The Sad Truth about Happiness Scales

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Abstract

Happiness is reported in ordered intervals (e.g. very, pretty, not too happy). We review and apply standard statistical results to determine when such data permit identification of two groups' relative average happiness. The necessary conditions for nonparametric identification are strong and unlikely to be ever satisfied. Standard parametric approaches cannot identify this ranking unless the variances are exactly equal. If not, ordered probit findings can be reversed by lognormal transformations. For nine prominent happiness research areas, conditions for nonparametric identification are rejected and standard parametric results are reversed using plausible transformations. Tests for a common reporting function consistently reject.

1 Introduction

A large literature has attempted to establish the determinants of happiness using ordered response data from questions such as "Taking all things together, how would you say things are these days – would you say that you are very happy, pretty happy, or not too happy?"[1] We review and synthesize how some well-known results from statistics and microeconomic theory apply to such data, and reach the striking conclusion that the results from the literature are essentially uninformative about how various factors affect average happiness.

The basic argument is as follows. There are a large (possibly infinite) number of states of happiness which are strictly ranked. In order to calculate a group's 'mean' happiness, these states must be cardinalized, but there are an infinite number of arbitrary cardinalizations, each producing a different set of means. The ranking of the means remains the same for all cardinalizations only if the distribution of happiness states for one group first order stochastically dominates that for the other. But, we do not observe the actual distribution of states. We instead observe their distribution in a small number of discrete categories, essentially a few intervals of their cumulative distribution functions.

Without additional assumptions we cannot rank the average happiness of two groups if each has responses in the highest and lowest category. Using observed covariates to achieve full nonparametric identification of the latent happiness distributions would require making assumptions that happiness researchers generally claim to reject. We are therefore forced to follow the standard approach and assume the latent distributions are from a common unbounded location-scale family (e.g., an ordered probit). If we do, it is (almost) impossible to get stochastic dominance, and the conclusion is therefore not robust to simple monotonic transformations of the scale. In the case of the normal, there are always distributions in the lognormal family that reverse the result. Even in the knife-edge case where it would be possible to get stochastic dominance, the result would still be subject to the assumption

[1] Our analysis applies, *mutatis mutandis*, to other common questions such as those with five, seven or ten response categories

that all individuals report happiness the same way (a common reporting function), something which we show empirically is unlikely to be the case.

We outline conditions under which we can identify the rank ordering of group happiness, and then apply them to nine prominent results from the happiness literature. Not a single one is satisfied in any case. We also describe a test for common reporting of happiness under the assumption that happiness follows a distribution from the normal family. Whenever the data allow us to perform such a test, we reject it.

2 Rank-Order Identification of Group Happiness

Suppose a researcher has two groups A and B, and she wishes to claim that members of group A are, on average, happier than members of group B. What assumptions are required to make such a claim?

Unfortunately, with happiness data we will never be able to simply compare the average group responses directly. That would require happiness to have been reported to the researcher on an interval scale, the impossibility of which should be uncontroversial.[2] Thus we assume we are presented with an ordinal ranking of individuals' happiness, and denote individual i's happiness in this order as H_i and the cdf of happiness for group k as F_k.[3] Provided this ranking is complete, transitive, and continuous, from Debreu (1954) there exists a cardinalization q such that, $H_i > H_j \Leftrightarrow q(H_i) > q(H_j)$. Thus, in principle, we can compare group means under this cardinalization. This approach is implicit in nearly the entire empirical happiness literature. However, we know from Pareto (1909, pp. 541-2), that q is not unique. There are infinite other cardinalizations, and changes in cardinalization can change the ranking of means unless, as is well-known, there is *first order stochastic*

[2] It would require some way of eliciting each individual's happiness on a scale where the difference between a "99" and a "98" is the same difference in happiness as between a "97" and a "96", or a "7" and a "6", and so on. See Stevens (1946).

[3] To draw anything at all from the happiness literature, it is absolutely essential that it is possible to make interpersonal utility comparisons, an assumption we maintain throughout. But this is, itself, a controversial topic. For a brief review, see Binmore (2009).

dominance (FOSD).[4] Therefore, to conclude that group A is happier than group B, we must observe that F_A first order stochastically dominates F_B.

In practice, happiness researchers never observe F_k directly. Instead they observe subjective responses in a small number of categories, such as "not too happy," "pretty happy," or "very happy." Suppose we have three categories $S = \{0, 1, 2\}$, and let r_S^k be the fraction of respondents in group k who report happiness S. It is plausible that individuals follow a coherent introspective reporting rule, so that they report 0 if $H_i \leq H_i^1$ and 1 if $H_i^1 \leq H_i \leq H_i^2$.[5] This will be uninformative about F_k if H_i^1 and/or H_i^2 vary across individuals; a large number of "very happy" responses in group A may indicate a high F_A or low H_i^2s. For the moment we assume $H_i^1 = H^1, H_i^2 = H^2 \forall i$, that is a *common reporting function*, so the subjective responses inform us of two points on each cdf: $F_k(H^1) = r_0^k$ and $F_k(H^2) = 1 - r_2^k$.

Unfortunately, $F_A(H^1) \leq F_B(H^1)$ and $F_A(H^2) \leq F_B(H^2)$ (i.e., "stochastic dominance" in the categories) does not directly imply F_A FOSD F_B. It simply narrows the set of possible group distributions of happiness (see, for example, Manski 1988) to the set of all combinations of cdfs for which $F_A(H^1) = r_0^A, F_B(H^1) = r_0^B, F_A(H^2) = 1 - r_2^A, F_B(H^2) = 1 - r_2^B$. In other words, any two distributions that produce the observed happiness distribution in categories, by group, describe the data equally well.

Following this, we say the *rank order* of A and B is *identified* only if for every pair of distributions consistent with the data we have F_A FOSD F_B or F_B FOSD F_A.[6] That is, if A and B are rank order identified, the rankings of $\bar{q}_A$ and $\bar{q}_B$ will be the same for any cardinalization of any distribution that can describe the data. Requiring rank-order identification should again be uncontroversial. Rejecting this, requires making definitive statements about rankings that hold for some arbitrary cardinalizations or equivalently some arbitrary distributions, but not others satisfying the same *a priori* restrictions and describing

[4]See Lehmann (1955). This result entered the economics literature in the late 1960s (e.g, Hader and Russell 1969; Hanoch and Levy 1969).

[5]We will use a 3-point happiness scale going forward for illustrative purposes, but the discussion easily extends to 4 or more categories.

[6]For a formal definition of rank order identification, see the Online Technical Appendix.

the data equally well.

We now explore the conditions under which group happiness is rank-order identified. We begin with methods that do not rely on distributional assumptions, then consider restricting the set of permissible distributions (i.e. parametric assumptions such as ordered probit).

2.1 Non-Parametric Identification

To simplify exposition, we normalize the cutoffs between the categories to $H^1 = 0$ and $H^2 = 1$. Put differently, we restrict ourselves to the set of cardinalizations with this property.

When is the ranking of A over B identified without assuming a distribution for F_A and F_B? If we use just the ordered responses, from Manski and Tamer (2002) we must have $r_0^A = 0, r_2^B = 0$, and $r_2^A \geq r_1^B$.[7] If both groups have responses in the lowest category, the data can be represented by distributions where nearly all the unhappy As are close to $-\infty$ and all the unhappy Bs close to $-\varepsilon$, and vice versa. Similar logic applies when both groups have responses in the highest category. Even if the lowest category for A and the highest category for B are empty, all As might be clustered at the bottom of their categories (i.e., ε and $1 + \varepsilon$) while Bs might be clustered at their tops (i.e., $-\varepsilon$ and $1 - \varepsilon$); $r_2^A > r_1^B$ ensures that the distribution of A still dominates B in these situations. In practice, such a strong set of conditions will never be satisfied (see Table 1 below) for a sample of any reasonable size. Thus if happiness is reported using a discrete ordered scale, in practice we cannot rank the mean happiness of two groups without additional information or restrictions on the happiness distribution.

Now, suppose we have a vector of observable determinants of happiness X, and assume we can partition i's latent happiness

$$h_i^* = \psi(X_i) + u_i \tag{1}$$

[7] If there are $S+1$ categories, we require that $r_0^A = 0$, $r_S^B = 0$ and $\Sigma_0^s r_j^A \geq \Sigma_0^{s-1} r_j^B \; \forall s = 1, ...S$. We follow the literature on focusing on comparing means. Conditions for comparing, for example, medians are weaker and sometimes satisfied in practice.

into an observable component X_i with distribution F_k^X in group k, and an additively separable unobservable component u_i with distribution F_k^u. The function ψ transforms the observable components from their reported scale (e.g. dollars of income) to happiness under the chosen cardinalization. Note that in addition to a common reporting function, we assume ψ does not vary across groups. This assumption is implausible and also not strictly necessary for identification, but we simplify the environment to achieve rank-order identification as easily as possible.[8]

As Manski (1988) shows for a binary response, and Cameron and Heckman (1998) extend to a general ordered response model, we can identify ψ, F^u, and F^h through assumptions on the relations among X, u, and h, thereby avoiding assumptions about the distribution of h or u.[9] In our context, the key condition for nonparametric identification (Carneiro, Hansen, and Heckman 2003, Cunha, Heckman, and Navarro 2007) is that the support of u is contained in the support of $\psi(X)$. As Manski discusses, this condition is critical;[10] yet it is problematic for happiness studies. The major observable determinants such as income and marital status are bounded in practice, while factors such as physical and psychological health are, at best, observed only in discrete ordered categories and at worst unobservable and unbounded.[11]

To illustrate this problem, consider some authors' claim that there is a "satiation point" beyond which income does not increase happiness.[12] If they are correct, then as $X \rightarrow \infty, \psi(X) \rightarrow \bar{\psi}$ where X is income. Above $-\bar{\psi}$ we can identify the distribution of u based on differences between reported happiness and that which would be predicted by $\psi(X)$. But

[8] In order to place both groups on the same cardinalization, it is necessary that either both groups follow the same reporting rule, or both groups have some common X that has the same effect on the true latent variable. See Urzua (2008).

[9] See the Online Technical Appendix for the full list of conditions.

[10] See Manski's (1988) discussion surrounding Proposition 2, Corollary 1.

[11] While the condition is not formally testable, since we do not observe all possible draws of X from F^X, we note that the individual with the lowest family income (as calculated by Stevenson and Wolfers 2009) in the General Social Survey reports being "pretty happy."

[12] Note that our appendix implicitly refutes such claims. Stevenson and Wolfers (2013) reviews a number of papers which argue for a satiation point with respect to income, and find no support for this claim in any dataset using methods conventional within the happiness literature. Nonetheless, this has not stopped such claims from being made. See, for example, Jebb et al. (2018).

we cannot learn anything about the distribution of u below $-\bar{\psi}$ since all values in this range result in a report of "not very happy" for any X. Within the set of admissible distributions, u could be concentrated just below $-\bar{\psi}$ for one group and concentrated near $-\infty$ for another. Even if A stochastically dominates B above $-\bar{\psi}$, the distributions could cross below $-\bar{\psi}$, thus we cannot have rank-order identification. A similar problem arises when X is bounded.

In sum, while theoretically possible, in practice we are unlikely to have the observables necessary to non-parametrically identify the tails of the happiness distribution, without which the means of two groups are never rank-order identified.

2.2 Parametric Identification

Absent nonparametric identification, we must either conclude that identification is impossible or rely on parametric identification. Happiness researchers almost universally assume either that the ordered responses are measured on a discrete interval scale, or that each group's latent happiness distribution is normal (i.e., ordered probit) or logistic (i.e., ordered logit). These different approaches often yield similar results, leading some researchers to conclude falsely that such assumptions are innocuous (e.g., Ferrer-i-Carbonell and Frijters 2004).[13]

Estimating ordered probit is equivalent to assuming the existence of a single cardinalization under which *both* groups' happiness is distributed normally, which is in and of itself very strong.[14] Further, the standard ordered probit happiness researchers use also assumes that under this hypothesized cardinalization the variance of happiness is equal for all groups.[15] The assumption is implausible and unnecessary for estimation, but *necessary* to obtain rank-

[13]This conclusion may be problematic even sidestepping the issues raised by this paper. Heckman and Singer (1984) show that despite three common distributional assumptions showing negative unemployment duration dependence (and two strongly so), using an estimator that does not impose a parametric assumption produces the expected positive sign.

[14]Note that imposing that a *single* group's happiness is distributed normally is simply selecting an arbitrary cardinalization.

