Correcting Measurement Error Bias in Conjoint Survey Experiments[1]

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Harvard Experiments Working Group, 2/9/2024

[1] Paper, software, slides, data: GaryKing.org/conjointE

[2] Based on work with Katherine Clayton, Yusaku Horiuchi, Aaron Kaufman, and Mayya Komisarchik

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- Evidence: 13+ surveys, 9,472 respondents, 137,785 questions

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Please carefully review the two potential candidates running for election to the U.S. House of Representatives, detailed below.

	Candidate 0	Candidate 1
Race/Ethnicity	Hispanic	Asian American
Age	52	60
Favorability rating among the public	70%	34%
Position on immigrants	Favors giving citizenship or guest worker status to undocumented immigrants	Opposes giving citizenship or guest worker status to undocumented immigrants
Party affiliation	Republican Party	Democratic Party
Position on abortion	Abortion is not a private matter (pro-life)	Abortion is a private matter (pro-choice)
Position on government deficit	Wants to reduce the deficit through tax increase	Wants to reduce the deficit through tax increase
Salient personal characteristics	Really cares about people like you	Really cares about people like you
Position on national security	Wants to cut military budget and keep the U.S. out of war	Wants to maintain strong defense and increase U.S. influence
Gender	Female	Female
Policy area of expertise	Education	Foreign policy
Family	Single (divorced)	Married (no child)
Experience in public office	12 years	4 years

If you had to choose between them, which of these candidates would you vote to be a member of the U.S. House of Representatives?

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  - Same: measurement error corrections

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- Casual effect: Average Marginal Component Effect (AMCE)

$$\theta(a_\ell, a'_\ell) = \rho(a_\ell) - \rho(a'_\ell).$$

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  2. Calculate: $\hat{\tau} = \dfrac{1-\sqrt{1-2(1-\text{IRR})}}{2}$
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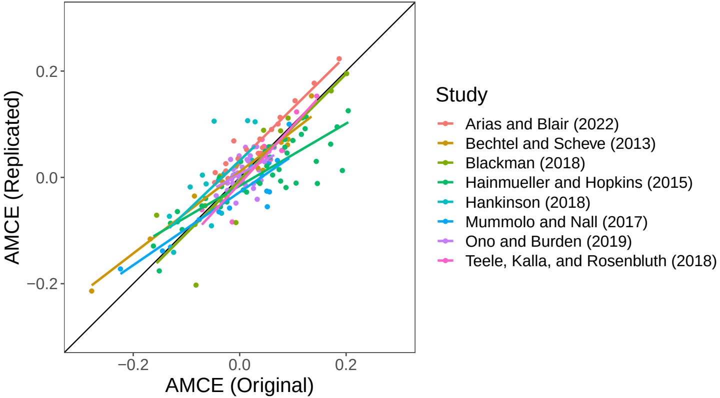

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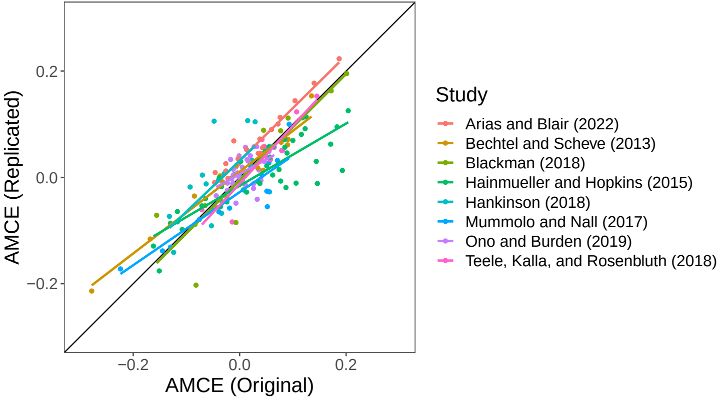

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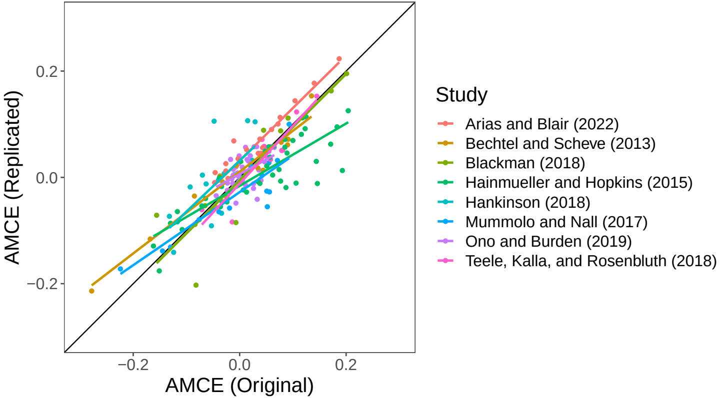

