FOOTPRINT OF PUBLICATION SELECTION BIAS ON META-ANALYSES IN MEDICINE, ECONOMICS, AND PSYCHOLOGY

A PREPRINT

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This is the authors’ version of the manuscript.

ABSTRACT

Publication selection bias undermines the systematic accumulation of evidence. To assess the extent of this problem, we survey over 26,000 meta-analyses containing more than 800,000 effect size estimates from medicine, economics, and psychology. Our results indicate that meta-analyses in economics are the most severely contaminated by publication selection bias, closely followed by meta-analyses in psychology, whereas meta-analyses in medicine are contaminated the least. The median probability of the presence of an effect in economics decreased from 99.9% to 29.7% after adjusting for publication selection bias. This reduction was slightly lower in psychology (98.9% → 55.7%) and considerably lower in medicine (38.0% → 27.5%). The high prevalence of publication selection bias underscores the importance of adopting better research practices such as preregistration and registered reports.
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Publication selection biases (PSB) are defined as the selective reporting of results in ways that deviate from the objective, complete scientific record. PSB may entail the suppression of “negative” findings or the conversion of “negative” results into more “positive” ones (e.g., those with more favorable p-values and/or with larger effect sizes) and might represent a problem in all scientific disciplines, e.g., [1] [2] [3] [4] [5]. Studies that examine the self-reported behavior of researchers show that 78% of researchers failed to report all dependent measures of a study [6] (however, see [7], for a response that suggests a lower proportion). Thus, there is clear evidence that PSB is likely to be highly prevalent. Some studies suggest that PSB might be modestly increasing in some areas, although the exact nature, prevalence, and impact of PSB is unknown and likely to be variable across scientific fields [8, 9].

To gauge the extent of the PSB, one would need to have access to the complete scientific record or a representative and wide-coverage sample of it. However, this is infeasible as much of the relevant data is not publicly recorded. Instead, the footprint of PSB is indirectly probed by re-analyzing meta-analyses in several specific fields with different statistical techniques [10, 11, 12, 13, 14, 15] and focusing on patterns in the published results that would herald the presence of PSB. All these available methods try to identify the footprint of PSB, and thus they need to be seen with caution, since these patterns (e.g., correlations of effect sizes and standard errors) may sometimes be due to other factors than PSB (e.g., genuine heterogeneity across studies). However, when large numbers of meta-analyses show the same patterns, this constitutes a clear footprint of PSB, which we can use to estimate its relative magnitude across different fields.

Previous field-wide assessments of PSB suggested that the prevalence of over-reporting positive results and other possible symptoms of bias increased moving from the physical, to the biological and the social sciences, and even suggested that problems might be worsening over time in the latter [9, 15, 16, 17, 18, 19, 20]. However, these estimates were based on proxy measures of PSB that have several limitations.

To our knowledge, no previous effort has surveyed the potential footprint of PSB across as many areas of research and disciplines using state-of-the-art methods. Our proposed approach is more comprehensive than past surveys: employing different strategies to identify potential PSB, using new measures of PSB, and analyzing a much larger number of research studies covering the fields of medicine, economics, and psychology.

1 Fields Surveyed

We used four large data sets from medicine, economics, and psychology (see Appendix A.1 for details). The data set from medicine comprises meta-analyses of continuous and dichotomous outcomes obtained from the Cochrane Database of Systematic Reviews published between 1997 and 2020. The data set from economics comprise the extended data set of meta-analyses of regression and correlation coefficients by Ioannidis and colleagues [10] published between 1967 and 2021. Finally, the data sets from psychology comprise the meta-analyses of mean differences and correlation coefficients by Stanley and colleagues [12] published between 2011 and 2016 combined with a random sample of meta-analyses published in psychological journals by Sladekova and colleagues [21] published in 2008 and 2018. Eighty-four meta-analyses were part of both the [10] and [12] data set. Since each of the meta-analyses could be classified in both fields, we did not remove them from either of the data sets. From each data set we only used meta-analyses with at least three standardized effect size metrics such as log odds ratios, standardized mean differences, and (partial) correlation coefficients that can be transformed to a common standardized mean difference effect size metric, Cohen’s d.