[15]The normalization in many statistical packages (such as STATA) imposes that the variance of the normally distributed unobservables is 1 and that the constant term is 0. If the ordered probit were applied separately without additional covariates, the program would report different cutpoints, implying a different reporting function but the same mean and variance for all groups. In the online appendix, we normalize the first two cutpoints to 0 and 1 and estimate separate means and variances for each group.

order identification through ordered probit. It is well known that for unbounded distributions from the location-scale family, one distribution is greater than the other in the sense of FOSD if and only if their location parameters differ and their scale parameters are equal.[16]

Moreover, in practice, as the sample size gets large, we will never estimate identical scale parameters even if the true scale parameters are equal.[17] Of course, we may be unable to reject equality, but we hardly need remind the reader that failure to reject and accepting the null are not equivalent. Thus, for large sample sizes, these techniques will never be able to identify which group is happier without further restrictions. Interestingly, this is true even if the condition in section 2.1 is satisfied.

What types of cardinalizations reverse the conclusion drawn from the normal? Suppose we estimate $\mu_A > \mu_B$, but $\sigma_A < \sigma_B$. The rank-ordering is preserved by all concave but not all convex transformations (Hanoch and Levy 1969).[18] One simple convex transformation is e^{ch^*}, where c is a positive constant. As is well known, the resulting distribution is log normal with mean

$$\mu^\tau = e^{c\mu + .5c^2\sigma^2} \tag{2}$$

which is increasing in σ. For c sufficiently large this transformation reverses the ranking. When $\mu_A > \mu_B$ and $\sigma_A > \sigma_B$, the ranking is preserved by convex transformations, but not concave ones, such as $-e^{-ch^*}$. This generates a left-skewed lognormal distribution, with mean

$$\mu^\tau = -e^{-c\mu + .5c^2\sigma^2} \tag{3}$$

which is decreasing in σ. Thus a sufficiently large c reverses the gap. These are both simple monotonic transformations of the latent happiness variable. Since happiness is ordinal, these

[16]The proof of this is a simple algebra exercise dating at least to Bawa (1975). A close corollary serves as an exercise in a popular graduate textbook (Casella and Berger 2002, p. 407). An alternative proof for the multivariate normal is in Müller (2001).

[17]Assuming estimation by maximum likelihood, the estimates will be asymptotically normal and their difference will also have a normal limiting distribution. See the working paper for more discussion.

[18]Hanoch and Levy show this result for any distribution which can be characterized by two parameters that are independent functions of the mean and variance of the distribution, a subset of the location-scale family.

transformations represent the responses equally well. It *is* possible to achieve stochastic dominance using bounded distributions from the location-scale family, such as the uniform. But, there is little or no reason to prefer a bounded distribution over unbounded ones, from the location-scale family or otherwise, that do not exhibit FOSD.

In sum, it is impossible to rank order groups using only the parametric assumptions made in the literature or any of the location/scale distributions typically used by empirical researchers. Identification *might* be achieved by applying additional restrictions to a standard distribution (i.e. placing restrictions on the set of permissable cardinalizations). Addressing whether a researcher could make a compelling case for such restrictions or the profession could reach a consensus on them would take us into the philosophy and sociology of science and beyond the scope of this paper. In the empirical section below we show that standard results can almost always be reversed using what we are confident are plausible transformations within the lognormal.

2.3 Reporting Function

It follows from our discussion that if true happiness is normally distributed with different variances between groups, there is always a reporting function such that the difference in mean reported happiness has the opposite sign from the true difference. But even this result assumes that all individuals report their happiness the same way. Up to now, it has been convenient to assume a common reporting function, but as we show in the empirical section, this assumption is unlikely to be correct.[19]

King et al. (2004) propose circumventing differences in reporting functions by using 'vignettes' to anchor the scale on which people report happiness. This requires that (1) individuals evaluate the vignettes on the same scale as they evaluate their own well-being ("response consistency"), and (2) each individual perceives the same value from the vignettes

[19] See also Ravallion, Himelein, and Beegle (2016), who find evidence of substantial differences in the reporting function ("scale heterogeneity" in their terminology) for subjective poverty status both within and across countries.

("vignette equivalence"). Both assumptions are strong, the second particularly so, given heterogenous preferences. Moreover, as discussed above, even if we could place all individuals' happiness on a common scale, monotonic transformations of this scale would reverse group rankings.

Still, it is often easy to test for a common reporting function under a given parametric assumption. Suppose, for example, happiness is reported in $N \geq 4$ categories, and we impose normality, setting the first two cutoffs to be 0 and 1. This 'identifies' the means and variances of the distributions and leaves $N - 3$ cutoffs free. It is straightforward to test whether the free cutoffs are the same for all groups. Of course, faced with a rejection, the researcher is free to conclude either that her initial conjecture about the cardinalization was wrong or that the reporting functions differ, but we believe that, at the very least, testing the joint hypothesis should be standard procedure.[20]

3 Empirical Tests of the Happiness Literature

In the previous section we outlined the conditions under which the rank order of happiness for groups can be identified using categorical data on subjective well-being. We now put these into practice for nine key results from the happiness literature: the Easterlin (1973, 1974) Paradox for the United States, whether happiness is U-shaped in age, the optimal policy trade-off between inflation and unemployment, rankings of countries by happiness, whether the Moving to Opportunity program increased happiness, whether marriage increases happiness, whether children decrease happiness, the relative decline of female happiness in the United States, and whether disabilities decrease happiness.[21] For each of these, we first ask if we can draw any conclusions without assuming a parametric distribution by applying the criterion in section 2.1. We then test whether we can reject equal variances under an

[20] Note that we can also reject for any cardinalization in which the latent variable and cutpoints can be represented by the same monotonic transformation of the normal.

[21] For details of the estimation procedures and literature review of these results, see the Online Empirical Appendix.

assumed normal distribution, and determine whether the conclusions can be reversed using a left-skewed or right-skewed lognormal transformation, as outlined in section 2.2, and the degree of skewness required. Finally, when we have sufficient happiness categories, we also test for equal reporting functions assuming the existence of a cardinalization from the normal family as discussed in section 2.3.

Table 1 summarizes the results. None of these results are identified non-parametrically. Moreover, in the eight cases for which we can test for equality of variances under a parametric normal assumption, we reject equality. Thus we never have rank order identification, and can always reverse the standard conclusion by instead assuming a left-skewed or right-skewed lognormal. Further, in the seven cases where we are able to test for stability of the reporting function, we reject every time.

Thus if researchers wanted to draw any conclusions from these data, they would have to eschew rank order identification. In other words, they would have to argue that it is appropriate to inform policy based on one arbitrary cardinalization of happiness but not another, or equivalently that some cardinalizations are "less arbitrary" than others. It is unclear from where such an argument would come, or why we should apply a different standard for happiness research than other branches of economics.

Even if someone were to make this case, we cannot see how such a standard would say that distributions that resemble objective economic variables would be implausible. In the Online Empirical Appendix we further show that nearly every result can be reversed by a lognormal transformation that is no more skewed than the wealth distribution of the United States.[22] Even within this class of distributional assumptions, we cannot draw conclusions stronger than "Nigeria is somewhere between the happiest and least happy country in the world," or "the effect of the unemployment rate on average happiness is somewhere between very positive and very negative." To be clear, we are not proposing that satisfying this minimal criterion would make a result convincingly robust. It is plausible that happiness

[22]The exceptions are that the disabled are less happy than the non-disabled and that married women are happier than unmarried women. In both cases, we reject a common reporting function.

is more skewed than wealth is. And it is certainly not self-evident that happiness must be normal or lognormal. Happiness could be left-skewed for men and right-skewed for women, and their distributions might come from different families. And any claims of robustness would have to address our consistent finding of different reporting functions across groups. While we cannot rule out the possibility that happiness researchers will be able to find cardinalizations that are both consistent with a common reporting function and are robust within some parametric restrictions that most economists will find compelling, we are not sanguine about this prospect.

4 Conclusion

It is essentially impossible to rank two groups based on their mean happiness using the types of survey questions prevalent in the literature. Because happiness is ordinal, two groups can be ranked only if the distribution of one group first order stochastically dominates the distribution of the other. We can infer FOSD from the ordered response data alone only in extreme cases that do not occur in practice. The conditions for full identification through variation in observables are also violated. The parametric assumptions in the literature are incapable of producing FOSD without untenably strong assumptions about the happiness distribution. All of these conclusions are direct implications of well-established and uncontroversial results.

What then can we learn from such data? The regression estimates from ordered probit or logit are only accurate for one particular, arbitrary (and possibly nonexistent) cardinalization of happiness. This does not discount the actual self-reports, themselves. If we are only concerned about the number of people who subjectively consider their emotional state "not too happy," we can estimate effects using conventional binary response models. But, it is important to recognize that such an interpretation is much narrower than proponents of the use of average happiness measures currently claim for them. Subjective perceptions are subjective and introspective, and generalizations drawn from such analysis are particularly sensitive to differences in the reporting function.

Researchers who wish to continue to interpret such questions more broadly need to be explicit about the assumptions underlying their conclusions, and justify their particular cardinalization or parametric assumption relative to other plausible alternatives. It is not clear what this justification could be, and our empirical work finds little evidence that even very strong restrictions will yield interpretable results. At a bare minimum, we would require a functional form assumption that survived the joint test of the parametric functional form and common reporting function across groups. Certainly calls to replace GDP with measures of national happiness are premature.

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Table 1: Rank Order-Identification in the Happiness Literature: A Summary of Results

	Non-Parametric (1)	Equal Variances (2)	Transformation to Reverse (3)	Equal Reporting (4)
Easterlin Paradox (U.S.): Happines does not increase with per capital income	No	Reject	Left-Skewed	[e]
Happiness is U-shaped with respect to age	No	Reject	[b]	Reject
Inflation/Unemployment Tradeoff	No	Reject	[c]	Reject
Moving to Opportunity increasd subjective well-being	No	[a]	Right-skewed	Reject
Country Rankings of Happiness	No	Reject	[c]	Reject
Marriage increases happiness	No	Reject	[d]	Reject
Children at home reduce happiness	No	Reject	Left-skewed	Reject
Relative female happiness has declined (U.S.)	No	Reject	Left-skewed	[e]
Disability reduces happiness	No	Reject	Right-skewed	Reject

Notes - For details of the procedures for each case, see the online appendix. Column (1) checks the condition for non-parametric identification discussed in section 2.1. Column (2) reports result of test of equal reporting functions conditional on the existance of a common cardinalization in the normal family. Column (3) reports result of test of equal variances under a normal cardinalization. Column (4) reports whether the results from the normal cardinalization are reversed by a left-skewed or right-skewed log normal.

[a] Not testable because calculated from published results.

[b] Depends on country.

[c] Left-skewed makes unemployment more important.

[d] Right-skewed for men, left-skewed for women.

[e] Not testable as only three happiness categories used.

A Online Empirical Appendix

In this appendix, for several of the most prominent research areas in the happiness literature, we test empirically the conditions for rank order identification described in the main text. As discussed there, and our results below confirm, the conditions under which the ranking of the mean happiness of two groups is nonparametrically identified are unlikely to be satisfied in practice. Therefore we are forced to rely on parametric identification.

The most common parametric assumption is that there exists a cardinalization under which the happiness of each of two groups is distributed normally. If we assume normality and the two groups have different means and variances, then if group A has a higher mean than group B, there also exists a cardinalization of happiness using the family of log-normal distributions under which group B has a higher mean than group A. We provide tests for, and reject, equal variances for each of the cases we consider.

We then explore empirically the types of cardinalizations that are required to reverse the major results in the happiness literature. While it is impossible for any single result to be irreversible, some results require more dramatic deviations from normality than others. Additionally, some results are only reversible by skewing the distribution to the left, while others are only reversible by skewing the distribution to the right. Our exercises indicate that the set of results one can claim from the happiness literature is highly dependent on one's beliefs about the underlying distribution of happiness in society, or the social welfare function one chooses to adopt.

Any conclusions reached from these parametric approaches rely on the assumption that all individuals report their happiness in the same way. When the data permit, we test for equal reporting functions, conditional on the existence of a common cardinalization from the normal family. We reject this assumption in all cases in which we test it.

This appendix is organized as follows. In section A.1, we discuss the methods we will use to implement our assessment. Section A.2 reviews our data sources. Our main results lie in section A.3, where we test for rank-order identification and determine the cardinalizations (within the log-normal family) that reverse nine key results from the happiness literature: the Easterlin Paradox, the 'U-shaped' relation between happiness and age, the happiness trade-off between inflation and unemployment, cross-country comparisons of happiness, the impact of the Moving to Opportunity program on happiness, the impact of marriage and children on happiness, the 'paradox' of declining female happiness, and the effect of disability on happiness. Section A.4 concludes.

A.1 Methods

A.1.1 Distribution-Free Comparisons

We begin each case by asking if it is possible to say anything about the groups being studied without assuming happiness can be cardinalized along some parametric probability distribution. Consider two groups A and B who report their happiness in three categories, where r_0^i, r_1^i, and r_2^i are the fraction of responses in each category for group i. As we discuss in the main text, in the absence of a distributional assumption, the ranking of A over B is identified only if $r_0^A = 0, r_2^B = 0$, and $r_2^A \geq r_1^B$. We thus look at the distribution of responses to the happiness question across each of the groups being studied, and see if any two pairs of groups satisfy this condition. In no case is this condition satisfied.