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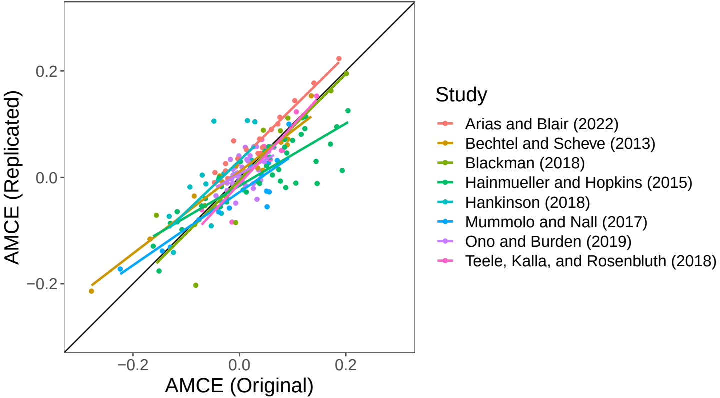

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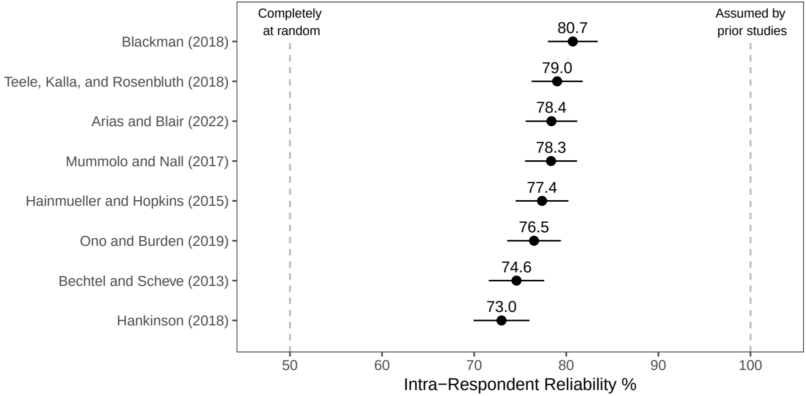

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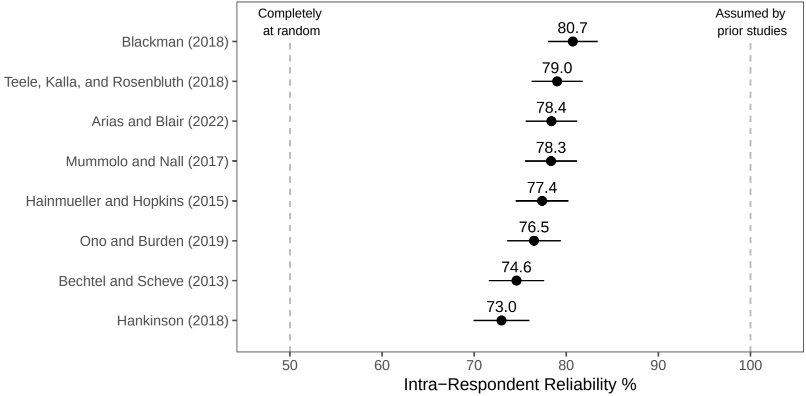

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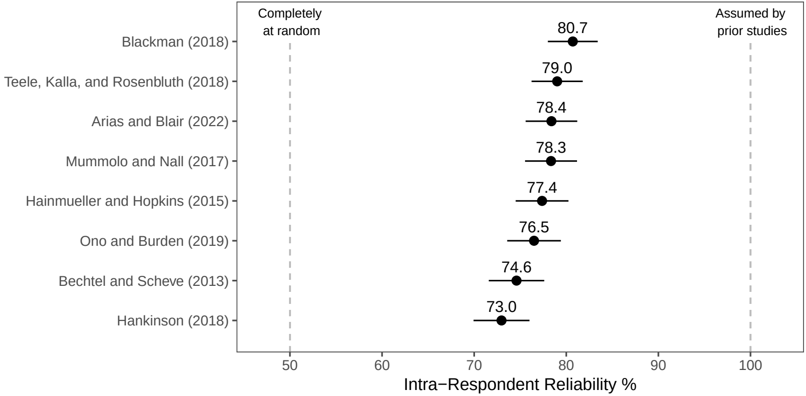

