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"Designing Silence: Peer Feedback under Reputational Concerns"

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Designing Silence: Peer Feedback under Reputational Concerns*

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Abstract

How should an organization control what its experts learn from one another between a first opinion and a final one? We study a platform that collects two independent binary forecasts and decides whether the second expert may see the first expert's lodged report before revising, when experts are rewarded for reputation rather than accuracy. The platform commits to a reveal-or-silence lottery conditioned on whether the lodged reports agree. Because non-revelation is informative, silence becomes an instrument of design rather than the absence of one. Our main result is a concealment-ray theorem: along policy rays that hold fixed the composition of the silent pool, the value of every finite downstream decision problem and every locked-report incentive slack is affine. A two-dimensional design problem therefore collapses to full disclosure and two one-dimensional boundaries. At an exact rational profile, a computer-assisted certificate identifies the unique state-classification optimum within the maintained class: disagreement is never revealed, while approximately 71.08 percent of agreements are revealed—just enough to make silence unfavourable news and eliminate a low-ability expert's tendency to stand by a stale forecast. The policy strictly outperforms both sealing and full disclosure, although the gain over full disclosure is modest, and remains uniquely optimal after recalibrating the threshold on an open set of nearby primitives. Two qualifications delimit its reach. Sealing and full disclosure are Blackwell incomparable, so no protocol is best for every downstream objective. Moreover, every policy admits an uninformative equilibrium, so the comparison is conducted within a maintained regular-monotone class.

Keywords: economic design; peer feedback; selective disclosure; career concerns; information aggregation

JEL: D82, D83, C73

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1 Introduction

A bank records its analysts' preliminary assessments before circulating a selected few of them; a diagnostic platform locks a radiologist's reading before showing her a colleague's; an intelligence unit collects independent estimates before deciding what a revising analyst may see; a forecasting tournament freezes entries before it opens a leaderboard.[1] What these arrangements share is a deliberate wedge between the moment at which an opinion is formed and the moment at which it may be influenced. The wedge is not costless. An organization that reveals nothing forgoes whatever its experts could have learned from one another; an organization that reveals everything invites the second opinion to become an echo of the first, and the echo is worth less than the opinion.

The central question of the present paper is therefore the following: if an organization can commit in advance to a rule governing what one expert is allowed to learn about another's locked forecast, and if the experts are paid not for being right but for the reputation that being right confers, what should that rule be? The question is a design question in the literal sense—the object being chosen is an information system internal to an organization—and the answer turns out to depend on a feature of the problem that is easy to overlook: when a rule sometimes conceals, the act of concealment is itself a message, and the organization chooses what that message says.

We study a two-expert version of the problem. Two experts receive private binary signals about a fixed state and simultaneously lodge initial forecasts. A platform commits, before any signal is observed, to a stochastic feedback rule. After the initial reports have been locked, expert B receives a second signal and either observes expert A's lodged report or is told that it has not been revealed; expert A receives no peer feedback at all. Both experts then submit terminal forecasts, a downstream decision maker acts on the resulting public history, and the state is subsequently revealed. Each expert is paid her posterior reputation for being highly able, and the platform designs its feedback rule to improve the information available for the downstream decision.[2]

Selective feedback matters here because non-revelation is informative and because it changes B's reputational incentives. The platform may reveal A's report with one probability when the lodged forecasts agree and with another when they disagree. With binary reports, however, a deterministic agreement-only or disagreement-only rule conceals nothing at all: B knows her own report and she knows the rule, so she simply infers the missing value. Randomization is therefore not a technical convenience but a necessity. It is what pools agreement and disagreement behind a single silent message, and the composition of that pool determines how strongly silence speaks in favour of B's old forecast. The behavioural target is familiar: after private evidence that conflicts with her own locked report, a low-ability expert may rationally cling to it, because a consistent record reads as

[1] The same instinct is codified in the Delphi method, which deliberately staggers the rounds in which panellists see one another's answers, and in the editorial practice of releasing a co-referee's report only once one's own has been filed. In each case the institution is not indifferent between showing everything and showing nothing: it wants the first opinion to be formed alone and the second to be formed with company.

[2] The policy governs interim feedback rather than permanent publication. A's lodged report becomes part of the complete public history once the terminal forecasts have been submitted, so the platform is choosing the timing of B's access to it, not whether it is ever disclosed.

competence, whereas a high-ability expert follows the new signal.

The main analytical result gives this design problem a geometry simple enough to reduce analytically. Consider policies that hold fixed the relative composition of the silent pool while varying the overall amount of concealment—policies that keep what silence *means* while changing how often it *occurs*. Along each such concealment ray, the likelihood ratio conveyed by silence, B's continuation behaviour, and the posterior experiment conditional on silence are all unchanged; only the frequencies of the revealed and silent branches move. It is shown in theorem 4.2 that the candidate value of *every* finite downstream decision problem is then affine along the ray, and that the same is true of the locked-report incentive slacks. A two-dimensional candidate search consequently reduces to full disclosure and two one-dimensional boundaries, on which either agreement or disagreement is never revealed. Locked-report incentives then decide which of the surviving candidates are equilibrium-feasible.

This reduction turns up a genuinely selective policy with a disciplinary reading. On one boundary the platform never reveals disagreement and randomizes after agreement. Revealing some agreements withdraws favourable observations from the silent pool, so that silence becomes unfavourable enough evidence about B's old forecast to extinguish the low type's inertia altogether. At the exact rational profile studied below, the computer-assisted certificate of theorem 5.1 identifies this policy as the unique global optimum for symmetric state classification within the maintained class and verifies its equilibrium feasibility: approximately 71.08 percent of agreements are revealed, and no disagreements are.[3] This result is not the obvious one, since common sense would suggest that an organization which wants its experts to aggregate information should either let them see each other's work or keep them apart—and that anything in between merely dilutes both. What the model says instead is that the interior is where the instrument lives: only a rule that conceals *sometimes* can make silence carry a message, and only a message can change behaviour.

Two boundaries on the result should be stated at once rather than discovered late. The first is that the optimum is objective-specific. The complete experiments induced by sealing and by full disclosure are Blackwell incomparable: each is preferred for some downstream decision problem. The concealment-ray reduction applies to every finite objective, but the preferred boundary and the optimal degree of concealment do not, and no general presumption in favour of opacity—or of transparency—survives this comparison. The second is an equilibrium qualification. Like every cheap-talk model with reputational payoffs, this one admits uninformative equilibria: under any policy there is a completely mixed sequential equilibrium in which reports ignore signals, wages stay at the prior, and the public history is uninformative about the state. Since that equilibrium is already completely mixed, refinements operating through beliefs after off-path actions cannot remove it. We therefore proceed as this literature ordinarily does and compare policies within a class of informative equilibria—here called regular-monotone—in which lodged signals are reported truthfully, confirming signals are followed, the high type follows conflicting new evidence, and the

[3]The rational fractions are chosen so that every comparison can be certified in exact arithmetic. They are not estimates and should not be read as a calibration; Proposition 5.2 and the diagnostics in the Appendix E are what carry the claim beyond the single profile.

low type may mix.[4]

The platform's problem is a constrained information-design problem. In Bayesian persuasion a designer commits to an experiment that influences a receiver's action (Kamenica and Gentzkow, 2011); more generally, information design studies how information structures shape strategic behaviour (Bergemann and Morris, 2019). Here the platform does not freely choose a signal about the state. Its primitive input is a peer report produced in equilibrium, and its interim message changes another expert's subsequent report, so that the public experiment is generated endogenously by the feedback rule rather than selected from a menu. The restriction also differs from a bound on message capacity, as in Aybas and Turkel (2026): the substantive constraint here is the report-contingent reveal-or-silence technology itself. Finally, silence is generated by a committed institutional lottery after reports have been locked and is not, as in Lee (2026), timed strategically by a privately informed sender. These features are what produce the concealment-ray structure and what separate the problem from a standard persuasion concavification.

The reputational building block is deliberately familiar. Terminal payoffs follow Ottaviani and Sørensen (2006a,b): once the state is observed, the accuracy of a report changes the evaluator's inference about an expert's information quality. With repeated reports, consistency can therefore acquire reputational value of its own, as in Trueman (1990); Ehrbeck and Waldmann (1996). Closest to the present setting, Li (2007) studies two reports by an expert who privately knows the quality of her information and obtains exactly the conflict pattern used here—the high-quality type follows the new signal, the low-quality type mixes between revising and standing pat—and Tajika (2021) likewise obtains persistence and mixing after conflicting signals. We do not offer a new explanation of forecast inertia. We take that familiar response as given and use it as the channel through which an institution's feedback policy changes the information its experts produce.[5]

The paper also speaks to the organization of expert communication under career concerns. Ottaviani and Sørensen (2001) analyse reputational information aggregation in sequential debate; Prat (2005) shows that transparency about an expert's action can induce conformism; Fehrler and Hughes (2018) show theoretically and experimentally that committee transparency can damage information aggregation; and, closest to the two-expert protocol used here, Bag and Sharma (2019) compare closed-door and transparent sequential advice. That transparency can be harmful is thus well established, and it is not what we claim to contribute.

