

Publication Bias under Aggregation Frictions: From Communication Model to New Correction Method

Chishio Furukawa*

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Abstract

To make informed decisions, readers often need to aggregate the results of multiple publications. However, due to cognitive limitations, they may focus on signs of effects rather than magnitudes or precision. This paper presents a model about how researchers will communicate their results under such aggregation friction, and uses its implications to develop an improved bias correction method. First, in the model, publication bias will emerge even when research is communicated optimally for readers. In particular, there will be omission of some noisy null estimates and inflation of some marginally insignificant ones. Second, as the model suggests publication selection process will not be parsimonious, the resulting bias cannot be adequately corrected by commonly used bias correction methods. This paper presents evidence consistent with these implications, and proposes a new, non-parametric *stem-based bias correction method* that is robust to the selection process implied by both the communication model presented here, and other models proposed in meta-analysis literature.

*cfurukawa@mit.edu. Department of Economics, Massachusetts Institute of Technology
https://github.com/Chishio318/stem-based_method provides the R code to implement the stem-based method. This paper could not have been written without long-term guidance and support of my mentors and friends. I am indebted to Abhijit Banerjee, Anna Mikusheva, and Stephen Morris for their guidance. For advice on theory, I thank Harry Di Pei, Arda Gitmez, Alan Olivi, Marco Ottaviani, Michael B. Wong, and Atsushi Yamagishi; for advice on econometric methods, I thank Alberto Abadie, Isaiah Andrews, Tetsuya Kaji, Hiro Kasahara, Rachael Meager, Yuya Sasaki, Whitney Newey. For discussions on meta-analyses, I thank Abel Brodeur, Joseph Cummins, Tomas Havránek, Ed Leamer, Ted Miguel, Tom Stanley, and Aleksey Tetenov; for sharing meta-analysis data, I thank Chris Doucouliagos. For fruitful comments and discussions, I thank Josh Angrist, Alonso Bucarery, Esther Duflo, Taiyo Fukai, Masao Fukui, Seema Jayachandran, Andrew Foster, Emir Kamenica, Max Kasy, Kohei Kawamura, Yuhei Miyauchi, Yusuke Narita, Daniel Prinz, Mahvish Shaukat, Wing Suen, Daniel Waldinger, and especially Neil Thakral. All errors are mine.

1 Introduction

In many settings, professionals often rely on scientific publication when making important decisions. For example, suppose doctors are deciding whether to prescribe a new medication. Suppose they find 10 studies, and out of them, 7 report positive results whereas 3 report negative¹ results. Since most of the evidence is positive, they decide to use the new drug. Later they read a *New York Times* article that writes “researchers and pharmaceutical companies never published about one third of drug trials that they conducted to win the government approval, misleading the doctors and consumers regarding the drug’s true effectiveness.” The article² reports that 94 percent of positive results were published whereas only 14 percent of negative results were published. Moreover, while there were 14 studies with negative results according to conventional statistical thresholds, 11 of them emphasized positive aspects of their conclusions. These forms of publication bias, both omission and inflation, are widely documented in economics and other areas of science.

Concern about publication bias plays a prominent role in discussions of scientific reporting and meta-analyses today (Christensen and Miguel 2018, Andrews and Kasy 2019). The basis of these discussions is a belief that, if the aim of research is to assist policymakers with their decisions, then all results must be published accurately. However, since researchers are known to omit or inflate many negative results, they must have biased objectives that compromise readers’ welfare (or, social welfare in the case of policymaker). When experiments depend financially on funding from industry, researchers may wish to report positive results that support them; when careers depend on publications, researchers may wish to report significant results that surprise journal editors and referees. While the bias may come from a variety of incentive structures, these concerns have led to a number of initiatives to reduce publication bias, ranging from developing registries of experimental protocols to introducing journal policies that de-emphasize statistical significance.³ In addition, most commonly used bias correction methods are based on either of these interpretations and assume that any sufficiently positive estimates or any statistically significant ones will have a higher likelihood of publication than all other estimates.

This paper proposes an alternative approach to publication bias and meta-analyses by re-examining the belief that underlies the above concerns: to maximize readers’ welfare, should researchers publish all their results just as they are? When policymakers can process all the information contained in the papers at no cost, then the answer will be *yes*, as accurate reporting always helps readers make more informed decisions. However, when they have cognitive

¹By “negative”, this paper refers to any non-positive results, including both results that are not statistically significant and statistically significant negative.

²This is based on an actual article titled “Anti-depressant unpublished” by Cray 2008.

³AEA RCT registry and clinical trial.gov. In economics, for example, the *American Economic Review* has banned stars in regression tables in 2016, and the *Journal of Development Economics* has promised result-independent reviews in 2018.

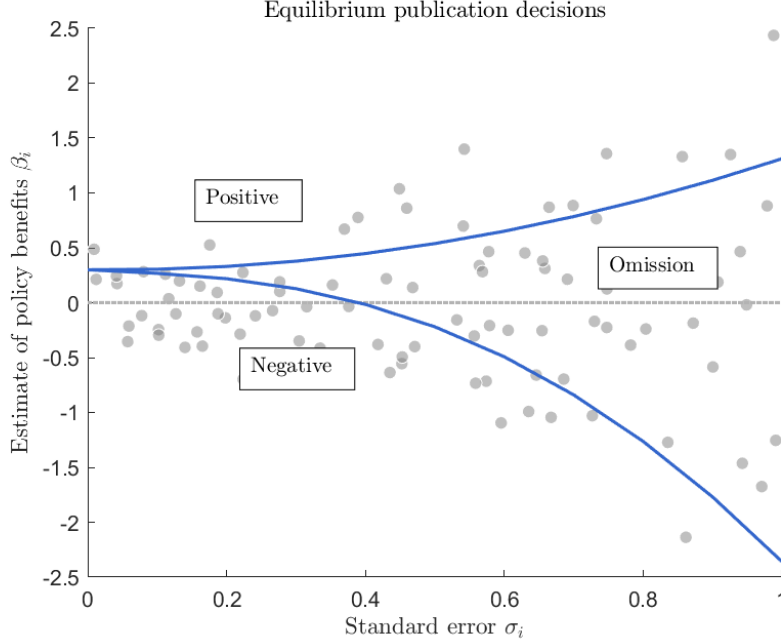


Figure 1: Equilibrium publication decision

Notes: Figure 1 is a “funnel plot” where a study i is plotted according to its coefficient estimate β_i on y -axis and its standard error σ_i on x -axis. The studies that have coefficient estimates and standard errors in the top region will be reported as positive; those in the bottom region will be reported as negative; those in the intermediate region will be omitted. Details of simulation environment are given in Section 2.4.2. Each dot is a simulated example rather than real-world data.

limitations to process the information, the answer will be *no*. Among the various possible frictions such as cost of communicating results, this paper will focus on an *aggregation friction*. Even though researchers know the details of statistical estimates, readers cannot fully process such details and thus only consider the binary (positive or negative) conclusions of each paper. This friction is documented in discussions of meta-analyses and some experiments⁴. The paper develops a model of communication between multiple researchers and one reader under aggregation frictions, and shows that the publication bias will emerge even when research is communicated optimally for readers. Various predictions of publication bias implied by this model can be summarized by a figure that plots the studies’ coefficient estimates and standard errors (Figure 1). It shows what sets of results will be published as either positive or nega-

⁴While this assumption may appear too simplistic, even aggregation in major policy decisions may rely on such vote-counting. For example, an influential campaign that reached President Obama in 2013 had summarized 12,000 articles without consulting statistical details; it merely wrote “97 percent of climate papers stating a position on human-caused global warming agree that global warming is happening” (The Consensus Project 2014). Some experiments suggest dichotomous interpretation is common even among experts in statistics (McChane and Gal 2017). Due to the cost of processing information, to the limited expertise to understand subtleties, or to the paucity of memory to recall details, readers may only consult binary conclusions of each study to make their decisions.

tive results. We use this implication on conditional publication probabilities to develop a new, non-parametric *stem-based* bias correction method that provides robust meta-analysis estimate relative to existing methods.

The first set of theoretical results is that there will be an omission of non-extreme and imprecise estimates and also a bias towards publishing more positive results than negative ones. To see why omission occurs, note that researchers wish to convey as much information as possible but the aggregation friction permits them to convey only the signs, but not the strengths, of their estimates. In this context, omission of “weak” (i.e. non-extreme or imprecise) results can, in equilibrium, convey more information because when studies are reported, even readers with aggregation frictions can know that those studies are “strong” (i.e. either extreme or precise). To see why the omission will be biased, note that researchers publish results to provide useful information that will improve the reader’s decision, jointly with other researchers. But without knowing what others researchers will report, a researcher can only guess the results of other research when their own reports are consequential. Now, suppose that the reader uses a supermajoritarian rule: that is, she chooses to adopt a policy (e.g. prescribe a new drug) whenever there are strictly more positive than negative results. In this situation, a single positive report will induce the reader to adopt the policy when other studies report an equal number of positive and negative results, while a single negative report will induce her to reject the policy when other studies report one more positive than negative results. Given these asymmetric conditions, in equilibrium, researchers will be more cautious of reporting negative results than positive results, leading to bias by omission. We show that the supermajoritarian rule is optimal for the reader among alternative aggregation rules that the reader could adopt.

The second main theoretical result is that, if journals only publish studies with sufficiently small p -values, then even unbiased researchers may inflate some marginal estimates to turn them statistically significant. To see why such inflation emerges, note that the Bayesian posterior mean of a normal distribution divides each coefficient estimate by its variance. However, null hypothesis testings rely on t -statistics, which divide each coefficient estimate by its standard error. Due to this sharp contrast between the use of variance versus standard errors, neither the researchers nor their readers will wish to strictly be concerned with hypothesis testing in deciding whether or not to adopt the policy. In this way, even though p -values could be a reasonable rule of thumb for publishing results that might appropriately guides the readers’ decision, there will be some room for inflation of results to improve reader welfare.

The third, additional result is that, even when the differences in underlying biases are small, the researchers will have large polarization of reporting rules to draw their binary conclusions. This amplification of small biases arises because the reporting decisions are strategic substitutes. That is, if another researcher reports positive results frequently, then a researcher would like to report positive results less frequently to offset the bias of another researcher, and this adjustment

induces another researcher to report positive results even more often. This result suggests that the reporting decisions will be highly sensitive to the objectives, making it difficult to model parsimoniously.

The paper presents a range of evidence to suggest that the above three theoretical results are highly relevant in the published literature of both economics in other sciences, and has important implications for the meta-analysis literature. First, under moderate assumptions, a range of reported evidence suggest all forms of publication bias are prevalent in the social sciences. Second, evidence derived in this paper shows that the communication model presented here can explain the pattern of omission more adequately than other models used in meta-analyses. Specifically, it suggests that noisy null results are likely to be omitted, whereas other models, for tractability, suggest either that any null results or any extremely negative results are likely to be so. Evidence from labor union effects (Doucouliagos et al. 2018), some of the largest meta-analytic data set in economics, shows that the prediction of the communication model presented in this paper holds, and thus, the bias correction methods that assume the parsimonious selection process may have misspecification problems.

Finally, this paper offers a solution for correcting publication bias in meta-analyses of the type described above. The challenge is that publication selection will depend on asymmetric and non-uniform omission, as well as inflation of marginal results, that cannot be parsimoniously modeled. Further, their exact process will depend on economic primitives unobservable to meta-analysts. Nonetheless, even without estimating the publication selection process, we can mitigate the bias by focusing on a subset of data that exhibits less bias under any selection models commonly used. Theory suggests that, across the parameters of communication models and many models, precise estimates are less biased than imprecise ones. Heuristically, more precise studies have more reliable estimates, and thus there is little reason not to publish. The stem-based method proposed in this paper derives the meta-analysis estimate from some n^* most precise studies, where n^* is chosen optimally. A simulation study with realistic parameter values suggests that the estimates from the stem-based method are significantly more robust than other methods (Hedges 1992, Duval and Tweedie 2001) because the stem-based method imposes much weaker assumptions on the publication selection process and underlying distributions than do other studies. Robustness is particularly crucial in meta-analyses, where the goal is to build a consensus among often contradictory results in the literature.

Related Literature. This paper relates to two sets of microeconomic theory literature on communication. It also relates to the statistics literature on bias correction methods.

First, this paper builds on and derives contrasting results from the canonical models of information aggregation and transmission. The results of (i) omission, (ii) bias, and (iii) amplification of small bias relate to the models of voting as information aggregation (Austen-Smith and Banks 1996, Feddersen and Pesendorfer 1996, 1997, 1998, 1999): (i) omission of incon-

clusive results is analogous to abstention of uninformed voters; (ii) biased reporting is similar to jurors’ bias to convict in order to counterbalance unanimity rules, but differs in that such biased reporting is socially optimal; (iii) amplification of small bias due to strategic substitution between researchers is an extension of the result of the non-partisan voters’ vote against the bias of partisan voters. Moreover, the result that coarseness of message⁵ space leads to biased reporting stands in contrast with the models of information transmission (Crawford and Sobel 1982, Li, Rosen, and Suen 2001): whereas bias of senders leads to coarse messages due to the incentive constraints in their model, technological restriction of coarse message space leads to biased reporting due to pivotality conditions in this model.

Second, this paper also relates to the growing literature of microeconomic models of scientific communication⁶ and, specifically, publication bias. The result of t -statistics relates to the microeconomic decision models of statistical testing (Manski 2004, Tetenov 2016). The broad conclusion that publication bias needs not be socially detrimental is consistent with papers with various reasoning, such as incentives for endogenous information acquisition with biased researchers (Glaeser 2006, Libgober 2015, Henry and Ottaviani 2014), or limited number of studies readers may process (de Winter and Happee 2012) or journal space for publication (Frankel and Kasy 2018). In contrast, this paper derives the result even when information is exogenously given, even when researchers are unbiased, and even when there is no limit or cost of communication. This paper instead focuses the cognitive friction, which some papers (Suen 2004, Fryer and Jackson 2008, Blume and Board 2013) have shown as a possible reason for biased communication and decisions, and applies to the context of scientific communication.

Finally, this paper also contributes to the large and growing (Simonsohn et al. 2014, Bom and Rachinger 2018, Andrews and Kasy 2019) literature on correction methods for publication bias in meta-analyses. In contrast with the most commonly used methods (Hedges 1992, Duval and Tweedie 2000) that rely on specific assumptions on publication selection process and underlying distribution, the stem-based method depends on assumptions that hold across various assumptions made in literature. The method extends approaches to focus on some arbitrary number of the most precise studies (Barth et al. 2013, Stanley et al. 2010) by providing a formal criteria and estimation methods to select the optimal number of studies to focus on.

The remainder of the paper is organized as follows: Section 2 presents the communication model and its related evidence; Section 3 develops and implements its empirical test; Section 4 proposes a bias correction method given this observation; and Section 5 concludes.

⁵Coarseness is also a key friction in papers such as Dewan et al. (2015). The difference is that signals are more coarse than states in their paper whereas messages are more coarse than signals in this paper.

⁶In a broad way, the paper contributes to the empirical analyses of communication models that have been advanced specifically in the research on media in the real world (Gentzkow et al. 2016, Puglisi and Snyder 2016) or on hypothetical communication settings in the laboratories (Crawford 1998, Battaglini et al. 2010). This paper advances these empirical studies by obtaining a direct measure of bias in the real world data.

2 A Communication Model of Publication Bias

This Section presents a communication model between multiple researchers and a policy maker with the friction that the researchers can only communicate yes-or-no conclusions even though they are informed of their experiments' estimates. The analysis will show that the aggregation friction can provide explanation for various kinds of publication bias, such as (i) omission of insignificant results, (ii) inflation of marginally insignificant results, and (iii) amplification of small researchers' bias. Results on omission will also provide an empirical prediction on the meta-analysis data sets.

2.1 Set-up

The set-up is based on a static communication model between N senders, called researchers, and 1 receiver, called a policymaker. Researchers receive private unbiased signals of the treatment effect of policy, β_i , and its standard error, σ_i , and report their results, m_i . Given the reports from the researchers, the policymaker decides whether to implement the policy $a \in \{0, 1\}$.

The model's key element is an *aggregation friction*: even though researcher's private signals, $\{\beta_i, \sigma_i\}$, take continuous values, researchers can only convey a positive result, $m_i = 1$, or a negative result, $m_i = 0$, or do not report their study, $m_i = \emptyset$. Given the standard error independently drawn from some distribution $\sigma_i \sim G(\sigma)$, the treatment effect estimate has a normal distribution around the true benefit, b , so that $\beta_i \sim \mathcal{N}(b, \sigma_i^2)$. However, the policymaker only considers what results the researchers have reported to make their decision. Henceforth, let us denote the number of positive results by $n_1 = \sum_{i=1}^N \mathbb{1}(m_i = 1)$, and negative results by $n_0 = \sum_{i=1}^N \mathbb{1}(m_i = 0)$.

Both the researchers and the policymaker maximize the social welfare:

$$a(\mathbb{E}b - c), \quad (1)$$

where c is the cost of policy implementation.⁷ They have a common prior $b \sim \mathcal{N}(0, \sigma_b^2)$. The number of players, their pay-offs, priors, and the cost of policy implementation c are public information and common knowledge.

The timeline is as follows: first, researchers⁸ receive their own signals, and simultaneously

⁷While this set-up may appear to assume no uncertainty in welfare when the policy is not implemented since it is fixed to be 0, it also represents such setting: suppose the welfare under policy is $u_1 \sim \mathcal{N}(\bar{u}_1, \sigma_{u1}^2)$ and the welfare in the absence of policy is $u_0 \sim \mathcal{N}(\bar{u}_0, \sigma_{u0}^2)$. Then, it is optimal to implement the policy if and only if $\bar{u}_1 - \bar{u}_0 \geq c$. Thus, defining $b \equiv \bar{u}_1 - \bar{u}_0$ and $\sigma_b^2 \equiv \sigma_{u1}^2 + \sigma_{u0}^2$ above will be an equivalent set-up.

⁸I suggest readers of this paper to think of researchers in this model not as individual authors in the real world, but as a collection of authors, referees, and editors who jointly make the publication decisions. In peer reviewed journals, individual researchers play both roles of authors and referees. Even if researchers may seek to maximize publications when they are authors, journals ask referees and editors to publish socially valuable

decide whether to publish their binary conclusions. Then, the policymaker sees the reports and makes her policy decision using her posterior belief. Finally, the payoffs are realized.

2.2 Analyses

The analysis will focus on Perfect Bayesian Nash Equilibria (PBNE), the standard equilibrium concept in communication models. The strategy of a researcher i , $s_i \in S_i$, is a mapping from his own signal $\{\beta_i, \sigma_i\}$ to probability distribution over his message m_i $s_i : \mathbb{R} \times \mathbb{R}_+ \mapsto \Delta \{1, \emptyset, 0\}$. The strategy of policymaker, π , is a mapping from the messages to the probability distribution over binary policy action $a \in \{0, 1\}$: that is, $\pi : \{1, \emptyset, 0\}^N \mapsto \Delta \{0, 1\}$. The policymaker's belief over the researchers' strategy is denoted by $\mu \in \Delta (\{S_i\}_{i=1, \dots, N})$.

Definition 1.1 : *An equilibrium is a tuple of strategies and belief, $\{s_1, \dots, s_N, \pi, \mu\}$ such that (i) researcher i ' strategy maximizes (1) given strategies of all other researchers and the policymaker, for all i ; (ii) policymaker's strategy maximizes (1) given strategies of researchers and belief; (iii) the policymaker's belief is consistent with Bayes' rule.*

As communication models always have multiple equilibria, including a babbling equilibrium, we introduce following criteria to focus on non-trivial and plausible equilibria:

Definition 1.2 : *An equilibrium is fully responsive if $\forall m_i, m'_i \exists m_{-i}$ such that $\pi(m_i, m_{-i}) \neq \pi(m'_i, m_{-i})$; and fully informative if $\mathbb{E}[b|m]$ is not constant analogously.*

In any fully responsive and fully informative equilibria⁹, both the policymaker's and researchers' strategy will be monotone in their information, at least in a benchmark set-up¹⁰:

Lemma 1 (Monotonicity of equilibrium strategies). *For $N=2$, for any c , and constant σ_i , any fully responsive and fully informative equilibrium has strategies that are monotone:*

- (i) *the policymaker's decision $\pi^*(m)$ is increasing in number of positive results (n_1) and decreasing in number of negative results (n_0) in the following sense. For every i*

$$\begin{aligned} \pi^*(m_i, m_{-i}) > 0 &\Rightarrow [\forall m'_i \text{ s.t. } m'_i \succ m_i, \pi^*(m'_i, m_{-i}) = 1] \\ \pi^*(m_i, m_{-i}) < 1 &\Rightarrow [\forall m'_i \text{ s.t. } m'_i \prec m_i, \pi^*(m'_i, m_{-i}) = 0] \end{aligned}$$

, where messages are ordered by $1 \succ \emptyset \succ 0$ without loss of generality.

information.

⁹Note that this definition differs from usual responsiveness and informativeness in that it requires all messages to be influential and informative. For example, the policy rule $a^* = 1 \Leftrightarrow n_1 = 2$ is not fully responsive in that the choice between $m = 0, \emptyset$ never alters the decision.

¹⁰As shown in Appendix A1.3, the monotonicity requires a constant standard error since the monotone likelihood ration property needs not hold under normal distribution with unknown standard errors.

(ii) each researcher i takes the threshold strategy: there exist $\underline{\beta}_i, \bar{\beta}_i \in (-\infty, \infty)$ such that

$$m_i^* = \begin{cases} 1 & \beta_i \geq \bar{\beta}_i \\ \emptyset & \text{if } \beta_i \in [\underline{\beta}_i, \bar{\beta}_i) \\ 0 & \beta_i < \underline{\beta}_i \end{cases}$$

Sketch of proof. By Bayes' rule, combined with the law of iterated expectation and monotonicity of the mean of a truncated normal distribution with respect to the mean of the underlying distribution. Appendix A1.3 contains a full proof. \square

Finally, to assess desirability and plausibility of particular equilibrium among non-trivial equilibria, we introduce the following definitions:

Definition 1.3: *An equilibrium is optimal if no other sets of strategies can attain strictly higher ex ante welfare; and locally stable if, for every neighborhood of the equilibrium, there exists a sub-neighborhood of the equilibrium from which a myopic and iterative adjustment of strategies stays in that neighborhood. Formally, a myopic and iterative adjustment on the tuple $\mathcal{E}_t \equiv \{\pi_t(m), \bar{\beta}_{1,t}, \underline{\beta}_{1,t}, \bar{\beta}_{2,t}, \underline{\beta}_{2,t}\}$, is a dynamic process for $t = 1, 2, \dots$ in which, in each t , (i) the policymaker plays best response to $\{\bar{\beta}_{1,t-1}, \underline{\beta}_{1,t-1}, \bar{\beta}_{2,t-1}, \underline{\beta}_{2,t-1}\}$, (ii) researcher 1 plays best response to $\{\pi_t(m), \bar{\beta}_{2,t-1}, \underline{\beta}_{2,t-1}\}$, and (iii) researcher 2 does so to $\{\pi_t(m), \bar{\beta}_{1,t}, \underline{\beta}_{1,t}\}$. An equilibrium \mathcal{E} is locally stable if for every $\hat{d} > 0$, there exists $\bar{d} > 0$ such that, given any disturbance ϵ such that $\sup \text{metric } d(\epsilon) < \bar{d}$, $d(\mathcal{E} - \mathcal{E}_\infty) < \hat{d}$; that is, the equilibrium stays in the neighborhood of the equilibrium.*

It is standard to focus on the most informative equilibrium in sender-receiver games, and on the optimal equilibrium in common interest games. Local stability assures robustness to small deviations from the equilibrium strategies.

Henceforth, the analysis will combine analytical and numerical approaches to show that the main mechanisms play important roles in plausible settings that satisfy the above criteria. Analytical results will illustrate the logic behind the kinds of publication bias that arises from the model by focusing on a tractable environment and equilibrium with various symmetry properties. Analytical results will focus primarily on the case of $N = 2$,¹¹ $c = 0$, and often constant σ . Then, numerical results will show that the mechanism will play important roles in asymmetric environment that is more plausible yet analytically difficult to solve.

¹¹Given that meta-analyses often include more than 2 studies, this set-up with $N = 2$ may appear restrictive. However, this simple setting is common in the committee decision-making literature to which this paper is closely related, such as Gilligan and Krehbiel 1989, Austen-Smith 1993, Krishna and Morgan 2001, and Hao, Rosen, and Suen 2001. Analytical characterization for $N \geq 3$ is difficult due to technical challenge of analytically evaluating multivariate normal's truncated mean. Instead, this paper takes numerical approach to settings with $N \geq 3$.

2.3 Main Result 1. Omission of Insignificant Results

The first main result is that, in the optimal and locally stable equilibrium, there will be an asymmetric omission of intermediate results such that the average estimates underlying published studies will have an upward bias.

2.3.1 Analytical Results

The following propositions will first show, in a symmetric environment with constant σ , there will be equilibria with asymmetric omission, no omission, and symmetric omission; and, second show that the equilibrium with asymmetric omission is both optimal and locally stable whereas other two kinds of equilibria are not. The relation to the information aggregation models in voting theory will be discussed.

Proposition 1.1 (Equilibrium with asymmetric omission). *Let $N = 2$, $c = 0$, and $\sigma_i = \sigma$. There exists an equilibrium with the following strategies. The policymaker's strategy is a supermajoritarian policy decision rule:*

$$\pi^* = \begin{cases} 1 & \text{if } n_1 > n_0 \\ 0 & \text{if } n_1 \leq n_0 \end{cases} \quad (2)$$

The researchers' strategies are identical to each other and characterized by the unique thresholds, $\bar{\beta}, \underline{\beta}$, that satisfy

$$\bar{\beta} > 0 > \underline{\beta} \text{ and } \bar{\beta} < -\underline{\beta} \quad (3)$$

so that there will be an upward bias in the estimates of the reported studies: $\mathbb{E}[\beta_i | m_i \neq \emptyset] > 0$.

Sketch of Proof: By a combination of information asymmetry among researchers and a message space that is coarser than a signal space. Suppose the policymaker adopts (2). Since a researcher does not know what another researcher will observe and report, he conditions his reporting decision on the state in which his own report will be pivotal and swing the policy decision in the direction of its conclusion. A positive result switches the policymaker from canceling to implementing the policy only when another researcher did not report his result as his signal had an intermediate value. Thus, the optimal threshold $\bar{\beta}$ satisfies the indifference condition, $\beta_i + \beta_{-i} = 0$, in expectation conditional on pivotality:

$$\bar{\beta} + \mathbb{E}[\beta_{-i} | \bar{\beta} > \beta_{-i} \geq \underline{\beta}, \beta_i = \bar{\beta}] = 0 \quad (4)$$

In contrast, a negative result leads the policymaker to cancel rather than to implement the policy only when his report is positive. Thus, the optimal threshold $\underline{\beta}$ satisfies:

$$\underline{\beta} + \mathbb{E}[\beta_{-i} | \beta_{-i} \geq \bar{\beta}, \beta_i = \underline{\beta}] = 0 \quad (5)$$

Because the binary conclusion cannot convey the strength and can only communicate the sign of the continuous signal each researcher receives, omission of intermediate results can better convey information than always reporting either positive or negative results. In addition, comparing the conditions (4) and (5), researchers are more cautious of reporting negative results than positive results and thus, given that results are reported, the coefficients are on average upward biased: $\mathbb{E}[\beta_i|m_i \neq \emptyset] > \mathbb{E}[\beta_i]$. Finally, it is strictly optimal for the policymaker to follow the supermajoritarian rule (2) since he focuses on the average value conditional on $\{m_i\}$ whereas the researcher focused on the marginal value. Appendix A2.1 contains a formal proof. \square

There will also be an equilibrium with asymmetric omission that generates a downward omission when $c = 0$. However, as Appendix Figure B3 shows, the equilibrium in Proposition 1.1 attains a strictly higher welfare when $c \geq 0$. In this sense, the “positive” results are defined as the messages that alter the default decisions whereas “negative” results are the ones that suggest to maintain the default. The following propositions will now show that there are also equilibria without bias of underlying estimates:

Proposition 1.2 (Equilibria with symmetric or no omission). *Let $N = 2$ and $c = 0$, and $\sigma_i = \sigma$. There exist equilibria with the following strategies:*

- *Symmetric omission: the policymaker follows*

$$\pi^* = \begin{cases} 1 & n_1 > n_0 \\ \frac{1}{2} & \text{if } n_1 = n_0 \\ 0 & n_1 < n_0 \end{cases} \quad (6)$$

and the researchers' thresholds satisfy $\bar{\beta} > 0 > \underline{\beta}$ and $\underline{\beta} = -\bar{\beta}$ so that $\mathbb{E}[\beta_i|m_i \neq \emptyset] = 0$.