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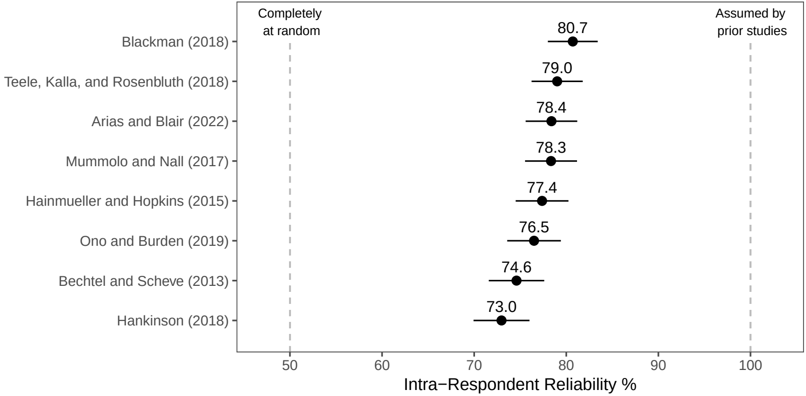

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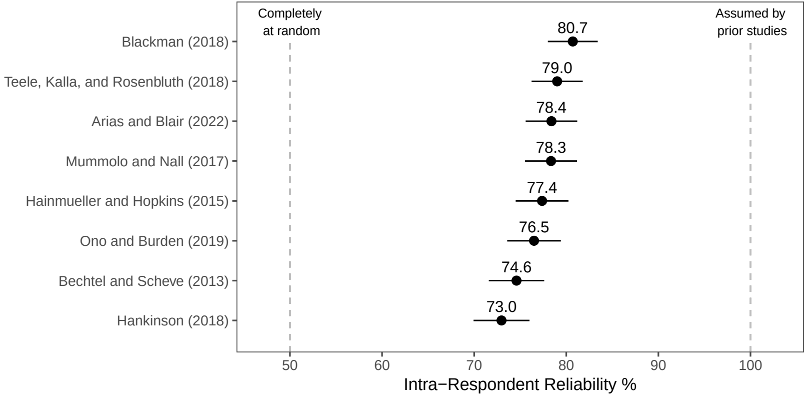

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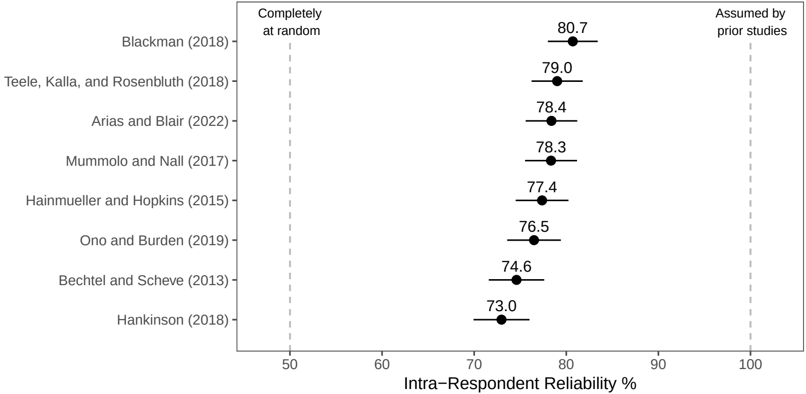

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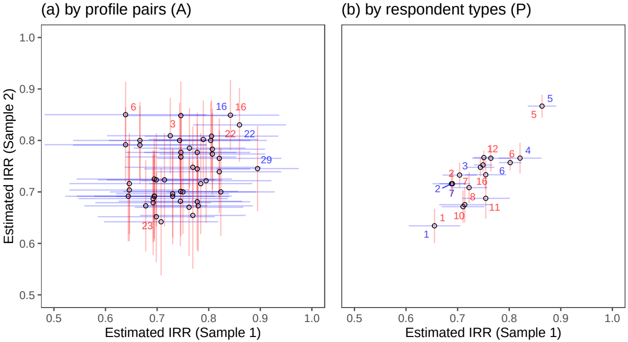