The distinction lies instead in the timing and the target of information control. In Liu and Sanyal (2012) an exogenous second opinion affects a reputational adviser's incentives and the decision

[4]The same step appears, explicitly or tacitly, in related reputational cheap-talk models: Ottaviani and Sørensen (2006b) and Li (2007) both characterize informative equilibria in environments where babbling survives. We state the multiplicity as a proposition rather than leaving it implicit (theorem 2.2) precisely because the design exercise is a comparison across policies, and it is worth being clear that the comparison is conditional. Regular monotonicity classifies equilibria; it does not narrow the set of deviations, and every prescribed action below is tested against the full set of reporting deviations, including those that change the feedback lottery itself.

[5]The same career-concern logic underlies reputational herding in Scharfstein and Stein (1990) and the changing responsiveness to information in Prendergast and Stole (1996). Related dynamic reporting environments include Woo (2025), on truth telling and early silence, and Valsecchi (2025), on repeated forecasts by an expert of unknown statistical bias.

maker's response; Ghosh et al. (2017) let an evaluator control the precision of a signal available to a reputational cheap-talk sender; Catonini et al. (2024) compare independent and collective expertise by varying whether experts communicate before giving advice. In each case the control is exercised over a signal, or over the presence of communication, rather than over the endogenous report of a peer. Here the initial forecasts are produced independently and cannot be rewritten, and only once they have been lodged does the platform condition feedback on the relation between them. This architecture preserves independent initial information production while altering one expert's subsequent use of private evidence, and the present paper tries to fill in that gap: what is characterized is the design geometry of a committed, report-contingent feedback technology, together with the exact optimum of a selective policy that uses silence to discipline revision.

The remainder of the paper is organized as follows. Section 2 presents the environment, the design objective, and the maintained regular-monotone prediction. Section 3 derives the experts' reputational response to revealed and concealed peer forecasts. Section 4 proves the concealment-ray reduction and characterizes disciplinary silence. Section 5 establishes the computer-assisted exact optimum, its robustness, and the objective dependence of the policy ranking. Section 6 concludes.

2 Environment and design problem

The platform of this model is a committed information intermediary and nothing more: it controls B's interim access to A's lodged report, but it neither chooses the experts' reports nor alters their reputational payoffs, and it cannot pay them. That is a deliberately weak instrument, and the point of the paper is to see how much can be done with it. This section sets out the informational environment, the feasible feedback technology, and the downstream objective against which policies are evaluated; it then states the equilibrium requirement and the maintained informative response on which the design analysis rests.

2.1 Experts and private information

There are two experts, indexed by $i \in \{A, B\}$, a platform, a downstream decision maker, and a competitive evaluator. The unknown state is $\theta \in \{0, 1\}$, with

$$\mathbb{P}(\theta = 0) = \mathbb{P}(\theta = 1) = \frac{1}{2}.$$

Expert i's privately known type is $\tau_i \in \{L, H\}$, with $\mathbb{P}(\tau_i = H) = \omega \in (0, 1)$. Types are independent of the state and of one another.

At dates $t \in \{1, 2\}$, expert i observes a binary signal s_{it}. Conditional on the state and types, the signals are independent across experts and dates and satisfy

$$\mathbb{P}(s_{it} = \vartheta \mid \theta = \vartheta, \tau_i = \tau) = p_{\tau t}, \qquad \frac{1}{2} < p_{Lt} < p_{Ht} < 1. \tag{1}$$

The symmetric state prior is what isolates the reputational mechanism from a directional prior bias:

with a skewed prior an expert would have a reason to lean towards the likely state that has nothing to do with her reputation.[6]

Define the signal odds and relative learning rates by

$$\kappa_{\tau t} = \frac{p_{\tau t}}{1 - p_{\tau t}}, \qquad \eta_\tau = \frac{\kappa_{\tau 2}}{\kappa_{\tau 1}}. \tag{2}$$

For example, after signals $(s_{i1}, s_{i2}) = (1, 0)$, type τ's posterior odds in favour of the state indicated by the first signal are

$$\frac{\mathbb{P}(\theta = 1 \mid s_{i1} = 1, s_{i2} = 0, \tau_i = \tau)}{\mathbb{P}(\theta = 0 \mid s_{i1} = 1, s_{i2} = 0, \tau_i = \tau)} = \frac{1}{\eta_\tau}. \tag{3}$$

Thus η_τ measures the weight of new evidence relative to old evidence. We shall focus throughout on the case $\eta_H > \eta_L$, in which a conflicting new signal counts for relatively more in the hands of the high type. This relative-learning condition separates the types' responses to a conflict: although the high type is better informed in levels, it is the difference in relative improvement, rather than the level of precision, that determines who revises.

2.2 Timing and feasible feedback rules

The timing is:

(i) The platform commits publicly to a feedback policy π.

(ii) Nature draws the state and the experts' types. Each expert observes only her own type.

(iii) Each expert observes a first signal, and the experts simultaneously submit locked reports r_{A1} and r_{B1}.

(iv) Each expert observes a second signal. The platform observes the locked reports and sends B an interim message; A receives no peer feedback.

(v) Both experts submit terminal reports r_{A2} and r_{B2}.

(vi) The report histories and platform message become public. The downstream decision maker chooses an action before observing the state.

(vii) The state is revealed. The evaluator updates beliefs about the experts' types and pays competitive reputational wages.

Write

$$y = r_{A1}, \qquad b = r_{B1}, \qquad r_i^2 = (r_{i1}, r_{i2}). \tag{4}$$

The message space is $M = \{R_0, R_1, N\}$, where R_y reveals A's locked report and N records non-revelation at the interim stage. The platform commits before any signal is observed to

[6] With an asymmetric state prior, conflicting signals need not cancel under stationary precision, so the boundary observation in theorem 3.4 would require adjustment. The analysis below maintains the symmetric prior throughout.

$\pi = (\alpha, \delta) \in [0,1]^2$, where

$$\mathbb{P}_\pi(R_y \mid y = b) = \alpha, \qquad \mathbb{P}_\pi(R_y \mid y \neq b) = \delta. \tag{5}$$

Thus α governs disclosure after agreement and δ after disagreement. Denote this label-symmetric, one-way reveal-or-silence class by Π^{RS}. Sealing is $\mathsf{S} = (0,0)$, and full disclosure is $\mathsf{F} = (1,1)$.

The feasible class embodies three institutional restrictions. Initial forecasts are produced independently and cannot be rewritten; feedback flows only from A to B; and the platform can either reveal A's lodged report or record non-revelation. Label symmetry makes the rule depend on the relation between the reports rather than on whether the reported state is zero or one. These restrictions isolate the design of interim peer feedback; they are not a description of the unrestricted set of information structures, and they are not meant to be.[7]

2.3 Reputation and the design objective

After the state is revealed, expert i's competitive wage is her terminal reputation,

$$\rho_i = \mathbb{P}(\tau_i = H \mid r_A^2, r_B^2, m, \theta). \tag{6}$$

Normalizing the productivity of type L to zero and type H to one makes this posterior the competitive wage.[8] Experts receive no interim payment and no direct reward for matching the state. Their payoff is ρ_i.

Let

$$Z = (r_A^2, r_B^2, m) \tag{7}$$

be the public outcome observed before state revelation. A finite downstream decision problem is $D = (\mathcal{A}_D, u_D)$, where $\mathcal{A}_D$ is a finite action set and $u_D(a, \theta)$ is the payoff from action a in state θ. Given policy π and assessment σ, let $P_\theta^{\pi,\sigma}(z)$ be the probability of outcome z conditional on state θ. Its ex ante value is

$$V_D(\pi, \sigma) = \sum_z \max_{a \in \mathcal{A}_D} \left\{ \frac{1}{2} \sum_{\theta \in \{0,1\}} P_\theta^{\pi,\sigma}(z) u_D(a, \theta) \right\}. \tag{8}$$

The platform is evaluated by V_D. It does not directly choose the conditional distribution $P_\theta^{\pi,\sigma}$: that public experiment is generated jointly by the feedback rule and the experts' equilibrium reports. This separation between the policy instrument and the induced experiment is the central design constraint. The downstream action does not affect experts' wages and need not enter the evaluator's terminal information set.

[7] The restriction to Π^{RS} is accordingly a design choice rather than a without-loss-of-generality claim. The class excludes label-dependent rules, noisy or richer interim messages, and feedback from B to A. Each exclusion corresponds to something an organization plausibly cannot or will not do—a rule that treats the two states asymmetrically is difficult to justify to the experts, while garbling a colleague's report may be less transparent than withholding it—but the restriction is a modelling decision and the results should be read as conditional on it.

[8] A positive affine transformation of type-dependent productivity leaves every reporting incentive unchanged.

