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RESEARCH PAPER

# The Relationship Between Subjective Wellbeing and Subjective Wellbeing Inequality: An Important Role for Skewness

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**Abstract**
We argue that the relationship between individual satisfaction with life (SWL) and SWL inequality is more complex than described by earlier research. Our measures of SWL inequality include indices designed specifically for ordinal data as well as often used (but inappropriate) measures suited to cardinal data. Using inequality indices derived by Cowell and Flachaire designed for use with ordinal data, our analysis shows that skewness of the SWL distribution, rather than inequality per se, matters for individual SWL outcomes. The empirical analysis is based on repeated cross-section data obtained from the World Values Survey. Our results are consistent with there being negative externalities for an individual's SWL arising from people who are low in the SWL distribution, with positive externalities arising from people who are high in the SWL distribution.

**Keywords** Subjective wellbeing · Ordinal data · Inequality · Skewness · WVS

## 1 Introduction

The importance of examining the impact of subjective wellbeing[1] inequality on people's welfare has been increasingly recognized following the pioneering work of Veenhoven (1990). Dickinson and Morrison (2022, p. 910), after reviewing a wide range of studies in the field, conclude: "The negative relationship between wellbeing and wellbeing inequality within the group therefore has widespread empirical support at various scales, ranging

[1] We use the terms 'subjective wellbeing', 'wellbeing', and 'satisfaction with life' interchangeably.

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from large groups such as countries down to smaller groups such as counties". Furthermore, some studies find that wellbeing inequality has a greater (negative) impact on individuals' wellbeing than does income inequality (Goff et al., 2018; Helliwell et al., 2020). These findings are significant in directing our attention beyond the effects of income or wealth inequality to inequality in broader measures of welfare that incorporate differences in aspects of utility beyond just material factors.

However, two wellbeing distributions that have identical values for an index of inequality may have differently shaped distributions. For instance, one distribution could be positively skewed (long right tail) and another could be negatively skewed (long left tail). An example is given as Fig. 4 in the appendix in which the distribution of 'satisfaction with life' in the Philippines (negatively skewed) is almost the mirror image of that in Ukraine (positively skewed); notably, the two distributions have the same mode and identical standard deviations.[2] If inter-personal comparisons affect individual utility (Clark et al., 2008; Duesenberry, 1949; Easterlin, 1974) then it is unlikely that these two differently skewed distributions will have the same effects on individual wellbeing despite their identical modes and standard deviations. This is especially the case since inter-personal comparisons may incorporate both upward-looking (Festinger, 1954) and downward-looking (Wills, 1981) elements. In an upward-looking comparison, an individual compares herself with those who are ranked higher than her in the dimension that is being compared; in a downward-looking comparison, the individual compares herself with those who are ranked lower than her. Reflecting these alternative forms of comparison, and given the example of differently skewed distributions in Fig. 4, we test whether the skewness of a country's wellbeing distribution matters in relation to the wellbeing of its individuals.

Our empirical work uses an ordinal measure of wellbeing based on a satisfaction with life (SWL) question for which answers are provided on a 10-point scale. The ordinal scale raises issues as to appropriate measures of inequality and skewness. Inequality measures designed for cardinal data have been applied to ordinal scale SWL data. For instance, Goff et al. (2018) and Grimes and Wesselbaum (2019) use the standard deviation to measure SWL inequality while Stevenson and Wolfers (2008) use the Gini coefficient. Applying these statistics to an ordinal variable requires strong assumptions about the underlying properties of the SWL scale. Studies using the level of SWL in regressions (as a dependent or explanatory variable) frequently find similar results when SWL is treated as a cardinal variable in an OLS regression or as an ordinal variable in an ordered response model (Ferrer-i-Carbonell & Frijters, 2004). Less attention has been paid to consistency of results for measures based on cardinal versus ordinal approaches when analysing impacts of wellbeing inequality. A further contribution of our paper—beyond its attention to skewness—is to test whether the specification of the wellbeing inequality variable (based on a cardinal or an ordinal treatment) matters in a regression context. Specifically, building on prior work by Goff et al. (2018), we test the sensitivity of the relationship between individual SWL and the country's inequality of SWL when different measures of SWL inequality are adopted. Indices include the standard deviation plus measures designed specifically for the case of ordinal data. A novel contribution of our analysis is that we pay particular attention to the inequality measures derived by Cowell and Flachaire (2017) which enable us to showcase the importance for individuals' SWL of skewness in the inequality distribution. Bérenger and Silber (BS, 2022) have also recently examined the sensitivity of inequality measurement to indices that are based on alternative cardinal and ordinal approaches. One

[2] The data for Fig. 4 (from World Values Survey, wave 3) form part of our broader dataset described later in the paper; the standard deviation of each distribution is 2.3 and the mode of each is 5.

intriguing finding that emerges from their comparison of these indices is that the standard deviation of life satisfaction (using World Values Survey data) has a higher correlation with indices based on an ordinal approach than with other indices based on cardinal approaches. The measures that they adopt, which emphasise the Apouey et al. (2020) indices of social welfare, differ from those in our study. They reference the Cowell and Flachaire (CF) indices but do not examine their application to the measurement of inequality, which is our focus.[3] In addition, BS do not examine skewness when considering life satisfaction distributions. Our study can therefore be seen as complementary to the BS study in which the properties (particularly skewness) highlighted by the CF indices are brought to the fore. Our analysis is based on repeated cross-section data from the World Values Survey (WVS) which also differentiates it from the BS and CF analyses which are based on single WVS cross-sections.

Our paper unfolds as follows. In Sect. 2, we review some key contributions on inequality measurement using ordinal data. Section 3 provides an empirical application to illustrate the sensitivity of results to differing inequality measures. The empirical application, which is based on World Values Survey (WVS) data, leverages one prominent study in the field that uses the standard deviation to measure SWL inequality, as a starting point to provide context for the analysis. The WVS is utilised both because it has been used in three related studies (Bérenger & Silber, 2022; Cowell & Flachaire, 2017; Goff et al., 2018) and because it covers a large number of countries over a long timespan, and these properties are required to illustrate the methodological points of the paper.[4] Our empirical example highlights sensitivity of results to the use of different inequality measures and demonstrates the importance of considering skewness. Our regression results indicate that a negative association between individual SWL and country-level SWL inequality (measured using the standard deviation of SWL) is not robust to the use of alternative inequality measures. When we use theoretically appropriate measures for summarizing SWL inequality—those due to Cowell and Flachaire (2017)—we find either a positive or a negative relationship between wellbeing inequality and individual SWL depending on which of the measures we use.

We therefore proceed to analyse the reasons behind these differing results and show that the skewness of the SWL distribution in a country may be at least as important as inequality per se in affecting individuals' SWL (Sect. 4). The importance of skewness—i.e. whether there is a long tail of individuals at either end of the SWL distribution—for people's overall welfare has strong intuitive appeal but has largely been overlooked as researchers have concentrated on inequality measures that are invariant to whether skewness is upwards or downwards. By emphasizing this feature, our use of the CF measures contributes new insights to the understanding of how the wellbeing distribution affects people's SWL. Section 5 contains our summary and conclusions.

[3] Jenkins (2021) discusses how the properties of the Apouey et al. (2020) and the CF measures differ.

[4] We acknowledge imperfections in the sampling process for WVS (e.g. see Appendix A of Pew Research Center, 2019). Having established the importance of skewness in the wellbeing distribution, we invite other scholars to apply our methods to additional cross-country or cross-regional datasets.