- *No omission: the policymaker follows*

$$\pi^* = \begin{cases} 1 & n_1 = 2 \\ \tilde{\pi} & \text{if } n_1 = 1, n_0 = 0 \\ 0 & n_1 \leq n_0, \end{cases} \quad (7)$$

where $\tilde{\pi} \in (0, 1]$ and the researchers' thresholds satisfy $\underline{\beta} = \bar{\beta} < 0$ so that $\mathbb{E}[\beta_i|m_i \neq \emptyset] = 0$.

Sketch of Proof: The equilibrium with symmetric omission exists because (i) the indifference conditions of researchers that determine $\bar{\beta}, \underline{\beta}$ will be symmetric to each other when $\pi = \frac{1}{2}$ when $n_1 = n_0$, and (ii) given symmetric thresholds, the policymaker will be indifferent between $a = 0, 1$ when $n_1 = n_0$. The equilibria with no omission exist because (i) the welfare gain from omission exists only when another researcher omits, and (ii) given that researchers always report $m_i = 0, 1$, the decision when there are omissions may be defined arbitrarily. \square

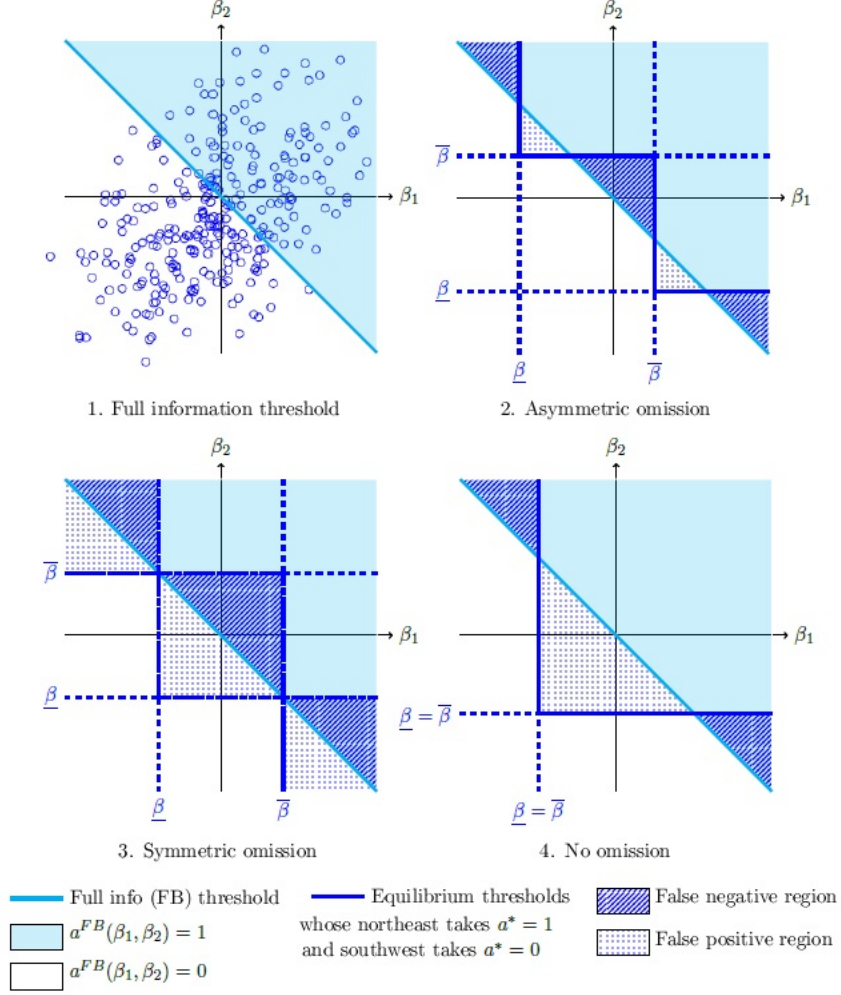


Figure 2: Equilibrium thresholds and policy decisions for $N = 2$, $c = 0$

Notes: Panel 1 plots the benchmark first-best policy implementation rule ($\beta_1 + \beta_2 \geq 0$) as given by the Bayes' rule and an example of the bivariate normal distribution of signal realizations $\{\beta_1, \beta_2\}$. Panel 2, 3, and 4 illustrate the equilibrium thresholds and policy decisions under three responsive and informative equilibria. The dotted line shows the thresholds for each equilibrium, and the policy is implemented if $\{\beta_1, \beta_2\}$ were in the region northwest to the solid line for Panel 1 and 2. For Panel 3, policy is implemented with $\frac{1}{2}$ probability in region surrounded by the dotted line. “False negative” (“False positive”) regions denote signal realizations such that the policy is (is not) implemented under the full information but is not (is) implemented in equilibrium. The figures' origin is $\{0, 0\}$.

While Proposition 1.2 shows that there are also fully informative and fully responsive equilibria without bias under reported studies, the following Proposition 1.3 shows that the equilibrium with bias of reported studies is more desirable and likely:

Proposition 1.3 (Optimality and local stability of equilibria). *The equilibrium*

with asymmetric omission as characterized in Proposition 1.1 is optimal and locally stable; the equilibria characterized in Proposition 1.2 are neither optimal nor locally stable.

Sketch of Proof: The heuristic reasons for optimality and local stability are summarized by Figure 2. The equilibrium with asymmetric omission is optimal because its policy implementation rule as in (2) described in Panel 2 most closely approximates the first best threshold of $\beta_1 + \beta_2 = 0$ as depicted in Panel 1; it minimizes the probabilities of false positive and false negative errors that leads to welfare losses. It is also locally stable since the policymaker's decision is based on strict preference and the researchers' strategies are only moderate substitutes of one another. On the other hand, the equilibria with symmetric or no omission are neither optimal nor locally stable as small perturbation of researchers' thresholds and policymaker's strategy can improve the welfare and its subsequent iterative adjustment leads to a different equilibrium. For example, in the symmetric equilibrium (Panel 3), consider a small decrease in researchers' strategy, $\bar{\beta}' = \bar{\beta} - \Delta$ and $\underline{\beta}' = \underline{\beta} - \Delta$. This perturbation leads to a first order welfare increase because it increases $\mathbb{E}[b|n_1 > n_0]$ by quantity proportional to Δ but only has a second order welfare loss, and thus increases the total welfare. The symmetric equilibrium is also not locally stable because the policymaker now prefers to implement the supermajoritarian rule. Analogous argument applies to the equilibrium with no omission; and Appendix A2.3 contains a complete proof. \square

The concepts of optimality and local stability are closely related to each other because the model is a common interest game: if an equilibrium is not locally stable, then it cannot be optimal since every steps of iterative adjustment must be intended to improve welfare.

These results relate to the models of information aggregation and transmission. First, it builds on the models of voting as information aggregation (Austen-Smith and Banks 1996, Feddersen and Pesendorfer 1996, 1997, 1998, 1999) as the result regarding omission is analogous to the result that uninformed and unbiased voters abstain when there are other informed and unbiased voters (Feddersen and Pesendorfer 1996). The result regarding biased reporting echoes the result that unanimity rule, counterintuitively, may increase the probability of false conviction if the jurors condition their votes on the states in which their votes are pivotal (Feddersen and Pesendorfer 1998). The novel result of this paper is that the biased reporting is socially optimal whereas it was argued to be sub-optimal in their voting theory. This difference is due to the information coarsening: while these voting models have often assumed *binary* states, this paper assumes *continuous* states even though the messages can only be yes, no, or abstention.

Second, this paper relates to communication models that show that biases of senders result in coarse messages, both with one sender (Crawford and Sobel 1982) and multiple senders (Hao, Rosen, and Suen 2001). In contrast, this paper shows that the technological restriction

of coarseness¹² leads to the biased reporting. In this sense, the relationship between conflict of interest and coarseness of information transmission may have causalities running in both ways.

2.3.2 Numerical Results

There are two results from the numerical simulation that are critical for understanding the asymmetric equilibrium characterized in Proposition 1.1. First, the probability of policy implementation is less than that in the environment where the estimates can be directly communicated: $\mathbb{P}(a = 1) \leq \frac{1}{2}$ (Appendix Figure B2). In this sense, the upward bias among the reported estimates is a way to mitigate the inherent conservativeness in supermajoritarian rule. Second, when $c > 0$, the welfare under the equilibrium with supermajoritarian rule, $\pi = 1 (n_1 > n_0)$, is higher than that with submajoritarian rule, $\pi = 1 (n_1 \geq n_0)$ (Appendix Figure B3). Therefore, while the equilibrium with $\pi = 1 (n_1 \geq n_0)$ also exists, this paper focuses on the case with $\pi = 1 (n_1 > n_0)$.

2.3.3 Evidence

A number of studies suggest that omission is prevalent by reporting a positive correlation between the coefficient magnitude and the standard error; on average, imprecisely estimated studies have higher coefficient values than precise studies¹³. In economics, important estimates such as the impact of minimum wage on employment (Card and Krueger, 1995), the return to schooling (Ashenfelter et al., 1999), and the intertemporal elasticity of substitution (Havránek, 2015), have evidence of a positive correlation. In environmental studies, estimates of the social cost of carbon, a key statistic for carbon tax policy, were shown to have the bias (Havránek et al., 2015). Moreover, the probability of omission around 30 percent is roughly consistent with some examples reported in Andrews and Kasy 2019.

¹²This assumption is similar to some papers that examined the implication of communication frictions on biases, such as Suen 2004, Fryer and Jackson 2008, and Blume and Board 2013.

¹³This could be due to researchers omitting studies unless they are positive statistically significant. If the study is imprecise, then a large coefficient magnitude is needed whereas if the study is precise, then coefficient magnitude can be modest (Hedges 1992). Alternatively, this could also be due to researchers omitting studies when the coefficient values are low (Duval and Tweedie 2000, Copas and Li 1997). There are two formal tests that examine the presence of publication bias through examining the correlation between coefficient magnitude and study precision: an ordinal test that examines their rank correlations (Begg and Mezuemder 1994) and a cardinal test that examines the correlation by regression (Egger et al. 1997). Second, there is occasionally excess variance in the estimates with an abundance of studies at the extreme values beyond significance thresholds and a scarcity of studies with intermediate coefficients (Stanley 2005).

2.4 Main Result 2. Inflation of Marginally Insignificant Results

The second main result is that, given heterogeneous standard errors, the equilibrium t -statistic threshold will not be constant across σ_i . This result has two empirical implications: (i) if journals apply a t -statistic threshold to publish positive results, then even unbiased researchers will inflate some marginally insignificant results; and (ii) there will be omission of imprecisely estimated null results.

2.4.1 Analytical Results

Analytical results show that the absolute value of t -statistics¹⁴ threshold will be increasing in σ_i . While the model set-up does not impose restrictions on the messages based on t -statistics, we can define the analogous t -statistics naturally in terms of the equilibrium threshold:

Definition 2 t -statistics: Define the t -statistics thresholds, $\bar{t}_i(\sigma_i)$ and $\underline{t}_i(\sigma_i)$, as the ratio between the threshold coefficient and standard error: $\bar{t}_i(\sigma_i) = \frac{\bar{\beta}(\sigma_i)}{\sigma_i}$, $\underline{t}_i(\sigma_i) = \frac{\underline{\beta}(\sigma_i)}{\sigma_i}$.

The following proposition claims that, in a unique symmetric equilibrium such that the two researchers apply the identical thresholds $\bar{t}(\sigma_i) = -\underline{t}(\sigma_i)$, the t -statistics thresholds will be increasing in σ_i so that precise studies will be more likely to be published than imprecise ones.

Proposition 1.2. (t -statistic threshold increasing in σ) Suppose $N = 2$, $c = 0$, $\sigma_b = \infty$, and $\text{Supp}(G)$ is some interval in \mathbb{R}_{++} . There exists a unique symmetric equilibrium such that the policymaker follows the mixed strategy π^* in (6), and the researchers adopt threshold strategies with cut-offs that depend on σ_i , as in Lemma 1.1. Then the t -statistics will be symmetric so that, $\bar{t}_i(\sigma_i) = -\underline{t}_i(\sigma_i) \equiv t(\sigma_i)$ for both $i = 1, 2$, and will be increasing in σ_i :

$$\frac{\partial t(\sigma_i)}{\partial \sigma_i} > 0$$

for every $\sigma_i \in \text{Supp}(G)$ for both researchers.

Sketch of Proof: By rearranging the indifference condition of researchers. By the Bayes' rule and law of iterated expectation, the researcher i 's indifference condition on $\bar{\beta}_i(\sigma_i)$ is

$$\mathbb{E} \left[\frac{\frac{\bar{\beta}_i(\sigma_i)}{\sigma_i^2} + \frac{\beta_j}{\sigma_j^2}}{\frac{1}{\sigma_i^2} + \frac{1}{\sigma_j^2}} \mid I_i, I_j \right] = 0, \quad (8)$$

where $I_i = \{\beta_i = \bar{\beta}_i(\sigma_i), \sigma_i\}$ is the information set of researcher i , and $I_j = \{\beta_j \in \text{Piv}(\sigma_j, \pi), \sigma_j\}$ is the information set of researcher j , where $\text{Piv}(\sigma_j, \pi)$ is the pivotality condition, and the ex-

¹⁴While it is formally a z -statistics since standard error is assumed to be known in the model, the paper uses the term t -statistics to be coherent with the way empirical studies usually conduct null hypothesis testing.

pectation is taken over I_j . Reorganizing this condition (8), the threshold $\bar{t}(\sigma_i)$ must satisfy

$$\bar{t}(\sigma_i) = \frac{\bar{\beta}(\sigma_i)}{\sigma_i} = \sigma_i \frac{\mathbb{E} \left[-\frac{\beta_j}{\sigma_j^2 + \sigma_i^2} | I_i, I_j \right]}{\mathbb{E} \left[\frac{\sigma_j^2}{\sigma_j^2 + \sigma_i^2} | I_i, I_j \right]} \quad (9)$$

In this way, the t -statistics threshold is increasing in σ_i since $\mathbb{E} \left[-\frac{\beta_j}{\sigma_j^2 + \sigma_i^2} | I_i, I_j \right]$ is positive in equilibrium. Appendix A2.2 contains a complete proof, which focuses on the symmetric equilibrium that provides a tractable environment where the term, $\mathbb{E} \left[-\frac{\beta_j}{\sigma_j^2 + \sigma_i^2} | I_i, I_j \right] \times \mathbb{E} \left[\frac{\sigma_j^2}{\sigma_j^2 + \sigma_i^2} | I_i, I_j \right]^{-1}$, does not change substantively enough to alter this sign. Analogous results hold for $\underline{t}(\sigma_i)$. \square

The impossibility of equating the optimal thresholds with a constant t -statistics threshold arises from the difference in the use of standard errors between the Bayesian updating and the null hypothesis testing. In Bayesian updating, the coefficient is divided by the variance, σ^2 , since the weights on each coefficient must be proportional to its information that increases at rate n in the absence of study-specific effects ($\sigma_0 = 0$). In null hypothesis testing, the coefficient is divided by the standard errors, σ , since t -statistics normalize the convergence of distribution of β_i that occurs at rate \sqrt{n} . In this model, the thresholds are determined by approximating the Bayes rule, which stands in contrast with the focus on the p -value that measures how unlikely that a given observation occurs under the null hypothesis of zero effect.

This observation, while highlighting the contrast between t -statistics and optimal thresholds, renders support for t -statistics as a rule of thumb since the threshold $\bar{\beta}(\sigma)$ is increasing and $\underline{\beta}(\sigma)$ is decreasing. This result relates to a decision-theoretic and statistics literature that examines the optimality of null hypothesis testing as criteria for choosing alternative treatments (Manski 2004). A recent paper (Tetenov 2016) rationalized the t -statistics approach based on communication in the settings with commonly known value of standard error. This model considers the environment where the standard error is a private information, and shows that the equilibrium t -statistics may not be constant across σ_i .

2.4.2 Numerical Results

The analytical results have shown that, in the symmetric equilibrium with $N = 2$, $c = 0$, $\sigma_b = \infty$, the constant t -statistics threshold will be sub-optimal. While tractable, symmetric equilibria will not be locally stable and thus less plausible than the asymmetric equilibrium analogous to that characterized in Proposition 1.1. The numerical analysis henceforth will show that the key qualitative predictions will hold even under asymmetric equilibrium and even with $N \geq 3$, $c \geq 0$, $\sigma_b < \infty$. Moreover, it quantifies the bias, omission, and welfare gains from omission and inflation, and derives empirical predictions.

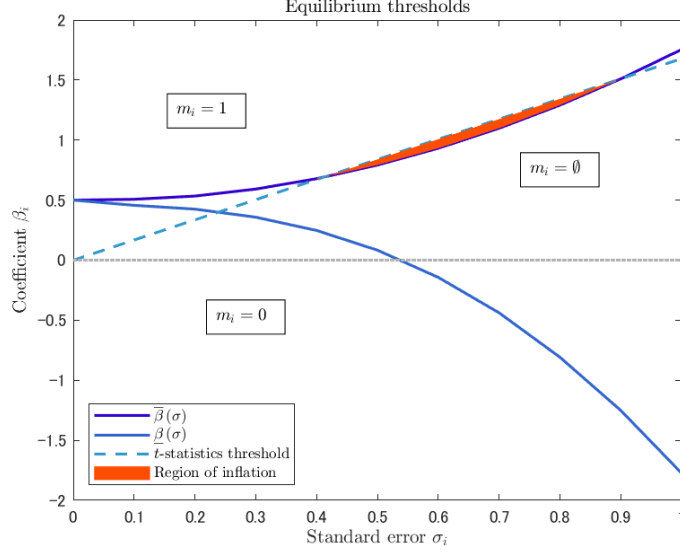


Figure 3: $\bar{\beta}(\sigma)$ and $\underline{\beta}(\sigma)$ thresholds

Notes: Figure 3 plots the $\bar{\beta}(\sigma), \underline{\beta}(\sigma)$ thresholds under the prior standard deviation $\sigma_b = 0.7$, no study-specific effect $\sigma_0 = 0$, and distribution of standard errors such that, σ_i , that approximates the empirical data as shown in B1.1, and policy cost $c = \frac{1}{2}$. The darker solid line is $\bar{\beta}(\sigma)$, the lighter solid line is $\underline{\beta}(\sigma)$, and the dashed line represents a linear t -statistic threshold. Studies in the shaded region draw positive conclusions even though they are marginally statistically insignificant. The Figure 1 in Introduction shows the equilibrium thresholds in identical environment except $c = 0.3$.

The equilibrium thresholds, $\bar{\beta}(\sigma), \underline{\beta}(\sigma)$, of the asymmetric equilibrium in a plausible environment (Figure 3) show that the two analytical results hold in a more general set-up. First, $\bar{\beta}(\sigma)$, the threshold between sending positive message or not reporting the study, is strictly convex in σ . Thus, if academic communities impose a rule-of-thumb t -statics level to claim positive results, there could be some studies in the shaded region that might still be considered as a “positive” result even though it is marginally insignificant. Second, the omission occurs most importantly among the imprecisely estimated studies with intermediate coefficients. That is, when negative results are reported, they will be either precisely estimated null results or imprecisely estimated and yet extremely negative results. Since precisely estimated studies will be less subject to asymmetric omission, there will also be less bias among them.

A numerical simulation, presented in Appendix B1.5, shows a substantive welfare gain from allowing some inflation and frequency of omission can be substantive across a range of parameter values. Imposing a constant one-sided t -statistic, $\bar{\beta}(\sigma) = t\sigma$, with no omission, will lead to $3 \sim 50$ percent of welfare loss relative to the environment in which estimates can be directly communicated, even when $t \in \mathbb{R}$ is chosen to minimize the welfare loss. Allowing for flexible

equilibrium threshold can more than halve the welfare losses, leading to only $1 \sim 23$ percent of welfare loss. The omission probability is roughly 7 percent among the most precisely estimated studies whereas it could be as large as 60 percent among the least precisely estimated studies. On average, omission probability is around $30 \sim 50$ percents. Similarly, the bias is minimal and $0 \sim 20$ percent of the underlying benefit distribution (σ_b) among the most precise studies whereas it could be very large among the least precise studies.

Numerical exploration also shows that the comparative static of thresholds with respect to N is ambiguous, and that the threshold for reporting negative results, $\underline{\beta}(\sigma)$, could be increasing in σ when c is high. Appendix B1.1 describes the details of the simulation set-up and procedure, and Appendices B1.2 and B1.3 contains a thorough discussion of these observations.

2.4.3 Evidence

There are various quantitative evidence of inflation and some qualitative evidence of omission that is heterogeneous across values of study precision.

Inflation: When the originally intended specification has a marginally insignificant t -statistic, researchers may inflate the statistical significance through the choice of specifications for outcome, control variables, and samples (Leamer 1978). If inflating t -statistic incurs search costs, then there will be an excess mass right above the threshold. In economics, Brodeur et al. (2016) argues that about 8% of results as statistically significant may be due to inflation. There is an excess mass right about the significance cut-off in sociology and political science, too (Gerber and Malhotra 2008a, 2008b). In psychology with lab experiments such that sample size can be adjusted subsequently, Simonsohn et al. (2014) reported density of p -values among the statistically significant tests were increasing in p -values and interpreted this as evidence of inflation.

Omission heterogeneity across study precision: There are some examples in which either precisely estimated null results and extremely negative results, while imprecisely estimated, are published. Some examples of precise null results¹⁵ include the large-scale clean cookstove study (Hanna et al. 2016), the air pollution regulation in Mexico (Davis 2008), and the community-based development programs (Casey et al. 2012). The examples of extreme negative results include the negative labor supply elasticities close to -1 among the taxi driver papers (Camerer 1997); the positive impact of inequality on economic growth (Forbes, 2000); the unexpected harmful effect of a therapeutic strategy on the cardiovascular events found in one trial (the Action to Control Cardiovascular Risk in Diabetes trial 2008). While these are

¹⁵There is one apparent counterexample: DEVTA study, the largest randomized trial that showed null effects of deworming and vitamin A supplementation on child mortality and health, was not published until 7 years after the data collection (Garner, 2013). While the delay required by the careful analysis of authors is extensive, that it was published in *the Lancet*, a top medical journal, is, in a way, reassuring of the academic journal's willingness to report precise negative results.

only some examples, the empirical analyses in Section 3 will provide a formal evidence.

2.5 Additional Result. Amplification of Small Bias of a Researcher

The main results have shown that, even when researchers are completely unbiased, there will still be publication bias with omission and inflation. Nonetheless, in the real world, researchers' and policymakers' objectives are not completely aligned with one another due to different information and interests regarding policies. This Section shows that there will be a large polarization of reporting rules among researchers even when a researcher's bias is small.

2.5.1 Analytical Results

Let us begin by introducing the *strategic multiplier* between researchers that quantifies on the strategic interdependence between them, keeping the policymaker's strategy fixed, given the researcher i 's objective, $a(\mathbb{E}b - c + d_i)$, so that d_i is his bias for policy implementation.

Definition 3 Strategic multiplier between researchers: *Define the strategic multipliers, $\bar{\zeta}, \underline{\zeta}$, as the ratio of the effect of small bias d_i of one researcher on the difference between thresholds of two researchers, between the environment with or without strategic effects, keeping the policymakers' strategy π^* fixed:*

$$\bar{\zeta} \equiv \frac{\partial(\bar{\beta}_i - \bar{\beta}_j)/\partial d_i}{\partial(\bar{\beta}_i - \bar{\beta}_j)/\partial d_i|_{\sigma_j = \sigma_j^*}} \text{ and } \underline{\zeta} \equiv \frac{\partial(\underline{\beta}_i - \underline{\beta}_j)/\partial d_i}{\partial(\underline{\beta}_i - \underline{\beta}_j)/\partial d_i|_{\sigma_j = \sigma_j^*}}.$$

In a tractable case of symmetric equilibrium, the following proposition shows that the strategic multiplier is larger than 1; that is, the effect of small bias of one researcher will be amplified:

Proposition 1.3. (Amplification of Bias of a Researcher) *Suppose $N = 2$, $c = 0$, and $\sigma_i = \sigma$ for both $i = 1, 2$. In a symmetric equilibrium in Proposition 1.2, the strategic multiplier between researchers satisfies $\bar{\zeta} = \underline{\zeta} \equiv \zeta$, and*

$$\zeta = \frac{Var_{total}}{Var_{total} - Var_{truncated}}, \quad (10)$$

where $Var_{truncated} \equiv Var(\beta_i | \beta_i \leq \bar{\beta})$ and $Var_{total} \equiv Var(\beta_i) = \sigma^2 + \sigma_b^2$. Thus, $\zeta > 1$.

Sketch of Proof: By deriving the comparative statics with the researchers' indifference condition. Let us focus on the indifference condition for $\bar{\beta}_i$; the condition for $\underline{\beta}_i$ can be derived analogously. We consider the symmetric equilibrium with no bias at the beginning. The indifference condition of researcher i with bias, d_i , is

$$\bar{\beta}_i + \mathbb{E}[\beta_j | \beta_j \leq \bar{\beta}_j] = - \left(2 + \frac{\sigma^2}{\sigma_b^2} \right) d_i, \quad (11)$$

where $d_i = 0$ at first. This expression (11) already shows that $\bar{\beta}_i$ will be decreasing in $\bar{\beta}_j$. The expression (10) is derived from the comparative statics of $\bar{\beta}_i$ on d_i with the expression (11). Since $Var_{total} > Var_{truncated}$ by definition of truncated distribution, $\zeta > 1$. Appendix 1.3 contains a complete proof. \square

In words, the two researchers' thresholds, $\bar{\beta}_i$ and $\bar{\beta}_j$, are strategic substitutes of one another: when a small increase in d_i shifts $\bar{\beta}_i$ downwards, $\bar{\beta}_j$ will be adjusted upwards to offset this effect, which then causes $\bar{\beta}_i$ to shift downwards even further, and so on. The strategic multiplier quantifies how the difference between $\bar{\beta}_i$ and $\bar{\beta}_j$ due to such repeated adjustments is larger than the case when there was only the first adjustment of $\bar{\beta}_i$, keeping $\bar{\beta}_j$ fixed.

The multiplier (10) shows, heuristically, that the strategic substitution effect is very large. If the equilibrium thresholds, $\bar{\beta}_i$ and $\bar{\beta}_j$, are low so that $Var_{truncated} = \frac{2}{3}$, then $\zeta = 3$: the equilibrium difference in reporting is three times larger than the primitive difference in objectives. When the conventional threshold, $\frac{\bar{b}}{\sigma} = 1.96$, is applied in the environment with zero true effect ($b = 0$) and small variation in true effects ($\sigma_b \simeq 0$), then $Var_{truncated} \simeq 0.88$, which suggests $\zeta \geq 8$: that is, the underlying difference in objectives is only 12 percent of the observed difference in reporting thresholds.

This amplification result builds on the results of information aggregation models (Feddersen and Pesendorfer 1996) that illustrates strategic substitution effects among voters. In the voting model, when there are partisan voters, independent voters vote against the bias of the partisan voters to offset their influence on electoral outcomes. In this model, when another researcher is biased in one direction, the researcher will bias her reporting in the opposite direction. The new result is that, because the voting model has considered binary decisions whereas this model considers continuous decisions of reporting thresholds, the original bias will be amplified in equilibrium.

2.5.2 Numerical Results

While the Proposition 1.3 focused on the analytically tractable case of symmetric equilibrium with $\bar{\beta} = -\underline{\beta}$, the same effect of strategic substitution also exists in the asymmetric equilibrium in Proposition 1.1. A numerical simulation shows strategic substitution can have a quantitatively important influence not only on symmetric equilibrium but also on asymmetric equilibrium that is locally stable. Let us consider an example with 2 researchers, $c = 0$, and $\sigma_0 = \sigma = 1$. If neither researcher is biased, then the equilibrium threshold is $\bar{\beta}_i = 0.19$. If researcher i has bias $d_i = -0.1$ so that he has bias towards policy implementation and researcher j does not have bias, $d_j = 0$, then their thresholds will become $\bar{\beta}_i = -0.25$ and $\bar{\beta}_j = 0.5$. Note that, if there were only 1 researcher, then the threshold for recommending policy only changes by -0.2 . Thus, the strategic multiplier is $\zeta \simeq 3$ in this example, consistent with the

back-of-the-envelope calculation above.

2.5.3 Evidence

A large body of public health research has shown that industry funded research are more likely to have positive outcomes, and thus, interpreted this as a result of publication bias. A meta-analysis of 30 studies has found that industry-funded research is roughly four times more likely to have positive outcomes than the publicly funded research (Lexchin 2003). Given such evidence, it is common to consider that the pharmaceutical companies have large bias towards drug approval with little regards for patients' welfare (Goldcare 2010). This model's amplification result suggests that, however, caution is warranted when interpreting the difference in reporting decisions as quantitatively reflective of the underlying differences in the objectives. While research funded by industries will perhaps have some bias towards the outcomes favorable to the industry, the bias in objectives need not be so large to explain the strong associations between results and identities of funding sources.

2.6 Discussions of Key Assumptions

The analyses have shown that coarse aggregation can explain various kinds of publication bias. Overall, the discussions henceforth will show that the main conclusions are not highly sensitive to some auxiliary assumptions, and the main assumptions are standard in economics literature and relevant in the real world. The caveat must be in place if there is a reviewer who directly meta-analyze the results, or if the conflict of interest is large.

