

# Publication Bias under Aggregation Frictions: Theory, Evidence, and a New Correction Method

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## Abstract

This paper questions the conventional wisdom that publication bias must result from the biased preferences of researchers. When readers only compare the number of positive and negative results of papers to make their decisions, even unbiased researchers will omit noisy null results and inflate some marginally insignificant estimates. Moreover, the equilibrium with such publication bias is socially optimal. The model predicts that published non-positive results are either precise null results or noisy but extreme negative results. This paper shows this prediction holds with some data, and proposes a new *stem-based bias correction method* that is robust to this and other publication selection processes.

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# 1 Introduction

Publication bias compromises the evidence that inform a number of socioeconomic, medical, educational, and environmental policies. Let us consider a doctor deciding whether to prescribe a new medication. Suppose she finds 10 studies. Suppose, out of them, 7 write it is effective while 3 write it is not. She concludes that the new drug appears effective and therefore starts using it. Later she reads a *New York Times* article, which reports that pharmaceutical companies “never published the results of about a third of the drug trials that they conducted to win government approval, misleading doctors and consumers about the drug’s true effectiveness” (Carey 2008). In particular, only 14 percent of negative results were published whereas 94 percent of positive results were published. Moreover, 11 out of 14 negative results conveyed a positive outcome. Even though the meta-analysis still concludes that the drug has positive overall effect, she is now unsure if evidence is truthful and trustworthy. Research have shown publication bias – systematic gap between the published literature and the subject it studies due to selective reporting – is prevalent and severe in economics (Leamer 1978, DeLong and Lang 1992, Olken 2015, Havránek 2015, Broudeur et al. 2016, Christensen and Miguel 2018) and other fields, including political science (Franco et al. 2014), psychology (Rosenthal 1979), medicine (Every-Palmer and Howick 2014), and environmental studies (Havránek et al. 2015).

Many authors and organizations have interpreted publication bias as a failure of incentive structure in the process of knowledge production, and have pursued efforts to mitigate it. To explain publication bias, they have assumed researchers are motivated by favoritism towards particular theories or affiliation with funding sources (Zilak and McCloskey 2008, Goldcare 2010, Doucouliagos and Stanley 2013b), or by career incentives to please journals that perceive only significant results as conclusive (Reinhart 2015). Some even consider it as a form of scientific misconduct (Chalmers 1990). Building on such interpretations, theorists have analyzed the design of researchers who seek publications (Glaeser 2008, Henry and Ottaviani 2014, Libgober 2015). Authoritative organizations such as the *American Statistical Association* (Wasserstein and Lazar, 2016) and the *International Committee of Medical Journal Editors* (2016) have issued official statements to encourage reporting of negative results. Calls for a reform in incentive structures by various authors (Ioannidis 2005) have led influential journals to take steps to reduce publication bias in economics: the *American Economic Review* has banned the use of asterisks in regression tables in 2016, and the *Journal of Development Economics* has begun result-independent registered reports in 2018 (Foster et al. 2018). Notwithstanding the effort, controversies remain as many others suggest that publication bias is far from being eliminated due to the lack of enforceability (Hunter and Schmidt 2004) indicated by limited influence of government-run registries of clinical trials (Boccia et al. 2016). Does the evidence of publication bias suggest a crisis of science that calls for transformation of researcher incentives?

What could readers do to make less biased inference if the literature will continue to have publication bias despite various initiatives?

This paper suggests, contrary to common views, publication bias could arise from aggregation frictions even among unbiased researchers with a sole motive to maximize social welfare; and moreover, that their reporting rules with publication bias is socially optimal. The paper analyzes a communication model between multiple researchers and a policymaker. It shows that aggregation frictions can explain various common forms of publication bias, including omission of noisy null results, inflation of marginally insignificant results, and amplification of biases in reporting decisions between researchers who have only small biases in their preferences. The results on omission suggest a publication selection process distinct from other processes assumed in existing meta-analysis methods to correct publication bias. This prediction holds in a dataset of meta-analysis. Given this empirical result, the paper concludes by proposing a new bias correction method that is robust to both existing and alternative publication selection process. In this way, the paper provides a new understanding of publication selection process based not on incentives problems but on information aggregation friction, and proposes a new way to address publication bias in meta-analyses.

The new friction of the model is a cognitive constraint that policymakers only consider the yes-or-no conclusions of the studies even when the papers may contain estimates of the treatment effects and their standard errors. While this assumption may appear too simplistic, even aggregation in major policy decisions may rely on such vote-counting. For example, an influential campaign that has 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.

The first main result is that, under this cognitive constraint, unbiased researchers will omit results with estimates of moderate magnitude in such a way that the average underlying estimates of reported studies will have an upward bias. When the policymaker cannot process more than the binary conclusions, the researchers can only communicate the sign of their estimates even though they wish to convey their strength and credibility. Thus, omission of intermediate and imprecise results can better convey information than always reporting either positive or negative<sup>1</sup> results. The upward bias arises from the asymmetry that the researchers will be more cautious of reporting negative results than positive results if the policymaker implements the

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<sup>1</sup>By “negative” results, this paper will refer to any non-positive results, including both statistically insignificant results and statistically significant negative results.

policy whenever there are strictly more positive than negative results. A researcher applies asymmetric standards because a negative result changes the policy decision only when another researcher reports a positive result, whereas a positive result changes it only when another researcher did not report any results. The omission and bias can be quantitatively important: under reasonable parameters, the omission rate can be as large as 40 percent on average, and 70-80 percent among the most imprecise studies; bias can be as large as one standard deviation of underlying variance. This result is consistent with the evidence of publication bias in economics, demonstrated by positive correlation between coefficients and standard errors across studies (Egger et al. 1997), found in many important meta-analyses, including 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).

The second main result is that the unbiased researchers may inflate some marginally insignificant results to convey positive conclusions if the journals require that  $p$ -values are below some constant thresholds. This is because Bayesian researchers adopt a  $t$ -statistics threshold that is increasing in standard errors to draw positive conclusions, contradicting frequentist null-hypothesis testing approach that requires a constant  $t$ -statistics threshold. The discrepancy occurs due to the difference in ways Bayes' rule and null hypothesis testing use standard errors. Algebraically, whereas Bayesian updating divides each coefficient by its variance because it is an aggregation with weights proportional to sample size  $n$ , the  $t$ -statistic divides the coefficient estimate by its standard error because it is a normalization for convergence that occurs at rate  $\sqrt{n}$ . Conceptually, whereas Bayesian researchers focus on how well binary conclusions can approximate the Bayesian posterior beliefs' threshold, the  $p$ -value requirement focuses on how unlikely a given observation occurs under the null hypothesis of zero effect. In this way, while publication decisions based only on  $p$ -value may be a rule-of-thumb that approximates the thresholds, some inflation can be a part of socially optimal scientific reporting. If searching for specification that satisfies the  $t$ -statistics is costly, then there will be a bunching of  $t$ -statistics right above the significant threshold, as found in economics (Brodeur et al. 2016), political science (Gerber and Malhotra 2008), and psychology (Simonsohn et al. 2014).

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 the 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. Quantitatively, under reasonable parameter values, the thresholds for reporting positive conclusions may be 7.5 times larger than the primitive difference in preference for policy implementation between two researchers. This result suggests that the evidence that industry-funded pharmaceutical

research reports more positive results than government-funded research (Lexchin 2003) needs not suggest industries are primarily driven by profit-making motives: while industries surely have stronger incentives to report positive results, their primitive bias needs not be large to explain the observed evidence of large bias in their reporting.

