s^H$ are as follows[33]:

$$\begin{aligned}
\nabla_{\boldsymbol{\alpha}_H} P_s^H =& + \Phi_S^H \left[1 - \Phi_S^H\right] \mathbb{1}_s^H\\
&- \Phi_{S-1}^H \left[1 - \Phi_{S-1}^H\right] \mathbb{1}_{s-1}^H\\
=& + D\left(\Phi_S^H\right) \mathbb{1}_s^H - D\left(\Phi_{S-1}^H\right) \mathbb{1}_{s-1}^H
\end{aligned}$$

and similarly for H replaced by L.

[33] If we define an $N \times (S-1)$ sparse matrix, $\mathbb{1}_S$, with 1s in columns corresponding to each observation's y-value, and another, $\mathbb{1}_{S-1}$ with 1s in columns corresponding to one less than each observation's y-value, we can write the above in terms of a $1 \times N$ row vector Φ_S^H of values for each respondent.

$$\begin{aligned}
D_{\alpha^H} P_s^H =& \Phi_S^H \odot \left[1 - \Phi_S^H\right] \odot \mathbb{1}_S\\
&- \Phi_{S-1}^H \odot \left[1 - \Phi_{S-1}^H\right] \odot \mathbb{1}_{S-1}
\end{aligned}$$

This way, all the components of ∇P_S can be put into a matrix with rows corresponding to observations, which is convenient for computation.

B.1.2 Hessian

Using again a functional dependence on the vector $v = \left[\beta_N' \; \beta_S' \; \alpha_H' \; \alpha_L'\right]$, the non-zero terms of the Hessian are as follows:

$$\begin{pmatrix} \partial_{z_j}\partial_{z_k}\mathcal{L} & 0 & 0 & 0 \\ 0 & \frac{\partial}{\partial_{\beta_j^s}}\frac{\partial}{\partial_{\beta_k^s}}\mathcal{L} & \frac{\partial}{\partial_{\beta_j^s}}\partial_{\alpha_k}P_s^H & \frac{\partial}{\partial_{\beta_j^s}}\partial_{\alpha_k}P_s^L \\ 0 & \frac{\partial}{\partial_{\beta_j^s}}\partial_{\alpha_k}P_s^H & \frac{\partial}{\partial_{\alpha_j}}\partial_{\alpha_k}P_s^H & 0 \\ 0 & \frac{\partial}{\partial_{\beta_j^s}}\partial_{\alpha_k}P_s^L & 0 & \frac{\partial}{\partial_{\alpha_j}}\partial_{\alpha_k}P_s^L \end{pmatrix}$$

Expanding the terms of the Hessian:

$$\begin{aligned} \frac{\partial}{\partial_{\beta_j^N}}\frac{\partial}{\partial_{\beta_k^N}}P_s =& \frac{\partial}{\partial_{\beta_j^N}}\left(\left[P_s^H - P_s^L\right] D\left(\Phi_N\right) z_k\right) \\ =& \left[P_s^H - P_s^L\right] D^2\left(\Phi_N\right) z_j z_k \end{aligned} \tag{15}$$

$$\begin{aligned} \frac{\partial}{\partial_{\beta_j^s}}\frac{\partial}{\partial_{\beta_k^N}}P_s &= \frac{\partial}{\partial_{\beta_j^s}}\left(\left[P_s^H - P_s^L\right] D\left(\Phi_N\right) z_k\right) \\ &= \left[\frac{\partial}{\partial_{\beta_j^s}}P_s^H - \frac{\partial}{\partial_{\beta_j^s}}P_s^L\right] D\left(\Phi_N\right) z_k \\ &= \left[-D\left(\Phi_S^H\right) + D\left(\Phi_{S-1}^H\right) + D\left(\Phi_S^L\right) - D\left(\Phi_{S-1}^L\right)\right] D\left(\Phi_N\right) x_j z_k \end{aligned}$$

$$\begin{aligned} \frac{\partial}{\partial_{\alpha_j^H}}\frac{\partial}{\partial_{\beta_k^N}}P_s =& \frac{\partial}{\partial_{\alpha_j^H}}\left(\left[P_s^H - P_s^L\right] D\left(\Phi_N\right) z_k\right) \\ =& D\left(\Phi_N\right) z_k \frac{\partial}{\partial_{\alpha_j^H}}\left(P_s^H\right) \qquad (16) \\ =& \left[D\left(\Phi_S^H\right) \mathbb{1}_s^H - D\left(\Phi_{S-1}^H\right) \mathbb{1}_{s-1}^H\right] D\left(\Phi_N\right) z_k \qquad (17) \end{aligned}$$

and

$$\begin{aligned} \frac{\partial}{\partial_{\alpha_j^L}}\frac{\partial}{\partial_{\beta_k^N}}P_s =& \frac{\partial}{\partial_{\alpha_j^L}}\left(\left[P_s^H - P_s^L\right] D\left(\Phi_N\right) z_k\right) \\ =& D\left(\Phi_N\right) z_k \frac{\partial}{\partial_{\alpha_j^L}}\left(-P_s^L\right) \qquad (18) \\ =& \left[D\left(\Phi_S^H\right) \mathbb{1}_s^H - D\left(\Phi_{S-1}^H\right) \mathbb{1}_{s-1}^H\right] D\left(\Phi_N\right) z_k \qquad (19) \end{aligned}$$

and the same for L. Next, the cross terms between elements of β_S:

$$\begin{aligned}
\frac{\partial}{\partial_{\beta_j^s}}\frac{\partial}{\partial_{\beta_k^s}}P_s &= \frac{\partial}{\partial_{\beta_j^s}}\left(P_H\frac{\partial}{\partial_{\beta_k^s}}P_s^H + [1-P_H]\frac{\partial}{\partial_{\beta_k^s}}P_S^L\right)\\
&= x_k\frac{\partial}{\partial_{\beta_j^s}}\left(P_H\left[-D\left(\Phi_S^H\right)+D\left(\Phi_{S-1}^H\right)\right]+[1-P_H]\left[-D\left(\Phi_S^L\right)+D\left(\Phi_{S-1}^L\right)\right]\right)\\
&= -x_jx_k\left(P_H\left[-D^2\left(\Phi_S^H\right)+D^2\left(\Phi_{S-1}^H\right)\right]+[1-P_H]\left[-D^2\left(\Phi_S^L\right)+D^2\left(\Phi_{S-1}^L\right)\right]\right)
\end{aligned}$$

and lastly, cross-terms between β_S and αs:

$$\begin{aligned}
\frac{\partial}{\partial_{\alpha_j^H}}\frac{\partial}{\partial_{\beta_k^s}}P_s &= \frac{\partial}{\partial_{\alpha_j^H}}\left(P_H\frac{\partial}{\partial_{\beta_k^s}}P_s^H + [1-P_H]\frac{\partial}{\partial_{\beta_k^s}}P_S^L\right)\\
&= \frac{\partial}{\partial_{\alpha_j^H}}\left(P_H\frac{\partial}{\partial_{\beta_k^s}}P_s^H\right)\\
&= x_kP_H\frac{\partial}{\partial_{\alpha_j^H}}\left(-D\left(\Phi_S^H\right)+D\left(\Phi_{S-1}^H\right)\right)\\
&= x_kP_H\left(-D^2\left(\Phi_S^H\right)\mathbb{1}_S^H+D^2\left(\Phi_{S-1}^H\right)\mathbb{1}_{S-1}^H\right)
\end{aligned}$$

$$\begin{aligned}
\frac{\partial}{\partial_{\alpha_j^L}}\frac{\partial}{\partial_{\beta_k^s}}P_s &= \frac{\partial}{\partial_{\alpha_j^L}}\left(P_H\frac{\partial}{\partial_{\beta_k^s}}P_s^H + [1-P_H]\frac{\partial}{\partial_{\beta_k^s}}P_S^L\right)\\
&\frac{\partial}{\partial_{\alpha_j^L}}\left([1-P_H]\frac{\partial}{\partial_{\beta_k^s}}P_S^L\right)\\
&= x_k[1-P_H]\frac{\partial}{\partial_{\alpha_j^L}}\left(\left[-D\left(\Phi_S^L\right)+D\left(\Phi_{S-1}^L\right)\right]\right)\\
&= x_k[1-P_H]\left(-D^2\left(\Phi_S^L\right)\mathbb{1}_S^L+D^2\left(\Phi_{S-1}^L\right)\mathbb{1}_{S-1}^L\right)
\end{aligned}$$

$$\begin{aligned}
\frac{\partial}{\partial_{\alpha_j^H}}\frac{\partial}{\partial_{\alpha_k^H}}P_S &= P_H\frac{\partial}{\partial_{\alpha_j^H}}\frac{\partial}{\partial_{\alpha_k^H}}P_S^H\\
&= P_H\left[\mathbb{1}_{j,k,s}D^2\left(\Phi_S^H\right)-\mathbb{1}_{j,k,s-1}D^2\left(\Phi_{S-1}^H\right)\right]
\end{aligned}$$

and similarly for low types but with $1-P_H$ replacing P_H, where the $\mathbb{1}$ is for the appropriate type.

B.1.3 Constraints

For Lagrangian-based constrained optimization, the constraints on α_H and α_L

$$0 < \alpha_H^{i+1} - \alpha_H^i < \infty$$

can be expressed in a matrix

$$\vec{0} < A \begin{pmatrix} \ddots & 0 & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & 0 & -1 & 1 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

B.2 Bayesian priors

For the Bayesian estimations carried out in this work, the following priors were used. All coefficients β_N and β_S are given normal priors with mean zero and standard deviation 3. As an example, the prior for β_S is shown by a thick grey line in Figure D.1(c). Given that typical estimates have $|\beta| < 1$, these are considered to be weak priors and to accommodate estimates of either sign. Cut points are initially assumed to be distributed with induced Dirichlet priors (Sethuraman, 1994).

C Synthetic data generating process

In order to investigate the implications of an overlap between $\boldsymbol{x}$ and $\boldsymbol{z}$, it is sufficient, and minimal, to consider only two predictors of subjective wellbeing, which I will in this section call education level z and another determinant of wellbeing, y. In the formulation given in Section 3, this means

$$\boldsymbol{x} = (z, y)$$

with just one predictor of numeracy, namely education, z.