2.6.1 Sensitivity to Alternative Assumptions

The following discussions show the implications of (i) sequential reporting, (ii) conflict of interests, (iii) unknown number of researchers, and (iv) risk aversion:

- (i) sequential vs simultaneous reporting: the characterized equilibria will still remain as equilibria even if the reporting is sequential when there are 2 researchers, since the analysis of simultaneous reporting had researchers condition their reports on pivotality. This logic is analogous to Dekel and Piccione 2000. If the later researcher observes the early researcher's estimate, then the later researcher can summarize both estimates through meta-analyses and full reporting of all estimates will be the optimal equilibrium.
- (ii) conflict vs consistency of interests: the Section 2.5 has shown that the omission and inflation results are robust to small conflict of interest. When there is a large conflict of

interest such as when merely profit-maximizing pharmaceutical firms report studies, however, the incentive constraints will bind: rigid publication rules to eliminate publication bias will be optimal.

- (iii) unknown vs known number of researcher: the analysis has assumed that, N , the number of researchers is a public information. The numerical analysis in Appendix B1.3 shows that, in a plausible setting, the policymaker's optimal strategy is to implement the policy if and only if there are strictly more positive results than negative results. In this sense, the reader needs not know how many researchers there are to implement the optimal rule (2).
- (iv) risk aversion vs risk neutrality: when the payoff exhibits risk aversion, the study precision has benefits of reducing the uncertainty in addition to its role in determining weights of Bayesian updating. Nonetheless, small risk aversion does not alter the results since the objective is continuous in risk aversion parameter; by Taylor approximation of constant relative risk aversion preference γ implies the decision rule $\frac{(\mathbb{E}b)^{1-\gamma}}{1-\gamma} - \frac{\gamma}{2} \frac{\text{Var}(b)}{(\mathbb{E}b)^{1+\gamma}} \geq c$.

2.6.2 Validity of Main Assumptions

The results rely on the key assumptions that the message space is smaller than signal space, and that researchers can make contingent reasoning. The following discussions explore their validity:

- (i) large state and signal space vs limited action and message space: the critical assumption that drives the results is the distinction between space of states and signals that are continuous, and the space of action and messages that are discrete. When either assumptions are modified, then the omission with bias no longer arises. However, I argue that this set of assumptions is particularly appropriate for scientific communication: the information the researchers have are rich and complex whereas the messages they can convey will be limited and must be simple. Binary actions also apply in key applications such as whether to adopt a particular medicine or policy.
- (ii) PBNE and contingent reasoning: the implicit yet important assumption is that the senders of information condition the reporting decision on events in which their reports are pivotal. This logic is key to and common across models of information aggregation that have been applied in a number of settings, including general public's voting (Feddersen and Pesendorfer 1996), juror's voting (Feddersen and Pesendorfer 1998), opinion polls (Morgan and Stocken 2008), and demonstrations (Battaglini 2017). While such sophisticated reasoning may appear unrealistic and some lab experiments show individuals are unable to engage in such reasoning (Esponda and Vespa 2013), there is also evidence from both

lab (Battaglini et al. 2010, Dickhaut 1995) and fields (Kawai and Watanabe 2013) that some people condition their voting decisions on others' decisions.

3 An Empirical Test of the Communication Model

The communication model has shown that, if aggregation frictions are a key reason of omission, then both precise null results and extremely negative results will be reported. This Section develops a new empirical test to compare this prediction against some other publication selection processes, and applies this to show it holds with an economics data set.

3.1 Various Models of Publication Bias

Various existing bias correction methods have assumed specific publication selection process. This sub-Section shows that the selection process based on the communication model makes different predictions than the two most commonly¹⁶ used methods assume.

3.1.1 Data Generating Process

The data generation process of the published estimates, $\{\beta_i, \sigma_i\}$, will be assumed to take three steps given various independence assumptions. First, the underlying effect, $b_i \sim F$, and the study precision, $\sigma_i \sim G$, are independently¹⁷ determined. Second, the random error, $\epsilon_i \sim \mathcal{N}(0, \sigma_i^2)$, is independently drawn and the coefficient, $\beta_i = b_i + \epsilon_i$, is determined. Third, the study is published with some probabilities, $P(\beta_i, \sigma_i)$, that depend on $\{\beta_i, \sigma_i\}$. We will denote $b_0 \equiv \int b_i dF$ and $\sigma_0^2 \equiv \int (b_i - b_0)^2 dF$ as the mean and variance of underlying effect. Moreover, let us denote $H(\beta_i)$ as the distribution of coefficient estimates given F and G . σ_0^2 measures heterogeneity of effects across studies, whereas σ_b^2 had measured heterogeneity of effects across policies.

¹⁶While there are also some other models, this paper focuses on the comparison with most commonly used models: as of December 2018, Duval and Tweedie (2000) that introduced trim-and-fill method is cited over 4,900 times, and Hedges and Vivea (2000) that extends Hedges (1992) is cited over 2,000 times on Google Scholar. It is beyond the scope of this paper to fully explore the other selection models: Copas and Li (1997) (note that the working paper version had contained full discussions), Fafchamps and Labonne (2016), and Frankel and Kasy (2018).

¹⁷This independence assumption imposes that the studies with small vs large effects have identical true effects. This assumption is violated, for example, when the sample size affects the quality of treatment. Nonetheless, it is also assumed in other influential meta-analysis papers, such as Hedges 1992, Duval and Tweedie 2000, and Andrews and Kasy 2019.

3.1.2 Distinct Predictions of Various Models of Publication Bias

The communication model of this paper makes a distinct prediction on a form of publication selection, $P(\beta_i, \sigma_i)$, compared to the selection assumption behind the 2 most commonly used bias correction methods. Let us denote $\tilde{G}_\emptyset(\sigma)$ as the distribution of all standard errors conditional on the study being the non-positive results without any selection, and G_\emptyset as its observed distribution with selection; let us also denote $\tilde{H}_0(\beta)$ as the distribution of coefficient estimates conditional on the study not rejecting the null hypothesis with threshold \bar{t} , and H_0 as its observed distribution with selection. The Figure 4 summarizes the distinct predictions.

(1) communication model-based selection: the model of this paper suggests that, under aggregation frictions, the imprecisely estimated results with coefficients with small absolute values will be omitted¹⁸. As has been discussed in Section 2.3 and illustrated in Figure 3, the omission probability shrinks to zero when the between-study heterogeneity, σ_0 , is small. Therefore, when negative results are published, they are either precise null results so that $G_\emptyset > \tilde{G}_\emptyset$, or imprecisely estimated but extremely negative results so that $H_0 > \tilde{H}_0$.

(2) uniform selection: the model behind “Hedges” bias correction method, proposed by Hedges 1992, suggests that the statistically insignificant results will be *uniformly* less likely to be published than statistically significant results¹⁹:

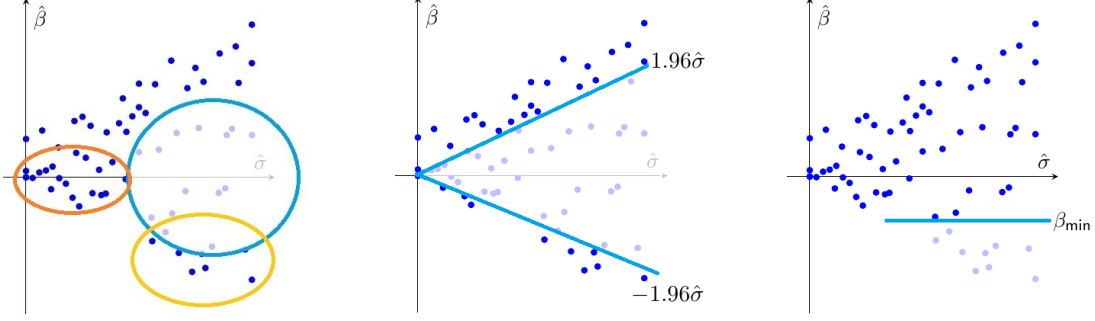
$$\mathbb{P}(\text{study } i \text{ is reported}) = \begin{cases} \eta_1 & \text{if } \frac{|\beta_i|}{\sigma_i} \geq 1.96 \\ \eta_0 & \text{if } \frac{|\beta_i|}{\sigma_i} < 1.96, \end{cases} \quad (12)$$

where $\eta_1 > \eta_0 > 0$. This suggests that the results that are not positively significant are systematically unlikely to be published. Thus, conditional on being null results, the distribution is identical to the underlying distribution of null results: $\tilde{G}_\emptyset = G_\emptyset$. Nonetheless, published negative results will be likely to be extreme negative results since results with intermediate coefficients have low t -statistics: $H_0 > \tilde{H}_0$. With an assumption that F is normal, this model is commonly used in economics with maximum likelihood estimation to correct for publication bias. (Hedges, 1992, Ashenfelter et al. 1999, McCrary et al. 2016, Andrews and Kasy 2019). This selection is consistent with the setting in which the researchers select based only on statistical significance to make their publication decisions.

(3) extremum selection: the model behind “trim-and-fill” bias correction method, proposed by Duval and Tweedie 2000, suggests that the most *extreme* negative results will be

¹⁸If the estimates can be directly communicated, then imprecise null results can be valuable (Abadie 2018).

¹⁹While the t -statistic thresholds can be specified more flexibly, it is common to apply the conventional threshold of $\bar{t} = 1.96$ on both positive and negative signs; since the sample size is often small in meta-analyses, it is practically difficult to estimate a model with many cut-offs.



(1) communication model: $\hat{G}_\emptyset > \tilde{G}_\emptyset$ and $\hat{H}_0 > \tilde{H}_0$ (2) uniform selection: $\hat{G}_\emptyset = \tilde{G}_\emptyset$ and $\hat{H}_0 > \tilde{H}_0$ (3) extremum selection: $\hat{G}_\emptyset > \tilde{G}_\emptyset$ and $\hat{H}_0 < \tilde{H}_0$

Figure 4: Selection models described in funnel plots

Notes: Using the funnel plot, the Figure 4 visualizes the (1) communication-based selection, (2) uniform selection, and (3) extremum selection models. The reported studies are depicted in dark dots, whereas the regions of omissions are approximated by the shaded area. The figures are generated by the author for an illustrative purpose, and do not reflect actual data.

omitted.

$$\mathbb{P}(\text{study } i \text{ is reported}) = \begin{cases} 1 & \text{if } \beta_i \geq \beta_{\min} \\ 0 & \text{if } \beta_i < \beta_{\min}, \end{cases} \quad (13)$$

where β_{\min} is some threshold. In common case where $\beta_{\min} < b_0$, there arises little selection among the most precise studies. Thus, null results are more likely to be reported when the standard error is small so that $G_\emptyset > \tilde{G}_\emptyset$. At the same time, the model also suggests that marginally insignificant negative results are not particularly more likely to be omitted since the selection is unrelated to the statistical significance milestones: $H_0 < \tilde{H}_0$. With an assumption that the underlying distribution of benefit, F , is symmetric, the trim-and-fill method imputes the most negative missing studies and computes the bias corrected estimate \hat{b}_0 . This reporting rule is consistent with the setting in which the researcher is biased towards positive results and do not hope to show extreme negative results, given a completely uninformed reader with improper uniform prior.

3.2 A Test to Distinguish the Various Models

Given that each model has distinct implications on the distribution of standard errors and coefficients of published studies, we develop an empirical test to examine them. The key obstacle is that the underlying distributions are unobserved. We (1) show that the underlying distribution can be predicted with some assumptions, and (2) describe the overview of the

estimation and testing steps.

3.2.1 Assumptions

To estimate the underlying distribution of $\{\beta_i, \sigma_i\}$ without selection, we need some regions of the estimates that do not suffer from selection, and need ways to extrapolate from those regions to other regions with selection. To operationalize these requirements, we will use the following assumptions²⁰ that are parsimonious and common in meta-analyses:

A1. *Constant selection within statistically significant results:* $P(\beta_i, \sigma_i) = \bar{P} \in (0, 1)$ for any $\frac{|\beta_i|}{\sigma_i} \geq \bar{t}$.

A2. *Underlying effects with independent normal distribution:* $b_i \stackrel{iid}{\sim} F(b_i) = \Phi\left(\frac{b_i - b_0}{\sigma_0}\right)$

Under the extremum selection model, A1 will be satisfied so long as $\beta_{\min} < 0$; under the uniform selection, both A1 and A2 will be satisfied. Note that A1 does not require that the publication probability is 1 for statistically significant results.

3.2.2 Semi-parametric Estimation and Testing Steps

We estimate the underlying distributions semi-parametrically using the Assumptions A1 and A2, and compare them against the observed distribution with a Kolmogorov-Smirnov (KS)-type test. The estimation is non-parametric along the dimension of σ while it assumes normal distribution along the dimension of β . While the complete description and discussion are relegated to the Appendix B2.1, the following overview describes the three steps of estimation and testing:

1. estimate $\{\hat{b}_0, \hat{\sigma}_0\}$ by the stem-based bias correction method that is robust to various kinds of distribution, $F(b_i)$, and selection, $P(\beta_i, \sigma_i)$;
2. estimate (i) the distribution $G_\emptyset(\sigma|\hat{b}_0, \hat{\sigma}_0)$ using the studies such that $|t_i| \geq 1.96$, and (ii) the distribution $H_0(\sigma|\hat{b}_0, \hat{\sigma}_0)$ using the distribution $G_\emptyset(\sigma|\hat{b}_0, \hat{\sigma}_0)$ estimated using the studies such that $t_i \geq 1.96$;
3. estimate the KS statistic for each distribution, D^G and D^H :

$$D^G = \sup_{\sigma} \left\{ \hat{G}_\emptyset(\sigma) - \tilde{G}_\emptyset(\sigma|\hat{b}_0, \hat{\sigma}_0) \right\} \text{ and } D^H = \sup_{\beta} \left\{ \hat{H}_0(\beta) - \tilde{H}_0(\beta|\hat{b}_0, \hat{\sigma}_0) \right\}$$

and associated one-sided p -values using the two-step bootstrap over estimates of b_0 and sampling of each study's σ_i and β_i .

²⁰These assumptions suggest that the bias due to inflation of marginal results is unimportant. With the limited sample sizes that is relevant for meta-analysis, it is infeasible to distinguish the inflation and omission; such test requires large sample size at the margin of statistical significance. While restrictive, this is an assumption applied in all other studies on bias correction.

3.3 Application

Using the test above, this sub-Section analyzes a meta-analysis data set with data selected from the papers that highlight the binary conclusions²¹. The result shows that the communication model-based selection pattern fits the data more adequately than the other two models.

3.3.1 Data

The data come from the set of 106 studies (i) that are included in the total of 111 studies meta-analysis of labor union’s effect on firm productivity (Doucouliagos et al. 2018) and (ii) that have the binary conclusions from t -statistics that match with the conclusions highlighted in the original papers. How the labor union affects firms is a highly contested issue, with various evidence supporting both positive and negative views. As each paper contains many estimates from various specification, the analysis uses its median value. To focus on the coefficients underlying the highlighted conclusions, two independent readers examined the abstract, introduction, and conclusions of each paper and excluded some papers whose highlighted conclusions in the paper did not match the implication of t -statistics in Doucouliagos et al.’s data set²².

3.3.2 Results

The results suggest that the reporting patterns of null and negative results²³ are consistent with the communication model-based selection process, but not with other processes. Figure 5 visualizes the two results. First, observed null results tend to be more precise than predicted distribution of null results: $\hat{G}_0 > \tilde{G}_0$. Concretely, while only 20 percent of studies are predicted to have standard errors less than .08, above 70 percent of studies have standard errors smaller than 0.8 ($p = .000$). This pattern is not consistent with the uniform omission model, which suggest that the two distributions will be roughly equal with one another. Second, observed negative results, including null results and negative significant results, tend to be more negative than their predicted distribution: $\hat{H}_0 > \tilde{H}_0$. Concretely, while only roughly 14 percent of studies are expected to have coefficient less than -0.125, the observed distribution has over 29 percent of

²¹A previous version of this paper (Furukawa 2016) also analyzes the data of Intertemporal Elasticity of Substitution, which highlight the “binary conclusions” less since the quantity of interest is a continuous estimate.

²²The detailed discussions on the inclusion criteria, as well as classification’s text evidence, are available in https://github.com/Chishio318/Data_publication_bias. The meta-analysis can include only one estimate from one study: when there are multiple estimates in one study, it is common to choose the estimates of median magnitude (for example, in Havránek 2015).

²³As Figure 2 suggests that no studies will be reported in an omission region, taken literally, the data may appear to contradict the communication model. However, existence of some studies in omission regions could be explained by dispersed beliefs across researchers that lead to different – even overlapping – thresholds of reporting positive vs negative results as illustrated in Section 2.5. The paper does not claim that aggregation friction is the only reason behind publication bias: instead, it only suggests that aggregation friction can explain some regularities of publication bias.

studies have such negative values ($p = .0311$). This pattern is not consistent with the extremum omission model, which suggest that the reported studies will have more moderate coefficient values. Taken together, among the three models, the communication-based selection process is the only one that can account for the pattern of omission in this data set.

- (1) distribution of σ_i of null results: (2) distribution of β_i of non-positive results:

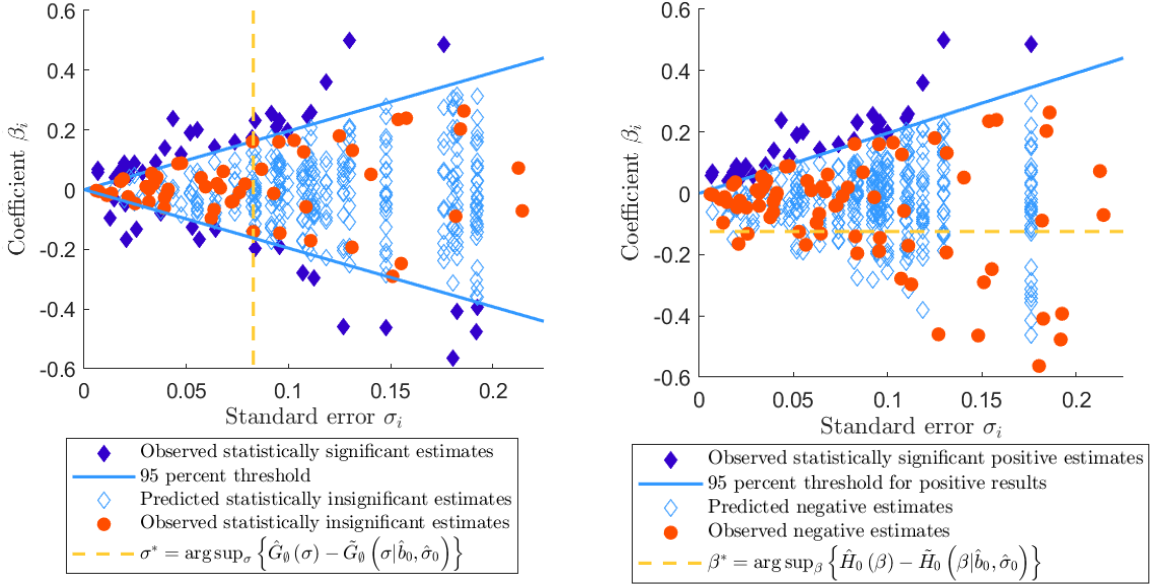


Figure 5: KS-type test illustrated in funnel plots

Notes: Figure 5 are the funnel plots that illustrate the KS-type test described in Section 3.2.2. The filled diamonds with dark blue are observed significant results; the empty diamonds are predicted non-positive results; and filled circle with orange are predicted non-positive results. The dashed lines represent the values at which the KS-type test is evaluated.

4 A New “Stem-based” Bias Correction Method

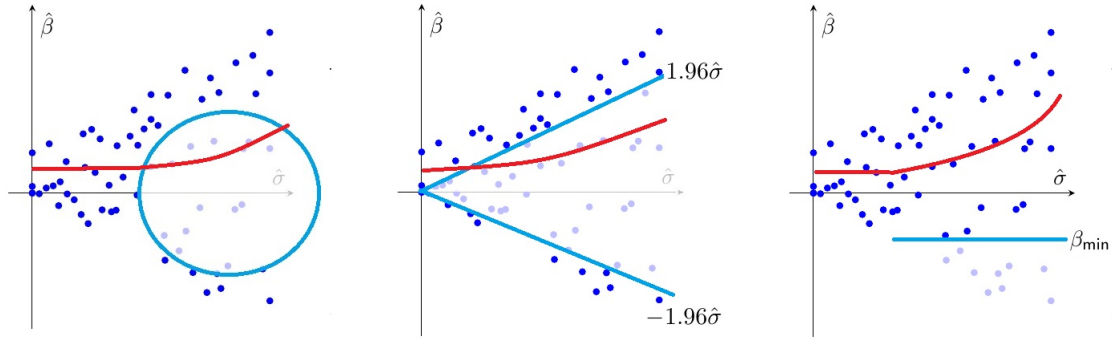
The communication model in Section 2 has suggested an alternative publication selection process, and the empirical analysis in Section 3 has shown its relevance in a real-world data set. Moreover, the model suggests, if aggregation friction is the important reason of publication selection, then the selection will depend on a number of economic primitives unobservable to meta-analysts. What could we do to alleviate the bias that arises from publication selection when aggregating various estimates?

This Section presents a new, non-parametric, fully data-dependent, and generally conservative bias correction method, to be called a “stem-based” bias correction method. The estimate uses the studies with highest precision, which correspond to the “stem” of the “funnel” plot, to

estimate a bias corrected average effect. It has both theoretical and empirical merits over other existing methods: theoretically, the estimate is based on weaker assumptions on the publication selection process and the underlying distribution than other methods; empirically, the simulation shows that the estimate has adequate coverage probabilities across different publication selection processes.

4.1 Main Argument

The stem-based bias correction method uses some of the most precise studies because, across various selection models, precise studies suffer less from publication bias than imprecise studies. In the communication model of this paper, the most precise studies are omitted less often, as visualized in Figure 1. In the two most commonly used models described in Section 3.1.2²⁴, the following Proposition shows that the bias is decreasing in study precision, and that, under some conditions, the bias is zero as studies become infinitely precise.



(1) communication model (2) uniform selection (3) extremum selection

Figure 6: Meta-analysis estimates in funnel plots

Notes: Using the funnel plot, the Figure 6 visualizes the (1) communication-based selection, (2) uniform selection, (3) extremum selection models. The reported studies are depicted in dark dots, whereas the regions of omissions are approximated by the shaded area. The thick red lines indicate the mean level of estimates at given values of standard errors. The figures are generated by the author for an illustrative purpose, and do not reflect actual data.

Proposition 2 (minimal bias among most precise studies across selection models).

Define the bias of studies with precision σ_i as $Bias(\sigma_i) \equiv \mathbb{E} [\beta_i | \sigma_i, \text{study } i \text{ reported}] - b_0$.

²⁴While rigorous analysis is beyond the scope of this paper, this pattern also holds with other models such as Copas and Li (1997), Fafchamps and Labonne (2016), and both static and dynamic models of Frankel and Kasy (2018).

1. (Monotonicity) $Bias(\sigma_i)^2$ is increasing in σ_i for all σ_i under the extremum selection models, and for $\sigma_i \in [0, \underline{\sigma}]$ for some $\underline{\sigma} > 0$ under the uniform selection model.
2. (Limit) $\lim_{\sigma_i \rightarrow 0} Bias(\sigma_i)^2 = 0$ if $\sigma_0 = 0$ and threshold β_{\min} is sufficiently low under the extremum selection model, and always under the uniform selection model.

Sketch of Proof. By comparison of conditional across values of σ_i expectation given the bias selection model. Appendix A5 contains a proof. \square

That is, more precise studies are less subject to the publication selection; and moreover, the bias approaches zero as the studies become infinitely precise under some conditions. Heuristically, concerns for low statistical significance or extremely negative values become unimportant when studies are precise.

The stem-based method chooses the number of studies, n_{stem} , to include by optimizing over the bias-variance trade-off. While focusing only on the most precise studies give the least biased estimate, it also suffers from high variance. Therefore, the stem-based method includes n_{stem} to minimize the Mean Squared Error (MSE) of the estimate while ensuring that the assumed and implied variance are consistent with one another. Denoting the publication selection process as P as in Section 3.1.1, it strives to solve:

$$\min_n MSE(\hat{b}_0^n | \sigma_0) = Var(\hat{b}_0^n, \sigma_0) + Bias^2(\hat{b}_0^n, b_0) \text{ subject to } Var(b_i | \hat{b}_0^n, P) = \sigma_0^2 \quad (14)$$

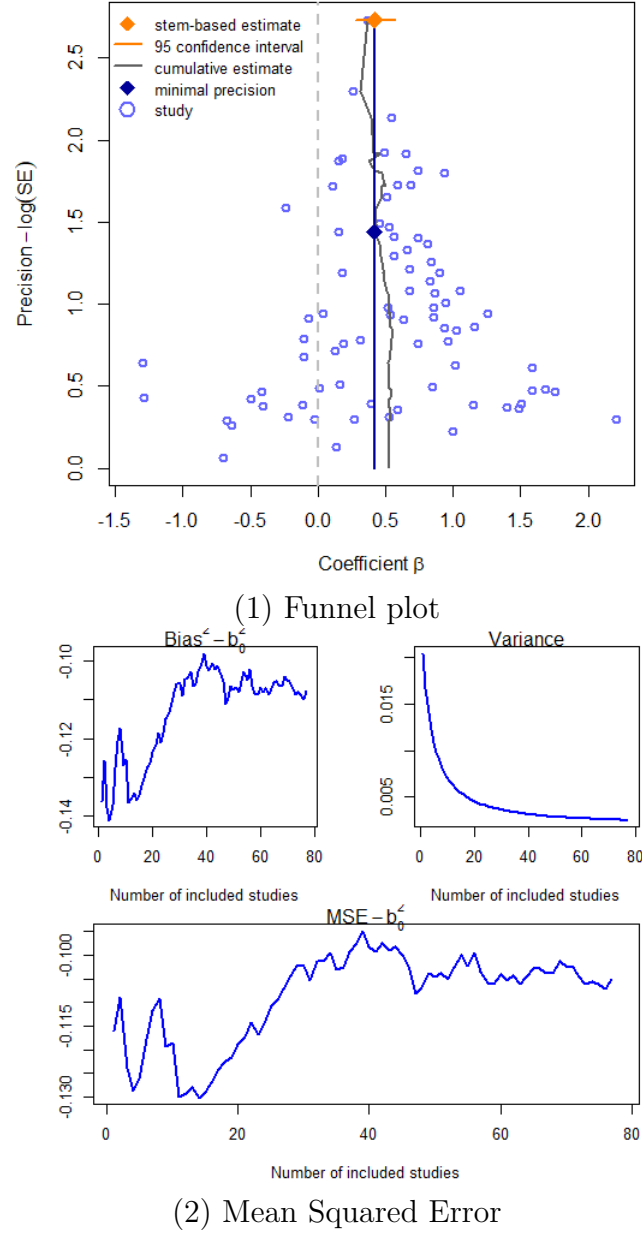
However, this problem of minimizing the exact MSE requires the knowledge of b_0 , true mean, and P , publication selection process. Since solving this criteria is infeasible, the method instead solves its empirical analogue:

$$\min_n \tilde{MSE}(\hat{b}_0^n, \hat{b}_0, \sigma_0) \text{ subject to } \hat{Var}(b_i | \hat{b}_0^n) = \sigma_0^2. \quad (15)$$

That is, the MSE is replaced by an unbiased estimate of its relevant component, $\tilde{MSE}(\hat{b}_0^n, \hat{b}_0, \sigma_0)$, and the implied variance term is replaced by its empirical analogue, $\hat{Var}(b_i | \hat{b}_0^n)$.

The estimates of stem-based method can be visually represented with a funnel plot (Figure 7): with uniform selection generating 80 studies in this simulation, it is optimal to include 17 studies, which is roughly an average number of studies included in simulations. Including all studies leads to an upward bias, as indicated by theory. On the other hand, only a few most precise study can be noisy, both because of between-study heterogeneity and of insufficient high within-study heterogeneity due to low total sample size, so that inclusion of more studies leads to a smaller 95 confidence interval that covers 0.4, the true mean value.

Figure 7: A visualization of stem-based method



Notes: Figure 7 are an illustration of (1) a funnel plot of stem-based bias correction method, and (2) the Mean Squared error criteria for choosing the n_{stem} , the optimal number of studies to include. The data comes from a simulation of 80 studies under the uniform selection model such that the number of included studies is 17. (1) The funnel plot, with y -axis denoting a measure of precision, describes the stem-based method. The orange diamond at the top indicates the stem-based estimate along with its 95 percent confidence interval. The connected line is the estimate with various $n_{stem} \in \{1, \dots, N\}$, indicating how aggregate estimates change. The diamond at the middle of the curve indicates minimal level of precision for the inclusion. Therefore, the stem-based estimate is given by the studies, represented by circle, whose precision are above this diamond. (2) The relevant components of Mean Squared Error is plotted, indicating that the $Bias^2$ is increasing while Var is decreasing in n_{stem} .