The results on omission suggests a publication selection process empirically distinct from other processes used in existing bias correction methods. While the model above suggests both precisely estimated null results and extremely negative results will be published, other models have suggested either even precise null results will be omitted (Hedges 1992) or extremely negative results will be omitted (Duval and Tweedie 2000). This paper develops and implements an econometric test to distinguish between these models. The test compares the distribution of reported vs predicted negative results, where prediction is made semi-parametrically from the distribution of positive results. The meta-analysis data of productivity impacts of labor unions (Doucouliagos et al. 2017) suggest the communication model explains the pattern of omission more adequately than the other two models.

Given the publication selection process different from existing models, this paper concludes by proposing a new *stem-based bias correction method* that performs reasonably across various models of publication selection. While the large meta-analyses literature has proposed at least five different models of publication selection, they share a common prediction that the more precise studies are less subject to publication bias. Using this common prediction, this new method produces the meta-analysis estimates with some most precise studies, which constitutes a “stem” of the “funnel” plot. The number of included studies is determined by the bias-variance trade-off determined with various non-parametric estimation techniques such as leave-one-out Cross Validation. Consistent with the theory, Monte-Carlo simulations show stem-based method can avoid extremely severe misspecification problem. The popular existing bias correction methods attain low coverage probability of 0.13 or 0.43 when the model assumption is incorrect. In contrast, the stem-based method’s coverage probability is 0.76 in such settings. While the stem-based method has larger confidence interval since it imposes less assumptions on the publication selection, it suffers much less from the problem that the exact publication selection process is unknown, contested by various researchers, and differs from parsimonious selection according to the communication model. Since the meta-analyses strive to build consensus across researchers, a conservative method that is robust across a wide range of proposed publication selection process has important advantages over existing methods.

**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 inconclusive 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 message space leads to biased reporting stands in contrast with the models of information transmission (Crawford and Sobel 1982, Hao, 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 communication<sup>2</sup> 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 journal space for publication (De Winter and Happee 2012, 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 publication. 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, Andrews and Kasy 2018, Bom and Rachinger 2018) literature on bias correction methods for publication bias in meta-analyses. In contrast with the most commonly used methods (Hedges 1992, Duval and Tweedie 2000) that have relied on specific assumptions on publication selection process and underlying distribution, the stem-based method depends on minimal assumptions that hold across the assumptions made in literature. This approach also extends some 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 number of studies to include.

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

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<sup>2</sup>In 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,  $\beta_i$ , and its standard error,  $\sigma_i$ , 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:

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

where  $c$  is the cost of policy implementation.<sup>3</sup> 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, researchers<sup>4</sup> receive their own signals, and simultaneously

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<sup>3</sup>While 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  $u_1 \sim \mathcal{N}(\bar{u}_1, \sigma_{u_1}^2)$  and the welfare in the absence of policy is  $u_0 \sim \mathcal{N}(\bar{u}_0, \sigma_{u_0}^2)$ . 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  $\sigma_b^2 \equiv \sigma_{u_1}^2 + \sigma_{u_0}^2$  above will be an equivalent set-up.

<sup>4</sup>I 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,  $\pi$ , 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  $\mu \in \Delta \left( \{S_i\}_{i=1, \dots, N} \right)$ .

**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 equilibria<sup>5</sup>, both the policymaker's and researchers' strategy will be monotone in their information, at least in a benchmark set-up<sup>6</sup>:

**Lemma 1 (Monotonicity of equilibrium strategies).** *For  $N=2$ , for any  $c$ , and constant  $\sigma_i$ , 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  $i$*

$$\begin{aligned} \pi^*(m_i, m_{-i}) > 0 &\Rightarrow [\forall m'_i \succ m_i \pi^*(m'_i, m_{-i}) = 1] \\ \pi^*(m_i, m_{-i}) < 1 &\Rightarrow [\forall m'_i \prec m_i \pi^*(m'_i, m_{-i}) = 0] \end{aligned}$$

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

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information.

<sup>5</sup>Note 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.

<sup>6</sup>As 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 equilibria 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  $\epsilon$  such that sup 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  $N = 2$ ,<sup>7</sup>  $c = 0$ , and often constant  $\sigma$ . Then, numerical results will show that the mechanism will play important roles in asymmetric environment that is more plausible yet analytically difficult to solve.

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<sup>7</sup>Given 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  $\sigma$ , 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.  $\square$

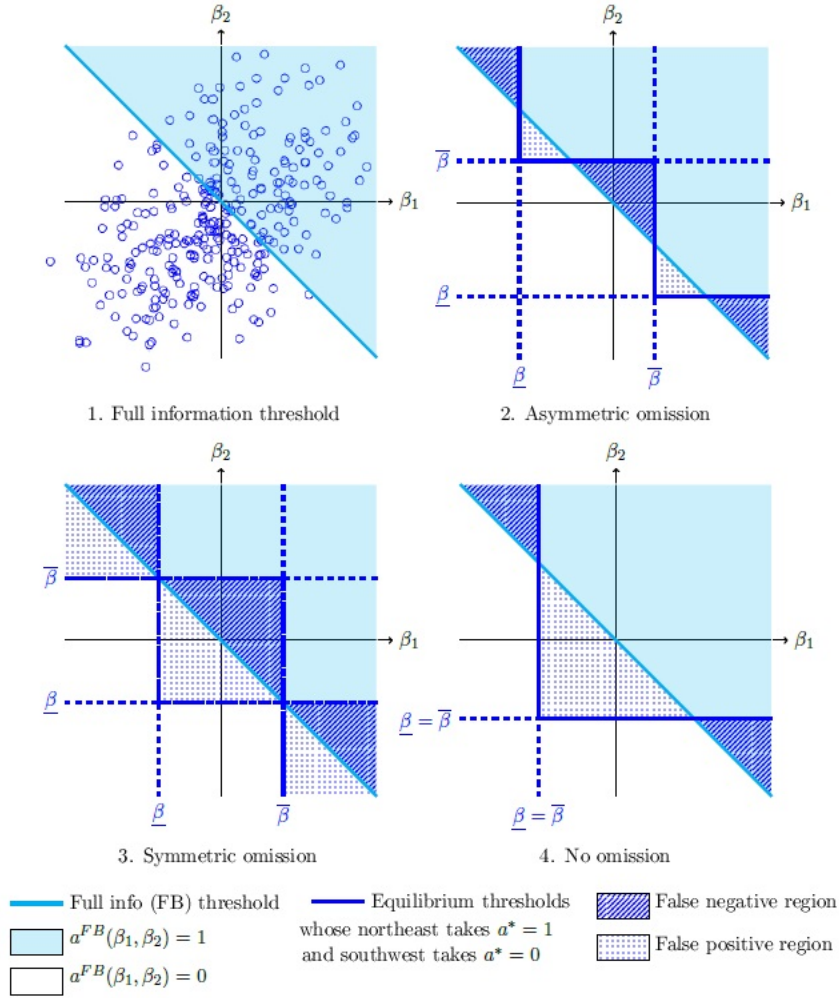


Figure 1: Equilibrium thresholds and policy decisions for  $N = 2$ ,  $c = 0$

*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 1. 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  $\Delta$  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 coarseness<sup>8</sup> 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 three 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  $\pi = 1(n_1 > n_0)$ . Third, omission is roughly 30 percent on average in a plausible setting, which is quantitatively important.

### 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 studies<sup>9</sup>. 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 2018.

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<sup>8</sup>This 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.

<sup>9</sup>This 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  $\sigma_i$ . 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  $t$ -statistics threshold will be increasing in  $\sigma_i$ . 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:  $\bar{t}_i(\sigma_i) = \frac{\bar{\beta}(\sigma_i)}{\sigma_i}$ ,  $\underline{t}_i(\sigma_i) = \frac{\beta(\sigma_i)}{\sigma_i}$ .

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  $\sigma_i$  so that precise studies will be more likely to be published than imprecise ones.