Table 1: Summary of the data sets from each field. The number of studies per meta-analysis (Studies/MA) and the mean effect size of studies in each meta-analysis (Effect Sizes (d)) are reported as medians with the (interquartile range). The proportion of the statistically significant (Prop. Significant) is based on a random-effect meta-analysis estimated via restricted maximum likelihood with \( \alpha = 0.05 \).

| Field       | Meta-Analyses | Studies | Studies/MA | Effect Sizes (d) | Prop. Significant |
|-------------|---------------|---------|------------|------------------|------------------|
| Medicine    | 25,447        | 696,663 | (5, 25)    | 0.21 (0.08, 0.41)| 0.43             |
| Economics   | 327           | 91,421  | (30, 283)  | 0.20 (0.09, 0.37)| 0.82             |
| Psychology  | 605           | 23,563  | (9, 40)    | 0.37 (0.18, 0.61)| 0.78             |

Table 1 compares the characteristics of the meta-analyses from each field. Typically, medical meta-analyses are less likely to be statistically significant and contain the smallest number of studies per meta-analysis. In contrast, economics meta-analyses have the largest number of studies per meta-analysis and the smallest median effect size. Notably, random-effects estimates of the mean effect in both economics and psychology are statistically significant almost twice as often as in medicine, even though psychology reports much larger average effect sizes. This disparity in the
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A proportion of statistically significant mean effect size estimates remains even when comparing meta-analyses with matched number of estimates, although the difference is somewhat smaller (see Table 1 in the Supplementary Materials).

2 Results

We summarize results from all meta-analyses, apart from one medical meta-analysis that did not converge. See Supplementary Materials for analyses showing that matching meta-analyses based on the number of primary studies within each meta-analysis do not meaningfully affect the conclusions.

2.1 Evidence for the Effect

Figure 1: Distribution of Posterior Probability for the Presence of the Effect Before and After Adjustment for Publication Selection Bias in Each Field

Note. The dark grey area indicates density, the light grey area indicates the interquartile range, and the black line indicates the median. The y-axis is scaled according to posterior probabilities assuming equal prior probabilities for models assuming presence vs absence of the effect. See the secondary y-axis for Bayes factors in favor of the effect that are independent of the assumed prior probability of the effect. (We display only a random sample of 5,000 meta-analyses from medicine to remove clutter and rendering issues.)

Figure 1 shows distributions of the posterior probability of an effect before and after adjusting for PSB. These distributions reveal several patterns. First, meta-analyses in economics and psychology predominantly show evidence for an effect before adjusting for PSB (unadjusted); whereas meta-analyses in medicine often display evidence against an effect. This disparity between the fields remains even when comparing meta-analyses with equal numbers of effect size estimates. When correcting for PSB, the posterior probability of an effect drops much more in economics and psychology (medians drop from 99.9% to 29.7% and from 98.9% to 55.7%, respectively) compared to medicine (38.0% to 27.5%). The pattern is especially striking in economics, where the median posterior probability of an effect drops by more than seventy percentage points after PSB correction. Mean decreases in posterior probabilities show a similar but less striking pattern (Table 1 in Supplementary Materials).

Furthermore, we quantify the inflation of evidence in favor of an effect in meta-analyses via the evidence inflation factor – the increase in evidence in favor of the effect due to the PSB. We find that meta-analyses in economics inflate the evidence by a median factor of 11,369, while the meta-analyses in psychology by ‘only’ 30.0 and medicine by a median factor of 1.4. These extreme differences between the fields are largely driven by the disparity in the typical number of estimates per meta-analysis (Table 1). We standardize the evidence inflation factor (sEIF) by the number of estimates per meta-analysis—see Equation (5) in the Appendix. We find that per study evidence inflation is the largest
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2.2 Effect Size Estimates

Table 2: Summary of the footprints of publication selection bias on the meta-analytic effect sizes in the form of absolute bias (in Cohen’s $d$) and overestimation factor.

| Field     | Absolute Bias ($d$) | Overestimation Factor |
|-----------|---------------------|-----------------------|
| Medicine  | 0.13 [0.12, 0.13]   | 1.74 [1.70, 1.78]     |
| Economics | 0.15 [0.13, 0.17]   | 2.16 [1.69, 2.64]     |
| Psychology| 0.13 [0.11, 0.14]   | 1.39 [1.24, 1.55]     |

Note. The results are based on the comparison of publication bias adjusted meta-analytic effect size estimates assuming presence of the effect to the mean effect sizes per meta-analysis. The Table displays means and 95% confidence intervals. (See Table 4 in the Supplementary Materials for medians and interquartile ranges.)