A simple data generating process for these variables is as follows. Observations (individuals) are characterized by z and y. These variables are drawn as follows:

$$\begin{aligned} z &= \mathcal{N}(0,1) \\ y &= \chi \cdot z + [1-\chi]\,\mathcal{N}(0,1) \end{aligned}$$

where the $\mathcal{N}(0,1)$ represent separate, independent draws from a normal distribution, and χ captures the correlation between education and the other predictor. As described in Section 3, the log odds of an individual being high numeracy type ($N{=}1$) is related to z by a logit function, i.e.,

$$\log\left(\frac{P(N=1)}{P(N=0)}\right) = \beta_N^0 + \beta_N^z z \tag{20}$$

The constant β_N^0 is another parameter of the synthetic data, varied systematically in exploratory tests of the method. A higher value of β_N^0 increases the propensity for high numeracy, unconditional on education z.

The numeracy type is not observable.[34] Another non-observable is the latent value $S^\star$, which corresponds to the experienced wellbeing, which is of normative (i.e., policy) interest. It is a function of z and y,

[34] In fact, one could rule out low numeracy for any respondent who responds with a non-focal value; however, this model eschews conditioning on the dependent variable.

$$S^\star = \beta_S^z h + \beta_S^y y + \varepsilon_S \tag{21}$$

and is constrained to have the same coefficients for high and low numeracy types.

Simulated SWB responses are generated from $S^\star$ using either two distinct cut-points, α_0^L and α_5^L (for $N = 0$) or 10 cut-points α_i^H (for $N = 1$). The cut-points $\boldsymbol{\alpha}^H$ are constructed as follows:

$$\alpha_i^H = T \times [i + .5 - \Omega] \quad \forall i \in [0, \ldots, 9]$$

Here, T is the *cut point scale* parameter and Ω is the *cut point offset* parameter. Larger T results in a tighter distribution of simulated responses. Larger Ω shifts the distribution of simulated responses to the right. The low-type cutoffs are set to $\alpha_0^L = \alpha_2^H$ and $\alpha_5^L = \alpha_7^H$ in a natural way relative to the high-type cut points (see Appendix A), although in empirical estimates I focus on the more flexible model, which allows for them to be estimated independently.

Observed dependent variable S_H values are integers, distributed as an ordered logit distribution with 10 cut points,

$$S_H = \text{ologit}_{11}(S^\star) \tag{22}$$

but these responses are only observed from high-type respondents. Similarly, low-type respondents project $\tilde{S}$ onto just the three focal values, which we can express with

$$S_L = \text{ologit}_3(S^\star) \tag{23}$$

again using the cut points defined above.

D Simulations: varying cut point offset

This section serves as a supplement to Section 4, which describes a single example of a synthetic simulation. While several parameters described in Appendix C were varied widely in a battery of simulations, Figure D.1 demonstrates just one slice through the parameter space – namely, varying the cut point offset, Ω.

The abscissa of Figure D.1 corresponds to values of the cut point offset, which is a uniform offset applied to $\boldsymbol{\alpha}^H$ (and corresponding values of $\boldsymbol{\alpha}^L$). Higher values of the offset shift the distribution of SWB responses to the right; in fact, it corresponds roughly to the mean value of SWB in the simulated data. Because the balance of upward-rounding versus downward-rounding varies with this position, the bias in mean SWB due to FVR changes sign multiple times as this offset increases, holding other parameters fixed. This is shown by the green line.

Figure D.1 also shows (in blue) the fractional bias in the coefficient β_S^z on z (“education”), obtained by estimating an ordered logit model in which SWB depends on z and y. As the cut point offset varies in this example, the bias in β_S^z varies, qualitatively and roughly speaking, inversely as the bias in mean SWB. That is because, if the FVR behavior is primarily from low-z respondents, then when rounding is predominantly upward (biasing mean SWB upwards), low-z respondents appear happier, i.e., making β_S^z appear lower.

Notice that the bias on β_S^z is mostly negative in the cases shown in Figure D.1. This can be understood by noting, first, that, except for relatively narrow distributions of latent SWB

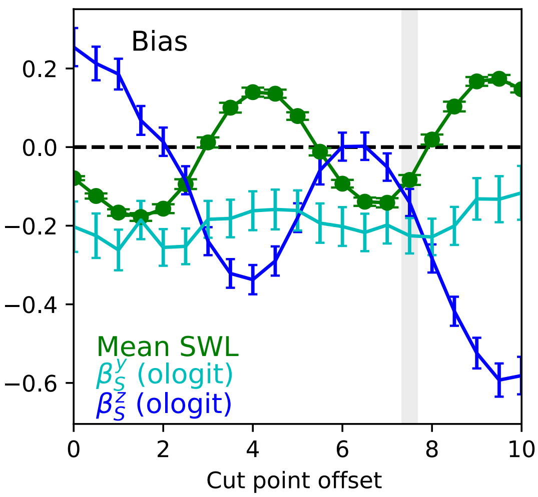


Figure D.1. Example estimates using synthetic data. (a) Biases, scaled to true values, for ordered logit estimates and mean LS; (b) predicted and latent response distributions for cut point offset =0.75; (c) posterior parameter values from mixture model for cut point offset =0.75, with vertical dashed lines showing true values, for $\boldsymbol{\beta}_S$, $\boldsymbol{\alpha}^H$, and $\boldsymbol{\alpha}^L$.

concentrated around 0 or 10, there will be some mixture of upward-rounding and downward-rounding by low types. This will tend to reduce the net bias for middle values of the cut point offset. Secondly, because z is correlated with latent SWB, low types with higher education are relatively more likely to round up to "10" rather than down to "5" (as compared with low types with lower education) when the bulk of latent SWB is to the right of "5". This reduces the net bias on β_S^z, in this range of cut point offset, more than it reduces the bias on mean SWB. This is true of the case shown in Figure 3(a) in the main text, where the latent distributions for high-education and low-education are shown. Figure 3 corresponds to the case highlighted by the grey vertical line in Figure D.1.

By comparison, when the bulk of latent SWB is to the left of "5", rounding down to "0" is not offset by anyone rounding *up* to "0", while those low types with higher education rounding up to "5" are partly offset by those with (even) higher education rounding *down* to "5". As a result, with the range of parameters in this example, positive biases on β_S^z are relatively small compared with negative biases. To summarize the intuition for this: because low types tend to have lower latent SWB than high types, distributions centered around 4 and 6 are not mirror images of each other around the central response of "5".

These qualitative effects change when the distribution of latent SWB is wider than the case in Figure D.1, and positive bias can become larger when the likelihood is lower that higher-education respondents are low type. For a more formal treatment of the contributions to large biases in this coefficient, see Proposition 2 in Appendix E.

Figure D.1 also shows the bias on the coefficient β_S^y of the other factor, y, predicting SWB, in an ordered logit model. This coefficient tends to be biased negatively, regardless of the correlation between z and y. The negative bias on β_S^y reflects the fact that z is controlled for in the latent SWB equation, limiting the effect of positive bias from the component of y correlated with z (see Case 2 in Proposition 2). By contrast, the impact of low-types' not changing their answers when latent SWB changes (see Case 1 in Proposition 2) leads to an attenuation bias for β_S^y.

E Theoretical maximum bias

Proposition 1. *Under focal value behavior in which a subset of respondents choose from responses {0,5,10} in a 0–10 scale, the largest possible bias on mean response is* ± 2.

Proof. Because the bias of the mean is the average of the (non-interacting) biases due to each individual, the maximum mean bias will occur when every individual's response is maximally biased. This means we can find the extremes among Dirac delta distributions (i.e., everyone identical) of latent wellbeing.[35] The maximum shift possible from a response function which rounds values to 0, 5, or 10 is from latent values very close to 2.5 or 7.5. These will be rounded to 0 or 5 (for 2.5), or 5 or 10 (for 7.5) under FVR, rather than to 2 or 3 (for 2.5) or to 7 or 8 (for 7.5) by those who use the 11-point scale. Therefore, the minimum and maximum possible biases are ± 2 points. □

Proposition 2. *Consider a (generalized) linear model explaining subjective responses on a 0–10 scale with an observed discrete characteristic* z. *Assume* z *has a positive influence on SWB. Then the largest possible negative and positive biases, due to FVR, on the inferred effect (raw coefficient)* β^z_S *of* z *on SWB are* $\min\left(\max\left(-5, -\beta^z_S\right), -2\right)$ *and* $+5$. *When* z *is continuous, the positive and negative biases are unbounded.*

Proof. Using the same argument as in Proposition 1, bias will be maximised by degenerate distributions, so we consider the case of an individual. FVR responses may be affected through z's influence on either the reporting function or on latent SWB. Consider first the impact *on the reporting function* of a *decrease* in z , i.e. which causes an individual to switch from using the full scale to using FVR rounding. The maximum possible changes in reported SWB are then as in Proposition 1; they occur when latent SWB is near 2.5 or 7.5. When z is discrete, this results in a maximum bias on the model coefficient of ± 2 per step in z. However, if z is continuous, then an infinitesimal decrease in z may lead to a discrete (i.e., up to ± 2) change in reported SWB, implying an unbounded positive or negative bias on the model coefficient describing marginal changes.

Now consider the other possible cause FVR changes, which is through the impact of z on latent SWB. This occurs only for respondents exhibiting FVR, so the extreme cases are for a population with 100% FVR behavior. For them, when latent SWB increases due to rising z, there are only two possible outcomes for reported SWB, considered below:

Case 1. Reported SWB does not respond at all to the rise in z, due to rounding. In this case the bias has value $-\beta^z_S$. This could be as large as -5 for discrete z when latent SWB changes from 2.5 to 7.5. (i.e., the effect of z on SWB).

Case 2. Reported SWB jumps from one focal value to another. An increase in z may cause a jump in reported SWB from 0 to 5 when latent SWB is near 2.5, or it may cause a jump from 5 to 10 when latent SWB is near 7.5. Under the assumption that z is positively associated with latent SWB, no negative jumps are possible. Therefore, the most extreme bias is $+5$ per step in z for discrete z, and an unbounded positive bias for the coefficient when z is continuous.