A.1.2 Normal Cardinalization

We then ask if we can make comparisons across groups assuming there exists a cardinalization of happiness under which the distribution would be normal within each group. As discussed in the main text, provided that the standard deviation of happiness does not vary across groups, the ranking of the means provided by the normal cardinalization would hold for any alternative cardinalization. In other words, the rankings are identified by this parametric assumption.

When happiness is recorded on a three-point scale, it is straightforward to calculate the means and variances under normality as the model is just identified. However, in some of our applications we will be interested in estimating the distribution of happiness net of factors such as income or employment status that vary across groups. To do this, we estimate a heteroskedastic probit model using the oglm command in STATA created by Williams (2010). Denote $S \in \{0, 1, 2\}$ as an individual's answer to a 3-point subjective well-being survey. The model assumes that S is determined by a latent variable h^*,

$$\begin{aligned} S &= 0 \text{ if } h^* < k_0 \\ S &= 1 \text{ if } k_0 \leq h^* \leq k_1 \\ S &= 2 \text{ if } k_1 < h^* \end{aligned} \tag{1}$$

and that

$$h_i^* = \alpha_m D_i + \beta_m X_i + \varepsilon_i \tag{2}$$

where k_0 and k_1 are cut-off values of the latent variable that determine the observed response, D_i is an indicator for the group we are studying, X_i is a vector of individual specific controls and ε_i is a normally distributed error term with mean 0 and variance σ_i with

$$\sigma_i = \bar{\sigma} \exp(\alpha_s D_i + \beta_s X_i) \tag{3}$$

In other words, the model varies from the classic ordered probit in that it allows the observable characteristics to influence the variance of the error term in the latent variable.

Just as with a textbook ordered probit, one cannot separately identify the cut points from the variance. The oglm routine normalizes $\bar{\sigma} = 1$ and estimates α_s, β_s, $a_m \equiv (\alpha_m/\bar{\sigma})$, and $b_m \equiv (\beta_m/\bar{\sigma})$. It easy to transform the oglm estimates into their equivalents under our preferred normalization, where $k_0 = 0$ and $k_1 = 1$. The estimated mean and variance for our control group $D_i = 0$ will be

$$\hat{\mu}_0 = -\hat{k}_0(\hat{\sigma}_o) \tag{4}$$

$$\hat{\sigma}_0 = \frac{1}{\hat{k}_1 - \hat{k}_0} \tag{5}$$

and for $D_i = 1$,

$$\hat{\mu}_1 = \hat{\sigma}_0 \hat{a}_m + \hat{\mu}_0 \tag{6}$$

$$\hat{\sigma}_1 = \hat{\sigma}_0 \exp(\hat{a}_s) \tag{7}$$

These produce estimates for the mean and variance of the distribution only at a specific set of values for controls, namely $X = 0$. When applicable, we de-mean the controls, so our estimates can be thought of as characterizing the distribution of happiness for individuals who differ in their group membership, but otherwise possess the mean characteristics throughout the entire population (regardless of group membership). This method extends easily to more groups.

Having estimates of the standard deviation across groups, we then perform a joint test of equality. Provided we reject that test, alternative cardinalizations will reverse the ordering of means provided by the normal. However we *strongly* emphasize that a failure to reject this test does *not* mean that the ranking is identified. Rank order identification through the normal assumption requires the standard deviations across groups are *exactly* equal, a hypothesis that we may fail to reject but can, of course, never accept.

A.1.3 Applying Other Cardinalizations

Once we have estimated μ and σ under the normality assumption, we can re-cardinalize happiness. We limit attention to cardinalizations that transform the distribution from normal to left-skewed and right-skewed log-normal distributions. Recall from the main text that for a given constant c, the mean of happiness once re-cardinalized to a right-skewed log-normal distribution will be

$$\mu^{\tau} = \exp(c\mu + \frac{1}{2}c^2\sigma^2), \tag{8}$$

while for a left-skewed log-normal

$$\mu^{\tau} = -\exp(-c\mu + \frac{1}{2}c^2\sigma^2). \tag{9}$$

As the transformed mean of the right-skewed log-normal distribution is increasing in the variance of the normal cardinalization, and the mean of left-skewed log-normal distribution is decreasing in the variance of the normal cardinalization, so long as $\sigma_1^2 \neq \sigma_2^2$, there will always be a c such that one of these transformations reverses the original ordering of two groups, where

$$c = \left| \frac{2(\mu_1 - \mu_2)}{\sigma_2^2 - \sigma_1^2} \right|. \tag{10}$$

A negative term within the absolute value indicates a left-skewed log normal is required.

We will explore how adopting various left-skewed and right-skewed log-normal transformations affects the conclusions one would draw from data and, when applicable, what c is required to reverse the result. Because of the nature of the transformations, increasing c increases the skewness of the resulting distribution. To provide some context to the amount of skewness our transformations imply, we will provide comparisons to the skewness of the income and wealth distributions of the United States, where the means are at the 74th and 80th percentiles, respectively (Diaz-Gimenez, Glover, and Rios-Rull, 2011).[1] These are reference points for the reader, not a guideline. If a researcher were willing to ignore our warnings and try to draw inference from assumed distributions, knowing full well that the results are identified only through functional form assumptions and only for a subset of cardinalizations implied by these assumptions, we believe it would still be exceedingly difficult to argue that results from other distributional assumptions that resemble real-life distributions of economic variables are not just as valid. The converse is certainly *not* true. Moreover, by limiting ourselves to log-normal transformations, we are not determining the minimum amount of skewness necessary to overturn any result. Instead we ask how extreme a transformation from a very restrictive class of distributions is required to reverse the result.

A.1.4 Reporting Function

The analysis thus far has rested on the assumption that individuals from different groups report their happiness in the same way. With a 3-point scale, such as the

[1] The percentile position of the mean for the lognormal distribution of transformation c is $\frac{1}{2} + \frac{1}{2}\operatorname{erf}(\frac{c\sigma}{2\sqrt{2}})$. This implies that the transformation that would generate equivalent skewness to the income distribution (as measured by the percentile ranking of the mean) is $c = \frac{1.29}{\sigma}$, and $c = \frac{1.68}{\sigma}$ for the wealth distribution.

popular GSS question, we do not have sufficient degrees of freedom to identify differences in reporting separately from differences in the latent variable.[2] In other words, such data cannot distinguish between men being happier than women and men having lower standards for reporting their happiness.

Adding a fourth categorical response, as is the case in the Eurobarometer Trend File and World Values Survey data we will use below, grants us the freedom to test this hypothesis, conditional on the true distribution being in the normal family (including members of the lognormal family), using a likelihood ratio test. Our unconstrained model estimates ordered probits separately for each group. The first two cut-points are normalized to 0 and 1, while the mean, variance, and highest cut-points are estimated from data. Our constrained model is a heteroskedastic ordered probit that allows for group-specific means and variances, but forces the highest cut-point to be identical. This generates a χ^2-statistic with degrees of freedom equal to the number of happiness categories above three, multiplied by the number of groups minus one.

A.2 Data

We use and describe here data common in the happiness literature.

[2] We have referred throughout this article to the way in which an individual transforms subjective feelings into a numerical value or category reported on a survey as the "reporting function," and that if two individuals transform their feelings into numerical values differently they lack a "common reporting function." This follows the language used by Oswald (2008). The problem has been alternatively referred to as "differential item functioning" by King et. al (2004), "scale recalibration" by Adler (2013), and "heterogeneous standards" by Fleurbaey and Blanchet (2013).

A.2.1 General Social Survey

The General Social Survey (GSS) is the most widely used data to study happiness in the United States. It has surveyed a nationally representative sample of Americans on a variety of social attitudes annually or biennially since 1972. It asks, "Taken all together, how would you say things are these days – would you say that you are very happy, pretty happy, or not too happy?" This language and its 3-point scale has been commonly adopted by other studies, including the assessments of the Moving to Opportunity project (MTO) which we discuss in the next section. While the question remains constant over time, its position in the survey does not, which could lead to biases in responses in different years.[3] We therefore use the publicly available replication file provided by Stevenson and Wolfers (2009), who use split-ballot experiments to modify the data to account for these differences.[4]

A.2.2 Eurobarometer Trend File

The Mannheim Eurobarometer Trend File 1970-2002 combines and harmonizes several different annual surveys of the European Community, thus enabling within- and cross-country comparisons over time. The surveys included a question on life satisfaction in 1973 and then continuously from 1975-2002. There were some slight differences in question wording in some years, but in general it asked, "On the whole, are you very satisfied, fairly satisfied, not very satisfied, or not at all satisfied with the life you lead?" The survey included Austria, Belgium, Denmark, Spain, Finland,

[3] For example, Stevenson and Wolfers (2009) note that in every year but 1972, the question followed a question on marital happiness, which may cause differences in the impact of one's marriage on his or her response to the general happiness assessment. See also Smith (1990).

[4] For details of this process, see appendix A of Stevenson and Wolfers (2008b).

France, West Germany, the United Kingdom, East Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, and Sweden, but typically only in years when these countries were members of the European Economic Area.

A.2.3 World Values Survey

Wave 6 of the World Values Survey (WVS) is a comprehensive global survey on prevailing beliefs and social attitudes across a large number of nations. This wave was conducted from 2010-2014 and included the following question on happiness, "Taking all things together would you say you are: very happy, rather happy, not very happy, or not at all happy."[5]

A.2.4 British Household Panel Survey[6]

The British Household Panel Survey (BHPS) is a panel survey which began in 1991 with a representative sample of 10,300 individuals. The BHPS included a question on life satisfaction in the waves from 1996 to 2008, with the exception of 2001.[7] The survey asked "Here are some questions about how you feel about your life. Please tick the number which you feel best describes how dissatisfied or satisfied you are with the following aspects of your current situation." (Box 1 is marked "Not satisfied at

[5] In the publicly available data file, it appears the happiness reports for Egypt were reversed, so we omit them throughout the analysis.

[6] University of Essex. Institute for Social and Economic Research, British Household Panel Survey: Waves 1-18, 1991-2009 [computer file]. 7th Edition. Colchester, Essex: UK Data Archive [distributor], July 2010. SN: 5151.

[7] The 2001 wave surveyed life satisfaction with a question that was worded slightly differently than the other years, and represented the scale with faces rather than simply by boxes. Most researchers have felt these differences were sufficiently minor to ignore. We are less sanguine and did not even download the data from that year.

all" while box 7 is marked "completely satisfied.") After questions about particular aspects of life, the survey continues "Using the same scale how dissatisfied or satisfied are you with your life overall?"

A.3 Empirical Results

In this section, we report c using the convention of reporting a negative c when we are referring to a left-skewed log normal. Similarly $c = 0$, refers to a standard normal. While there is some risk of confusion, it greatly simplifies presentation to refer to, for example, values of $c = -1, -.5, 0, .5$ and 1 rather than explaining that the first two are left-skewed log normals, the third is standard normal and the last two right-skewed log normals.

A.3.1 Easterlin Paradox

No question in the happiness literature has received more attention than the "Easterlin Paradox," the observation that in some settings higher incomes are not associated with higher levels of happiness. Easterlin (1973, 1974) found that income and subjective well-being assessments were strongly and positively correlated within a country in a given year, but not over time and across countries. This, and subsequent studies, led Easterlin (1995) to conclude, "Will raising the incomes of all increase the happiness of all? The answer to this question can now be given with somewhat greater assurance than twenty years ago... It is 'no'." Easterlin instead concludes that the individuals judge their happiness relative to their peers and not on an absolute scale.

The paradox was recently called into question in a comprehensive study by

Stevenson and Wolfers (2008a).[8] They use ordered probit both across countries and over time within countries and find a strong relation between happiness and economic development. However, they find that the United States is an exception. Happiness has not increased despite substantial growth in per capita income. They attribute this to the substantial rise in income inequality over the last 30 years which occurred simultaneously with the rise in real GDP.

These ordered probit results implicitly assume the existence of a cardinalization in which happiness is distributed normally across all years, and that under that cardinalization the variance of happiness is constant across years. Using happiness data from the GSS and per capita income data from the Federal Reserve Bank of St. Louis, we first examine whether it is possible to make such a claim without relying on a distributional assumption. Unsurprisingly, this is not the case. Each year, a positive fraction of individuals report their happiness in each category, violating the condition expressed in Section 2.1 of the main paper.

Table A-1: Easterlin Paradox: Marginal Effect of Log Per Capita Income on Mean and Standard Deviation of Happiness

	(1)	(2)
Mean	-0.031*	-0.043***
	(0.016)	(0.016)
Standard Deviation		-0.079***
		(0.011)

Notes - Robust standard errors in parenthesis. Estimated marginal effects (at the mean) of log per capita income on the mean and standard deviation of happiness assuming a normal distribution. $*p \leq 0.1$, $**p \leq 0.05$, $***p \leq 0.01$.
Source - GSS Stevenson-Wolfers file (1973-2006) and St. Louis Federal Reserve.