**Proposition 1.2. (Increasing  $t$ -statistic threshold)** 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  $\pi^*$  in (6), and the researchers adopt threshold strategies with cut-offs that depend on  $\sigma_i$ , 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  $\sigma_i$ :

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

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

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

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-

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  $\sigma_i$  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,  $\sigma^2$ , 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,  $\sigma$ , since  $t$ -statistics normalize the convergence of distribution of  $\beta_i$  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  $\sigma_i$ .

## 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.

The equilibrium thresholds,  $\bar{\beta}(\sigma)$ ,  $\underline{\beta}(\sigma)$ , of the asymmetric equilibrium in a plausible envi-



ronment (Figure 2) 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  $\sigma$ . 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 that the welfare gain from allowing some inflation and frequency of omission can be substantive across a range of parameter values. Imposing a constant and symmetric  $t$ -statistic,  $\bar{\beta}(\sigma) = -\underline{\beta}(\sigma) = t\sigma$ , will lead to 3 ~ 30 percent of welfare loss relative to the environment in which estimates can be directly communicated, allowing for flexible equilibrium threshold can roughly halve the welfare losses. When the study-specific variance is low, the omission probability is roughly 1 ~ 3 percent among the most precisely estimated studies whereas it could be as large as 70 ~ 80 percent among the least precisely estimated studies. On average, omission probability is around 30 percents. Similarly, the bias is minimal and 0 ~ 3 percent of the underlying benefit distribution ( $\sigma_b$ ) among the most precise studies whereas it could be as large as over 100 percent 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  $\sigma$  when  $c$  is high. Appendix B1.1 describes the details of the simulation set-up and procedure, and 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 and 2008b). In psychology with lab experiments such that sample

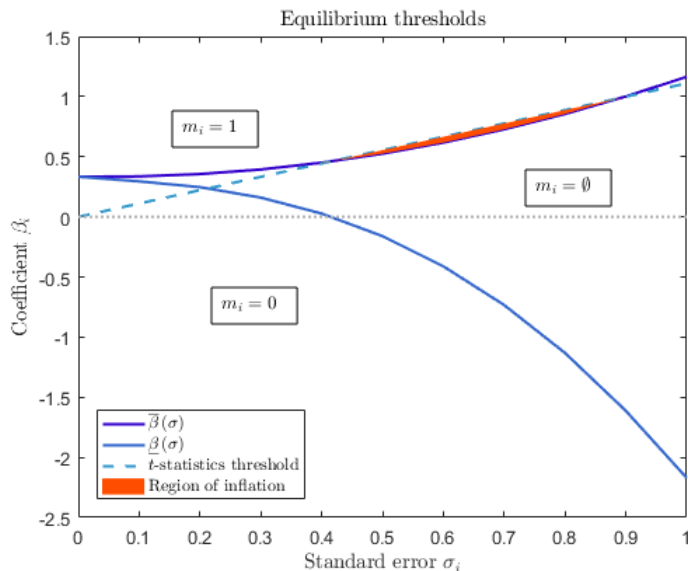


Figure 2:  $\bar{\beta}(\sigma)$  and  $\underline{\beta}(\sigma)$  thresholds

Notes: Figure 3 plots the  $\bar{\beta}(\sigma)$ ,  $\underline{\beta}(\sigma)$  thresholds under the prior standard deviation  $\sigma_b = 1$ , no study-specific effect  $\sigma_0 = 0$ , and policy cost  $c = 0$ . The darker solid line is  $\bar{\beta}(\sigma)$ , the lighter solid line is  $\underline{\beta}(\sigma)$ , and the dashed line represents some linear  $t$ -statistic threshold. Studies in the shaded region draw positive conclusions even though they are marginally statistically insignificant.

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 results<sup>10</sup> 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 only some examples, the empirical analyses in Section 3 will provide a formal evidence.

<sup>10</sup>There 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.

## 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 researchers' 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:

**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  $\pi^*$  fixed:*

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

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  $\beta_i$  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 difference between  $\bar{\beta}_i$  and  $\bar{\beta}_j$  if 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,  $\frac{\bar{\beta}}{\sigma} = 1.96$ , 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  $\gamma$  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 commonly<sup>11</sup> 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 independently<sup>12</sup> 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  $G$ .  $\sigma_0^2$  measures heterogeneity of effects across studies, whereas  $\sigma_b^2$  had measured heterogeneity of effects across policies.

##### 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  $\tilde{G}_\theta(\sigma)$  as the distribution of all standard errors conditional on the study being the non-positive results without any selection, and  $G_\theta$  as its observed distribution with selection; let us also denote  $\tilde{H}_0(\beta)$  as the distribution of coefficient

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<sup>11</sup>While 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).

<sup>12</sup>This 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 2018.

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 3 summarizes the distinct predictions.

**(1) communication model-based selection:** the model of this paper suggests that the imprecisely estimated results with coefficients with small absolute values will be omitted. As has been discussed in Section 2.3 and illustrated in Figure 2, the omission probability shrinks to zero when the between-study heterogeneity,  $\sigma_0$ , 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 results<sup>13</sup>:

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

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 2018). 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 omitted.

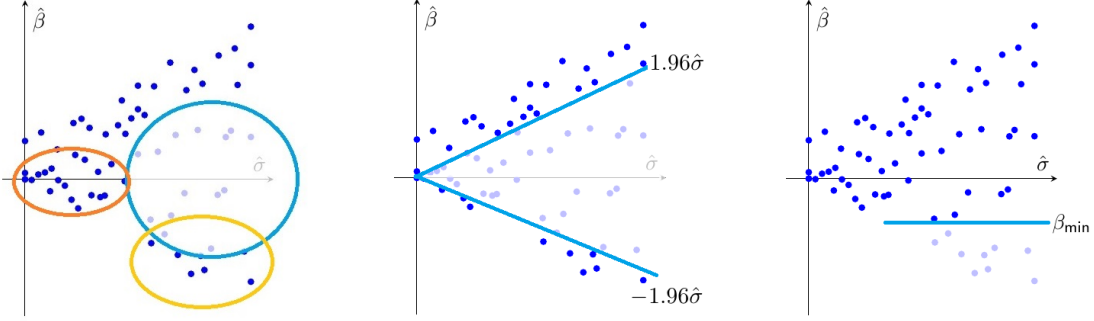
$$\mathbb{P}(\text{study } i \text{ is reported}) = \begin{cases} 1 & \text{if } \beta_i \geq \beta_{\min} \\ 0 & \text{if } \beta_i < \beta_{\min}, \end{cases} \quad (13)$$

where  $\beta_{\min}$  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

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<sup>13</sup>While 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 3: Selection models described in funnel plots

*Notes:* Using the funnel plot, the Figure 3 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.

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

assumptions<sup>14</sup> 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  $\sigma$  while it assumes normal distribution along the dimension of  $\beta$ . 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  $G_\theta(\sigma|\hat{b}_0, \hat{\sigma}_0)$  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  $G_\theta(\sigma|\hat{b}_0, \hat{\sigma}_0)$  estimated using the studies such that  $t_i \geq 1.96$ ;
3. estimate the KS statistic for each distribution,  $D^G$  and  $D^H$ :

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

and associated one-sided  $p$ -values using the two-step bootstrap over estimates of  $b_0$  and sampling of each study's  $\sigma_i$  and  $\beta_i$ .

## 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 conclusions<sup>15</sup>. The result shows that the communication

<sup>14</sup>These 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.

<sup>15</sup>A working paper version of this paper also analyzes the data of Intertemporal Elasticity of Substitution, which highlight the “binary conclusions” less since the quantity of interest is a continuous estimate.

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 96 studies (i) that are included in the total of 110 studies meta-analysis of labor union’s effect firm productivity (Doucouliagos et al. 2017) 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 set<sup>16</sup>.