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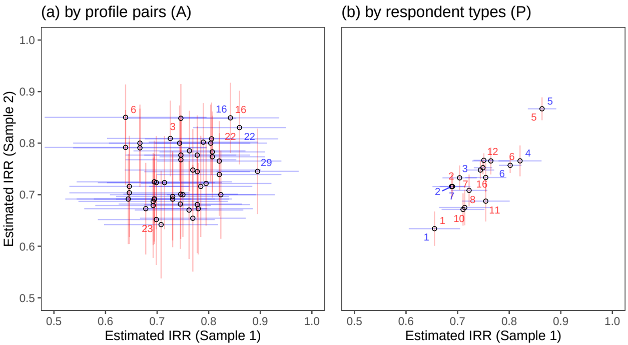

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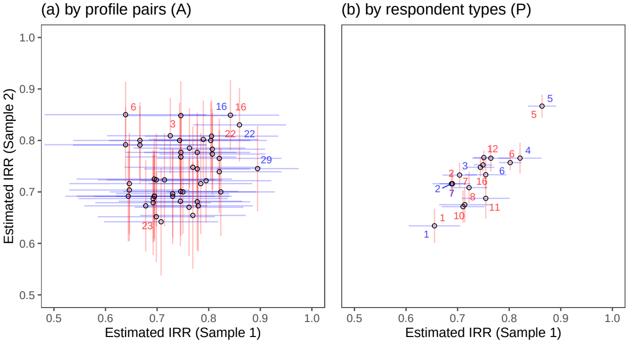

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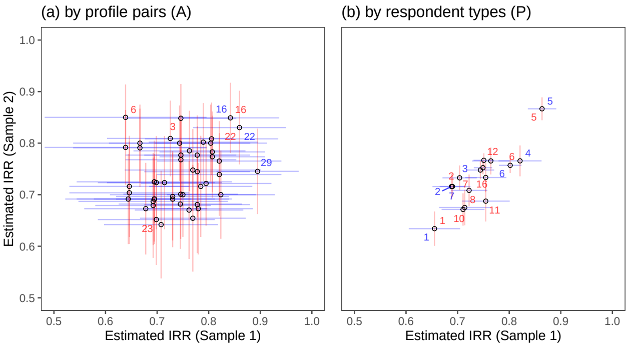

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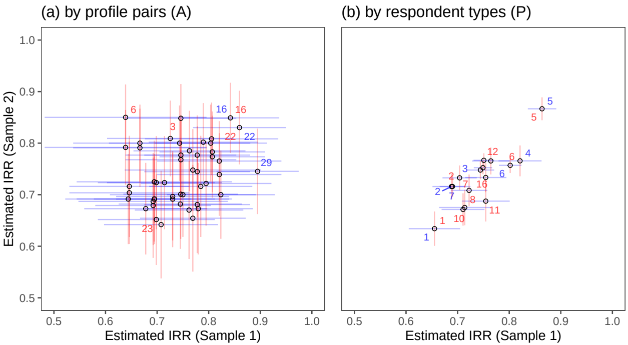

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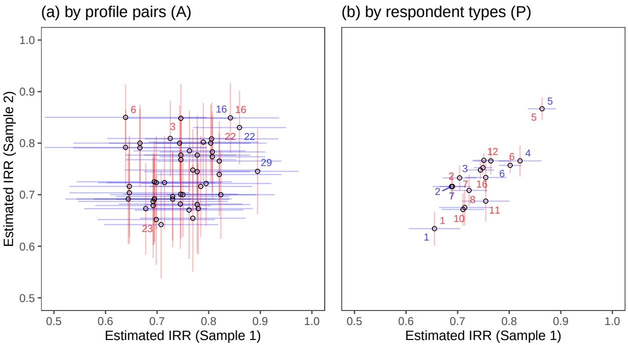

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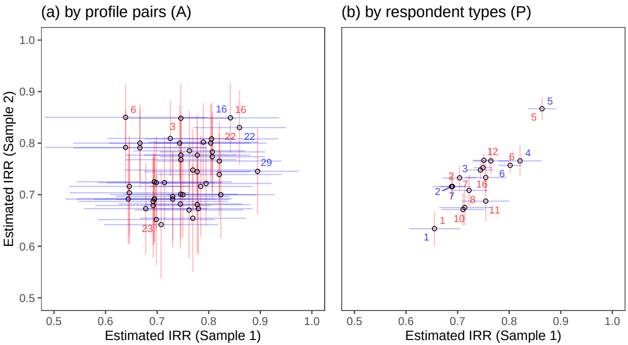