It may still be possible to determine the relation under the assumed normal

[8] See also Deaton (2008) who finds similar results from the Gallup World Poll using OLS on a basic 10-point scale.

cardinalization. The first column of Table A-1 estimates the marginal effect of log per capita on happiness via ordered probit assuming a constant variance. Consistent with both Easterlin (1973,1974) and Stevenson and Wolfers (2008a), we find that national income is negatively associated with national mean happiness in the United States. However, in column (2) we allow the variance of happiness to also be influenced by log per capita income. We find a strong negative impact of national income on the variance of happiness, and can reject the constant variance assumption.[9] Thus any conclusion about the relation between per capita income and happiness will be determined by the cardinalization assumed through a functional form assumption.

As per capita income decreases both the mean and the variance of happiness under normality, we know the paradox can be reversed if happiness is cardinalized to follow a left-skewed log normal distribution. To find such a cardinalization, we calculate the mean and variance under normality for each year and estimate the OLS relation between these means and the log of per capita GDP, which we display graphically in Figure A-1. We then search across values of c to find a left-skewed log-normal transformation that reverses this positive relation. We find that the marginal case is approximately $c = -.68$; at this transformation there is a positive but approximately 0 correlation between mean happiness and log per capita GDP. For any $c < -.68$ then we find the expected positive relation, and the strength of the relationship will increase as we allowed the distribution to become more skewed. At $c = -1.87$, the relation becomes statistically significant at the 10% level, and at the 5% level for

[9] This may be somewhat surprising given the increase in income inequality over the time period, but is consistent with previous work by Stevenson and Wolfers (2008b) and Dutta and Foster (2013). Clark, Fleche and Senik (2014, 2016) argue that this is a standard pattern – growth reduces happiness inequality.

Figure A-1: Happiness and Per Capita GDP assuming Normality: OLS Estimate

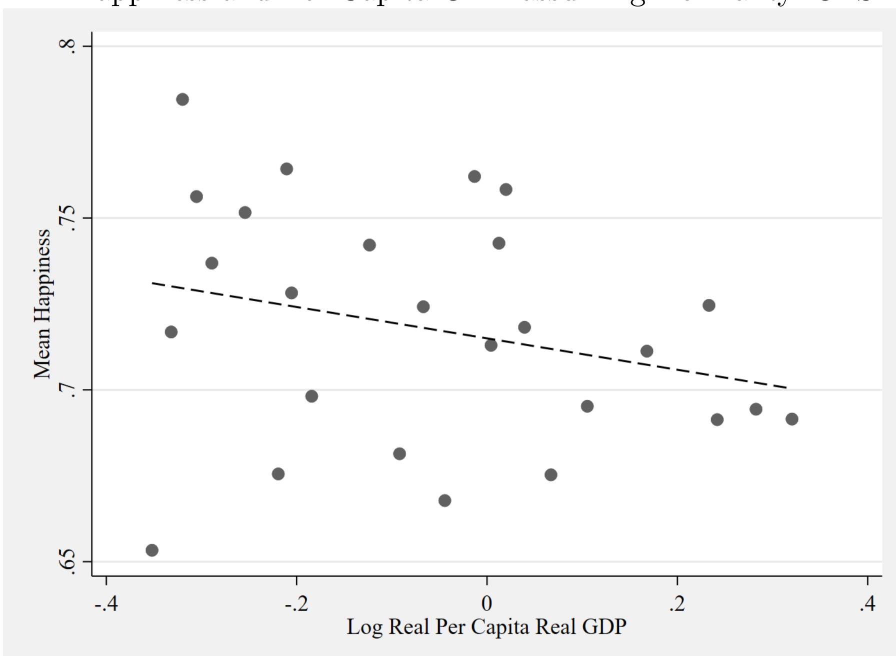
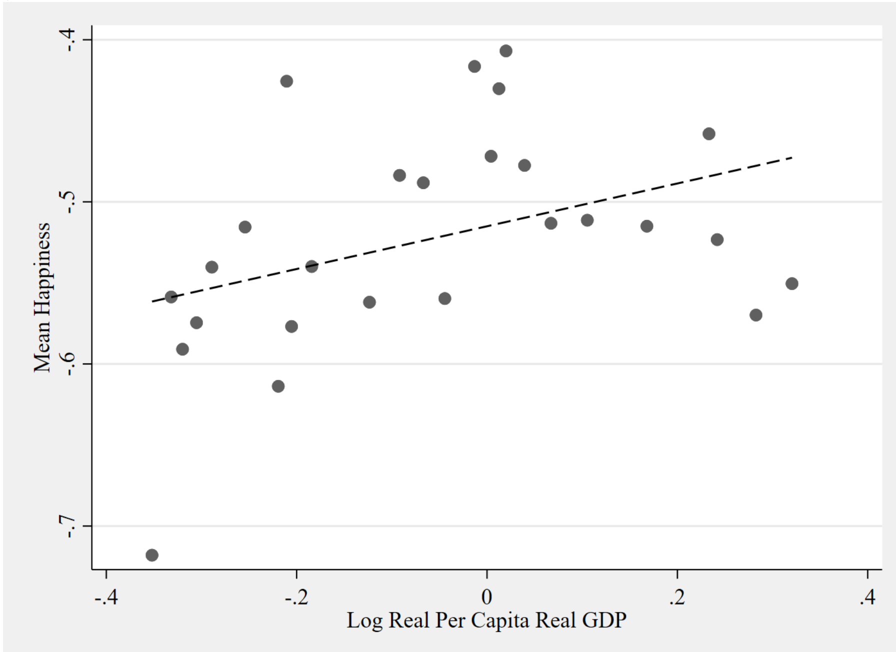


Figure A-2: Happiness and Log Per Capita GDP Assuming Left-Skewed Log-Normality: OLS Estimate



$c = -2.25$. By point of comparison, the skewness of the happiness distribution for the average year in the sample resembles the income distribution at $c = 2.10$, and the wealth distribution at $c = 2.74$. We display the $c = -2.25$ case in Figure A-2.

Even these conclusions are subject to the caveat that they assume the reporting function of happiness does not itself vary with per capita income. There is no way to test this assumption given that the GSS only reports happiness in three categories.

A.3.2 Happiness over the Lifecycle

There is a substantial literature that finds happiness is U-shaped over the lifecycle.[10] Individuals begin their adulthood fairly happy, see a decrease during much of their working life, and then rebound in happiness as they reach retirement. Blanchflower and Oswald (2008) obtain this result across over 70 countries, and there is even some evidence that it holds in apes (Weiss et al., 2012). This claim is, however, not without controversy. In some data sets, the shape depends on the choice of control variables, and whether one uses fixed effects or a pooled regression (e.g., Glenn, 2009; Kassenboehmer and Hasiken-DeNew, 2012).

Of course, such conclusions rely on particular cardinalization assumptions. To test the robustness of these results to alternative cardinalizations, we utilize the Eurobarometer, which as previously discussed uses a 4-point life satisfaction scale. We restrict attention to men in the twelve members of the European Union as of 1986, as these countries have the most years of data. Following Blanchflower and Oswald (2008), we group individuals into 5 year age bins, although we group all individuals over 80 into single bin due to the small number of people in this age range.

We first ask whether it is possible to rank age groups by their mean happiness without making any assumptions on the underlying distribution, applying the criterion laid out in Section 2.1 of the main paper. In fact, it is not possible to rank *any* two age groups within *any* country. All age-country groups have a positive number

[10]For some recent reviews, see Frijters and Beatton (2012), and Steptoe, Deaton, and Stone (2015)

of respondents in each category.

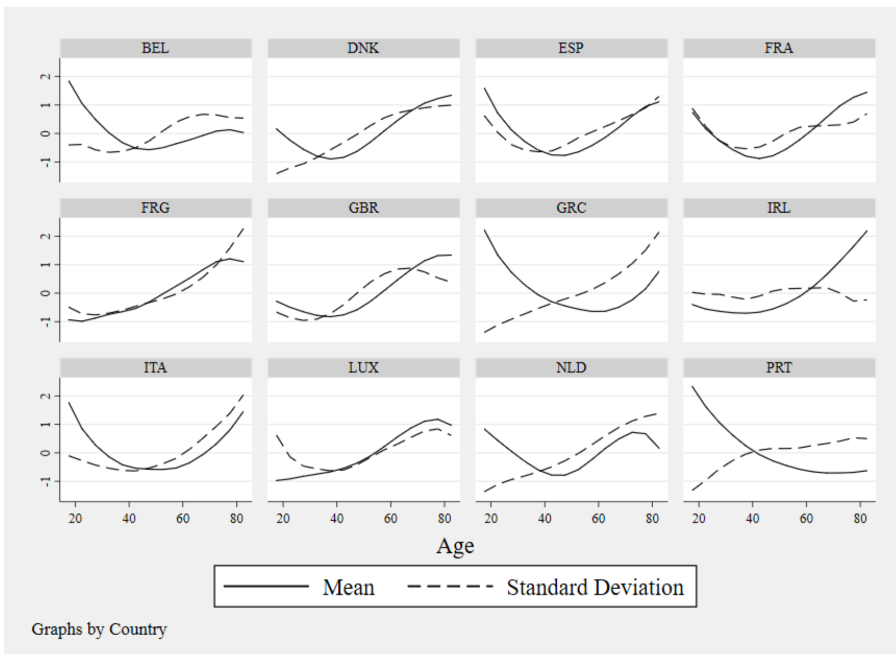
We then turn to whether we can rank age groups assuming that the distribution of happiness is distributed normally within each country-age group. We estimate an ordered probit for each country allowing the means and standard deviations to differ by age group. In Figure A-3, we plot the lowess smoothed results of this exercise. To emphasize the shape of the patterns, we normalize both sets of estimates to be distributed with mean 0 and standard deviation 1 within country. We observe a U-shaped pattern of means in a majority of countries, although it is more pronounced in some than others. West Germany and Luxembourg appear more consistent with an upward sloping age-happiness profile, while Portugal is more consistent with a downward sloping profile.[11]

However, these conclusions about the age-happiness profile in means are independent of cardinalization choice only if the variances are constant with age. While there is no consistent pattern across countries in the age-standard deviation profile, there is clear variation across age groups. In West Germany, Denmark, Greece, and the Netherlands, the standard deviation of happiness appears to increase in age. Luxembourg, Italy, and Spain are more consistent with a U-shape. France, Ireland, and Portugal in contrast seem to have a relatively stable relation between age and the variance of happiness. A joint test of the standard deviation being independent of age in these countries yields a χ^2_{156}-statistic of 545; we can reject the hypothesis at any conventional significance level.

Since, under the assumption of normality, the variance of happiness changes with

[11] The Eurobarometer continued to survey the areas of the former West Germany as a separate unit after reunifcation.

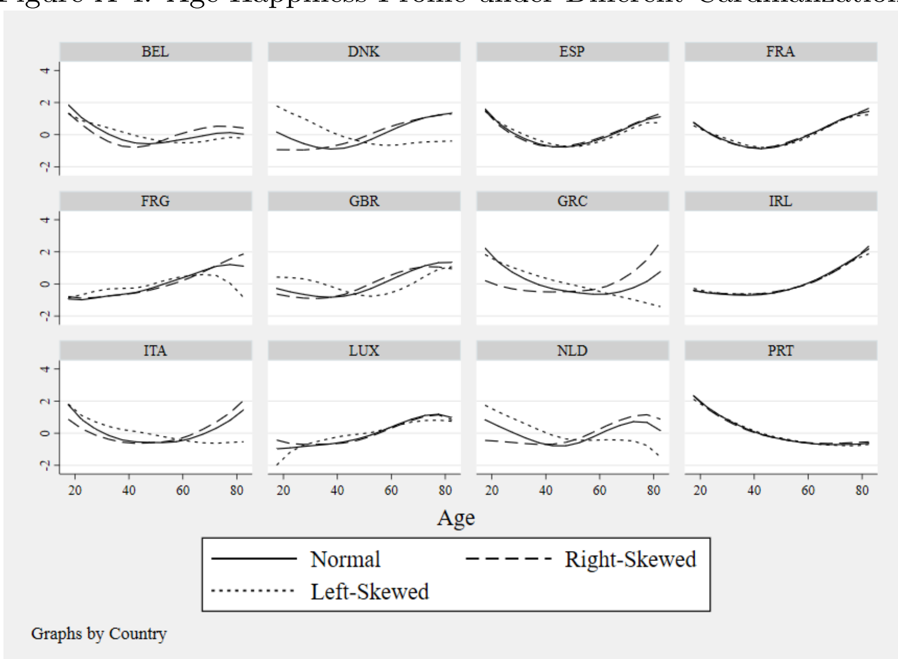
Figure A-3: Mean and Standard Devation of Happiness under Normal Cardinalization



age, alternative cardinalizations will yield different patterns in the means. Given the average variance across country-years, a transformation of $c = 4/3$ would provide similar skewness to the wealth distribution. We plot the age-happiness profile by country under the left-skewed and right-skewed version of this cardinalization, as well as the normal, in Figure A-4. We again subtract the average age-group mean and divide by the standard deviation of these averages within country and transformation (so that our estimates have a distribution of mean 0, standard deviation 1) to ease comparison of the shapes. The patterns differ dramatically under different cardinalizations. Italy, and the Netherlands, which are U-shaped under the normal, become downward sloping with a left-skewed transformation. This same transformation moves West Germany from upward sloping to hump-shaped. Denmark, which was approximately U-shaped under the normal, is monotonically upward sloping under a right-skewed transformation and monotonically downward under a left. The United Kingdom gains a stronger U-shape when left-skewed, but becomes closer to hump-shaped under a right. In contrast, Spain, France, Ireland, and Portugal have fairly stable relations across transformations, though different patterns from each other.