- (1) distribution of  $\sigma_i$  of null results:      (2) distribution of  $\beta_i$  of non-positive results:

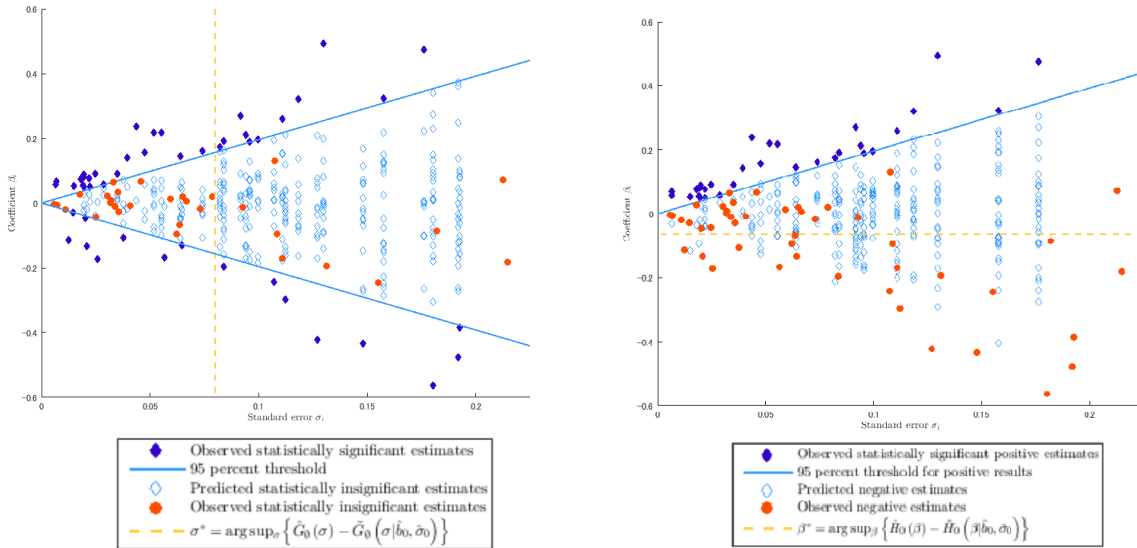


Figure 4: KS-type test illustrated in funnel plots

*Notes:* Figure 4 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.

<sup>16</sup>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).

### 3.3.2 Results

The results suggest that the reporting patterns of null and negative results<sup>17</sup> are consistent with the communication model-based selection process, but not with other processes. Figure 4 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 15 percent of studies are expected to have coefficient less than -0.06, the observed distribution has over 45 percent of studies have such negative values ( $p = .003$ ). 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.

## 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?

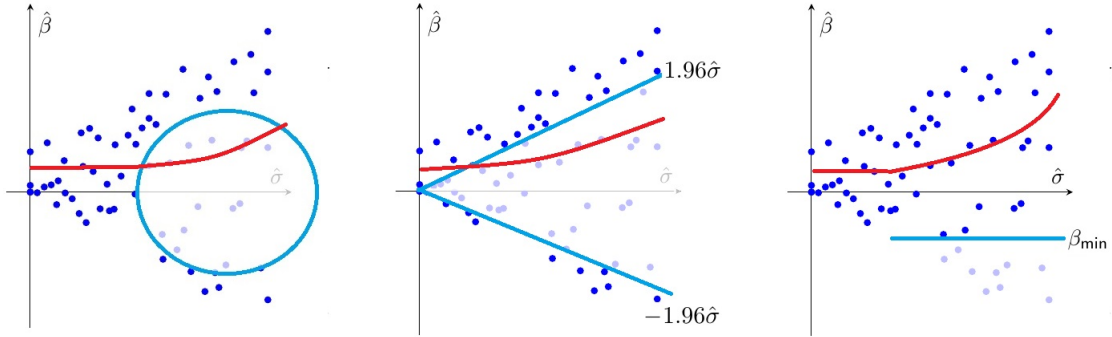
This Section presents a new, non-parametric, and generally conservative bias correction method, to be called a “stem-based” bias correction method. The estimate uses the studies with highest precision, which correspond to the “stem” of the “funnel” plot, to estimate a bias corrected average effect. It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

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<sup>17</sup>As 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.

## 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 2. In the two most commonly used models described in Section 3.1.2<sup>18</sup>, 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 5: Bias squared in funnel plots

*Notes:* Using the funnel plot, the Figures 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  $\sigma_i$  as  $Bias(\sigma_i) \equiv \mathbb{E}[\beta_i | \sigma_i, \text{study } i \text{ reported}] - b_0$ .

1. (Monotonicity)  $Bias(\sigma_i)^2$  is increasing in  $\sigma_i$  for all  $\sigma_i$  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  $\beta_{\min}$  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  $\sigma_i$  expectation given the bias selection model. Appendix A5 contains a proof. □

<sup>18</sup>While 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).

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,  $n_{\text{stem}}$ , 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  $n_{\text{stem}}$  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:

$$\min_n Var(\hat{b}_0^n, \sigma_0) + \tilde{Bias}^2(\hat{b}_0^n, b_0) \text{ subject to } \hat{Var}(b_i | \hat{b}_0^n) = \sigma_0^2. \quad (15)$$

That is, the bias squared term is replaced by an unbiased estimate of its relevant component,  $\tilde{Bias}^2(\hat{b}_0)$ , and the implied variance term is replaced by its empirical analogue,  $\hat{Var}(b_i | \hat{b}_0)$ .

The estimates of stem-based method can be visually represented with a funnel plot: with uniform selection generating 80 studies in this simulation, it is optimal to include 24 studies. Including all studies leads to an upward bias, as indicated by theory. On the other hand, the most precise study alone can be noisy so that inclusion of more studies leads to an adequate 95 confidence interval that covers 0.5, the true mean value.

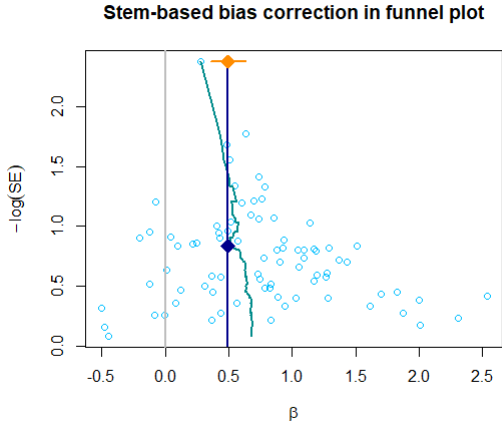
## 4.2 Estimation

Given the objective (14), this sub-Section describes a particular approximation (15), illustration estimation steps, and discuss the assumptions necessary to ensure its reliability. It is a fully data dependent process.

### 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  $\sigma_0^2$ ; the outer algorithm computes the implied variance and ensure that it is consistent with its assumed value.

(1) Funnel plot



(2) Mean Squared Error

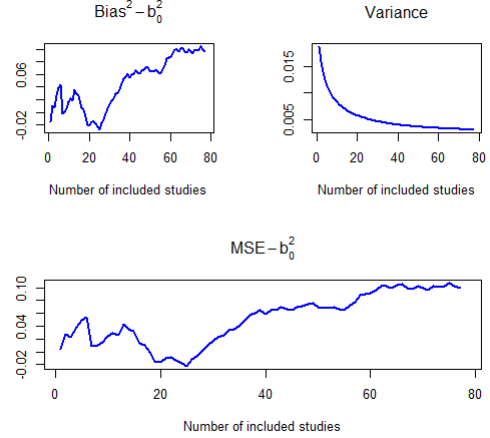


Figure 6: A visualization of stem-based method

*Notes:* Figure 5 are 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 24, a roughly average number. (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  $n_{stem}$ .

