Adjusting for Publication Bias Reveals Mixed Evidence for the Impact of Cash Transfers on Subjective Well-Being and Mental Health

František Bartoš^{1,*}, Maximilian Maier^{2,*}, T. D. Stanley^{3,4}, Eric-Jan Wagenmakers¹

* Both authors contributed equally

¹ Department of Psychological Methods, University of Amsterdam

² Department of Experimental Psychology, University College London

³ Deakin Laboratory for the Meta-Analysis of Research (DeLMAR), Deakin University

⁴ Department of Economics, Deakin University

Correspondence concerning this article should be addressed to:

František Bartoš,

University of Amsterdam, Department of Psychological Methods,
Nieuwe Achtergracht 129-B, 1018 VZ, Amsterdam, The Netherlands
f.bartos96@gmail.com

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Cash transfers are among the most popular poverty interventions. Indeed the charity evaluator GiveWell even lists GiveDirectly - a charity that directly sends your donations as cash to people in extreme poverty - as one of their top-rated charities [<https://www.givewell.org/charities/give-directly>]. McGuire, Kaiser, and Bach-Mortensen¹ conducted a timely and comprehensive meta-analysis on the impact of cash transfers on subjective well-being and mental health, featuring 45 studies with a combined total of 116,999 individuals. McGuire and colleagues¹ conclude “CTs [cash transfers] have a small but statistically significant positive effect on both SWB [subjective well-being] (Cohen’s $d = 0.13$, 95% confidence interval (CI) 0.09, 0.18) and MH [mental health] ($d = 0.07$, 95% CI 0.05, 0.09) among recipients.” We show that once publication bias is properly accounted for, this effect is - depending on the outcome measure - either greatly reduced or completely diminished.

McGuire and colleagues¹ test for publication bias using Egger regression and p -curve. Neither the Egger regression nor the p -curve shows evidence for publication bias, and they conclude, “In general, there appears little evidence of publication bias or cherry-picking of results.” However, both Egger regression and p -curve were shown to perform poorly under high heterogeneity^{2,3,4,5,6,7}.

We reanalyse McGuire et al.’s¹ (2022) results using a novel publication bias adjustment method: robust Bayesian meta-analysis (RoBMA)⁴. RoBMA contains different types of models that emerge from competing assumptions about the publication process. First, RoBMA contains models based on the relationship of effect sizes and standard errors (PET-PEESE)⁸. Second, RoBMA contains different models based on selection for statistical significance^{9,10}. These selection models are further split into six selection models with step weight functions at different p -value intervals (see Bartoš and colleagues⁹ for technical details). RoBMA then uses Bayesian model-averaging such that inference is impacted most strongly by those models that predicted the data best¹⁰. In other words, the individual models are combined according to their posterior model probabilities into the RoBMA ensemble.

By simultaneously applying an ensemble of models, RoBMA is more robust to model misspecification. In addition, RoBMA has been shown to perform well in simulation studies as well as on empirical tests^{4,9}. Furthermore, in RoBMA evidence for the presence as well as the absence of an effect can be quantified using Bayes factors. As a rule of thumb, Bayes factors between 1 and 3 are

regarded as weak evidence, Bayes factors between 3 and 10 are regarded as moderate evidence, and Bayes factors larger than 10 are regarded as strong evidence¹² (Appendix 1). When quantifying evidence for the null, i.e., evidence for the *absence* of an effect, the Bayes factor is simply inverted (i.e., $BF_{01} = 1/BF_{10}$).

Figure 1 shows the results of a publication bias-adjusted reanalysis using all studies; Table 1 shows the results for all studies and after omitting studies with high risk of bias (based on qualitative coding by McGuire and colleagues¹). Little evidence for an overall impact of cash transfers is apparent. For instance, there is a smidgen of evidence against the presence of a small overall effect (i.e., $BF_{01} = 1.46$; posterior mean $\delta = 0.03$). Furthermore, the evidence of impact of cash transfers by different outcome, study, and transfer types is indecisive and mixed. Specifically, there is moderate evidence against the effect of cash transfers on subjective well being, $BF_{01} = 4.62$, and moderate evidence in favour of the effect on mental health, $BF_{10} = 3.15$. As expected, the evidence against the overall impact and subjective well being fluctuates across a wide range of robustness checks, but it never provides more than weak evidence in support of a small effect. Similar results hold for the mostly positive evidence in favour of the impact on mental health (see Supplementary Materials for details). Evidence in favour of publication bias is moderate and strong for both the overall impact and the subjective well-being outcome, whereas it is mixed and weak for the mental health outcomes.