There are many equally plausible conclusions one could draw from Figure A-4. If we had a strong prior that happiness is always normally distributed within age group and country, then we would believe that most countries have U-shaped happiness/age profiles but that Portugal, Luxembourg, and West Germany violate this pattern. If we had a strong belief that happiness follows a U-shape across the lifecycle (and that the skewness of the distribution does not change with age), then

Figure A-4: Age-Happiness Profile under Different Cardinalizations



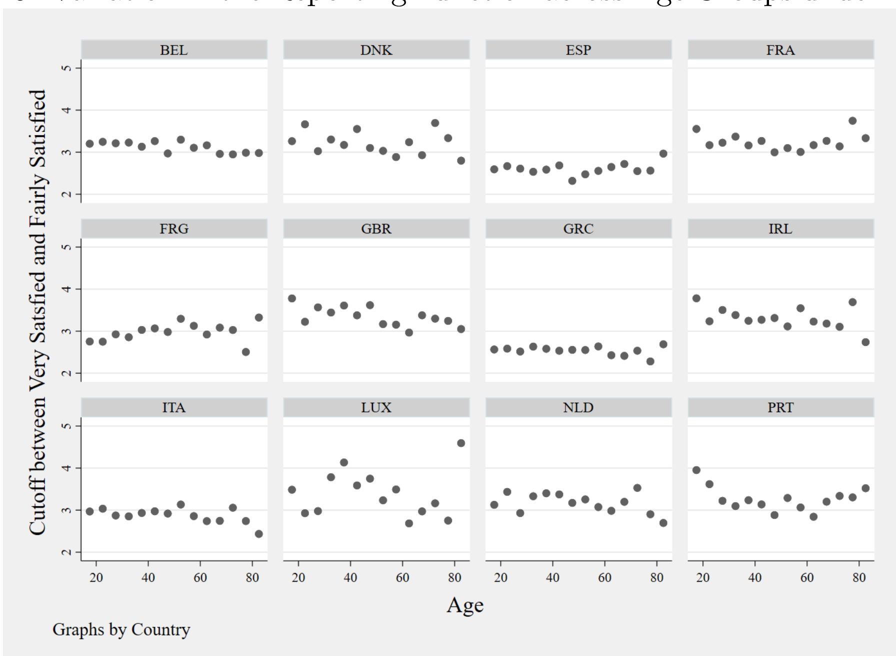
we would have to conclude that happiness is right-skewed in Luxembourg, but must not be in Denmark. In the absence of any prior, we might conclude that Spain, France, Portugal, and Ireland have a well-determined happiness/age relation, but that we lack sufficient evidence to say anything with confidence about the other EU countries

However any such conclusions would have to be made with a giant caveat; they assume a stable relation between experienced happiness and reported happiness throughout the life-cycle. An alternative view of Figure A-4 might state that happiness is constant throughout the lifecycle, but that in most EU countries, middle aged-individuals have a higher standard for reporting satisfaction with their life. Fortunately, this hypothesis is testable with the 4-category life satisfaction question under the maintained assumption that happiness can be cardinalized to be in the normal family (including the log normal).

In Figure A-5, we plot the implied thresholds (normalizing the first two cutoffs to be zero and one) from a series of ordered probits for reporting life satisfaction in the highest threshold across age and country. While we again see no consistent pattern in the relation between age and reporting function across countries, we see substantial variation within countries. To test formally for reporting function stability, we perform a likelihood ratio test between these ordered probits and the country-specific ordered probits that allow for the mean and standard deviation of happiness to vary with age but forces the highest cutoff to be stable.[12] This test generates a χ^2_{156}-statistic of 195, and we can reject stable reporting functions at the 5% level.

[12] In other words, we test a model where the reporting function is age- and country-specific against a model where the reporting function is country-specific.

Figure A-5: Variation in the Reporting Function across Age Groups under Normality



A.3.3 The Unemployment-Inflation Trade-off

Many happiness researchers have advocated evaluating policy based on its ability to raise the 'average' response on measures of subjective well-being. The application that has perhaps received the most widespread interest is correcting the misery index. While the misery index was developed as a political slogan, the idea that both unemployment and inflation are costly is intuitive. But it is by no means obvious that the proper weights, even assuming linearity, are equal.

Di Tella, MacCulloch, and Oswald (2001, hereafter DMO) provide one prominent attempt to use subjective well-being data to determine the appropriate trade-off between unemployment and inflation. They match estimated national well-being from happiness surveys with time-series data on inflation and unemployment across countries. They find that both unemployment and inflation are negatively related to national happiness but that the cost of unemployment is 1.7 times that of inflation. Thus the politically-derived "misery index" (inflation plus unemployment) biases policy towards too much unemployment relative to inflation.

To explore the robustness of this result, we follow DMO and use happiness data from the Eurobarometer Trend File, and national unemployment and inflation data from the Organisation for Economic Co-operation and Development (OECD). DMO study the time period 1975-1991. However, the OECD currently only offers harmonized unemployment data for European nations beginning in 1983.[13] We therefore focus on 1983-2002, which is slightly later than DMO but of similar duration. We

[13] These data are also not complete. For example, most countries have no data until they enter the European Union, while Greece (which we exclude because of sample size) is not available until 1999.

exclude any country which we observe for fewer than 6 years, since our method requires the estimation of 5 parameters: effects of inflation and unemployment on both the mean and the variance of life satisfaction, and the threshold for reporting life satisfaction in the highest category. This yields a sample of 14 countries: Austria, Belgium, Denmark, Spain, Finland, France, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Sweden, and the United Kingdom.

Making a determination on the appropriate calibration of the misery index requires much stronger conditions than those we consider in the main text. An effort to evaluate the effect of inflation and unemployment must first be able to rank various years based on their average happiness either absolutely or within a country. The condition in Section 2.1 of the main text lays out when such comparisons are possible without making a distributional assumption. Analyzing the yearly data from the Eurobarometer we find there is not a single year in which a single country had a single life satisfaction category that did not have a positive number of responses. Thus even determining if high unemployment years are less happy than low unemployment years must rely on assumptions about the distribution of life satisfaction.

Assuming the existence of a normal cardinalization, we can at least determine whether inflation and/or unemployment lowers happiness provided that these variables do not influence the variance of happiness. To test for a constant variance, for each country we estimate an ordered probit that allows the mean and variance to be affected by inflation and unemployment. We then perform a joint test that neither inflation nor unemployment has any effect on the variance of happiness in any country in our sample. This yields a χ^2_{28}-statistic of 611, and we can easily reject the null hypothesis at any conventional level. Thus even the statement that the national unemployment and inflation rates lower average life satisfaction, a much weaker statement than the optimal policy trade-off between inflation and unemployment, is only true for some cardinalizations of happiness.

To explore conclusions that can be drawn from alternative distributional assumptions, we first estimate country-specific heteroskedastic ordered probits using individual-level data on life satisfaction from the Eurobarometer Trend File. In these regressions we control for marital status, education, a quadratic in age, and a set of year dummies.[14] From these, we calculate the mean and standard deviation of happiness in each country in each year (at the mean of our controls in the EU) using the estimated coefficients on the year dummies by the method discussed in section A.1. We then follow DMO by estimating a pooled regression of mean happiness on annual unemployment, inflation, a set of year fixed effects, country fixed effects, and country-specific time trends, which represents DMO's preferred specification.[15] We also estimate this regression under alternative right-skewed and left-skewed transformations of happiness. To provide comparability across estimates, we normalize each transformation so that the distribution of happiness is mean zero with standard deviation one across country-years.

[14] Unlike DMO, we do *not* control for unemployment status in these first stage regressions. This would cause our second stage to understate the true welfare cost of national unemployment. DMO recognize this problem and adjust their results using the estimated effect of unemployment on happiness in the first stage. However, changes in the distribution of happiness will also change the estimated effect of unemployment on individual-level happiness, so performing such an adjustment would be inappropriate in our context.

[15] DMO use 3-year moving averages of inflation and unemployment rather than the annual values. It is not clear whether this is due to a data limitation or a preference for smoothing year-to-year variation in these variables. We use the annual figures as our results more closely resemble DMO's under a normal distribution than when using 3-year moving averages.

In the first panel of Table A-2, we report the effect of inflation and unemployment on the mean and variance of happiness under the assumption of normality. Despite the different time horizon, our result is remarkably similar to those in DMO. Both inflation and unemployment have large and statistically significant negative effects on national happiness. The effect of unemployment is larger, suggesting that a 1 percentage point increase in unemployment would have the same negative impact on welfare as a 1.73 percentage point increase in inflation, nearly identical to the ratio estimated by DMO.[16] However, as we show in the second row, unemployment also has a statistically significant and positive impact on the variance of happiness. Therefore transformations that skew happiness to the right will decrease the estimated impact of unemployment on national happiness, while those which skew left will increase its estimated impact.

In Panel B, we first explore right-skewed distributions using the standard log-normal transformation used throughout the appendix. Remarkably, the "misery index," where employment and inflation receive equal weight, becomes optimal policy with a very modestly right-skewed distribution of $c = 0.375$. As we increase right-skewness to approach the income distribution ($c = 1.075$), unemployment begins to have a positive effect on national well-being, though neither its effect nor that of inflation is statistically significant. Thus, another interpretation is that, if happiness is log-normal, the key macroeconomic variables targeted by policymakers are inconsequential. Increasing skewness to that of the wealth distribution ($c = 1.4$)

[16] DMO estimate the trade-off as 1.66 after adjusting for the direct effect of being unemployed on well-being, which is unnecessary for us given that we did not control for employment status in the first stage.

Table A-2: Effect of Inflation and Unemployment on Happiness under Various Distributional Assumptions

	Unemployment (1)	Inflation (2)	Trade-off (3)
Panel A: Normal Distribution			
μ	-5.167***	-2.992**	1.727
	(1.222)	(1.468)	
σ	1.453***	-0.167	
	(0.403)	(0.390)	
Panel B: Right-Skewed Log-Normal			
c=0.375	-2.556**	-2.556*	1.000
	(1.287)	(1.498)	
c=1.075	2.514	-2.668	-0.942
	(2.299)	(2.505)	
c=1.400	5.122*	-2.968	-1.726
	(3.110)	(3.271)	
Panel C: Left-Skewed Log-Normal			
c=-0.375	-7.890***	-3.833**	2.058
	(1.519)	(1.853)	
c=-1.075	-13.388***	-6.379*	2.099
	(2.790)	(3.404)	
c=-1.400	-15.921***	-7.701*	2.067
	(3.574)	(4.267)	

Notes - Each row represents the results of a separate regression on mean happiness. All regressions include year and country fixed effects and country specific time-trends. "Trade-off" represents the implied trade-off in the social welfare function between unemployment and inflation and is computed as the ratio of the point estimate for unemployment to the point estimate for inflation. Robust standard errors in parenthesis. $^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$
Source - Eurobarometer Trend File (1984-2002) and Organization for Economic Co-operation and Development

makes the positive effect of unemployment statistically significant, consistent with arguments that recessions are "good for your health" (Ruhm 2000).

In contrast, as we show in Panel C, when we allow happiness to become left-skewed, unemployment becomes more important for well-being. At $c = -0.375$, a one percentage point increase in unemployment lowers happiness by 2.05 times as much as a one percentage point increase in inflation, and similarly 2.1 times at $c = -1.075$ and 2.07 times at $c = -1.4$.