**I. Inner algorithm:** estimate  $\hat{b}_{stem}$ ,  $SE(\hat{b}_{stem})$ ,  $\bar{n}_{stem}$  given an assumed value of  $\sigma_0$ .

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 bias squared,  $Bias^2(n)$ , and the variance,  $Var(n)$ , as follows: given weights  $w_i \equiv \frac{1}{\sigma_i^2 + \sigma_0^2}$ ,

$$(i) \text{ relevant bias squared: } Bias^2(n) = \frac{\sum_{i=2}^n \sum_{j \neq i}^n w_i w_j \beta_i \beta_j}{\sum_{i=2}^n \sum_{j \neq i}^n w_i w_j} - 2\beta_1 \frac{\sum_{i=2}^n w_i \beta_i}{\sum_{i=2}^n w_i}$$

$$(ii) \text{ variance: } Var(n) = \sum_{i=1}^n w_i$$

3. compute the optimal number of included studies,  $n_{stem}$ :  $n_{stem}$  minimizes the sum of variance and relevant bias squared, so that

$$n_{stem} \in \arg \min_n Var(n) + Bias^2(n)$$

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  $\hat{b}_{\text{stem}}$  applies the inverse variance weights since they minimize the variance of the estimator. This weighting also ensures that the total variance,  $Var(n)$ , is decreasing in the number of included studies  $n$ .

**II. Outer algorithm:** search over values of  $\sigma_0^2$  such that the implied  $\hat{Var}(b_i|\hat{b}_0^n)$  is consistent. Throughout, we adopt the formula of variance proposed by DerSimonian and Laird (1996)<sup>19</sup>: given weights  $w'_i \equiv \frac{1}{\sigma_i^2}$ ,  $\hat{Var}(\beta_i|\hat{b}_0) = \max\left\{\hat{Var}(\beta_i|\hat{b}_0), 0\right\}$ , where

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

Here,  $\hat{b}_0$  is the stem-based estimate.

1. set two initial estimates of  $\sigma_0^2$  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  $\sigma_0^2$  to give a conservative confidence interval of  $\hat{b}_{\text{stem}}$  given unknown  $P$ :

**Unbiased Cross-Validation criteria for  $b_0$ :** we can replace the component,  $Bias^2(\hat{b}_0^n, b_0)$ , by its relevant term,  $\tilde{Bias}^2(\hat{b}_0^n, b_0)$ , since they differ only by a constant<sup>20</sup>. The formula proposed in the inner algorithm provides an approximately unbiased estimate of  $\tilde{Bias}^2(\hat{b}_0)$  under

<sup>19</sup>This 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.

<sup>20</sup>To see this, we can expand the bias squared term:

$$\tilde{Bias}^2(\hat{b}_0) \equiv \hat{b}_0^2 - 2b_0\hat{b}_0 = (\hat{b}_0 - b_0)^2 - b_0^2 = Bias^2(\hat{b}_0) - b_0^2.$$



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

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

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 term<sup>21</sup>. More importantly, the second term applies a Cross-Validation (CV) technique by replacing the true value of  $b_0$  by its estimate. Since  $\beta_1$  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  $Var(b_i|\hat{b}_0^n) = \hat{\sigma}_0^2$ :** the outer algorithm likely leads to a large estimate of  $\sigma_0^2$  for three reasons. (i) While the exact selection process,  $P$ , is unknown, the variance is overestimated when it is the intermediate results that is omitted; (ii) The estimation  $Var(b_i|\hat{b}_0^n)$  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  $\sigma_0^2$  that are consistent with one another, the method uses a larger one. By choosing the specification such that the estimate of  $\sigma_0^2$  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 bias term 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,  $Var(b_i|\hat{b}_0^n) \simeq \sigma_0^2$ . These conditions may not be satisfied when the underlying variance,  $\sigma_0^2$ , 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 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.

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<sup>21</sup>The method requires at least  $N = 3$  studies to compute the relevant bias squared,  $\mathbb{E}Bias^2(n)$ , term.

## 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 values<sup>22</sup>.

### 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,  $\sigma_i$ , 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 distribution of  $\sigma^2$  that is  $\chi^2$  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  $b_i \sim \mathcal{N}(\mu_b, \sigma_b^2)$  and  $\epsilon_i \sim \mathcal{N}(0, \sigma_i^2)$  and is independently drawn.  $\sigma_b = 0.3$  so that match the degree of heterogeneity in the labor union data set;  $\mu_b = 0.4$  so that the average effect size ( $\frac{\mu_b}{\sqrt{2}\sigma_b} \simeq 0.94$ ) 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 methods<sup>23</sup>, 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,  $\eta_1, \eta_0$ , are based on the estimates from Andrews and Kasy 2018, 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)

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<sup>22</sup>There 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.

<sup>23</sup>Each estimation has utilized the canned command available in R. The trim-and-fill correction uses a package in `metafor`, 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`.

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 selection; 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 selectio.; On the other hand, the stem-based estimates have coverage probabilities of above 0.76 across selection models.

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	0.94	0.92
	[0.25]	[0.40]	[0.29]	[0.42]	[0.23]	[0.38]	[0.52]	[0.60]
uniform	0.26	0.63	0.88	0.76	0.43	0.69	0.76	0.82
	[0.25]	[0.41]	[0.31]	[0.42]	[0.22]	[0.37]	[0.51]	[0.60]
extremum	0.26	0.62	0.13	0.47	0.64	0.67	0.76	0.77
	[0.21]	[0.33]	[0.20]	[0.34]	[0.20]	[0.31]	[0.40]	[0.46]
$N$	80	30	80	30	80	30	80	30

*Notes.* Table 1. reports the coverage probability and 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.

The improvement of robustness of stem-based methods comes with the disadvantage of larger interval lengths. The simulation underlying the Table 1 finds, on average, roughly  $n_{stem}^* = 9 \sim 11$  studies for  $N = 30$ , and  $n_{stem}^* = 16 \sim 24$  studies for  $N = 80$  since the distribution  $\hat{G}(\sigma)$  has high density of very precise studies.<sup>24</sup> Table 1 shows that the average interval length is roughly

<sup>24</sup>The 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

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.

## 4.4 Final Remarks

The two most influential bias correction methods have relied on specific assumptions about the publication selection process,  $P$ , and the underlying distribution<sup>25</sup>,  $F$ . 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 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.

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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.

<sup>25</sup>Even 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.

## 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 than 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 behind publication bias.

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 that it cannot be represented by another parsimonious process. 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 meta-analysis tool that is attractive not only to meta-analysts who believe in different theories and forms of publication bias, and but also to meta-analysts who wish to build a consensus that does not rely on contested assumptions but on common features among 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  $\mu$  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  $\beta_i$  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  $\beta'_i$  such that  $r(\beta'_i|m_{-i}) < 0$  and some other  $\beta''_i$  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  $\beta_i$ , 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  $\beta_i$  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  $\beta_i$  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  $\beta_i$  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  $\pi^*$  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  $\bar{K}_j = \frac{\partial \mathbb{E}[\beta_j | \bar{\beta}_j > \beta_j \geq \underline{\beta}_j, \beta_i = \bar{\beta}_i]}{\partial \bar{\beta}_j}$ ,  $\underline{K}_j = \frac{\partial \mathbb{E}[\beta_j | \bar{\beta}_j > \beta_j \geq \underline{\beta}_j, \beta_i = \bar{\beta}_i]}{\partial \bar{\beta}_j}$ ,  $\bar{K}_i = \frac{\partial \mathbb{E}[\beta_i | \beta_i \geq \bar{\beta}_i, \beta_j = \underline{\beta}_j]}{\partial \bar{\beta}_i}$ , and  $\underline{L}_j = \frac{\partial \mathbb{E}[\beta_i | \beta_i \geq \bar{\beta}_i, \beta_j = \underline{\beta}_j]}{\partial \bar{\beta}_j}$  and  $\bar{L}_i = \frac{\partial \mathbb{E}[\beta_i | \beta_i \geq \bar{\beta}_i, \beta_j = \underline{\beta}_j]}{\partial \bar{\beta}_i}$ , the system of derivatives satisfy:

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

Inverting the matrix, we have

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

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 (??) 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 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  $\beta_1$  is symmetrically distributed,  $\phi\left(\frac{\Delta}{\bar{\sigma}}\right) = \phi\left(-\frac{\Delta}{\bar{\sigma}}\right)$ . Moreover,

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

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

- \* on the term multiplied by  $\Delta$ ,

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

\* on the term multiplied by  $\beta_2$ ,

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

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  $m_2 = 0$ .

$$\mathbb{E}[b \mid n_1 = n_0 = 1] = \frac{\frac{1}{\sigma_2^2}}{\frac{1}{\sigma_1^2} + \frac{2}{\sigma_2^2}} \mathbb{E}[\beta_1 + \beta_2 \mid \beta_1 \geq \bar{\beta}, \beta_2 \leq \underline{\beta}]$$

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,  $\frac{\partial W}{\partial \pi}|_{\pi=1} > 0$ ,  $\frac{\partial W}{\partial \pi}|_{\pi=0} < 0$ ,  $\frac{\partial W}{\partial \pi}|_{\pi \in (0,1)} = 0$  (where the derivative at the boundaries are either or left or right derivatives) and by researchers' optimalization,  $\frac{\partial W}{\partial \beta_i} = \frac{\partial W}{\partial \underline{\beta}_i} = 0$  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  $\beta_i$  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.  $\square$

### 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  $\sigma_i$ . 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  $\sigma_i$ : 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,

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

where the expectation is taken over another researcher's signals  $\{\sigma_j, \beta_j\}$  and the policymaker's strategy  $\pi$ .  $\text{Piv}(\sigma_j)$  is a set of values of  $\beta_j$  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

$\beta_j$  conditional on  $\beta_i$ , 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  $\sigma_j$ .

- (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  $\sigma_i$  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  $K(\sigma_r) = \sqrt{\frac{2}{1+\sigma_r^2}}$ ,  $L(\sigma_r) = \mathbb{E} \left[ \tau | \tau \geq \sqrt{\frac{2}{1+\sigma_r^2}} (t_i - t_j \sigma_r) \right]$ ,

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

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  $\sigma_i$ , 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  $\tau_0, \tau_1$ . 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  $\tau_0, \tau_1$  are differentiable with respect to  $\sigma$  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  $\tau$  so that

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

for both  $s = 0, 1$ , for all  $\sigma$ . 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  $\tau$  and for any  $\delta$ , 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  $\sigma$ ), 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  $\tau$ ; 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  $\delta$ .  $\blacksquare$

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

**Sub-Lemma 3.** *For any  $\tau$  and for any  $\delta$ , 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  $\Sigma \equiv \sqrt{\frac{2}{1+(\frac{\sigma_j^*}{\sigma_j})^2}} \{t(\sigma^* | \{\tau + \delta\}) - [\tau(\sigma_j) + \delta] \frac{\sigma_j^*}{\sigma_j}\}$  for notational ease, we can derive the bound on  $-\frac{\partial}{\partial \delta} t(\sigma^*(\delta) | \{\tau + \delta\})$ : given (24),

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

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

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

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  $\frac{1}{1+(\frac{\sigma_j^*}{\sigma_j})^2} < 1$ , we note that  $2 - \int \frac{1}{1+(\frac{\sigma_j^*}{\sigma_j})^2} \frac{\partial \mathbb{E}[\tau | \tau \geq \Sigma]}{\partial \Sigma} g(\sigma_j) d\sigma_j > 1$ .

Combining,

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



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

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

Combining the three steps, we conclude that the Sub-Lemma 3 holds.  $\blacksquare$

Since the expression (24) implies that the equilibrium threshold must be differentiable with respect to  $\sigma$ , 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  $\sigma$  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  $\sigma$ . 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  $\beta_i$  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 parts<sup>26</sup>. 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

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<sup>26</sup>Concretely, we can write:

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

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

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

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

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

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

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

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

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

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

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  $\sigma_i$ .
- We show that there exists some range  $[0, \underline{\sigma}]$  such that  $K(\sigma_i)$  will be increasing in  $\sigma_i$ :

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

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  $\sigma_i$  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  $\sigma_i$  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  $\sigma_i$ . While Proposition 2.1 concerning the thresholds under heterogeneous  $\sigma_i$ , 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,  $\sigma_b^2$ , and between-study heterogeneity,  $\sigma_0^2$ . 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,  $\beta_{new}$ , by  $\beta_{new} = \Delta \beta_{sol} + (1 - \Delta) \beta_{conjecture}$ , where  $\Delta$  is a step of adjustment, looping over every  $\sigma_i$ . 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  $\sigma$  in the labor union data set (Doucouliagos et al. 2017). Since the observed distribution of  $\sigma$  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 ( $G(\sigma) = \frac{1}{C} \sum_i \left( 1 - \Phi \left( \frac{1.96\sigma_i - \hat{b}_0}{\sqrt{\sigma_i^2 - \hat{\sigma}_0^2}} \right) \right)^{-1} \mathbb{1}(\sigma \geq \sigma_i)$ ), 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  $\chi^2$  distribution with 2 degrees of freedom with support  $[0, 4]$  approximates the empirical distribution of variance,  $\sigma^2$ , reasonably.

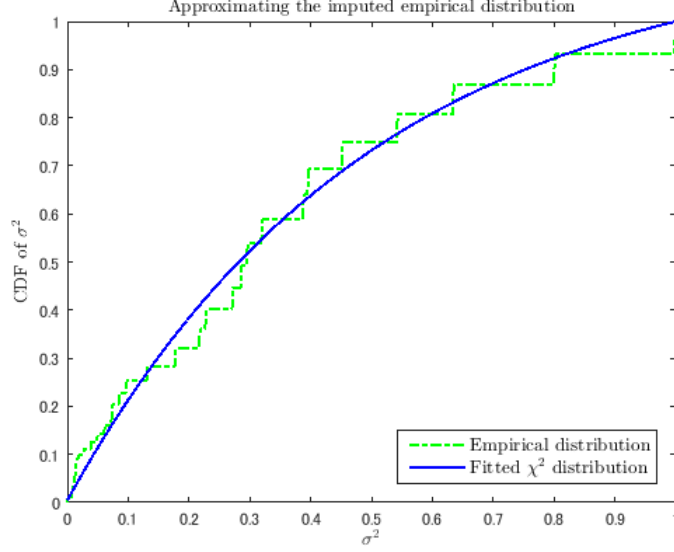


Figure B1: Approximation of empirical distribution

*Notes:* Figure B1 plots the imputed empirical distribution of variance,  $\sigma^2$  against  $\chi^2$  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,  $\sigma_0^2$ , 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  $\sigma_i$  due to the sampling variance, the true variance,  $\sigma_i^{2*}$ , 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.