[35] I refer to latent SWB values on a continuous 0-10 scale. The arguments to follow hold for any individual's quantifiable latent SWB scale, as long as the reporting function mapping it onto the integers 0, ..., 10 is monotonic.

□

Remark. Thus, the focal value problem is capable in principle of accounting for anomalous negative estimates of the value of education, but it is equally capable of explaining positive biases. Because there are several qualitatively distinct contributions to the bias, the overall effect is a complicated function of the distribution of respondents.

Some intuition from the proof might be summarized as follows, and is depicted in Appendix Figure E.1. When there is a mass of possibly-low types near 2.5 or 7.5 (i.e., in terms of latent SWB) amplification of true effects on SWB are likely. When there is a mass of possibly-low types around middle values (near 5) or near the end points, attenuation results instead from a lack of responsiveness. When FVR is also dependent on (or covaries with) the variable of interest, then possibly-offsetting biases occur when susceptible respondents lie above 7.5 (downwards), between 5 and 7.5 (upwards), between 2.5 and 5 (downwards), or below 2.5 (upwards).

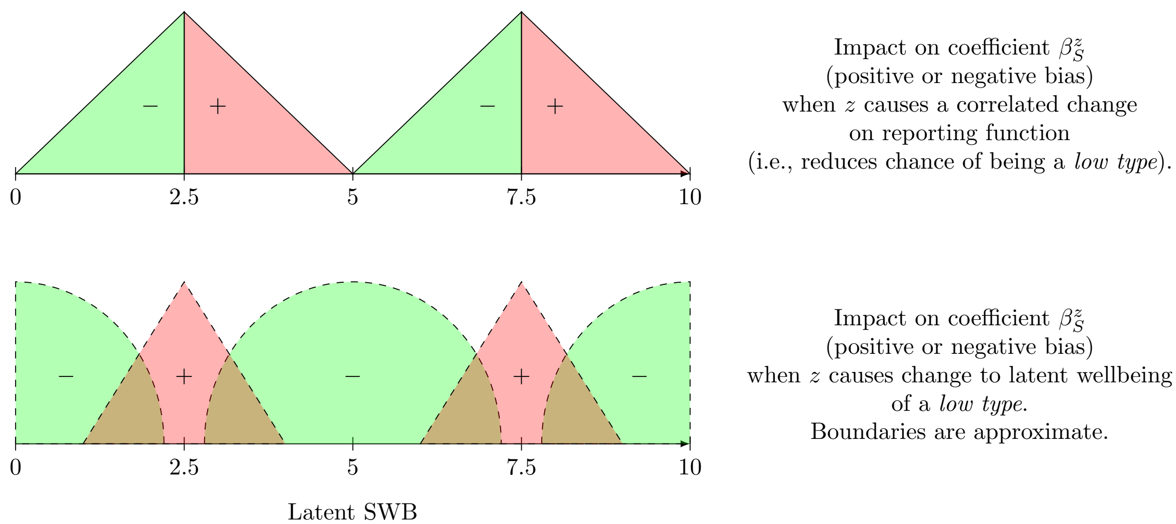
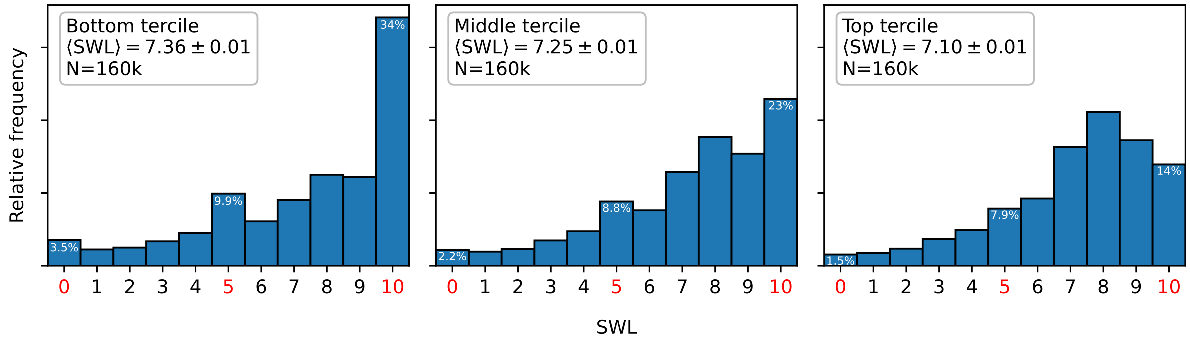
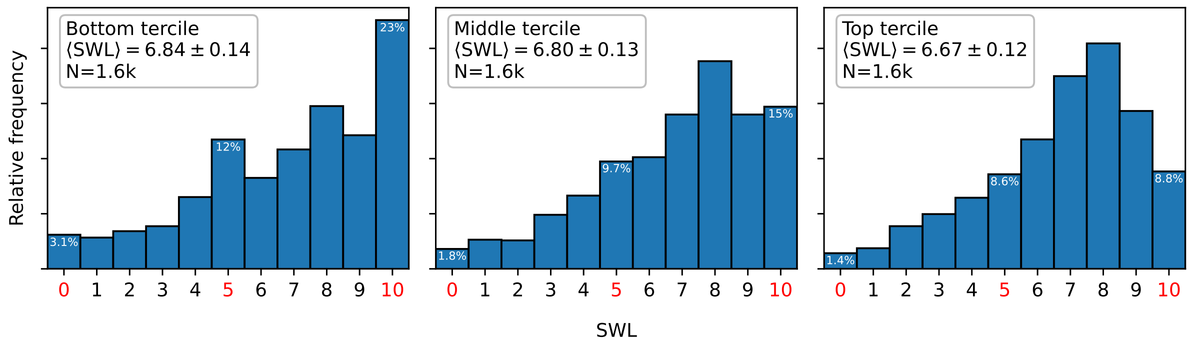


Figure E.1. Simultaneous channels of bias in model coefficients

F Supplementary figures and tables



(a) Global sample



(b) USA sample

Figure F.1. Math scores and focal value rounding behavior from 2018 PISA.

	CCHS 2017–2018	HILDA 2010
Less than secondary school graduation	2.12%	0.092%
Secondary school graduate	0.63%	0.039%
Post-secondary certificate, diploma, or university degree	0.36%	0

Table F.1. Education and “don’t know” responses to subjective wellbeing, for two surveys. Sample sizes are 106212 for CCHS and 10804 for HILDA. Not surprisingly, question response rates are higher for the panel (HILDA) than the cross-sectional (CCHS) respondents.

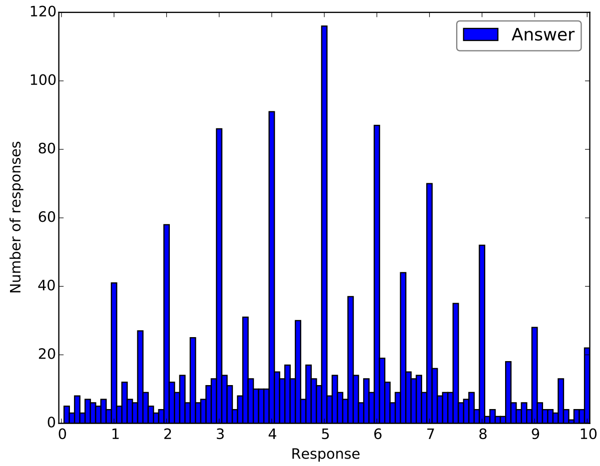


Figure F.2. Distribution of responses to a 100-point SWB question (framed on a 0–10 scale) answered with a computer interface.

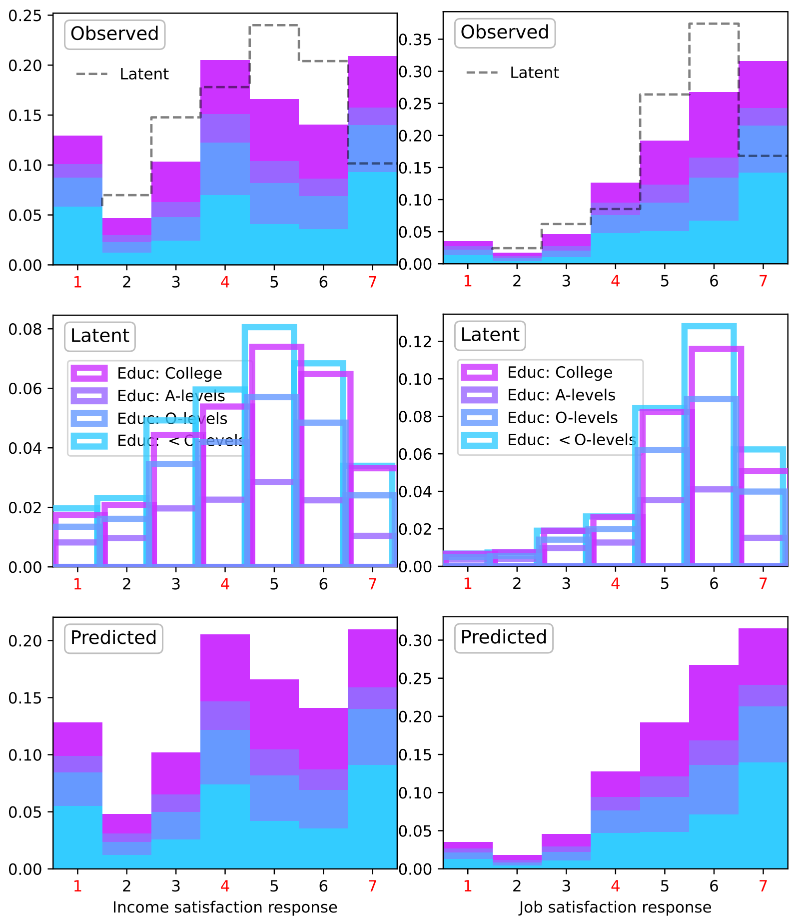


Figure F.3. Observed, latent, and predicted distributions for BHPS, corresponding to estimate shown in Table 2 and Table 3.