On a somewhat optimistic note, our results make intuitive sense. We would expect that unemployment would generally make people less happy, a result consistent with a large literature using self-reported happiness (e.g. Clark and Oswald, 1994; Blanchflower, 2001; Blanchflower and Oswald, 2004). It is at least plausible that those who are most directly affected by unemployment are located in the left-tail of the happiness distribution. Increasing the left-skewness of happiness is equivalent to using a social welfare function that places more weight on the least happy individuals relative to the happiest. When unemployment increases, there are more unhappy unemployed individuals, and the more weight we place on these individuals, the larger the social cost will appear. In contrast, a right-skewed transformation increases the weight on the happiest individuals relative to the least happy. Since the happiest people will disproportionately hold stable jobs, increases in unemployment are unlikely to bother them. Even a positive effect of unemployment is plausible for a highly right-skewed social welfare function if, as some have suggested, individuals report happiness based on their relative circumstances.[17] When many are without a

[17] See Clark, Frijters, and Shields (2008) for a review of the empirical evidence that social comparisons are important for happiness.

job, those still employed may report particularly high levels of happiness.[18]

Even if there were some strong *a priori* reason to adopt a specific cardinalization, these results would still require the assumption that the reporting function itself is stable across time. This assumption is testable as the Eurobarometer life-satisfaction questions uses a 4-point scale. Applying the method discussed in section A.1.4, we perform a likelihood ratio test for equal reporting functions across year within country, and construct the joint test across these countries. That is we allow the reporting function to vary across country, but not within, an even weaker assumption than that required to estimate Table A-2. This yields a χ^2_{197}-statistic of 491, and we can thus strongly reject the hypothesis that the data support the existence of a normal cardinalization with a stable reporting function across time.

A.3.4 Cross-Country Comparisons

In previous sections we found that the ranking of happiness across groups is highly sensitive to distributional assumptions. To explore this sensitivity in a larger context, we use the WVS to rank nations based on mean happiness. Constructing such a ranking without a distributional assumption requires the data to satisfy the condition from section 2.1 in the main text. Looking at the distribution of responses by country, remarkably none of the 1,300 Malaysian respondents report being "not at all happy" with their life. However, every other country's respondents utilize every category; consequently, we still are unable to rank Malaysia against any other country or to

[18] While Clark (2003) presents evidence that macro-level unemployment has a negative impact on the average well-being of the employed, this does not necessarily mean that macro-level unemployment has a negative impact on the well-being of the happiest employed individuals, who would be weighted most heavily by a right-skewed social welfare function.

form a ranking of countries in general.

Assuming happiness is distributed normally in each country, we can rank these countries based on their estimated means so long as the variances are identical across countries. We test this assumption using a heteroskedastic ordered probit, and easily reject it at any conventional level ($\chi^2_{58} = 2920$). Thus the ordering of the countries will always depend on the chosen cardinalization.

We explore alternative cardinalizations in Table A-3. The order of countries represents their happiness ranking when happiness is assumed to be normally distributed; the columns give their ranking under log-normal transformations with $c = 1.72, .5, -.5$, and -1.72; given our estimated variances, $c = 1.72$ would make the average country's happiness as skewed as the U.S. wealth distribution. Although the implied degree of skewness varies across countries, moving from left to right in the columns represents moving from a more right-skewed to a more left-skewed distribution. Doing so has dramatic effects on the rank-ordering of happiness. The five happiest countries when happiness is right-skewed are Nigeria, Ghana, Mexico, Trinidad and Tobago, and Pakistan. Remarkably, Nigeria becomes the *least* happy country under the left-skewed transformation, and Ghana and Pakistan also fall into the bottom ten. The top five under the left-skewed distribution of happiness (Qatar, Uzbekistan, Malaysia, Kyrgyzstan, and Sweden) fare relatively better under right-skewed happiness, though only Uzbekistan remains in the top ten. The rank-correlation between the log-normal transformations with $c = 1.72$ and $c = -1.72$ is .19.

Table A-3: Country Rankings by Mean Happiness and Threshold for Reporting Happiness

	c=1.72	c=0.5	c=-0.5	c=-1.72	Cutoff
Mexico	3	1	1	8	53
Uzebekistan	8	4	2	2	41
Ecuador	7	5	5	12	42
Colombia	6	6	6	16	55
Nigeria	1	2	18	59	51
Malaysia	12	8	4	3	[a]
Ghana	2	3	17	57	57
Qatar	15	11	3	1	2
Trinidad and Tobago	4	7	7	31	56
Phillipines	10	9	9	24	48
Pakistan	5	10	25	54	31
Sweden	24	16	8	5	20
Kuwait	20	14	11	13	18
Thailand	21	18	13	14	3
Rwanda	18	15	16	19	34
Kyrgzystan	33	24	10	4	12
Singapore	25	20	14	10	30
Zimbabwe	11	12	28	44	54
Australia	30	22	12	7	27

Table A-3 Continued

New Zealand	32	27	15	6	4
United States	26	23	21	17	23
Brazil	27	25	20	15	19
Libya	14	19	26	33	8
Turkey	13	17	32	42	21
Netherlands	36	30	19	9	15
India	16	21	30	34	29
South Africa	9	13	39	58	49
Japan	28	29	22	22	32
Uruguay	22	26	31	30	28
Kazahkstan	31	33	23	20	52
Argentina	29	32	29	25	35
Taiwan	38	35	27	18	11
Peru	17	28	37	45	58
Poland	45	37	24	11	5
Armenia	19	31	41	47	14
Cyprus	23	34	38	41	25
Hong Kong	43	38	33	23	10
Germany	41	39	34	27	22
Chile	40	40	35	29	45
Azerbaijan	34	36	40	36	37
South Korea	53	45	36	21	6

Table A-3 Continued

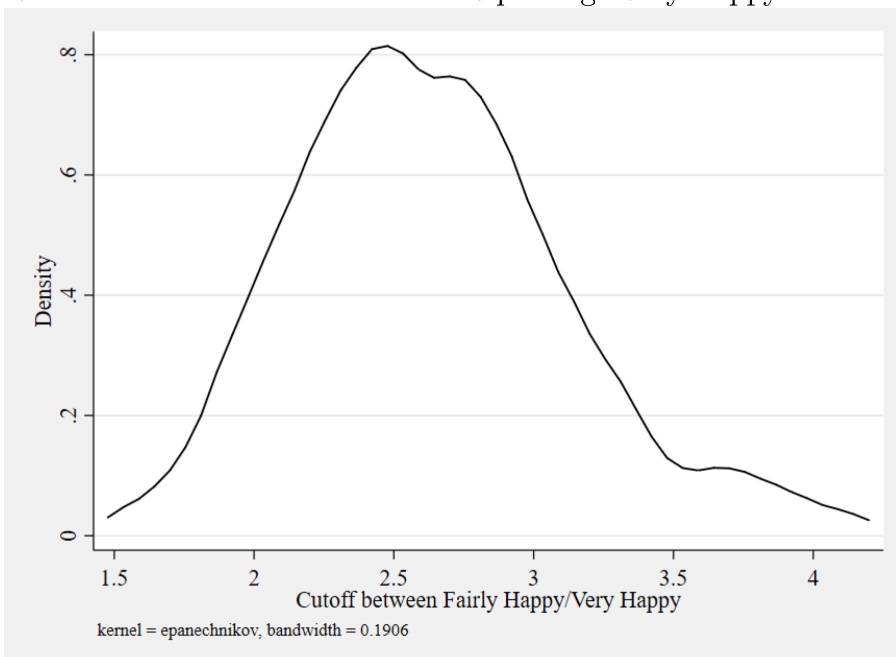
Jordan	42	41	45	35	1
Slovenia	46	43	44	32	26
China	51	47	43	28	24
Spain	54	49	42	26	17
Morocco	39	42	48	48	13
Algeria	44	46	47	40	16
Lebanon	50	50	46	37	39
Tunisa	49	51	49	43	7
Bahrain	35	44	53	56	33
Russia	52	53	50	39	46
Georgia	37	48	54	55	50
Yemen	48	52	52	49	47
Estonia	56	55	51	38	38
Ukraine	47	54	55	53	40
Palestine	57	56	56	46	9
Romania	55	57	58	52	44
Belarus	58	58	57	50	43
Iraq	59	59	59	51	36

Notes - Columns (1)-(4) provide rank of estimated country mean happiness under various log-normal transformations. Column (5) provides ranking of cut-off value between rather happy and very happy, with 1 being the highest cutoff. Countries listed in order of estimated mean happiness under normal distribution.

[a] - Malaysia has no responses in lowest category, so an upper category under a comparable normalization cannot be computed.

Source - World Values Survey, Wave 6 (2010-2014)

Figure A-6: Distribution of Thresholds for Reporting "Very Happy" under Normality



There are some countries whose rank remains fairly stable across the transformations. Uzbekistan is the second happiest country under a normal distribution and its rank varies between 2 and 8 under the skewed distributions. Iraq, the world's least happy country under the normal distribution, is never able to rise out of the bottom ten in the skewed transformations. These cases are counterbalanced by countries like the previously mentioned Nigeria, as well as South Africa, which falls near the middle of the distribution when happiness is normally distributed, is able to rise as high as 7th when happiness is right-skewed, but falls all the way to 3rd lowest when happiness is left-skewed.

All of these rankings relied on the reporting function of happiness being stable across countries, a heroic assumption in light of the questionnaires being administered in a large number of different languages. In Figure A-6, we relax the common reporting function assumption and construct a density plot of the thresholds for reporting in the highest happiness category. The variation is substantial. Using a likelihood ratio test, we can strongly reject common reporting functions at any conventional level ($\chi^2_{58} = 593$). The fifth column of Table A-2 ranks our countries from highest to lowest based on their threshold for reporting being very happy, assuming normality. The happiest countries in our normal ranking were substantial benefactors of having populations with low thresholds for reporting "very happy"; 3 of the top 5 ranked in the bottom 10 for cutoffs, while the two others ranked in the bottom twenty. On the other hand, Qatar's 8th ranking under normality appears quite remarkable given its residents had the second highest standard for reporting in the top category.

A.3.5 Moving to Opportunity

Happiness data have also been used to evaluate micro-level policies, as in the case of the Moving to Opportunity (MTO) program. Motivated by the positive results of the Gautreaux desegregation program in Chicago, the MTO experiment targeted families living in public housing in high poverty areas.[19] Eligible families were invited to apply for the chance to receive a Section 8 housing (rental assistance) voucher. Applicants were randomly assigned to three groups: no voucher (Control group), Section 8 voucher that could only be used in an area with a poverty rate below 10% (Experimental group), and a standard Section 8 voucher (Section 8 group). The

[19] The Gautreaux program came out of a court-ordered desegration program in Chicago in the 1970s. See Rosenbaum (1995) for a detailed analysis.

program has been assessed at multiple stages.[20] A long-term follow-up (Ludwig et al., 2012, 2013) emphasizes that subjects in the experimental group were substantially happier than those in the control group. We reexamine the evidence for this conclusion.

The participants in the long-term MTO evaluation study were asked the standard GSS happiness question, "Taken all together, how would you say things are these days – would you say that you are very happy, pretty happy, or not too happy?" Ludwig et al. (2012, table S2) report the distribution of responses across the experimental and control group, which we reproduce in Table A-4. They calculate intent-to-treat estimates using intervals of 1 unit between the categories, as is common in the literature, but also ordered probit and logit. In all three cases, they find positive effects on average happiness that fall just short of significance at the .05 level.

Table A-4: Distribution of Happiness - Moving to Opportunities

	Control Compliers	Experimental Compliers
Very Happy	0.242	0.262
Pretty Happy	0.470	0.564
Not Too Happy	0.288	0.174

Notes - Distribution of happiness responses across categories by treatment group. Experimental estimates are treatment on the treated
Source - Ludwig et al. (2012), table S2

From the distribution of responses in Table A-4, it is clear we cannot form a ranking without imposing a parametric distribution. Assuming the distribution is normal, we find that the control group has a lower mean (.44 v. .60), but also a higher variance (.79 v. .63).[21] The cdfs cross at the 83rd percentile, which is 1.20

[20] For an early evaluation, see Katz, Kling, and Liebman (2001). For an intermediate-term evaluation, see Kling, Liebman, and Katz (2007).

[21] We cannot formally test for equal variances as the underlying data from which Ludwig et al.

units of happiness (and also in the extreme left tail of the distributions). Thus if we simply transform the underlying happiness data to increase the values above 1.20 we can reverse the mean happiness. This cardinalization would explain the data equally well.