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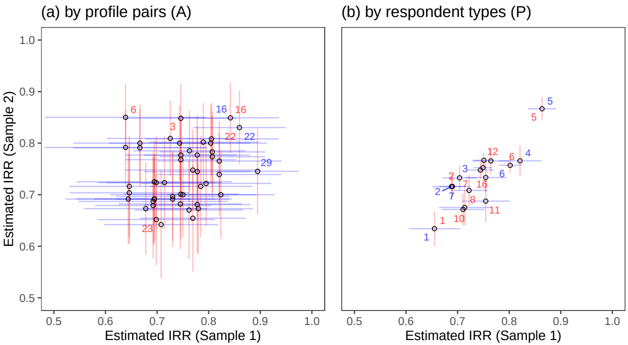

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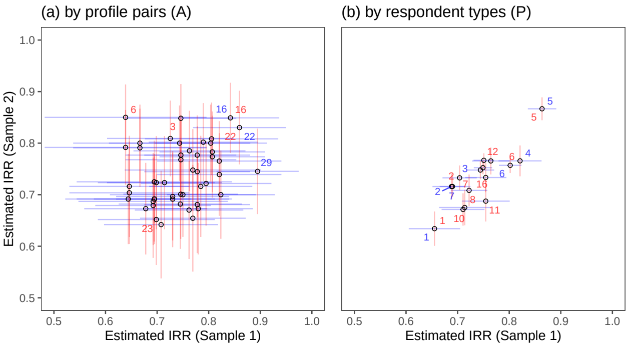

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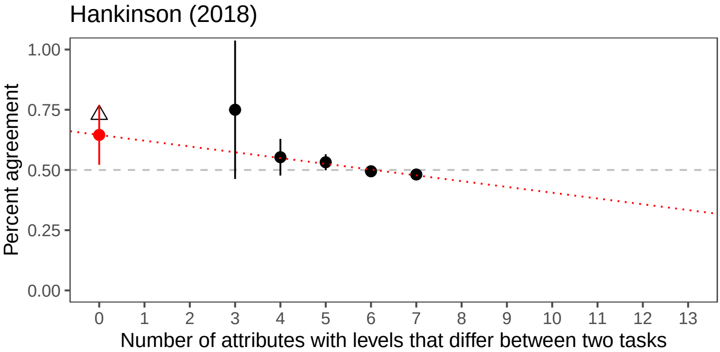

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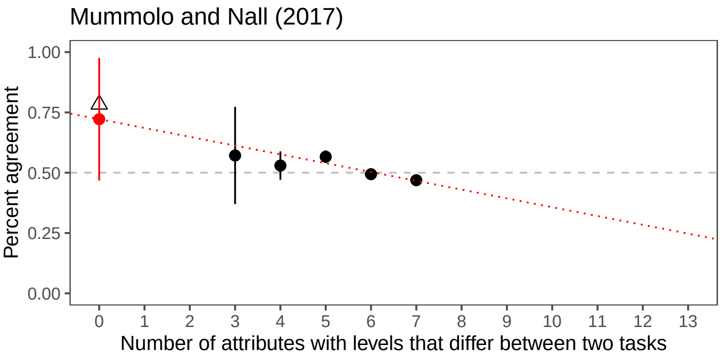

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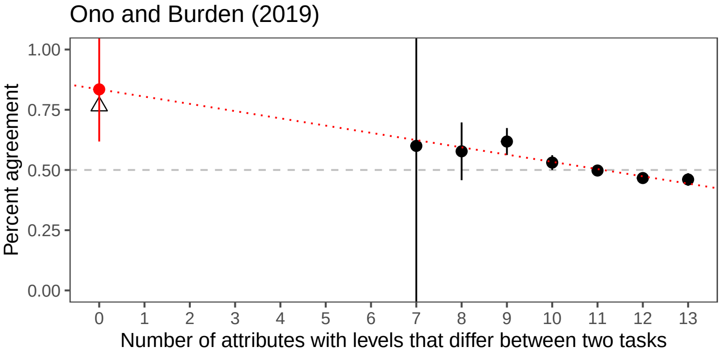

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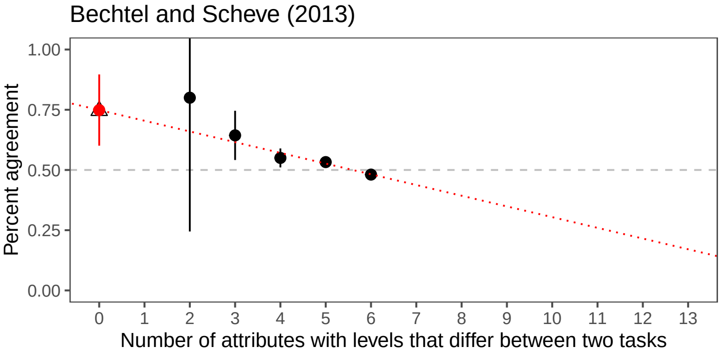

