Anchoring Vignettes for Interpersonally Incomparable Survey Responses

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Readings

- Gary King and Jonathan Wand. "Comparing Incomparable Survey Responses: Evaluating and Selecting Anchoring Vignettes," *Political Analysis*, 15, 1 (Winter, 2007): 46–66.

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- Gary King; Christopher J.L. Murray; Joshua A. Salomon; and Ajay Tandon. "Enhancing the Validity and Cross-cultural Comparability of Measurement in Survey Research," *American Political Science Review*, Vol. 98, No. 1 (February, 2004): 191–207.

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- Papers, FAQ, examples, software, conferences, videos: http://GKing.Harvard.edu/vign

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    - Amartya Sen (2002): "The state of Kerala has the highest levels of literacy. . . and longevity. . . in India. But it also has, by a very wide margin, the highest rate of reported morbidity among all Indian states. . . . At the other extreme, states with low longevity, with woeful medical and educational facilities, such as Bihar, have the lowest rates of reported morbidity in India."

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   - Brady (1985): "Individuals understand the 'same' questions in vastly different ways."

Anchoring Vignettes & Self-Assessments: Political Efficacy (about voting)

How much say [does 'name' / do you] have in getting the government to address issues that interest [him / her / you]?

(a) Unlimited say, (b) A lot of say, (c) Some say, (d) Little say, (e) No say at all

Anchoring Vignettes & Self-Assessments: Political Efficacy (about voting)

- "[Alison] lacks clean drinking water. She and her neighbors are supporting an opposition candidate in the forthcoming elections that has promised to address the issue. It appears that so many people in her area feel the same way that the opposition candidate will defeat the incumbent representative."

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- "[Jane] lacks clean drinking water because the government is pursuing an industrial development plan. In the campaign for an upcoming election, an opposition party has promised to address the issue, but she feels it would be futile to vote for the opposition since the government is certain to win."
- "[Moses] lacks clean drinking water. He would like to change this, but he can't vote, and feels that no one in the government cares about this issue. So he suffers in silence, hoping something will be done in the future."

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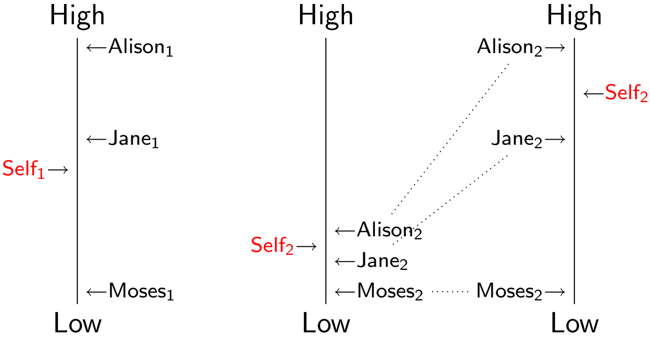
Does R_1 or R_2 have More Political Efficacy?



- The only reason for vignette assessments to change over respondents is DIF
- Assumption holds because investigator creates the anchors (Alison, Jane, Moses)
- Our simple (nonparametric) method works this way.

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$$C_i = \begin{cases} 1 & \text{if } y_i < z_{i1} \\ 2 & \text{if } y_i = z_{i1} \\ 3 & \text{if } z_{i1} < y_i < z_{i2} \\ \vdots & \vdots \\ 2J+1 & \text{if } y_i > z_{iJ} \end{cases}$$

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- Requires vignettes and self-assessments asked of all respondents
- (Our parametric method doesn't)

Comparing China and Mexico

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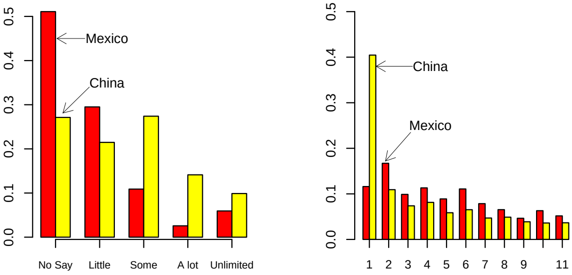
Mexico

Opposition leader Vicente Fox elected President.
71-year rule of PRI party ends.
Peaceful transition of power begins.