4.2 Estimation

Given the objective (14), this sub-Section describes a particular approximation to (15) that this paper proposes, illustrates estimation steps, and discusses the assumptions necessary to ensure its reliability.

4.2.1 Estimation Steps

The stem-based method computes the estimates with the following inner and outer algorithms: the inner algorithm computes the bias corrected mean given an assumed value of σ_0^2 ; the outer algorithm computes the implied variance and ensure that it is consistent with its assumed value.

I. Inner algorithm: estimate \hat{b}_{stem} , $SE(\hat{b}_{\text{stem}})$, n_{stem} given an assumed value of σ_0 .

1. rank and index studies in the ascending order of standard error so that $\sigma_1 \leq \sigma_2 \dots \leq \sigma_N$
2. for each $n = 2, \dots, N$, compute the relevant mean squared error, $M\tilde{S}E(n)$, as follows:
given weights $w_i \equiv \frac{1}{\sigma_i^2 + \sigma_0^2}$,

$$M\tilde{S}E(n) = \frac{\sum_{i=2}^n \sum_{j \neq i}^n w_i w_j \beta_i \beta_j}{\sum_{i=2}^n \sum_{j \neq i}^n w_i w_j} - 2\beta_1 \frac{\sum_{i=2}^n w_i \beta_i}{\sum_{i=2}^n w_i}$$

3. compute the optimal number of included studies, n_{stem} : n_{stem} minimizes the relevant components of MSE, so that

$$n_{\text{stem}} \in \arg \min_n M\tilde{S}E(n)$$

Thus, the stem-based estimate is $\hat{b}_{\text{stem}} \equiv \frac{\sum_{i=1}^{n_{\text{stem}}} w_i \beta_i}{\sum_{i=1}^{n_{\text{stem}}} w_i}$, $SE(\hat{b}_{\text{stem}}) \equiv \frac{1}{\sqrt{\sum_{i=1}^{n_{\text{stem}}} w_i}}$. The estimation of \hat{b}_{stem} applies the inverse variance weights since they minimize the variance of the estimator given the sample.

II. Outer algorithm: search over values of σ_0^2 such that the implied $\hat{V}ar(b_i | \hat{b}_0^n)$ is consistent. Throughout, we adopt the formula of variance proposed by DerSimonian and Laird (1996)²⁵: given weights $w'_i \equiv \frac{1}{\sigma_i^2}$, $\hat{V}ar(\beta_i | \hat{b}_0^n) = \max \left\{ \hat{V}ar(\beta_i | \hat{b}_0^n), 0 \right\}$, where

$$\hat{V}ar(\beta_i | \hat{b}_0^n) = \frac{\sum_{i=1}^N w'_i (\beta_i - \hat{b}_0^n)^2 - (N-1)}{\sum_{i=1}^N w'_i - \frac{\sum_{i=1}^N w_i'^2}{\sum_{i=1}^N w'_i}}. \quad (16)$$

²⁵This formula is commonly used in non-parametric estimations of F . For example, trim-and-fill proposed by Duval and Tweedie (2000) also uses this originally. While there are some criticisms to this approach (Veroniki et al. 2015), it is left for future work to explore how between-study heterogeneity can be adequately estimated.

Here, $\hat{b}_0^n \equiv \frac{\sum_{i=1}^n w_i \beta_i}{\sum_{i=1}^n w_i}$ is the estimate based on n studies.

1. set two initial estimates of σ_0^2 by applying (16) to $\hat{b}_0^{\min} = \frac{\sum_{i=1}^N w'_i \beta_i}{\sum_{i=1}^N w'_i}$ and $\hat{b}_0^{\max} = \sum_{i=1}^N \beta_i$.
2. compute the implied stem-based estimates and their variance by applying (16)
3. iterate step 2 until it converges; if the limit of maximum and minimum disagree, then choose the maximum.

4.2.2 Additional Arguments

Turning an ideal problem (14) into a feasible problem (15) had required ways to approximate the knowledge of b_0 , true mean, and P , publication selection process. The method had applied non-parametric estimation techniques of unbiased Cross-Validation criteria to approximate b_0 ; and estimated σ_0^2 to give a conservative confidence interval of \hat{b}_{stem} given unknown P :

Unbiased Cross-Validation criteria for b_0 : we can replace the component, $MSE(n)$, by its relevant term, $M\tilde{S}E(n)$, since they differ only by a constant²⁶. The formula proposed in the inner algorithm provides an approximately unbiased estimate of $M\tilde{S}E(n)$ under some assumptions: if (A1) $\mathbb{E}\beta_1 \simeq b_0$ and (A2) $\mathbb{E}\hat{b}_{2,n} \simeq \mathbb{E}\hat{b}_{1,n}$, then

$$\begin{aligned} \mathbb{E}M\tilde{S}E(n) &= \mathbb{E} \frac{\sum_{i=2}^n \sum_{j \neq i}^i w_i w_j \beta_i \beta_j}{\sum_{i=2}^n \sum_{j \neq i}^i w_i w_j} - 2\mathbb{E}\beta_1 \frac{\sum_{i=2}^n w_i \beta_i}{\sum_{i=2}^n w_i} \\ &= \frac{\sum_{i=2}^n \sum_{j \neq i}^i w_i w_j \mathbb{E}\beta_i \mathbb{E}\beta_j}{\sum_{i=2}^n \sum_{j \neq i}^i w_i w_j} - 2\mathbb{E}\beta_1 \mathbb{E} \frac{\sum_{i=2}^n w_i \beta_i}{\sum_{i=2}^n w_i} \\ &\simeq \hat{b}_0^2 - 2b_0 \hat{b}_0 \end{aligned}$$

There are two statistical techniques involved in these steps: the first term computes the squared term by leaving one sample out in order to avoid the bias that arises due to the squared term²⁷. More importantly, the second term applies a Cross-Validation (CV) technique by replacing the true value of b_0 by its estimate. Since β_1 is the least biased estimate of b_0 , we apply the “leave-one-out” method in CV technique by splitting the sample into the most precise estimate that constitutes a testing set and all other estimates that constitute a training set.

Equating $\hat{Var}(b_i | \hat{b}_0^n) = \hat{\sigma}_0^2$: the outer algorithm likely leads to a large estimate of σ_0^2 for three reasons. (i) While the exact selection process, P , is unknown, the variance is overestimated

²⁶To see this, we can expand the bias squared term:

$$M\tilde{S}E(\hat{b}_0) \equiv \hat{b}_0^2 - 2b_0 \hat{b}_0 = (\hat{b}_0 - b_0)^2 - b_0^2 = MSE(\hat{b}_0, b_0) - b_0^2.$$

²⁷The method requires at least $N = 3$ studies to compute the relevant MSE.

when it is the intermediate results that is omitted as suggested by theory; (ii) the estimation of $\hat{Var}(b_i|\hat{b}_0^n)$ uses the entire sample so as to avoid underestimating the variance with only few samples used in stem-based estimation; and (iii) when there are multiple values of σ_0^2 that are consistent with one another, the method uses a larger one. By choosing the specification such that the estimate of σ_0^2 is large, the method strives to make a conservative estimate of the 95 confidence interval for \hat{b}_{stem} .

4.2.3 Summary of Assumptions

In summary, for the stem-based method to generate a reliable estimate, we need that the MSE can be well-approximated, (A1) $\beta_1 \simeq b_0$ and (A2) $\hat{b}_{2,n} \simeq \hat{b}_{1,n}$, and that the variance implied is close to the true variance, $\hat{Var}(b_i|\hat{b}_0^n) \simeq \sigma_0^2$. These conditions may not be satisfied when the underlying variance, σ_0^2 , is large since even the most precise studies may not approximate the true underlying mean. While the method imposes no assumptions on underlying distribution, F , and only monotonicity assumption on the selection process, P , it instead relies on these assumptions to mitigate publication bias.

One implicit and important assumption is that the studies' precision is correctly reported. An inflation of t -statistics through under-reporting the standard error, such as through choice of units of clustering, can compromise the reliability of this method. I recommend investigating the specifications of most precise studies in detail to avoid severe misreporting of study precision.

4.3 Assessment

Given the theoretical foundations and the assumptions made in estimation steps, how does stem-based bias correction method perform across various selection processes? The simulation henceforth shows that the stem-based correction method provides a more reliable estimate of confidence intervals than other commonly used methods in meta-analysis settings calibrated to plausible values²⁸.

4.3.1 Simulation set-up

This simulation will compute the coverage probabilities and interval lengths with a Monte Carlo experiment. The studies' standard errors, σ_i , is drawn from $G(\sigma)$ that approximates the implied distribution from the labor union data sets (Appendix B1.1). Concretely, $\hat{G}(\sigma)$ has the

²⁸There are new methods that have been developed, including regression-based approach of PET-PEESE (Stanley 2008), maximum likelihood approach (Andrews and Kasy 2018), selection model analogous to Heckman's two step process (Copas and Li 1997), other methods that focus on precise studies such as top10 (Stanley et al. 2010) and kink-based methods (Bomy and Rachinger 2018), and bias correction using only significant studies (Simonsohn et al. 2014). It is left for future work to exhaustively investigate the relative merits and demerits of these methods.

distribution of σ^2 that is χ^2 distribution with 2 degrees of freedom with support of $[0, 4]$ that is re-scaled such that $Supp(G) = [0, 1]$. The studies' coefficients are determined by $\beta_i = b_i + \epsilon_i$, where $b_i \sim \mathcal{N}(b_0, \sigma_0^2)$ and $\epsilon_i \sim \mathcal{N}(0, \sigma_i^2)$ and is independently drawn. $\sigma_0 = 0.3$ so that match the degree of heterogeneity in the labor union data set; $b_0 = 0.4$ so that the average effect size ($\frac{b_0}{\sqrt{2}\sigma_0} \simeq 0.94$) is large but reasonable. We consider the data with 30 and 80 published studies to investigate how sample size affects the reliability of estimates; these are the range of small and large meta-analysis data also used in other simulation studies (Duval and Tweedie 2000, Stanley and Doucouliagos 2014).

There will be three sets of data generating processes and four estimation methods²⁹, as presented in Table 1. We begin by simulating the data without selection (row 1) and the estimation method without any bias correction (columns (i) and (ii)). Then, row 2 presents the estimates with uniform selection model in which statistically insignificant results with $t = 1.96$ thresholds are reported with only 30 percent of the time ($\eta_1 = 1, \eta_0 = 0$), and columns (iii) and (iv) show the uniform MLE method (Hedges 1992, Hedges and Vevea 2005) that assumes this; row 3 presents the estimates with extremum selection model in which some very negative results are reported ($\hat{\beta} = -0.1$), and columns (v) and (vi) presents the trim-and-fill method that assumes such selection process. The selection parameters, η_1, η_0 , are based on the estimates from Andrews and Kasy 2019, and the parameter $\hat{\beta}$ is chosen so that the coverage probability with no correction is roughly equal between the two selection models. Finally, columns (vii) and (viii) presents estimation results using the stem-based method. In this way, with realistic parameter values, this simulation will assess not only how each method performs given the selection process that the method assumes, but also how each performs given the process that it does *not* assume.

4.3.2 Results

The main result is that the confidence intervals based on the stem-based correction method are more reliable across various selection models than those based on other methods. With estimation with no correction (columns (i) and (ii)), the coverage probabilities are close 0.95 when there is no publication selection but are 0.26 when there is serious omission; with estimation with correction methods, the coverage probabilities are reasonable when their respective assumed selection process is correct, they can be low when it is different. With uniform MLE, it is roughly 0.76~0.88 given uniform selection model, but is 0.13~0.47 with extremum selec-

²⁹Each estimation has utilized the canned command available in R. The trim-and-fill correction uses a package in `metafor` (Viechtbauer 2010), with between-study variance estimated using DerSimonian and Laird method as proposed in the original paper by Duval and Tweedie 2000. The uniform correction uses the package `weightr` (Coburn and Vevea 2017). Note that each algorithm had implementation difficulties due to non-convergence in trim-and-fill, and non-singularity of Hessian. In this simulation, each estimation method was evaluated with the data sets that do not have these estimation problems.

tion; with trim-and-fill method, the coverage probability is roughly 0.64~0.67 given extremum selection model, but is 0.43~0.69 with uniform selection; On the other hand, the stem-based estimates have coverage probabilities of above 0.78 across selection models.

The improvement of robustness of stem-based methods comes with the disadvantage of larger average interval lengths. The simulation underlying the Table 1 finds, on average, roughly $n_{stem}^* = 9$ studies for $N = 30$, and $n_{stem}^* = 15$ studies for $N = 80$ since the distribution $\hat{G}(\sigma)$ has high density of very precise studies.³⁰ Table 1 shows that the average interval length is roughly 1.5 to 2 times larger than the other methods that use all data points. Nonetheless, when a less permissive estimation methods such as stem-based methods reject the null hypotheses, one can be more confident that the conclusion is not driven by particular selection method that the method has imposed.

Table 1. simulation of bias correction methods across various models

	no correction		uniform MLE		trim-and-fill		stem-based	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
no selection	0.94	0.93	0.89	0.78	0.85	0.83	0.95	0.93
	[0.25]	[0.40]	[0.29]	[0.42]	[0.23]	[0.38]	[0.55]	[0.64]
uniform	0.26	0.63	0.88	0.76	0.43	0.69	0.80	0.85
	[0.25]	[0.41]	[0.31]	[0.42]	[0.22]	[0.37]	[0.58]	[0.65]
extremum	0.26	0.62	0.13	0.47	0.64	0.67	0.78	0.79
	[0.21]	[0.33]	[0.20]	[0.34]	[0.20]	[0.31]	[0.43]	[0.48]
N	80	30	80	30	80	30	80	30

Notes. Table 1. reports the coverage probability and average interval length (noted in []) for the sample in which there are $N = 80$ studies and $N = 30$ studies. The simulation is based on a 1,000 replications of the data sets.

4.4 Final Remarks

The two most influential bias correction methods with high citations have relied on specific assumptions about the publication selection process, P , and the underlying distribution³¹, F . Various authors defend their own assumptions against each other: Duval and Tweedie (2000) justifies the extremum selection model by writing “A number of authors ... have pointed out

³⁰The number of included studies, n_{stem}^* , varies substantially across replication data sets within the same simulation environment. This heterogeneity of n_{stem}^* suggests the advantage of stem-based method relative to the rule-of-thumb approach that uses some fixed number or fraction of all studies. At the same time, there are many studies with only a few studies included. While n_{stem}^* may appear to indicate severity of publication selection since $n_{stem}^* = N$ in the absence of any selection, simulation indicates that the difference in n_{stem}^* between the data with or without selection is limited.

³¹Even the “trim-and-fill” method’s assumption that F is symmetric can be problematic when economists hope to produce a meta-analysis estimates of elasticity, on which microeconomic theories impose sign restrictions.

that this simple p -value suppression scenario is rather simplistic since it fails to acknowledge the role of other criteria, such as size of study.” Simonsohn (2014) criticizes this approach and writes “In most fields, however, publication bias is governed by p -values rather than effect size.” The communication model of this paper suggests both criticisms are valid: while the selection process can be approximated by the constant t -statistics approach, study precisions also have important impact on publication decisions.

The stem-based bias correction method takes a different approach that uses the monotonicity property of various selection processes, and makes no assumptions on the underlying distribution unlike in other methods that assumed normality or symmetry. While there are other assumptions in estimation steps to perform well, the numerical simulation shows that the method has more adequate coverage probabilities across a range of publication selection processes. In fact, there have been authors who have suggested to focus on some arbitrary number of most precise studies (Barth et al. 2013, Stanley et al. 2010). This paper builds on their ideas, proposes a formal theoretical justification of this approach, and develops an algorithm to choose an optimal number of most precise studies to include. In this way, the method can provide a meta-analysis tool that has merits to the researchers who believe in either processes of publication selection and who wish to build consensus among researchers who believe in different processes.

5 Conclusion

There are two thought experiments that question the common interpretation that (i) the publication bias must arise from the biased motives of journals and researchers, and that (ii) it will be socially optimal if journals publish all binary conclusions:

- (i) if readers prefer publication outlets with full reporting of all results, then a journal or a researcher can singularly announce that they will publish all results that they observe. Given the current technology of record keeping and replication, this statement can be verifiable. Then, the demand for such journals and researchers must increase, resulting in a higher demand that journals and researchers are seeking. Yet this deviation from the current communication equilibrium with publication bias is not observed today.
- (ii) if researchers report all results of null hypothesis testing and readers wish to use any drugs with positive effects but consider only the binary conclusions, then readers must use the drug even when only 3 percent of studies are positive and 97 percent of studies are negative. This is because, with a conventional null hypothesis testing, zero effect implies exactly 2.5 percent of positive and 97.5 percent of negative results; thus, when there are many studies, having positive results more than 2.5 percent of the time implies that the

true underlying effect is positive. Yet ordinary readers will, I think, interpret 97 percent negative results not as an approval but as a disapproval of the drug.

While most discussions on publication bias have focused on biased incentives of researchers, the model of this paper, along with these thought experiments, suggest aggregation frictions may play important roles in understanding reasons why publication bias is prevalent and persistent.

Publication bias is commonly believed to contradict the unbiasedness of researchers, which has been put forth as a core ethos of science (Merten 1947). If information can be fully and costlessly communicated, then conveying all results, as they are, is what unbiased researchers must do. Yet this paper has shown that aggregation frictions can explain various kinds of publication bias. The casual expressions such as “exciting” vs “boring” results appear to suggest biases and irrationality among researchers. This paper is an attempt to provide a rational theory of “interesting results” – they are results whose binary conclusions can influence the decisions of the readers, when other results are collectively inconclusive.

The model also suggests that the publication selection process under aggregation frictions will not only differ from commonly assumed parsimonious processes, but also cannot have other parsimonious representations. This impossibility arises because (i) omission will be asymmetric between positive and negative results; (ii) inflation due to nonlinear thresholds will be difficult to address; and (iii) exact thresholds will depend critically on primitives – objectives and prior beliefs – that are unobservable to meta-analysts. Shared across commonly assumed processes and this model is the prediction that more precisely estimated studies suffer less from publication bias. This paper extends the existing methods that use arbitrary number of most precise studies (Stanley et al. 2010, Barth et al. 2013) by developing a formal method to choose an optimal number of studies to include. In this way, this paper provides a tool that has merits not only to meta-analysts who believe in different forms of publication bias, and but also to those who wish to build a consensus by relying not on contested assumptions but only on regularities common across them.

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Appendix A. Proofs

Appendix A presents the proofs of propositions and some additional analytical results. Appendix A1 presents some preliminary results to prepare for the main analyses; Appendix A2 presents proofs of propositions in Section 2.3; Appendix A3 presents the proof of Section 2.4; Appendix A4 presents the proof of Section 2.5; Appendix A5 presents an example in Section 2.5; Appendix A6 presents the proof of Section 4.1. For notational ease, let us denote $\pi(n_1, n_0)$ as the policymaker's strategy given the number of positive and negative results.

A1. Preliminaries

We begin by proving three lemmas that will be relevant throughout the proofs: with normally distributed random variable, (1) conditional mean of will be increasing in the mean of its underlying distribution, (2) higher conditional mean implies that the likelihood ratio will be increasing in the mean of its underlying distribution, and (3) strategies will be monotone as in Lemma 1 in any fully responsive and fully informative equilibria. While these properties need not hold in general, normal distribution imposes sufficient structure to facilitate the analyses of the model.

A1.1. Monotonicity of Conditional Mean

Lemma A1 will show that the conditional mean of normally distributed random variable with any arbitrary condition will equal the ratio of conditional variance to total variance. This is a generalization of the proof for truncated normal distribution by Alecos Papadopoulos (2013).

Lemma A1. Derivative of conditional mean with respect to unconditional mean.

Given any $s_m(\beta) \equiv \mathbb{P}(s = 1|\beta)$, the derivative of conditional mean $\mathbb{E}[\beta s | s_m(\beta)]$ of $\beta \sim \mathcal{N}(\mu, \sigma^2)$ with respect to its mean μ satisfies

$$\frac{\partial \mathbb{E}[\beta s | s_m(\beta)]}{\partial \mu} = \frac{Var_m}{\sigma^2}, \quad (17)$$

where $Var_m \equiv \mathbb{E}\{\beta - \mathbb{E}[\beta s | s_m(\beta)]\}^2$ is the variance of the random variable conditional on the message.

Proof. By applying the property of density of normal distribution. We will first express the conditional mean, then take the derivative by the chain rule, and finally reorganize the expression to see that (17) holds for any $s(\beta)$.

First, by definition, we have

$$\mathbb{E}[\beta s | s_m(\beta)] = \frac{f_1(\mu)}{f_2(\mu)},$$

where $f_1(\mu) \equiv \int \beta s_m(\beta) \phi\left(\frac{\beta-\mu}{\sigma}\right) d\beta$, $f_2(\mu) \equiv \int s_m(\beta) \phi\left(\frac{\beta-\mu}{\sigma}\right) d\beta$, and $\phi(\cdot)$ is the density of standard normal distribution.

Second, we can apply the chain rule to obtain

$$\frac{\partial \mathbb{E}[\beta s | s_m(\beta)]}{\partial \mu} = \frac{f'_1(\mu) f_2(\mu) - f_1(\mu) f'_2(\mu)}{[f_2(\mu)]^2}, \quad (18)$$

where

$$f'_1(\mu) = -\frac{1}{\sigma} \int \beta s_m(\beta) \phi'\left(\frac{\beta-\mu}{\sigma}\right) d\beta \text{ and } f'_2(\mu) = -\frac{1}{\sigma} \int s_m(\beta) \phi'\left(\frac{\beta-\mu}{\sigma}\right) d\beta.$$

Third, using the property of normal density that $\phi'\left(\frac{\beta-\mu}{\sigma}\right) = -\frac{\beta-\mu}{\sigma} \phi\left(\frac{\beta-\mu}{\sigma}\right)$, we can reorganize them as

$$\begin{aligned} f'_1(\mu) &= \frac{1}{\sigma^2} \int \beta s_m(\beta) (\beta - \mu) \phi\left(\frac{\beta-\mu}{\sigma}\right) d\beta = \frac{f_3(\mu) - \mu f_1(\mu)}{\sigma^2} \\ f'_2(\mu) &= \frac{1}{\sigma^2} \int s_m(\beta) (\beta - \mu) \phi\left(\frac{\beta-\mu}{\sigma}\right) d\beta = \frac{f_1(\mu) - \mu f_2(\mu)}{\sigma^2} \end{aligned}$$

where $f_3(\mu) \equiv \int \beta^2 s_m(\beta) \phi\left(\frac{\beta-\mu}{\sigma}\right) d\beta$. By substituting into the condition (18),

$$\begin{aligned} \frac{\partial \mathbb{E}[\beta s | s_m(\beta)]}{\partial \mu} &= \frac{1}{\sigma^2} \frac{(f_3 - \mu f_1) f_2 - f_1 (f_1 - \mu f_2)}{f_2^2} \\ &= \frac{1}{\sigma^2} \frac{f_3 f_2 - f_1^2}{f_2^2} \\ &= \frac{1}{\sigma^2} \left[\frac{f_3}{f_2} - \left(\frac{f_1}{f_2} \right)^2 \right] \\ &= \frac{1}{\sigma^2} \left\{ \mathbb{E}[\beta^2 s_m | s(\beta)] - (\mathbb{E}[\beta s_m | s(\beta)])^2 \right\} \\ &= \frac{Var_m}{\sigma^2} \end{aligned}$$

where the last line followed by the definition of variance. □

A1.2. Monotonicity of Mean Likelihood Ratios

Lemma A2. will show that the messages with higher conditional mean will also be more likely to be sent when the mean of underlying distribution increases. This monotonicity of likelihood ratio is not equivalent to the standard Monotone Likelihood Ratio Property of normal distribution with known variance, since the standard statement is concerned with each value whereas the following lemma addresses the average value. This property is key to deriving the

Lemma 1 monotonicity of equilibrium strategies: the analogue of Lemma 1 will not hold when the standard errors are heterogeneous and unknown.

Lemma A2. Equivalence of change in likelihood ratio and mean ranking. *Consider two strategies, $s_m(\beta)$ and $s_{\tilde{m}}(\beta)$, given $\beta \sim \mathcal{N}(\mu, \sigma^2)$ and the associated likelihood ratio of each messages, $LR(\mu) \equiv \frac{\mathbb{P}(m|\mu)}{\mathbb{P}(\tilde{m}|\mu)}$. Then, $LR'(\mu) > 0$ if and only if $\mathbb{E}[\beta s|s_m(\beta)] > \mathbb{E}[\beta s|s_{\tilde{m}}(\beta)]$.*

Proof. By definition,

$$LR(\mu) \equiv \frac{\int s_m(\beta) \phi\left(\frac{\beta-\mu}{\sigma}\right) d\beta}{\int s_{\tilde{m}}(\beta) \phi\left(\frac{\beta-\mu}{\sigma}\right) d\beta}$$

By chain rule and the property of normal density that $\phi'\left(\frac{\beta-\mu}{\sigma}\right) = -\frac{\beta-\mu}{\sigma} \phi\left(\frac{\beta-\mu}{\sigma}\right)$,

$$\begin{aligned} LR'(\mu) &\equiv -\frac{1}{\sigma} \frac{\int s_m \phi' \times \int s_{\tilde{m}} \phi - \int s_m \phi \times \int s_{\tilde{m}} \phi'}{(\int s_{\tilde{m}} \phi)^2} \\ &= \frac{\int [\beta - \mu] s_m \phi \times \int s_{\tilde{m}} \phi - \int s_m \phi \times \int [\beta - \mu] s_{\tilde{m}} \phi}{(\sigma \int s_{\tilde{m}} \phi)^2} \\ &= \frac{\int \beta s_m \phi \times \int s_{\tilde{m}} \phi - \int s_m \phi \times \int \beta s_{\tilde{m}} \phi}{(\sigma \int s_{\tilde{m}} \phi)^2} \end{aligned}$$

Therefore,

$$\begin{aligned} LR'(\mu) > 0 &\Leftrightarrow \int \beta s_m \phi \times \int s_{\tilde{m}} \phi > \int s_m \phi \times \int \beta s_{\tilde{m}} \phi \\ &\Leftrightarrow \frac{\int \beta s_m \phi}{\int s_m \phi} > \frac{\int \beta s_{\tilde{m}} \phi}{\int s_{\tilde{m}} \phi} \\ &\Leftrightarrow \mathbb{E}[\beta s|s_m(\beta)] > \mathbb{E}[\beta s|s_{\tilde{m}}(\beta)] \end{aligned}$$

where the last line followed by the definition of conditional mean. \square

A1.3. Monotonicity of Equilibrium Strategies

Lemma 1 in Section 2.2 claims that, for any c and $\sigma_i = \sigma$, the strategies will be monotone if the equilibrium is fully responsive and fully informative: (i) researchers will apply threshold strategies and (ii) the policymaker's probability of policy implementation will be increasing in positive results and decreasing in negative results.

Proof. Since the result of monotonicity of policymaker's strategy will be used for that of researcher's strategy, we will first derive the result of policymaker's and then that of researchers'.

(i) Policymaker's strategy: suppose $\pi^*(n_1, n_0) > 0$ for some n_1, n_0 . Then, by the policymaker's optimization condition, $\mathbb{E}[b|n_1, n_0] \geq c$. By full informativeness and Bayes' rule, $\mathbb{E}[b|n_1 + k, n_0] > \mathbb{E}[b|n_1, n_0]$ for $k \in \{1, 2\}$ and thus, $\mathbb{E}[b|n_1 + k, n_0] \geq c$. By the policy-

maker's optimization, $\pi^*(n_1 + k, n_0) > 0$. Analogous argument holds for $\pi^*(n_1, n_0) < 1 \Rightarrow \pi^*(n_1, n_0 + k) = 0$.

(ii) Researchers' strategies: by the Bayes' rule, full responsiveness, and domain of signals. The proof consists of three steps: the first step organizes the indifference conditions, and the second step shows the existence of solution, and the third step shows the uniqueness.

Step 1. indifference conditions: given any policymaker's strategy $\pi(m_i, m_{-i})$ and another researcher's strategy $s(\beta_{-i})$, the expected welfare of reporting message m_i given the signal β_i can be written as

$$W(m_i, \beta_i) = \sum_{m_{-i}} \pi(m_i, m_{-i}) \mathbb{P}(m_{-i}|\beta_i) \left\{ \frac{\frac{1}{\sigma^2}}{\frac{1}{\sigma_b^2} + \frac{2}{\sigma^2}} [\beta_i + \mathbb{E}[\beta_{-i}|m_{-i}, \beta_i]] - c \right\}$$

by the objective (1).