## 2 Inequality Indices for Ordinal Data

SWL measures based on integer-value scales are inherently ordinal. A key characteristic of ordinal data is that the order of values is well-defined but the magnitudes of differences between scale levels are not. To compare SWL distributions, one must assume that there is a common and fixed 'reporting function', across time for the same individual and across individuals at a given time, so that the intrinsic meaning of the SWL scale levels is the same for all individuals and does not change over time.[5] However, even assuming a common and fixed reporting function—as virtually all SWL researchers do, and we do too—the ordinal nature of the SWL scale means that there are no grounds for saying that the difference between, say, a 6 and a 7 on a 10-point scale is of the same magnitude as the difference between a 7 and an 8. To do this, and thereby make SWL responses cardinally measurable, we need to make additional assumptions about the scale.[6]

Even if one assumes cardinality, the bounded nature of SWL scales may cause 'true' SWL inequality to be under-estimated by the standard deviation (*SD*). Delhey and Kohler (2011) present one method to address this issue.[7] They propose an index that standardises the *SD* in relation to the maximum possible value. DK note, assuming cardinality, that the maximum standard deviation possible for a given mean SWL ($SD_{MAX}$) is:

$$SD_{MAX} \equiv \sqrt{\frac{(U-\mu)(\mu-L)N}{N-1}} \tag{1}$$

where $U$ is the SWL scale's maximum value, $L$ is the minimum value, $\mu$ is mean SWL, and $N$ is the number of observations in the analysis sample. $SD_{MAX}$ reaches its greatest value when $\mu$ is midway between $U$ and $L$, and decreases as $\mu$ approaches either $U$ or $L$. DK's 'instrument-effect-corrected' index is:

$$SD^* = \frac{SD}{SD_{MAX}} \tag{2}$$

Hence $SD^*$ is inflated relative to $SD$ as $\mu$ approaches either $U$ or $L$. We use $SD^*$ as one of several alternatives to *SD* in our empirical work.

Using a calibrated example, Delhey and Kohler (2011) argue that their measure 'works'. But their approach remains based on an assumption of cardinality and so only corrects for one potential issue regarding *SD*.

A related fundamental issue with the *SD* and other indices based on mean SWL is that rankings of distributions of ordinal variables based on them are not robust to changes in the scale ('scale dependent'). Scale dependence also implies that that the mean is not a robust measure of central tendency for ordinal data such as these.[8]

[5] These assumptions must also hold across countries for cross-country analyses. If the assumptions are not fully met, then use of the data in regression analysis rests on an assumption that factors causing differences in reporting are not correlated with other regressors.

[6] Bond and Lang (2019) discuss these issues in detail. For a more positive interpretation regarding what can be inferred, see Kaplan and Zhuo (2019).

[7] For additional approaches, see Erreygers (2009) and Bérenger and Silber (2022).

[8] For instance, if one applies a transformation to the numerical labels associated with the categories, e.g. using an exponential function, the mean changes. For further discussion of this point, see Bond and Lang (2019) and Jenkins (2020a).

Allison and Foster (2004) argue instead that, for ordinal data applications, the median should be used to measure central tendency and be the fundamental reference point underpinning inequality indices. Allison and Foster's concept of *S*-dominance encapsulates this idea: for two SWL distributions $X$ and $Y$ with cumulative distribution functions $F_X$ and $F_Y$ respectively, and the same median $k$, distribution $Y$ *S*-dominates distribution $X$ if and only if: (a) for all categories below the median, $F_Y \leq F_X$; and (b) for all categories at or above the median category, $F_Y \geq F_X$. Building on this idea, Allison and Foster develop an inequality index (*AF*) which equals the difference between the mean SWL response for median-and-above categories minus the mean SWL response for below-median categories. For an integer scale (and assuming cardinality), *AF* is the average across respondents of the number of scale points required to move from the observed SWL value to the median. Allison and Foster (2004) argue that *AF* has intuitive appeal but acknowledge that it is scale-dependent and so recommend checking the robustness of results to changes in the scale.[9]

Scale-independent inequality indices appropriate for ordinal data have been developed using axiomatic approaches by, for example, Abul Naga and Yalcin (2008), Apouey (2007), and Cowell and Flachaire (2017). All three classes of inequality index allow for different degrees of sensitivity to inequality when summarizing dispersion across individuals.[10] However, only the Cowell and Flachaire (CF, 2017) approach also allows other features to be accounted for straightforwardly, notably skewness, as we explain shortly. For this reason, we focus on a portfolio of CF indices in this paper (in addition to the *SD*, *SD**, and *AF* indices).

Derivation of CF indices has three components: definition of each individual's 'status' (related to SWL), specification of the reference status value (inequality is conceptualised in terms of differences in individuals' status from the reference value), and assumptions about inequality sensitivity (how differences in status from the reference value are aggregated).

Status is the position of a person in the distribution of an ordinal variable (e.g. SWL) within society. CF distinguish between downward-looking status (i.e. measuring your position by the proportion of people with lower or the same SWL than you) and upward-looking status (measuring your position by the proportion of people with the same or higher SWL than you). For each of these concepts, status can be either peer-inclusive or peer-exclusive. The peer-inclusive status measures are as explained in the previous sentence; peer-exclusive measures exclude the people with the same SWL response as you when calculating the proportions. In this paper, we focus on peer-inclusive measures of status which are also what CF worked with.

In order to make inequality comparisons, we need both a definition of equality and a method of characterizing departures from equality. Equality is the situation in which all individuals have the same status; for peer-inclusive measures, CF argue persuasively that the natural reference point is the maximum value of status.

Having defined status and the reference point, CF summarize inequality by aggregating across individuals the 'distances' between each person's status and the status reference

9 See Dutta and Foster (2013) for an application to US trends in the inequality of happiness.

10 Use of SD to proxy wellbeing inequality also implicitly assumes an inequality sensitivity parameter since SD is a special case (with $\beta$=2) of the more general expression for summarising deviations from the mean ($\mu$) of a distribution, (*DEV*), in which: $DEV = [(\sum_i |X_i - \mu|^{\beta})/N]^{1/\beta}$; the mean absolute deviation corresponds to $\beta$=1. There are no a priori reasons to suppose that squared (or linear) deviations from the mean are what matter most for determining the impacts of inequality. One advantage of using measures such as the Atkinson Inequality Index for cardinal data (Atkinson, 1970) or the CF indices for ordinal data is that the inequality sensitivity parameter is made explicit rather than being left implicit.

point. There are different ways of characterizing 'distance'[11]; CF do so using a one-parameter family of distance functions suitable for ordinal data, for which the parameter $\alpha$ represents the degree of inequality sensitivity—the extent to which large distances are given greater weight than small distances in the aggregation across individuals.[12] CF's peer-inclusive downward-looking inequality index, $I_\alpha$, is shown in (3) where $s_i$ is person $i$'s status, being the proportion of people with the same or lower response for SWL as person $i$, and $N$ is the number of people surveyed:

$$I_\alpha = \frac{1}{\alpha(\alpha-1)}\left[\frac{1}{N}\sum_{i=1}^{N} s_i^\alpha - 1\right], 0 < \alpha < 1.$$

$$I_0 = -\frac{1}{N}\sum_{i=1}^{N}\log\left(s_i\right). \tag{3}$$

CF's peer-inclusive upward-looking inequality index is defined analogously with $s_i$ redefined to be the proportion of people with the same or higher response for SWL as person $i$. We denote the downward-looking versions of the indices $I_\alpha^D$ and the upward-looking versions $I_\alpha^U$. All of CF's indices are scale-independent. For a given distribution, a larger $\alpha$ —greater inequality sensitivity—results in a higher index value.[13]

A useful feature of CF's upward- and downward-looking indices for our analysis is that they differ in their sensitivity to the skewness of the SWL distribution. To our knowledge, there is no generally recognised statistic to describe the skewness of an ordinal distribution that does not assume scale-dependence. (We note that one could construct a scale-dependent measure based on the Allison and Foster approach whereby steps of the distribution above the median are compared to steps below the median.) By contrast, comparison of the upward- and downward-looking CF indices provide a scale-independent approach to characterise skewness.

