

Exploring blinding in peer review system

Fu Zixuan

January 4, 2025

1 Introduction

I always find it intriguing, and perhaps disheartening, that in some fields of research, it takes several years, even up to a decade, for a paper to be published. The publication cycle varies greatly across disciplines and venues, ranging from natural sciences to economics journals as tabulated by Hadavand et al. (2024). One crucial step in the publication process is the widely adopted peer review system, which serves as the gatekeeper for the profession. Delays in this process can stem from late submission of referee reports, authors postponing revisions, or editors delaying the assignment of papers for review or publication. At first glance, the idea of peer review seems straightforward, but it can encompass numerous configurations in terms of who has access what information at what time of the publication cycle (Soergel et al., 2013). This complexity motivates me to examine one specific aspect of it—the degree of blinding or anonymity. Table 1 illustrates the different anonymity configurations in peer review mechanisms.

Authors	Reviewers	
	Anonymized	Identified
Anonymized	Double blind	x
Identified	Single blind	Open review

Table 1: Review mechanisms based on the anonymity of authors and reviewers.

In 2003, Bachand and Sawallis (2003) conducted a survey of 554 journals across 18 disciplines, finding that 58% of journals use double-blind reviews, 37% single-blind, and only 5% open peer review. However, a journal’s decision on the review mechanism is not static. For instance, as documented by Pontille and Torny (2014), the American Economic Review (AER) has gone through several changes regarding its choice of anonymity (single-double-single-double-single) from 1973 to 2011. One may observe a certain pattern that the majority of a certain field prefers one system to another, with advocates and opponents each offering compelling reasons for their positions.

”The move to single-blind refereeing (where referees’ identities remain undisclosed) is effective from July 1, 2011. Easy access to search engines increasingly limits the effectiveness of the double-blind process in maintaining anonymity. Further, it increases the administrative cost of the journals and makes it harder for referees to identify an author’s potential conflicts of interest arising, for example, from consulting.” (AER, 2011).

In double-blind reviews, neither authors nor reviewers know each other’s identities during the review process. This system is designed to eliminate potential biases related to the author’s affiliation or reputation and to enable reviewers to provide honest feedback without fear of retaliation. In single-blind reviews, authors’ identities are revealed to reviewers, but reviewers remain anonymous.

Advocates of more transparent practices have called for open review systems, where all identities are revealed, and feedback is made publicly accessible to enhance accountability and fairness. However, double- and single-blind reviews remain the norm in scientific research.

Anonymity also influences reviewer’s behavior. Anecdotal evidence suggests that some reviewers may prefer knowing the authors’ identities, as it allows them to form prior beliefs about the paper’s quality based on the authors’ reputations. These priors can help reviewers allocate their time more efficiently—for example, by focusing less on verifying technical details if the author has a strong publication track record. This raises important questions about how such heuristics impact the review process and whether they align with the goal of ensuring high-quality, unbiased reviews.

The peer review system has two main objectives: to screen out bad science from being published and to help authors improve the quality of their paper before publication (Tan, 2018). In this paper, I focus only on the first function—discovering the true quality of the paper. The journal editor aims to maximize welfare by accepting high-quality papers and rejecting poor ones. However, the task of evaluating submissions is delegated to reviewers, whose effort levels and biases can influence the accuracy of their recommendations. To simplify the analysis, I limit the scope to binary cases of paper quality and author type.

The next section introduces the field of research on research itself, known as *journalology*, along with some empirical evidence and explanations. Section 3 formalizes the intuition presented here. Section 4 provides a preliminary analysis of the factors influencing a journal’s choices. The final section discusses issues deliberately ignored or overlooked in the earlier sections.

2 Related Literature

There is a large body of literature on the topic of peer review, upon which a new scientific field, *journalology*, has been built.

Many empirical studies focus on detecting bias, evaluating fairness, and measuring the quality of peer review under different blinding mechanisms, notably single-blind and double-blind. Interestingly, as summarized in the book chapter by Largent and Snodgrass (2016),

experimental and statistical results are divided. Even now, there is no consensus on the effects or non-effects of peer review practices Blank (1991); Tomkins et al. (2017).