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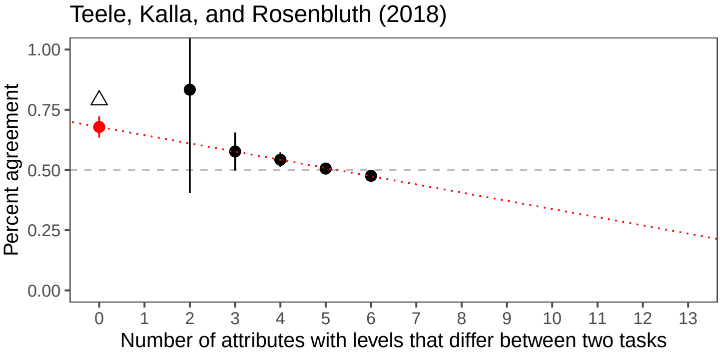

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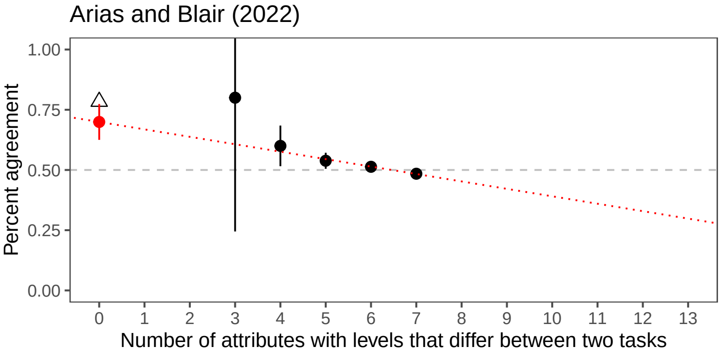

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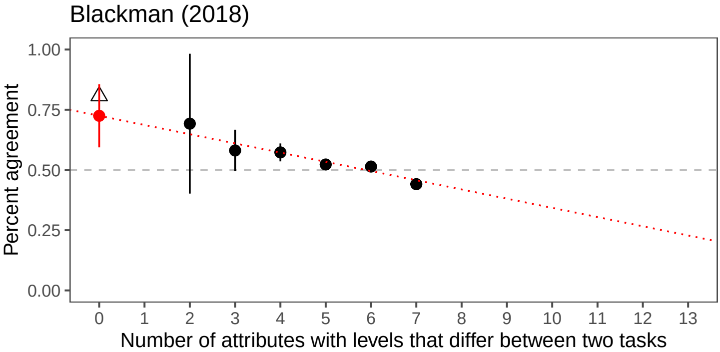

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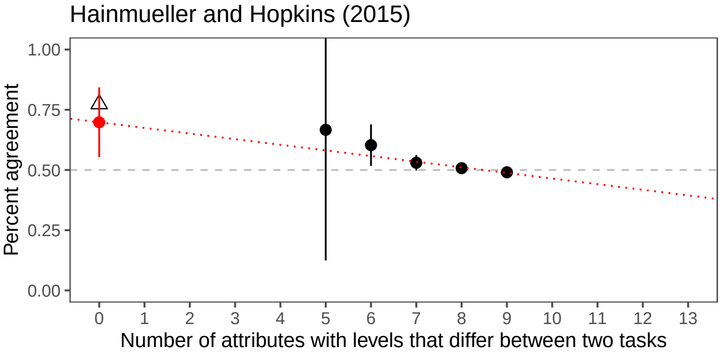

Reducing Bias and Mean Square Error

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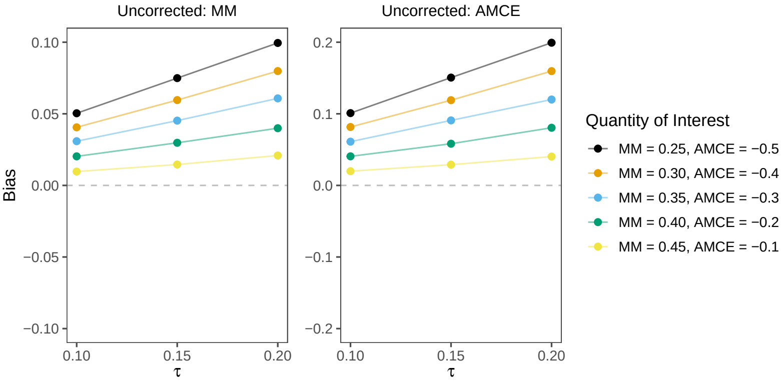