The absolute bias is the difference between the mean effects and the PSB-adjusted estimates assuming presence of the effect. Mean effects in all fields suffer from a similar degree of absolute bias (first column of Table 2). The absolute bias is more than half as large as the average reported effect sizes in economics and medicine. Due to the right skew of the distribution of biases, the median bias in each field is lower than the mean bias (see Table 4 in the Supplementary Materials). The absolute bias decreases with increasing numbers of effect size estimates per meta-analysis (apart from the largest economics and psychology meta-analyses).

The overestimation factor is the ratio of the average mean effect and the corresponding average PSB-adjusted estimate in each field. In contrast to absolute bias, the overestimation factor quantifies the relative overestimation of effect sizes. Economics meta-analyses show the largest overestimation factor; however, the overestimation factor for the medical meta-analyses is nearly as large and both are notably larger than psychology. Psychology’s smaller overestimation is due to its larger average effect sizes (i.e., a similar absolute bias results in lower overestimation factors). The median per-ma-analysis computed overestimation factor in each field is again lower than the mean overestimation factor due to the right skew of the latter’s distribution (see Table 4 in the Supplementary Materials). The median overestimation factor is relatively stable/decreasing with the increasing number of effect size estimates per meta-analysis (apart from the largest economics and psychology meta-analyses).

2.3 Evidence for Publication Selection Bias

Figure 2 shows distributions of the posterior probability of the publication selection bias for each field. The figure reveals that the majority of meta-analyses in economics shows evidence for PSB (BF$_{PSB} > 1 = 74.0\%$) whereas the results are more undecided in psychology (57.5\%) and medicine (49.3\%). Furthermore, the distributions of posterior probability of PSB is concentrated at higher evidence in favor of the PSB in economics (median = 87.9\%) than in psychology (median = 57.4\%) and medicine (median = 49.5\%). Meta-analyses with a larger number of effect size estimates present slightly more evidence in favor of the PSB than meta-analyses with a lower number of effect size estimates, however, the overall disparity between the fields remains even when comparing meta-analyses with the corresponding number of effect size estimates.

3 Concluding Comments

We present a comprehensive assessment of publication selection bias and its effects on meta-analyses across medicine, psychology, and economics. Novel methods and measures allowed us to quantify the evidence for the absence or presence of the mean effect and publication selection bias, as well as inflation of the evidence of the effect due to the publication selection bias. Furthermore, we estimated the bias and overestimation factor of the effect sizes of average studies included in meta-analyses.

Our analysis is based on effect size estimates included in meta-analyses and irrespective of what the analyzed outcomes are. One can classify outcomes into three categories. First, some outcomes may have been pre-specified as being of primary interest to show a desirable effect (e.g., effectiveness for a medication in reducing death risk). Second, some other outcomes are not pre-specified but may still be used to demonstrate the same desirable point and thus may suffer from larger analytical flexibility and potential PSB (e.g., some secondary measures of effectiveness). Third, still other...
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Figure 2: Distribution of Evidence for Publication Bias in Each Field.

Note. The dark grey area indicates density, the light grey area indicates the interquartile range, and the black line indicates the median. The y-axis is scaled according to posterior probabilities assuming equal prior probabilities for models assuming presence vs absence of the publication selection bias. See the secondary y-axis for Bayes factors in favor of the publication selection bias that are independent of the assumed prior probability of the publication selection bias. (We display only a random sample of 5,000 meta-analyses from medicine to remove clutter and rendering issues.)

outcomes may have been collected and analyzed without any strong interest to show some significant result, or even with some incentive to show non-significant results (e.g., outcomes on collected adverse events). PSB is expected mostly in the second category, while it may be less in the first category [22] and may be entirely absent in the third category.