The exact result below uses symmetric state classification, $\mathcal{A}_D = \{0,1\}$ and $u_D(a,\theta) = \mathbf{1}\{a = \theta\}$, which is the natural benchmark when nothing is known about the asymmetry of the downstream stakes. The concealment-ray theorem, by contrast, applies to every finite D, and we shall be careful in section 5.4 to distinguish what has been proved for the general objective from what has been certified for this particular one.

2.4 Strategies, beliefs, and sequential equilibrium

Locked-report strategies condition on type and first signal. A's terminal strategy conditions on her type, private signals, and locked report; B's also conditions on the platform message:

$$\sigma_{i1}(\cdot \mid \tau_i, s_{i1}) \in \Delta(\{0,1\}), \tag{9}$$

$$\sigma_{A2}(\cdot \mid \tau_A, s_A^2, r_{A1}) \in \Delta(\{0,1\}), \tag{10}$$

$$\sigma_{B2}(\cdot \mid \tau_B, s_B^2, r_{B1}, m) \in \Delta(\{0,1\}). \tag{11}$$

Definition 2.1. *For a fixed policy, an assessment is a sequential equilibrium if reporting is sequentially optimal at every private history, terminal wages equal Bayesian posterior reputations, and beliefs are limits of Bayes-consistent beliefs induced by completely mixed reporting strategies.*

The downstream decision maker's posterior-optimal action is already taken into account by the maximization in eq. (8). Because the feedback rule depends on whether the lodged reports agree, an initial lie can change the disclosure lottery. Policy feasibility therefore requires both sequentially optimal continuation reporting and incentive compatibility of the lodged reports. All equilibrium verifications below include initial-report deviations and optimal continuations after them.

2.5 The maintained informative response

Before the design analysis can begin, the class of equilibria within which policies are to be compared must be fixed. As in every cheap-talk model, an uninformative equilibrium exists; here it exists under every policy, which is worth recording explicitly, since a design exercise is a comparison across policies and the reader is entitled to know that the comparison is conditional.

Proposition 2.2. *For every $\pi \in \Pi^{\mathrm{RS}}$, there is a sequential equilibrium in which each type of each expert chooses each report with probability $1/2$ at every private history, independently of signals and messages. Every wage equals ω, the public outcome is independent of the state, and symmetric state-classification accuracy is $1/2$.*

Proof. Signal-independent locked reports make the reports and platform message independent of the state and types. Uniform terminal randomization makes each complete history equally likely across types. Every terminal reputation is therefore ω, so every report is optimal. The reporting strategy is already completely mixed. At a policy boundary, mechanically impossible chance branches can be completed without affecting sequential rationality. □

Definition 2.3. *A sequential equilibrium under π is* regular-monotone *if:*

(i) both experts and both types report their first signals truthfully;

(ii) after confirming private signals, each expert repeats her locked report;

(iii) after conflicting private signals, the high type reports the second signal;

(iv) after conflicting private signals, the low type may mix label-symmetrically between the locked report and the second signal, assigning positive probability to the second signal;

(v) B's requirements in (ii)–(iv) apply at every positive-probability message branch, whereas A receives no peer feedback; and

(vi) behaviour following a locked-report deviation is unrestricted except by sequential rationality and consistency.

Two things should be said about this definition. The first is that regular monotonicity classifies equilibria; it does not narrow the deviation set. Every prescribed action below is tested against the full set of reporting deviations, and in particular truthful lodged reporting must survive deviations that change the feedback lottery itself—a point that matters here more than it usually does, because B can manipulate the disclosure probabilities through her first report. The second is that the equilibrium of theorem 2.2 is completely mixed, so that refinements which operate through beliefs after off-path actions have no purchase on it.[9] What follows is therefore a comparison of feedback rules within a maintained class of informative equilibria—the same step, taken for the same reason, as in the reputational cheap-talk literature from which the reporting problem is borrowed—and not a refinement or an implementation result.

3 Reputational response to peer feedback

What does a feedback rule actually do to an expert? It affects reporting only through the information available to B before she files her terminal forecast, and two quite different forces are bundled inside that information. A message changes the evidential support for B's locked forecast—this is the statistical force—while the anticipated reporting behaviour of each type determines the reputational return to standing by that forecast or abandoning it—this is the strategic force. The whole of this section is an attempt to separate them. The first force turns out to be summarized by a single message-specific likelihood ratio, and the second by a single endogenous wage ratio; comparing the two collapses the continuation problem to one dimension. The payoff is that sealing, revealed agreement, revealed disagreement, and randomized silence—four objects that look quite unlike one another—can afterwards be placed on the same scale and read off against each other.

[9] Appendix A records two attempts at selection that fail: a small accuracy stake, and a full-support perturbation of the terminal reporting technology. Neither eliminates the uninformative equilibrium while retaining an interior disciplinary policy, which is why we do not present regular monotonicity as a refinement.

3.1 Factorization and a one-dimensional revision cutoff

The reduction begins with a separation of the two experts' reputational problems, and this separation is what makes the rest of the analysis tractable. Because types and signals are independent across experts conditional on the state, peer feedback moves B's belief about the state without creating any direct reputational linkage between the two experts: A's report is evidence about θ for B, but it is not evidence about B for the evaluator.

Lemma 3.1. *For every committed policy $\pi \in \Pi^{\mathrm{RS}}$,*

$$\mathbb{P}(\tau_A = H \mid r_A^2, r_B^2, m, \theta) = \mathbb{P}(\tau_A = H \mid r_A^2, \theta), \tag{12}$$

$$\mathbb{P}(\tau_B = H \mid r_A^2, r_B^2, m, \theta) = \mathbb{P}(\tau_B = H \mid r_B^2, y, m, \theta). \tag{13}$$

Thus A faces the sealed-feedback problem. The policy affects B through her interim state belief and the message-contingent distribution of her report history.

Proof. Conditional on the state and types, the probability of a complete history factors into A's reporting likelihood, the policy lottery, and B's reporting likelihood. The latter two factors cancel from A's type odds. A's reporting factor cancels from B's type odds, and the policy probability carries no residual dependence on B's type after (y, b) is conditioned upon. □

The lemma has two consequences. First, A's reporting problem is independent of the feedback policy. Second, the message affects B's continuation incentives through her belief about the state and through the wage schedule generated by her own reporting behaviour. To characterize those incentives, assume temporarily that the locked reports are truthful. A's locked report then has accuracy

$$q = \omega p_{H1} + (1-\omega) p_{L1} > \frac{1}{2}, \qquad \gamma = \frac{q}{1-q} > 1. \tag{14}$$

Thus γ is the likelihood ratio conveyed by A's report in favour of the state it names. Conditional on the state, y is independent of B's type, so it changes B's state belief without directly changing the evaluator's prior odds of her ability.

Consider a positive-probability feedback branch. Suppose that, after conflicting private signals, the low type repeats her locked report with probability $h \in [0, 1)$, the high type follows the new signal, and both types repeat after confirmation. The parameter h is the low type's persistence probability at that branch.[10] Once the state is revealed, the evaluator can classify B's two reports by $\chi \in \mathcal{C} = \{CC, CI, IC, II\}$, where the first letter records whether the locked report is correct and the second whether the terminal report is correct. If $\ell_\tau^\chi(h)$ is the likelihood of pattern χ under type τ, the corresponding wage is

$$W_\chi(h) = \frac{\omega \ell_H^\chi(h)}{\omega \ell_H^\chi(h) + (1-\omega)\ell_L^\chi(h)}. \tag{15}$$

[10] Persistence here is an equilibrium response to career concerns, not a failure of Bayesian updating: after a conflict, the low type may rationally retain her locked forecast because the evaluator interprets report consistency as evidence of ability.

Define

$$G_C(h) = W_{CC}(h) - W_{CI}(h), \qquad G_I(h) = W_{IC}(h) - W_{II}(h), \qquad Q(h) = \frac{G_I(h)}{G_C(h)}. \tag{16}$$

These two gaps price the terminal choice at a conflict. If the locked report is correct, retaining it produces CC rather than CI, giving reputational gain $G_C(h)$. If the locked report is incorrect, revising produces IC rather than II, giving reputational gain $G_I(h)$. The correctness-pattern likelihoods and the corresponding Bayes calculations are reported in the Appendix B.

Let λ denote the likelihood ratio supplied by the feedback branch in favour of the state indicated by B's locked report. At a conflict, type τ's posterior odds in favour of that state are λ/η_τ. Her expected reputational gain from repeating rather than reversing is

$$\mathcal{G}_\tau(h;\lambda) = \frac{\lambda G_C(h) - \eta_\tau G_I(h)}{\lambda + \eta_\tau}. \tag{17}$$

Hence, on the interval where $G_C(h) > 0$, repeating is optimal precisely when $\lambda/\eta_\tau \geq Q(h)$. This is the organizing comparison for the section: λ measures the informational pressure exerted by the message, whereas $Q(h)$ measures the endogenous reputational price of changing the report. Because that price itself depends on the anticipated persistence probability, equilibrium requires a fixed point.