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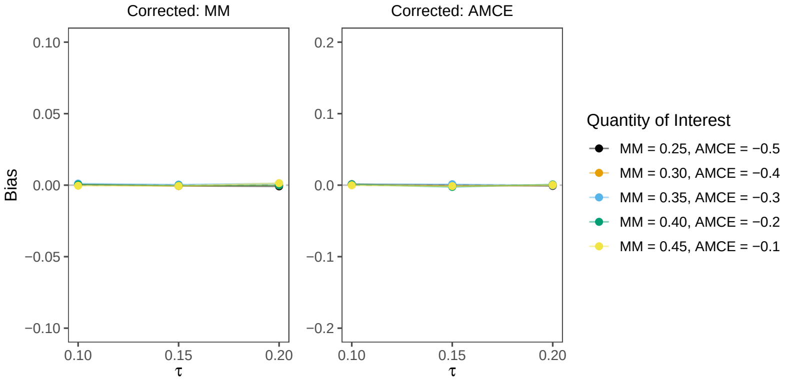

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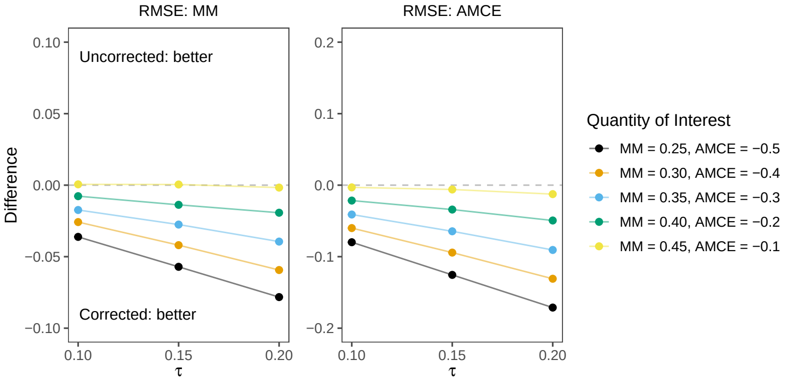
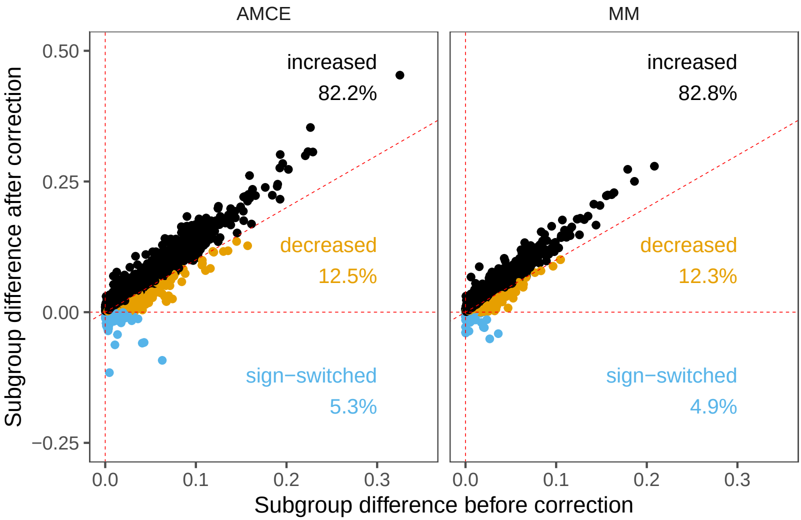


Consequences of Bias Correction in 8 Studies



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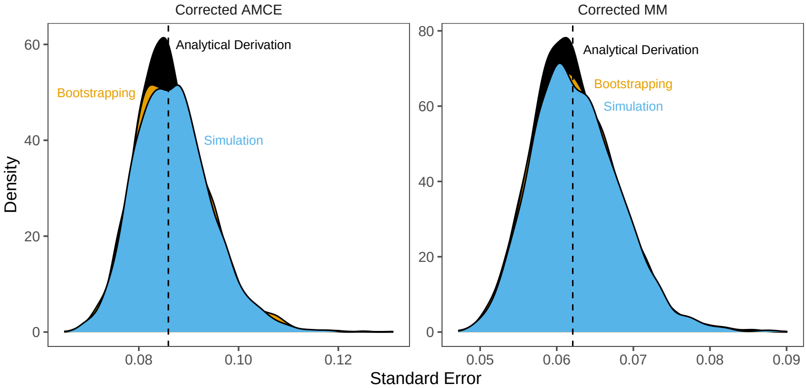