Application of RoBMA shows that whereas the 84 randomised controlled trials - the gold standard of evidence¹³ - yield no evidence for an effect ($BF_{01} = 1.41$), the 28 quasi-experimental designs do yield strong evidence ($BF_{10} = 13.07$). However, these positive results appear to be fragile, as the exclusion of the 12 studies with high risk of bias reverses the direction of the evidence ($BF_{01} = 2.93$). With respect to transfer type, there is slightly stronger evidence of absence for unconditional cash transfers ($BF_{01} = 3.06$) than for conditional cash transfers ($BF_{01} = 1.21$), even though this finding is not robust across our sensitivity analyses.

Our reanalysis finds that the evidence for cash transfers on subjective well-being and mental health is at best scant and mixed. Across all model specifications, we robustly find no evidence for an overall effect nor evidence in favour of an increase in subjective well being. The evidence in favour of the effect on mental health depends on model specification. Evidence in the other categories is also sensitive to model specification; however, none of the categories shows robust evidence across all model specifications. Furthermore, all effect sizes reported by McGuire and colleagues¹ and our reanalysis are quite small, smaller than what might reasonably be regarded as the ‘smallest effect size of interest.’ The uncertain evidence in regards to the presence of the effects and the clear evidence of publication bias shows that more research is needed, ideally in the form of randomised control trials that are publication bias resistant, such as registered reports¹⁴. Our analysis suggests that if the effect does exist, it is so small that the sample sizes needed to study may be large – almost 17,500 participants per group of a two-sample *t*-test to achieve 80% power for detecting effect size of Cohen’s $\delta = 0.03$.

Figure 1

Correcting for Publication Bias Suggests Mixed Evidence of Cash Transfers

Note. RoBMA_{PSMA} model-averaged posterior mean effect size estimates with 95% credible intervals and Bayes factors for the absence of the effect for the combined sample or split by either the domain or intervention category (ignoring the clustering of standard errors). BF_{01} quantifies evidence for the null hypothesis. BF_{01} larger than 1 corresponds to evidence in favour of the null hypothesis and BF_{01} lower than 1 corresponds to evidence in favour of the alternative hypothesis (evidence for the alternative hypothesis can be obtained by inverting the Bayes factor; $BF_{10} = 1/BF_{01}$). As a rule of thumb, Bayes factors between 3 and 10 indicate moderate evidence and Bayes factors larger than 10 indicate strong evidence.

Table 1

Comparison of Unadjusted and Adjusted Effect Size Estimates for All Studies and for Subsets of Studies Based on Different Study, Outcome, and Transfer Types

	Random-Effects	RoBMA _{PSMA}	RoBMA _{PSMA} (Low Bias)
Combined	0.09 [0.07, 0.12] t(40) = 9.39	0.03 [0.00, 0.11] BF ₀₁ = 1.46	0.03 [0.00, 0.11] BF ₀₁ = 2.18
Study Type:			
Randomised Control Trial	0.11 [0.08, 0.14] t(22) = 7.11	0.04 [0.00, 0.12] BF ₀₁ = 1.41	0.07 [0.00, 0.13] BF ₀₁ = 0.54
Quasi-Experimental Study	0.08 [0.05, 0.10] t(17) = 7.31	0.07 [0.00, 0.09] BF ₀₁ = 0.08	0.01 [0.00, 0.07] BF ₀₁ = 2.93
Outcome Type:			
Mental Health	0.07 [0.05, 0.09] t(28) = 7.40	0.05 [0.00, 0.08] BF ₀₁ = 0.32	0.04 [0.00, 0.09] BF ₀₁ = 0.51
Self-Reported Well Being	0.13 [0.09, 0.17] t(24) = 6.55	0.01 [0.00, 0.13] BF ₀₁ = 4.62	0.03 [0.00, 0.16] BF ₀₁ = 2.09
Transfer Type:			
Unconditional	0.11 [0.09, 0.13] t(27) = 9.42	0.02 [0.00, 0.12] BF ₀₁ = 3.06	0.05 [0.00, 0.14] BF ₀₁ = 1.13
Conditional	0.05 [0.03, 0.08] t(13) = 5.48	0.02 [0.00, 0.07] BF ₀₁ = 1.21	0.03 [0.00, 0.07] BF ₀₁ = 0.92

Note. Random-effects meta-analysis estimates with 95% confidence interval based on clustered standard errors, all p -values < 0.001. RoBMA_{PSMA} model-averaged posterior mean effect size estimates with 95% credible intervals and Bayes factor for the presence of the effect using either all estimates or studies with low risk of bias. Results differ slightly from the moderator analysis presented in the article because we analysed each subfield separately to allow (a) the testing for the presence of the effect in each category/domain in the Bayesian framework and (b) publication bias to operate differently in different subdomains.