Plenty of political efficacy

China: How much say do you have in getting the government to address issues that interest you?

Nonparametric Estimates of Political Efficacy



- The left graph is a histogram of the observed categorical self-assessments.
- The right graph is a histogram of C, our nonparametric DIF-corrected estimate of the same distribution.

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   (c) The scale being tapped is perceived as unidimensional.
3. In other words: we allow response-category DIF but assume stem question equivalence.

Ties and Inconsistencies Produce *Ranges*

Example	Survey Responses	1: $y < z_1$	2: $y = z_1$	3: $z_1 < y < z_2$	4: $y = z_2$	5: $y > z_2$	C

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12	$z_2 < y = z_1$		T			T	{2,3,4,5}
13	$z_2 < z_1 < y$					T	{5}

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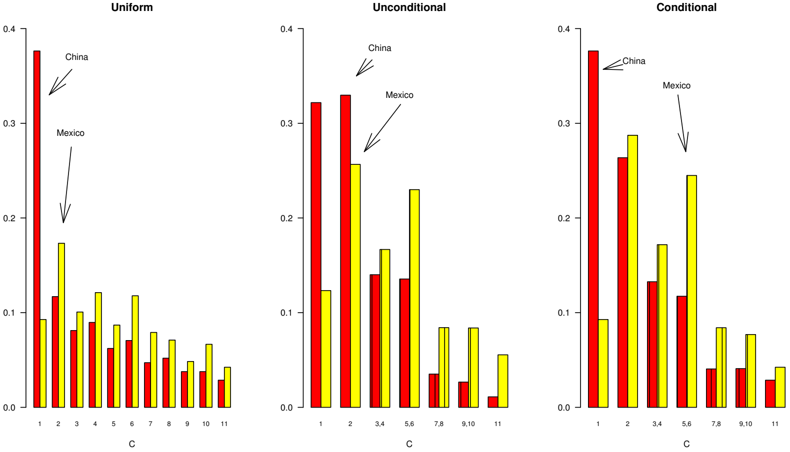
Improved Efficiency in Practice



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    - More formally: $H(p_1, p_2, p_3, p_4, p_5) = H(p_1, p_2, q) + qH(p_3, p_4, p_5)$

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- Only question remaining: How do we calculate entropy when C is vector valued, and thus the p's are unknown?

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- Thus, we also want "known entropy".

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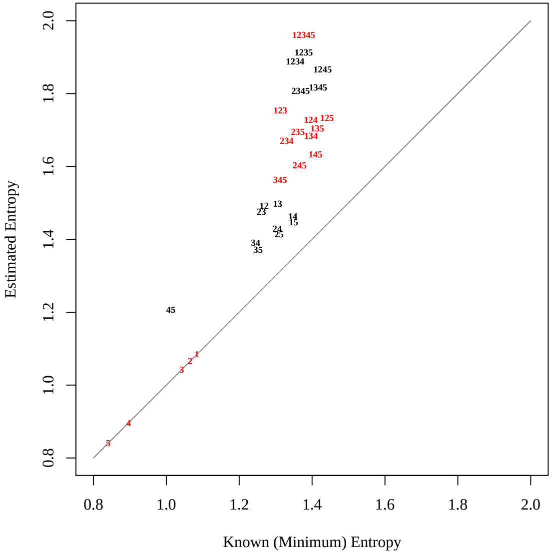
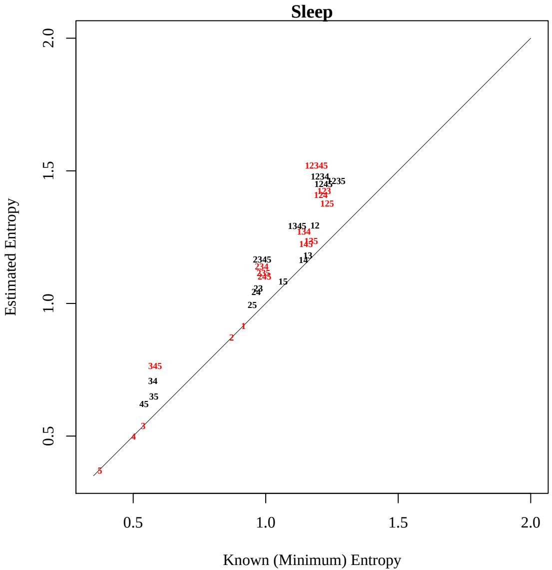
We now compute *estimated entropy* and *known entropy* for all possible subsets of vignettes.