Tan (2018) provides a summary of the strengths and weaknesses of different referee practices. For example, single-blind reviews may result in reviewers favoring well-known authors compared to double-blind reviews, where identifying information about the authors is removed. However, double-blind reviews raise questions about true anonymity and the additional cost of preparing papers for such reviews. Snodgrass (2007) identifies six benefits of double-blind review compared to 21 potential costs, while noting that complete masking of authorship is often infeasible in practice. Some researchers advocate for a more open process with varying degrees of transparency, ranging from open feedback to open reviewer identity. Unsurprisingly, concerns arise from all sides (editor, reviewer, author) about the implications of maximal openness in the review process. In this context, I particularly appreciate the project by Soergel et al. (2013), which led to the creation of the platform OpenReview.net. This platform supports a variety of configurations, enabling journals and conferences to experiment with different dimensions of open scholarship.¹

Finally, since peer review is not discipline-specific, studies approach it from diverse angles. From an economic theory perspective, I was first inspired by the work of García et al. (2015), which proposes a reward system for reviewers under a moral hazard framework where the editor is the principal and the reviewer is the agent. Other works examine the interplay between reviewers and editors (Garcia et al., 2021), authors and editors (Garcia et al., 2022), and authors and reviewers (Radzvilas et al., 2023). Much of this research is published in the journal *Scientometrics*, which is dedicated to the study of scholarly literature. It is fascinating to see how economic theories are applied in a concrete setting as such.

Drawing on the relevant literature, I base my model on empirical evidence showing that the most commonly used peer review mechanisms are single-blind and double-blind. Consequently, I study only the editor’s binary choice of mechanism. Furthermore, since no consensus exists on which mechanism is superior, I assume that journals make their decisions according to the specificity of the discipline. Although I recognize the principal-agent nature of this setting, I do not model the classical adverse selection or moral hazard problems as under the two mechanisms I study, the reviewer’s identity is masked, and they receive no reward for their work. Incentives or the manipulation of incentives are thus not considered. The full model is presented in the next section.

3 Model

Consider a peer review system with one journal editor and one reviewer. The system is described as follows.

1. A paper is submitted to the journal editor. It has a true quality that is either low or high, represented by $h_i \in \{0, 1\}$.

¹”The word ”open” denotes access to information. To characterize a system, then, we must state who has access to what information, and when. (Additionally, there may be special conditions on that access).” Soergel et al. (2013)

2. The author of the paper has a binary type, denoted by $a_i \in \{o, e\}$. The notation here stands for *old* and *new*, which can be interpreted as:
 - *old*: more experienced, well-known in the research field
 - *new*: less experienced researchers
3. After receiving the paper, the editor needs to make a decision on acceptance, denoted by $\delta_i \in \{0, 1\}$. The editor aims to accept good papers ($\delta_i = 1$ when $h_i = 1$) and reject bad papers. However, the true quality of the paper is unknown to the editor.
4. Since the editor will not evaluate the paper herself, she delegates the referee task to a reviewer.
5. The reviewer reads the paper with varying levels of effort, denoted by e . Based on this evaluation, the reviewer makes a recommendation to either accept or reject the paper.
6. The reviewer cannot fully discover the true quality of the paper. The probability that the reviewer recommends acceptance when the paper is of high quality is denoted by p_1 , and the probability that he recommends rejection when the paper is of low quality is denoted by p_0 . Formally:

$$\mathbb{P}(\delta_i = 1 \mid h_i = 1) = p_1,$$

$$\mathbb{P}(\delta_i = 0 \mid h_i = 0) = p_0.$$

- From the editor's perspective, higher values of p_1 and p_0 lead to more accurate decisions.
- From the reviewer's perspective, higher accuracy requires greater effort e . Both p_1 and p_0 increase with the level of effort exerted by the reviewer. Specifically:

$$\frac{\partial p_1(e)}{\partial e} > 0, \quad \frac{\partial p_0(e)}{\partial e} > 0.$$

7. The editor strictly follows the reviewer's recommendation when making the final decision.

3.1 Reviewer

Reviewer's Effort The reviewer exerts effort to evaluate papers. The cost of effort is measured in time, denoted by $c(e)$, where $\frac{\partial c(e)}{\partial e} > 0$, indicating that the cost increases with effort.

The reviewer faces one of two reviewing systems: {Double-blind, Single-blind}. In a double-blind system, the author's identity is concealed from the reviewer, while in a single-blind system, only the reviewer is anonymous. Below, I discuss the two extreme cases of complete anonymity and full knowledge of the author's identity.