For given $\alpha$, $I_\alpha^D = I_\alpha^U$ if the distribution in question is symmetric. When the distribution is negatively skewed (i.e. has a long left tail), $I_\alpha^D > I_\alpha^U$, whereas $I_\alpha^D < I_\alpha^U$ when the distribution is positively skewed (a long right tail). Inequality sensitivity also plays a role: for asymmetric distributions, the difference between $I_\alpha^D$ and $I_\alpha^U$ is smaller, the larger that $\alpha$ is. The practical lesson, which we exploit below, is that downward- and upward-looking CF inequality indices used in combination allow one to take account of distributional skewness in addition to inequality per se. Because findings are potentially sensitive to the choice of the inequality sensitivity parameter, we use a range of values for $\alpha$ (0, 0.5, and 0.9).

To fix ideas, we illustrate the effects of skewness and inequality sensitivity on the CF indices in Table 1, which reproduces and extends the examples presented in CF's Tables 2 and 3. CF focus on the case $\alpha = 0$; we also consider the cases of $\alpha = 0.5$ and $\alpha = 0.9$. In the table, Case 0 is negatively skewed, Case 3 is positively skewed, and Cases 1 and 2 are

[11] For cardinal variables, standard inequality indices summarize inequality by aggregating across individuals the distances between each person's value and the mean. But, as explained earlier, the mean is an inappropriate reference point when measuring the inequality of ordinal data.

[12] In our application, $\alpha$ refers to the degree to which an individual's wellbeing is harmed by the inequality in their country's wellbeing distribution. We cannot know, a priori, what value this parameter will take and so present results for three different values of $\alpha$.

[13] In principle, the range of alpha is $(-\infty, 1)$, not (0, 1) as in Eq. (3). We work with the smaller range because it is for this subclass of CF indices that there are inequality dominance results (Jenkins 2021), and because the range provides sufficient variation in inequality sensitivity to derive the interesting results that we report below.

**Table 1** SWL inequality estimates for 4 hypothetical distributions

| | Case 0 | Case 1 | Case 2 | Case 3 |
|---|---|---|---|---|
| SWL level | *Population proportions* | | | |
| 1 | 0.25 | 0.25 | 0.0 | 0.0 |
| 2 | 0.25 | 0.25 | 0.5 | 0.5 |
| 3 | 0.5 | 0.25 | 0.5 | 0.25 |
| 4 | 0.0 | 0.25 | 0.0 | 0.25 |
| Index | *Inequality estimates* | | | |
| $I_0^D$ | 0.5199 | 0.5918 | 0.3465 | 0.4185 |
| $I_0^U$ | 0.4185 | 0.5918 | 0.3465 | 0.5199 |
| $I_{0.5}^D$ | 0.7929 | 0.9269 | 0.5858 | 0.7198 |
| $I_{0.5}^U$ | 0.7198 | 0.9269 | 0.5858 | 0.7929 |
| $I_{0.9}^D$ | 3.2693 | 3.9029 | 2.5784 | 3.2120 |
| $I_{0.9}^U$ | 3.2120 | 3.9029 | 2.5784 | 3.2693 |

Examples based on CF's Tables 2 and 3. SWL categories 1, 2, 3, 4 in the top panel correspond to CF's categories N, G, E, B respectively; population proportions in each case correspond to those in CF's Table 2. Case 0 is negatively (left) skewed, Cases 1 and 2 are symmetric, and Case 3 is positively (right) skewed. In the lower panel, values reported for $I_0^D$ and $I_0^U$ replicate those in CF's Table 3; $I_{0.5}^D$, $I_{0.5}^U$, $I_{0.9}^D$ and $I_{0.9}^U$ are calculated as in the text

symmetric. The table shows that each of $I_\alpha^D$ and $I_\alpha^U$ increases with higher $\alpha$ no matter what the skewness. For each of the symmetric distributions, $I_\alpha^D = I_\alpha^U$, while for the asymmetric (skewed) distributions, $I_\alpha^D > I_\alpha^U$ when the distribution is negatively skewed (i.e. there is an asymmetric left tail) and $I_\alpha^D < I_\alpha^U$ when the distribution is positively skewed (i.e. there is an asymmetric right tail); each of these results occurs irrespective of the value of $\alpha$.

CF use World Values Survey (WVS) data for 58 countries from wave 5 to illustrate their inequality indices. We use their data from this wave to calculate a range of inequality indices (using the *ineqord* software of Jenkins, 2020b), and to investigate the bivariate relationships between the nine SWL inequality indices discussed above: *SD*, *SD**, *AF*, and six CF indices: $I_0^D$, $I_0^U$, $I_{0.5}^D$, $I_{0.5}^U$, $I_{0.9}^D$, $I_{0.9}^U$.

Table 2 presents Spearman rank correlation coefficients for the nine indices. All correlations are positive and in some cases are close to one. For instance, *AF* ranks countries almost identically to *SD*, while *SD** is also closely correlated with *SD*.

As inequality sensitivity increases, the country rankings for CF indices become more similar to the rankings produced by the other three indices, possibly because skewness is de-emphasized in the CF indices as $\alpha$ increases (and the other indices are insensitive to skewness). One of the lowest rank correlations, 0.32, is between $I_0^D$ and $I_0^U$, indicating that the upward- and downward-looking indices measure different aspects reflecting skewness (recalling that $I_\alpha^D = I_\alpha^U$ only for symmetric distributions). A scatterplot of $I_0^D$ and $I_0^U$ for the WVS wave 5 data is included as Appendix Fig. 5 showing the positive, but imprecise, relationship between the two measures. As $\alpha$ increases, the country rankings from the upward- and downward-looking indices become very similar (correlation 0.99 for $\alpha = 0.9$), again indicating that skewness is more relevant when inequality sensitivity is relatively low. In Sect. 4, we investigate the relationship between skewness and the upward- and downward-looking CF indices in greater depth with reference to variations both across countries and time in $I_0^U$ and $I_0^D$ for differently skewed SWL distributions.

**Table 2** Rank correlations between 9 indices of inequality applied to SWL data

| | $SD$ | $SD*$ | $AF$ | $I_0^U$ | $I_0^D$ | $I_{0.5}^U$ | $I_{0.5}^D$ | $I_{0.9}^U$ | $I_{0.9}^D$ |
|---|---|---|---|---|---|---|---|---|---|
| $SD$ | 1.00 | | | | | | | | |
| $SD*$ | 0.88 | 1.00 | | | | | | | |
| $AF$ | 0.93 | 0.71 | 1.00 | | | | | | |
| $I_0^U$ | 0.50 | 0.14 | 0.55 | 1.00 | | | | | |
| $I_0^D$ | 0.53 | 0.44 | 0.42 | 0.32 | 1.00 | | | | |
| $I_{0.5}^U$ | 0.70 | 0.39 | 0.69 | 0.93 | 0.55 | 1.00 | | | |
| $I_{0.5}^D$ | 0.78 | 0.57 | 0.70 | 0.70 | 0.83 | 0.88 | 1.00 | | |
| $I_{0.9}^U$ | 0.78 | 0.53 | 0.75 | 0.85 | 0.66 | 0.98 | 0.95 | 1.00 | |
| $I_{0.9}^D$ | 0.80 | 0.56 | 0.75 | 0.81 | 0.71 | 0.96 | 0.97 | 0.99 | 1.00 |

Based on data for 58 countries from WVS wave 5. The inequality indices, which are explained in the main text, are: SD (standard deviation), SD* (Delhey and Kohler's 'instrument-effect-corrected' standard deviation), AF (Allison and Foster's inequality index), and 6 variants of Cowell and Flachaire's index, I, with differing values for α (0, 0.5, 0.9) each with upward-looking and downward-looking status (U and D)