	Base model				With income in β_N				With age etc			
	OLS (1)	ologit (2)	FVRI→0 (3)	Mixture (4)	OLS (5)	ologit (6)	FVRI→0 (7)	Mixture (8)	OLS (9)	ologit (10)	FVRI→0 (11)	Mixture (12)
Life satisfaction (β_S)												
School: ≥Secondary	−.002	−.075*	−.073†	.098†	−.002	−.075*	−.073†	.060*	.075†	.015	.017	.11†
	(.019)	(.023)	(.021)	(.024)	(.019)	(.023)	(.021)	(.024)	(.018)	(.024)	(.021)	(.023)
School: Post-secondary	.069†	*.038*	.038*	.20†	.069†	*.038*	.038*	.17†	.079†	.062†	.064†	.16†
	(.014)	(.015)	(.015)	(.017)	(.014)	(.015)	(.015)	(.018)	(.013)	(.015)	(.015)	(.017)
log(HH income)	.55†	.53†	.53†	.62†	.55†	.53†	.53†	.62†	.39†	.38†	.38†	.44†
	(.009)	(.011)	(.010)	(.010)	(.009)	(.011)	(.010)	(.011)	(.009)	(.011)	(.011)	(.011)
age/100									4.3	.88	−11.5†	−12.6†
									(5.0)	(5.5)	(1.27)	(1.29)
$(\text{age}/100)^2$									*−35.1*	*−28.1*+	9.3*	10.5†
									(14.5)	(16.2)	(3.3)	(3.3)
$(\text{age}/100)^3$									64.7†	60.2*	12.4*	12.5*
									(18.0)	(20.2)	(4.0)	(4.1)
$(\text{age}/100)^4$									−35.5†	−35.0†	−13.2†	−13.9†
									(8.0)	(9.1)	(1.95)	(1.99)
male									−.12†	−.16†	−.16†	−.13†
									(.011)	(.012)	(.012)	(.012)
married									.45†	.54†	.54†	.59†
									(.012)	(.014)	(.013)	(.014)
community belonging									2.0†	2.3†	2.3†	2.4†
									(.026)	(.033)	(.030)	(.032)
immigrant									−.11†	−.13†	−.13†	−.15†
									(.014)	(.016)	(.016)	(.017)
constant	2.0†				2.0†				2.6†			
	(.093)				(.093)				(.62)			
Numeracy (β_N)												
constant				.98†				1.09†				1.34†
				(.039)				(.043)				(.046)
School: ≥Secondary				.44†				.45†				.41†
				(.036)				(.038)				(.043)
School: Post-secondary				.43†				.53†				.58†
				(.040)				(.045)				(.047)
log(HH income)								.22†				.31†
								(.028)				(.025)
age/100												−1.11
												(2.1)
$(\text{age}/100)^2$												−1.23
												(3.8)
$(\text{age}/100)^3$												−.41
												(4.5)
$(\text{age}/100)^4$												1.68
												(2.8)
male												.26†
												(.035)
High types												
Cut point 0		.42†	−5.4†	−6.0†		.42†	−5.4†	−7.3†		−.56	−5.3†	−7.2†
		(.12)	(.047)	(.40)		(.12)	(.050)	(.85)		(.69)	(.049)	(.72)
Cut point 1		.81†	−5.0†	−5.1†		.81†	−5.0†	−5.5†		−.17	−4.9†	−5.5†
		(.12)	(.041)	(.16)		(.12)	(.042)	(.15)		(.69)	(.042)	(.13)
Cut point 2		1.38†	−4.4†	−4.3†		1.38†	−4.4†	−4.5†		.41	−4.3†	−4.4†
		(.12)	(.033)	(.074)		(.12)	(.034)	(.064)		(.68)	(.035)	(.058)
Cut point 3		1.89†	−3.9†	−3.7†		1.89†	−3.9†	−3.8†		.93	−3.8†	−3.7†
		(.12)	(.027)	(.046)		(.12)	(.028)	(.041)		(.68)	(.030)	(.039)
Cut point 4		2.4†	−3.4†	−3.1†		2.4†	−3.4†	−3.2†		*1.43*	−3.3†	−3.1†
		(.11)	(.024)	(.033)		(.11)	(.024)	(.031)		(.68)	(.026)	(.031)
Cut point 5		3.4†	−2.4†	−2.3†		3.4†	−2.4†	−2.5†		2.5†	−2.2†	−2.4†
		(.11)	(.019)	(.046)		(.11)	(.020)	(.060)		(.68)	(.022)	(.043)
Cut point 6		3.9†	−1.88†	−1.65†		3.9†	−1.88†	−1.80†		3.0†	−1.67†	−1.67†
		(.11)	(.018)	(.032)		(.11)	(.019)	(.039)		(.68)	(.021)	(.031)
Cut point 7		4.9†	−.95†	−.56†		4.9†	−.95†	−.69†		4.0†	−.69†	−.50†
		(.11)	(.017)	(.023)		(.11)	(.018)	(.028)		(.68)	(.020)	(.025)
Cut point 8		6.2†	.40†	1.09†		6.2†	.40†	.92†		5.5†	.75†	1.15†
		(.11)	(.017)	(.027)		(.11)	(.017)	(.030)		(.68)	(.020)	(.026)
Cut point 9		7.1†	1.33†	2.7†		7.1†	1.33†	2.3†		6.4†	1.73†	2.4†
		(.12)	(.017)	(.084)		(.12)	(.018)	(.063)		(.68)	(.021)	(.035)
Low types												
Cut point 0				−4.0†				−3.6†				−3.3†
				(.21)				(.11)				(.099)
Cut point 1				−1.75†				−1.31†				−.77†
				(.091)				(.080)				(.054)
FVRI			0†	.16†			0†	.14†			0†	.10†
			(0)	(.008)			(0)	(.008)			(0)	(.004)
Mean response: low-type:				9.3†				8.9†				8.5†
				(.064)				(.082)				(.069)
Mean response: high-type:			8.1†	7.8†			8.1†	7.9†			8.0†	8.0†
			(.011)	(.017)			(.011)	(.017)			(.011)	(.012)
Mean response: latent:				7.8†				7.9†				8.0†
				(.016)				(.016)				(.011)
empirical mean			8.1†	8.1†			8.1†	8.1†			8.1†	8.1†
			(.009)	(.009)			(.009)	(.009)			(.009)	(.009)
obs.	91796	91796	91796	91796	91796	91796	91796	91796	91796	91796	91796	91796
log likelihood	−177641	−160572	−160596	−159612	−177641	−160572	−160597	−159586	−173440	−156322	−156360	−155325

Significance: 0.1%† 1%* *5%* *10%*+

Table F.2. Further estimates of mixture model on CCHS data. The middle four columns correspond to those in Table 1. Columns (1)–(4) represent a simpler model in which only education (not income) is allowed to explain FVR behavior. The final four columns include other determinants of LS, as well as extra demographic variables to explain FVR behavior; gender is significant but not age, and education coefficients are not significantly changed.

	Base model					With age etc				
	oprobit (1)	OLS (2)	ologit (3)	FVRI→0 (4)	Mixture (5)	oprobit (6)	OLS (7)	ologit (8)	FVRI→0 (9)	Mixture (10)
Job Satisfaction (β_S)										
log(HH income)	.016	.074	.015	.006	*.14*	.016	.074	.015	.006	**.22***
	(.036)	(.049)	(.060)	(.060)	(.076)	(.036)	(.049)	(.060)	(.060)	(.077)
EDUC: College degree	**−.15**†	*−.14*	**−.27**†	**−.25**†	.001	**−.15**†	*−.14*	**−.27**†	**−.25**†	.10
	(.046)	(.061)	(.078)	(.075)	(.11)	(.046)	(.061)	(.078)	(.075)	(.10)
EDUC: A-levels (approx)	**−.26**†	**−.31**†	**−.45**†	**−.43**†	*−.24*	**−.26**†	**−.31**†	**−.45**†	**−.43**†	*−.15*$^+$
	(.055)	(.076)	(.095)	(.094)	(.11)	(.055)	(.076)	(.095)	(.095)	(.12)
EDUC: O-levels (approx)	*−.10*	−.096	*−.19*	**−.18***	.013	*−.10*	−.096	*−.19*	**−.18***	.089
	(.046)	(.060)	(.078)	(.075)	(.092)	(.046)	(.060)	(.078)	(.076)	(.095)
Log job hours	**−.27**†	**−.35**†	**−.45**†	**−.44**†	**−.46**†	**−.27**†	**−.35**†	**−.45**†	**−.44**†	**−.47**†
	(.054)	(.071)	(.092)	(.088)	(.099)	(.054)	(.071)	(.092)	(.088)	(.11)
age	**−.033**†	**−.037***	**−.055**†	**−.051**†	**−.051***	**−.033**†	**−.037***	**−.055**†	**−.051**†	*−.038*
	(.009)	(.012)	(.015)	(.015)	(.017)	(.009)	(.012)	(.015)	(.015)	(.018)
$\text{age}^2/1000$	**.53**†	**.59**†	**.88**†	**.83**†	**.84**†	**.53**†	**.59**†	**.88**†	**.83**†	**.61***
	(.11)	(.15)	(.19)	(.18)	(.21)	(.11)	(.15)	(.19)	(.18)	(.23)
female	**.24**†	**.35**†	**.41**†	**.41**†	**.45**†	**.24**†	**.35**†	**.41**†	**.41**†	**.43**†
	(.036)	(.050)	(.061)	(.062)	(.069)	(.036)	(.050)	(.061)	(.062)	(.072)
constant		**6.3**†					**6.3**†			
		(.32)					(.32)			
Numeracy (β_N)										
constant					**.41***					**.35***
					(.16)					(.16)
log(HH income)					**.49**†					**.47**†
					(.084)					(.079)
EDUC: College degree					**1.30**†					**.98**†
					(.28)					(.22)
EDUC: A-levels (approx)					**.86**†					**.74**†
					(.21)					(.18)
EDUC: O-levels (approx)					**.69**†					**.55**†
					(.14)					(.13)
age										*.032*$^+$
										(.024)
$\text{age}^2/1000$										*−.58*
										(.29)
female										*−.18*$^+$
										(.12)
High types										
Cut point 0	**−2.9**†		**−5.1**†	**−3.6**†	**−4.0**†	**−2.9**†		**−5.1**†	**−3.6**†	**−3.5**†
	(.25)		(.41)	(.093)	(.45)	(.25)		(.41)	(.091)	(.35)
Cut point 1	**−2.7**†		**−4.7**†	**−3.2**†	**−3.1**†	**−2.7**†		**−4.7**†	**−3.2**†	**−2.9**†
	(.25)		(.41)	(.080)	(.21)	(.25)		(.41)	(.078)	(.20)
Cut point 2	**−2.3**†		**−4.0**†	**−2.5**†	**−2.2**†	**−2.3**†		**−4.0**†	**−2.5**†	**−2.00**†
	(.24)		(.41)	(.067)	(.13)	(.24)		(.41)	(.066)	(.13)
Cut point 3	**−1.79**†		**−3.0**†	**−1.49**†	**−1.51**†	**−1.79**†		**−3.0**†	**−1.49**†	**−1.23**†
	(.24)		(.41)	(.057)	(.16)	(.24)		(.41)	(.057)	(.16)
Cut point 4	**−1.23**†		**−2.1**†	**−.55**†	*−.21*	**−1.23**†		**−2.1**†	**−.55**†	.057
	(.24)		(.41)	(.053)	(.12)	(.24)		(.41)	(.053)	(.14)
Cut point 5	*−.51*		*−.93*	**.62**†	**1.64**†	*−.51*		*−.93*	**.62**†	**2.4**†
	(.24)		(.41)	(.053)	(.25)	(.24)		(.41)	(.054)	(.68)
Low types										
Cut point 0					**−2.7**†					**−3.2**†
					(.30)					(.54)
Cut point 1					**−.86**†					**−1.29**†
					(.19)					(.26)
FVRI				**0**†	**.28**†				**0**†	**.32**†
				(0)	(.036)				(0)	(.039)
Mean response: low-type:					**5.9**†					**6.2**†
					(.17)					(.18)
Mean response: high-type:				**5.5**†	**5.3**†				**5.5**†	**5.1**†
				(.031)	(.070)				(.031)	(.094)
Mean response: latent:					**5.3**†					**5.2**†
					(.072)					(.096)
empirical mean				**5.5**†	**5.5**†				**5.5**†	**5.5**†
				(.023)	(.023)				(.023)	(.023)
obs.	4730	4730	4730	4730	4730	4730	4730	4730	4730	4730
log likelihood	−7522	−8573	−7516	−7531	−7466	−7522	−8573	−7516	−7531	−7461

