Young & Stewart (unpublished manuscript) recently carried out a multiverse analysis of the data from Silberzahn et al.'s (2018) crowdsourcing data analysis initiative. Y&S found that two of the largest effects in magnitude reported in our paper were brought more in line with the remaining estimates after simple statistical adjustments were made.

The table below provides a summary of both the old (Silberzahn et al., 2018) and new (Y&S) estimates and methodologies used by these two analysis teams, specifically team 21 and team 27.

Team	Original method	Original odds ratio	New method	New odds ratio
21	Tobit regression	2.88	Fractional regression	1.31
27	Poisson regression	2.93	Poisson regression, removing non-significant interactions	1.29

We (Silberzahn, Martin, Uhlmann, Nosek) agree that the revised estimates proposed by Y&S are sensible, and further comparably more defensible or "correct" than the estimates provided by the crowd analysts in Silberzahn et al. (2018).

And yet, the changes seen in the table above only underscore the main arguments made in the original paper. Crowdsourcing data analysis highlights that different methodologies chosen by different researchers, some of which are more defensible than others in certain situations, can result in different empirical estimates and interpretations.

A crowd analysis captures the "research reality," or actuarial question of what would happen if someone else analysed the data to test the same hypothesis. In contrast, a multiverse carries out all defensible specifications from the point-of-view of a single analyst or small team. Thus, a multiverse may leave out some of the rough-and-tumble nature of the research process, where not all specifications are explored for various reasons (e.g., statistical training, intellectual allegiances, ideological bias), and different researchers diverge on what they perceive as a defensible analytic approach. A crowd analysis is at once both less and more than a multiverse analysis.

That said, correcting or even entirely removing the two outlying estimates highlighted in the table above does not change the conclusions draw in Silberzahn et al. (2018). A number of analytical teams, given the same data, may specify and advocate different models, and thus reach different conclusions. This variability is another component of the research process that deserves better understanding to help improve research on complex datasets across fields. We are delighted to see so many researchers delving into this topic in new and interesting ways.

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Note. The content of this brief online note is from a planned article, discussing among other topics crowd analyses vs. multiverse analyses.