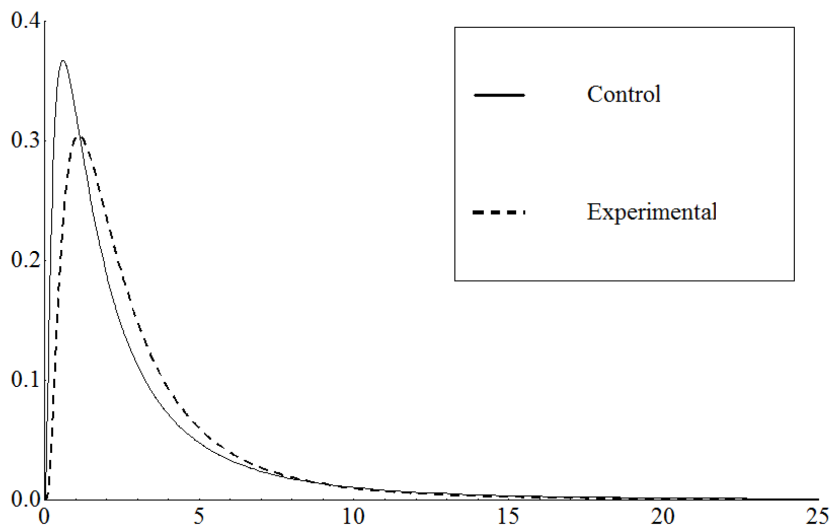
Since the control group has a higher variance of happiness, it will be possible to reverse this result by applying a right-skewed distribution. From our point estimates, the required transformation is just slightly more skewed than a standard log-normal; we need only apply a $c = 1.33$. We plot the resulting distributions in Figure A-7. Both distributions are less skewed than the income distribution, with the mean of the control group lying at the 70th percentile, and the mean of the experimental group at the 72nd percentile. One plausible interpretation of the data is that moving to a low poverty area increased happiness for most people, but that there is a group of people who were extremely happy in their old environment who could not match positive aspects of their former social environment in their new community. Of course, this all assumes that moving to a new environment did not influence the way in which individuals report their happiness, a possible scenario that is not testable given that the happiness scale used by the researchers has only 3 points.

A.3.6 Marriage and Children

One of the most robust results in the happiness literature is that married individuals are happier than non-married individuals. This phenomenon has been observed both across countries and across time (e.g., Stack and Eshelman, 1998; Diener et. al, 2000;

(2012) calculated the distribution of their responses are not publicly available.

Figure A-7: MTO Log-Normal Happiness Distribution with Equal Means



Blanchflower and Oswald, 2004).[22] In contrast, happiness researchers generally find that individuals with children are less happy than those without (e.g., Alesina et. al, 2004; Blanchflower, 2009; Stanca, 2012; Deaton and Stone, 2015).[23] These conflicting results present a bit of a conundrum. As both getting married and having children are actions that individuals (generally) take voluntarily, revealed preference suggests they should both raise happiness although as Deaton and Stone (2015) point out, if only people who expect children to make them happier become parents, in a cross-section having children and happiness might be unrelated. Likewise, most parents are unwilling to express publicly that their children are a source of unhappiness.

In this section we explore the robustness of cross-section comparisons between those who are married and those who are not, and those who live with and without children using the BHPS. We restrict attention to those aged 16-60 and separate individuals by gender. In our analysis of married individuals, we exclude those who are widowed, separated, or divorced; for our analysis of children we focus only on those who are married.

We first ask if it is possible to make any comparison without assuming a functional form for the distribution of happiness by comparing the distribution of responses within each of these groups. In no case is this possible. Regardless of gender, marital status, or child cohabitation status, we find in every case a positive number of responses in every life satisfaction category. Therefore we cannot say anything

[22] Note this is a distinct question from whether marriage *causes* individuals to become happier, which is a much more controversial claim. Lucas et al. (2003), for instance, present evidence consistent with the idea that becoming married causes a short term increase in one's well-being, but that the individual eventually 'adapts' and returns to his or her pre-marital happiness.

[23] There are important exceptions however. For example, Angeles (2010) finds positive effects of children on the happiness of married individuals in Britain.

about the impact of marriage or children on life satisfaction without a parametric assumption.

We next test for equality of variances, a necessary condition in order to have rank-order identification under normality. We estimate the mean and variance by gender and marital status, and then conduct a joint test that these variances are equal conditional on gender. This generates a $\chi^2_2 = 122$, and we can thus reject the hypothesis at any conventional level. We perform the same test for those living with and without children and obtain a $\chi^2_2 = 95$, and thus we can again strongly reject. Any conclusion one would draw on the relation between marriage, children, and happiness would therefore depend on choice of cardinalization.

Table A-5: Estimated Happiness Distributions by Family Situation under Normality

	Men		Women	
	(1)	(2)	(3)	(4)
	Panel A: Marriage			
	Never Married	Married	Never Married	Married
Normal Mean	5.264	5.395	5.427	5.807
Normal Variance	5.788	4.970	6.129	6.411
Required c	0.321		-2.689	
	Panel B: Children			
	No Child	Child	No Child	Child
Normal Mean	5.774	5.501	5.944	5.685
Normal Variance	6.081	5.347	6.853	6.048
Required c	-0.744		-0.643	

Notes - Estimated means and variances assuming normal distribution. "Requred c" is the parameter of log-normal transformation that would reverse ordering of means given by normal distribution.
Source - British Household Panel Survey, 1996-2008.

We display the estimated distributional parameters assuming a normal by gender in Table A-5. We first consider the impact of marriage in Panel A. Both married men and married women appear to be happier on average than their single counterparts.

However, we also observe that married men have a lower variance of happiness than single men. Thus, we can reverse this relationship with a right-skewed log-normal transformation. The required transformation itself is quite modest; with $c = .32$, single men become happier. By comparison, the distribution for single men would not reach the skewness of the income distribution until $c = .54$. In contrast, married women appear to have a higher variance of life satisfaction than single women. We thus require a left-skewed log-normal to reverse. For any $c \leq -2.69$, we would conclude that single women are happier than married women. These distributions are skewed substantially to the left; the mean of married women lies within the .1th percentile. However, transformations outside the lognormal family could certainly reverse the result with less skewness, and there is no particular reason to believe that getting married does not itself affect the skewness of happiness.

In Panel B, we turn to the impact of children on life satisfaction. Consistent with most of the literature, we find that, assuming normality, both men and women who live with children are less happy than those who do not. However, in both cases we estimate that individuals living without children have a higher variance of happiness than those living with children. Thus, we can reverse these results with a left-skewed log normal. The required transformations are similar, for men we require $c = -.74$, for women $c = -.64$, and produce distributions with skewness similar to the wealth distribution of the United States (though in the opposite direction).[24]

Finally all of these results assume a common reporting function. It is plausible

[24] Under the reversing transformations, the mean of the child-less male distribution falls in the 18th percentile, 19th percentile for male with child, 20th percentile for child-less female, and 21st percentile for female with child.

that marriage and having children change the way that people report their happiness. Because the BHPS measures life satisfaction on a 7-point scale, this assumption is testable. For each of our outcomes, we perform a likelihood ratio test of equality of the reporting function for men and women separately, and then calculate the joint test. That is, our null hypothesis allows gender, but not family status, to affect the reporting of happiness. For marital status, our resulting test statistic is $\chi^2_8 = 84$; for living with children we find $\chi^2_8 = 21$. We can thus reject a common reporting function for both cases at the 1%-level.

A.3.7 The Paradox of Declining Female Happiness

One surprising result from the happiness literature, documented by Stevenson and Wolfers (2009), is that in the United States women's happiness appears to have fallen relative to men's from 1972-2006 despite the great social and economic progress women made during this period.[25] We explore the robustness of this result using these same data.

Fundamentally, the question seeks to order the average happiness of women's happiness by year relative to men. As discussed previously a necessary (but not sufficient) condition to be able to make such a comparison without imposing a distributional assumption on happiness is that there are some groups which never report in the highest category, and some which never report in the lowest. Analyzing the data year by year, we see this criterion is never met for men or women in any year

[25] By labeling this "surprising," we do not mean to imply that it could not be true. In a related area, Black et al. (2009) suggest that apparent black-white earnings convergence was accompanied by black mobility to higher cost localities, suggesting much less convergence in real incomes.

of the GSS. Thus comparisons cannot be made without distributional assumptions, and any conclusion will rest on the functional form assumed.

If we are willing to assume a cardinalization exists in which, in each year of the data, both men and women's happiness is distributed normally, we can make comparisons that are robust to any alternative cardinalization provided the variance is constant across all years for each gender. Using a heteroskedastic ordered probit, we estimate the means and standard deviation of happiness by gender for each year assuming normality and test whether the standard deviation is constant. This generates a $\chi^2_{51} = 144$, and we can reject equality of variances at any conventional level of statistical significance. Thus conclusions about trends in relative male to female happiness will depend on the cardinalization chosen by the researcher.

In Figure A-8 we plot the mean happiness for men and women under the normality assumption. Consistent with Stevenson and Wolfers, we see a sharp decline in women's happiness, while men's remains relatively constant, indicating that under this cardinalization, women have lost ground relative to men. However, in Figure A-9, we plot the standard deviations across time, and consistent with our above test, find substantial changes here as well. While the standard deviation has generally declined for both genders, women's has fallen relative to men's. Thus the pattern in means can be reversed by a left-skewed log-normal.

In Figure A-10 we plot the estimated linear (10-year) trend in relative happiness from an OLS regression as a function of the c chosen in the left-skewed log-normal along with the 95% confidence interval. As we add more skewness, the trend begins to favor men less and women more. By $c = -.35$, the trend is already statistically

Figure A-8: Mean Happiness over Time under Normality

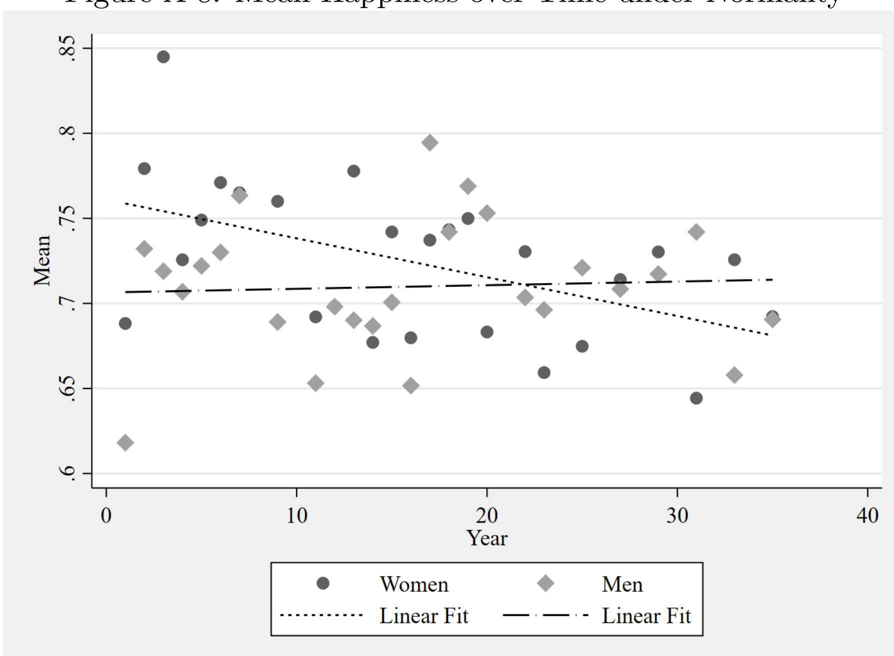


Figure A-9: Standard Deviation of Happiness over Time under Normality

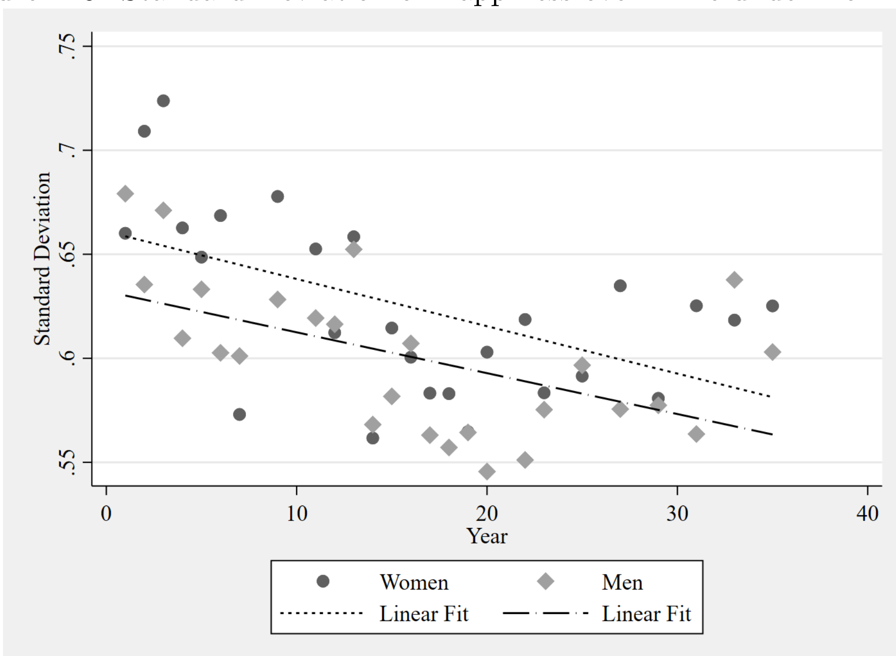
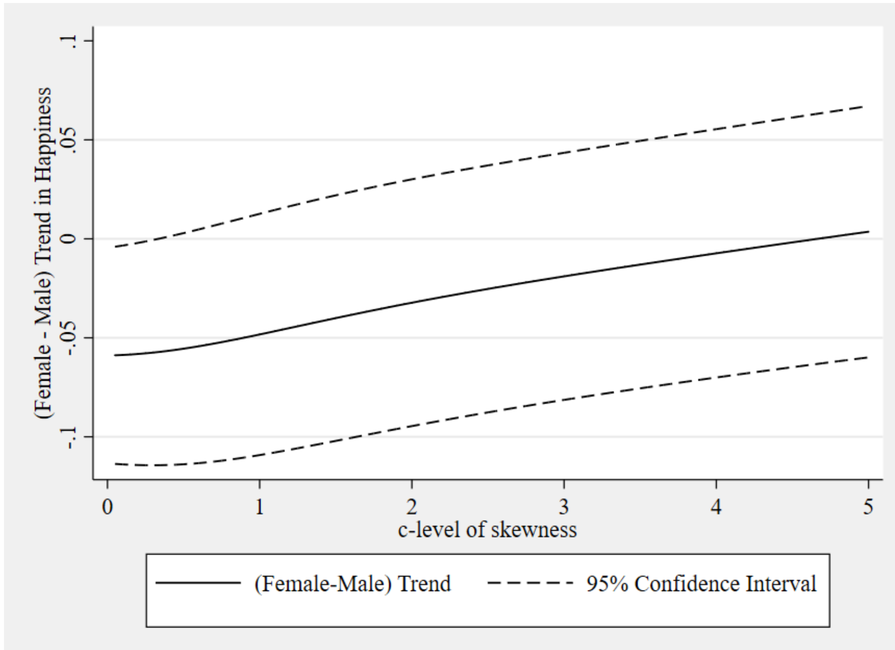


Figure A-10: Difference in Female-Male Happiness Trend for Left-Skewed Log-Normal



insignificant at the 5% level, which would involve substantially less skewness than the income distribution ($c = 2.10$). It is, however, not until $c = -4.7$ that the trend reverses in sign.