In an ideal world where double-blind review ensures complete anonymity², the reviewer applies a uniform effort level e_b across all papers. Given N papers, the total effort cost is:

$$Nc(e_b).$$

On the other hand, if the reviewer knows the author's identity in a single-blind system, I assume that they can infer perfectly the author's type $a_i \in \{o, e\}$. Since it is natural to trust more experienced people, the reviewer would exert less effort checking the paper (e.g., proofs, theorems) if he knows the author is of type o . Formally, I assume:

$$e_o < e_n,$$

If there are $k\%$ authors of type o , the total cost of effort under single-blind is:

$$N(kc(e_o) + (1 - k)c(e_n)).$$

It is worth mentioning that in practice, even in a double-blind system, complete anonymity is rarely achieved. Reviewers can often guess the author's identity based on writing style, topic, or prior knowledge. Let us assume that $\lambda\%$ of the time, the reviewer knows the author's type despite the double-blind setup. Then the total cost is:

$$N[\lambda(kc(e_o) + (1 - k)c(e_n)) + (1 - \lambda)c(e_b)].$$

The parameter λ measures the level of non-anonymity in a research field. A higher λ represents a setting where it is easier for reviewers to identify the author's identity.

Reviewer's indifference The reviewer does not receive any monetary reward for referee work. This altruistic action arises from professional ethics. At the same time, the reviewer faces time constraints (e.g., own research, teaching, personal time) and therefore will not spend excessive effort on reviewing. I assume that reviewers allocate a **fixed amount of time** to refereeing, as they have no incentive to increase or decrease the time spent on it. They are indifferent between double-blind and single-blind systems if the total cost of effort remains the same under both mechanisms. Formally, this condition is expressed as:

$$\lambda_{sq}(kc(e_o) + (1 - k)c(e_n)) + (1 - \lambda_{sq})c(e_b) = kc(e_o) + (1 - k)c(e_n),$$

where λ_{sq} represents the level of non-anonymity in the status quo under the double-blind system.

Reviewer's bias As mentioned before, if the reviewer knows the author's identity, they may exert more or less effort depending on the author's type. From the editor's perspective, it is preferable that reviewers exert more effort by treating all authors as type n (new). However, in reality, knowing the author's type can introduce bias into the review process.

²This assumes no pre-prints, public presentations, or other identifiable clues.

To be more specific, let us define new probabilities $p_1(e, a)$ and $p_0(e, a)$, which depend on both the reviewer's effort level and their knowledge of the author's type. The bias associated with type o (old) manifests as a reduction in the probability of rejection for low-quality papers. Formally:

$$p_0(e, o) = p_0(e) - b_o,$$

which means that, conditional on the paper being of low quality, the reviewer is more tolerant if they know the author is of type o . On the other hand, the bias for type n (new) occurs in the probability of acceptance for high-quality papers:

$$p_1(e, n) = p_1(e) - b_n,$$

indicating that, conditional on the paper being of high quality, the reviewer is more skeptical when the author is of type n .

Summarizing both cases, we have the following expressions for $p_1(e, a)$ and $p_0(e, a)$:

$$p_1(e, a) = \begin{cases} p_1(e) & \text{if } a = o, \\ p_1(e) - b_n & \text{if } a = n, \end{cases}$$

$$p_0(e, a) = \begin{cases} p_0(e) - b_o & \text{if } a = o, \\ p_0(e) & \text{if } a = n. \end{cases}$$

3.2 Editor

Editor's Objective The editor acts in the interest of the journal, wanting to accept good papers and reject bad ones. Recall that the decision is denoted by δ_i and the true quality of the paper by h_i . There are four possible outcomes that can enter the editor's objective function, as shown in Table 2.

	$h_i = 1$ (High quality)	$h_i = 0$ (Low quality)
$\delta_i = 1$	Correct acceptance ($h_i \delta_i$)	False positive ($(1 - h_i) \delta_i$)
$\delta_i = 0$	False rejection ($h_i (1 - \delta_i)$)	Correct rejection ($(1 - h_i)(1 - \delta_i)$)

Table 2

Consider the case where the editor aims to maximize the number of correctly accepted and correctly rejected papers, that is, $\sum_i h_i \delta_i$ and $\sum_i (1 - h_i)(1 - \delta_i)$.

