The Sad Truth About Happiness Scales

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- Can (almost) never rank two groups with respect to mean happiness without strong additional assumptions
  - Even assuming everyone has the same reporting function
- Applications to:
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  - Changes in male/female happiness
  - Easterlin paradox
- Suggest some partial solutions

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- **Key point: Stochastic Dominance in Categories $\nrightarrow$ Rankable Means**

Example with Normality

Example 1

	Group A	Group B
Very happy	20	15
Pretty happy	25	30
Not too happy	55	55

- Group A happier if we impose common variance (would be rejected with reasonable sample size)
- With different variances/same cutoffs
  - Mean for group A $= -.18$
  - Mean for group B $= -.14$

A More Extreme Example

Example 2

	Group A	Group B
Very happy	45	0
Pretty happy	0	45
Not too happy	55	55

- Mean for group A $= -\infty$
- Mean for group B $= 0$

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- Then mean and variance of distribution are identified
- Seems to imply ranking of mean happiness/utility

An Example with the "Right" Ranking

Logistic Distribution

Example 3

	Group A	Group B
Very happy	.20	.28
Pretty happy	.60	.53
Not too happy	.20	.19

- Mean for group A = .50; Spread parameter=.36
- Mean for group B = .61; Spread parameter=.42
- CDFs cross at 14th percentile.

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- Note:two assumptions above sufficient, not necessary

MTO

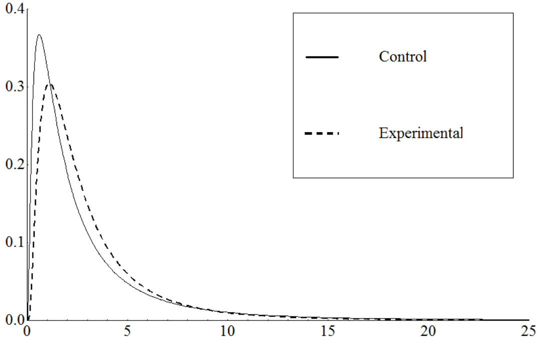
Table: Distribution of Happiness - Moving to Opportunities

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

Source: Ludwig et al (2013), Appendix Table 7.

Experimental estimates are TOT.

MTO Log-Normal Happiness Distribution with Equal Means



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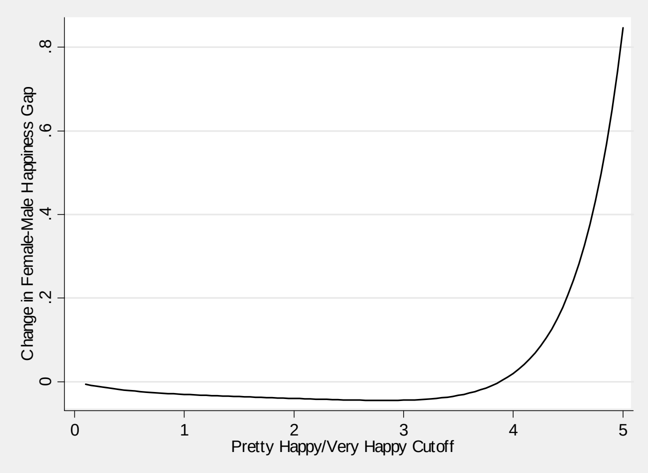
- Beneficial results for psychological well-being are unchanged conditional on accepting medical scales