The milder publication selection bias in medical meta-analyses corroborates previous findings [9, 16, 19] and might have multiple concurring explanations. Compared to psychology and economics, medical studies measure phenomena that are simpler and more stable, using methods that are more solidly and universally codified, which reduces researchers “degrees of freedom” in generating and publishing evidence [9, 16]. It is also possible that the milder publication selection bias seen in medical meta-analyses is reflecting a larger share of meta-analyses that belonged to a category of outcomes with less pressure for PSB. Moreover, medical research makes wider use of research integrity practices, such as clinical trial registration, which might reduce the risk of publication selection bias [23]. Furthermore, medical meta-analyses may be of higher methodological quality and less subject to bias [9]. Whilst the specific causes of the patterns observed are likely to vary widely across fields, the social sciences would benefit from adopting practices to mitigate publication selection bias, including preregistration, greater transparency, and registered reports [24, 25, 26].

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A Appendix

A.1 Data Sets

A.1.1 Medicine

The data set from medicine comprises meta-analyses of continuous and dichotomous outcomes obtained from the Cochrane Database of Systematic Reviews (CDSR) published between 1997 and 2020. We identified systematic reviews in the CDSR through PubMed, limiting the period to Jan 2000 – May 2020. For that, we used the NCBI's EUtils API with the following query: “Cochrane Database Syst Rev”[journal] AND (“2000/01/01”[PDAT]: “2020/05/31”[PDAT]). For each review, we downloaded the XML meta-analysis table file (rm5-format) associated with the review’s latest version. We extracted the tables with continuous and dichotomous outcomes from these rm5-files with a custom Javascript and R programs ([https://github.com/wmotte/cochrane2022](https://github.com/wmotte/cochrane2022)).

We selected meta-analysis tables based on the highest aggregation reported in the CDSR. For each meta-analysis, we removed studies with estimates based on one or fewer participants in the control or treatment group and used all meta-analyses with at least three effect size estimates. See the purple density in Figure 3 for the distribution of the number of effect sizes estimates per meta-analysis.

A.1.2 Economics

The data set from economics comprise the extended data set of meta-analyses of regression and correlation coefficients of Ioannidis and colleagues [10] published between 1967 and 2021. The meta-analyses were identified using various search engines (e.g. Econlit and Scopus), publisher sites (e.g., Science Direct, Sage, and Wiley), webpages of researchers known to publish meta-analyses, and by searching all volumes of individual journals that are known to publish meta-analyses. We also emailed 109 research teams (associated with either sole authored or co-authored meta-analyses) for data, with a 67% response rate. The search for data ended May 30th, 2021.

We selected meta-analyses of standardized mean differences, (partial) correlation coefficients, and mean differences (if enough information was available to compute the standardized mean differences). See the turquoise density in Figure 3 for the distribution of the number of effect sizes estimates per meta-analysis.

A.1.3 Psychology

The data set from psychology comprise the data set of meta-analyses of mean differences and correlation coefficients of Stanley and colleagues [12] published between 2011 and 2016 combined with data from Sladekova and colleagues [21], a random sample of 433 meta-analyses from 90 articles published in 2008 and 2018. See [12] and [21] for more details about the collected data sets. None of the meta-analyses by [21] were published in Psychological Bulletin, precluding overlap with Stanley and colleagues [12] dataset. See the yellow density in Figure 3 for the distribution of the number of effect sizes estimates per meta-analysis.
Figure 3: Distribution of number of effect size estimates per meta-analysis for each field.

Note. Meta-analyses with more than 300 effect sizes estimates are omitted from the display: 195 medical meta-analyses, 77 economics meta-analyses, and 5 psychology meta-analyses.

A.1.4 Effect Size Calculation

In cases where the data set did not already feature standardized effect size (Cohen’s $d$, correlation coefficient $r$, log($OR$), or Fisher’s $z$), we used the metafor R package [27] to calculate the standardized effect sizes. For dichotomous outcomes with zero cell counts, we used the default empty cell correction, adding $1/2$ to empty cells. Finally, we converted all standardized effect sizes to Fisher’s $z$ by using the formulas in [28].