The editor's objective function can be expressed as:

$$\max \mathbb{E}[\sum_i \delta_i h_i] + \tau \mathbb{E}[\sum_i (1 - \delta_i)(1 - h_i)] \quad (1)$$

where τ represents the relative weight the editor assigns to correctly rejecting low-quality papers compared to correctly accepting high-quality papers. This is equivalent to writing:

$$\max \{ \mathbb{P}(\delta_i = 1 | h_i = 1) \mathbb{P}(h_i = 1) + \tau \mathbb{P}(\delta_i = 0 | h_i = 0) \mathbb{P}(h_i = 0) \}$$

Editor's Payoff I first define some institutional settings then present the editor's payoff under different scenarios,

- α is the proportion of high-quality papers, $\mathbb{P}(h_i = 1)$.
- β_o is the proportion of high-quality papers from authors of type o , and β_n from authors of type n , satisfying:

$$k\beta_o + (1 - k)\beta_n = \alpha.$$

Now, I write the editor's payoff under different scenarios.

- **Base Case:** I assume that without reading the paper or delegating anyone to review it, the editor accepts and rejects papers with equal probability, $\mathbb{P}(\delta_i = 1 | h_i) = 1/2$.³ Her payoff in this case is:

$$\frac{1}{2}\alpha + \tau\frac{1}{2}(1 - \alpha).$$

- **Double-Blind with $\lambda = 0$:** If full anonymity can be achieved under a double-blind system ($\lambda = 0$), the editor's payoff is:

$$p_1(e_b)\alpha + \tau p_0(e_b)(1 - \alpha).$$

- **Single-Blind with $\lambda = 1$:** Under a single-blind system, the payoff conditioning on the author's type a_i is

$$\begin{aligned} & \mathbb{E}[\delta_i h_i + \tau(1 - \delta_i)(1 - h_i) | a_i] \\ &= \mathbb{P}(\delta_i = 1 | h_i = 1, a_i) \mathbb{P}(h_i = 1 | a_i) + \tau \mathbb{P}(\delta_i = 0 | h_i = 0, a_i) \mathbb{P}(h_i = 0 | a_i) \\ &= p_1(e_a, a) \beta_a + \tau p_0(e_a, a) (1 - \beta_a) \end{aligned}$$

Therefore, the total payoff is

$$k [p_1(e_o) \beta_o + \tau(p_0(e_o) - b_o)(1 - \beta_o)] + (1 - k) [(p_1(e_n) - b_n) \beta_n + \tau p_0(e_n)(1 - \beta_n)]$$

- **Double-Blind with $0 < \lambda < 1$:** the editor's payoff is a linear combination of the two cases above.

3.3 Problem Formulation

The institutional parameters are $\{k, \lambda_{sq}, \alpha, \beta_o, \beta_n, \tau\}$. The editor's preference parameter is τ , while the reviewer's bias is characterized by $\{b_o, b_n\}$. The reviewer solves the following equation (indifference condition) to determine the respective effort levels e_b^* , e_o^* , and e_n^* :

$$\lambda_{sq}(kc(e_o) + (1 - k)c(e_n)) + (1 - \lambda_{sq})c(e_b) = kc(e_o) + (1 - k)c(e_n). \quad (2)$$

³This does not imply that $\delta_i = 1/2$ is the optimal decision rule under ignorance.

Given the effort levels e_b^* , e_o^* , and e_n^* , the editor solves the following (maximization) problem to determine the optimal mechanism from {double-blind, single-blind}:

$$\begin{aligned} \max_{\lambda \in \{\lambda_{sq}, 1\}} \lambda (k [p_1(e_o)\beta_o + \tau(p_0(e_o) - b_o)(1 - \beta_o)] + (1 - k) [(p_1(e_n) - b_n)\beta_n + \tau p_0(e_n)(1 - \beta_n)]) \\ + (1 - \lambda) (p_1(e_b)\alpha + \tau p_0(e_b)(1 - \alpha)) \end{aligned} \quad (3)$$

Therefore, by emulating a principal-agent problem, the combined problem can be formulated as:

$$\begin{aligned} \max_{\lambda \in \{\lambda_{sq}, 1\}, e_b, e_n, e_o} \quad & \text{editor's payoff} \\ \text{s.t.} \quad & \text{reviewer's indifference.} \end{aligned} \quad (4)$$