Lemma 3.2. *There is a unique $h^\dagger \in (0,1)$ with $G_C(h^\dagger) = 0$. On $[0, h^\dagger)$, G_C and G_I are positive and*

$$Q : [0, h^\dagger) \longrightarrow [Q_0, \infty), \qquad Q_0 = Q(0),$$

is continuous and strictly increasing. Let

$$\bar{\lambda} = \eta_L Q_0. \tag{18}$$

At a conflicting private history:

(i) if $\lambda \leq \bar{\lambda}$, the low type uses the second signal; at equality she is indifferent when $h = 0$;

(ii) if $\lambda > \bar{\lambda}$, there is a unique $h(\lambda) \in (0, h^\dagger)$ satisfying

$$Q(h(\lambda)) = \frac{\lambda}{\eta_L}; \tag{19}$$

(iii) if $\eta_H > \eta_L$, the high type strictly uses the second signal at both the pure and interior low-type solutions.

Proof. As h rises, low-type probability moves toward patterns CC and II and away from CI and IC. Consequently, W_{CC} and W_{II} fall, while W_{CI} and W_{IC} rise. Thus G_C decreases strictly and G_I increases strictly. At $h = 0$, both gaps are positive. As $h \uparrow 1$, W_{CI} converges to one whereas W_{CC}

remains below one, so G_C has a unique zero $h^\dagger$. It follows that Q is strictly increasing on $[0, h^\dagger)$ and diverges at its upper endpoint.

By eq. (17), low-type indifference is equivalent to $Q(h) = \lambda/\eta_L$. The range of Q gives (i) and (ii). At an interior low-type root, $\lambda/\eta_H < \lambda/\eta_L = Q(h)$ when $\eta_H > \eta_L$, so the high type strictly reverses. The same inequality applies at the pure solution. □

The cutoff has a direct reading, and it is the reading on which the design analysis will turn. Feedback with $\lambda \leq \bar{\lambda}$ is simply not favourable enough to the locked forecast to make persistence worth the low type's while after a conflict; above the cutoff, the equilibrium persistence probability climbs with the support the message lends that forecast. The high type revises throughout, not because she is more honest, but because her second signal is relatively more informative when $\eta_H > \eta_L$, so the same reputational price buys her less. It is worth pausing on what $\bar{\lambda}$ is: a threshold that the designer cannot move directly, since it is determined by the primitives, but that the designer can arrange for silence to straddle.

3.2 Sealing: the no-feedback benchmark

Under sealing, B receives no information about A's report. The neutral likelihood ratio $\lambda = 1$ therefore nests the no-feedback benchmark in the preceding cutoff calculation. An interior low-type persistence probability exists precisely when $\bar{\lambda} < 1$. Denote it by h^{S}; it is the unique solution of

$$Q(h^{\mathsf{S}}) = \frac{1}{\eta_L}. \tag{20}$$

Corollary 3.3. *Suppose $\bar{\lambda} < 1$ and $\eta_H > \eta_L$. Conditional on truthful locked reports, the sealed branch has a unique regular-monotone continuation: both types repeat after confirmation, the high type uses the second signal after a conflict, and the low type repeats the locked report with probability h^{S} after a conflict.*

Proof. Apply theorem 3.2 with $\lambda = 1$. Confirmation is strict because each signal is informative and the private signals agree. □

The separation between the types is driven by relative learning rates, and not by precision as such. At the wage schedule that leaves the low type indifferent, conflicting new evidence receives greater weight in the hands of the high type exactly when $\eta_H > \eta_L$. Differences in absolute precision do affect how the evaluator reads a report history, but on their own they do not deliver this strict separation—a point the next remark makes sharp by removing the relative difference entirely.

Remark 3.4. *If $p_{\tau 1} = p_{\tau 2}$ for both types, then $\eta_H = \eta_L = 1$. Under the symmetric state prior, two conflicting signals cancel for both types. At a common public history and wage schedule, one type cannot strictly retain the old report while the other strictly follows the new signal.*

3.3 Feedback messages on a common likelihood-ratio scale

Each possible feedback message can now be represented by its support for B's locked forecast. Revealed agreement supplies likelihood ratio γ, revealed disagreement supplies $1/\gamma$, and sealing supplies one. After non-revelation under $\pi = (\alpha, \delta)$, the likelihood ratio is

$$\lambda_N(\alpha, \delta) = \frac{q(1-\alpha) + (1-q)(1-\delta)}{(1-q)(1-\alpha) + q(1-\delta)}. \tag{21}$$

This ratio is the entire informational content of silence for B's continuation problem. Whenever silence has positive probability,

$$\lambda_N > 1 \iff \delta > \alpha, \qquad \lambda_N = 1 \iff \delta = \alpha.$$

If disagreement is disclosed more often than agreement, then non-revelation is favourable news about the locked forecast; reversing the disclosure ranking makes silence unfavourable news instead. The observation that matters most, however, is the last one: λ_N depends on the *relative* concealment rates after agreement and disagreement and not at all on their common scale. The designer thus has two margins that look like one—what silence says, and how often it is said—and section 4 is essentially the exploitation of that fact.

Under revealed agreement, define h^{F} by

$$Q(h^{\mathsf{F}}) = \frac{\gamma}{\eta_L}. \tag{22}$$

Because $\gamma > 1$, $h^{\mathsf{F}} > h^{\mathsf{S}}$: peer confirmation strengthens the low type's incentive to preserve her old forecast.

The conditions in the next proposition keep all message branches in a common, economically transparent region. The first two reproduce interior low-type persistence and strict high-type revision under sealing. The lower bound on γ makes low-type revision strict after revealed disagreement, while the upper bound ensures that a disagreeing peer report does not overturn two confirming private signals.

Proposition 3.5. *Suppose*

$$\bar{\lambda} < 1, \qquad \eta_H > \eta_L, \qquad \frac{1}{\eta_L Q_0} < \gamma < \frac{\kappa_{L1}\kappa_{L2}}{Q_0}. \tag{23}$$

Conditional on truthful locked reports, there is a unique regular-monotone continuation at every positive-probability feedback branch:

(i) both types repeat after confirming signals, and the high type uses the second signal after every conflict;

(ii) after revealed agreement, the low type repeats at a conflict with probability h^{F};

(iii) after revealed disagreement, the low type uses the second signal;

(iv) whenever silence has positive probability, the low type uses the second signal if $\lambda_N \leq \bar{\lambda}$*, and otherwise repeats with the unique* $h_N \in (0, h^\dagger)$ *satisfying*

$$Q(h_N) = \frac{\lambda_N}{\eta_L}. \tag{24}$$

At $\lambda_N = \bar{\lambda}$*, pure use of the second signal is optimal but weak.*

Proof. Theorem 3.2 gives every conflict decision. Revealed agreement sets $\lambda = \gamma$, revealed disagreement sets $\lambda = 1/\gamma$, and silence sets $\lambda = \lambda_N$. The lower bound on γ makes low-type revision strict after revealed disagreement. The upper bound preserves confirmation when the peer disagrees with two confirming private signals. Confirmations on the other branches follow from $\kappa_{L2} > 1$, and the high type's greater signal precisions preserve strictness. Uniqueness is within regular monotonicity and conditional on truthful locked reports. □

Selective feedback therefore operates on behaviour and not merely on beliefs. Revealed agreement raises low-type persistence; revealed disagreement induces revision; and the composition of the silent pool decides which of these two responses silence itself elicits. The platform, by choosing its disclosure probabilities, is choosing how often each of these distinct reporting environments arises—which is a rather different instrument from the one a persuader ordinarily holds, since the platform is buying behaviour with frequencies rather than selecting a posterior.

For a positive-probability silence branch, set $h_N = 0$ when $\lambda_N \leq \bar{\lambda}$, and otherwise let h_N denote the root in eq. (24). For the equilibrium and design calculations below, the message-contingent wage after correctness pattern χ can then be written compactly as

$$\widetilde{W}_\chi(m, y, b) = \begin{cases} W_\chi(h^{\mathsf{F}}), & m = R_y \text{ and } y = b, \\ W_\chi(0), & m = R_y \text{ and } y \neq b, \\ W_\chi(h_N), & m = N. \end{cases} \tag{25}$$

Although y is eventually released, it is conditionally independent of B's type once (θ, b) is fixed. It changes B's interim state belief but does not add a type-dependent term to eq. (25).

3.4 From continuation behaviour to equilibrium feasibility

Everything so far has been conditioned on truthful locked reports, and that condition is anything but innocuous. By lying at the lodged-report stage, B can change whether the two reports agree, and in doing so she changes both the feedback lottery she faces and the information she will subsequently receive. An expert who expects silence to be bad news for her forecast has a motive to manufacture agreement. Continuation optimality alone therefore establishes nothing about equilibrium feasibility, and the constraints introduced next are not a formality: at the exact profile of section 5 they are

checked by explicit enumeration, and it is precisely because they bind on part of the policy square that the feasible boundary can fall strictly inside it.

For each policy, let $\widehat{\sigma}^{\pi}$ be the candidate consisting of truthful locked reports, A's sealed continuation, B's message-contingent continuation, and an optimal terminal report at every private history following a locked-report deviation. At zero-probability chance branches, choose any sequentially optimal consistent completion; it does not affect the induced public experiment.