Significance: **0.1%**† **1%*** *5%* *10%*$^+$

Table F.3. Further estimates of mixture model on BHPS job satisfaction. The first five columns correspond to those in Table 2. The final five columns include other demographic determinants of numeracy.

	Base model					With age etc				
	oprobit (1)	OLS (2)	ologit (3)	FVRI→0 (4)	Mixture (5)	oprobit (6)	OLS (7)	ologit (8)	FVRI→0 (9)	Mixture (10)
Pay Satisfaction (β_S)										
log(HH income)	**.50**†	**.92**†	**.88**†	**.87**†	**.96**†	**.50**†	**.92**†	**.88**†	**.87**†	**.99**†
	(.038)	(.062)	(.065)	(.059)	(.068)	(.038)	(.062)	(.065)	(.062)	(.069)
EDUC: College degree	**−.17**†	**−.26**†	**−.31**†	**−.30**†	**−.26**⋆	**−.17**†	**−.26**†	**−.31**†	**−.30**†	***−.20***
	(.045)	(.077)	(.078)	(.071)	(.089)	(.045)	(.077)	(.078)	(.073)	(.093)
EDUC: A-levels (approx)	**−.14**⋆	***−.20***	**−.25**⋆	**−.24**⋆	***−.20***	**−.14**⋆	***−.20***	**−.25**⋆	**−.24**⋆	*−.16*+
	(.053)	(.097)	(.090)	(.091)	(.10)	(.053)	(.097)	(.090)	(.090)	(.10)
EDUC: O-levels (approx)	−.029	−.019	−.051	−.042	.005	−.029	−.019	−.051	−.042	.037
	(.045)	(.077)	(.077)	(.072)	(.081)	(.045)	(.077)	(.077)	(.073)	(.083)
Log job hours	**−.82**†	**−1.42**†	**−1.44**†	**−1.43**†	**−1.46**†	**−.82**†	**−1.42**†	**−1.44**†	**−1.43**†	**−1.47**†
	(.058)	(.089)	(.10)	(.091)	(.094)	(.058)	(.089)	(.10)	(.092)	(.097)
age	**−.043**†	**−.072**†	**−.077**†	**−.071**†	**−.074**†	**−.043**†	**−.072**†	**−.077**†	**−.071**†	**−.075**†
	(.009)	(.015)	(.015)	(.014)	(.015)	(.009)	(.015)	(.015)	(.015)	(.015)
age^2/1000	**.62**†	**1.03**†	**1.10**†	**1.03**†	**1.06**†	**.62**†	**1.03**†	**1.10**†	**1.03**†	**1.06**†
	(.11)	(.19)	(.19)	(.18)	(.18)	(.11)	(.19)	(.19)	(.18)	(.19)
female	**.27**†	**.48**†	**.45**†	**.44**†	**.45**†	**.27**†	**.48**†	**.45**†	**.44**†	**.44**†
	(.035)	(.064)	(.059)	(.059)	(.064)	(.035)	(.064)	(.059)	(.061)	(.062)
constant		**3.8**†					**3.8**†			
		(.40)					(.40)			
Numeracy (β_N)										
constant					*.22*+					***.33***
					(.17)					(.18)
log(HH income)					**.49**†					**.43**†
					(.075)					(.085)
EDUC: College degree					**1.26**†					**1.12**†
					(.23)					(.19)
EDUC: A-levels (approx)					**1.10**†					**.88**†
					(.24)					(.22)
EDUC: O-levels (approx)					**.72**†					**.60**†
					(.15)					(.14)
age										***−.042***
										(.026)
age^2/1000										.26
										(.31)
female										*−.21*+
										(.15)
High types										
Cut point 0	**−1.00**†		**−1.77**†	**−2.2**†	**−3.1**†	**−1.00**†		**−1.77**†	**−2.2**†	**−2.8**†
	(.24)		(.40)	(.061)	(.47)	(.24)		(.40)	(.063)	(.36)
Cut point 1	**−.78**†		**−1.38**†	**−1.77**†	**−2.1**†	**−.78**†		**−1.38**†	**−1.76**†	**−1.98**†
	(.24)		(.40)	(.059)	(.18)	(.24)		(.40)	(.059)	(.18)
Cut point 2	*−.43*+		*−.77*+	**−1.15**†	**−1.13**†	*−.43*+		*−.77*+	**−1.15**†	**−1.03**†
	(.24)		(.40)	(.053)	(.10)	(.24)		(.40)	(.055)	(.11)
Cut point 3	.15		.18	**−.21**†	**−.30**⋆	.15		.18	**−.21**†	*−.19*+
	(.24)		(.40)	(.051)	(.12)	(.24)		(.40)	(.052)	(.12)
Cut point 4	***.59***		***.90***	**.52**†	**.77**†	***.59***		***.90***	**.52**†	**.90**†
	(.24)		(.40)	(.052)	(.10)	(.24)		(.40)	(.053)	(.11)
Cut point 5	**1.04**†		**1.65**†	**1.27**†	**2.2**†	**1.04**†		**1.65**†	**1.27**†	**2.5**†
	(.24)		(.40)	(.055)	(.22)	(.24)		(.40)	(.056)	(.28)
Low types										
Cut point 0					**−1.11**†					**−1.24**†
					(.13)					(.16)
Cut point 1					.083					−.062
					(.14)					(.16)
FVRI				**0**†	**.31**†				**0**†	**.30**†
				(0)	(.041)				(0)	(.038)
Mean response: low-type:					**4.5**†					**4.8**†
					(.17)					(.20)
Mean response: high-type:				**4.5**†	**4.5**†				**4.5**†	**4.4**†
				(.039)	(.074)				(.039)	(.078)
Mean response: latent:					**4.5**†					**4.4**†
					(.076)					(.080)
empirical mean				**4.5**†	**4.5**†				**4.5**†	**4.5**†
				(.029)	(.029)				(.029)	(.029)
obs.	4730	4730	4730	4730	4730	4730	4730	4730	4730	4730
log likelihood	−8642	−9689	−8635	−8648	−8540	−8642	−9689	−8635	−8648	−8531

Significance: **0.1%**† **1%**⋆ ***5%*** *10%*+

Table F.4. Further estimates of mixture model on BHPS pay satisfaction. The first five columns correspond to those in Table 3. The final five columns include other demographic determinants of numeracy.