4 Analysis

The reviewer's indifference condition simplifies to:

$$c(e_b) = kc(e_o) + (1 - k)c(e_n).$$

Since the decision on λ^* is binary, the editor's optimization problem boils down to comparing the first and second terms in equation 3. Rearranging the terms, I need to compare:

$$\begin{aligned} k\beta_o p_1(e_o) + (1 - k)\beta_n p_1(e_n) + \tau(k(1 - \beta_o)p_0(e_o) + (1 - k)(1 - \beta_n)p_0(e_n)) \\ - \underbrace{k\tau b_o(1 - \beta_o) - (1 - k)\tau b_n\beta_n}_{\text{bias}} \end{aligned}$$

with

$$\alpha p_1(e_b) + \tau(1 - \alpha)p_0(e_b).$$

I first make the comparison without considering the bias term.

Linear Case Starting with the simplest case, I assume that $c(e) = p_1(e) = p_0(e) = e$. The comparison between $k\beta_o p_1(e_o) + (1 - k)\beta_n p_1(e_n)$ and $\alpha p_1(e_b)$ reduces to:

$$[k\beta_o \quad (1 - k)\beta_n] \left(\begin{bmatrix} e_o \\ e_n \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} [k \quad 1 - k] \begin{bmatrix} e_o \\ e_n \end{bmatrix} \right) \stackrel{?}{\leq} 0$$

Simplifying further:

$$k\beta_o(k - 1) + (1 - k)\beta_n k \quad \Leftrightarrow \quad \beta_n - \beta_o \stackrel{?}{\leq} 0.$$

By definition, $\beta_n < \beta_o$, which implies that the second term (under the double-blind system) is larger than the first term (under the single-blind system) even without accounting for the bias. Adding back the bias term, it is clear that the editor prefers the double-blind system.

General Case My intuition is that if $c''(e) > p''(e) \forall e$, then even without the bias term, the editor prefers the double-blind mechanism. To begin with, I assume $p(e) = e$ and $c(e) = \frac{1}{2}e^2$. The condition can then be written as:

$$[k\beta_o \quad (1-k)\beta_n] \begin{pmatrix} p(e_o) \\ p(e_n) \end{pmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} p(e_b) \stackrel{?}{\leq} 0$$

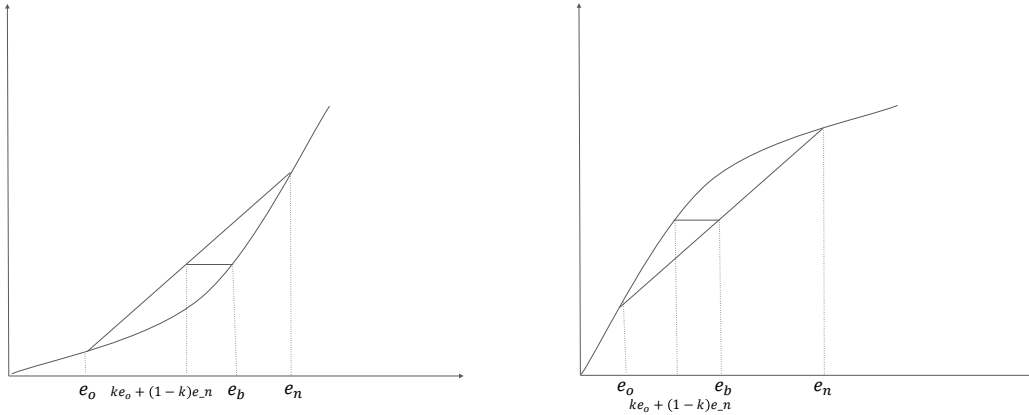
where:

$$e_b^2 = ke_o^2 + (1-k)e_n^2 \Leftrightarrow e_b = k^*e_o + (1-k^*)e_n \text{ for some } k^* < k.$$

In this case, the condition becomes more negative:

$$k\beta_o(k^* - 1) + (1-k)\beta_n k^* < \beta_n - \beta_o < 0.$$

Next, I assume $c(x) = \log(x+1)$ and $p(x) = x$. In this case, since $e_b = k^*e_o + (1-k^*)e_n$ for some $k^* > k$ (see Figure 1), the condition $k\beta_o(k^* - 1) + (1-k)\beta_n k^*$ becomes ambiguous. If β_n is not too small compared to β_o (i.e., the proportion of good papers from n authors is not significantly different from that of o authors), and the biases b_o and b_n are not too large, it is possible that the editor prefers the single-blind mechanism with $\lambda = 1$.