Let $V_{B\tau}^{T,\pi}$ be B's value from truthfully lodging her first signal and following the candidate. Let $V_{B\tau}^{D,\pi}$ allow her to lie, thereby changing the agreement status and feedback lottery, and then choose an optimal terminal report after every resulting history. Define

$$\Delta_{B\tau}^{\pi} = V_{B\tau}^{T,\pi} - V_{B\tau}^{D,\pi}. \tag{26}$$

The deviation value optimizes B's terminal report after every history generated by the lie; it does not hold her continuation behaviour fixed. Label symmetry supplies the same constraint after either first signal. By theorem 3.1, A's incentive problem is policy-independent; write $\Delta_{A\tau}^{\mathsf{S}}$ for her sealed truthful-report slack.

Let $\Pi^{\mathrm{C}} \subseteq \Pi^{\mathrm{RS}}$ contain the policies for which all positive-probability branches satisfy the continuation conditions of theorem 3.5. Define

$$\Pi^{\mathrm{RM}} = \left\{ \pi \in \Pi^{\mathrm{C}} : \Delta_{A\tau}^{\mathsf{S}} \geq 0 \text{ and } \Delta_{B\tau}^{\pi} \geq 0 \text{ for } \tau \in \{L, H\} \right\}. \tag{27}$$

For $\pi \in \Pi^{\mathrm{RM}}$, write $V_D^{\pi} = V_D(\pi, \widehat{\sigma}^{\pi})$ for the induced regular-monotone equilibrium value. Appendix B gives the generic finite deviation sums.

Proposition 3.6. *For every $\pi \in \Pi^{\mathrm{RM}}$, the candidate $\widehat{\sigma}^{\pi}$, together with Bayesian terminal wages and sequentially optimal continuations following locked-report deviations, is a regular-monotone sequential equilibrium. If all four locked-report slacks are strict, both types of both experts lodge their first signals strictly truthfully.*

Proof. Theorem 3.5 supplies terminal optimality at all on-path branches. The maximizations defining deviation values supply terminal optimality after a locked-report lie. The four nonnegative slacks give optimality at the locked-report stage. Bayes' rule gives on-path wages, and the positive-probability correctness patterns admit consistent beliefs. □

We should be clear about what this proposition does and does not deliver. It establishes informative behaviour within the maintained class; it neither removes policy-independent babbling nor ranks policies over the unrestricted equilibrium correspondence. Within the class, however, the continuation problem has been made one-dimensional—a branch's likelihood ratio fixes both its reporting response and its wage schedule—and what is left of the design problem is a question about frequencies: how often should the platform generate each branch, subject to keeping the locked reports truthful? That is the question section 4 answers.

4 Designing selective feedback

Section 3 reduced B's continuation problem to a single number: the likelihood ratio supplied by whichever feedback branch she finds herself on. The platform, however, chooses two disclosure probabilities, one after agreement and one after disagreement, and these two numbers jointly determine two quite different things—what the silent pool is made of, and how often silence occurs. The main result of this section is that these two design margins can be separated cleanly. Once separated, the problem becomes tractable. Randomization is what allows silence to conceal anything at all; policies sharing the composition of silence then lie along rays on which reporting behaviour is frozen and only branch frequencies move; and value is affine along those rays. The candidate search consequently collapses onto two boundary families and full disclosure. One of those boundaries contains a threshold at which non-revelation becomes just unfavourable enough to eliminate low-type persistence altogether, and it is this disciplinary threshold that the exact analysis of section 5 singles out.

4.1 Why selective feedback requires randomization

For feedback to be selective in any meaningful sense, B must remain uncertain about A's lodged report after at least one message. With binary reports this is a surprisingly demanding requirement, because any deterministic disclosure of one relational category renders the other perfectly inferable from silence: an expert who knows her own report and knows the rule has nothing left to be uncertain about.

Lemma 4.1. *With binary locked reports, every policy $\pi = (\alpha, \delta) \in \Pi^{\mathrm{RS}}$ satisfying $\alpha = 1$ or $\delta = 1$ gives B the same interim information about A's locked report as full disclosure. Under the regular-monotone candidate, it consequently induces the same reporting behaviour and the same value for every downstream decision problem as full disclosure.*

Proof. If $\alpha = 1$, silence implies disagreement. Since reports are binary and B knows b, she infers $y = 1 - b$. If $\delta = 1$, silence implies agreement and hence $y = b$. A revealed message identifies y directly. B therefore knows y after every message in either case, and candidate behaviour coincides with full disclosure. Once (y, b) is fixed, any residual policy lottery is independent of the state and types and merely partitions an otherwise identical public outcome. Such a state-independent partition leaves every posterior decision value unchanged. □

Deterministic agreement-only or disagreement-only disclosure is therefore not selective in informational terms, whatever it may look like from the outside. To pool agreement and disagreement behind a single silent message the platform must conceal each of them with positive probability. Randomization is thus necessary—but it is not sufficient, since equal concealment rates leave silence uninformative and simply reproduce sealed incentives on the silent branch. The instrument lives strictly between these two failures.[11]

[11] The necessity result uses binary lodged reports and the restricted reveal-or-silence technology, and both matter.

4.2 Concealment rays

To separate the composition of silence from its frequency, write the probabilities of concealing agreement and disagreement as

$$c_A = 1 - \alpha, \qquad c_D = 1 - \delta. \tag{28}$$

Whenever silence has positive probability,

$$\lambda_N(c_A, c_D) = \frac{qc_A + (1-q)c_D}{(1-q)c_A + qc_D}. \tag{29}$$

Only the ratio c_A/c_D matters. For every $(c_A, c_D) \neq (0,0)$, write

$$(c_A, c_D) = t(\bar{c}_A, \bar{c}_D), \qquad t = \max\{c_A, c_D\}, \qquad \max\{\bar{c}_A, \bar{c}_D\} = 1. \tag{30}$$

The normalized pair $(\bar{c}_A, \bar{c}_D)$ fixes the composition of the silent pool, while $t \in (0,1]$ is the scale of concealment. The normalized endpoint lies on either $\alpha = 0$ or $\delta = 0$, and the origin is full disclosure.

The reduction is first stated for the candidate assessment constructed in section 3.4, whether or not its locked-report constraints hold. Let $\widehat{P}^{\pi}_{\theta}(z)$ be the resulting probability of public outcome z conditional on state θ, and let $\widehat{V}^{\pi}_{D}$ be the value obtained by replacing $P^{\pi,\sigma}_{\theta}$ with $\widehat{P}^{\pi}_{\theta}$ in eq. (8). On Π^{RM}, the candidate is an equilibrium and $\widehat{V}^{\pi}_{D} = V^{\pi}_{D}$; outside that set, the hatted value is only a comparison device. In the theorem below, $\widehat{V}_D(c_A, c_D)$ is shorthand for the candidate value under policy $(1 - c_A, 1 - c_D)$.

The following theorem is the main general design result. It applies to every finite downstream decision problem rather than only to the classification objective studied in section 5.

Theorem 4.2. *Fix primitives for which the candidate continuation is defined on* Π^{RS}. *For every concealment ray and every finite downstream decision problem* D,

$$\widehat{V}_D(t\bar{c}_A, t\bar{c}_D) = (1-t)\widehat{V}_D(0,0) + t\widehat{V}_D(\bar{c}_A, \bar{c}_D), \qquad t \in [0,1]. \tag{31}$$

Moreover:

(i) each of B's locked-report incentive slacks is affine in t*;*

(ii) each of A's locked-report incentive slacks is constant in t*; and*

(iii) a global candidate maximizer over Π^{RS} *can be selected from full disclosure and the two policy boundaries* $\alpha = 0$ *and* $\delta = 0$.

Proof. Along a ray, the ratio c_A/c_D, and hence λ_N, is constant. Theorem 3.5 then implies that the silent-branch strategy and wage schedule are fixed. Each silent public outcome has probability t times

With richer report or message spaces an intermediary could manufacture partial revelation in other ways—by garbling the peer report, for instance, rather than withholding it—and the necessity of randomization would then be an artefact of the technology rather than a feature of the problem.

its probability at the normalized endpoint. A revealed-agreement outcome has the state-independent frequency factor

$$1 - t\bar{c}_A = (1 - t) + t(1 - \bar{c}_A),$$

and a revealed-disagreement outcome has the analogous factor $1 - t\bar{c}_D$. Thus the two-state likelihood vector attached to each public outcome is multiplied by a nonnegative scalar that is affine in t. The optimized contribution of an outcome to a finite decision problem is homogeneous of degree one in that vector. Summing gives eq. (31).