	Base model				With income in β_N				With age etc			
	OLS (1)	ologit (2)	FVRI→0 (3)	Mixture (4)	OLS (5)	ologit (6)	FVRI→0 (7)	Mixture (8)	OLS (9)	ologit (10)	FVRI→0 (11)	Mixture (12)
Life satisfaction (β_S)												
log(HH income)	**.13†**	**.11†**	**.10†**	**.21†**	**.13†**	**.11†**	**.10†**	**.20†**	**.29†**	**.35†**	**.33†**	**.42†**
	(.019)	(.027)	(.024)	(.026)	(.019)	(.027)	(.024)	(.026)	(.021)	(.033)	(.027)	(.030)
educHigh	**−.15†**	**−.27†**	**−.26†**	−.055	**−.15†**	**−.27†**	**−.26†**	*−.088*	−.037	*−.11*	**−.10⋆**	*.066+*
	(.032)	(.044)	(.041)	(.045)	(.032)	(.044)	(.042)	(.046)	(.033)	(.045)	(.043)	(.048)
educCollege	.042	.055	.054	*.087+*	.042	.055	.056	*.091+*	.020	.013	.011	.051
	(.047)	(.052)	(.057)	(.059)	(.047)	(.052)	(.056)	(.063)	(.046)	(.053)	(.057)	(.060)
age/100									*19.1+*	19.2	**−14.0†**	**−14.1†**
									(9.8)	(12.8)	(2.0)	(2.0)
$(\text{age}/100)^2$									**−83.6⋆**	*−93.0*	**13.5†**	**13.7†**
									(28.7)	(37.9)	(4.1)	(4.0)
$(\text{age}/100)^3$									**135†**	**158†**	**15.9†**	**15.8⋆**
									(35.5)	(47.6)	(4.9)	(4.9)
$(\text{age}/100)^4$									**−70.1†**	**−84.9†**	**−17.4†**	**−17.4†**
									(15.8)	(21.5)	(2.9)	(3.0)
male									**−.077⋆**	**−.12†**	**−.12†**	**−.095⋆**
									(.028)	(.035)	(.035)	(.038)
constant	**6.4†**				**6.4†**				**3.3⋆**			
	(.21)				(.21)				(1.23)			
Numeracy (β_N)												
constant				**1.47†**				**1.65†**				**1.85†**
				(.074)				(.12)				(.11)
educHigh				**.93†**				**.89†**				**1.02†**
				(.081)				(.13)				(.17)
educCollege				*.30*				*.42*				**.86⋆**
				(.15)				(.30)				(.47)
log(HH income)								**.38†**				**.38†**
								(.061)				(.075)
age/100												2.3
												(3.1)
$(\text{age}/100)^2$												−3.6
												(4.6)
$(\text{age}/100)^3$												−3.3
												(5.3)
$(\text{age}/100)^4$												4.9
												(4.0)
male												**.26⋆**
												(.11)
High types												
Cut point 0		**−5.9†**	**−7.0†**	**−7.7†**		**−5.9†**	**−7.0†**	**−8.1†**		−2.1	**−7.0†**	**−8.3†**
		(.43)	(.30)	(.91)		(.43)	(.30)	(1.05)		(1.63)	(.30)	(1.09)
Cut point 1		**−5.0†**	**−6.1†**	**−6.1†**		**−5.0†**	**−6.2†**	**−6.2†**		−1.22	**−6.2†**	**−6.3†**
		(.36)	(.19)	(.27)		(.36)	(.19)	(.27)		(1.61)	(.19)	(.27)
Cut point 2		**−4.1†**	**−5.2†**	**−5.0†**		**−4.1†**	**−5.2†**	**−5.1†**		−.27	**−5.2†**	**−5.1†**
		(.32)	(.12)	(.14)		(.32)	(.12)	(.14)		(1.60)	(.12)	(.14)
Cut point 3		**−3.2†**	**−4.4†**	**−4.1†**		**−3.2†**	**−4.4†**	**−4.2†**		.59	**−4.4†**	**−4.2†**
		(.31)	(.084)	(.090)		(.31)	(.083)	(.091)		(1.60)	(.086)	(.092)
Cut point 4		**−2.5†**	**−3.7†**	**−3.4†**		**−2.5†**	**−3.7†**	**−3.5†**		1.29	**−3.7†**	**−3.5†**
		(.31)	(.063)	(.068)		(.31)	(.064)	(.070)		(1.60)	(.064)	(.069)
Cut point 5		**−1.54†**	**−2.7†**	**−2.7†**		**−1.54†**	**−2.7†**	**−2.8†**		2.3	**−2.7†**	**−2.8†**
		(.30)	(.046)	(.11)		(.30)	(.047)	(.13)		(1.60)	(.048)	(.093)
Cut point 6		**−.89⋆**	**−2.1†**	**−1.92†**		**−.89⋆**	**−2.1†**	**−2.0†**		*2.9+*	**−2.0†**	**−1.98†**
		(.30)	(.040)	(.069)		(.30)	(.041)	(.072)		(1.60)	(.042)	(.063)
Cut point 7		.31	**−.86†**	**−.59†**		.31	**−.86†**	**−.66†**		**4.2⋆**	**−.83†**	**−.64†**
		(.30)	(.035)	(.047)		(.30)	(.037)	(.046)		(1.60)	(.038)	(.048)
Cut point 8		**1.79†**	**.62†**	**1.13†**		**1.79†**	**.62†**	**1.03†**		**5.7†**	**.70†**	**1.04†**
		(.30)	(.034)	(.049)		(.30)	(.035)	(.056)		(1.60)	(.038)	(.053)
Cut point 9		**3.2†**	**2.0†**	**5.8†**		**3.2†**	**2.0†**	**3.9†**		**7.1†**	**2.1†**	**3.2†**
		(.30)	(.041)	(1.32)		(.30)	(.043)	(.75)		(1.60)	(.044)	(.20)
Low types												
Cut point 0				**−5.6†**				**−5.1†**				**−4.8†**
				(.92)				(.67)				(.57)
Cut point 1				**−1.93†**				**−1.41†**				**−1.38†**
				(.38)				(.22)				(.23)
FVRI			**0†**	**.11†**			**0†**	**.10†**			**0†**	**.076†**
			(0)	(.009)			(0)	(.015)			(0)	(.010)
Mean response: low-type:				**9.3†**				**8.9†**				**8.9†**
				(.21)				(.20)				(.21)
Mean response: high-type:			**7.8†**	**7.6†**			**7.8†**	**7.7†**			**7.8†**	**7.7†**
			(.022)	(.028)			(.023)	(.029)			(.022)	(.026)
Mean response: latent:				**7.6†**				**7.7†**				**7.7†**
				(.028)				(.029)				(.026)
empirical mean			**7.8†**	**7.8†**			**7.8†**	**7.8†**			**7.8†**	**7.8†**
			(.018)	(.018)			(.018)	(.018)			(.018)	(.018)
obs.	10744	10744	10744	10744	10744	10744	10744	10744	10744	10744	10744	10744
log likelihood	−19290	−18185	−18211	−18104	−19290	−18185	−18211	−18075	−19091	−17949	−17997	−17871

Significance: **0.1%†** **1%⋆** *5%* *10%+*

Table F.5. Further estimates of life satisfaction in HILDA.

Note that the education variables here are defined as cumulative attainments, so the estimate for College is the effect of attaining a college degree, given that one has already attained High School

state	N	Cantril Ladder	σ(Cantril Ladder)	log(HH income)	σ(log(HH income))	Education (0–4)	σ(Education (0–4))	$= 0$	$= 5$	$= 10$	$\in 0, 5, 10$
AK	212	7.0	1.97	10.7	1.37	2.1	1.13	.030	.086	.084	.20
AL	1645	6.8	2.0	10.3	1.49	1.74	1.22	.003	.14	.092	.23
AR	1126	6.8	2.0	10.2	1.38	1.65	1.11	.011	.12	.096	.23
AZ	2338	7.0	1.85	10.6	1.28	2.0	1.18	.003	.11	.088	.20
CA	10500	7.0	1.81	10.8	1.21	2.1	1.24	.003	.12	.081	.20
CO	2309	7.0	1.75	10.8	1.09	2.3	1.18	.0009	.093	.055	.15
CT	1407	7.0	1.87	10.6	1.52	2.2	1.24	.010	.11	.085	.20
DC	261	7.0	1.62	10.9	1.45	2.9	1.24	.005	.033	.030	.068
DE	383	7.2	1.67	10.8	1.22	2.0	1.25	0	.13	.081	.22
FL	6904	6.9	1.91	10.6	1.17	1.96	1.18	.006	.13	.085	.22
GA	2979	7.0	1.90	10.5	1.37	1.95	1.24	.005	.12	.098	.23
HI	496	7.1	1.98	10.9	1.11	2.2	1.15	0	.13	.11	.24
IA	1607	7.0	1.91	10.6	1.27	1.89	1.14	.011	.13	.059	.20
ID	757	7.0	1.73	10.7	1.04	1.96	1.05	0	.13	.058	.18
IL	4591	6.8	1.81	10.7	1.22	2.1	1.22	.002	.13	.057	.19
IN	2650	7.0	1.83	10.6	1.15	1.77	1.18	.002	.10	.075	.18
KS	1332	6.9	1.94	10.6	1.18	2.0	1.20	.002	.13	.083	.22
KY	1661	6.8	2.0	10.4	1.36	1.69	1.27	.002	.15	.10	.26
LA	1339	6.9	2.1	10.2	1.45	1.65	1.22	.013	.12	.13	.27
MA	2647	6.9	1.80	10.8	1.23	2.3	1.29	.003	.12	.058	.18
MD	2174	7.0	1.73	10.8	1.22	2.2	1.29	.004	.13	.063	.19
ME	653	7.0	1.94	10.7	.97	1.96	1.16	.008	.088	.071	.17
MI	4354	6.8	1.95	10.6	1.16	1.92	1.18	.010	.12	.062	.19
MN	2859	7.0	1.87	10.8	1.03	2.1	1.14	.004	.096	.075	.17
MO	2725	6.9	1.96	10.5	1.29	1.95	1.23	.016	.13	.076	.22
MS	916	6.8	2.1	10.0	1.52	1.65	1.22	.008	.18	.13	.31
MT	485	7.3	1.58	10.6	1.18	2.0	1.08	0	.11	.067	.18
NC	3657	6.9	1.91	10.4	1.35	2.0	1.20	.004	.12	.080	.21
ND	339	7.2	1.72	10.7	1.21	1.92	1.12	.002	.090	.099	.19
NE	1002	6.9	1.83	10.5	1.40	1.86	1.13	.007	.13	.070	.20
NH	603	7.1	1.73	11.0	1.04	2.1	1.15	.006	.10	.070	.18
NJ	2813	6.9	1.92	10.8	1.25	2.1	1.25	.007	.11	.083	.20
NM	784	6.9	2.0	10.3	1.42	1.91	1.24	.003	.11	.099	.21
NV	849	7.1	1.74	10.8	.99	1.71	1.15	.003	.13	.079	.21
NY	6005	6.8	1.94	10.6	1.36	2.1	1.28	.005	.13	.083	.21
OH	5164	6.8	1.90	10.6	1.24	1.84	1.19	.003	.14	.082	.22
OK	1378	6.7	2.1	10.4	1.34	1.70	1.18	.011	.16	.089	.26
OR	1826	6.9	1.84	10.7	1.17	2.1	1.19	.004	.14	.074	.21
PA	5593	6.9	1.87	10.7	1.13	1.86	1.24	.004	.13	.079	.22
RI	439	7.1	2.0	10.8	1.07	1.95	1.26	.014	.079	.13	.22
SC	1884	6.9	1.97	10.3	1.50	1.80	1.24	.005	.16	.11	.27
SD	401	7.2	1.88	10.8	1.01	2.1	1.07	.001	.080	.12	.20
TN	2446	6.9	1.89	10.4	1.37	1.85	1.17	.001	.13	.077	.21
TX	7090	7.0	1.95	10.5	1.36	1.95	1.23	.006	.13	.10	.23
UT	1211	7.1	1.75	10.9	.89	2.1	1.12	.001	.093	.065	.16
VA	3165	6.9	1.90	10.8	1.25	2.2	1.27	.010	.11	.082	.20
VT	283	7.0	1.80	10.8	1.11	1.98	1.23	0	.10	.080	.18
WA	3033	6.9	1.74	10.9	1.02	2.2	1.15	.001	.092	.057	.15
WI	3236	7.0	1.85	10.7	1.12	1.88	1.15	.0007	.11	.069	.18
WV	666	6.6	2.1	10.1	1.51	1.70	1.14	.018	.19	.072	.28
WY	219	7.1	1.75	10.6	1.04	1.93	1.13	.003	.17	.066	.23