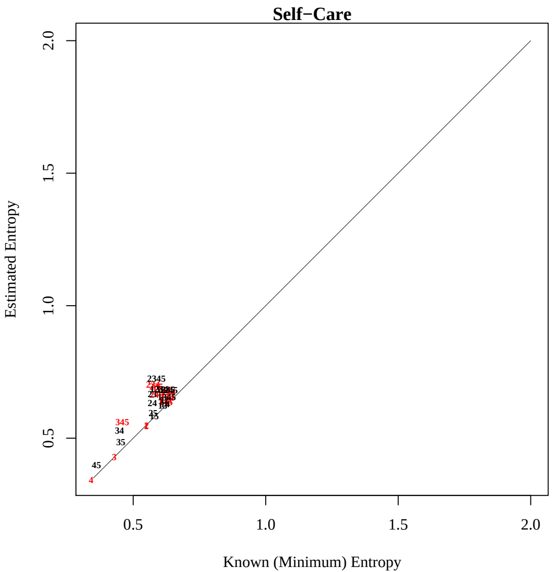
Political Efficacy (Mex & China)



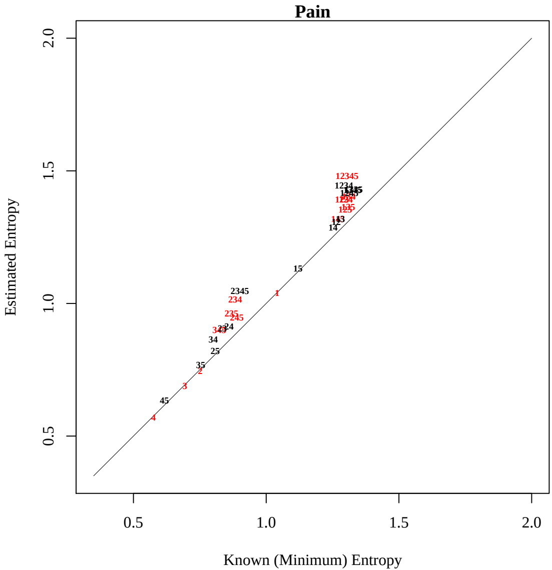
One vignette can be better than three: Sleep (China)



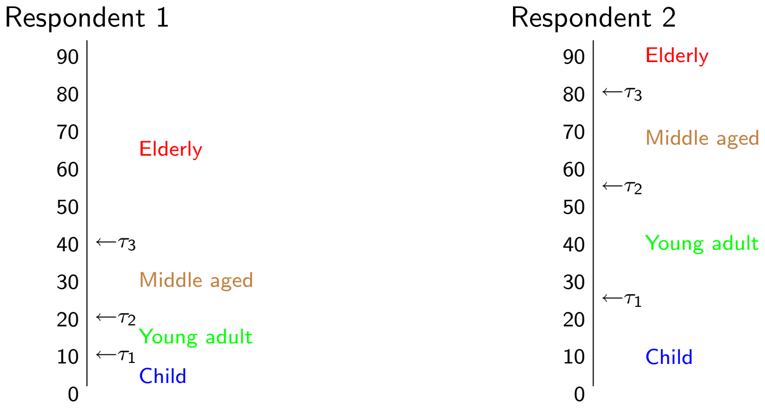
Some vignette sets are uninformative: Self-Care (China)



Some covariates are unhelpful: Pain (China)



Categorizing Years of Age



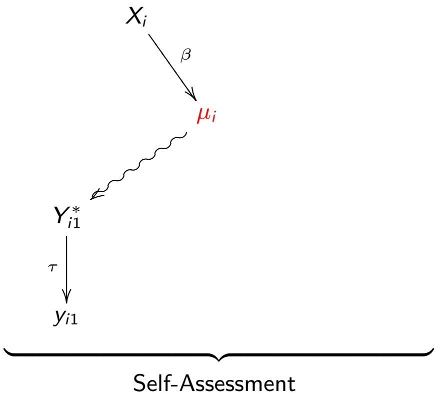
- If thresholds vary, categorical answers are meaningless.
- Our parametric model works by estimating the thresholds.
- Vignettes provide identifying information for the τ's.

