

Summary

- ◆ The descriptions of the certain option in the classic risky-choice framing effect are incomplete and mismatched in gains and losses.
- ◆ The certain and risky options can each be described completely or incompletely. Using different combinations of matched and mismatched descriptions can amplify, eliminate, or reverse the framing effect.¹⁻⁴
- ◆ Versions of the explicated valence account (EVA)^{2,4} and fuzzy-trace theory (FTT)¹⁻³ can account for these effects, but prospect theory cannot.
- ◆ However, a framing effect persists when option descriptions are matched in gains and losses, even when the certain and risky options are described completely.²

Background and Framework

Options in the Classic Disease Problem

Gain Frame	Certain Option	200 people will be saved.
	Risky Option	There is a 1/3 probability that 600 people will be saved and a 2/3 probability that no people will be saved.
Loss Frame	Certain Option	400 people will die.
	Risky Option	There is a 1/3 probability that no people will die and a 2/3 probability that 600 people will die.

- ◆ In principle, an option description can include only the good aspect (Valence = +1), only the bad aspect (Valence = -1), or both (Valence = 0). In our model, preference for the risky option is a function of $Valence(risky) - Valence(certain)$.² These valence differences are shown in cells G1–G9 and L1–L9 in the table below.
- ◆ In the classic problem, the risky option is complete in both frames (Valence = 0), but the certain option includes only the good aspect in gains (Valence = +1) and only the bad aspect in losses (Valence = -1), leading to the usual framing effect. This mismatched comparison corresponds to G4 vs. L6 in blue.
- ◆ Completing the certain option (e.g., 200 people will be saved and 400 people will not be saved in gains) yields a matched comparison (G5 vs. L5 in green) in which the framing effect is often eliminated.
- ◆ Other combinations can amplify (purple) or reverse (orange) the framing effect. Not all combinations have been studied.

Option Valences and Valence Differences in 18 Option Pairs

GAINS			
Risky Option	Certain Option		
	Good Aspect (+1)	Both Aspects (0)	Bad Aspect (-1)
Good Aspect (+1)	G1 (0)	G2 (+1)	G3 (+2)
Both Aspects (0)	G4 (-1) Std.	G5 (0)	G6 (+1)
Bad Aspect (-1)	G7 (-2)	G8 (-1)	G9 (0)
LOSSES			
Risky Option	Certain Option		
	Good (+1)	Both (0)	Bad (-1)
Good Aspect (+1)	L1 (0)	L2 (+1)	L3 (+2)
Both Aspects (0)	L4 (-1)	L5 (0)	L6 (+1) Std.
Bad Aspect (-1)	L7 (-2)	L8 (-1)	L9 (0)

In cells G1–G9 and L1–L9, higher numbers indicate stronger predicted preferences for the risky option.