## 3 Empirical Application

Our empirical application concerns the relationship between individual SWL and well-being inequality within countries. To focus our analysis, we use as our starting point an example from Goff, Helliwell and Mayraz (GHM, 2018) who examined how wellbeing inequality is associated with individuals' SWL after controlling for income inequality, region and personal characteristics. GHM's core regression model specification is of the form:

$$SWL_{ijt} = \alpha + \beta_1 SD_{ijt} + \beta_2 G_{ijt} + \beta_3 Y_{ijt} + \beta_4{}' X_{ijkt} + \beta_5{}' R_{ijkt} + \varepsilon_{ijt}, \tag{4}$$

where $SWL_{ijt}$ denotes the SWL of person $j$ in country $i$ and wave $t$,[14] $SD_{ijt}$ denotes the country-wave standard deviation of SWL, $G_{ijt}$ is the country-wave Gini coefficient of income, $Y_{ijt}$ is the country-wave logarithm of GDP per capita in purchasing power parity (PPP) terms, $X_{ijkt}$ is a set of individual-level controls for sex, age, education, employment, and marital status, and $R_{ijkt}$ is a set of 5 'region' indicator variables for: West (Europe, North America, Oceania); Latin America; Asia; Middle East and North Africa; and Sub-Saharan Africa. As with GHM, we define 'clusters' as country-wave groups of observations. GHM recognize several issues regarding their core specification including the issue of bounded scales and treatment of SWL as a cardinal and linear measure, and consequently undertake a set of robustness checks.[15]

[14] WVS data are collected in waves which can cover multiple adjacent years, e.g. wave 2 covered 1990–94. We match our non-WVS variables for each country to the specific year in which the country was surveyed.

[15] Robustness checks include: (i) adding as a regressor an interaction between SWL inequality ($SD_{ijt}$) and a variable summarizing whether an individual thinks inequality is too high; (ii) fitting the core specification using a non-linear model; (iii) substituting the $SD$ SWL inequality index with the 'ordinal variation ratio' index (the proportion of observations not equal to the mode); and (iv) including country fixed effects in one specification. Country fixed effects are not included in their core specification and wave fixed effects are excluded in all GHM specifications.

**Table 3** OLS estimates (standardised beta coefficients)

| | Dependent variable: SWL (1–10 scale) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| SWL *SD* | –0.17*** | –0.151*** | –0.048 | 0.002 |
| | (–6.01) | (0.027) | (0.034) | (0.036) |
| Income Gini coefficient | –0.01 | 0.027 | –0.189*** | -0.132** |
| | (–0.18) | (0.030) | (0.061) | (0.054) |
| Log(GDP per capita) | 0.21*** | 0.196*** | 0.202*** | 0.045 |
| | (5.81) | (0.033) | (0.059) | (0.064) |
| Individual controls | Yes | Yes | Yes | Yes |
| Region dummies | Yes | Yes | No | No |
| Country dummies | No | No | Yes | Yes |
| Wave dummies | No | No | No | Yes |
| No. of observations | 271,667 | 302,919 | 302,919 | 302,919 |
| $R^2$ | - | 0.106 | 0.157 | 0.160 |

Estimates are weighted using the WVS-supplied sample weights. Countries are weighted equally. Cluster-robust standard errors in parentheses (clusters are country-wave combinations). Individual-level controls comprise sex, age, age squared, education (dummies), and marital status (dummies). Statistical significance indicators: $*p<0.1$; $**p<0.05$; $***p<0.01$. Column (1) reproduces the corresponding column from GHM Table 3; $R^2$ is not reported by GHM. Columns (2)–(4) are based on our WVS sample

The World Values Survey (WVS) is one of three data sources used by GHM, and this repeated cross-section survey forms the basis for our empirical application. The SWL question asked in the WVS is: ‘*All things considered, how satisfied are you with your life as a whole these days?*’. Respondents provide an answer on an integer-valued scale running from 1 to 10, with 1 labelled ‘completely dissatisfied’ and 10 ‘completely satisfied’.

Two of GHM’s key findings, using the WVS data, that are relevant to our analysis are: (i) the SWL *SD* has a consistent negative association with individual-level SWL ($\widehat{\beta}_1 < 0$); and (ii) in the core specification this association nullifies any effect of income inequality on individual SWL ($\widehat{\beta}_2 \approx 0$). GHM’s estimates derived from their core specification [our Eq. (4)], estimated using ordinary least squares (OLS) are reproduced in the first column of Table 3.

Although reported sensitivity checks suggest that the negative association between individual SWL and their country’s SWL inequality is robust, there are both conceptual and econometric reasons that could challenge this conclusion. The conceptual reasons are outlined in Sect. 2 above, principally relating to whether the SWL measure should be treated as being cardinal or ordinal (together with the issue of scale boundedness). Given that the SWL measure is ordinal, the CF indices are more appropriate and they enable us to investigate the role of skewness of the SWL distribution in affecting individual-level SWL outcomes. The econometric concerns include the exclusion of country and wave fixed effects. In our analysis, we control for the effects of time-invariant unobservable factors within countries (through inclusion of country fixed effects) and common shocks across countries (through inclusion of wave fixed effects).

To ensure that our empirical application closely reproduces that of GHM, we downloaded data on life satisfaction (SWL), employment status, education, marital status, gender and age from the WVS website (Inglehart et al., 2014). The information covers 6 waves and 100 countries with a total of 348,532 individual-level observations.[16] Like GHM, we obtained data for GDP per capita (real, PPP terms) and for the Gini coefficient of income from the World Bank's World Development Indicators dataset,[17] and used linear interpolation to impute values that were missing.

Our dataset includes a slightly larger number of observations than GHM's (302,919 compared with their 271,677), reflecting extensions to the GDP and Gini series enabled by our use of updated data sources. Nevertheless, our results, shown in column (2) of Table 3, are very similar to theirs. *SD* has an estimated (standardised) coefficient of –0.15 using our sample compared with $-0.17$ in GHM's (significant at $p<0.001$ in each case). The coefficients on per capita GDP are also almost identical for the two samples (both significant at $p<0.001$) while the income Gini coefficient is insignificantly different from zero in both cases.

The specifications in columns (1) and (2) include region indicators (defined earlier). These control for time-invariant unobservable differences across regions but not within regions. Column (3) displays estimates with country fixed effects replacing region dummies. The coefficient on per capita GDP retains its size and significance but the relative importance of SWL inequality and income inequality switches: the coefficient on the Gini is now negative and significant, while *SD* is no longer significant (albeit remaining negative). In column (4) we add wave dummies to control for global developments. The Gini coefficient remains negative and significant (at the 5% level) while per capita GDP is no longer significant (while remaining positive), potentially because the wave indicators capture the impact of globally-increasing incomes over time. The coefficient on *SD* is now virtually zero.

One interpretation of the estimates from the specifications that include country dummies is that the significant negative impact of *SD* that we find for specifications without country indicators reflects cross-national differences in SWL inequality (i.e. unobservable country circumstances rather than within-country SWL inequality per se).

Another possibility is that OLS estimation of the relationship is inappropriate since the dependent variable (SWL) is ordinal rather than cardinal. Henceforth, we concentrate on ordered logit (OLogit) estimates because they respect the ordinality of the dependent variable.[18] Table 4 presents estimates from OLogit models using regressor specifications corresponding to column (4) of Table 3.[19] Table 6 in the Appendix presents estimates based on column (2) of Table 3 i.e. including region fixed effects and excluding country and wave fixed effects. These are included for comparison purposes to indicate sensitivity of results to equation specification, but are not our preferred estimates given the absence of country fixed effects. In each case, we report log odds coefficients and standard errors are clustered by country-wave combination.

[16] We lose 13% of WVS observations owing to incomplete data, so our sample size is 302,919.

[17] We retrieved World Bank World Development Indicators GDP per capita in constant prices (Purchasing Power Parity, 2011 international dollars) from https://datacatalog.worldbank.org/search?search_api_views_fulltext_op=AND&query=GDP%20Per%20Capita,%20PPP%20(Constant%202011%20International%20$)&nid=&sort_by=search_api_relevance&sort_order=DESC, and World Bank World Development Indicators Gini data from https://data.worldbank.org/indicator/si.pov.gini?fbclid=IwAR07jKjrl6UaI3tsnIY4d7dgqJV4_3eRTfzj0a1BFBCBeZbMN1lp-x7mBeg. Data for the Gini coefficient in New Zealand were missing from World Development Indicators; we obtained estimates from the OECD database.