At some thresholds, $\bar{\beta}$ and $\underline{\beta}$, in which the researcher will be willing to switch the messages, the indifference conditions $W(1, \bar{\beta}) = W(\emptyset, \bar{\beta})$ and $W(0, \underline{\beta}) = W(\emptyset, \underline{\beta})$ must be satisfied. Rewriting, for each threshold, the conditions are,

$$I(1, \emptyset, \bar{\beta}) = 0 \text{ and } I(\emptyset, 0, \underline{\beta}) = 0,$$

where

$$I(m_i, m'_i, \beta_i) \equiv \sum_{m_{-i}} p(m_i, m'_i|m_{-i}) q(m_{-i}|\beta_i) r(\beta_i|m_{-i}),$$

where

$$\begin{aligned} p(m_i, m'_i|m_{-i}) &\equiv \pi(m_i, m_{-i}) - \pi(m'_i, m_{-i}) \\ q(m_{-i}|\beta_i) &\equiv \mathbb{P}(m_{-i}|\beta_i) \\ r(\beta_i|m_{-i}) &\equiv \beta_i + \mathbb{E}[\beta_{-i}|m_{-i}, \beta_i] - c \left(2 + \frac{\sigma^2}{\sigma_b^2} \right) \end{aligned}$$

By full responsiveness, there must exist some m_{-i}, m'_{-i} such that $\pi(1, m_{-i}) > \pi(\emptyset, m_{-i})$ and $\pi(\emptyset, m'_{-i}) > \pi(0, m'_{-i})$. Thus, these conditions are not vacuous. The meaning of messages is, without loss of generality, assigned to be consistent with the set-up.

Step 2. existence: for all m_{-i} , another researcher's strategy, $s(\beta_{-i})$, by Lemma A1, there exist some β'_i such that $r(\beta'_i|m_{-i}) < 0$ and some other β''_i such that $r(\beta''_i|m_{-i}) > 0$. Since $p(1, \emptyset|m_{-i}) > 0$ and $q(m_{-i}|\beta_i) > 0$ and $q(\cdot)$ and $r(\cdot)$ are continuous functions of β_i , there must exist some $\bar{\beta}$ and $\underline{\beta}$ that satisfy the indifference condition by intermediate value theorem.

Step 3. uniqueness: to show that there is a unique value that satisfies an indifference condition, we first show that $p(m_i, m'_i|m_{-i}) = 0$ for at least 1 m_{-i} and then show $\partial I(m_i, m'_i, \beta_i) / \partial \beta_i > 0$ when evaluated at $I(m_i, m'_i, \beta_i) = 0$ so that there is a unique value of β_i that satisfies this.

- $p(m_i, m'_i | m_{-i}) = 0$ for at least 1 m_{-i} : first, note that $\pi(1, 1) = 1$ and $\pi(0, 0) = 0$. To see why, suppose $\pi(1, 1) < 1$. Then by policymaker's optimization, $\pi(1, \emptyset) = \pi(\emptyset, 1) = 0$, which then implies $\pi(0, m_{-i}) = 0$ for all m_{-i} and $\pi(m_i, 0) = 0$ for all m_i , contradicting full responsiveness. Second, we consider three cases of $\pi(\emptyset, \emptyset)$:
 - when $\pi(\emptyset, \emptyset) = 1$, $\pi(1, \emptyset) = \pi(\emptyset, 1) = 1$ by policymaker's monotonicity. Thus, $p(1, \emptyset | \emptyset) = p(1, \emptyset | 1) = 0$. Moreover, by full responsiveness for another researcher, either $\{\pi(0, \emptyset), \pi(0, 1)\} = \{0, \bar{\pi}\}$ with $\bar{\pi} > 0$ or $\{\pi(0, \emptyset), \pi(0, 1)\} = \{\bar{\pi}, 1\}$ with $\bar{\pi} < 1$. If former, $p(\emptyset, 0 | 0) = 0$ another researcher and if later, $p(\emptyset, 0 | 1) = 0$ for the researcher himself. In this way, $p(m_i, m'_i | m_{-i}) = 0$ for at least 1 m_{-i} for both $\{m_i, m'_i\} \in \{\{1, \emptyset\}, \{\emptyset, 0\}\}$ in any fully responsive equilibria.
 - when $\pi(\emptyset, \emptyset) = 0$, a symmetric argument analogous to above applies.
 - when $\pi(\emptyset, \emptyset) = \bar{\pi}$ for $\bar{\pi} \in (0, 1)$, $\pi(1, \emptyset) = \pi(\emptyset, 1) = 1$ and $\pi(0, \emptyset) = \pi(\emptyset, 0) = 0$ by policymaker's monotonicity. Thus, $p(1, \emptyset | 1) = 0$ and $p(\emptyset, 0 | 0) = 0$.
- $\partial I(m_i, m'_i, \beta_i) / \partial \beta_i > 0$ at $I(m_i, m'_i, \beta_i) = 0$: for each $\{m_i, m'_i\} \in \{\{1, \emptyset\}, \{\emptyset, 0\}\}$, let us consider two cases:
 - when $p(m_i, m'_i | m_{-i}) = 0$ for 2 values of m_{-i} : denoting m_{-i}^* as the value such that $p(m_i, m'_i | m_{-i}^*) > 0$, the indifference condition is $p(m_i, m'_i | m_{-i}^*) r(\beta_i | m_{-i}^*) = 0$. $r(\beta_i | m_{-i})$ is strictly increasing.
 - when $p(m_i, m'_i | m_{-i}) = 0$ for only 1 value of m_{-i} : denoting m_{-i}^*, m_{-i}^{**} as the value such that $p(m_i, m'_i | m_{-i}) > 0$,

$$p(m_i, m'_i | m_{-i}^*) \tilde{q}(m_{-i}^* | \beta_i) r(\beta_i | m_{-i}^*) + p(m_i, m'_i | m_{-i}^{**}) \tilde{q}(m_{-i}^{**} | \beta_i) r(\beta_i | m_{-i}^{**}) = 0,$$

where $\tilde{q}(m_{-i} | \beta_i) \equiv \frac{q(m_{-i} | \beta_i)}{q(m_{-i}^* | \beta_i) + q(m_{-i}^{**} | \beta_i)}$ is the normalized probability. The derivative of the indifference condition with respect to β_i is

$$p(m_i, m'_i | m_{-i}^*) \tilde{q}(m_{-i}^* | \beta_i) r'(\beta_i | m_{-i}^*) + p(m_i, m'_i | m_{-i}^{**}) \tilde{q}(m_{-i}^{**} | \beta_i) r'(\beta_i | m_{-i}^{**}) \\ + p(m_i, m'_i | m_{-i}^*) \tilde{q}'(m_{-i}^* | \beta_i) r(\beta_i | m_{-i}^*) + p(m_i, m'_i | m_{-i}^{**}) \tilde{q}'(m_{-i}^{**} | \beta_i) r(\beta_i | m_{-i}^{**})$$

* by Lemma A1, $r'(\beta_i | m_{-i}^*) > 0$ and $r'(\beta_i | m_{-i}^{**}) > 0$.

* by Lemma A1 and full responsiveness, $r(\beta_i | m_{-i}^*) < 0$ and $r(\beta_i | m_{-i}^{**}) > 0$ must hold at the indifference condition $I(m_i, m'_i, \beta_i) = 0$ since all other terms are positive (the meaning of m_{-i}^*, m_{-i}^{**} is without loss of generality.) By Lemma A2, $\tilde{q}'(m_{-i}^* | \beta_i) < 0$ and $\tilde{q}'(m_{-i}^{**} | \beta_i) > 0$: higher mean implies higher relative likelihood of message m_{-i}^{**} sent by another researcher.

Since all terms are thus positive, $\partial I(m_i, m'_i, \beta_i) / \partial \beta_i > 0$ at $I(m_i, m'_i, \beta_i) = 0$.

Since $p(m_i, m'_i | m_{-i}) = 0$ at least for 1 value of m_{-i} , we saw that the indifference condition must be increasing in β_i when it is satisfied so that the solution will be unique.

□

A2. Proofs of 2.3 Omission of Insignificant Results

This sub-Section presents the proofs of propositions in Section 2.2. A2.1 proves Proposition 1.1; A2.2 proves Proposition 1.2; A2.3 proves Proposition 1.3.

A2.1. Proof of Proposition 1.1

Proposition 1.1 claims that there exists an equilibrium in which the policymaker adopts a supermajoritarian decision rule and the researchers apply a threshold that is asymmetric such that the estimates underlying reported studies will have an upward bias. The proof will show first that the policymaker's strategy is a part of the equilibrium, and second the researchers' strategies are also a part of the equilibrium.

(i) Policymaker's strategy: If the decision rule (2) is consistent with policymaker's optimization, we need that $\mathbb{E}[b | n_1 > n_0] \geq 0$ and $\mathbb{E}[b | n_1 \leq n_0] \leq 0$ given thresholds (3). This holds because the researchers' strategy must satisfy the indifference condition at the margin whereas the policymaker assess whether the condition holds on average. To see why $\mathbb{E}[b | n_1 > n_0] \geq 0$, note that $\mathbb{E}[b | n_1 = 1, n_0 = 0] \geq 0$ since

$$\begin{aligned} \mathbb{E}[b | m_1 = 1, m_2 = \emptyset] &= \frac{\frac{1}{\sigma^2}}{\frac{1}{\sigma_b^2} + \frac{2}{\sigma^2}} \mathbb{E}[\beta_1 + \mathbb{E}[\beta_2 | \bar{\beta} > \beta_2 \geq \underline{\beta}, \beta_1] | \beta_1 \geq \bar{\beta}] \\ &> \frac{\frac{1}{\sigma^2}}{\frac{1}{\sigma_b^2} + \frac{2}{\sigma^2}} \left\{ \bar{\beta} + \mathbb{E}[\beta_2 | \bar{\beta} > \beta_2 \geq \underline{\beta}, \beta_1 = \bar{\beta}] \right\} \\ &= 0, \end{aligned}$$

where the last equality holds due to the researchers' indifference condition. Analogous arguments also hold for $\mathbb{E}[b | n_1 \leq n_0] \leq 0$, showing (2) is an equilibrium.

(ii) Researchers' strategy: given the supermajoritarian voting rule in (2), the equilibrium thresholds will (1) be unique and symmetric between researchers, (2) lead to some omissions ($\bar{\beta} \geq 0 > \underline{\beta}$), (3) be asymmetric between the thresholds for positive vs negative results ($\bar{\beta} < -\underline{\beta}$), so that together will (4) have an upward bias of reported studies $\mathbb{E}[\beta_i | m_i \neq \emptyset] > 0$. The following proof shows these results in turn.

- (1) uniqueness of symmetric solution: given π^* as in (2), the thresholds will be unique since the researchers' strategies are moderate strategic substitutes of one another. When the best response function satisfies $\frac{\partial \bar{\beta}_i(\bar{\beta}_j)}{\partial \bar{\beta}_j} \in (-1, 0)$, there can be at most one value that satisfies the equilibrium conditions and will be symmetric between researchers so that $\bar{\beta}_i = \bar{\beta}_j = \bar{\beta}$ and $\underline{\beta}_i = \underline{\beta}_j = \underline{\beta}$. The following Lemma A3 shows $\frac{\partial \bar{\beta}_i(\bar{\beta}_j)}{\partial \bar{\beta}_j} \in (-1, 0)$:

Lemma A3. (Moderate Strategic Substitution). *Define $\bar{\beta}_i(\bar{\beta}_j)$ as the best response to some threshold $\bar{\beta}_j$ that satisfies the equilibrium conditions:*

$$\begin{aligned}\bar{\beta}_i + \mathbb{E}[\beta_j | \bar{\beta}_j > \beta_j \geq \underline{\beta}_j, \beta_i = \bar{\beta}_i] &= 0 \\ \underline{\beta}_j + \mathbb{E}[\beta_i | \beta_i \geq \bar{\beta}_i, \beta_j = \underline{\beta}_j] &= 0\end{aligned}$$

Then

$$-1 < \frac{\partial \bar{\beta}_i(\bar{\beta}_j)}{\partial \bar{\beta}_j} < 0$$

Proof. By totally differentiating the equilibrium conditions. Writing $\bar{K}_j = \frac{\partial \mathbb{E}[\beta_j | \bar{\beta}_j > \beta_j \geq \underline{\beta}_j, \beta_i = \bar{\beta}_i]}{\partial \bar{\beta}_j}$, $\underline{K}_j = \frac{\partial \mathbb{E}[\beta_j | \bar{\beta}_j > \beta_j \geq \underline{\beta}_j, \beta_i = \bar{\beta}_i]}{\partial \beta_j}$, $\bar{K}_i = \frac{\partial \mathbb{E}[\beta_i | \beta_i \geq \bar{\beta}_i, \beta_j = \underline{\beta}_j]}{\partial \bar{\beta}_i}$, and $\underline{L}_j = \frac{\partial \mathbb{E}[\beta_i | \beta_i \geq \bar{\beta}_i, \beta_j = \underline{\beta}_j]}{\partial \underline{\beta}_j}$ and $\bar{L}_i = \frac{\partial \mathbb{E}[\beta_i | \beta_i \geq \bar{\beta}_i, \beta_j = \underline{\beta}_j]}{\partial \beta_i}$, the system of derivatives satisfy:

$$\begin{bmatrix} 1 + \bar{K}_i & \underline{K}_j \\ \bar{L}_i & 1 + \underline{L}_j \end{bmatrix} \begin{bmatrix} \frac{\partial \bar{\beta}_i}{\partial \bar{\beta}_j} \\ \frac{\partial \underline{\beta}_j}{\partial \bar{\beta}_j} \end{bmatrix} = \begin{bmatrix} -\bar{K}_j \\ 0 \end{bmatrix}$$

Inverting the matrix, we have

$$\begin{bmatrix} \frac{\partial \bar{\beta}_i}{\partial \bar{\beta}_j} \\ \frac{\partial \underline{\beta}_j}{\partial \bar{\beta}_j} \end{bmatrix} = \frac{1}{(1 + \bar{K}_i)(1 + \underline{L}_j) - \underline{K}_j \bar{L}_i} \begin{bmatrix} 1 + \underline{L}_j & -\bar{L}_i \\ -\underline{K}_j & 1 + \bar{K}_i \end{bmatrix} \begin{bmatrix} -\bar{K}_j \\ 0 \end{bmatrix}$$

Thus,

$$\frac{\partial \bar{\beta}_i}{\partial \bar{\beta}_j} = \frac{-\bar{K}_j(1 + \underline{L}_j)}{(1 + \bar{K}_i)(1 + \underline{L}_j) - \underline{K}_j \bar{L}_i}$$

By the definition of truncated distribution, $\bar{K}_i + \bar{K}_j + \underline{K}_j = 1$ and $\bar{L}_i + \underline{L}_j = 1$. Moreover, all terms, $\bar{K}_j, \underline{K}_j, \bar{K}_i, \underline{L}_j, \bar{L}_i$, are positive and less than 1 by Lemma A1. Thus,

$$-\frac{\partial \bar{\beta}_i}{\partial \bar{\beta}_j} < -1 \text{ since } \bar{K}_j(1 + \underline{L}_j) < (1 + \bar{K}_i)(1 + \underline{L}_j) - \underline{K}_j \bar{L}_i \Leftrightarrow (1 - \bar{K}_i - \bar{K}_j)(1 - \underline{L}_j) < (1 + \bar{K}_i - \bar{K}_j)(1 + \underline{L}_j)$$

$$- \frac{\partial \bar{\beta}_i}{\partial \beta_j} < 0 \text{ since } (1 + \bar{K}_i) (1 + \underline{L}_j) > \underline{K}_j \bar{L}_i. \quad \blacksquare$$

Given that $\bar{\beta}_i = \bar{\beta}_j = \bar{\beta}$ and $\underline{\beta}_i = \underline{\beta}_j = \underline{\beta}$, we will be able to substitute the threshold values to derive the results.

- (2) omission $\bar{\beta} > 0 > \underline{\beta}$: towards contradiction, suppose $\bar{\beta} \leq 0$. By the indifference condition (4) and by (1) $\bar{\beta}_i = \bar{\beta}_j = \bar{\beta}$, $\bar{\beta} = -\mathbb{E} [\beta_{-i} | \beta_{-i} \in [\underline{\beta}, \bar{\beta}), \beta_i = \bar{\beta}] > 0$ since $\mathbb{E} [\beta_{-i} | \beta_{-i} < \bar{\beta}] < 0$ regardless of other conditions. Because this contradicts the assumption, $\bar{\beta} \geq 0$. Substituting this into (5), $\underline{\beta} = -\mathbb{E} [\beta_{-i} | \beta_{-i} > \bar{\beta}, \beta_i = \underline{\beta}] < 0$.
- (3) asymmetry $\bar{\beta} < -\underline{\beta}$: towards contradiction, suppose $\bar{\beta} \geq -\underline{\beta}$ given $\bar{\beta} \geq 0$. Then, $\bar{\beta} = -\mathbb{E} [\beta_{-i} | \beta_{-i} \in [\underline{\beta}, \bar{\beta}), \beta_i = \bar{\beta}] < 0$ because the combinations of conditions $\beta_{-i} \in [\underline{\beta}, \bar{\beta})$ by (1) and $\beta_i = \bar{\beta}$ imply $\mathbb{E} [\beta_{-i} | \beta_{-i} \in [\underline{\beta}, \bar{\beta}), \beta_i = \bar{\beta}] > 0$. Since this contradicts the assumption, $\bar{\beta} < -\underline{\beta}$ must hold.
- (5) bias of estimates underlying reported studies $\mathbb{E} [\beta_i | m_i \neq \emptyset] > 0$: the following algebraic argument formally shows that the asymmetry in (3) leads to the upward bias:

$$\begin{aligned} & \mathbb{E} [\beta_i | m_i \neq \emptyset] \\ &= \mathbb{P} [m_i = 1 | m_i \neq \emptyset] \mathbb{E} [\beta_i | m_i = 1] + \mathbb{P} [m_i = 0 | m_i \neq \emptyset] \mathbb{E} [\beta_i | m_i = 0] \\ &= \frac{1 - \Phi(\bar{\beta})}{1 - \Phi(\bar{\beta}) + \Phi(\underline{\beta})} \sqrt{\sigma^2 + \sigma_b^2} \frac{\phi(\bar{\beta})}{1 - \Phi(\bar{\beta})} - \frac{\Phi(\underline{\beta})}{1 - \Phi(\bar{\beta}) + \Phi(\underline{\beta})} \sqrt{\sigma^2 + \sigma_b^2} \frac{\phi(\underline{\beta})}{\Phi(\underline{\beta})} \\ &= \sqrt{\sigma^2 + \sigma_b^2} \frac{\phi(\bar{\beta}) - \phi(\underline{\beta})}{1 - \Phi(\bar{\beta}) + \Phi(\underline{\beta})} > 0 \end{aligned}$$

Since both the policymaker and researchers' strategies satisfy the indifference conditions given the strategy of one another, and beliefs are consistent with the Bayes' rule, the strategies in Proposition 1.1. constitutes an equilibrium. \square

A2.2. Proof of Proposition 1.2

Proposition 1.2 claims that there are both (1) an equilibrium with symmetric omission with policymaker's decision rule, $\pi(n_0 = n_1) = \frac{1}{2}$, and (2) an equilibrium with no omission with policymaker's decision rule, $\pi(n_1, n_0) = 1$ ($n_1 = 2$) and $\pi(n_1 = 1, n_0 = 0) \in (0, 1]$. We will prove this for the one with (1) symmetric omission, and then with (2) no omission.

(1) Proof for equilibrium with symmetric omission. The policymaker's strategy is an equilibrium because, given $n_0 = n_1$, the researcher will be indifferent between implementing or not implementing the policy. The researchers' strategies will constitute an equilibrium because,

given $\pi(n_0 = n_1) = \frac{1}{2}$, the criteria for the thresholds $\bar{\beta}$ and $\underline{\beta}$ will be symmetric with one another.

(i) Policymaker's strategy: For the policymaker's strategies to be optimal, it is necessary that $\mathbb{E}[b \mid n_1 = n_0] = 0$; moreover, this condition is also sufficient due to the monotonicity as in Lemma 1. We consider two cases, $n_1 = n_0 = 0$ and $n_1 = n_0 = 1$ in turn given the researchers' strategies such that $\bar{\beta} = -\underline{\beta}$:

- Case of $n_1 = n_0 = 0$: by Bayes' rule,

$$\mathbb{E}[b \mid n_1 = n_0 = 0] = \frac{\frac{1}{\sigma^2}}{\frac{1}{\sigma_b^2} + \frac{2}{\sigma^2}} \mathbb{E}[\beta_1 + \beta_2 \mid \beta_1, \beta_2 \in [\underline{\beta}, \bar{\beta}]]$$

- When $\beta_1 = \Delta$,

$$\mathbb{E}[\beta_1 + \beta_2 \mid \beta_1 = \Delta, \beta_2 \in [\underline{\beta}, \bar{\beta}]] = \phi\left(\frac{\Delta}{\bar{\sigma}}\right) \int_{\underline{\beta}}^{\bar{\beta}} (\Delta + \beta_2) \phi\left(\frac{\beta_2 - \rho\Delta}{\bar{\sigma}}\right) d\beta_2$$

- When $\beta_1 = -\Delta$,

$$\mathbb{E}[\beta_1 + \beta_2 \mid \beta_1 = -\Delta, \beta_2 \in [\underline{\beta}, \bar{\beta}]] = \phi\left(-\frac{\Delta}{\bar{\sigma}}\right) \int_{\underline{\beta}}^{\bar{\beta}} (-\Delta + \beta_2) \phi\left(\frac{\beta_2 + \rho\Delta}{\bar{\sigma}}\right) d\beta_2$$

- Since β_1 is symmetrically distributed, $\phi\left(\frac{\Delta}{\bar{\sigma}}\right) = \phi\left(-\frac{\Delta}{\bar{\sigma}}\right)$. Using the two expressions above, we have

$$\mathbb{E}[\beta_1 + \beta_2 \mid \beta_1 = \Delta, \beta_2 \in [\underline{\beta}, \bar{\beta}]] + \mathbb{E}[\beta_1 + \beta_2 \mid \beta_1 = -\Delta, \beta_2 \in [\underline{\beta}, \bar{\beta}]] = 0$$

for the following two reasons by $\bar{\beta} = -\underline{\beta}$:

- * on the term multiplied by Δ ,

$$\begin{aligned} & \int_{\underline{\beta}}^{\bar{\beta}} \Delta \left[\phi\left(\frac{\beta_2 - \rho\Delta}{\bar{\sigma}}\right) - \phi\left(\frac{\beta_2 + \rho\Delta}{\bar{\sigma}}\right) \right] d\beta_2 \\ &= \Delta \left\{ \left[\Phi\left(\frac{\bar{\beta} - \rho\Delta}{\bar{\sigma}}\right) - \Phi\left(\frac{\underline{\beta} - \rho\Delta}{\bar{\sigma}}\right) \right] - \left[\Phi\left(\frac{\bar{\beta} + \rho\Delta}{\bar{\sigma}}\right) - \Phi\left(\frac{\underline{\beta} + \rho\Delta}{\bar{\sigma}}\right) \right] \right\} \\ &= \Delta \left\{ \left[\Phi\left(\frac{\bar{\beta} - \rho\Delta}{\bar{\sigma}}\right) - \Phi\left(\frac{\underline{\beta} - \rho\Delta}{\bar{\sigma}}\right) \right] - \left[\Phi\left(-\frac{\underline{\beta} - \rho\Delta}{\bar{\sigma}}\right) - \Phi\left(-\frac{\bar{\beta} - \rho\Delta}{\bar{\sigma}}\right) \right] \right\} \\ &= \Delta \left\{ \left[\Phi\left(\frac{\bar{\beta} - \rho\Delta}{\bar{\sigma}}\right) - \Phi\left(\frac{\underline{\beta} - \rho\Delta}{\bar{\sigma}}\right) \right] - \left[1 - \Phi\left(\frac{\underline{\beta} - \rho\Delta}{\bar{\sigma}}\right) - \left[1 - \Phi\left(\frac{\bar{\beta} - \rho\Delta}{\bar{\sigma}}\right) \right] \right] \right\} \\ &= 0 \end{aligned}$$

* on the term multiplied by β_2 ,

$$\begin{aligned}
& \int_{\underline{\beta}}^{\bar{\beta}} \beta_2 \left[\phi \left(\frac{\beta_2 - \rho\Delta}{\bar{\sigma}} \right) - \phi \left(\frac{\beta_2 + \rho\Delta}{\bar{\sigma}} \right) \right] d\beta_2 \\
&= \int_0^{\bar{\beta}} \beta_2 \left[\phi \left(\frac{\beta_2 - \rho\Delta}{\bar{\sigma}} \right) - \phi \left(\frac{\beta_2 + \rho\Delta}{\bar{\sigma}} \right) \right] d\beta_2 \\
&\quad + \int_{\underline{\beta}}^0 \beta_2 \left[\phi \left(\frac{\beta_2 - \rho\Delta}{\bar{\sigma}} \right) - \phi \left(\frac{\beta_2 + \rho\Delta}{\bar{\sigma}} \right) \right] d\beta_2 \\
&= \int_0^{\bar{\beta}} \beta_2 \left[\phi \left(\frac{\beta_2 - \rho\Delta}{\bar{\sigma}} \right) - \phi \left(\frac{\beta_2 + \rho\Delta}{\bar{\sigma}} \right) \right] d\beta_2 \\
&\quad - \int_0^{\bar{\beta}} \beta_2 \left[\phi \left(\frac{-\beta_2 - \rho\Delta}{\bar{\sigma}} \right) - \phi \left(\frac{-\beta_2 + \rho\Delta}{\bar{\sigma}} \right) \right] d\beta_2 \\
&= \int_0^{\bar{\beta}} \beta_2 \left\{ \left[\phi \left(\frac{\beta_2 - \rho\Delta}{\bar{\sigma}} \right) - \phi \left(\frac{\beta_2 + \rho\Delta}{\bar{\sigma}} \right) \right] - \left[\phi \left(\frac{-\beta_2 - \rho\Delta}{\bar{\sigma}} \right) - \phi \left(\frac{-\beta_2 + \rho\Delta}{\bar{\sigma}} \right) \right] \right\} d\beta_2 \\
&= 0
\end{aligned}$$

where the last line followed by $\phi \left(\frac{\beta_2 + \rho\Delta}{\bar{\sigma}} \right) = \phi \left(-\frac{\beta_2 + \rho\Delta}{\bar{\sigma}} \right)$ and $\phi \left(\frac{\beta_2 - \rho\Delta}{\bar{\sigma}} \right) = \phi \left(-\frac{\beta_2 - \rho\Delta}{\bar{\sigma}} \right)$.

- Case of $n_1 = n_0 = 1$: by Bayes' rule, without loss of generality, let us consider $m_1 = 1$ and $m_2 = 0$.

$$\mathbb{E}[b \mid n_1 = n_0 = 1] = \frac{\frac{1}{\sigma^2}}{\frac{1}{\sigma_b^2} + \frac{2}{\sigma^2}} \mathbb{E}[\beta_1 + \beta_2 \mid \beta_1 \geq \bar{\beta}, \beta_2 \leq \underline{\beta}]$$

Note that we can express $\mathbb{E}[\beta_1 + \beta_2 \mid \beta_1 \geq \bar{\beta}, \beta_2 \leq \underline{\beta}]$ as

$$\int_{-\infty}^{\underline{\beta}} \int_{\bar{\beta}}^{-\beta_2} [\beta_1 + \beta_2] \tilde{\phi}(\beta_1, \beta_2) d\beta_1 d\beta_2 + \int_{\bar{\beta}}^{\infty} \int_{-\beta_1}^{\underline{\beta}} [\beta_1 + \beta_2] \tilde{\phi}(\beta_1, \beta_2) d\beta_2 d\beta_1$$

By the change of variable using the symmetry of distribution,

$$\int_{-\infty}^{\underline{\beta}} \int_{\bar{\beta}}^{-\beta_2} [\beta_1 + \beta_2] \tilde{\phi}(\beta_1, \beta_2) d\beta_1 d\beta_2 + \int_{\bar{\beta}}^{\infty} \int_{-\beta_2}^{\underline{\beta}} [\beta_1 + \beta_2] \tilde{\phi}(\beta_1, \beta_2) d\beta_1 d\beta_2$$

At each $\beta_2 = \Delta$,

$$\begin{aligned}
& \int_{\bar{\beta}}^{-\Delta} [\beta_1 + \Delta] \phi\left(\frac{\beta_1 - \rho\Delta}{\bar{\sigma}}\right) d\beta_1 + \int_{-\Delta}^{\underline{\beta}} [\Delta + \beta_1] \phi\left(\frac{\beta_1 - \rho\Delta}{\bar{\sigma}}\right) d\beta_1 \\
&= \int_{\bar{\beta}}^{-\Delta} \{[\beta_1 + \Delta] - [\Delta + \beta_1]\} \phi\left(\frac{\beta_1 - \rho\Delta}{\bar{\sigma}}\right) d\beta_1 \\
&= 0
\end{aligned}$$

Thus, taking together, $\mathbb{E}[\beta_1 + \beta_2 | \beta_1 \geq \bar{\beta}, \beta_2 \leq \underline{\beta}] = 0$, satisfying the policymaker's indifference condition. \blacksquare

(ii) Researchers' strategy: given the policymaker's strategy, the researchers' indifference conditions are given by

$$\begin{aligned}
\bar{\beta} + \frac{1}{2} \sum_{m_{-i} \in \{0, \emptyset\}} \left\{ \mathbb{P}(m_{-i} | \bar{\beta}, m_{-i} \in \{0, \emptyset\}) \mathbb{E}[\beta_{-i} | m_{-i}, \bar{\beta}] \right\} &= 0 \\
\underline{\beta} + \frac{1}{2} \sum_{m_{-i} \in \{0, 1\}} \left\{ \mathbb{P}(m_{-i} | \underline{\beta}, m_{-i} \in \{0, 1\}) \mathbb{E}[\beta_{-i} | m_{-i}, \underline{\beta}] \right\} &= 0
\end{aligned}$$

Applying the formula of truncated normal distribution,

$$\begin{aligned}
\bar{\beta}_i + \frac{1}{2} \mathbb{E}[\beta_{-i} | \beta_{-i} \leq \bar{\beta}_{-i}, \bar{\beta}_i] &= 0 \\
\underline{\beta}_i + \frac{1}{2} \mathbb{E}[\beta_{-i} | \beta_{-i} \geq \underline{\beta}_{-i}, \underline{\beta}_i] &= 0
\end{aligned}$$

Note that when $\bar{\beta}_i = -\underline{\beta}_i$ and $\bar{\beta}_{-i} = -\underline{\beta}_{-i}$, these conditions are equivalent to each other. Moreover, the solution $\bar{\beta}_i$ is strictly decreasing in $\bar{\beta}_{-i}$. Combining, there exists a unique solution $\bar{\beta}_i = -\underline{\beta}_i = \bar{\beta}_{-i} = -\underline{\beta}_{-i}$ that satisfies the researchers' indifference conditions. \blacksquare

(2) Proof for equilibrium with no omission. the policymaker's strategy will be a part of the equilibrium by an immediate implication of researchers' indifference condition; the researchers strategy $\bar{\beta}, \underline{\beta}$ will be determined by the identical conditions, leading to $\bar{\beta} = \underline{\beta}$.