Model Summary

Actual:

Perceived:

Reported:



An ordinal probit model.

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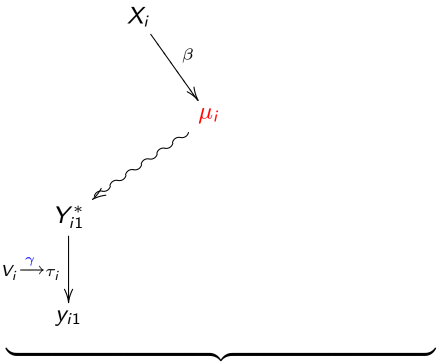
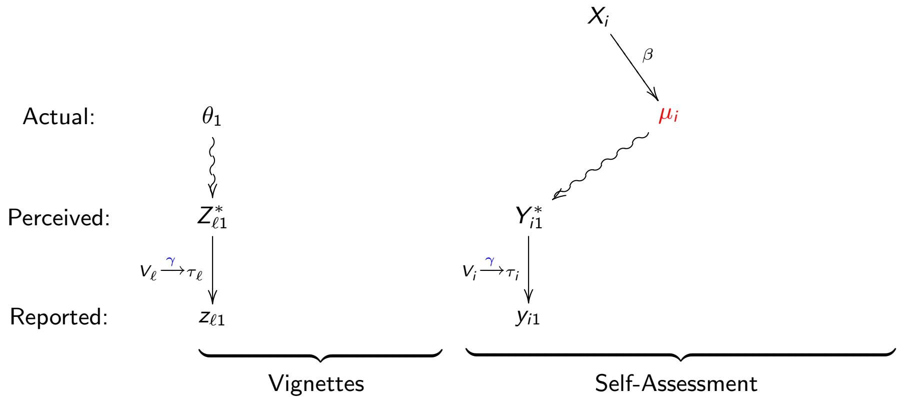


Self-Assessment

An ordinal probit model.
with varying thresholds,

Model Summary



An ordinal probit model.
with varying thresholds,
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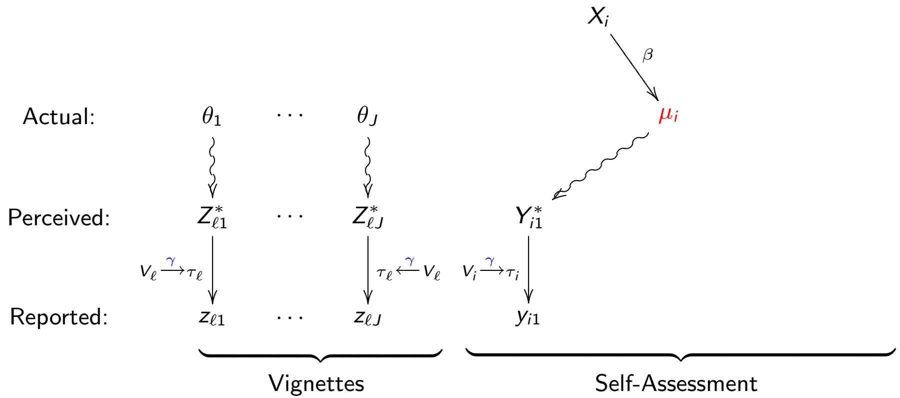
Model Summary