[18] While OLogit respects the ordinality of the dependent variable, it does rely on a number of assumptions including that the model has an error term with known distribution and that the relationship between each pair of outcome groups is the same (i.e. the proportional odds assumption).

[19] To maintain consistency with Table 3, the explanatory variables are standardised in Table 4.

**Table 4** The relationship between SWL and SWL inequality, by inequality index (ordered logit estimates, with country and wave dummies; log odds coefficients reported)

| | Dependent variable: SWL (1–10 scale) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| SWL inequality index: | *SD* | *SD** | *AF* | $I_0^U$ | $I_0^D$ | $I_{0.5}^U$ | $I_{0.5}^D$ | $I_{0.9}^U$ | $I_{0.9}^D$ |
| SWL inequality | 0.0573 | 0.131** | −0.0100 | −0.369*** | 0.220*** | −0.156** | 0.100 | −0.0254 | 0.0179 |
| | (0.0706) | (0.0596) | (0.0543) | (0.0926) | (0.0725) | (0.0627) | (0.0743) | (0.0615) | (0.0650) |
| Income Gini coefficient | −0.276** | −0.286*** | −0.262** | −0.206** | −0.230** | −0.249** | −0.261** | −0.262** | −0.264** |
| | (0.109) | (0.104) | (0.111) | (0.0865) | (0.0973) | (0.105) | (0.108) | (0.110) | (0.111) |
| Log(GDP per capita) | 0.0731 | 0.0845 | 0.0806 | 0.0898 | 0.0247 | 0.0947 | 0.0623 | 0.0830 | 0.0771 |
| | (0.125) | (0.126) | (0.126) | (0.101) | (0.108) | (0.121) | (0.123) | (0.126) | (0.126) |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Region dummies | No | No | No | No | No | No | No | No | No |
| Country dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Wave dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of observations | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 |
| Pseudo-$R^2$ | 0.0747 | 0.0749 | 0.0747 | 0.0758 | 0.0755 | 0.0749 | 0.0748 | 0.0747 | 0.0747 |

Estimates are weighted using the WVS-supplied sample weights. Countries are weighted equally. All variables are standardised. Cluster-robust standard errors in parentheses (clusters are country-wave combinations). Individual-level controls comprise sex, age, age squared, education (dummies), and marital status (dummies). Statistical significance indicators: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4 (and 6) includes estimates based on nine (standardised) SWL inequality indices. We find that in each case the coefficient on the income Gini is negative and significant; thus an increase in income inequality within countries is associated with lower individual SWL. Per capita GDP remains positive but is insignificant in each case, with the wave dummies likely to be capturing the effects of globally increasing incomes over time.

We find no association between individual SWL and each of the *SD*, *AF*, $I^D_{0.5}$, $I^U_{0.9}$ or $I^D_{0.9}$ measures of SWL inequality. *SD** has a positive and statistically significant association with individual SWL but, since it is based on a cardinality assumption, we do not place emphasis on this result other than noting it as a counter-example to that obtained from using the (unadjusted) *SD*.

$I^U_0$ and $I^D_0$ both yield significant estimates, as does $I^U_{0.5}$. The upward-looking indexes, $I^U_0$ and $I^U_{0.5}$, indicate that increased SWL inequality within a country is associated with a decline in individual SWL. $I^U_0$ delivers (marginally) the highest explanatory power of any of the SWL inequality measures. By contrast with the upward-looking measures, we find a positive relationship (significant at the 1% level) between individual SWL and SWL inequality when the latter is measured by $I^D_0$.[20] A similar pattern of oppositely signed coefficients occurs for $\alpha = 0.5$. Thus different inequality measures (despite being positively correlated with one another) indicate a different direction of relationship between individual SWL and SWL inequality of a country. In Sect. 4, we investigate why the upward- and downward-looking CF indices provide these apparently conflicting results, paying attention to the importance of skewness.

## 4 Upward- Versus Downward-Looking Inequality Indices and a Role for Skewness

We take advantage of the distinctive features of the CF approach to inequality measurement to investigate the roles of skewness and of upward-looking versus downward-looking status. As shown in Table 1, upward-looking and downward-looking CF indices generally provide different estimates of inequality (for given $\alpha$) unless the distribution of responses is symmetric. Furthermore, skewness has a greater differentiating impact on the CF indices for low $\alpha$.

We illustrate the relationship of skewness to $I^U_0$ and $I^D_0$ (i.e. with $\alpha = 0$) using the WVS data.[21] These examples show, both across and within countries, that two country-waves can have: identical $I^U_0$ values with different $I^D_0$ values, identical $I^D_0$ values with different $I^U_0$ values, or identical $I^U_0$ and identical $I^D_0$ values.

Figure 1 presents histograms for SWL in Vietnam and Nigeria (in wave 4). Nigeria's distribution exhibits negative skewness while Vietnam's distribution is positively skewed.[22] Each country has $I^U_0 = 0.735$, while $I^D_0 = 0.819$ for Nigeria and 0.759 for Vietnam. For comparison, across all country-waves in our sample, mean $I^U_0 = 0.721$ (with standard deviation of 0.064), and mean $I^D_0 = 0.780$ (with standard deviation of 0.037). Thus, while $I^U_0$ is identical for the two countries, the difference between their $I^D_0$ values is substantial (i.e.

[20] The signs and significance of each of $I^U_0$, $I^D_0$ and $I^U_{0.5}$ are replicated in Table 6 which includes regional fixed effects but excludes country and wave fixed effects.

[21] Given that we compare values of the upward- and downward-looking indices within countries, we use the raw (unstandardised) CF indices in this section, including in Tables 5 and 7.

[22] In the absence of an ordinal measure of skewness (other than that afforded by comparison of the CF indices), the references here to skewness of the histograms relies on a visual interpretation which is akin to using an Allison and Foster-based approach to measuring skewness. The CF indices provide a rigorous way to represent the skewness.

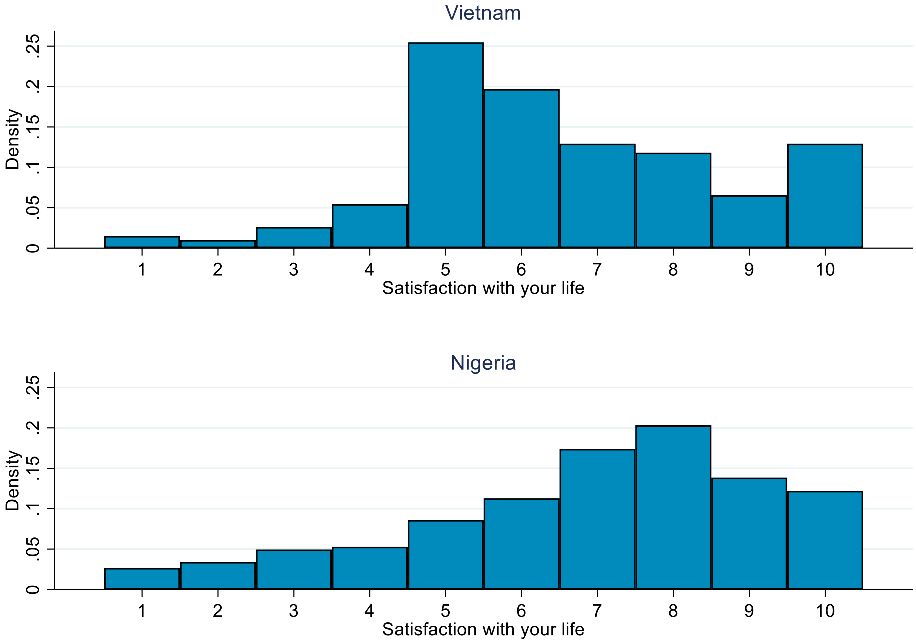



**Fig. 1** Satisfaction with life distributions in Vietnam and Nigeria (WVS, wave 4): same $I_0^U$, different $I_0^D$. *Note* Vietnam $I_0^U = 0.735$, $I_0^D = 0.759$; Nigeria $I_0^U = 0.735$, $I_0^D = 0.819$