Three Preregistered Studies

Method

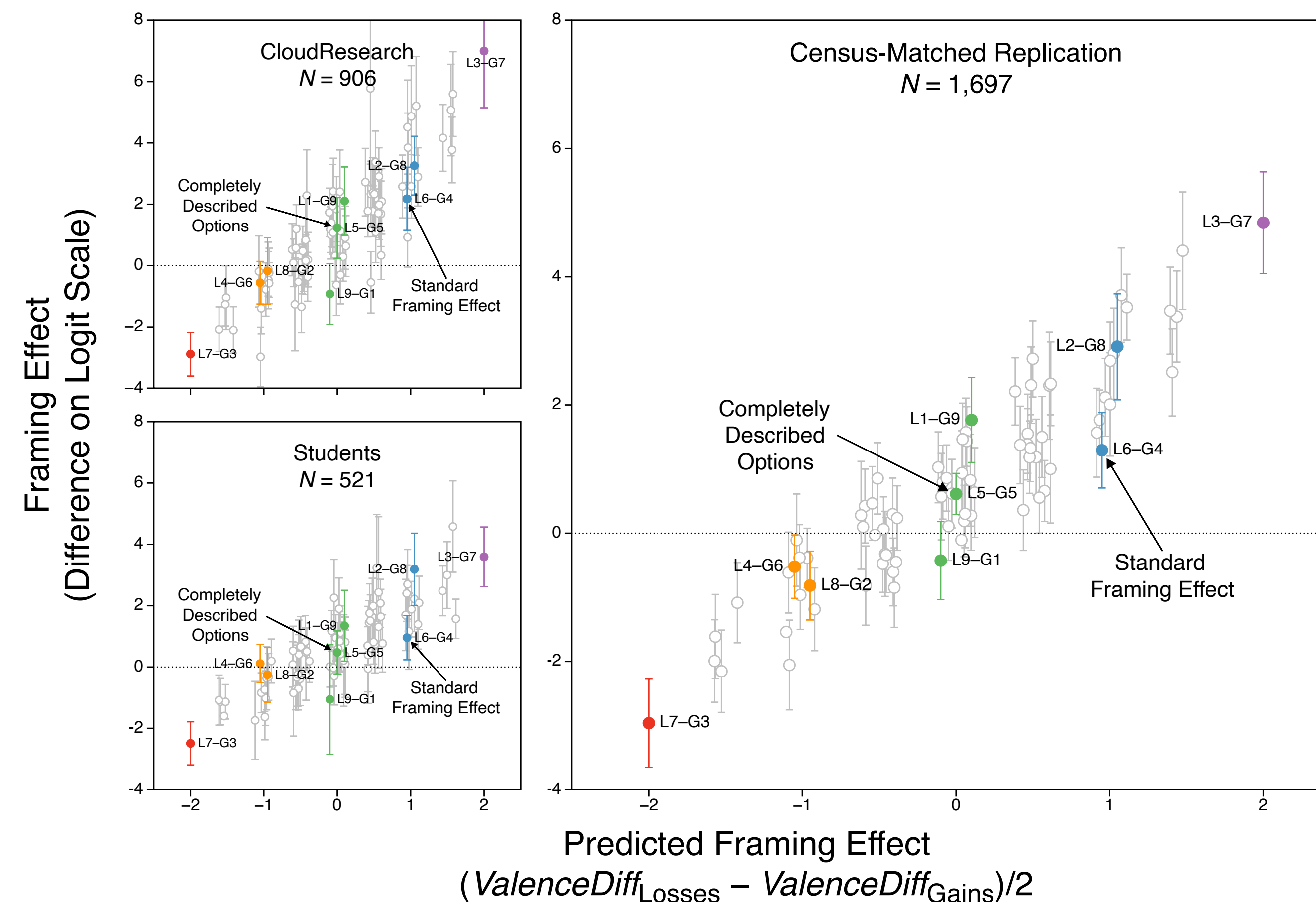
- ◆ Each participant made 4 choices (disease, drought, investment, and wildfire) in one of the 18 gain or loss cells (G1–G9, L1–L9).

Samples

- ◆ In DeKay and Dou (2024, *Psych. Sci.*)², we used CloudResearch ($N = 906$) and student ($N = 521$) samples. All N s are after exclusions.
- ◆ In a large replication ($N = 1,697$), we used CloudResearch Connect to match the sample to U.S. Census data on age, gender, race, ethnicity, region, and personal income.