A.2 Methods

We use a state-of-the-art PSB detection and correction technique RoBMA-PSMA [29,30]. RoBMA combines the best of two well performing methods: selection models [31] and PET-PEESE [32], through Bayesian model-averaging and achieves better performance in both simulation studies and real data examples than either of the methods alone [30].

RoBMA uses Bayesian model-averaging to combine Bayesian implementation of selection models and PET-PEESE adjustments for PSB. In other words, RoBMA combines these methods based on their predictive adequacy, such that models that predict well have a large impact on the inference. Predictive adequacy is also a yardstick to compare different subsets of models and methods directly. In that way, we can evaluate the evidence in favor or against the hypothesis of PSB without the need to commit to a single specific estimation method, e.g., [33].

In addition, RoBMA incorporates both models based on the correlation between effect sizes and standard errors (i.e., PET-PEESE) and those based on selection for significance (i.e., 3PSM). This allows us to compare these different types of models with each other and to use the strength of each to calculate a corrected estimate.

We use the RoBMA model that specifies the following types of publication bias models:

1. Publication bias operating on a correlation between effect sizes and standard errors
   (a) A model with correlation between effect sizes and standard errors (PET).
   (b) A model with a correlation between effect sizes and standard errors squared (PEESE).
2. Publication bias operating on $p$-values
   (a) two-sided selection (at two-sided $p$-value 0.05)
   (b) two-sided selection (at two-sided $p$-values 0.05 and 0.10)
(c) one-sided selection (at one-sided $p$-value 0.05)
(d) one-sided selection (at one-sided $p$-values 0.025 and 0.05)
(e) one-sided selection (at one-sided $p$-values 0.05 and 0.50)
(f) one-sided selection (at one-sided $p$-values 0.05, 0.10, and 0.50)

A.2.1 Bayes Factors

The Bayes factor is the key inference criterion for much of Bayesian statistics, e.g., [34, 35]. It compares the relative predictive accuracy (i.e., likelihood of the data) under competing hypotheses. It can also be expressed as the ratio of prior and posterior model odds as in Equation 1.

$$\frac{p(\text{data} | H_1)}{p(\text{data} | H_0)} = \frac{p(H_1 | \text{data})}{p(H_0 | \text{data})} \frac{p(H_1)}{p(H_0)}.$$  

Although the Bayes factor is a continuous measure of the strength of evidence, the following rules of thumb may aid interpretation: Bayes factors between 1 and 3 are commonly regarded as weak evidence, Bayes factors between 3 and 10 as moderate evidence, and Bayes factors larger 10 as strong evidence for the alternative (or the hypothesis at the top of Equation 1). When the evidence for the null is considered, the Bayes factor is simply inverted. In other words, a Bayes factor between 1/3 and 1 is considered weak evidence, a Bayes factor between 1/10 and 1/3 moderate and smaller 1/10 strong evidence for the null.

A.2.2 Measures

We use the following measures to assess the degree and effects of PSB in the different fields. We use $k = 1, \ldots, K$ to denote the individual meta-analyses. Each meta-analysis is based on $N_k$ studies that are characterized with data describing the effect size $y_{k,n}$ and standard error $se_{k,n}$.

**Posterior probability of the effect** quantifies the posterior probability for the presence of the effect in each meta-analysis. We compute the posterior probability of the effect using a PSB unadjusted model, $p_{\text{unadj}}(H_1 | \text{data}_k)$, and PSB-adjusted model, $p_{\text{adj}}(H_1 | \text{data}_k)$, (the complete RoBMA-PSMA ensemble). We set equal prior odds for models assuming the presence vs absence of the effect, heterogeneity, and publication bias as specified in default RoBMA [29, 30]. We also compute inclusion Bayes factors for the presence of the effect in both the PSB unadjusted models, $BF_{10, \text{unadj}}$, and PSB-adjusted models, $BF_{10, \text{adj}}$. Since Bayes factors quantify the change from prior to posterior odds for the presence of the effect and are independent of the prior odds for the presence of the effect. Consequently, Bayes factors quantify the evidence for the presence of the effect contained in the data.