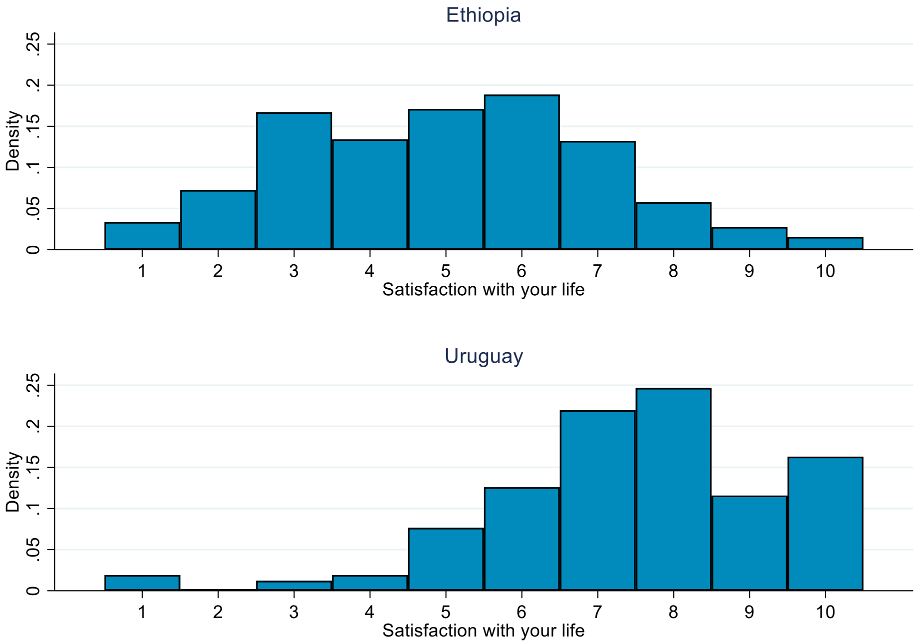



**Fig. 2** Satisfaction with life distributions in Ethiopia and Uruguay (WVS, wave 5): different $I_0^U$, same $I_0^D$. *Note* Ethiopia $I_0^U = 0.793$, $I_0^D = 0.775$; Uruguay $I_0^U = 0.689$, $I_0^D = 0.775$

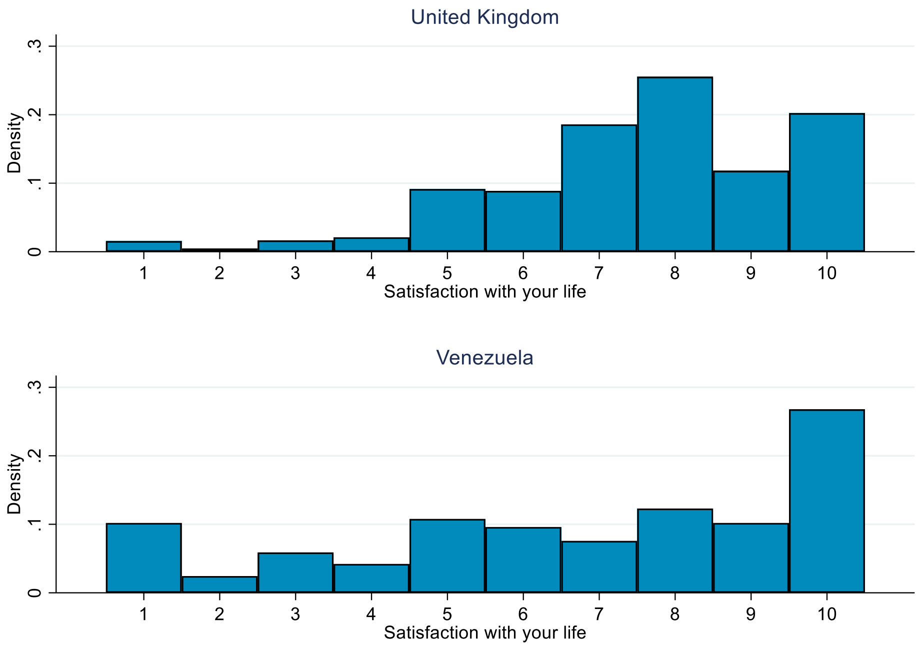



**Fig. 3** Satisfaction with life distributions in United Kingdom and Venezuela (WVS, wave 3): same $I_0^U$, same $I_0^D$. *Note* United Kingdom $I_0^U$= 0.670, $I_0^D$= 0.784; Venezuela $I_0^U$= 0.670, $I_0^D$= 0.784

1.6 standard deviations of the distribution of $I_0^D$). A within-country example is provided by Moldova for which $I_0^U = 0.807$ in each of waves 3 and 4 whereas $I_0^D$ increased from 0.649 to 0.745 across the two waves.

Figure 2 presents an example, for Ethiopia and Uruguay in wave 5, in which $I_0^D$ is identical across the countries (=0.775) while $I_0^U$ differs substantially (0.793 in Ethiopia and 0.689 in Uruguay). Uruguay's SWL distribution is negatively skewed whereas Ethiopia's is slightly positively skewed. A within-country example is provided by Slovenia in which $I_0^D = 0.792$ in each of waves 3 and 6 whereas $I_0^U = 0.756$ in wave 3 and = 0.703 in wave 6.

A third example is presented in Fig. 3, covering the United Kingdom and Venezuela in wave 3. The two countries have identical $I_0^U$ (=0.670) and identical $I_0^D$ (=0.784) despite having different modes. Another feature of this example is that despite the identical $I_0^U$ and $I_0^D$ values across the two countries, the standard deviation of SWL differs substantially with SD = 1.949 in the United Kingdom and SD = 3.001 in Venezuela.[23]

These examples illustrate that $I_0^U$ and $I_0^D$ in practice provide independent information on the SWL distributions observed across country-waves.[24] These insights assist us in interpreting and extending the results from Table 4.

[23] This example contrasts with the example in Fig. 4 in which two very different distributions had identical SD. For comparison, across all country-waves in our sample, mean SD = 2.189 (with standard deviation of 0.329).

[24] The United Kingdom-Venezuela example also shows that the ordinal measures provide different information relative to a measure that treats the data as cardinal.

Recall that $I_0^U > I_0^D$ when positive skewness is present, i.e. when the mass of individuals is concentrated towards lower categories coupled with a right tail of high-SWL individuals (as illustrated by Case 3 in Table 1). Given the negative coefficient on $I_0^U$ in Table 4, one might conclude that individuals' SWL is lowered in a country in which there is an over-representation of low SWL people relative to a symmetric distribution. In effect, there appears to be a negative externality from observing a preponderance of unhappy individuals in society.

Conversely, $I_0^D > I_0^U$ when negative skewness is present, i.e. when the mass of individuals is concentrated towards higher categories coupled with a left tail of low-SWL individuals (as illustrated by Case 0 in Table 1). Given the positive coefficient on $I_0^D$ in Table 4, one might conclude that individuals' SWL is raised in a country in which there is an over-representation of high SWL people relative to a symmetric distribution: there is a positive externality from observing a preponderance of happy individuals in society. This latter relationship is consistent with the 'tunnel effect' observed in transition countries in which envy of others' success is replaced by a positive demonstration effect that individuals have the scope to improve their lot when they see others succeed (Ravallion & Lokshin, 2000).