Data & Materials

Data and analysis script is available at <https://osf.io/6nj8p/>.

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Competing interests

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Author Contribution

FB and MM analysed the data and wrote the first draft of the manuscript, all authors edited and approved the final version of the manuscript.

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Supplementary Materials

We further analysed the data with an informed prior distribution, $\delta \sim \text{Normal}(0, 0.30^2)$, which concentrates most of the prior on small effects. Those results should provide the highest evidence in the favour of the effect (Table A1).

Since publication bias adjustment methods cannot directly accommodate the three-level meta-analytic structure, i.e., multiple estimates obtained from the same study; we also analysed the data using only the most precise estimates. Selecting the most precise estimate from each study mitigates the dependency between estimates, however, it discards a substantial amount of information. Furthermore, some authors argue that the PET-PEESE publication adjustment correction might be driven by small study effects and overcorrects for the publication bias. Therefore, we also re-analysed the data with restricted version of RoBMA that only adjusts for publication bias operating on p -values, i.e., only using selection models (Table A2).

Table A1

Evaluating the evidence for the absence of the effect of cash transfers with RoBMA_{PSMA} under an informed alternative hypothesis specifying small standardised effects sizes, $\delta \sim \text{Normal}(0, 0.30^2)$.

	Complete Sample	Low Risk of Bias	Most Precise
Combined	BF ₀₁ = 0.45	BF ₀₁ = 0.48	BF ₀₁ = 2.95
Study Type:			
Randomised Control Trial	BF ₀₁ = 0.44	BF ₀₁ = 0.17	BF ₀₁ = 1.95
Quasi-Experimental Study	BF ₀₁ = 0.02	BF ₀₁ = 0.07	BF ₀₁ = 0.09
Outcome Type:			
Mental Health	BF ₀₁ = 0.10	BF ₀₁ = 0.11	BF ₀₁ = 0.43
Self-Reported Well Being	BF ₀₁ = 1.42	BF ₀₁ = 0.65	BF ₀₁ = 2.82
Transfer Type:			
Unconditional	BF ₀₁ = 0.96	BF ₀₁ = 0.30	BF ₀₁ = 3.70
Conditional	BF ₀₁ = 0.37	BF ₀₁ = 0.18	BF ₀₁ = 1.64

Table A2

Evaluating the evidence for the presence vs absence of the effect with only the selection models publication bias adjustment part of RoBMA.

	Complete Sample	Low Risk of Bias	Most Precise
Combined	0.02 [0.00, 0.11] BF ₀₁ = 2.30	0.02 [0.00, 0.11] BF ₀₁ = 3.57	0.00 [0.00, 0.06] BF ₀₁ = 12.11
Study Type:			
Randomised Control Trial	0.02 [0.00, 0.12] BF ₀₁ = 2.54	0.05 [0.00, 0.13] BF ₀₁ = 1.06	0.00 [-0.00, 0.09] BF ₀₁ = 8.34
Quasi-Experimental Study	0.07 [0.00, 0.09] BF ₀₁ = 0.08	0.05 [0.00, 0.08] BF ₀₁ = 0.14	0.05 [0.00, 0.08] BF ₀₁ = 0.32
Outcome Type:			
Mental Health	0.04 [0.00, 0.08] BF ₀₁ = 0.58	0.03 [0.00, 0.08] BF ₀₁ = 0.94	0.02 [0.00, 0.08] BF ₀₁ = 2.31
Self-Reported Well Being	0.01 [-0.01, 0.11] BF ₀₁ = 6.69	0.02 [0.00, 0.16] BF ₀₁ = 3.52	-0.01 [-0.17, 0.03] BF ₀₁ = 8.35
Transfer Type:			
Unconditional	0.01 [0.00, 0.12] BF ₀₁ = 4.57	0.03 [0.00, 0.13] BF ₀₁ = 2.08	-0.00 [-0.05, 0.03] BF ₀₁ = 12.12
Conditional	0.05 [0.00, 0.07] BF ₀₁ = 0.07	0.04 [0.00, 0.07] BF ₀₁ = 0.17	0.01 [0.00, 0.06] BF ₀₁ = 3.04