(a) $c(e) = \frac{1}{2}e^2$

(b) $c(e) = \log(e+1)$

Figure 1: It is the difference between the curvature of the $c(e)$ and $p(e)$ that matters. This figure is only illustrative.

Proposition 4.1. If $c''(e) \geq p''(e)$ for all e , the editor always prefers the double-blind mechanism, subject to a status quo level of anonymity λ_{sq} . However, when this condition does not hold, and the differences in author productivity and reviewer biases are not too large, the editor may prefer the single-blind mechanism.

While I initially expected that the status quo anonymity level λ_{sq} ⁴ would play a role in

⁴That is, how difficult it is for the paper to remain truly anonymous.

the editor’s decision $\lambda \in \{\lambda_{sq}, 1\}$, it turns out that it does not matter at all under the current model setup. This question is explored in the next section.

5 Discussion

In this section, I discuss several aspects of the model that I have considered but intentionally ignored in the previous section.

Non-Anonymity Level λ_{sq} Several studies provide evidence that in certain research fields, implementing a double-blind review system offers little to no benefit. Since reviewers are typically assigned papers within their own fields, there is a high likelihood that they have already encountered the work as a preprint on an archive, as a working paper, or through attending the author’s presentation. This is particularly true for niche research areas. These findings suggest that, intuitively, a higher level of λ_{sq} (the status quo non-anonymity level) should favor the single-blind mechanism.

As discussed in Section 4, the editor will always choose the double-blind mechanism if full anonymity yields a higher payoff than full disclosure. However, in practice, full anonymity is rarely achieved, even under a double-blind system, because there is an inherent level of non-anonymity λ_{sq} for each research field. All else being equal, a research field where it is easier to maintain true anonymity (i.e., a low λ_{sq}) is more likely to adopt a double-blind system, whereas a field where everyone knows everyone (i.e., a high λ_{sq}) is more likely to adopt a single-blind system.

To incorporate this intuition into the model, I propose introducing a fixed anonymization cost c for the editor when implementing a double-blind mechanism. This cost represents the additional effort required to anonymize papers⁵. The fixed cost is assumed to be the same across all fields.

Therefore, even if:

$$\begin{aligned} \alpha p_1(e_b) + \tau(1 - \alpha)p_0(e_b) &> k\beta_o p_1(e_o) + (1 - k)\beta_n p_1(e_n) \\ &+ \tau(k(1 - \beta_o)p_0(e_o) + (1 - k)(1 - \beta_n)p_0(e_n)) \\ &\underbrace{- k\tau b_o(1 - \beta_o) - (1 - k)\tau b_n \beta_n}_{\text{bias}} \end{aligned}$$

the fixed anonymization cost may be large enough to make the double-blind mechanism unappealing if the weight $(1 - \lambda_{sq})$ on the larger term $\alpha p_1(e_b) + \tau(1 - \alpha)p_0(e_b)$ is small.

By incorporating a fixed anonymization cost into the model, the editor’s choice of mechanism becomes dependent on the status quo non-anonymity level λ_{sq} , as desired.

⁵This includes more than just removing author names; it also involves verifying that no identifying information is inadvertently included in the submission.

Reviewer’s Indifference Condition I have assumed that the reviewer is indifferent between the two mechanisms since they do not receive any compensation or reward for their time spent, as is the case in reality. This indifference condition serves as a constraint in the combined problem 4. However, I argue that this condition alone is not sufficient to pin down the effort levels (e_b, e_o, e_n) given all the parameters specified earlier. This is because, for either $\lambda \in \{\lambda_{sq}, 1\}$, the editor’s payoff is maximized when the reviewer’s effort is as high as possible. Yet there is no constraint on the upper bound of $c(e)$. To address this, an additional constraint should be imposed, such as:

$$kc(e_o) + (1 - k)c(e_n) < \bar{c},$$

so that all decision variable λ, e_b, e_o, e_n can be pinned down.