**Table 5** The relationship between SWL and SWL inequality including upward-looking and downward-looking CF measures; plus reparameterised measures of inequality ($INEQ_\alpha$) and skewness ($SKEW_\alpha$) (ordered logit estimates, with country and wave dummies; log odds coefficients reported)

| | Dependent variable: SWL (1–10 scale) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | $\alpha=0$ | $\alpha=0.5$ | $\alpha=0.9$ | $\alpha=0$ | $\alpha=0.5$ | $\alpha=0.9$ |
| $I_\alpha^U$ | −8.878*** | −15.64*** | −22.57*** | | | |
| | (0.406) | (0.885) | (1.519) | | | |
| $I_\alpha^D$ | 9.587*** | 16.49*** | 22.85*** | | | |
| | (0.634) | (1.070) | (1.563) | | | |
| $INEQ_\alpha$ | | | | 0.709 | 0.856* | 0.276 |
| | | | | (0.507) | (0.511) | (0.171) |
| $SKEW_\alpha$ | | | | −18.46*** | −32.13*** | −45.42*** |
| | | | | (0.936) | (1.895) | (3.078) |
| Income Gini coefficient | −0.0110** | −0.0149*** | −0.0169*** | −0.0110** | −0.0149*** | −0.0169*** |
| | (0.00462) | (0.00562) | (0.00633) | (0.00462) | (0.00562) | (0.00633) |
| Log(GDP per capita) | −0.00902 | 0.0306 | 0.0521 | −0.00902 | 0.0306 | 0.0521 |
| | (0.0645) | (0.0741) | (0.0813) | (0.0645) | (0.0741) | (0.0813) |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Region indicators | No | No | No | No | No | No |
| Country indicators | Yes | Yes | Yes | Yes | Yes | Yes |
| Wave indicators | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of observations | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 |
| Pseudo-$R^2$ | 0.0782 | 0.0777 | 0.0774 | 0.0782 | 0.0777 | 0.0774 |

Estimates are weighted using the WVS-supplied sample weights. Countries are weighted equally. $INEQ_\alpha \equiv (I_\alpha^U + I_\alpha^D)/2$; $SKEW_\alpha \equiv (I_\alpha^U - I_\alpha^D)/2$. Variables are not standardised. Cluster-robust standard errors in parentheses (clusters are country-wave combinations). Individual-level controls comprise sex, age, age squared, education (dummies), and marital status (dummies). Statistical significance indicators: *$p<0.1$; **$p<0.05$; ***$p<0.01$

We investigate these conjectures further by including both $I_0^U$ and $I_0^D$ in the same regression equation (a specification that includes country and wave fixed effects). For completeness, we also employ specifications including either $I_{0.5}^U$ and $I_{0.5}^D$ or $I_{0.9}^U$ and $I_{0.9}^D$. The estimates are presented in columns (1)–(3) of Table 5. In each case, the upward-looking index has a statistically significant negative coefficient and the downward-looking index has a statistically significant positive coefficient. Thus, the same patterns arise regardless of the degree of inequality sensitivity (with $\alpha = 0$ again providing greatest explanatory power). The coefficient on income inequality is significantly negative in each specification.

We can reparameterise the regressions reported in columns (1)–(3) of Table 5 to separate out the effects of inequality versus skewness.[25] To do so, we take the mean of $I_\alpha^U$ and $I_\alpha^D$ to represent inequality ($INEQ_\alpha$) and—given prior results and the discussion of skewness in CF—we take (half the) difference to represent skewness ($SKEW_\alpha$):

$$INEQ_\alpha \equiv (I_\alpha^U + I_\alpha^D)/2$$

$$SKEW_\alpha \equiv (I_\alpha^U - I_\alpha^D)/2$$

Columns (4)–(6) of Table 5 present results for this reparameterisation. SWL is significantly related to the skewness variable for each value of $\alpha$ but is not significantly related to the (average) inequality variable (at the 5% level). The Gini coefficient (measuring income inequality) does, however, remain significant throughout. It is possible that the wellbeing inequality measure is correlated with the Gini coefficient of income, and that the inclusion of both variables is affecting the estimate for $INEQ_\alpha$. To test this possibility, we omit the Gini coefficient from the regression, with results presented in Appendix Table 7. The estimates for $INEQ_\alpha$ and $SKEW_\alpha$ are almost unchanged from those in Table 5.[26] The implication of these results is that while a country's income inequality affects individual SWL, it is the skewness of wellbeing—rather than its inequality per se—that matters for the SWL of individuals.

Our estimates indicate that having a proportionately large group of people who are low in the SWL distribution (i.e. high $I_\alpha^U$ relative to $I_\alpha^D$) is associated, *ceteris paribus*, with lower individual SWL whereas having a large group of people who are high in the SWL distribution (high $I_\alpha^D$ relative to $I_\alpha^U$) is associated with higher individual SWL. Our results are consistent with the idea that individuals experience negative externalities when there are large groups of fellow citizens with low SWL and experience positive side-effects when there are large groups of fellow citizens with high SWL.

The externality explanation that relates individual SWL to the shape of the country's SWL distribution is appealing, but another possibility is that the results simply reflect an arithmetic association between individual SWL and the indices in the presence of time-varying unobservable factors that affect SWL for some individuals. We are therefore reticent to make claims that there is a causal relationship between individual SWL and skewness (or inequality) of the wellbeing distribution. Undoubtedly, however, individual SWL is associated with the distribution's skewness. The externality explanation related to

[25] We thank a reviewer for this helpful suggestion.

[26] We have also re-estimated the equations shown in columns (4)–(6) of Table 5 omitting $INEQ_\alpha$ to test the sensitivity of the coefficients on $SKEW_\alpha$ in the absence of the wellbeing inequality variable. The estimates for $SKEW_\alpha$ remain virtually unchanged (−18.29, −31.69, −44.63 respectively) with almost identical standard errors.

skewness provides a richer interpretation of the effects of the SWL distribution on individual SWL than is accorded by analysis of inequality alone. However, this interpretation remains a conjecture, and investigation into other potential explanations is warranted.

## 5 Summary and Conclusions

It is plausible that societal inequality impacts on individuals' wellbeing through negative externalities that arise when others are faring poorly. It is also plausible that positive externalities may arise when other people are faring well. Prior research has shown an association between income inequality and individual wellbeing. More recently, a range of contributions indicate an association between individual wellbeing and SWL inequality.

We extend the analysis of the relationship between individual wellbeing and SWL inequality using inequality measures that have been derived specifically for use with ordinal data. Some of these measures provide support to the consensus finding that greater SWL inequality contributes negatively to individuals' satisfaction with life. These include the upward-looking peer-inclusive CF inequality indices incorporating low to moderate degrees of inequality sensitivity ($I_0^U$ and $I_{0.5}^U$). Paradoxically, when a high degree of sensitivity to inequality ($\alpha = 0.9$) is assumed, the relationship between $I_\alpha^U$ and SWL evaporates; but that could be because such a high parameter value does not appropriately represent society's preferences. More paradoxical still is the finding that CF's downward-looking peer-inclusive inequality index indicates the opposite relationship: greater SWL inequality is associated with higher individual wellbeing.

We leverage a property of the CF family of indices to show that skewness of the SWL distribution matters for (or, at least, has a strong association with) individual SWL. Our estimates are consistent with a hypothesis that individuals experience negative externalities when many of their fellow citizens have low SWL, whereas they experience positive side-effects when many citizens have high SWL. This explanation is certainly plausible. The negative externalities may arise from altruistic components to the utility function or from negative societal effects (e.g. crime) arising from people with predominantly low SWL. The positive externalities may arise from a tunnel effect when observing people doing well, so providing an aspirational example, and/or from their provision of beneficial amenities for the wider population.