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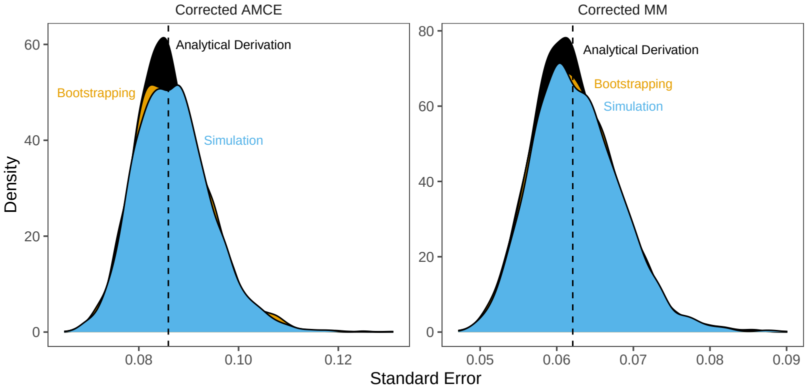

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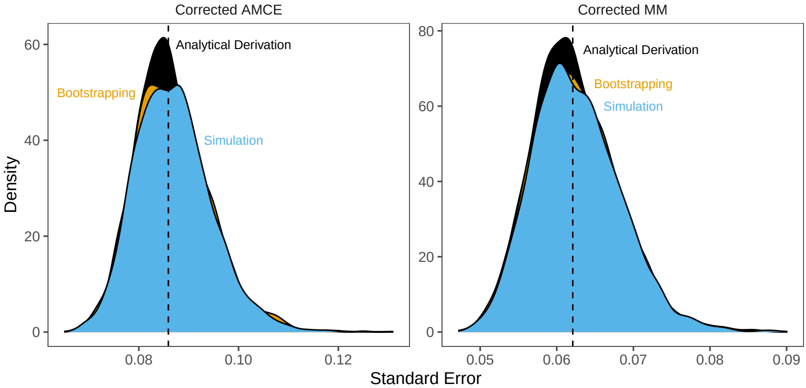

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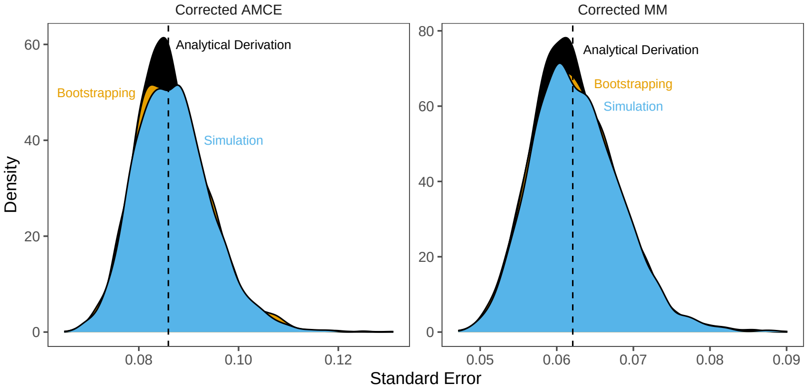

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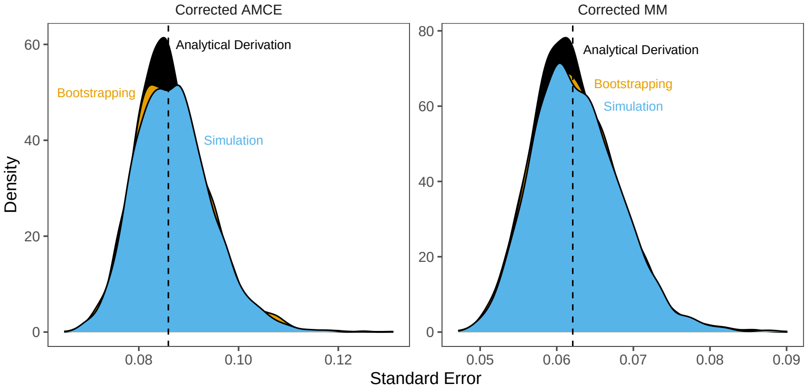

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- Our "Projoint" software: Implements them all

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