The same scaling applies to B's payoff from a truthful locked report. After a locked-report lie, each private history and message generates a conditional payoff vector multiplied by one of the same nonnegative factors. Relative state weights within that vector are fixed along the ray, so an optimal terminal report following the lie does not switch with t. The deviation value and locked-report slack are therefore affine. A's slack is policy-independent by theorem 3.1. Finally, an affine function on a ray is maximized at the origin or normalized endpoint; taking the union over rays gives the candidate boundary reduction. □

One caveat should be attached to the boundary conclusion, since it is easy to over-read. The conclusion concerns the complete candidate experiment and not the feasible equilibrium set. Along a ray the intersection with Π^{RM} is an interval—possibly empty—because every locked-report constraint is affine in t; and if some constraint binds before the policy boundary is reached, then the feasible endpoint lies strictly inside the policy square. An infeasible candidate boundary policy cannot be substituted for that endpoint in the equilibrium design problem. In short, the theorem tells us where to look, and feasibility tells us how far along that line we are permitted to walk.

Corollary 4.3. *Let $\pi^* \in \Pi^{\mathrm{RM}}$. If*

$$\widehat{V}_D^{\pi^*} \geq \widehat{V}_D^{\pi} \qquad \textit{for every } \pi \in \Pi^{\mathrm{RS}},$$

then π^* maximizes the regular-monotone equilibrium value over Π^{RM}. If the candidate inequality is strict away from π^*, the regular-monotone maximizer is unique.

Proof. Candidate and equilibrium values coincide on Π^{RM}. □

It is worth restating the content of the theorem in words, because the statement is more mechanical than the idea. A concealment ray holds fixed what silence means and varies only how often it is heard. The platform may therefore be thought of as choosing the composition of the silent pool first and its scale second; and once the composition has been chosen, continuation behaviour, downstream value, and initial-report incentives all move affinely in the scale. All of the nonlinearity in the design problem is thus confined to the composition choice, which is exactly what the two boundary families parameterize. This is the sense in which a two-dimensional problem has been made one-dimensional without approximation.

4.3 Disciplinary silence

One boundary has a particularly transparent behavioural role. Consider $\delta = 0$, on which disagreement is never revealed. Increasing α selectively removes agreements from the silent pool and thereby makes silence less favourable to B's locked forecast. Its likelihood ratio is

$$\lambda(\alpha) = \frac{1 - q\alpha}{1 - (1 - q)\alpha}. \tag{32}$$

It decreases continuously from one under sealing to $1/\gamma$ at $\alpha = 1$. The continuation conditions imply $1/\gamma < \bar{\lambda} < 1$. There is consequently a unique interior agreement-disclosure probability at which silence reaches the low type's pure-revision threshold:

$$\alpha^{\mathrm{DS}} = \frac{1 - \bar{\lambda}}{q - (1 - q)\bar{\lambda}} = \frac{1 - \eta_L Q_0}{q - (1 - q)\eta_L Q_0}. \tag{33}$$

The mechanism deserves to be stated plainly. The platform never reveals disagreement, yet B cannot tell whether any particular silence is hiding a disagreement or an agreement that simply went unrevealed; and it is this ambiguity, deliberately manufactured, that the designer prices. At α^{DS}, just enough favourable observations have been withdrawn from the silent pool to make non-revelation unfavourable enough to extinguish the low type's reputational inertia on that branch. Further agreement disclosure no longer changes the silent-branch response; whether it is valuable then depends on the downstream objective.

Proposition 4.4. *Suppose the conditions of theorem 3.5 hold and $\pi^{\mathrm{DS}} = (\alpha^{\mathrm{DS}}, 0) \in \Pi^{\mathrm{RM}}$. Then:*

(i) silence satisfies $\lambda_N = \bar{\lambda}$;

(ii) after silence, the low type is indifferent and uses the second signal, while the high type strictly uses the second signal at a conflict;

(iii) after revealed agreement, the low type retains the locked report with probability h^{F} at a conflict, while the high type uses the second signal;

(iv) all confirmation actions are strict; and

(v) together with truthful locked reports, these strategies form a regular-monotone sequential equilibrium.

Proof. Substituting α^{DS} into eq. (32) gives $\lambda_N = \bar{\lambda}$. Theorem 3.2 makes $h_N = 0$ optimal for the low type, weakly, and high-type revision strict. Theorem 3.5 gives behaviour after revealed agreement and all confirmation choices. Membership in Π^{RM} supplies the locked-report incentives. □

The policy thus manufactures two distinct reporting environments out of a single instrument. Revealed agreement sustains low-type persistence; silence induces both types to follow their second signal after a conflict. This separation is achieved entirely through the informational content of

non-revelation—the platform issues no instruction, pays no bonus, and indeed possesses no means of doing either.

At the threshold, the low type's silent-conflict action is weak. Choosing $\alpha^{\mathrm{DS}} + \varepsilon$ makes revision strict, and candidate decision value converges to its threshold value as $\varepsilon \downarrow 0$.

For reduced-form interpretation, let $r = \bar{\lambda}$ and $D_\alpha = q-(1-q)r$. Holding the other reduced-form object fixed,

$$\frac{\partial \alpha^{\mathrm{DS}}}{\partial q} = -\frac{1-r^2}{D_\alpha^2} < 0, \qquad \frac{\partial \alpha^{\mathrm{DS}}}{\partial r} = \frac{1-2q}{D_\alpha^2} < 0. \tag{34}$$

A more informative peer report, or a higher low-type revision threshold, requires less revealed agreement to make silence disciplinary. Since q and r are functions of the primitives, these are mechanical reduced-form comparisons, not primitive comparative statics.

Disciplinary silence identifies a behavioural threshold, not an objective-free optimum. Whether downstream value peaks there depends on the decision problem and the primitives. The next section shows that the threshold is the unique global candidate optimum for symmetric state classification at one exact rational profile, verifies equilibrium feasibility, and then examines robustness and objective dependence.

5 Exact optimality, robustness, and objective dependence

The concealment-ray theorem reduces candidate policy design to two boundary families and full disclosure, but it does not say which boundary a given downstream objective prefers, and it cannot: that comparison is genuinely nonlinear. We therefore specialize to symmetric state classification and exhibit an exact profile at which the disciplinary-silence threshold is the unique global candidate optimum. Computer assistance enters only after the analytical reduction has been carried out, and only to certify two one-dimensional boundary comparisons—the structure of the problem is proved by hand, and the machine is asked a finite question with a rational answer.[12]

5.1 The exact profile and classification objective

A Bayesian decision maker observes the complete public outcome and guesses the state. Candidate classification accuracy is

$$\widehat{\mathcal{A}}^{\pi} = \frac{1}{2}\sum_{z} \max\{\widehat{P}_0^{\pi}(z), \widehat{P}_1^{\pi}(z)\}. \tag{35}$$

On Π^{RM}, write $\mathcal{A}^{\pi}$ for the corresponding regular-monotone equilibrium value.

Set $\omega = 2/5 = 0.4$. The profile has three relevant features. Both types receive a more accurate second signal, so retaining the first forecast after a conflict sacrifices current information. The

[12] By "computer-assisted" we mean that finite root-count, sign, and interval claims are certified in exact rational arithmetic: the theorem does not rest on a floating-point grid search, and every quantity reported below is either a rational number or a rational enclosure of one.

Table 1: Exact rational profile

primitive	low type	high type
first-signal precision	$p_{L1} = 11/20 = 0.55$	$p_{H1} = 33/40 = 0.825$
second-signal precision	$p_{L2} = 5/8 = 0.625$	$p_{H2} = 19/20 = 0.95$

improvement is much stronger for the high type:

$$\eta_L = \frac{15}{11} \approx 1.364, \qquad \eta_H = \frac{133}{33} \approx 4.030.$$

High ability is also the minority type. A truthful peer report has accuracy $q = 0.66$, so peer feedback is informative but imperfect. The fractions are selected so that every comparison can be verified exactly; they are not estimates and should not be read as an empirical calibration. The improvement in the high type's second-signal precision is deliberately pronounced, which is what makes the local robustness and sensitivity qualifications below worth taking seriously rather than treating as boilerplate.

At this profile,

$$q = \frac{33}{50}, \qquad \gamma = \frac{33}{17}, \qquad Q_0 = \frac{202419}{394279}, \qquad \bar{\lambda} = \frac{3036285}{4337069} \approx 0.7001. \tag{36}$$

The continuation inequalities in theorem 3.5 hold strictly, and the disciplinary threshold is interior.

5.2 Computer-assisted exact optimality

At the exact profile the disciplinary threshold is itself rational, which is a convenience but not the point. The point is the coincidence recorded in the theorem below: the policy that solves the classification problem is not some unrelated numerical maximizer that happens to sit in the interior, but exactly the behaviourally defined threshold at which silence stops sustaining the low type's inertia. The optimum, in other words, is the point at which the instrument does the thing it was built to do.