(i) Policymaker's strategy: given that the researcher will be indifferent at the switching point, $\bar{\beta} = \underline{\beta}$, the policymaker will also be indifferent between implementing or not implementing the policy since the policymaker knows $\beta_i = \bar{\beta} = \underline{\beta}$ if $m_i = \emptyset$ (even though $m_i = \emptyset$ occurs with probability zero). Since the decisions when $m_i \neq \emptyset$ for both i can be given by the monotonicity of Lemma 1, the policy rule (7) is a part of the equilibrium. \blacksquare

(ii) Researchers' strategy: suppose that another researcher follows $\bar{\beta} = \underline{\beta}$ and the policymaker adopts the policy rule as (7). Then, regardless of one's own signal, $\mathbb{P}(m_{-i} = \emptyset | \beta_i) =$

0. Therefore, one can write the indifference conditions as

$$\mathbb{P}(m_{-i} = 1|\bar{\beta}_i)(1 - \tilde{\pi}) \frac{\frac{1}{\sigma^2}}{\frac{1}{\sigma_b^2} + \frac{2}{\sigma^2}} \left[\mathbb{E}[\beta_{-i}|\beta_{-i} \geq \bar{\beta}_{-i}, \bar{\beta}_i] + \bar{\beta}_i \right] = 0 \quad (19)$$

$$\mathbb{P}(m_{-i} = 1|\underline{\beta}_i) \tilde{\pi} \frac{\frac{1}{\sigma^2}}{\frac{1}{\sigma_b^2} + \frac{2}{\sigma^2}} \left[\mathbb{E}[\beta_{-i}|\beta_{-i} \geq \bar{\beta}_{-i}, \underline{\beta}_i] + \underline{\beta}_i \right] = 0 \quad (20)$$

Since these conditions are proportional to each other, researcher i 's optimal strategy has $\bar{\beta}_i = \underline{\beta}_i$. \square

A2.3. Proof of Proposition 1.3

Proposition 1.3 claims that the asymmetric equilibrium is locally stable whereas equilibria with symmetric or no omission are not; the former is also optimal whereas later are not. We will first prove the results of local stability, and then that of optimality.

Proof of local stability: we will focus on the concept of local stability in Definition 1.3, which is adopted from Defition 6.1 in Chapter 1 of Fudenberg and Levine (1998) with a particular order of adjustment. The equilibria satisfying local stability are more plausible to emerge than those without local stability since small perturbation of strategies likely occur in the real world.

We consider a perturbation of equilibrium with monotone strategies, $\mathcal{E} \equiv \{\pi(n), \bar{\beta}_1, \underline{\beta}_1, \bar{\beta}_2, \underline{\beta}_2\}$, and consider the distance between two equilibria, $\mathcal{E}, \tilde{\mathcal{E}}$, as $d(\mathcal{E} - \tilde{\mathcal{E}}) \equiv \max_s \{|\epsilon_s|\}$, where $\epsilon \equiv \mathcal{E} - \tilde{\mathcal{E}}$. While one could consider a richer perturbation on researchers' strategies as the mapping from the signals $\beta_i \times \sigma_i \in \mathbb{R}^2$ into probability distribution over messages, this definition is intuitive and analytically tractable. Moreover, Lemma 1 has shown that all fully responsive and fully informative equilibria will take this form. We first consider the asymmetric equilibrium in Proposition 1.1, and then analyze the other equilibria in Proposition 1.2.

(1) *Asymmetric equilibrium in Proposition 1.1. is locally stable:* Let us denote the perturbation of researcher $i = 1, 2$'s strategies by the set of perturbations, $\{\bar{\epsilon}_i, \underline{\epsilon}_i\}$ so that $\bar{\beta}_{i,0} = \bar{\beta} + \bar{\epsilon}_i, \underline{\beta}_{i,0} = \underline{\beta} + \underline{\epsilon}_i$. Without loss of generality, suppose that the researcher 2 receives a larger perturbation so that $\max\{|\bar{\epsilon}_2|, |\underline{\epsilon}_2|\} \geq \max\{|\bar{\epsilon}_1|, |\underline{\epsilon}_1|\}$.

The proof takes four steps: first, we observe that the policymaker's strategy does not change; second, consider researcher 1's adjustment in $t = 1$; third, consider researcher 2's adjustment in $t = 1$; and finally argue that these results show the local stability of the asymmetric equilibrium.

Step 1. policymaker's strategy: in $t = 1$, even with small perturbation of researchers' strategy, the policymaker's strategy will not change since it relied on strict preference. Thus, the strategy (2) will continue to be played.

Step 2. researcher 1's strategy: given the supermajoritarian rule (2) and the researcher 2's initial strategy $\bar{\beta}_{2,0}, \underline{\beta}_{2,0}$, the researcher 1's strategy will satisfy

$$\begin{aligned} |\bar{\beta}_{1,1}(\bar{\beta}_{2,0}, \underline{\beta}_{2,0}) - \bar{\beta}| &< \max\{|\bar{\epsilon}_2|, |\underline{\epsilon}_2|\} \\ |\underline{\beta}_{1,1}(\bar{\beta}_{2,0}) - \underline{\beta}| &< |\bar{\epsilon}_2| \end{aligned}$$

by the property of derivative of the truncated normal distribution.

Step 3. researcher 2's strategy: given the supermajoritarian rule (2) and the researcher 1's strategy after adjustment $\bar{\beta}_{1,1}, \underline{\beta}_{1,1}$, the researcher 2's strategy will satisfy

$$\begin{aligned} |\bar{\beta}_{2,1}(\bar{\beta}_{1,1}, \underline{\beta}_{1,1}) - \bar{\beta}| &< \max\{|\bar{\epsilon}_2|, |\underline{\epsilon}_2|\} \\ |\underline{\beta}_{2,1}(\bar{\beta}_{1,1}) - \underline{\beta}| &< |\bar{\epsilon}_2| \end{aligned}$$

by the property of derivative of the truncated normal distribution.

Step 4. relating to the definition of local stability: for equilibrium \mathcal{E} to be locally stable, we need for every $\hat{d} > 0$, there exist some \bar{d} such that

$$d(\mathcal{E} - \mathcal{E}_0) < \bar{d} \Rightarrow d(\mathcal{E} - \mathcal{E}_\infty) < \hat{d}.$$

By Step 2 and 3, we know that $d(\mathcal{E} - \mathcal{E}_1) < \max\{|\bar{\epsilon}_2|, |\underline{\epsilon}_2|\} = d(\mathcal{E} - \mathcal{E}_0)$. Iterating the adjustment ad infinity, we have $d(\mathcal{E} - \mathcal{E}_\infty) < d(\mathcal{E} - \mathcal{E}_0)$. Thus, setting any $\bar{d} \leq \hat{d}$ can satisfy the condition.

(2) *Equilibria in Proposition 1.2. are not locally stable:*

Lemma A3: *any equilibrium such that $\pi^*(n_1, n_0) \in (0, 1)$ for some n_1, n_0 is not locally stable.*

Proof. This is because the policymaker must be exactly indifferent between whether or not implementing the policy; that is, the posterior belief $\mathbb{E}[b|n_1, n_0] = 0$ must hold for such n_1, n_0 . However, even with a small perturbation of some thresholds $\{\bar{\beta}_i, \underline{\beta}_i\}$, the policymaker will have $\mathbb{E}[b|n_1, n_0] \neq 0$ so that his optimal strategy in $t = 1$ will be either $\pi^*(n_1, n_0) \in \{0, 1\}$ for that n_1, n_0 . Since the modification in policymaker's strategy is large, the researchers' strategies will not converge back to the original strategies. ■

On the equilibrium with no omission such that $\tilde{\pi} = 1$, we can consider how a small perturbation of another researcher's strategy, $\bar{\beta}_i + \Delta$, makes the probability of omission to be strictly positive; that is, with such perturbation, the iterative adjustment to examine the local stability will lead to the asymmetric equilibrium characterized in Proposition 1.1. □

Proof of optimality: we will first show that the equilibria characterized in Proposition 1.2 are not optimal by using the relationship to the concept of local stability; then show that

the equilibrium in Proposition 1.1 is optimal by examining all other possible equilibria.

(1) *Equilibria in Proposition 1.2 are not optimal:* since the model is a common interest game, we have the following close relationship between local stability and optimality:

Lemma A3: *if an equilibrium \mathcal{E} is optimal, then it is locally stable.*

Proof. Let us write the welfare attained in the equilibrium $\mathcal{E} \equiv \{\pi(n), \bar{\beta}_1, \underline{\beta}_1, \bar{\beta}_2, \underline{\beta}_2\}$ as $W(\pi(n), \bar{\beta}_1, \underline{\beta}_1, \bar{\beta}_2, \underline{\beta}_2)$. By policymaker's optimization, $\frac{\partial W}{\partial \pi}|_{\pi=1} \geq 0$, $\frac{\partial W}{\partial \pi}|_{\pi=0} \leq 0$, $\frac{\partial W}{\partial \pi}|_{\pi \in (0,1)} = 0$ (where the derivative at the boundaries are either or left or right derivatives) and by researchers' optimalization, $\frac{\partial W}{\partial \beta_i} = \frac{\partial W}{\partial \beta_i} = 0$ when evaluated at the equilibrium since W is continuous in each element. If an equilibrium is optimal, then it is locally stable since W must be locally concave at each local maximum. \blacksquare

Using the contrapositive of Lemma A3, if an equilibrium is not locally stable, then it is not optimal. Since the equilibria in Proposition 1.2 are not locally stable, it is not optimal.

(2) *Asymmetric equilibrium in Proposition 1.1 is optimal:* while optimality implies local stability, the converse does not hold. The proof consists of arguing that (i) any optimal equilibria must be fully responsive, and (ii) there are only two fully responsive and locally stable equilibria: one with $\pi^*(m) = 1$ ($n_1 \geq n_0$) and another with $\pi^*(m) = 1$ ($n_1 > n_0$). Then, since these two equilibria are symmetric to one another, they attain the identical level of welfare.

- (i) if an equilibrium is not fully responsive or not fully informative, then it is not optimal. Suppose there exists m_i, m'_i such that $\pi(m_i, m_{-i}) = \pi(m'_i, m_{-i})$ or $\mathbb{E}[b|m_i, m_{-i}] = \mathbb{E}[b|m'_i, m_{-i}]$ for all m_{-i} . Then, by changing the reporting strategies of m_i, m'_i , the researcher i can better convey the private information β_i to the policymaker. Since this is a common interest game, this strictly improves welfare.
- (ii) the only fully responsive equilibria that are also locally stable have $\pi^*(m) = 1$ ($n_1 \geq n_0$) or $\pi^*(m) = 1$ ($n_1 > n_0$). By Lemma A4, local stability requires $\pi(m_i, m_{-i}) \in \{0, 1\}$ for all m_i, m_{-i} . Moreover, by Lemma 1, $\pi(m_i, m_{-i})$ will be monotone.
 - if $\pi(m_i, m_{-i}) = 0$ for all $m_i \in \{\emptyset, 0\}$ for either i , then it is not fully responsive. Thus, the fully responsive equilibria with minimum number of $\pi = 1$ is $\pi^*(m) = 1$ ($n_1 > n_0$).
 - suppose $\pi^*(m) = 1$ if $m_i = 1$ and $\{m_i, m_{-i}\} = \{\emptyset, 1\}$. Then for another researcher, whether $m_{-i} = \emptyset$ or 0 does not make any difference. Suppose $\pi^*(m) = 1$ if $m_i \neq 0$ for both researchers. Then, for either researcher, whether $m_{-i} = \emptyset$ or 1 does not make any difference. Thus, the fully responsive equilibria with the second minimum number of $\pi = 1$ is $\pi^*(m) = 1$ ($n_1 \geq n_0$).

Since we can consider $\pi = 0$ symmetrically, we have considered all equilibria with monotone strategy of researchers and $\pi(m_i, m_{-i}) \in \{0, 1\}$ for all m_i, m_{-i} . Verifying that

$\pi^*(m) = 1(n_1 > n_0)$ and $\pi^*(m) = 1(n_1 \geq n_0)$ satisfies full responsiveness, we have that there can be at most two equilibria.

Note that the two equilibria $\pi^*(m) = 1(n_1 > n_0)$ and $\pi^*(m) = 1(n_1 \geq n_0)$ are symmetric to one another when $c = 0$, and thus, attains identical welfare. Since the welfare under $\pi^*(m) = 1(n_1 \geq n_0)$ is not strictly higher than that under $\pi^*(m) = 1(n_1 > n_0)$, the equilibrium characterized in Proposition 1.1 is an optimal equilibrium. Since an optimal set of strategies must constitute an equilibrium, the equilibrium that attains weakly higher welfare than any other equilibria must also be optimal. \square

A3. Proof of 2.4 Inflation of Marginally Insignificant Results

This sub-Section presents the proof of Proposition 1.2 in Section 2.4.

Proof of Proposition 1.2 The Proposition 1.2 claims that there exists a unique symmetric equilibrium (researchers' thresholds are identical with one another, and their thresholds are symmetric so that $\bar{\beta}(\sigma) = -\underline{\beta}(\sigma)$), and in that equilibrium the absolute value of the t-statistics must be increasing in σ_i . The proof proceeds in three steps: first, we express and simplify the researchers' indifference conditions assuming the policymakers' strategy in Proposition 1.2; second, we show the existence of the solution and characterize that solution; and finally, we verify that the researchers' and policymakers' strategies constitute an equilibrium.

Step 1. researchers' indifference conditions with heterogeneous σ_i : we express the indifference conditions by extending the expression of thresholds derived in Proposition 1.2(i) in three sub-steps.

First, by researcher i 's optimization, the posterior belief on expected benefit must equal zero at the thresholds at every $\sigma_i \in \text{Supp}(\sigma)$: by Bayes' rule and the law of iterated expectations,

$$\int \frac{\frac{\bar{\beta}_i}{\sigma_i^2} + \frac{\mathbb{E}[\beta_j | \sigma_j, \beta_j \in \text{Piv}(\sigma_j), \pi, \beta_i = \bar{\beta}_i]}{\sigma_j^2}}{\frac{1}{\sigma_b^2} + \frac{1}{\sigma_i^2} + \frac{1}{\sigma_j^2}} g(\sigma_j) d\sigma_j = 0, \quad (21)$$

where the expectation is taken over another researcher's signals $\{\sigma_j, \beta_j\}$ and the policymaker's strategy π . $\text{Piv}(\sigma_j)$ is a set of values of β_j such that the researcher i 's message can alter the policymaker's decision.

Second, we rearrange the condition (21) by (i) assumption of policymaker's strategy, (ii) improper prior assumption ($\sigma_b = \infty$), (iii) change of variables from $\bar{\beta}_i$ to $t(\sigma_i)$, and (iv) re-expressing the inverse Mills ratio:

- (i) as shown in Section A2.2, if policymaker adopts the strategy in symmetric equilibrium (6), then $\mathbb{E}[\beta_j | \sigma_j, \beta_j \in \text{Piv}(\sigma_j, \pi), \bar{\beta}_i] = \rho_{ij}\bar{\beta}_i - \sigma_{ij} \frac{\phi(\cdot)}{\Phi(\cdot)}$, where $\rho_{ij} = \frac{\sigma_b^2}{\sqrt{\sigma_i^2 + \sigma_b^2} \sqrt{\sigma_j^2 + \sigma_b^2}}$ is

the correlation coefficient, $\sigma_{ij} = \sqrt{\sigma_i^2 + \sigma_b^2} \sqrt{\sigma_j^2 + \sigma_b^2} - \sigma_b^2$ is the standard deviation of β_j conditional on β_i , and the argument of inverse Mills ratio is $\frac{\bar{\beta}_j(\sigma_j) - \rho_{ij}\bar{\beta}_i}{\sigma_{ij}}$ with $\bar{\beta}_j(\sigma_j)$ denoting the researcher j 's threshold conditional on σ_j .

- (ii) by the assumption $\sigma_b = \infty$, $\frac{1}{\sigma_b^2} = 0$, $\rho_{ij} = 1$, and $\sigma_{ij} = \sqrt{\frac{\sigma_i^2 + \sigma_j^2}{2}}$. Therefore, the indifference condition (21) is equivalent to

$$2\bar{\beta}_i - \frac{\sigma_i}{\sqrt{2}} \int \sqrt{\frac{\sigma_i^2}{\sigma_i^2 + \sigma_j^2}} \frac{\phi(\cdot)}{\Phi(\cdot)} g(\sigma_j) d\sigma_j = 0, \quad (22)$$

where the argument of $\phi(\cdot)$ and $\Phi(\cdot)$ is $\frac{\bar{\beta}_j(\sigma_j) - \bar{\beta}_i}{\sqrt{\frac{\sigma_i^2 + \sigma_j^2}{2}}}$.

- (iii) dividing the condition (22) by σ_i and writing $t_i = \frac{\bar{\beta}_i(\sigma_i)}{\sigma_i}$ for brevity,

$$t_i = \frac{1}{4} \int \sqrt{\frac{2}{1 + \sigma_r^2}} \frac{\phi(t_j \sigma_r - t_i)}{\Phi(t_j \sigma_r - t_i)} g(\sigma_j) d\sigma_j, \quad (23)$$

where $\sigma_r \equiv \frac{\sigma_j}{\sigma_i}$.

- (iv) we can express the condition (23) as a conditional mean of a truncated standard normal distribution using some hypothetical random variables: Noting that, for some random variable, $\tau_1 \sim \mathcal{N}\left(t_i, \frac{1 + \sigma_r^2}{2}\right)$, $\mathbb{E}[\tau_1 | \tau_1 \leq t_j \sigma_r] = t_i - \sqrt{\frac{1 + \sigma_r^2}{2}} \frac{\phi(t_j \sigma_r - t_i)}{\Phi(t_j \sigma_r - t_i)}$,

$$\begin{aligned} \frac{\phi(t_j \sigma_r - t_i)}{\Phi(t_j \sigma_r - t_i)} &= \sqrt{\frac{2}{1 + \sigma_r^2}} \{t_i - \mathbb{E}[\tau_1 | \tau_1 \leq t_j \sigma_r]\}, \\ &= \sqrt{\frac{2}{1 + \sigma_r^2}} \{-\mathbb{E}[\tau_2 | \tau_2 \leq t_j \sigma_r - t_i]\}, \text{ where } \tau_2 \sim \mathcal{N}\left(0, \frac{1 + \sigma_r^2}{2}\right) \\ &= \sqrt{\frac{2}{1 + \sigma_r^2}} \mathbb{E}[\tau_2 | \tau_2 \geq t_i - t_j \sigma_r] \\ &= \sqrt{\frac{2}{1 + \sigma_r^2}} \mathbb{E}\left[\sqrt{\frac{1 + \sigma_r^2}{2}} \tau_3 \mid \sqrt{\frac{1 + \sigma_r^2}{2}} \tau_3 \geq t_i - t_j \sigma_r\right], \text{ where } \tau_3 \sim \mathcal{N}(0, 1) \\ &= \mathbb{E}\left[\tau_3 \mid \tau_3 \geq \sqrt{\frac{2}{1 + \sigma_r^2}} (t_i - t_j \sigma_r)\right] \end{aligned}$$

Combining with (23), the indifference condition is

$$t_i = \frac{1}{4} \int \sqrt{\frac{2}{1 + \sigma_r^2}} \mathbb{E}\left[\tau \mid \tau \geq \sqrt{\frac{2}{1 + \sigma_r^2}} (t_i - t_j \sigma_r)\right] g(\sigma_j) d\sigma_j, \quad (24)$$

where $\tau \sim \mathcal{N}(0, 1)$.

Step 2. characterization: using the formula (25), we can show that $\frac{\partial t(\sigma_i)}{\partial \sigma_i} > 0$. Writing $K(\sigma_r) = \sqrt{\frac{2}{1+\sigma_r^2}}$, $L(\sigma_r) = \mathbb{E}[\tau | \tau \geq \sqrt{\frac{2}{1+\sigma_r^2}}(t_i - t_j \sigma_r)]$,

$$\frac{\partial t_i(\sigma_i)}{\partial \sigma_i} = \frac{\partial \sigma_r}{\partial \sigma_i} \times \frac{1}{4} \int [K(\sigma_r) L'(\sigma_r) + K'(\sigma_r) L(\sigma_r)] g(\sigma_j) d\sigma_j \quad (25)$$

by the chain rule. Note that $L'(\sigma_r) < 0$ since

$$\begin{aligned} \frac{\partial \sqrt{\frac{2}{1+\sigma_r^2}}(t_i - t_j \sigma_r)}{\partial \sigma_r} &= -t_j \sqrt{\frac{1+\sigma_r^2}{2}} - (t_i - t_j \sigma_r) \left(\frac{1}{2}\right)^{\frac{3}{2}} (1+\sigma_r^2)^{-\frac{1}{2}} \\ &= -\frac{1}{2} \sqrt{\frac{1+\sigma_r^2}{2}} \left[2t_j + \frac{t_i - t_j \sigma_r}{1+\sigma_r^2} \right] \\ &= -\frac{1}{2} \sqrt{\frac{1+\sigma_r^2}{2}} \left\{ \frac{t_i + 2t_j [(1-\sigma_r)^2 + \sigma_r]}{1+\sigma_r^2} \right\} < 0 \end{aligned}$$

Together with observations that $\frac{\partial \sigma_r}{\partial \sigma_i} < 0$, $K(\sigma_r) > 0$, and $L(\sigma_r) > 0$ and $K'(\sigma_r) < 0$, $\frac{\partial t_i(\sigma_i)}{\partial \sigma_i} > 0$ holds at every σ_i , as stated by Proposition 1.2.

Step 3. existence and uniqueness of researchers' strategies in symmetric equilibrium: to show that the equilibrium characterization is meaningful, we will show the existence of such threshold $t(\sigma_i | \{t_j\})$ defined by (24). We will apply the contraction mapping theorem, which also shows that the thresholds will be unique.

The functional equation $t(t_j)$ (a simplification of notation $t(\sigma_i | \{t_j\})$) is said to be a contraction mapping if there exists some constant $k \in (0, 1)$ such that $d\{t(\tau_0), t(\tau_1)\} \leq kd\{\tau_0, \tau_1\}$ for any τ_0, τ_1 . Here, let us define the distance between two strategies, $\tau_0(\sigma)$ and $\tau_1(\sigma)$, as the sup metric:

$$d\{\tau_0, \tau_1\} = \sup_{\sigma} |\tau_0(\sigma) - \tau_1(\sigma)|.$$

We first show that $t(\sigma_i | \{t_j\})$ is a contraction mapping when τ_0, τ_1 are differentiable with respect to σ in three sub-steps, and then apply the contraction mapping theorem.

- (i) Sub-step 1: we first show that we can consider a corresponding totally ordered two functions, rather than considering directly the arbitrary functions that may not be totally ordered.

Sub-Lemma 1. Define $\bar{\tau}(\sigma) \equiv \max\{\tau_0(\sigma), \tau_1(\sigma)\}$ and $\underline{\tau}(\sigma) \equiv \min\{\tau_0(\sigma), \tau_1(\sigma)\}$. For any k , if $d\{t(\bar{\tau}), t(\underline{\tau})\} \leq kd\{\bar{\tau}, \underline{\tau}\}$, then $d\{t(\tau_0), t(\tau_1)\} \leq kd\{\tau_0, \tau_1\}$.

Proof. The expression (24) shows that $t(\tau)$ is strictly decreasing in τ so that

$$t(\sigma | \{\bar{\tau}\}) \leq t(\sigma | \{\tau_s\}) \leq t(\sigma | \{\underline{\tau}\})$$

for both $s = 0, 1$, for all σ . Thus, $d\{t(\bar{\tau}), t(\underline{\tau})\} \geq d\{t(\tau_0), t(\tau_1)\}$. Since $\tau_0(\sigma)$ and $\tau_1(\sigma)$ are assumed to be differentiable, it is continuous and attains the maximum and minimum. Since $d\{\bar{\tau}, \underline{\tau}\} = d\{\tau_0, \tau_1\}$, the Sub-Lemma 1 holds. \blacksquare

- (ii) Sub-step 2: we then show that we can consider the derivative of function to prove that the two functions satisfy the condition to be a contraction map.

Sub-Lemma 2. *If there exists some k such that*

$$\frac{\partial d\{t(\tau + \delta), t(\tau)\}}{\partial \delta} < k$$

for any τ and for any δ , then the function t satisfies $d\{t(\bar{\tau}), t(\underline{\tau})\} \leq kd\{\bar{\tau}, \underline{\tau}\}$ for any totally ordered $\{\bar{\tau}, \underline{\tau}\}$.

Proof. Given any $\{\bar{\tau}, \underline{\tau}\}$ that is totally ordered (i.e. $\bar{\tau}(\sigma) > \underline{\tau}(\sigma)$ for all σ), let $\delta \equiv \sup_{\sigma} \{\bar{\tau}(\sigma) - \underline{\tau}(\sigma)\}$. Then

$$\begin{aligned} d\{t(\bar{\tau}), t(\underline{\tau})\} &\leq d\{t(\underline{\tau} + \delta), t(\underline{\tau})\} \\ &= \underbrace{d\{t(\underline{\tau}), t(\underline{\tau})\}}_{=0} + \int_0^{\delta} \underbrace{\frac{\partial d\{t(\tau + \tilde{\delta}), t(\tau)\}}{\partial \tilde{\delta}}}_{\leq k} d\tilde{\delta} \\ &\leq k\delta \\ &= kd\{\bar{\tau}, \underline{\tau}\} \end{aligned}$$

The first line follows because t is strictly decreasing in τ ; the second line follows from the fundamental theorem of calculus; the third line follows by assumption of Sub-Lemma 2; and the fourth line by definition of δ . \blacksquare

- (iii) Sub-step 3: using the expression (24), we derive the expression of the bound on the derivative.

Sub-Lemma 3. *For any τ and for any δ , with t defined as (24),*

$$\frac{\partial d\{t(\tau + \delta), t(\tau)\}}{\partial \delta} < \frac{1}{2}$$

Proof. There are three steps to prove this: first, we note that analyzing $\frac{\partial}{\partial \delta} t(\sigma^*(\delta) | \{\tau + \delta\})$

will be sufficient:

$$\begin{aligned}
\frac{\partial d\{t(\tau + \delta), t(\tau)\}}{\partial \delta} &= \frac{\partial}{\partial \delta} [t(\sigma^*(\delta) | \{\tau\}) - t(\sigma^*(\delta) | \{\tau + \delta\})], \\
&\text{where } \sigma^*(\delta) \equiv \arg \max_{\sigma} \{t(\sigma | \{\tau + \delta\}) - t(\sigma | \{\tau\})\} \\
&= -\frac{\partial}{\partial \delta} t(\sigma^*(\delta) | \{\tau + \delta\}) \\
&\quad + \frac{\partial}{\partial \sigma} [t(\sigma^*(\delta) | \{\tau\}) - t(\sigma^*(\delta) | \{\tau + \delta\})] |_{\sigma=\sigma^*(\delta)} \times \frac{\partial \sigma^*(\delta)}{\partial \delta} \\
&= -\frac{\partial}{\partial \delta} t(\sigma^*(\delta) | \{\tau + \delta\})
\end{aligned}$$

where the first equality followed by definition (the maximum exists since $Supp(G)$ is closed and bounded), the second equality followed by the chain rule, and the third equality followed by the envelope theorem given differentiability of t .