Although these explanations are plausible, they need to be tested further lest other (possibly time-varying unobservable) factors are responsible for the associations that we find. In extending the research in this direction, a key requirement will be to adopt inequality and skewness measures, and estimation techniques, that are appropriate for ordinal data. Our analysis shows that while the practice of applying an inequality index developed for cardinal data is inappropriate when dealing with ordinal data, we can learn a lot by using the appropriate tools. A key message is that, when applying these tools, the focus should be on the role of skewness—as well as inequality—for understanding how a country's SWL distribution affects individual SWL.

## Appendix

See Tables 6 and 7 and Figs. 4 and 5

**Table 6** The relationship between SWL and SWL inequality, by inequality index (ordered logit estimates, with region dummies; log odds coefficients reported)

| | Dependent variable: SWL (1–10 scale) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| SWL inequality index: | *SD* | *SD** | *AF* | $I_0^U$ | $I_0^D$ | $I_{0.5}^U$ | $I_{0.5}^D$ | $I_{0.9}^U$ | $I_{0.9}^D$ |
| SWL Inequality | −0.253*** | −0.0586 | −0.319*** | −0.624*** | 0.182*** | −0.457*** | −0.124* | −0.322*** | −0.266*** |
| | (0.0540) | (0.0553) | (0.0525) | (0.0970) | (0.0568) | (0.0978) | (0.0737) | (0.0858) | (0.0815) |
| Income Gini coefficient | 0.0604 | 0.00503 | 0.0640 | −0.0416 | −0.0363 | 0.00622 | 0.00322 | 0.0206 | 0.0197 |
| | (0.0592) | (0.0643) | (0.0573) | (0.0404) | (0.0582) | (0.0480) | (0.0598) | (0.0538) | (0.0560) |
| Log(GDP per capita) | 0.359*** | 0.465*** | 0.330*** | 0.251*** | 0.471*** | 0.316*** | 0.463*** | 0.376*** | 0.403*** |
| | (0.0629) | (0.0597) | (0.0630) | (0.0531) | (0.0512) | (0.0636) | (0.0603) | (0.0643) | (0.0637) |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Region dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country dummies | No | No | No | No | No | No | No | No | No |
| Wave dummies | No | No | No | No | No | No | No | No | No |
| No. of observations | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 |
| Pseudo-$R^2$ | 0.0597 | 0.0573 | 0.0607 | 0.0695 | 0.0584 | 0.0644 | 0.0577 | 0.0610 | 0.0598 |

Estimates are weighted using the WVS-supplied sample weights. Countries are weighted equally. All variables are standardised. Cluster-robust standard errors in parentheses (clusters are country-wave combinations). Individual-level controls comprise sex, age, age squared, education (dummies), and marital status (dummies). Statistical significance indicators: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

**Table 7** The relationship between SWL and SWL inequality including upward-looking and downward-looking CF measures; plus reparameterised measures of inequality ($INEQ_{\alpha}$) and skewness ($SKEW_{\alpha}$) excluding Gini coefficient (ordered logit estimates, with country and wave dummies; log odds coefficients reported)

| | Dependent variable: SWL (1–10 scale) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | $\alpha=0$ | $\alpha=0.5$ | $\alpha=0.9$ | $\alpha=0$ | $\alpha=0.5$ | $\alpha=0.9$ |
| $I_{\alpha}^{U}$ | −8.983*** | −15.86*** | −22.91*** | | | |
| | (0.417) | (0.902) | (1.544) | | | |
| $I_{\alpha}^{D}$ | 9.691*** | 16.71*** | 23.18*** | | | |
| | (0.631) | (1.070) | (1.583) | | | |
| $INEQ_{\alpha}$ | | | | 0.708 | 0.850* | 0.275* |
| | | | | (0.521) | (0.504) | (0.167) |
| $SKEW_{\alpha}$ | | | | −18.67*** | −32.56*** | −46.09*** |
| | | | | (0.934) | (1.914) | (3.123) |
| Log(GDP per capita) | −0.0131 | 0.0258 | 0.0470 | −0.0131 | 0.0258 | 0.0470 |
| | (0.0741) | (0.0884) | (0.0982) | (0.0741) | (0.0884) | (0.0982) |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Region indicators | No | No | No | No | No | No |
| Country indicators | Yes | Yes | Yes | Yes | Yes | Yes |
| Wave indicators | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of observations | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 | 302,919 |
| Pseudo-$R^2$ | 0.0782 | 0.0777 | 0.0773 | 0.0782 | 0.0777 | 0.0773 |

Estimates are weighted using the WVS-supplied sample weights. Countries are weighted equally. $INEQ_{\alpha} \equiv (I_{\alpha}^{U} + I_{\alpha}^{D})/2$; $SKEW_{\alpha} \equiv (I_{\alpha}^{U} - I_{\alpha}^{D})/2$. Variables are not standardised. Cluster-robust standard errors in parentheses (clusters are country-wave combinations). Individual-level controls comprise sex, age, age squared, education (dummies), and marital status (dummies). Statistical significance indicators: *$p<0.1$; **$p<0.05$; ***$p<0.01$

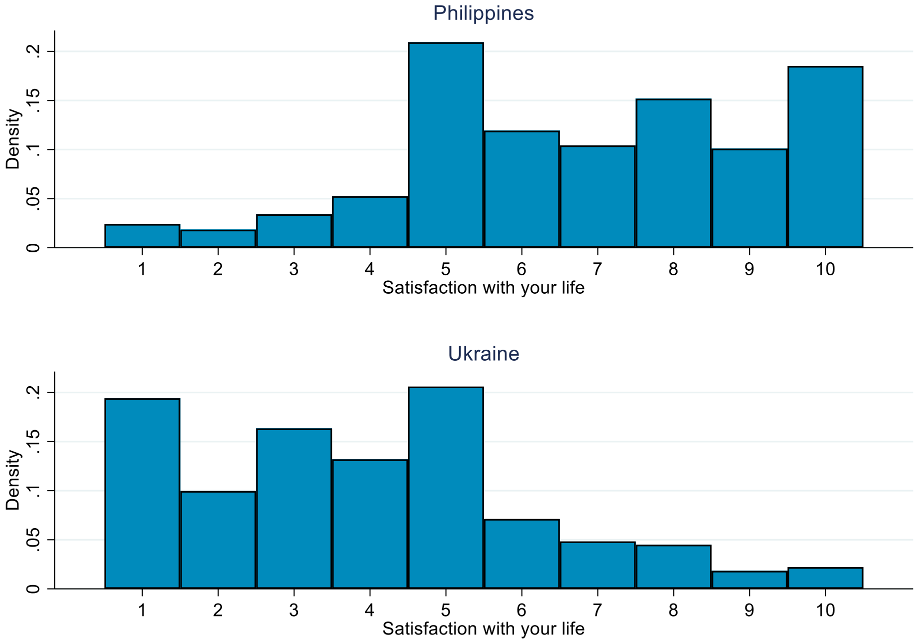
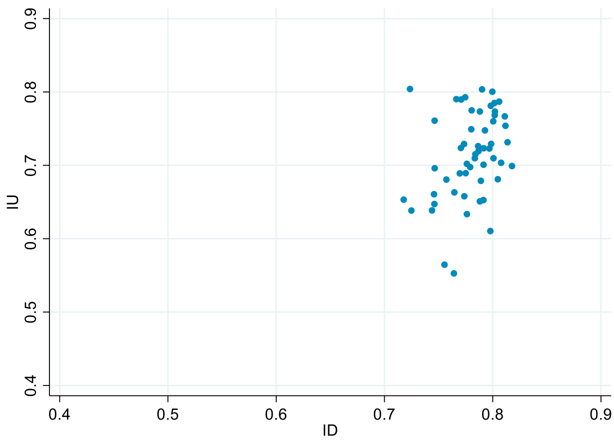



**Fig. 4** Satisfaction with life distributions in Philippines and Ukraine (WVS, wave 3)

**Fig. 5** Scatterplot of $I_0^U$ and $I_0^D$ (WVS, wave 5)

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## Declarations

**Conflict of interests** The authors have no relevant financial or non-financial interests to disclose.



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