Theorem 5.1. *At the exact profile in table 1, let*

$$\pi^* = \pi^{\mathrm{DS}} = (\alpha^*, 0), \qquad \alpha^* = \alpha^{\mathrm{DS}} = \frac{2032475}{2859576} \approx 0.710760966. \tag{37}$$

Then:

(i) $\pi^* \in \Pi^{\mathrm{RM}}$*, and both types of both experts lodge their first signals strictly truthfully;*

(ii) π^* *uniquely and globally maximizes candidate classification accuracy over* Π^{RS}*; and*

(iii) consequently, π^* *is the unique maximizer of regular-monotone equilibrium accuracy over* Π^{RM}*.*

Table 2: Classification values at the exact profile

policy	feedback rule	low-type conflict response	accuracy
Sealing S	no peer report is revealed	repeats with $h^{\mathsf{S}} \approx 0.2243$	0.778347
Full disclosure F	every peer report is revealed	repeats with $h^{\mathsf{F}} \approx 0.5379$ after agreement; revises after disagreement	0.789032
Disciplinary silence π^*	reveal agreement with probability α^*; never reveal disagreement	revises after silence; mixes only after revealed agreement	0.792049

Disciplinary silence improves classification accuracy by approximately 1.3702 percentage points over sealing and by 0.3017 over full disclosure. The second of these gains is strict but quantitatively modest, and we would rather say so than not.[13]

Proof. The concealment-ray reduction is analytical. The remaining exact certificate proceeds as follows.

(1) Exact rational brackets isolate the sealed and revealed-agreement roots:

$$h^{\mathsf{S}} \approx 0.2243083282, \qquad h^{\mathsf{F}} \approx 0.5379129780.$$

(2) Exact enumeration of terminal actions and every locked-report deviation verifies all four strict first-report inequalities. A deviation by B is allowed to change the feedback lottery, after which she chooses an optimal terminal report at every resulting private history and message.

(3) Theorem 4.2 reduces the candidate comparison over the policy square to full disclosure and the boundaries $\delta = 0$ and $\alpha = 0$.

(4) On $\delta = 0$, exact outcome-gap factorization identifies the sole behavioural kink at $\alpha^* = \alpha^{\mathrm{DS}}$. Candidate classification value has a strictly positive left derivative and a strictly negative right derivative there. Beyond the kink, convexity reduces the remaining comparison to α^* and full disclosure.

(5) On $\alpha = 0$, candidate value is monotone between the polar protocols. Exact Sturm sequences certify the relevant root counts, action regions, and derivative signs.

(6) The strict global candidate comparison, together with $\pi^* \in \Pi^{\mathrm{RM}}$, gives the equilibrium conclusion through theorem 4.3.

Appendices C and D report the rational brackets, exact payoff intervals, outcome-gap factorizations, one-sided derivative bounds, and Sturm-variation counts. □

[13]The comparison against full disclosure is the demanding one, and it is the one that should be read as the paper's quantitative claim. Its size is not the contribution: what the certificate establishes is that the interior policy is *uniquely* optimal and that the optimum sits exactly at the behavioural threshold, which is a statement about the structure of the design problem rather than about the magnitude of the prize. The one-at-a-time diagnostics of Section OA.5 place the gain between roughly 0.15 and 0.52 percentage points across the perturbations considered, always with the same sign.

It is worth recording how much room the incentive constraints leave. The smallest locked-report slack across both experts and both types exceeds 0.01931, and for B alone the lower bound exceeds 0.02050. Exact optimality is thus not obtained by quietly ignoring B's ability to manipulate the feedback lottery through her lodged report—the deviation is available, its value is computed, and it loses. The low type is indifferent at a silent conflict at the threshold and, as required for mixing, after revealed agreement. All locked-report actions, all high-type conflict actions, and all confirmation actions satisfy the strict conditions reported in the Appendix.

5.3 Open-set robustness and sensitivity

Proposition 5.2. *Let*

$$\xi = (\omega, p_{L1}, p_{L2}, p_{H1}, p_{H2})$$

collect the primitives and let ξ^0 be the exact profile. There is an open neighborhood U of ξ^0, relative to the maintained parameter region, such that for every $\xi \in U$, the recalibrated disciplinary policy

$$\pi^{\mathrm{DS}}(\xi) = (\alpha^{\mathrm{DS}}(\xi), 0)$$

belongs to Π^{RM}, makes all four locked reports strictly truthful, and is the unique global maximizer of candidate classification accuracy over Π^{RS}. It is consequently the unique regular-monotone equilibrium maximizer over Π^{RM} and strictly outperforms sealing and full disclosure.

Proof. At ξ^0, the low-type indifference roots are simple; the four first-report margins, all high-type conflict margins, and all confirmation margins are strict; the relevant public-outcome likelihood gaps are nonzero; and the one-sided slopes at the disciplinary kink have strict signs. The roots and recalibrated threshold therefore vary continuously, locally smoothly, with the primitives. The surrounding action regions and local peak persist nearby. Outside a small neighborhood of the threshold, compactness and the exact strict global comparison supply a uniform value gap, which also persists under a sufficiently small perturbation. □

The proposition is qualitative: it asserts that a neighbourhood exists without identifying its radius, and we make no claim beyond that. Section OA.5 reports one-at-a-time diagnostics. Across those perturbations, the recalibrated policy remains equilibrium-feasible, strictly beats both polar protocols, and is a strict local classification peak. The minimum locked-report slack remains above 0.0126. At the same time, α^{DS} ranges from approximately 0.56 to 0.85, and the gain over full disclosure ranges from approximately 0.15 to 0.52 percentage points. The mechanism, in other words, is locally stable while its quantitative prescription is not: an organization could be confident that some agreements should be revealed and that no disagreements should be, and quite unable to say whether the right figure is a half or five sixths without knowing its primitives rather precisely. The non-baseline rows are local diagnostics and do not carry new global Sturm certificates.

5.4 Dependence on the downstream decision problem

A classification-optimal feedback rule is not the same thing as an objectively most informative experiment, and conflating the two would overstate what has been proved. Following Blackwell (1953), we compare the complete equilibrium experiments by asking whether one of them yields weakly greater value in *every* finite downstream decision problem. Two cautions attach to this comparison. It is an ex post comparison of experiments induced in equilibrium; and it does not license the reading that the platform selects an experiment about the state, since what the platform selects is report-contingent interim feedback, which then changes the experts' subsequent behaviour.

For $k \in (0,1)$, define the posterior call value

$$C^{\pi}(k) = \frac{1}{2} \sum_{z} \left[(1-k) P_1^{\pi}(z) - k P_0^{\pi}(z) \right]_+ . \tag{38}$$

This is the value of a binary decision problem in which action 1 yields $1-k$ in state 1 and $-k$ in state 0, while action 0 yields zero. At $k = 1/2$,

$$\mathcal{A}^{\pi} = \frac{1}{2} + 2C^{\pi}(1/2).$$

Proposition 5.3. *At the exact profile, the complete regular-monotone equilibrium experiments generated by sealing and full disclosure are Blackwell incomparable.*

Proof. Exact rational interval evaluation gives:

cutoff k	$C^{\mathsf{F}}(k) - C^{\mathsf{S}}(k)$	preferred experiment
1/10	approximately -0.0023336	sealing
1/2	approximately 0.0053426	full disclosure

If either experiment Blackwell dominated the other, it would have weakly higher value in every decision problem. The strict ranking reversal proves incomparability. Appendix F gives exact sign intervals. □

The exact optimality theorem is therefore objective-specific, and deliberately so. Even the two polar protocols—sealing and full disclosure, the two arrangements an organization would most naturally consider—cannot be ranked without first specifying what the downstream decision problem is. This rules out any universal presumption for or against interim transparency, which is a useful negative result in a literature that has sometimes been read as supplying one.[14]

[14] It does not, by itself, establish that the optimizer *within* the selective-policy class changes with the loss function, and we make no such claim: the incomparability is demonstrated between the two polar protocols, which is enough to defeat a universal ranking but not enough to characterize how the interior optimum moves.

6 Conclusion

How should a committed intermediary design interim peer feedback once experts have produced independent, locked forecasts? The answer offered here has a definite shape, and it is worth separating what is established from what is maintained.

What is established is a piece of geometry. Randomization is what allows silence to pool agreement and disagreement, and pooling is what gives non-revelation a likelihood ratio of its own; a concealment ray then holds that ratio fixed—holding fixed what silence means and how B responds to it—while varying only how often silence occurs. It is shown that along such a ray the candidate value of every finite downstream decision problem is affine, as are the locked-report incentive slacks, so that a two-dimensional design problem reduces without approximation to full disclosure and two one-dimensional boundaries. This reduction is exact, it is analytical, and it does not depend on the particular finite downstream objective. For symmetric state classification at the exact rational profile, the unique optimum within the maintained class never reveals disagreement and reveals just enough agreement to eliminate low-type persistence after silence—and it strictly improves on both polar protocols, although the margin over full disclosure is modest. The optimum survives on an open set of nearby primitives, even though the optimal disclosure probability itself is quantitatively sensitive.

This result is not the one common sense proposes. Faced with two experts and a wish to aggregate their information, an organization would naturally consider showing each of them the other's work, or keeping them apart, and would think of anything intermediate as a compromise between the two. The model says something different: the interior is not a compromise but the only place where the instrument exists at all. A rule that always reveals and a rule that never reveals both leave silence mute, and a mute silence changes nobody's behaviour. It is precisely by concealing *sometimes* that an organization acquires a second message, and the design problem is the problem of deciding what that message should say.