**Evidence inflation factor** (EIF) quantifies the degree to which the evidence in favor of the presence of the effect in each unadjusted analysis ($BF_{10, \text{unadj}}$) was inflated due to the PSB in comparison to the adjusted analysis ($BF_{10, \text{adj}}$),

$$\text{EIF}_k = \frac{BF_{10, \text{unadj}}}{BF_{10, \text{adj}}}.$$  

An evidence inflation factor larger than one indicates evidence of PSB. To further account for the fact that EIF is dependent on the number of studies, $N_n$, in each meta-analysis, we standardize the EIF by the number of studies,

$$s\text{EIF}_k = \text{EIF}_k \frac{1}{N_k}.$$  

$s\text{EIF}$ represents the marginal contribution per study to the aggregate evidence of PSB in a meta-analysis.

**Absolute bias** (bias) quantifies the degree to which the average effect sizes in each meta-analysis,

$$\hat{y}_k = \frac{1}{N_k} \sum_{n=1}^{N_k} y_{k,n},$$

overestimates the PSB-adjusted effect size estimate assuming the presence of the effect $\mu_{\text{adj}}$,

$$\text{bias}_k = \hat{y}_k - \mu_{\text{adj}}.$$  

Absolute bias larger than zero indicates that PSB leads to inflated effect size estimates. We compare the average effect sizes to the PSB-adjusted effect sizes assuming the presence of the effect (conditional effect size estimates) rather than averaging across all models. Excluding models assuming the absence of a mean effect mitigates the pooling towards
0 in meta-analyses more consistent with the null hypothesis. Tables 5 and 6 in the Supplementary Materials use the PSB-adjusted effect sizes model-averaged across all models, including models assuming the absence of a mean effect. The comparisons to the conditional PSB-adjusted effect size estimates (Table 2) offer a more conservative view of the extent of publication bias (i.e., smaller biases) across the disciplines.

**Overestimation factor** (OF) quantifies the degree to which the average effect sizes in meta-analyses overestimate the PSB-adjusted effect size estimates assuming the presence of the effect,

\[
\text{OF} = \frac{1}{K} \sum_{k=1}^{K} \hat{\eta}_k / \sum_{k=1}^{K} \mu_{\text{adj},k}.
\]

(5)

An overestimation factor larger than one is evidence of PSB. We use delta method to obtain confidence interval of the overestimation factor. In the Supplementary Materials, we also report medians and interquartile ranges of per meta-analysis overestimation factors,

\[
\text{OF}_k = \frac{\hat{\eta}_k}{\mu_{\text{adj},k}}.
\]

(6)

However, note that OF$_k$ can lead to non-sensible results as a meta-analysis with a positive mean effect and very small negative PSB-adjusted effect sizes estimate results in an extremely large negative OF$_k$.

**Bayes factor in favor of the presence of PSB** (BF$_{\text{psb}}$[^1]) quantifies the evidence in favor of PSB by comparing the relative predictive performance of meta-analytic models assuming presence of PSB to meta-analytic models assuming the absence of PSB. A Bayes factor in favor of the presence of PSB larger than one provides evidence in favor of the presence of PSB and lower than one provides evidence against the presence of PSB [29][30].

**Relative publication probabilities** quantify the relative probability of a study being published for a given $p$-value interval compared to studies with statistically significant $p$-values. We use one-sided $p$-values, resulting in $p$-values larger than 0.5 corresponding to estimates in the opposite direction. To facilitate the interpretation we visualize a weight function that shows the change of relative publication probabilities across the range of $p$-values. We report the results only in Supplementary Materials.

**Effect size inflation in imprecise studies** quantifies the relationship between the effect sizes and their standard errors. To facilitate the interpretation of the funnel asymmetry test we visualize the bias in effect sizes as a function of standard errors (incorporating the quadratic term from the RoBMA model). We report the results only in Supplementary Materials.

[^1]: In other publications abbreviated as BF$_{p\text{b}}$ or BF$_{\omega_{\text{psb}}}$.