Supplementary Information

Materials and Methods

We aspired to obtain a specific but complete body of research reports and several search methods were used to ensure a thorough examination of potential candidate reports.

Multiple-database searches. We used a set of paired keywords — misinformation OR misbelief* OR false information OR belief perseverance OR continued influence, with another series of keywords — retract* OR correct* to search multiple online databases. The initial search yielded 76 reports.

Other searches, personal contact, and electronic platforms. By further culling the reference lists of the review papers obtained in the database searches, we identified an additional eight articles. By contacting scholars who conducted research in this area, we identified two other reports. Finally, we received relevant materials from one researcher as a result of posting requests to online forums and e-mail list servers (e.g., Society for Personality and Social Psychology).

We did not include studies measuring naturally occurring misbeliefs in a community (e.g., Carretta & Moreland, 1982; Kuklinski, Quirk, Jerit, Schwieder, & Rich, 2000; Lai, 2015; Lewandowsky, Stritzke, Oberauer, & Morales, 2005), because of the lack of an experimental manipulation. We also excluded studies that described the initial information as hypothetical (e.g., Anderson & Kellam, 1992) or uncertain (e.g., Koller, 1993). By February 15, 2015, this meta-analysis included eight research reports (see Figure 1).

Assessments of Bias

We searched for the presence of a major type of bias that leads to the greater likelihood of samples yielding statistically significant findings being submitted and accepted for publication (for example, see Rothstein, Sutton, & Borenstein, 2005) and thus being included in our meta-analysis. Funnel plot is a visual aid of which assumes individual effect sizes to be distributed around the expected mean in the shape of an inverted-funnel. In the absence of bias, studies with a larger *N*, which have greater precision and smaller standard errors, are likely to cluster around the expected mean near to the top of the figure, whereas studies with a smaller *N* (i.e., lesser precision and larger standard errors) should yield effect sizes far from the expected mean, near the middle/bottom of the figures (e.g., Sterne, Becker, & Egger, 2005). If the bias is present, the funnel plot should appear asymmetrical and may have gaps in the bottom right-hand or bottom left-hand side of the plot.

Contour-enhanced funnel plots. Funnel plots can be enhanced by adding contours of statistical significance and an expected fixed-effect centered at 0 to aid the interpretation (Peters, Sutton, Jones, Abrams, & Rushton, 2008). The effect sizes and standard errors are displayed in three contour-enhanced funnel plots in Figure 2. We also marked the observed fixed effects to aid the interpretation. Contemporary bias detection techniques such as trim-and-fill method (Borenstein et al., 2009; Duval, 2005), however, go beyond a visual inspection of plots. Additionally, the contour-enhanced funnel plots with the trim and fill procedures are designed to distinguish different forms of bias and estimate the statistical significance of the missing studies. The contours delineate three regions: (a) the white-colored region corresponds to $p > .10$; (b) the gray-colored region corresponds to $.05 < p < .10$; (c) the dark gray-colored region corresponds to $.01 < p < .05$; and (d) the region outside of the funnel corresponds to corresponds to $p < .01$ (Peters et al., 2010). As shown in the bottom panel of Figure 2, all filled samples corresponding to the misinformation-persistence effect appear in region of $p < .01$, suggesting publication bias is a plausible explanation. However, there are several other possible explanations for funnel-plot asymmetry (see Lau, Ioannidis, Terrin, Schmid, & Olkin, 2006; Sterne & Harbord, 2004 for review). We assessed the presence of bias using selection models (Bishop & Thompson, 2016; Coburn & Vevea, 2015; McShane, Böckenholt, & Hansen, 2016).

Selection models. We used Vevea and Hedges (1995) weight-function models to explore the range of estimates that possibly result from various forms of and severity of publication bias. The results revealed stable estimates regardless of the selection models assumed for the effects of misinformation, $M_{\text{diff}} = 0.14 – 0.38$, and misinformation-persistence, $M_{\text{diff}} = 0.24 – 0.30$. However, the debunking estimates varied considerably based on the selection models, $M_{\text{diff}} = 2.21$, which suggests that publication bias may drive the unadjusted estimate. Next, we assessed the presence of bias with publication status as a moderator.

Publication status (or online vs. lab data collection). We examined whether the effects sizes varied with the publication status. For misinformation, no significant result of publication status was present, MEM: $b = -2.20$, $SE = 1.11$, $p = .0476$, whereas, a significant moderating role of publication status was observed in the debunking and misinformation persistence effects: Published studies reported a significantly weaker debunking effect, MEM: $b = -2.56$, $SE = 0.59$, $p < .0001$, and a stronger persistence effect than did unpublished ones, i.e., dissertations vs. other sources, MEM: $b = 1.05$, $SE = 0.32$, $p = .0012$. A similar pattern of results was yielded in the analyses with the removal of outliers. However, publication status overlaps with online vs. lab data collection. The difference between published and unpublished impacts can also attributable to differences in data collection settings (lab vs. online).

***P*-curve and *p*-uniform.** These approaches assume that the distribution of p values conditional on the population effect size is uniform. All half and full p-curve tests were right-skewed with $p < .1$, which indicates the presence of *evidential value*, i.e., the lack of evidence of publication bias (Simonsohn, Simmons, & Nelson, 2015). Additionally, p-uniform is a method to assess publication bias, which assumed the population effect size to be fixed rather than heterogeneous (van Aert, Wicherts, & van Assen, 2016). The results, regardless of the outliers, showed no evidence of *p*-hacking for the effects of misinformation, debunking, or misinformation-persistence (*p*s $\geq .05$).

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