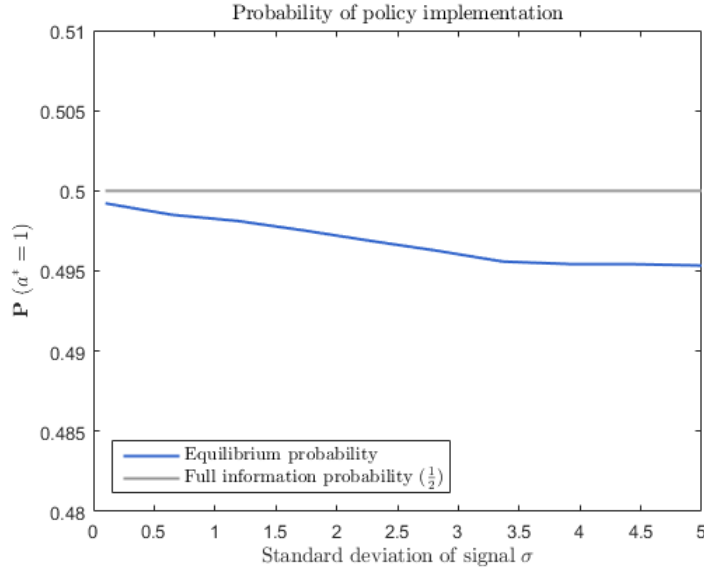


Figure B2: Likelihood of policy implementation

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,  $\sigma$ , 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.

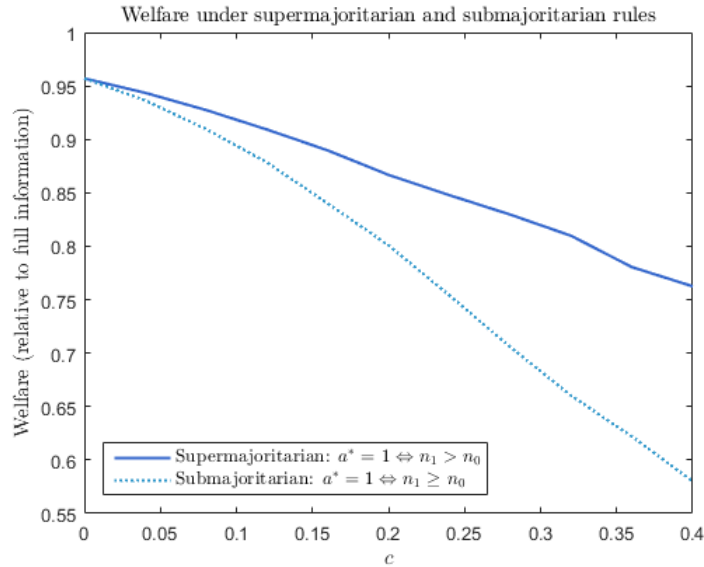


Figure B3: Optimality of supermajoritarian voting rule

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  $c > 0$ . Figure B2 illustrates this in a setting with  $N = 2$ ,  $c = \frac{2}{3}$ ,  $\sigma_b = \frac{1}{3}$ ,  $\sigma_0 = 0$  and heterogeneous  $G(\sigma)$ . This result suggests that the pattern of omission and inflation may be very different between positive and negative results.

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  $\sigma_i^2$ . 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  $N$ .

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.<sup>27</sup>

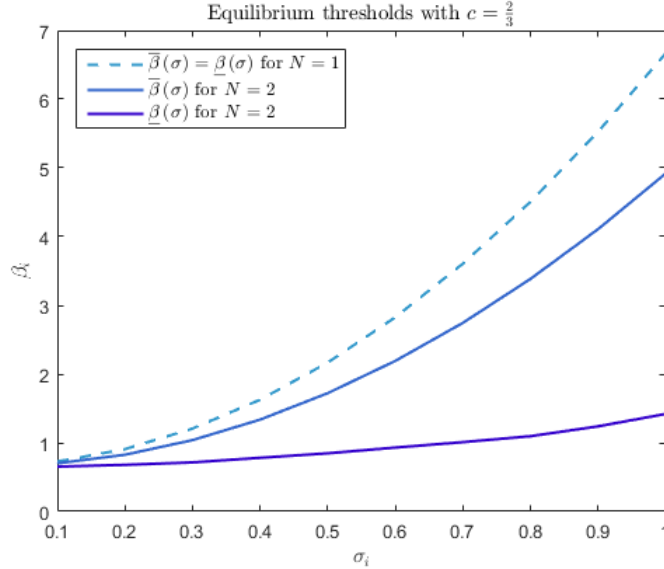


Figure B4: Example of convex  $\underline{\beta}(\sigma)$

Notes: Figure B4 plots the thresholds  $\overline{\beta}(\sigma)$  and  $\underline{\beta}(\sigma)$  for  $N = 2$ ,  $c = \frac{2}{3}$ ,  $\sigma_b = \frac{1}{3}$ ,  $\sigma_0 = 0$  and heterogeneous  $G(\sigma)$ .

Second, the researchers' omission probability gradually increases as  $N$  increases. The Figure B5 depicts the example equilibrium thresholds for  $N = 1, \dots, 4$  keeping all other environment constant when (A)  $\sigma_b$  is high and  $\sigma_0$  is high, (B)  $\sigma_b$  is low and  $\sigma_0$  is low, and (C)  $\sigma_b$  is high and  $\sigma_0$  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  $\sigma_i$ . This is because, as  $N$  increases, the total information owned by other researchers rises and leaving the decisions to others' papers becomes more desirable.<sup>28</sup>

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.<sup>29</sup> 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  $\overline{\beta}$  in ambiguous directions, potentially mitigating the bias as  $N$  increases.<sup>30</sup> As Figure B6(B) shows, the decreasing effect

<sup>27</sup>The 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.

<sup>28</sup>This result is consistent with the literature on voting theory that shows that the abstention probability increases as the number of voters increases.

<sup>29</sup>This 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).

<sup>30</sup>Consider, for example, the pivotality conditions for  $N = 2$  and  $N = 3$ .  $\underline{\beta}(N = 2)$  is lower than  $\underline{\beta}(N = 3)$

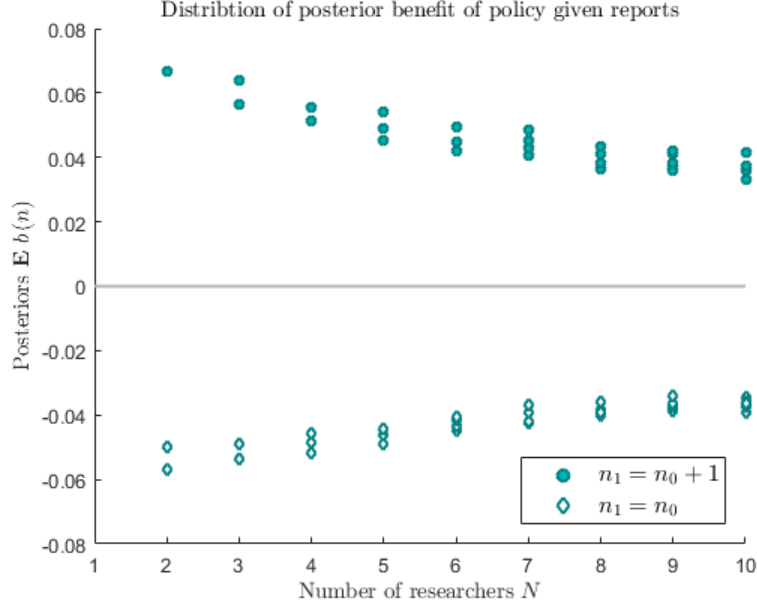


Figure B5: consistency of policymakers' posterior beliefs

*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. The Figure B3 is suggestive that this remains to be an equilibrium for larger  $N$  as the posterior belief steadily approaches posterior  $\mathbb{E}b(n) = 0$ . This result of consistency of supermajoritarian policy rule holds for various values of  $c$ . Here, the analysis restricts to the case of constant  $\sigma$  due to the computational feasibility.

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.

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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.