Female-Male Happiness Gap

Table: Distribution of Happiness - General Social Survey

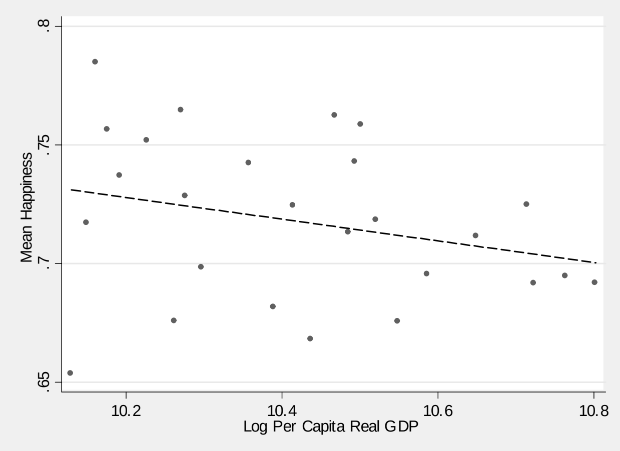
	Male	Female
Panel A: 1972-1976		
Very Happy	0.337	0.384
Pretty Happy	0.530	0.493
Not Too Happy	0.132	0.122
Normal Mean	0.727	0.798
Normal Variance	0.424	0.471
Panel B: 1998-2006		
Very Happy	0.330	0.339
Pretty Happy	0.566	0.553
Not Too Happy	0.104	0.109
Normal Mean	0.742	0.748
Normal Variance	0.346	0.367

Gap Change for Different Degrees of Skewness



Easterlin Paradox: United States

Assuming Normality



Variance: United States

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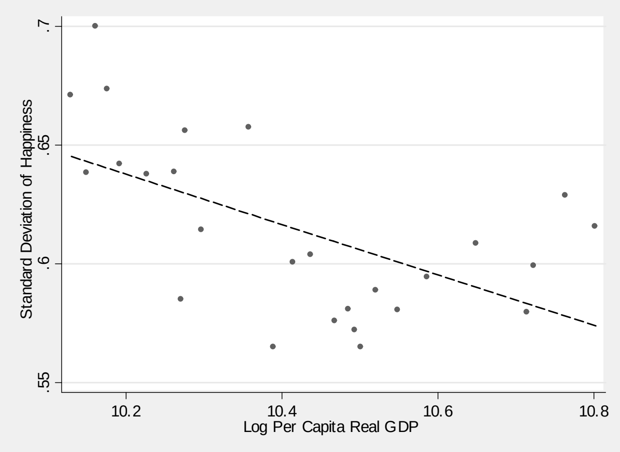
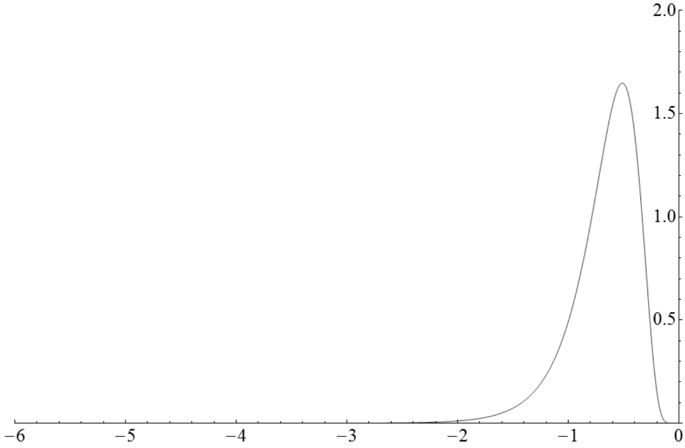


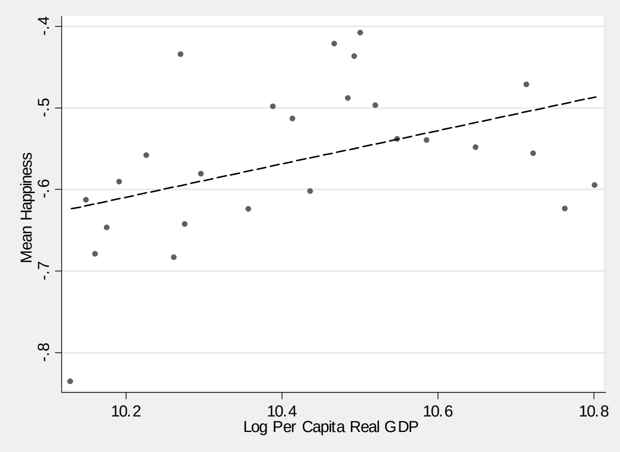
Eliminating Easterlin Paradox: United States

Assuming Left-Skewed LogNormality (C=.7)



Reversing the Easterlin Paradox: United States

Assuming Left-Skewed LogNormality (c=2.6)



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- Rank-correlation between log-normal transformations with $C = 2$ and $C = -2$ is .156.

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  - Tolstoy assumption