An ordinal probit model.
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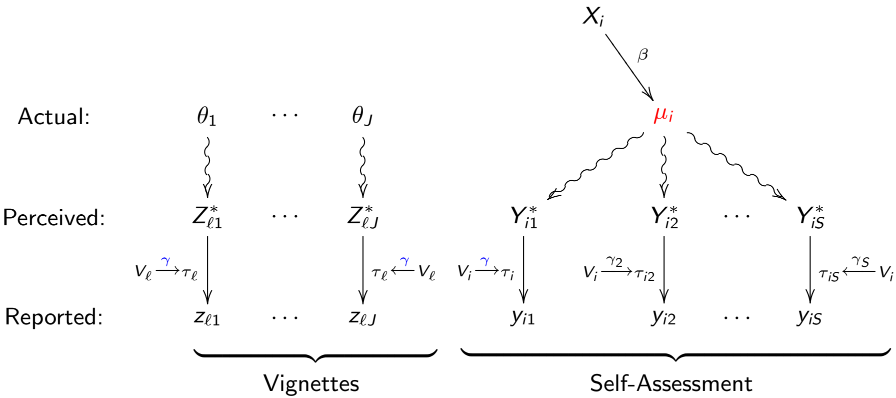
more vignettes for better discrimination,

Model Summary



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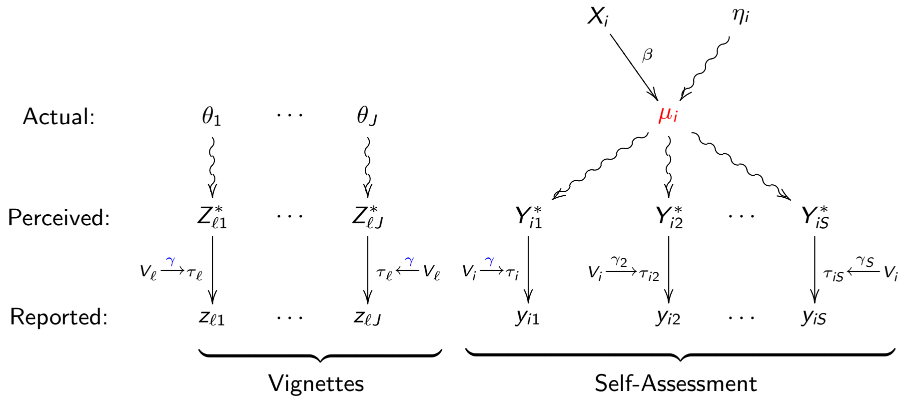
Model Summary



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optional multiple self-assessment questions,
and an optional random effect.

Self-Assessments v. Medical Tests

Self-Assessment:
In the last 30 days, how much difficulty did [you/name] have in seeing and recognizing a person you know across the road (i.e. from a distance of about 20 meters)?

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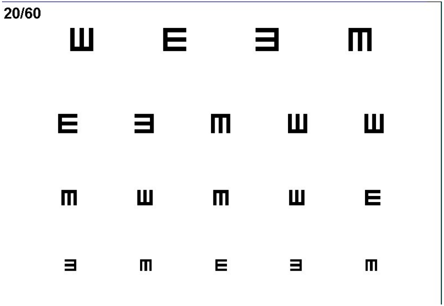
The Snellen Eye Chart Test:



Fixing DIF in Self-Assessments of Visual (Non)acuity

	Snellen Eye Chart		Ordinal Probit		Chopit	
	Mean	(s.e.)	μ	(s.e.)	μ	(s.e.)
Slovakia	8.006	(.272)	.660	(.127)	.286	(.129)
China	10.780	(.148)	.673	(.073)	.749	(.081)
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- The medical test shows Slovakians see much better than the Chinese
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- Chopit reproduces the same result as the medical test (though on different scale)

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For More Information

http://GKing.Harvard.edu/vign

Includes:

- Academic papers
- Anchoring vignette examples by researchers in many fields,
- Frequently asked questions,
- Videos
- Conferences
- Statistical software

Anchoring Vignettes Measure DIF, not Vision: A Heuristic

Define μ as the quantity of interest; D as DIF.

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    - Since the same person generates both D_s and D_v, (b) will usually be smaller.
3. Conclusion: Anchoring vignettes will usually help reduce bias. They will sometimes not make a difference. They will almost never exacerbate bias.