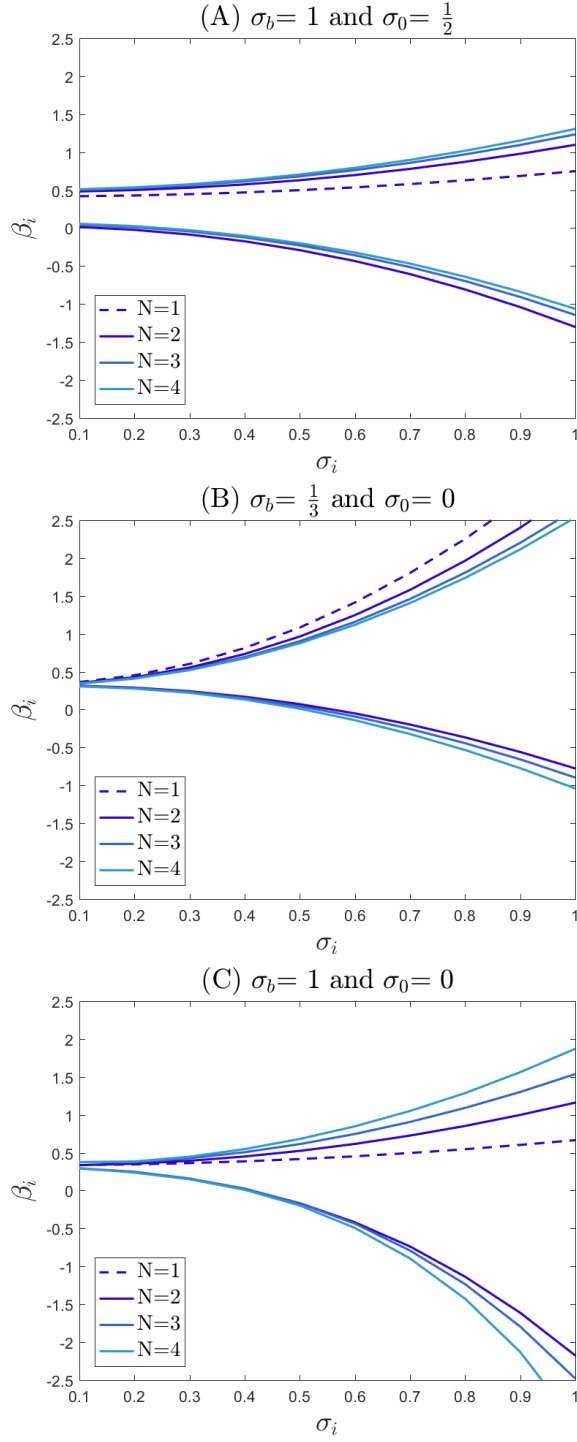


Figure B6.  $\bar{\beta}(\sigma), \underline{\beta}(\sigma)$  thresholds under various  $\sigma_b$  and  $\sigma_0$

*Notes:* Figure B6 plots the  $\bar{\beta}(\sigma), \underline{\beta}(\sigma)$  thresholds under  $c = \frac{1}{3}$  and varying standard deviations  $N, \sigma_b$  and  $\sigma_0$ . 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.

Table B1: Bias, omission, and welfare

		(1)	(2)	(3)	(4)	(5)
		Baseline	High $\sigma_b$	High $\sigma_0$	High $c$	High $N$
(A) Bias:	i. overall	0.34	0.20	0.26	-0.56	0.31
	ii. $\sigma_i = 0.1$	0.00	0.00	0.01	-0.03	0.00
	iii. $\sigma_i = 1$	1.01	0.96	0.60	-1.27	1.07
(B) Omission probability:	i. overall	0.43	0.32	0.44	0.42	0.48
	ii. $\sigma_i = 0.1$	0.03	0.01	0.30	0.03	0.03
	iii. $\sigma_i = 1$	0.70	0.67	0.60	0.77	0.80
(C) Welfare:	i. unrestricted	0.97	0.99	0.96	0.88	0.96
	ii. restricted	0.90	0.97	0.89	0.67	0.91
Specification changes from baseline		-	$\sigma_b = 1$	$\sigma_0 = \frac{1}{2}$	$c = \frac{1}{3}$	$N = 3$

*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  $\sigma_i$  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  $\sigma_b = \frac{1}{3}$ ,  $\sigma_0 = 0$ ,  $c = 0$ , and  $N = 2$ . Columns (2)-(4) modifies this environment for each specification as presented. The simulation is based on heterogeneous  $G(\sigma)$  with  $\chi^2$  distribution of 4 degrees of freedom with support  $[0, 10]$  normalized as  $[0, 1]$ , which was consistent with the Doucouliagos and Laroche 2003 data set.

### 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.

In many specifications, Panel (A) suggests sizable upward bias in unweighted<sup>31</sup> average estimates. Consistent with Figures 3 and 4, 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.<sup>32</sup> Quantitatively, despite its symmetric set-up with  $c = 0$ , among the least precise studies, the model can explain the bias as large as one standard deviation of the underlying distribution of benefits.

Panel (B) shows that the average omission rate can be as high as roughly 30 to 50 percents. While most precise studies have only 1 to 3 percent omission rate in the absence of study-specific effects ( $\sigma_0 = 0$ ), most noisy studies may be omitted roughly 70 to 80 percents. On the

<sup>31</sup>Note 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.

<sup>32</sup>This prediction of downward bias also occurs with the Hedges selection model discussed in Section 4.1.

other hand, belief regarding high  $\sigma_0$  can raise the omission rate even among the most precise studies to around 30 percent. Combined with the result in (A), the baseline case demonstrates that, among the 30 percent of reported noisy studies ( $\sigma_i = 1$ ), 28 percents are positive results and only 2 percents are negative results. Conversely, most precise studies have mostly negative conclusions roughly to the extent that the full reporting suggests. This is consistent with researchers' expectation that, when their set-up is noisy, their studies are publishable only when they are significant and "right-signed."

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:  $G_\theta(\sigma)$ , 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

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

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

where  $C = \sum_{i|\beta_i \geq \bar{t}\sigma_i} \frac{\Phi\left(\frac{\bar{t}\sigma_i - \hat{b}_0}{\sqrt{\sigma_i^2 + \hat{\sigma}_0^2}}\right) - \Phi\left(\frac{-\bar{t}\sigma_i - \hat{b}_0}{\sqrt{\sigma_i^2 + \hat{\sigma}_0^2}}\right)}{\left[1 - \Phi\left(\frac{\bar{t}\sigma_i - \hat{b}_0}{\sqrt{\sigma_i^2 + \hat{\sigma}_0^2}}\right)\right] \mathbb{1}(\beta_i \geq \bar{t}\sigma_i) + \Phi\left(\frac{\bar{t}\sigma_i - \hat{b}_0}{\sqrt{\sigma_i^2 + \hat{\sigma}_0^2}}\right) \mathbb{1}(\beta_i < \bar{t}\sigma_i)}$  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  $\frac{\Phi\left(\frac{\bar{i}\sigma_i - b_0}{\sigma}\right) - \Phi\left(\frac{-\bar{i}\sigma_i - b_0}{\sigma}\right)}{1 - \Phi\left(\frac{\bar{i}\sigma_i - b_0}{\sigma}\right)} \times n_1$  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 ( $\hat{G}_\theta(\sigma)$  and  $\hat{H}_0(\beta)$ ) and predicted distributions, defined by the KS-type statistics,  $D^G = \sup\{\hat{G}_\theta(\sigma) - \tilde{G}_\theta(\sigma|\hat{b}_0, \hat{\sigma}_0)\}$  and  $D^H = \sup\{\hat{H}_0(\beta) - \tilde{H}_0(\beta|\hat{b}_0, \hat{\sigma}_0)\}$ . 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  $D^G = \hat{G}_\theta(.08) - \tilde{G}_\theta(.08) = 0.47$  and  $D^H = \hat{H}_0(-.09) - \tilde{H}_0(-.09) = 0.26$ .