Second, writing $\Sigma \equiv \sqrt{\frac{2}{1 + \left(\frac{\sigma^*}{\sigma_j}\right)^2}} \{t(\sigma^* | \{\tau + \delta\}) - [\tau(\sigma_j) + \delta] \frac{\sigma^*}{\sigma_j}\}$ for notational ease, we can derive the bound on $-\frac{\partial}{\partial \delta} t(\sigma^*(\delta) | \{\tau + \delta\})$: given (24),

$$\frac{\partial}{\partial \delta} t(\sigma^* | \{\tau + \delta\}) = \frac{1}{4} \int \sqrt{\frac{2}{1 + \left(\frac{\sigma^*}{\sigma_j}\right)^2}} \frac{\partial \mathbb{E}[\tilde{\tau} | \tilde{\tau} \geq \Sigma]}{\partial \Sigma} \times \frac{\partial \Sigma}{\partial \delta} g(\sigma_j) d\sigma_j \quad (26)$$

By the chain rule, $\frac{\partial \Sigma}{\partial \delta} = \sqrt{\frac{2}{1 + \left(\frac{\sigma^*}{\sigma_j}\right)^2}} \left\{ \frac{\partial}{\partial \delta} t(\sigma^* | \{\tau + \delta\}) - \frac{\sigma^*}{\sigma_j} \right\}$. Thus, rearranging (26),

$$-\frac{\partial}{\partial \delta} t(\sigma^* | \{\tau + \delta\}) = \frac{\int \frac{\frac{\sigma^*}{\sigma_j}}{1 + \left(\frac{\sigma^*}{\sigma_j}\right)^2} \frac{\partial \mathbb{E}[\tau | \tau \geq \Sigma]}{\partial \Sigma} g(\sigma_j) d\sigma_j}{2 - \int \frac{1}{1 + \left(\frac{\sigma^*}{\sigma_j}\right)^2} \frac{\partial \mathbb{E}[\tau | \tau \geq \Sigma]}{\partial \Sigma} g(\sigma_j) d\sigma_j}$$

Note that $\frac{\partial \mathbb{E}[\tau | \tau \geq \Sigma]}{\partial \Sigma} < 1$ because it is a derivative with respect to a truncated normal distribution. Given $\frac{1}{1 + \left(\frac{\sigma^*}{\sigma_j}\right)^2} < 1$, we note that $2 - \int \frac{1}{1 + \left(\frac{\sigma^*}{\sigma_j}\right)^2} \frac{\partial \mathbb{E}[\tau | \tau \geq \Sigma]}{\partial \Sigma} g(\sigma_j) d\sigma_j > 1$.

Combining,

$$-\frac{\partial}{\partial \delta} t(\sigma^* | \{\tau + \delta\}) < \int \frac{\frac{\sigma^*}{\sigma_j}}{1 + \left(\frac{\sigma^*}{\sigma_j}\right)^2} g(\sigma_j) d\sigma_j.$$

Third, note that $\frac{\frac{\sigma^*}{\sigma_j}}{1 + \left(\frac{\sigma^*}{\sigma_j}\right)^2} \leq \frac{1}{2}$ for any σ^* and σ_j since

$$0 \leq (\sigma_i - \sigma_j)^2 \Rightarrow 2\sigma_i\sigma_j \leq \sigma_i^2 + \sigma_j^2 \Rightarrow \frac{\sigma_i\sigma_j}{\sigma_i^2 + \sigma_j^2} = \frac{\frac{\sigma^*}{\sigma_j}}{1 + \left(\frac{\sigma^*}{\sigma_j}\right)^2} \leq \frac{1}{2}.$$

Combining the three steps, we conclude that the Sub-Lemma 3 holds. ■

Since the expression (24) implies that the equilibrium threshold must be differentiable with respect to σ , we do not have to consider functions $\tau(\sigma)$ that is not differentiable. Since (i) $k = \frac{1}{2} < 1$ and (ii) the space of continuous functions is a complete metric space under sup metric, we can apply the contraction mapping theorem to claim that the function $t(\sigma)$ satisfying (24) exists and is unique.

Step 4. verifying the policymaker's indifference condition: To show that the policymaker will be willing to follow the strategy in the symmetric equilibrium (6), we need to show $\mathbb{E}[b|n_1 = n_0] = 0$. $\underline{\beta}(\sigma) = -\bar{\beta}(\sigma)$ holds at every σ by the uniqueness of the threshold that satisfies the indifference condition. By the proof of existence of symmetric equilibrium in A2.2, $\mathbb{E}[b|n_1 = n_0, \sigma] = 0$ for all σ . Thus,

$$\mathbb{E}[b|n_1 = n_0] = \int \mathbb{E}[b|n_1 = n_0, \sigma] g(\sigma) d\sigma = 0.$$

By combining Steps 1 to 4, the result $\frac{\partial t(\sigma_i)}{\partial \sigma_i} > 0$ holds in the unique symmetric equilibrium.

□

A4. Proof of 2.5 Amplification of Small Bias of a Researcher

This sub-Section proves the Proposition 1.3 in Section 2.5.

A3 Proof of Proposition 1.3 The Proposition 1.3 provides an expression for the strategic multiplier between researchers, and claims that it will be greater than 1. The proof consists of two steps: first, we derive comparative statics in equilibrium; and second, derive the multiplier and show that it is greater than 1. Note that the results for $\underline{\beta}_i$ can be derived analogously.

Step 1. comparative static with researchers' indifference conditions: as derived in Appendix [], in a symmetric equilibrium with $d_i = d_j = 0$, the indifference conditions are given by

$$\bar{\beta}_i + \mathbb{E}[\beta_j | \beta_j \leq \bar{\beta}_j, \beta_i = \bar{\beta}_i] = - \left(2 + \frac{\sigma^2}{\sigma_b^2} \right) d_i \quad (27)$$

$$\bar{\beta}_j + \mathbb{E}[\beta_i | \beta_i \leq \bar{\beta}_i, \beta_j = \bar{\beta}_j] = - \left(2 + \frac{\sigma^2}{\sigma_b^2} \right) d_j \quad (28)$$

Totally differentiating the indifference conditions with respect to d_i , we have

$$\begin{bmatrix} 1 & \frac{Var_{truncated}}{Var_{total}} \\ \frac{Var_{truncated}}{Var_{total}} & 1 \end{bmatrix} \begin{bmatrix} \partial \bar{\beta}_i / \partial d_i \\ \partial \bar{\beta}_j / \partial d_i \end{bmatrix} = - \begin{bmatrix} 2 + \frac{\sigma^2}{\sigma_b^2} \\ 0 \end{bmatrix}$$

since $\frac{\mathbb{E}[\beta_j | \beta_j \leq \bar{\beta}_j, \beta_i = \bar{\beta}_i]}{\partial \bar{\beta}_i} = \rho \frac{Var_{truncated}}{\sigma^2}$ with $\rho = \frac{\sigma^2}{Var_{total}}$, and $\bar{\beta}_i = \bar{\beta}_j$ in the symmetric equilibrium. Rearranging,

$$\begin{bmatrix} \partial \bar{\beta}_i / \partial d_i \\ \partial \bar{\beta}_j / \partial d_i \end{bmatrix} = - \frac{1}{1 - \left(\frac{Var_{truncated}}{Var_{total}} \right)^2} \begin{bmatrix} 1 & -\frac{Var_{truncated}}{Var_{total}} \\ -\frac{Var_{truncated}}{Var_{total}} & 1 \end{bmatrix} \begin{bmatrix} 2 + \frac{\sigma^2}{\sigma_b^2} \\ 0 \end{bmatrix}$$

Therefore, we have

$$\frac{\partial (\bar{\beta}_i - \bar{\beta}_j)}{\partial d_i} = - \frac{2 + \frac{\sigma^2}{\sigma_b^2}}{1 - \frac{Var_{truncated}}{Var_{total}}} \quad (29)$$

Step 2. deriving and interpreting the strategic multiplier: using the expression (29), we can derive the expression of the multiplier, and show that it will always be greater than 1.

- expression: in the absence of strategic effects,

$$\frac{\partial (\bar{\beta}_i - \bar{\beta}_j)}{\partial d_i} \Big|_{\sigma_j = \sigma_j^*} = \frac{\partial \bar{\beta}_i}{\partial d_i} \Big|_{\sigma_j = \sigma_j^*} - \frac{\partial \bar{\beta}_j}{\partial d_i} \Big|_{\sigma_j = \sigma_j^*} = - \left(2 + \frac{\sigma^2}{\sigma_b^2} \right) - 0 = - \left(2 + \frac{\sigma^2}{\sigma_b^2} \right).$$

Thus, the multiplier is $\zeta = \frac{1}{1 - \frac{Var_{truncated}}{Var_{total}}}$.

- interpretation: by the definition of truncated distribution, $\frac{Var_{truncated}}{Var_{total}} \in (0, 1)$. Thus, $\zeta \in (1, +\infty)$.

□

A5. Proof of 4.1 A New “Stem-based” Bias Correction Method

This sub-Section contains the proof of Proposition 2 in Section 4.1, concerning the properties of bias used for the stem-based bias correction method.

A3.1. Proof of Proposition 2.

Proposition 2 claims that the bias squared is increasing in the standard error of the studies under some conditions, both for the extremum and uniform selection models. We will prove the result for the extremum selection, and then for the uniform selection. For notational ease, let us henceforth write $\bar{\sigma} = \sqrt{\sigma_0^2 + \sigma_i^2}$.

Proof of bias under extremum selection. We derive the monotonicity and limit results from the definition of truncated normal distribution. For notational ease, we the true mean, b_0 , to zero.

(i) Monotonicity: let us write

$$Bias(\sigma_i) = -\bar{\sigma} \frac{\phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)}{\int_{\beta_{\min}}^{\infty} \phi\left(\frac{\beta}{\bar{\sigma}}\right) d\beta} = -\bar{\sigma} \left[\underbrace{\int_{\beta_{\min}}^{|\beta_{\min}|} \frac{\phi\left(\frac{\beta}{\bar{\sigma}}\right)}{\phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)} d\beta}_{=0} + \int_{|\beta_{\min}|}^{\infty} \frac{\phi\left(\frac{\beta}{\bar{\sigma}}\right)}{\phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)} d\beta \right]^{-1}$$

where the second line considered the case when $\beta_{\min} < 0$. By the chain rule, $Sign\left(\frac{\partial |Bias(\bar{\sigma})|}{\partial \bar{\sigma}}\right) = Sign(D)$, where

$$\begin{aligned} D &= \int_{|\beta_{\min}|}^{\infty} \frac{\phi\left(\frac{\beta}{\bar{\sigma}}\right)}{\phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)} d\beta - \bar{\sigma} \frac{\partial}{\partial \bar{\sigma}} \int_{|\beta_{\min}|}^{\infty} \frac{\phi\left(\frac{\beta}{\bar{\sigma}}\right)}{\phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)} d\beta \\ &= \int_{|\beta_{\min}|}^{\infty} \exp\left(\frac{\beta_{\min}^2 - \beta^2}{\bar{\sigma}^2}\right) - 2 \frac{\beta^2 - \beta_{\min}^2}{\bar{\sigma}^2} \exp\left(\frac{\beta_{\min}^2 - \beta^2}{\bar{\sigma}^2}\right) d\beta \\ &= \int_{|\beta_{\min}|}^{\infty} \left[1 + 2 \frac{\beta_{\min}^2 - \beta^2}{\bar{\sigma}^2}\right] \exp\left(\frac{\beta_{\min}^2 - \beta^2}{\bar{\sigma}^2}\right) d\beta \\ &= \int_{|\beta_{\min}|}^{\infty} \left[1 + 2 \frac{\beta_{\min}^2}{\bar{\sigma}^2}\right] \exp\left(\frac{\beta_{\min}^2 - \beta^2}{\bar{\sigma}^2}\right) d\beta + \int_{|\beta_{\min}|}^{\infty} -2 \frac{\beta^2}{\bar{\sigma}^2} \exp\left(\frac{\beta_{\min}^2 - \beta^2}{\bar{\sigma}^2}\right) d\beta \\ &= |\beta_{\min}| \\ &> 0, \end{aligned}$$

where the last line followed by the integration by parts³². Thus,

$$\frac{\partial Bias^2(\sigma_i)}{\partial \sigma_i} = 2Bias(\bar{\sigma}) \frac{\partial Bias(\bar{\sigma})}{\partial \bar{\sigma}} \frac{\partial \bar{\sigma}}{\partial \sigma_i} > 0.$$

(ii) Limit: let us consider the two cases in turn while considering the original expression

³²Concretely, we can write:

$$\begin{aligned} \int_{|\beta_{\min}|}^{\infty} -2 \frac{\beta^2}{\bar{\sigma}^2} \exp\left(\frac{\beta_{\min}^2 - \beta^2}{\bar{\sigma}^2}\right) d\beta &= \int_{|\beta_{\min}|}^{\infty} \beta \times \frac{\partial}{\partial \beta} \exp\left(\frac{\beta_{\min}^2 - \beta^2}{\bar{\sigma}^2}\right) d\beta \\ &= \beta \times \exp\left(\frac{\beta_{\min}^2 - \beta^2}{\bar{\sigma}^2}\right) \Big|_{|\beta_{\min}|}^{\infty} - \int_{|\beta_{\min}|}^{\infty} \exp\left(\frac{\beta_{\min}^2 - \beta^2}{\bar{\sigma}^2}\right) d\beta \\ &= |\beta_{\min}| - \int_{|\beta_{\min}|}^{\infty} \exp\left(\frac{\beta_{\min}^2 - \beta^2}{\bar{\sigma}^2}\right) d\beta \end{aligned}$$

$Bias(\sigma_i) = -\bar{\sigma} \frac{\phi(\frac{\beta_{\min}}{\bar{\sigma}})}{1 - \Phi(\frac{\beta_{\min}}{\bar{\sigma}})}$: by using the L'Hopital's rule wherever applicable,

- $\beta_{\min} < 0$:

$$\lim_{\bar{\sigma} \rightarrow 0} Bias(\bar{\sigma}) = -\lim_{\bar{\sigma} \rightarrow 0} \bar{\sigma} \frac{\lim_{\bar{\sigma} \rightarrow 0} \phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)}{\lim_{\bar{\sigma} \rightarrow 0} [1 - \Phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)]} = -0 \times \frac{0}{1} = 0$$

- $\beta_{\min} = 0$:

$$\lim_{\bar{\sigma} \rightarrow 0} Bias(\bar{\sigma}) = -\lim_{\bar{\sigma} \rightarrow 0} \bar{\sigma} \frac{\lim_{\bar{\sigma} \rightarrow 0} \phi(0)}{\lim_{\bar{\sigma} \rightarrow 0} [1 - \Phi(0)]} = -0 \times \frac{\phi(0)}{\frac{1}{2}} = 0$$

- $\beta_{\min} \geq 0$:

$$\begin{aligned} \lim_{\bar{\sigma} \rightarrow 0} Bias(\bar{\sigma}) &= -\frac{\lim_{\bar{\sigma} \rightarrow 0} \bar{\sigma} \phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)}{\lim_{\bar{\sigma} \rightarrow 0} [1 - \Phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)]} \\ &= -\frac{\lim_{\bar{\sigma} \rightarrow 0} \left[\phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right) - \frac{\beta_{\min}}{\bar{\sigma}^2} \bar{\sigma} \phi'\left(\frac{\beta_{\min}}{\bar{\sigma}}\right) \right]}{\lim_{\bar{\sigma} \rightarrow 0} \left[\frac{\beta_{\min}}{\bar{\sigma}^2} \phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right) \right]} \\ &= -\frac{\lim_{\bar{\sigma} \rightarrow 0} \left[\phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right) + \left(\frac{\beta_{\min}}{\bar{\sigma}}\right)^2 \phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right) \right]}{\lim_{\bar{\sigma} \rightarrow 0} \left[\frac{\beta_{\min}}{\bar{\sigma}^2} \phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right) \right]} \\ &= -\left[\lim_{\bar{\sigma} \rightarrow 0} \frac{\bar{\sigma}^2 \phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)}{\beta_{\min} \phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)} + \lim_{\bar{\sigma} \rightarrow 0} \beta_{\min} \frac{\phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)}{\phi\left(\frac{\beta_{\min}}{\bar{\sigma}}\right)} \right] \\ &= \beta_{\min}, \end{aligned}$$

where the third line followed by the property of normal density that $\phi'(x) = -x\phi(x)$.

Thus, the most precise study is unbiased as $\sigma_i \rightarrow 0$ when $\sigma_0 = 0$ if and only if $\beta_{\min} \leq 0$. ■

Proof of bias under uniform selection. We derive the monotonicity and limit results from the definition of truncated normal distribution: we can write the bias as

Denoting $\bar{\beta} = \frac{t\sigma_i - b_0}{\bar{\sigma}}$ and $\underline{\beta} = \frac{-t\sigma_i - b_0}{\bar{\sigma}}$, we can write the bias as

$$\begin{aligned} Bias(\bar{\sigma}) &= \bar{\sigma} \frac{\eta_1 [-\phi(\underline{\beta}) + \phi(\bar{\beta})] - \eta_0 [\phi(\bar{\beta}) - \phi(\underline{\beta})]}{\eta_1 [\Phi(\underline{\beta}) + 1 - \Phi(\bar{\beta})] + \eta_0 [\Phi(\bar{\beta}) - \Phi(\underline{\beta})]} \\ &= -\bar{\sigma}^2 \frac{\partial \ln \{ \eta_1 + (\eta_1 - \eta_0) \Delta \Phi(b_0) \}}{\partial b_0}, \end{aligned}$$

where $\Delta \Phi(b_0) = \Phi(\bar{\beta}) - \Phi(\underline{\beta}) > 0$.

(i) Monotonicity: let us write (from the expression above, we can write

$$Bias(\bar{\sigma}) = \bar{\sigma} \frac{(\eta_1 - \eta_0)}{\eta_1 + (\eta_1 - \eta_0) \Delta\Phi(b_0)} K(\sigma_i),$$

where $K(\sigma_i) = \phi(\bar{\beta}) - \phi(\underline{\beta})$

- By an assumption $\eta_1 - \eta_0 > 0$, we know that $\frac{(\eta_1 - \eta_0)}{\eta_1 + (\eta_1 - \eta_0) \Delta\Phi(b_0)}$ is increasing in σ_i .
- We show that there exists some range $[0, \underline{\sigma}]$ such that $K(\sigma_i)$ will be increasing in σ_i :

$$\frac{\partial K(\sigma_i)}{\partial \sigma_i} = \phi'(\bar{\beta}) \frac{\partial \bar{\beta}(\sigma_i)}{\partial \sigma_i} - \phi'(\underline{\beta}) \frac{\partial \underline{\beta}(\sigma_i)}{\partial \sigma_i}$$

By the definitions above,

$$\begin{aligned} \frac{\partial \bar{\beta}(\sigma_i)}{\partial \sigma_i} &= \frac{t\bar{\sigma} - (t\sigma_i - b_0) \times \frac{1}{2}\bar{\sigma}^{-1} \times 2\sigma_i}{\bar{\sigma}^2} = \frac{t}{\bar{\sigma}} - \frac{(t\sigma_i - b_0)\sigma_i}{\bar{\sigma}^3} \\ \frac{\partial \underline{\beta}(\sigma_i)}{\partial \sigma_i} &= \frac{-t\bar{\sigma} - (-t\sigma_i - b_0) \times \frac{1}{2}\bar{\sigma}^{-1} \times 2\sigma_i}{\bar{\sigma}^2} = -\frac{t}{\bar{\sigma}} + \frac{(t\sigma_i + b_0)\sigma_i}{\bar{\sigma}^3} \end{aligned}$$

Substituting,

$$\begin{aligned} \frac{\partial K(\sigma_i)}{\partial \sigma_i} &= \phi'(\bar{\beta}) \left[\frac{t}{\bar{\sigma}} - \frac{(t\sigma_i - b_0)\sigma_i}{\bar{\sigma}^3} \right] - \phi'(\underline{\beta}) \left[-\frac{t}{\bar{\sigma}} + \frac{(t\sigma_i + b_0)\sigma_i}{\bar{\sigma}^3} \right] \\ &= \frac{1}{\bar{\sigma}} \left\{ t[\phi'(\underline{\beta}) - \phi'(\bar{\beta})] + t \frac{\sigma_i}{\bar{\sigma}} [\phi'(\underline{\beta}) \underline{\beta} - \phi'(\bar{\beta}) \bar{\beta}] \right\} \end{aligned}$$

When σ_i is small, term $[\phi'(\underline{\beta}) - \phi'(\bar{\beta})]$ determines the sign of $\frac{\partial K(\sigma_i)}{\partial \sigma_i}$. Since $\bar{\beta} > \underline{\beta}$, $\phi'(\underline{\beta}) > \phi'(\bar{\beta})$, and thus, $\frac{\partial K(\sigma_i)}{\partial \sigma_i} > 0$. On the other hand, When σ_i is large, the term, $\phi'(\underline{\beta}) \underline{\beta} - \phi'(\bar{\beta}) \bar{\beta} = \phi(\bar{\beta}) \bar{\beta}^2 - \phi(\underline{\beta}) \underline{\beta}^2$ will be important, and can be negative since $\phi(\underline{\beta}) > \phi(\bar{\beta})$ when the thresholds are at the tail of normal distribution.

(ii) Limit: since the cumulative distribution function is continuously differentiable, we can analyze by distributing the limit:

$$\begin{aligned} \lim_{\sigma_i \rightarrow 0} Bias(\sigma_i) &= - \lim_{\sigma_i \rightarrow 0} \bar{\sigma}^2 \times \frac{\partial \ln \{ \eta_1 + (\eta_1 - \eta_0) \lim_{\sigma_i \rightarrow 0} \Delta\Phi(b_0) \}}{\partial b_0} \\ &= -\sigma_0^2 \times \frac{\partial \ln \{ \eta_1 + (\eta_1 - \eta_0) [\Phi(\frac{-b_0}{\bar{\sigma}}) - \Phi(\frac{-b_0}{\bar{\sigma}})] \}}{\partial b_0} \\ &= 0 \end{aligned}$$

Thus, $\lim_{\sigma_i \rightarrow 0} Bias(\sigma_i) = 0$ for any parameter values. ■

□

Appendix B. Supplementary Numerical Discussions

Appendix A has provided various analytical proofs. Due to limited analytical tractability, however, this paper has extensively employed numerical approach. Appendix B provides details of numerical simulations and presents some additional results: B1 will illustrate equilibrium thresholds under the general environments, and B2 describes details of empirical tests.

B1. Thresholds under General Environments

This Section describes the simulation of thresholds, $\bar{\beta}(\sigma_i)$ and $\underline{\beta}(\sigma_i)$, in a more general environment and in an equilibrium that is the main focus of the analysis. The environment is more general since the simulation can consider settings with $N \geq 3$, $c > 0$, $\sigma_b < \infty$, and heterogeneous values of σ_i . While Proposition 2.1 concerning the thresholds under heterogeneous σ_i , for analytical tractability, focused on the symmetric equilibrium such that $\bar{\beta}(\sigma_i) = -\underline{\beta}(\sigma_i)$, the numerical analysis can explore the properties of the asymmetric equilibrium with $\bar{\beta}(\sigma_i) < -\underline{\beta}(\sigma_i)$.

This analysis will show when the analytical results are robust to alternative environments. B1.1 will first describe the overview of simulation algorithm; B1.2 shows some additional results regarding omission; B1.3 shows that the threshold $\underline{\beta}(\sigma)$ need not be concave when c is high; B1.4 explores the implication of N , the number of researchers, on the thresholds; B1.5 summarizes the magnitude of omission, bias, and welfare consequences of various reporting rules.

B1.1 Simulation Step Overview

We compute the equilibrium thresholds, $\bar{\beta}(\sigma_i), \underline{\beta}(\sigma_i)$, that are symmetric between N researchers, given primitive environments' parameters such as threshold policy effectiveness, c , and number of researchers, N , as well as underlying variance, σ_b^2 , and between-study heterogeneity, σ_0^2 . By discretizing the support of standard errors to $\{\sigma_1, \sigma_2, \dots, \sigma_S\}$ with $\sigma_1 \leq \sigma_2 \leq \dots \leq \sigma_S$, the equilibrium thresholds at each standard error, $\bar{\beta}(\sigma_i), \underline{\beta}(\sigma_i)$, is given by a system of $2 \times S$ equations:

$$\bar{\beta}(\sigma_i) = \frac{\sigma_i^2}{\mathbb{E}^{\sigma-i} \left[\frac{1}{\sum_{j=0}^N \sigma_j^{-2}} \middle| Piv_1 \right]} \left\{ c - \mathbb{E}^{\sigma-i} \left[\frac{\mathbb{E}^{m-i} \left[\mathbb{E}^{\beta-i} \sum \frac{\beta_{-i}}{\sigma_{-i}^2} \middle| Piv_1 \right]}{\sum_{j=0}^N \sigma_j^{-2}} \middle| Piv_1 \right] \right\} \quad (30)$$

$$\underline{\beta}(\sigma_i) = \frac{\sigma_i^2}{\mathbb{E}^{\sigma-i} \left[\frac{1}{\sum_{j=0}^N \sigma_j^{-2}} \middle| Piv_0 \right]} \left\{ c - \mathbb{E}^{\sigma-i} \left[\frac{\mathbb{E}^{m-i} \left[\mathbb{E}^{\beta-i} \sum \frac{\beta_{-i}}{\sigma_{-i}^2} \middle| Piv_0 \right]}{\sum_{j=0}^N \sigma_j^{-2}} \middle| Piv_0 \right] \right\}, \quad (31)$$

where the Piv_m for $m \in \{0, 1\}$ denotes the other's message realization such that the researchers' switch between \emptyset and m is pivotal. Concretely, denoting the number of others' positive results and negative results as n'_1, n'_0 respectively, Piv_1 is $n'_1 = n'_0$ and Piv_0 is $n'_1 = n'_0 + 1$ in the asymmetric equilibrium with supermajoritarian rule (2).

The algorithm solves the above system of $2 \times S$ equations with $2 \times S$ unknowns iteratively by inner and outer loops. The inner loop computes $\mathbb{E}^{m-i} \left[\cdot \middle| Piv_m \right]$ for every combination of m_{-i} in Piv_m ; the outer loop computes $\mathbb{E}^{\sigma_{-i}} [\cdot]$ for every $\sigma_{-i} \in \{\sigma_1, \sigma_2, \dots, \sigma_S\}^N$. Since there is no analytical solution of mean of correlated multi-variate normal distribution, $\mathbb{E}^{\beta_{-i}} [\cdot]$, the algorithm used numerical integration with rejection sampling. The iterative adjustment takes the estimated thresholds under $N-1$ researchers as an input conjecture, $\beta_{conjecture}$, and computes the updated thresholds, β_{new} , by $\beta_{new} = \Delta \beta_{sol} + (1 - \Delta) \beta_{conjecture}$, where Δ is a step of adjustment, looping over every σ_i . The initial values for $N = 2$ are some linear functions $\bar{\beta}(\sigma) = A\sigma + c$, $\underline{\beta}(\sigma) = -A\sigma + c$; but the thresholds are not sensitive to the choice of $A > 0$. The algorithm stops when the updates, $|\beta_{new} - \beta_{conjecture}|$, are smaller than some tolerance level.

For a sufficiently large S that permits fine grid for $Supp(\sigma)$, the computational time increases exponentially as N increases. This is because dimensions of the inputs into computation increase exponentially: the weights on probabilities given message realizations take S^N dimensions and the message realizations take $\sum_{k=0}^{\lfloor N/2 \rfloor} \binom{N}{k} \times (N-1)$ dimensions to compute. Moreover, we have set $\Delta = 0.5$ and tolerance level to be 0.05. For the simulation with heterogeneous priors, we chose $\{\sigma_1, \sigma_2, \dots, \sigma_S\} = \{0.1, 0.2, \dots, 1\}$ so that $S = 10$. Due to limitations of feasibility, the simulation with heterogeneous thresholds compute only up to $N = 4$.

To approximate some real-world settings with reasonable algorithms, we choose a distribution of $G(\sigma)$ close to the distribution of σ in the labor union data set (Doucouliagos et al. 2018). Since the observed distribution of σ in the data set is the distribution with publication selection, we impute the underlying distribution with the positive significant results from the example of labor union ($G(\sigma) = \frac{1}{C} \sum_i \left(1 - \Phi \left(\frac{1.96\sigma_i - \hat{b}_0}{\sqrt{\sigma_i^2 - \hat{\sigma}_0^2}} \right) \right)^{-1} \mathbf{1}(\sigma \geq \sigma_i)$), where $C = \sum_i \left(1 - \Phi \left(\frac{1.96\sigma_i - \hat{b}_0}{\sqrt{\sigma_i^2 - \hat{\sigma}_0^2}} \right) \right)^{-1}$ is the normalizing constant, and $\{\hat{b}_0, \hat{\sigma}_0^2\}$ are estimated with the stem-based method. The largest standard error is normalized to be 1. The figure shows that χ^2 distribution with 2 degrees of freedom with support $[0, 4]$ approximates the empirical distribution of variance, σ^2 , reasonably.