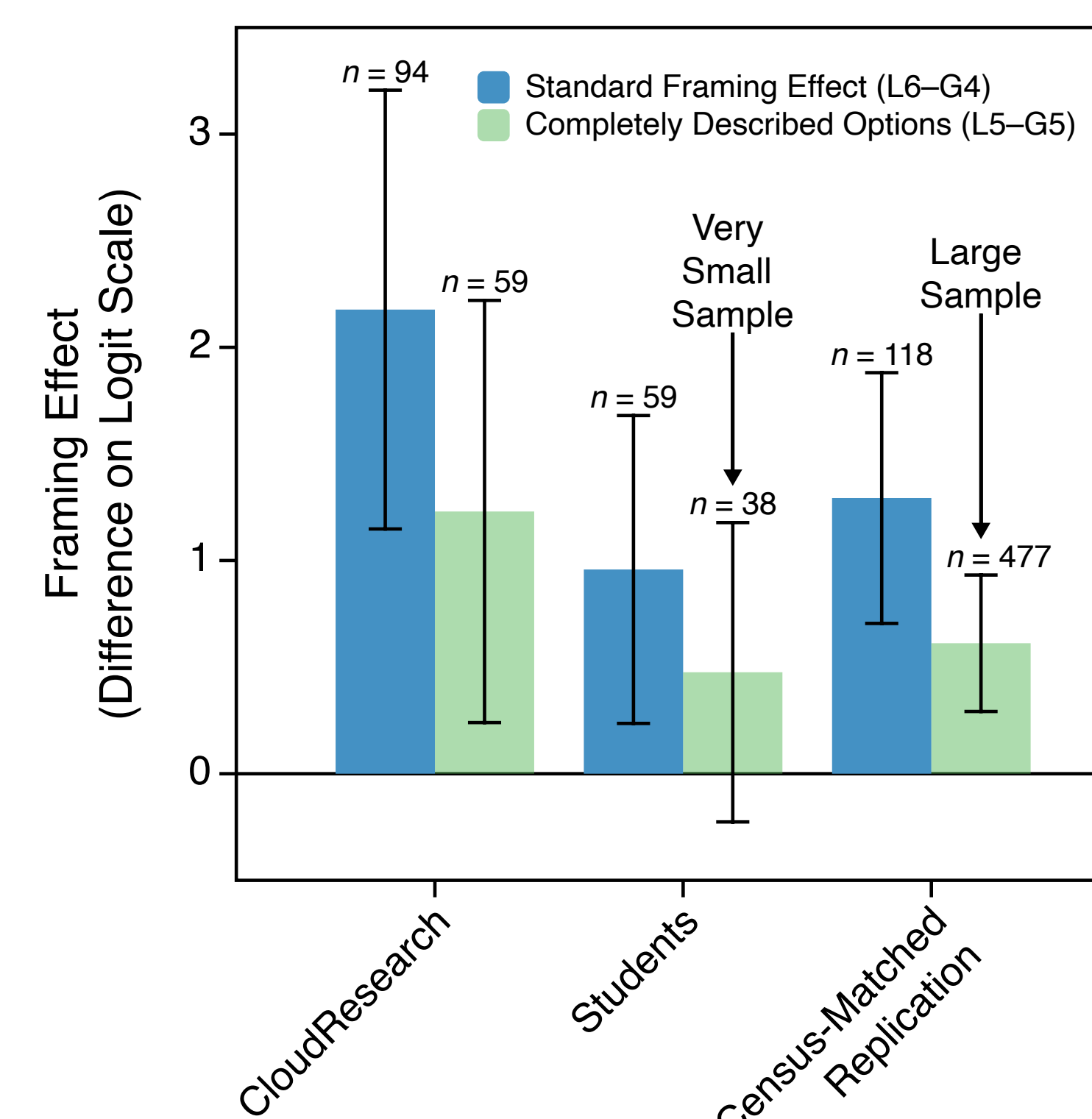
Result 1

- ◆ There are $9 \times 9 = 81$ ways to pair gain and loss cells to assess framing effects. Most of these pairs are mismatched because the option descriptions contain different information in gains and losses.
- ◆ The direction and magnitude of framing effects can be pushed around by pairing option descriptions in different ways. The pattern was the same in all three samples.