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The Likelihood Function: Self-Assessment Component

If η_i were observed:

$$P(y_i|\eta_i) = \prod_{i=1}^{n}\prod_{s=1}^{S}\prod_{k=1}^{K_s}\left[F(\tau_{is}^{k}|X_i\beta+\eta_i,1) - F(\tau_{is}^{k-1}|X_i\beta+\eta_i,1)\right]^{\mathbf{1}(y_{is}=k)}$$

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In the special case where $S=1$, this simplifies to

$$L_s(\beta,\omega^2,\gamma|y) = \prod_{i=1}^{n}\prod_{k=1}^{K_1}\left[F(\tau_{i1}^{k}|X_i\beta,\,1+\omega^2) - F(\tau_{i1}^{k-1}|X_i\beta,\,1+\omega^2)\right]^{\mathbf{1}(y_{i1}=k)}$$

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The *vignette component* is a J-variate ordinal probit with varying thresholds:

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The *joint likelihood* shares parameter γ:

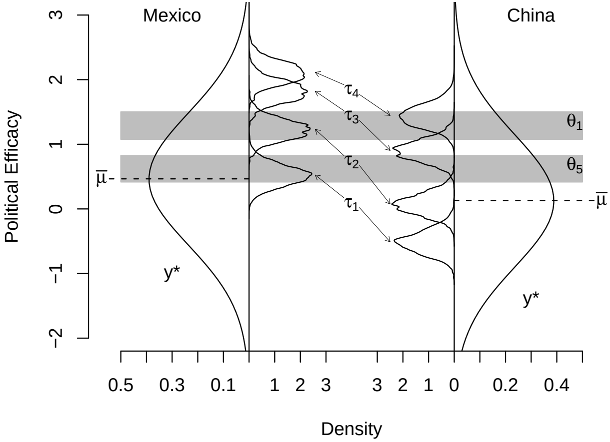
$$L(\beta, \sigma^2, \omega^2, \theta, \gamma|y, z) = L_s(\beta, \sigma^2, \omega^2, \gamma|y) \times L_v(\theta, \gamma|z).$$

and nests the ordinal probit model as a special case.

Fixing DIF in China and Mexico

		Ordinal Probit		Chopit	
Eqn.	Variable	Coeff.	(s.e.)	Coeff.	(s.e.)
μ	China	.670	(.081)	−.362	(.090)
	age	.004	(.003)	.006	(.003)
	male	.087	(.076)	.113	(.081)
	education	.020	(.008)	.019	(.008)
Vignettes	θ_1			1.393	(.190)
	θ_2			1.304	(.190)
	θ_3			.953	(.189)
	θ_4			.902	(.188)
	θ_5			.729	(.188)
	$\ln \sigma$			−.238	(.042)

The Source of DIF in China and Mexico: Threshold Variation



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   - E.g., we can use the mean, $X_c\hat{\beta}$ as a point estimate of the actual level when $X = X_c$.

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   - So the new method takes roughly the weighted average of the model prediction $\hat{\mu}_E$ and the observed y_E, with weights determined by the how good a prediction it is.

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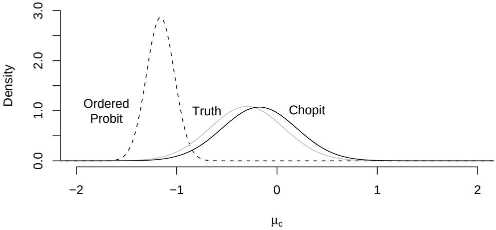
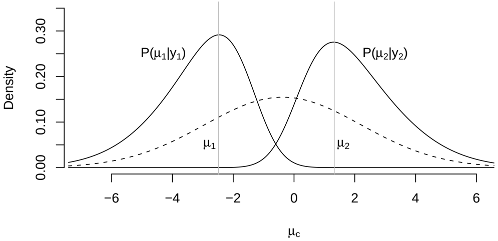
Key Difference:	$P(\mu_i\|y)$	works for out-of-sample prediction
	$P(\mu_i\|y, y_i)$	works better when y_i is available

Unconditional Posterior



Unconditional posterior for a hypothetical 65-year-old respondent in country 1, based on one simulated data set.

Conditional Posteriors



Conditional posteriors for two different 21 year old respondents. Person 1 gave responses (1,1) on the two self-evaluation questions; Person 2 gave responses (4,3). The unconditional posterior, drawn with a dashed line, gives less specific predictions. Each curve was computed from one simulated data set.