We note several strong caveats. First, our transformations assume that the skewness of the distribution (as measured by c) is constant over time. Wealth and income and have become more skewed over time, thus it would make sense to allow cardinalizations of happiness to become so as well. Because women have lower mean and variance of happiness in the later years, allowing for a more skewed distribution would raise their happiness relative to men in these years, and thus flatten any estimated trends. Second, we assume that men and women report their happiness in the same way, and that the way in which they report their happiness does not change overtime. An equally plausible explanation is that over time the social and economic progress made by women has led them to raise the standard with which they evaluate happiness, which would artificially lower their reported happiness. Because the GSS only measures happiness on a 3-point scale, we cannot test for changes in the reporting function.

A.3.8 Adaptation to Disability

One of the most striking results in the happiness literature is the finding that people adapt to disability. Kahneman (2011) suggests that the experienced utility of paraplegics and nonparaplegics is fairly similar after a period of adaptation. Whether adaptation is complete is controversial, but partial adaptation is widely accepted. For example, Oswald and Powdthavee (2008) argue that the widely cited Brickman et al. (1978) study has been misinterpreted and also find notable but only partial recovery of happiness from what they define as moderate and severe disability. Yet the question of adaptation to disability and other adverse events is, perhaps, unusually sensitive to concerns about the reporting function. Individuals may reconcile themselves to such events either by becoming less unhappy about them or by reducing the standard for reporting themselves as happy.

We approach this question using the BHPS, which includes the measure on life satisfaction discussed before and asks respondents about their disabilities. We note there are some inconsistencies in the disability question across waves that we are forced to ignore in the interest of having an adequate time series. From 1996 to

2000, we use the question "Can I check, are you registered as a disabled person, either with Social Services or with a green card?" For 2002 and 2003, we use "Can I check, are you registered as a disabled person?" Finally, from 2004 on, we use "Can I check, do you consider yourself to be a disabled person?" On the face of things, we would expect the largest difference to be between 2003 and 2004 when the question shifts from being purely factual to one of self-image. In fact the difference between 2002-3 and 2004-8 is negligible. There is a large jump between 2000 and 2002, but this seems largely to reflect an upward trend between 1996 and 2002.

Unfortunately, the BHPS does not have a large enough sample of long-term disabled individuals to test for adaptation within an individual. Instead, we construct a sample of individuals who ever report being disabled, and compare the distribution of responses in years where these individuals were disabled with the distribution of responses in years where they were not. We limit the sample to individuals ages 16 to 60, and exclude anyone who was disabled upon entering the sample. If the information on disability was missing in any given year, we used the response from the previous year or, if that was missing either because of non-response or because the missing year was the respondent's first in the sample, we use the response from the following year. Any remaining missing cases were recoded as not disabled.

We first test if it is possible to conclude whether disabled years were less happy than non-disabled years (or vice-versa). Comparing the distribution of categorical responses, we observe that both the disabled and the non-disabled utilize all of the seven categories of life satisfaction. Thus, under the condition derived in section 2.1 of the main text, it is not possible to determine whether the disabled or non-disabled are happier without a parametric assumption.

Conclusions drawn from assuming a normal are robust to other cardinalizations only if the variance of the distribution is independent of disability status. A simple test of this assumption yields a $\chi_1^2 = 43$, and we can easily reject it. In Table A-6, we show the estimated parameters of the happiness distribution, assuming normality, for disabled and non-disabled years. While disabled people appear to be less happy, they also have a higher variance of their happiness. Therefore, we can reverse this relation with a lognormal transformation. For any $c \geq 1.41$, we find the opposite, that becoming disabled makes people happier. This would result in a happiness distribution for disabled people which was substantially more skewed than the wealth distribution ($c = .65$). We again emphasize that this does not prove robustness to all cardinalizations or even those with no more than this level of skewness. We only explore cardinalizations from a restrictive class of distributions and other plausible distributions might reverse the result. On the other hand, we do not find it difficult to believe that under a broad range of cardinalizations average happiness would be lower among the disabled.

Table A-6: Estimated Means and Variances of Life Satisfaction under Normality

	Disabled (1)	Non-Disabled (2)
Normal Mean	3.453	4.409
Normal Variance	6.646	5.288
Required c	1.409	

Notes - Estimated means and variances assuming normal distribution. "Requred c" is the parameter of log-normal transformation that would reverse ordering of means given by normal distribution.
Source - British Household Panel Survey, 1996-2008.

The above analysis assumed that disability has no impact on the scale on which individuals report their happiness. As discussed above, an alternative theory to the widely cited adaptation literature is that individuals adapt their reporting function. Once disabled, they lower their thresholds for reporting the highest levels of life satisfaction. Because the BHPS measures life satisfaction on a 7-point scale, we can again test, under the maintained normal cardinalization, whether the disabled and the non-disabled use the same reporting function. A likelihood ratio test generates a $\chi^2_4 = 23$, and thus we can reject equal reporting functions at any conventional level of significance.

In Table A-7, we report the estimated cutoff values for the latent life satisfaction variable for reporting in the 7 different categories. The first two cutoff values are normalized to be 0 and 1. We see strong evidence that disabled individuals have lower standards for reporting satisfaction with their life, particularly for the highest two cutoffs. This suggests that applying the standard normality assumption will first lead us to underestimate the negative effects of disability on happiness, and second to overestimate adaptation to disability. At least some 'adaptation' comes from changes in the reporting function rather than the true level of happiness.

Table A-7: Estimated Cutpoints under Normality

	Disabled (1)	Not Disabled (2)
1 to 2	0	0
2 to 3	1	1
3 to 4	2.23	2.19
4 to 5	3.44	3.61
5 to 6	4.93	5.50
6 to 7	6.74	7.73

Source - British Household Panel Survey, 1996-2008.

A.4 Closing Remarks

This appendix demonstrates clearly the empirical problems of the happiness literature. In not a single case could we draw any conclusions from the data without a parametric assumption. In no case did following the literature and assuming a normal distribution lead to a robust conclusion. Even if we were to restrict ourselves to distributions in the log-normal family that are no more skewed than the U.S. wealth distribution, we would find alternative cardinalizations that reverse or eliminate nearly all the major results in the happiness literature. The sole exceptions are that the disabled are less happy than those who are not disabled and that married women are happier than unmarried women, but even here, we remind the reader that we have not ruled out the possibility of transformations outside the lognormal that would be less skewed. In every case where we could test for reporting-function equality across groups, we rejected this assumption.

We note that our exercises take nothing away from studies addressing similar questions using objective data. While we cannot rule out that MTO had no impact on the average happiness of voucher recipients, we still know from Ludwig et. al (2013) that it reduced the prevalence of diabetes among adults and mental health problems among young girls. Likewise, while the pattern of a 'U-shaped' relation between age and happiness depends heavily on the cardinalization choice of the researcher, we know that anti-depressant usage peaks at mid-life across 27 European nations (Blanchflower and Oswald 2016) , and that the age distribution of admittance to psychiatric hospitals is 'hump-shaped' (Le Bon and Le Bon 2014).

This presents the possibility that one could use objective measures to calibrate cardinalizations of happiness, as Bond and Lang (forthcoming) do with test scores. However, this would not address the fundamental problems associated with the use of discrete categories. Moreover, it is unclear why using the subjective well-being data would be better than using objective data if these objective outcomes are what we care about.

B Online Technical Appendix

B.1 Rank Order Identification

In the main text, we focused on the intuition behind rank order identification. We provide a formal definition below.

Denote H_i as an individual's happiness, and the cdf of happiness for group k as F_k. Suppose we observe subjective categorical happiness responses in three categories $S = \{0, 1, 2\}$, and that individuals follow a common reporting function. We can then express S_i as

$$S_i = 1[H_i > H^1] + 1[H_i > H^2] \tag{11}$$

where $1[\cdot]$ is a function which equals 1 whenever the argument is true, H^1 is the minimum level of happiness required to report in category 1, and similarly H^2 for category 2.

Following the notation of Manski (1988), let Φ be the set of all probability distributions, and $\Omega_k \subseteq \Phi$ be the set of all probability distributions that satisfy any *a* *priori* restrictions placed on group $k's$ happiness distribution. Denote

$$P_0 = \int_{-\infty}^{H^1} dF_k \tag{12}$$

$$P_1 = \int_{H^1}^{H^2} dF_k \tag{13}$$

F_k is identified relative to G_k if $G_k \notin \Omega_k$, $\int_{-\infty}^{H^1} dG_k \neq P_0$, or $\int_{H^1}^{H^2} dG_k \neq P_1$. Define $\tilde{\Omega}_k \subseteq \Omega_k$ as the set of all distributions from which F_k is not identified. That is, every $\tilde{\Omega}_k$ describes the data equally well.

Definition 1 *The mean happiness of group A and group B is said to be rank order identified if* $\forall G_A \in \tilde{\Omega}_A, G_B \in \tilde{\Omega}_B$, *either* $G_A(H_i) \geq G_B(H_i) \forall i$ *or* $G_B(H_i) \geq G_A(H_i) \forall i$.

In other words, the rank order is identified only if every distribution from which F_A is not separately identified first order stochastically dominates every distribution from which F_B is not separately identified, or vice versa.

B.2 Conditions for Non-Parametric Identification using Variation in Observables

Suppose we have a vector of observable determinants of happiness X that provide additional information about the happiness distribution. We can partition i's latent happiness

$$h_i^* = \psi(X_i) + u_i \tag{14}$$

into an observable component X_i with distribution F_k^X in group k, and an additively separable but unobservable component u_i with distribution F_k^u. The function ψ transforms the observable components from their reported scale (e.g. dollars of income) to happiness as measured by the chosen cardinalization. Normalizing $H^1 = 0$ and $H^2 = 1$, and assuming ψ does not vary across groups, the ordered response problem then becomes

$$S_i = 1[\psi(X_i) + u_i > 0] + 1[\psi(X_i) + u_i > 1] \tag{15}$$

with the obvious extension to the case of more than three categories.

Manski (1988) shows for a binary response, and Cameron and Heckman (1998) extends to a general ordered response model, that ψ, F^u, and F^h are nonparametrically identified provided

1. F^h is absolutely continuous with density $f(u)$ almost everywhere in the support of $u = (L, U)$ where L and U can be $-\infty$ or ∞, respectively.

2. u is stochastically independent of X and F^u is not a function of X.

3. The support of u is contained in the support of $\psi(X)$. X lives in a subset of $\mathbb{R}^{N_X}$ where N_X is the dimension of the X regressors. There exists no proper linear subspace of $\mathbb{R}^{N_X}$ having probability 1 under F^X.

4. $\psi(X)$ is a member of a class of functions listed in Matzkin (1992). The simplest case of which is $\psi(X) = X\beta$.

Conditions 1 and 2 are provided in Cameron and Heckman (1998, Theorem 1), while 3 and 4 are slightly weaker conditions relative to the analogous conditions in Cameron and Heckman provided by Carneiro, Hansen, and Heckman (2003, Theorem 1) and Cunha, Heckman, and Navarro (2007, Theorem 2).[26]

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