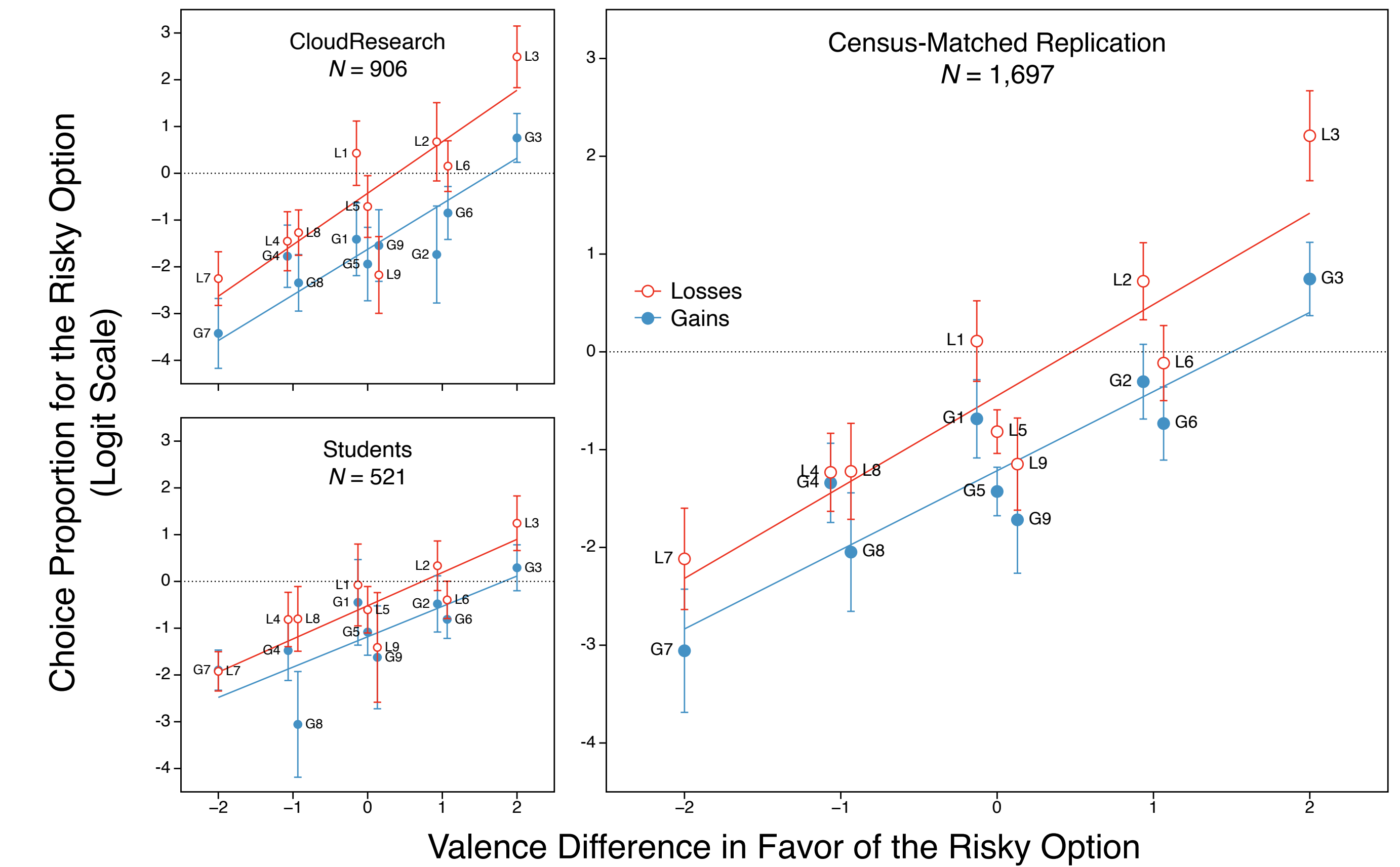
Result 2

- ◆ Surprisingly, the framing effect was significant in many of the 9 matched pairs (e.g., G1 vs. L1).
- ◆ When the certain and risky options were described completely (G5 vs. L5), the framing effect was half as large as the standard framing effect and was significant in the two larger samples (note the n in the replication).
- ◆ This result contradicts previous null results.¹



Result 3

- ◆ Our model predicted choice proportions in the 18 cells very well, but there was still a residual framing effect when we had accounted for the valence of the option descriptions. The pattern was the same in all three samples.



Result 4

- ◆ All versions of EVA and FTT predicted choice proportions well, but none of the models completely explained the framing effect.
- ◆ Our model, called interval-scaled EVA, outperformed two other versions of EVA and two versions of FTT. The order of model performance was the same in all three samples.

Mixed-Effects Logistic Regression Models for Predicting Choice of the Risky Option in the Replication Sample Only

Theory or Account	Valence Comparison	Valence or Gist Difference	Frame	BIC	BIC Rank
EVA (interval-scaled)		0.87***	0.78***	7556.2	1 (best)
EVA (original)		1.27***	0.77***	7633.9	4
EVA (free valence diffs.)	Pos. vs. mixed	0.86***	0.78***	7566.3	2
	Mixed vs. neg.	0.57***			
	Pos. vs. neg.	1.83***			
FTT (interpretation 1)		0.93***	0.79***	7690.8	5
FTT (interpretation 2)		1.05***	0.50***	7579.8	3

Remaining Questions

- ◆ Why is there a residual framing effect that is not accounted for by EVA or FTT, even when the option descriptions are complete?
- ◆ Where should we publish our census-matched replication?

References and Acknowledgement

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