Table F.6. Gallup Daily Poll (2019) descriptive statistics

State	$\beta_S^{\log(\text{HHincome})}$	β_S^{HS}	β_S^{SC}	β_S^{Coll}	β_S^{Grad}	β_N°	$\beta_N^{\log(\text{HHincome})}$	β_N^{HS}	β_N^{SC}	β_N^{Coll}	β_N^{Grad}	$\beta_S^{\log(\text{HHincome})}$	β_S^{HS}	β_S^{SC}	β_S^{Coll}	β_S^{Grad}
	Ordered logit					Mixture										
AL	**.37†**	.016	−.078	−.088	.17	**2.3†**	***.29***	.44	.61	.68	.78	**.43†**	.16	.066	.063	.35
	.047	.21	.21	.23	.22	.47	.13	.41	.42	.61	.56	.050	.22	.21	.23	.23
AR	**.44†**	.15	.15	*.41*+	.36	**1.88†**	.047	.037	.20	*1.04*+	***1.31***	**.45†**	.21	.24	***.61***	***.62***
	.056	.24	.24	.25	.26	.47	.16	.42	.42	.59	.61	.059	.25	.25	.28	.29
AZ	**.45†**	−.040	.11	.24	.38	**1.95†**	−.053	.092	.56	***1.14***	***1.13***	**.47†**	.022	.27	***.49***	**.65⋆**
	.043	.24	.23	.23	.23	.40	.13	.39	.40	.50	.52	.045	.24	.23	.24	.24
CA	**.56†**	−.035	−.046	.048	***.26***	**1.97†**	**.22†**	.11	**.67⋆**	**1.23†**	**1.57†**	**.60†**	.010	.074	*.23*+	**.49†**
	.022	.12	.11	.11	.11	.27	.061	.22	.22	.29	.42	.025	.12	.11	.12	.12
CO	**.67†**	***.56***	.41	*.44*+	***.61***	**3.1†**	***.45***	−.10	.45	***1.34***	*1.11*+	**.74†**	***.66***	***.58***	***.64***	**.81⋆**
	.053	.27	.26	.26	.26	.56	.18	.49	.48	.68	.65	.059	.27	.26	.26	.26
CT	**.60†**	.41	.068	.21	*.46*+	**2.6†**	**.35⋆**	−.35	*.94*+	.64	*1.19*+	**.66†**	.36	.20	.33	***.64***
	.056	.28	.27	.28	.27	.49	.14	.44	.53	.55	.63	.062	.30	.29	.30	.30
FL	**.55†**	.047	.075	.18	***.36***	**2.4†**	**.25⋆**	.36	***.64***	**.97⋆**	**1.58⋆**	**.63†**	.17	*.24*+	**.40⋆**	**.63†**
	.027	.14	.14	.14	.14	.30	.089	.27	.27	.36	.49	.029	.14	.14	.14	.15
GA	**.58†**	***.50***	.23	.26	**.52⋆**	**2.2†**	**.29⋆**	.32	***.67***	**1.57⋆**	**1.75⋆**	**.69†**	**.73†**	**.52⋆**	**.64⋆**	**.94†**
	.039	.20	.19	.20	.20	.36	.10	.33	.34	.54	.57	.045	.20	.19	.20	.20
IA	**.60†**	.32	.086	.15	.39	**1.91†**	.21	.23	.52	***1.08***	.92	**.63†**	.37	.11	.22	.46
	.054	.26	.26	.27	.28	.56	.14	.45	.45	.55	.57	.057	.27	.27	.29	.29
IL	**.51†**	.28	*.28*+	***.34***	**.65†**	**2.4†**	*.19*+	.25	.19	***.96***	***1.26***	**.54†**	*.30*+	*.29*+	***.41***	**.77†**
	.031	.17	.16	.17	.17	.40	.097	.34	.33	.44	.59	.034	.16	.16	.17	.17
IN	**.58†**	.065	−.14	.050	.24	**1.87†**	*.17*+	−.16	.35	**1.45⋆**	.58	**.60†**	.091	−.11	.14	*.32*+
	.044	.18	.18	.19	.19	.36	.096	.31	.32	.54	.39	.045	.18	.18	.19	.19
KS	**.66†**	.29	−.16	.22	.29	**1.68⋆**	.14	.13	*.85*+	***1.15***	***1.29***	**.69†**	.34	−.063	.37	*.47*+
	.062	.27	.25	.26	.27	.51	.19	.44	.44	.51	.56	.065	.27	.26	.27	.28
KY	**.52†**	*.37*+	.30	.35	**.60⋆**	**1.77†**	.078	.35	***.82***	***.88***	***1.19***	**.56†**	***.51***	**.53⋆**	**.60⋆**	**.96†**
	.048	.20	.19	.21	.21	.40	.13	.34	.36	.43	.51	.053	.20	.19	.22	.22
LA	**.34†**	−.048	−.057	−.10	.099	**1.93†**	***.25***	−.069	.57	*1.01*+	.83	**.43†**	.008	.16	.15	.37
	.049	.22	.21	.22	.23	.41	.12	.36	.41	.55	.51	.057	.23	.22	.24	.25
MA	**.59†**	.072	.13	.063	*.36*+	**2.0†**	**.29⋆**	−.34	.36	***1.21***	***1.25***	**.64†**	.086	.20	.17	***.51***
	.045	.22	.21	.22	.21	.38	.096	.35	.35	.48	.52	.047	.22	.21	.22	.22
MD	**.48†**	−.058	−.036	−.11	.16	**2.0†**	**.31⋆**	.11	.27	***.95***	***1.15***	**.53†**	−.026	.026	.001	.31
	.048	.26	.26	.26	.26	.43	.099	.39	.38	.45	.52	.054	.26	.26	.26	.26
ME	**.53†**	.38	.47	*.58*+	*.58*+	**2.0†**	.20	.26	.84	.34	***1.29***	**.57†**	.50	***.64***	***.71***	***.82***
	.088	.33	.32	.34	.33	.49	.24	.52	.57	.57	.63	.096	.33	.32	.34	.34
MI	**.53†**	*.29*+	−.063	.19	***.41***	**2.3†**	**.33†**	.042	***.75***	***1.07***	**1.63⋆**	**.57†**	*.29*+	.008	*.29*+	**.57†**
	.032	.16	.15	.16	.16	.34	.098	.31	.35	.45	.53	.036	.16	.16	.17	.17
MN	**.60†**	*.39*+	.32	***.52***	**.71⋆**	**2.8†**	*.34*+	.54	*.85*+	***1.05***	*1.01*+	**.65†**	***.56***	***.52***	**.75⋆**	**.94†**
	.045	.23	.22	.23	.23	.50	.18	.46	.50	.53	.60	.048	.23	.23	.23	.24
MO	**.50†**	.15	.085	.28	**.50⋆**	**2.0†**	.11	.10	***.79***	**1.74⋆**	***1.22***	**.53†**	.16	.18	***.48***	**.69†**
	.042	.19	.19	.20	.20	.38	.12	.35	.37	.57	.53	.044	.19	.19	.21	.20
MS	**.30†**	.36	.11	.41	***.62***	**1.56†**	*.20*+	.47	**1.51⋆**	.59	*1.14*+	**.38†**	***.54***	*.45*+	***.63***	**.98†**
	.060	.25	.23	.26	.26	.42	.12	.41	.48	.48	.58	.065	.26	.26	.28	.28
NC	**.54†**	.20	.019	.25	.28	**2.4†**	**.28⋆**	−.045	*.55*+	***1.08***	***.86***	**.62†**	.23	.16	***.46***	***.48***
	.034	.18	.17	.18	.18	.35	.097	.33	.33	.49	.42	.038	.19	.19	.20	.20
ND	**.58†**	.22	.14	.33	.47	**2.2†**	.069	−.11	***1.41***	.76	.44	**.60†**	.34	.44	.58	.66
	.11	.40	.37	.39	.41	.57	.28	.64	.69	.66	.70	.12	.40	.38	.40	.41
NE	**.49†**	*.49*+	.19	.41	***.68***	**2.5†**	.22	.33	.99	.80	.70	**.51†**	***.59***	.30	*.54*+	**.82⋆**
	.066	.29	.28	.30	.30	.58	.22	.58	.62	.65	.69	.071	.30	.29	.30	.31
NH	**.49†**	−.009	−.14	.070	.35	**1.99†**	**.59⋆**	.021	.89	.80	.68	**.64†**	.16	.18	.36	*.70*+
	.10	.40	.39	.40	.39	.50	.20	.52	.55	.56	.55	.12	.39	.37	.39	.39
NJ	**.51†**	**.69⋆**	.21	***.48***	**.63⋆**	**2.4†**	***.21***	−.51	.51	***.94***	***1.13***	**.56†**	**.62⋆**	.33	**.67⋆**	**.85†**
	.045	.21	.21	.21	.21	.38	.10	.35	.36	.47	.56	.049	.22	.22	.22	.22
NM	**.62†**	*.54*+	.37	.33	***.70***	**1.78†**	−.095	.067	*.97*+	*.99*+	***1.26***	**.64†**	*.59*+	***.63***	*.59*+	**1.06†**
	.071	.32	.30	.31	.30	.50	.19	.50	.52	.58	.59	.070	.32	.29	.31	.31
NV	**.59†**	*.57*+	***.66***	*.52*+	**.77⋆**	**2.1†**	**.57⋆**	−.21	−.096	***1.33***	.61	**.64†**	***.61***	***.68***	***.66***	**.90⋆**
	.082	.29	.27	.30	.30	.52	.18	.50	.45	.67	.62	.091	.29	.27	.29	.30
NY	**.52†**	.047	.030	−.012	.23	**1.94†**	*.16*+	.24	**.93†**	**1.43†**	**1.20⋆**	**.58†**	.17	***.30***	***.31***	**.56†**
	.028	.15	.15	.15	.15	.26	.084	.24	.25	.33	.37	.028	.15	.15	.16	.15
OH	**.55†**	*.28*+	.12	*.27*+	**.49⋆**	**1.94†**	.15	*.50*+	**.86⋆**	**1.68†**	**1.23⋆**	**.60†**	**.43⋆**	***.32***	**.57†**	**.78†**
	.030	.15	.15	.15	.15	.31	.100	.26	.27	.48	.42	.032	.15	.15	.16	.16
OK	**.59†**	.39	−.021	.28	***.56***	**1.81†**	.087	*.93*+	***1.10***	***1.19***	***1.44***	**.61†**	***.56***	.14	*.46*+	**.80⋆**
	.052	.25	.24	.26	.26	.49	.17	.52	.45	.60	.64	.056	.25	.24	.26	.27
OR	**.56†**	−.16	−.014	.23	***.59***	**2.3†**	*.23*+	.58	.61	.45	.56	**.65†**	.003	.17	.41	**.83⋆**
	.052	.26	.25	.26	.26	.41	.12	.45	.40	.44	.51	.058	.28	.26	.27	.27
PA	**.53†**	.053	−.085	.12	***.29***	**1.51†**	**.24†**	.36	**.82†**	**1.30†**	**1.61†**	**.57†**	.062	−.033	.21	**.43⋆**
	.030	.14	.14	.14	.14	.28	.067	.22	.24	.32	.45	.034	.14	.14	.16	.16
RI	**.53†**	−.079	.060	.17	.51	**2.4†**	.29	.32	.58	.66	.81	**.52†**	−.008	.13	.31	*.63*+
	.10	.34	.30	.32	.31	.60	.39	.70	.66	.72	.71	.11	.35	.31	.33	.32
SC	**.42†**	.12	−.005	.15	*.34*+	**1.39†**	**.25⋆**	.15	.43	.53	***.95***	**.49†**	.12	.044	.19	***.47***
	.044	.21	.20	.21	.21	.38	.076	.31	.30	.35	.45	.048	.21	.20	.22	.22
TN	**.56†**	−.26	***−.45***	−.15	.065	**2.00†**	.065	*.74*+	*.63*+	***1.39***	***1.07***	**.59†**	−.086	−.30	.096	.31
	.041	.19	.19	.20	.20	.44	.14	.38	.36	.54	.53	.042	.19	.19	.21	.20
TX	**.43†**	−.060	−.083	.12	.20	**2.2†**	**.28†**	.27	**.77†**	**1.42†**	**1.89†**	**.53†**	.049	.15	**.43†**	**.54†**
	.024	.13	.12	.13	.13	.22	.058	.22	.23	.35	.52	.027	.13	.13	.13	.13
UT	**.50†**	.20	.47	***.73***	**.91⋆**	**2.3†**	.032	−.12	.17	.41	*1.16*+	**.52†**	.34	*.57*+	**.88⋆**	**1.15†**
	.069	.32	.30	.31	.31	.48	.21	.63	.46	.51	.65	.069	.32	.30	.31	.32
VA	**.50†**	.17	.007	.17	.24	**1.98†**	.11	.25	.48	**1.63†**	**1.89†**	**.53†**	.31	.18	***.52***	**.62⋆**
	.038	.20	.20	.20	.20	.33	.10	.32	.31	.49	.54	.043	.20	.20	.21	.21
WA	**.61†**	.33	.26	***.48***	**.60⋆**	**2.2†**	.10	.18	.32	.60	**1.51⋆**	**.65†**	*.40*+	*.35*+	**.63⋆**	**.85†**
	.043	.22	.20	.21	.21	.41	.13	.39	.37	.40	.58	.046	.22	.21	.22	.22
WI	**.60†**	−.12	−.18	.006	.28	**2.2†**	*.23*+	.34	***.85***	**1.33⋆**	***1.21***	**.65†**	.004	−.013	.22	***.52***
	.042	.20	.19	.20	.20	.47	.13	.36	.38	.51	.55	.042	.20	.20	.21	.21
WV	**.48†**	.40	.23	.36	*.51*+	**2.4†**	.17	.095	.047	.92	.66	**.50†**	.46	.27	.42	*.58*+
	.069	.28	.28	.32	.31	.63	.18	.59	.54	.69	.69	.069	.28	.28	.33	.32