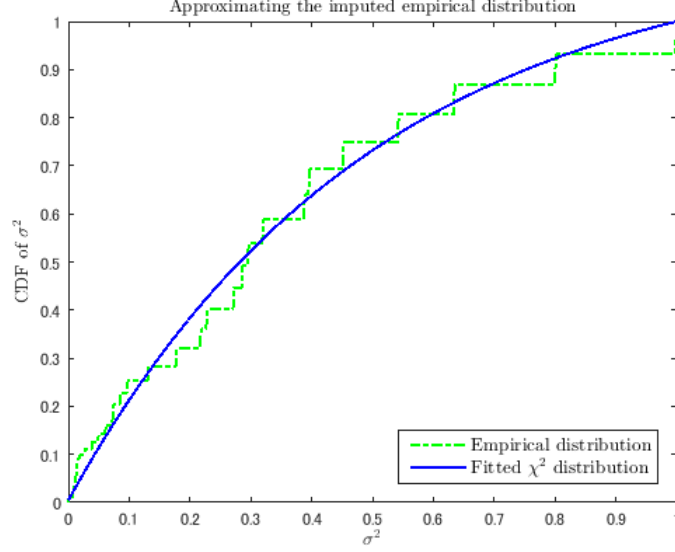


Figure B1: Approximation of empirical distribution

Notes: Figure B1 plots the imputed empirical distribution of variance, σ^2 against χ^2 distribution with 2 degrees of freedom with support of $[0, 4]$ normalized to support of $[0, 1]$.

The simulation henceforth will incorporate between-study heterogeneity, σ_0^2 , on equilibrium thresholds. When there is study-specific effects on underlying benefits, $b_i = b + \zeta_i$ with $\zeta_i \sim \mathcal{N}(0, \sigma_0^2)$, the estimates are generated by $\beta_i = b_i + \epsilon_i = b + \zeta_i + \epsilon_i$. Thus, given the estimated standard error σ_i due to the sampling variance, the true variance, σ_i^{2*} , satisfies $\sigma_i^{2*} = \sigma_i^2 + \sigma_0^2$. As the formula shows, we can consider these heterogeneities by shifting the values of inverse variance weights used in Bayesian updating.

B1.2 Numerical results on omission

The following two figures show that $\mathbb{P}(a = 1) < \frac{1}{2}$ under supermajoritarian rule, and that the welfare attained under supermajoritarian rule is higher than those under submajoritarian rule.

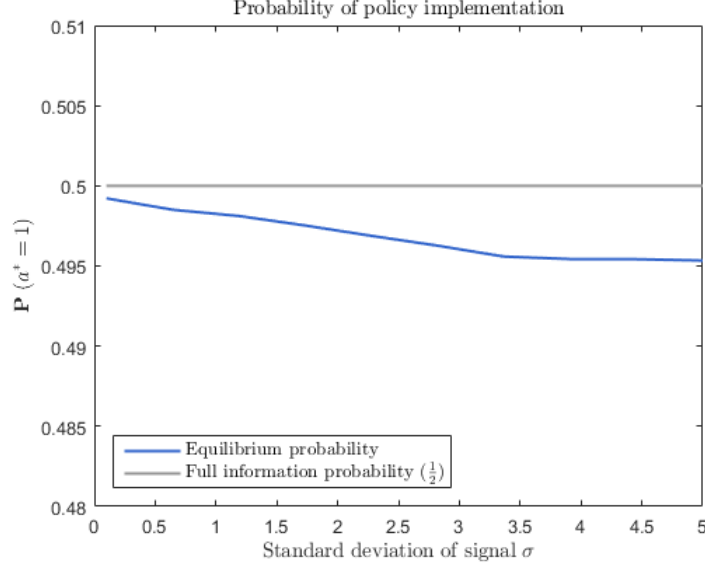


Figure B2: Likelihood of policy implementation

Notes: Figure B2 plots the probability of policy implementation $\mathbb{P}(a = 1)$ for $N = 2$, $c = 0$, $\sigma_b = \frac{1}{3}$, and various values of standard error of signal, σ , in the equilibrium characterized by Proposition 1. It shows that, relative to the policy implementation probability under communication of estimates, $\mathbb{P}(a = 1) = \frac{1}{2}$, policy is slightly less likely to be implemented. This is primarily due to the conservative rule of supermajoritarian voting rule $a^* = 1 \Leftrightarrow n_1 > n_0$, largely mitigated by the thresholds $\bar{\beta}, \underline{\beta}$ that lead to the upward bias of the estimates that underlie reported studies.

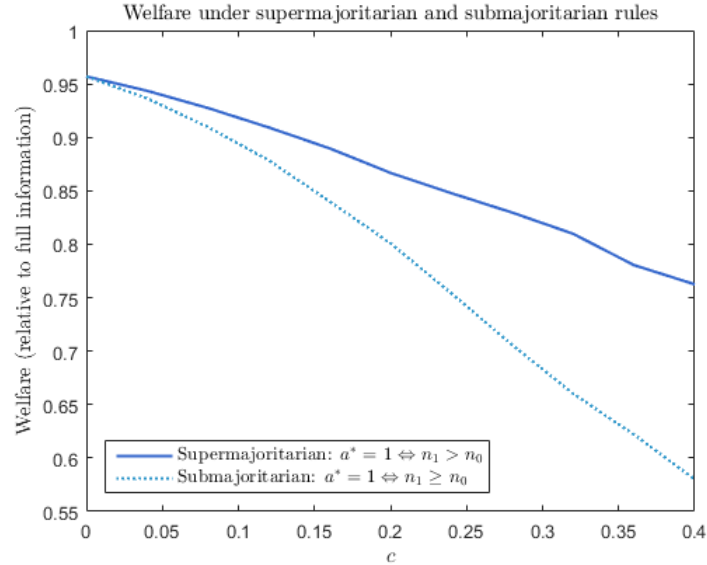


Figure B3: Optimality of supermajoritarian voting rule

Notes: Figure B3 plots the welfare (measured as a fraction of benchmark case with communication of estimates) under a supermajoritarian rule ($a^* = 1 \Leftrightarrow n_1 > n_0$) and a submajoritarian rule ($a^* =$

$1 \Leftrightarrow n_1 \geq n_0$) for $N = 2$, $\sigma_b = \sigma = 1$, and various values of $c \geq 0$. It shows that the supermajoritarian rule attains higher welfare than the submajoritarian rule for $c > 0$, and identical welfare for $c = 0$. The supermajoritarian rule is better than the submajoritarian rule especially when c is high and thus there is large relative welfare loss.

B1.3 Shape of $\underline{\beta}(\sigma)$ under high $c > 0$

Simulations show that, while Proposition 2.1 suggested that $\underline{\beta}(\sigma_i)$ will be concave in the symmetric equilibrium with $c = 0$, it can be convex in the asymmetric equilibrium with large $c > 0$ and supermajoritarian voting rule. Figure B2 illustrates this in a setting with $N = 2$, $c = 2$, $\sigma_b = \frac{3}{4}$, $\sigma_0 = 0$ and distribution $G(\sigma)$ that approximates an empirical distribution as discussed in Section B1.1. This result suggests that the pattern of omission and inflation may be very different between positive and negative results.

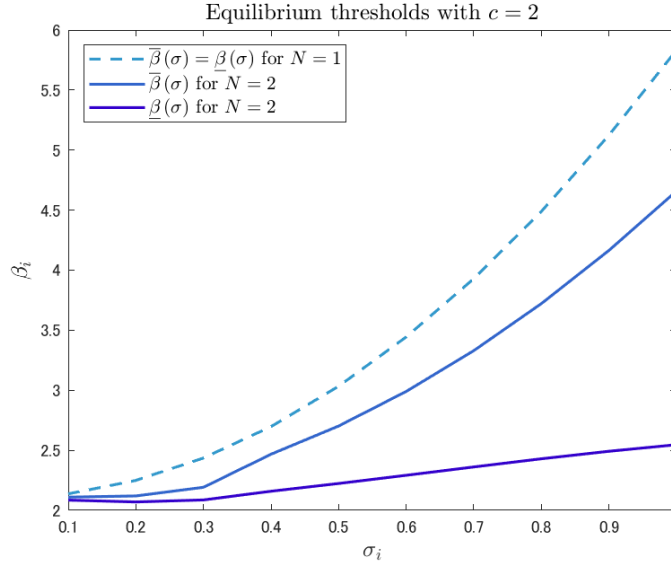


Figure B4: Example of convex $\underline{\beta}(\sigma)$

Notes: Figure B4 plots the thresholds $\bar{\beta}(\sigma)$ and $\underline{\beta}(\sigma)$ for $N = 2$, $c = 2$, $\sigma_b = \frac{3}{4}$, $\sigma_0 = 0$ and distribution $G(\sigma)$ that approximates an empirical distribution as discussed in Section B1.1.

This result is driven by the prior belief of effectiveness, $\mathbb{E}b$, that is more conservative than the target effectiveness, c . By Bayes' rule, when the estimates can be conveyed, it is optimal to implement the policy if and only if the average signal $\hat{\beta}$ satisfies $\hat{\beta} \geq \frac{c - \mathbb{E}b}{\sigma_b^2} \frac{\sigma_i^2}{N}$: that is, whenever the prior is conservative so that $c > \mathbb{E}b$, the required level of average signal $\hat{\beta}$ is convex in σ_i^2 . When c is large, this force can dominate the effect of less information as characterized in Proposition 2.1, turning the threshold $\underline{\beta}(\sigma_i)$ to be convex rather than concave.

This result clarifies that the omission is not driven by the uninformedness of researchers per se, but by the lack of strong belief in whether it is optimal to implement the policy. In the most stark example, the omission probability approaches zero as the researchers' signals become imprecise ($\sigma_i \rightarrow \infty$). This observation clarifies the discussion of informedness and abstention in voting theories (Feddersen and Pesendorfer 1999): the lack of information needs not arise from lack of signal, but can also arise from lack of strong prior belief.

B1.4 Implications of Many Researchers (High N)

Due to the analytical tractability, the propositions did not examine the implications of many researchers on the equilibria. This sub-Section shows that the supermajoritarian rule holds even with high N , and analyzes how the omission and bias change given high N .

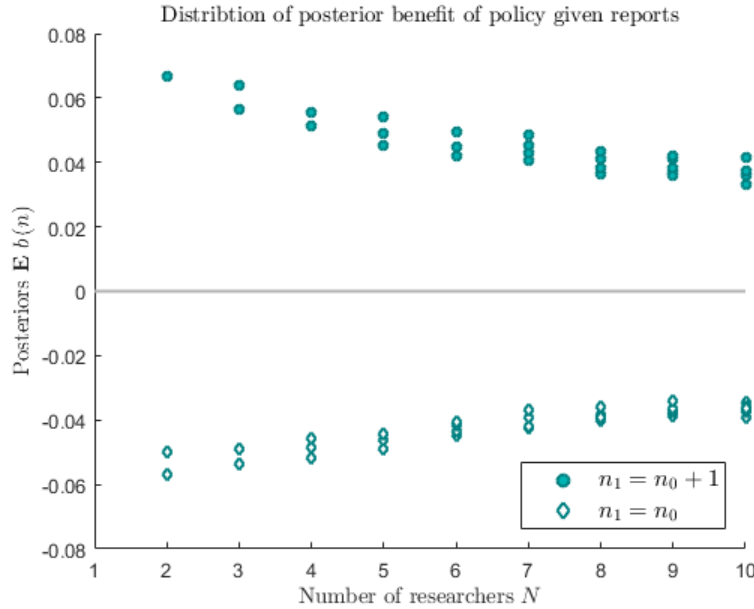


Figure B5: consistency of policymakers' posterior beliefs

Notes: Figure B5 plots the distribution of posterior belief $\mathbb{E}b(n)$ in the equilibrium of supermajoritarian policy rule ($a^* = 1 \Leftrightarrow n_1 \geq n_0$) with $\sigma_b = \sigma = 0$ and $c = 0$ for $N = 2, \dots, 10$. It shows that, when there are marginally more positive results than negative results ($n_1 = n_0 + 1$), then the posterior belief is positive; conversely, when there are equal numbers of positive and negative results ($n_1 = n_0$), then the posterior belief is negative. Since the posterior beliefs are monotone in the number of positive and negative results, this confirms that the conjectured supermajoritarian policy rule ($a^* = 1 \Leftrightarrow n_1 \geq n_0$) is consistent with the belief and utility maximization of the policymaker. This result of consistency of supermajoritarian policy rule holds for various values of c . Here, the analysis restricts to the case of constant σ due to the computational feasibility.

First, the policymaker's supermajoritarian rule ($a^* = 1 \Leftrightarrow n_1 > n_0$) holds in a communication equilibrium even for $N = 3, \dots, 10$ (Figure B5). This suggests that even if the policymaker

does not know the number of underlying studies, they can still compare the number of reported positive vs negative results to make the decisions they would have taken with knowledge of N . While this result may rely on risk neutrality as will be discussed in sensitivity analysis, it suggests that the assumption that the policymaker knows N needs not be critical.³³

Second, the researchers' omission probability gradually increases as N increases. The Figure B6 depicts the example equilibrium thresholds for $N = 1, \dots, 4$ keeping all other environment constant when (A) σ_b is high and σ_0 is high, (B) σ_b is low and σ_0 is low, and (C) σ_b is high and σ_0 is low. In all cases, the probability of omission conditional on study precision, $\mathbb{P}(m_i = \emptyset | \sigma_i)$, increases with N for any values of σ_i . This is because, as N increases, the total information owned by other researchers rises and leaving the decisions to others' papers becomes more desirable.³⁴

Nevertheless, the bias on the coefficients that underlie reported studies may increase or decrease as increase in N may shift the thresholds in either directions.³⁵ This is because there are three channels through which N alters the thresholds. As Figure B6(A) shows, the effect of changing pivotality condition shifts $\underline{\beta}$ upwards and $\bar{\beta}$ in ambiguous directions, potentially mitigating the bias as N increases.³⁶ As Figure B6(B) shows, the decreasing effect of conservative prior shifts both $\bar{\beta}$ and $\underline{\beta}$ downwards. When there are more researchers, each researcher needs less extreme signals to overturn the default decision. As Figure B6(C) suggests, there is also the effect of equilibrium thresholds adjustment that shifts both $\bar{\beta}$ and $\underline{\beta}$ in directions that offset the effect of the first two effects. For example, $\underline{\beta}$ may shift downwards due to upward shift in $\bar{\beta}$ especially among noisy studies, increasing the bias. These considerations jointly determine the conditions under which the increase in number of researchers, N , may increase or decrease the bias.

³³The set-up needs to maintain the assumption that the researchers know how many other researchers exist on the same subject. First, this appears to be closer to actual scientific practice than the assumption that the readers also know number of researchers. Second, the Figure B4 demonstrates that the thresholds do not change qualitatively with N and the changes are not quantitatively large: thus, even if there were uncertainty in N from researchers' perspective, they may still be able to choose approximately optimal thresholds.

³⁴This result is consistent with the literature on voting theory that shows that the abstention probability increases as the number of voters increases.

³⁵This inquiry relates to the literature on media that explores the impact of market competition on media bias, and finds that the higher number of competing senders may increase the bias arising from taste and decrease bias arising from reputation motives (Gentzkow et al., 2016).

³⁶Consider, for example, the pivotality conditions for $N = 2$ and $N = 3$. $\underline{\beta}(N = 2)$ is lower than $\underline{\beta}(N = 3)$ because it satisfies the indifference condition (30) when one researcher receives high signal as opposed to when one receives high signal and another receives intermediate signal. $\bar{\beta}(N = 2)$ may be lower or higher than $\bar{\beta}(N = 3)$ because it satisfies the indifference condition (31) when only one another researcher receives intermediate negative signal as opposed to two researchers receiving intermediate negative signals or one receiving positive and another receiving negative signals.

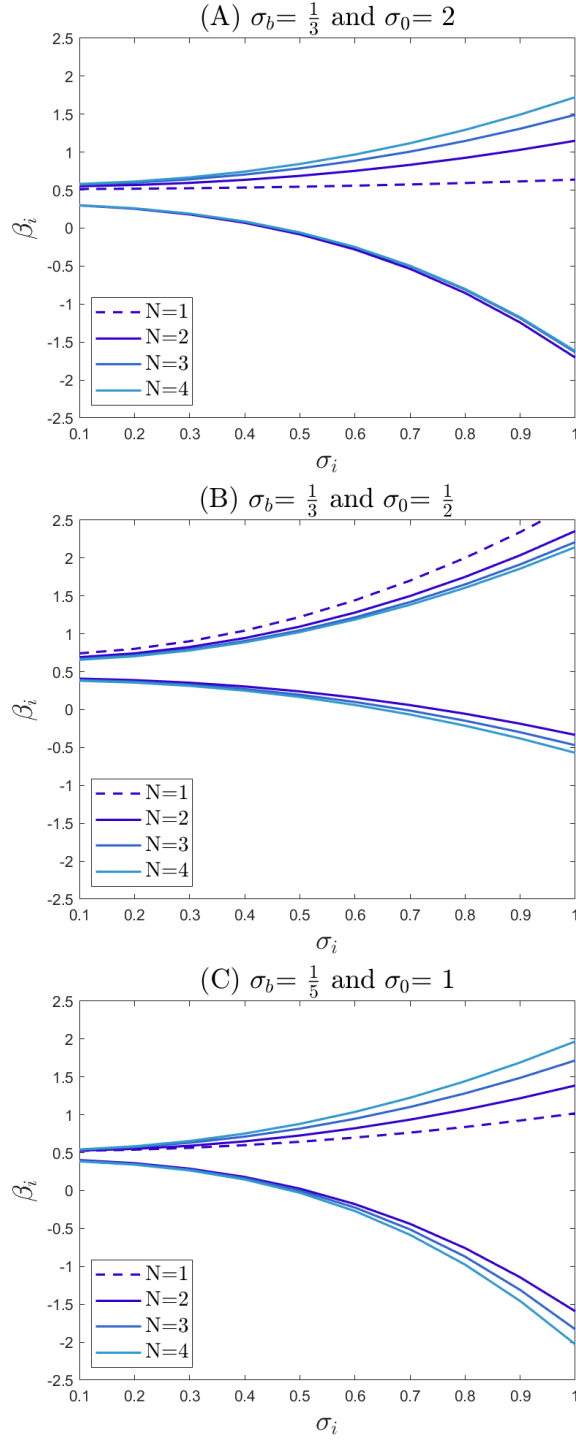


Figure B6. $\bar{\beta}(\sigma), \underline{\beta}(\sigma)$ thresholds under various σ_b and σ_0

Notes: Figure B6 plots the $\bar{\beta}(\sigma), \underline{\beta}(\sigma)$ thresholds under $c = 2$ and distribution $G(\sigma)$ that approximates an empirical distribution as discussed in Section B1.1, and varying N , σ_b and σ_0 . In each figure, the convex solid lines are $\bar{\beta}(\sigma)$ and concave solid lines are $\underline{\beta}(\sigma)$. There is only one threshold for $N = 1$ since there is no benefit of omission when there is only one researcher.

B1.5 Quantifying bias, omission, and welfare

The discussions of bias, omission, and welfare in Section 2.4.2 were based on a simulation under various parameters. This Appendix describes the simulation more fully. The results are presented in Table B1.

Table B1: Bias, omission, and welfare

		(1) Baseline	(2) High σ_b	(3) High σ_0	(4) High c	(5) High N
(A) Bias:	i. overall	0.42	0.27	0.22	-0.78	0.38
	ii. $\sigma_i = 0.1$	0.06	0.19	0.00	-0.31	0.04
	iii. $\sigma_i = 1$	0.93	0.40	0.73	-1.06	0.92
(B) Omission probability:	i. overall	0.49	0.46	0.33	0.54	0.53
	ii. $\sigma_i = 0.1$	0.24	0.41	0.07	0.36	0.26
	iii. $\sigma_i = 1$	0.69	0.53	0.62	0.65	0.77
(C) Welfare:	i. unrestricted	0.95	0.95	0.99	0.77	0.93
	ii. restricted	0.85	0.85	0.97	0.46	0.84
Specification changes from baseline		-	$\sigma_b = 1$	$\sigma_0 = 1$	$c = .05$	$N = 3$

Notes: Table B1 summarizes (A) bias $\mathbb{E}[\beta_i | m_i \neq \emptyset, \sigma_i]$, (B) omission probability $\mathbb{P}(m_i = \emptyset | \sigma_i)$, and (C) ex-ante welfare $\mathbb{E}[a^*(m^*(\beta_i, \sigma_i)) [\mathbb{E}b(\beta_i, \sigma_i) - c]]$ under various settings. In (A) and (B), i. overall values are expected values unconditional on σ_i realization; ii focuses on the most precise studies ($\sigma_i = 0.1$); and iii focuses on the least precise studies ($\sigma_i = 1$). In (C), welfare is computed as a fraction of full information welfare. i. unrestricted refers to the environment without linear t -statistics rule whereas ii. restricted refers to the hypothetical setting in which no omission is allowed and the threshold is restricted to follow $\bar{\beta}(\sigma) = t\sigma$. Here, t is computed to be the optimal value. Since there is no omission by the exogenous restriction, bias and omission probability are both zero. The baseline specification applies $\sigma_b = 0.25$, $\sigma_0 = 0.1$, $c = 0$, and $N = 2$. Columns (2)-(4) modifies this environment for each specification as presented. The simulation is based on heterogeneous $G(\sigma)$ that approximates an empirical distribution as discussed in Section B1.1.

In many specifications, Panel (A) suggests sizable upward bias in unweighted³⁷ average estimates. Consistent with Figures 2, these biases are driven by noisy studies. In contrast, most precise studies have very small biases. Note, for large $c > 0$, there can be downward bias because the studies whose coefficients near c are omitted. Quantitatively, despite its symmetric set-up with $c = 0$, among the lease precise studies, the model can explain the bias greater than one standard deviation of the underlying distribution of benefits.

³⁷Note that this is different from the meta-analysis estimates with Bayes' rule, which puts higher weight on the more precise studies. Many meta-analysis studies often discuss these unweighted estimates.

Panel (B) shows that the average omission rate can be as high as roughly 30 to 50 percents. While most precise studies have only 7 percent omission rate, most noisy studies may be omitted roughly 70 to 80 percents.

Finally, the model can quantify welfare gains from permitting publication bias relative to imposing restriction that every binary conclusion of null hypothesis testing needs to be reported. As discussed in the introduction, coarse communication can be largely welfare-reducing, and even with sophisticated readers who compute the posterior correctly and flexible adjustment of t -statistics, there is roughly 3 to 30 percent welfare loss relative to the full information benchmark. The gain from allowing for some omission and inflation is to roughly halve these welfare losses to 1 to 12 percents. This analysis demonstrates that the welfare consequences can be quantitatively important.

B2. Estimation and Testing Steps

Section 3.2.2 has described the overview of the estimation and testing steps of the semi-parametric Kolmogorov-Smirnov (KS)-type test. This Appendix Section adds additional description and discussion of computing the p -values in this test, and provides some results supplementary to Section 3.3.2.

The computation of KS statistics requires estimating the two theoretical distributions: $G_\emptyset(\sigma)$, the distribution of standard errors of null results, and $H_0(\beta)$, the distribution of coefficients of negative results. The estimates use the stem-based estimates of $\{\hat{b}_0, \hat{\sigma}_0\}$ and apply

$$\tilde{G}_\emptyset(\sigma|\hat{b}_0, \hat{\sigma}_0) = \frac{1}{C} \sum_{i||\beta_i| \geq \bar{t}\sigma_i} \frac{\Phi\left(\frac{\bar{t}\sigma_i - \hat{b}_0}{\bar{\sigma}}\right) - \Phi\left(\frac{-\bar{t}\sigma_i - \hat{b}_0}{\bar{\sigma}}\right)}{\left[1 - \Phi\left(\frac{\bar{t}\sigma_i - \hat{b}_0}{\bar{\sigma}}\right)\right] \mathbb{1}(\beta_i \geq \bar{t}\sigma_i) + \Phi\left(\frac{\bar{t}\sigma_i - \hat{b}_0}{\bar{\sigma}}\right) \mathbb{1}(\beta_i < \bar{t}\sigma_i)} \mathbb{1}(\sigma \geq \sigma_i) \quad (32)$$

$$\tilde{H}_0(\beta|\hat{b}_0, \hat{\sigma}_0) = \frac{1}{n_0} \sum_{i|\beta_i \geq \bar{t}\sigma_i} \min \left\{ \frac{\Phi\left(\frac{\beta - \hat{b}_0}{\bar{\sigma}}\right)}{\Phi\left(\frac{\bar{t}\sigma_i - \hat{b}_0}{\bar{\sigma}}\right)}, 1 \right\}, \quad (33)$$

$$\text{where } C = \sum_{i||\beta_i| \geq \bar{t}\sigma_i} \frac{\Phi\left(\frac{\bar{t}\sigma_i - \hat{b}_0}{\sqrt{\sigma_i^2 + \hat{\sigma}_0^2}}\right) - \Phi\left(\frac{-\bar{t}\sigma_i - \hat{b}_0}{\sqrt{\sigma_i^2 + \hat{\sigma}_0^2}}\right)}{\left[1 - \Phi\left(\frac{\bar{t}\sigma_i - \hat{b}_0}{\sqrt{\sigma_i^2 + \hat{\sigma}_0^2}}\right)\right] \mathbb{1}(\beta_i \geq \bar{t}\sigma_i) + \Phi\left(\frac{\bar{t}\sigma_i - \hat{b}_0}{\sqrt{\sigma_i^2 + \hat{\sigma}_0^2}}\right) \mathbb{1}(\beta_i < \bar{t}\sigma_i)} \text{ and } \bar{\sigma} = \sqrt{\sigma_i^2 + \sigma_0^2}.$$

We can understand these formula by considering how many null or negative studies in some intervals of parameters there must have been in order to have the number of observed positive or significant studies. For example, let us consider some interval with length $\Delta > 0$ that has n_1 positive studies. If the mean and variance of underlying normal distribution is given by

$\{b_0, \sigma_0\}$, then in expectation, there must have been $\frac{\Phi\left(\frac{\bar{\tau}\sigma_i - b_0}{\bar{\sigma}}\right) - \Phi\left(\frac{-\bar{\tau}\sigma_i - b_0}{\bar{\sigma}}\right)}{1 - \Phi\left(\frac{\bar{\tau}\sigma_i - b_0}{\bar{\sigma}}\right)} \times n_1$ null results. The formulas (32) and (33) are constructed with this logic.

p -values: we wish to compute the probability of observing the discrepancy between observed ($\hat{G}_\emptyset(\sigma)$ and $\hat{H}_0(\beta)$) and predicted distributions, defined by the KS-type statistics, $D^G = \sup \left\{ \hat{G}_\emptyset(\sigma) - \tilde{G}_\emptyset(\sigma | \hat{b}_0, \hat{\sigma}_0) \right\}$ and $D^H = \sup \left\{ \hat{H}_0(\beta) - \tilde{H}_0(\beta | \hat{b}_0, \hat{\sigma}_0) \right\}$. We cannot apply the standard KS tests since they compare either one theoretical and one empirical, or two empirical distributions; here, the predicted distribution contains uncertainties not only in studies used for estimation but also in the estimates of parameters $\{\hat{b}_0, \hat{\sigma}_0\}$; ignoring the uncertainty in two-step estimation (Newey and McFadden 1994) may underestimate the p -values.

The p -value of this test equals the average p -values given each value of $\{b_0, \sigma_0\}$ simulated given errors in their estimates. This is because the overall p -value is defined as the probability that the maximum difference between the empirical and predicted distributions is at least as large as the observed difference. For each draw of $\{b_0, \sigma_0\}$ and resultant predicted distribution, the algorithm applies the inverse cumulative distribution function method to generate a simulated distribution with sample size n_0 . Then, the p -value given each value of $\{b_0, \sigma_0\}$ is the fraction of simulated estimates such that their KS statistic is at least as large as D^G and D^H respectively. The test computes one-sided p -values, and repeats the simulation until the estimated p -value converges.

The bootstrap estimates are appropriate since the parameters $\{b_0, \sigma_0\}$ are not the extremum statistics of the distribution. Since the stem-based method treats as a nuisance parameter, the estimation employs the bootstrap method to obtain the distribution of $\{\hat{b}_0, \hat{\sigma}_0\}$ estimates. Since each study has equal level of information on the distribution of study-specific effects, b_i , each study has equal weight in the bootstrap method. The stem-based method suggests $\{\hat{b}_0, \hat{\sigma}_0\} = \{-0.02, 0.05\}$ in this data set. In addition, the KS-type statistics are $D^G = \hat{G}_\emptyset(.08) - \tilde{G}_\emptyset(.08) = 0.40$ and $D^H = \hat{H}_0(-.13) - \tilde{H}_0(-.13) = 0.15$.