Another potential extension is to introduce the reviewer’s incentives in their effort decision. Currently, both mechanisms *blind* the reviewer’s identity, meaning they receive only a generic acknowledgment such as, “We thank the anonymized reviewers for their helpful feedback.” It would be interesting to explore ways to reward reviewers in non-pecuniary ways such as implementing a reputation system (Soergel et al., 2013). Alternatively, we could imagine a world where the reviewer’s feedback is openly accessible, or even where the reviewer’s identity is disclosed. If reviewers are incentivized in some way, the original question takes on the flavor of a classical principal-agent problem. In that case, the editor (principal) would need to juggle multiple factors in her choice of mechanism.

Editor’s Objective Function I have briefly alluded to the four types of outcomes that concern the editor, as shown in Table 2. Intuitively, the editor seeks to maximize the diagonal terms (correct acceptance and correct rejection) while minimizing the off-diagonal terms (false acceptance and false rejection). I argue that it is sufficient to focus on two out of the four outcomes, provided that a countervailing pair is selected, such as $h_i\delta_i$ and $-\delta_i$. By labeling the elements in the table horizontally, I can select pairs such as $(1, 2)$, $(1, 4)$, $(2, 4)$, $(2, 3)$, or $(4, 3)$. Alternatively, considering only (4) also works if I attach equal importance to the two objectives (accept good and reject bad).

Concluding words In this research proposal, I model the journal editor’s choice between double-blind and single-blind peer review mechanisms, assuming the reviewer spends a fixed amount of time on reviewing. The peer review process is framed as a tool to discover paper quality rather than improve it, with the reviewer exhibiting bias toward two author types. I briefly explore the conditions under which the editor prefers one mechanism over the other and discuss how a fixed anonymization cost can make the choice dependent on the field’s status quo non-anonymity level.

References

- (2011). Notes. *The Journal of Economic Perspectives*, 25(3):241–244.
- Bachand, R. G. and Sawallis, P. P. (2003). Accuracy in the identification of scholarly and peer-reviewed journals and the peer-review process across disciplines. *The Serials Librarian*, 45(2):39–59.
- Blank, R. M. (1991). The effects of double-blind versus single-blind reviewing: Experimental evidence from the american economic review. *The American Economic Review*, pages 1041–1067.
- García, J. A., Rodriguez-Sánchez, R., and Fdez-Valdivia, J. (2015). The principal-agent problem in peer review. *Journal of the Association for Information Science and Technology*, 66(2):297–308.
- Garcia, J. A., Rodriguez-Sánchez, R., and Fdez-Valdivia, J. (2021). The interplay between the reviewer’s incentives and the journal’s quality standard. *Scientometrics*, 126:3041–3061.
- Garcia, J. A., Rodriguez-Sanchez, R., and Fdez-Valdivia, J. (2022). Fraud, specialization, and efficiency in peer review. *Research Evaluation*, 31(1):15–23.
- Hadavand, A., Hamermesh, D. S., and Wilson, W. W. (2024). Publishing economics: How slow? why slow? is slow productive? how to fix slow? *Journal of Economic Literature*, 62(1):269–293.
- Largent, E. A. and Snodgrass, R. T. (2016). Blind peer review by academic journals. *Blinding as a solution to bias: strengthening biomedical science, forensic science, and law*, pages 75–95.
- Pontille, D. and Torny, D. (2014). The blind shall see! the question of anonymity in journal peer review. *The Question of Anonymity in Journal Peer Review*.
- Radzvilas, M., De Pretis, F., Peden, W., Tortoli, D., and Osimani, B. (2023). Incentives for research effort: an evolutionary model of publication markets with double-blind and open review. *Computational Economics*, 61(4):1433–1476.
- Snodgrass, R. T. (2007). Single-versus double-blind reviewing.
- Soergel, D., Saunders, A., and McCallum, A. (2013). Open scholarship and peer review: a time for experimentation .
- Tan, M. H. (2018). Peer review—past, present, and future. In *Medical and Scientific Publishing*, pages 55–68. Elsevier.
- Tomkins, A., Zhang, M., and Heavlin, W. D. (2017). Reviewer bias in single-versus double-blind peer review. *Proceedings of the National Academy of Sciences*, 114(48):12708–12713.