Table F.7. State-level estimates of life evaluations. β_N are coefficients predicting focal value behavior in the mixture model, while β_S predict wellbeing. Indicators for education level are compared to those not finishing high school, and are denoted HS for high school, SC for some college, Coll for college completion, and Grad for graduate studies.

G Question wordings and survey descriptive statistics

The following sections specify the different SWB question wordings for data presented in this paper, along with the OECD standard for life satisfaction.

G.1 OECD (2013) guidelines

The following question asks how satisfied you feel, on a scale from 0 to 10. Zero means you feel “not at all satisfied” and 10 means you feel “completely satisfied”.

Overall, how satisfied are you with life as a whole these days?

G.2 Canadian Community Health Survey (CCHS), 2010 revision

Using a scale of 0 to 10 where 0 means "Very dissatisfied" and 10 means "Very satisfied", how do you feel about your life as a whole right now?

G.3 British Household Panel Study (BHPS)

I’m going to read out a list of various aspects of jobs, and for each one I’d like you to tell me from this card which number best describes how satisfied or dissatisfied you are with that particular aspect of your own present job.

WHERE 1 = COMPLETELY DISSATISFIED;
7 = COMPLETELY SATISFIED; 4 = NEITHER SATISFIED NOR DISSATISFIED)

Pay: The total pay, including any overtime or bonuses ....KJSSAT1 .

...

Job: All things considered, how satisfied or dissatisfied are you with your present job overall using the same 1 - 7 scale?

Note that the wording with 3 verbal cues is from before the changes studied by Conti and Pudney (2011), in which verbal descriptions were added for all seven response options.

G.4 Household, Income and Labour Dynamics in Australia (HILDA)

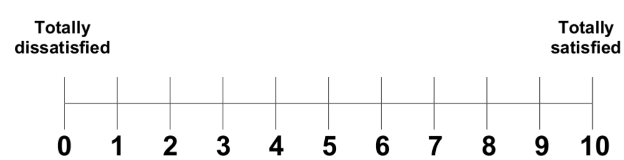
I want you to pick a number between 0 and 10 to indicate how satisfied or dissatisfied you are with the following aspects of your job. The more satisfied you are, the higher the number you should pick. The less satisfied you are, the lower the number.

...

All things considered, how satisfied are you with your life?

Again, pick a number between 0 and 10 on SHOWCARD K5 to indicate how satisfied you are.

SHOWCARD K5



G.5 Equality, Security and Community (ESC) Survey

Now a question about life satisfaction. On a scale of 1 - 10 where ONE means dissatisfied and TEN means satisfied, all things considered, how satisfied are you with your life as a whole these days?

G.6 General Social Survey Cycle 24 (Canada)

Using a scale of 1 to 10 where 1 means “Very dissatisfied” and 10 means “Very satisfied”, how do you feel about your life as a whole right now?

G.7 Gallup Daily Poll

The Cantril Self-Anchoring Striving Scale (Cantril, 1965; Gallup, 2014) is phrased as follows: “Please imagine a ladder with steps numbered from zero at the bottom to 10 at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?”

10 Best possible life
09
08
07
06
05
04
03
02
01
00 Worst possible life

G.8 Descriptive statistics

Distributions of subjective wellbeing responses are given as histograms throughout the main text. On the next page, distributions for education and incomes are tabulated.

CCHS		BHPS		HILDA		ESC main		ESC aboriginal		Daily Poll	
N	91800	***N***	4730	***N***	10700	***N***	5570	***N***	395	***N***	109000
Education		**Education**		**Education**		**Education**		**Education**		**Education**	
< high school	0.107	Primary	0.335	< high school	0.299	0	0.000897	0	0.00759	< high school	0.0991
Graduated high school	0.208	O-level	0.236	Graduated high school	0.599	1	0.0158	1	0.0658	HS	0.282
Post-secondary	0.684	A-level	0.121	College	0.101	2	0.026	2	0.0481	Some college	0.29
		College	0.308			3	0.12	3	0.367	College	0.165
						4	0.22	4	0.208	Post grad	0.163
						5	0.0687	5	0.0304		
						6	0.179	6	0.0861		
						7	0.0878	7	0.0709		
						8	0.198	8	0.104		
						9	0.0547	9	0.00759		
						10	0.0284	10	0.00506		
Income		**Income**		**Income**		**Income**		**Income**		**Income**	
10000	0.0609	mean	978	mean	82300	mean	51100	mean	34500	360	0.0321
30000	0.128	std	683	std	60000	std	25900	std	23500	3360	0.0447
50000	0.145	min	13	min	0	min	10000	min	10000	9000	0.0449
70000	0.131	max	9310	max	489000	max	100000	max	100000	18000	0.105
90000	0.536									30000	0.12
										42000	0.0953
										54000	0.0969
										75000	0.165
										105000	0.113
										130000	0.184

Table G.1. Distributions of education and income responses by survey. For incomes reported as continuous values, descriptive statistics are listed. For categorically-reported values of income and education, weighted count fractions are reported. For ESC, the ten education categories are as follows: "No schooling", "Some elementary school", "Completed elementary school", "Some secondary / high school", "Completed secondary / high school", "Some technical, community college, cegep, college classique", "Completed technical, community college, cegep, c. classique", "Some university", "Bachelor's degree", "Master's degree", "Professional degree or doctorate".