What is maintained, and should be stated once more, is the equilibrium selection. Every reveal-or-silence policy admits a completely mixed babbling equilibrium, so unrestricted sequential equilibrium ranks no policies against any others; the analysis proceeds within a regular-monotone class in which reports remain informative. This maintained class parallels the treatment of informative equilibria in the reputational cheap-talk literature, but it remains an equilibrium selection—not a refinement, and not an implementation result—and the policy conclusions inherit that qualification.[15]

Nor is the ranking universal. Sealing and full disclosure are Blackwell incomparable, so their order can reverse with the downstream decision problem, and no general presumption in favour of interim opacity is available.

The institutional lesson is accordingly narrower than either "transparency is beneficial" or "secrecy is beneficial," and rather more useful than both. By committing to a report-contingent lottery, an organization can turn non-revelation into an active signal and use it to change how

[15]Two natural attempts to convert the selection into a refinement are recorded in the Appendix A and both fail within this technology, which is the honest reason for maintaining the class rather than deriving it.

reputationally motivated experts respond to new evidence—without paying them, instructing them, or seeing their signals. Whether richer message spaces, two-way feedback, or endogenous institutional features might also select the informative equilibrium is left open here, and seems to us the most promising direction in which this analysis could be extended. Within the present model, carefully designed silence disciplines revision—under the maintained regular-monotone response, and only there.

A Unrestricted multiplicity and failed selection

This section supplies the counterexamples behind the qualification maintained throughout the main text. The first two are constructed in the unperturbed game. The remaining results ask a question that any reader will ask, namely whether some small and natural perturbation—a modest payment for accuracy, or a little type-independent noise in the recording of reports—would select the regular-monotone outcome and so convert the maintained class into a derived one. Within the present technology, neither does.

A.1 Two policy-independent equilibria

Proposition A.1. *For every reveal-or-silence policy, there is a sequential equilibrium in which both types of both experts choose each report with probability* $1/2$ *at every information set, independently of signals and messages. Every terminal wage equals* ω *and the state-classification value is* $1/2$*.*

Proof. Every complete report history has the same conditional likelihood under types H and L. Locked reports are independent of the state, and the platform message is generated only from these reports and the committed policy. Consequently, the message is also independent of the state and types. Bayes' rule assigns wage ω to each expert after every positive-probability history. Every report is therefore optimal. The reporting strategy is already completely mixed, so no off-path wage supports the equilibrium. □

There is also an informative but nonregular policy-independent equilibrium. Define the reputations attached to a correct and an incorrect first report by

$$W_C^{(1)} = \frac{\omega p_{H1}}{\omega p_{H1} + (1-\omega) p_{L1}}, \qquad W_I^{(1)} = \frac{\omega(1-p_{H1})}{\omega(1-p_{H1}) + (1-\omega)(1-p_{L1})}. \tag{39}$$

Proposition A.2. *For every reveal-or-silence policy, there is a sequential equilibrium in which both experts report their first signals truthfully and every type subsequently repeats the locked report, independently of the second signal and the platform message.*

Proof. On path, a correct first report produces pattern CC and an incorrect first report produces II, with wages in eq. (39). Consider a sequence of completely mixed terminal strategies in which a high type's probability of a revision history vanishes faster than a low type's probability at every

private history. The limiting wages after CI and IC are then zero. If x is the expert's probability that her first report is correct, repetition rather than reversal has the strictly positive gain

$$xW_C^{(1)} + (1-x)W_I^{(1)} > 0. \tag{40}$$

Given subsequent repetition, reporting the first signal rather than its opposite has gain

$$(2p_{\tau 1} - 1)(W_C^{(1)} - W_I^{(1)}) > 0. \tag{41}$$

Conditional independence makes the same construction valid for both experts and every platform message. The specified tremble sequence supplies consistent beliefs. □

These two constructions do rather different work. The completely mixed equilibrium explains why off-path belief refinements cannot solve the selection problem: there are no off-path events for them to operate on. The full-repetition equilibrium makes a second and less obvious point—that even truthful locked reporting is not enough to render the disclosure policy behaviourally relevant, since an expert who never revises has no use for information about her peer.

A.2 A small accuracy stake does not select

Consider the perturbed payoff

$$U_i = \rho_i + \varepsilon_1 \mathbf{1}\{r_{i1} = \theta\} + \varepsilon_2 \mathbf{1}\{r_{i2} = \theta\}, \qquad \varepsilon_1, \varepsilon_2 \geq 0. \tag{42}$$

Any $\varepsilon_2 > 0$ destroys the uniform babbling profile because terminal reports then respond to the expert's state posterior. It does not destroy full repetition.

Proposition A.3. *If $0 \leq \varepsilon_2 < W_I^{(1)}$, the full-repetition equilibrium in theorem A.2 persists for every policy and every $\varepsilon_1 \geq 0$.*

Proof. Using the same limiting off-path wages, the gain from repetition at a terminal history is

$$x(W_C^{(1)} + \varepsilon_2) + (1-x)(W_I^{(1)} - \varepsilon_2) > 0 \tag{43}$$

for every $x \in [0,1]$. Truthful first reporting has gain

$$(2p_{\tau 1} - 1)(W_C^{(1)} - W_I^{(1)} + \varepsilon_1 + \varepsilon_2) > 0. \tag{44}$$

□

At the exact profile used in the paper,

$$W_C^{(1)} = \frac{1}{2}, \qquad W_I^{(1)} = \frac{7}{34}. \tag{45}$$

Thus every small accuracy stake of the kind one would contemplate as a local perturbation leaves a policy-independent equilibrium intact. The reason is worth noting: a stake large enough to break full repetition need no longer be a local perturbation; it materially changes the expert's objective and therefore the problem being studied.

A.3 Full support does not repair the problem

Suppose an expert chooses an intended terminal report $\widehat{r}_2$, which is recorded correctly with probability $1-\zeta$ and flipped with probability $\zeta \in (0, 1/2)$, independently of types, signals, messages, and the policy. The terminal accuracy payment in eq. (42) is based on the recorded report. Let c_τ be the probability of intending to repeat after confirming signals, and let h_τ be the probability of intending to repeat after a conflict. For type τ, define

$$u_\tau = \zeta + (1-2\zeta)\{p_{\tau 2} c_\tau + (1-p_{\tau 2}) h_\tau\}, \tag{46}$$

$$v_\tau = \zeta + (1-2\zeta)\{(1-p_{\tau 2})(1-c_\tau) + p_{\tau 2}(1-h_\tau)\}. \tag{47}$$

The four observed correctness-pattern likelihoods are

$$\ell_{\tau,CC} = p_{\tau 1} u_\tau, \quad \ell_{\tau,CI} = p_{\tau 1}(1-u_\tau), \quad \ell_{\tau,IC} = (1-p_{\tau 1}) v_\tau, \quad \ell_{\tau,II} = (1-p_{\tau 1})(1-v_\tau). \tag{48}$$

Recording noise makes every likelihood strictly positive. Let W_χ be the corresponding Bayesian wage and write

$$G_C = W_{CC} - W_{CI}, \qquad G_I = W_{IC} - W_{II}. \tag{49}$$

If x is the posterior probability that the locked report is correct, the gain from intending repetition rather than reversal, divided by the positive factor $1-2\zeta$, is

$$x(G_C + \varepsilon_2) - (1-x)(G_I + \varepsilon_2). \tag{50}$$

Hence every terminal action is optimal at every signal history and message whenever

$$G_C = G_I = -\varepsilon_2. \tag{51}$$

The obstruction can be constructed continuously. For $t \in [0,1]$, set

$$h_L(t) = c_H(t) = \frac{1-t}{2}, \qquad h_H(t) = \frac{1+t}{2}, \tag{52}$$

and choose $c_L(t)$ to solve $G_C = G_I$. Holding t fixed, $G_C - G_I$ is strictly decreasing in c_L: an increase in c_L lowers G_C and raises G_I. After positive denominators are cleared, Sturm sequences give, uniformly on $t \in [0,1]$,

$$[G_C - G_I]_{c_L=0} > 0, \qquad [G_C - G_I]_{c_L=1} < 0. \tag{53}$$

Thus $c_L(t) \in (0,1)$ exists uniquely and continuously.

At the paper's exact profile and $\zeta = 10^{-4}$, the path begins at uniform terminal randomization and ends at

$$c_L(1) = 0.625106534357\ldots, \qquad (h_L, c_H, h_H) = (0, 0, 1), \tag{54}$$

where

$$G_C = G_I = -0.495597025155\ldots. \tag{55}$$

Continuity therefore gives a fully supported accuracy-offset equilibrium for every

$$0 < \varepsilon_2 < 0.495597025155\ldots. \tag{56}$$

Along the interior of the path the intended strategies are completely mixed, and recording noise keeps all correctness patterns on path. Moreover, $W_{CI} > W_{II}$ along the path, so the truthful-versus-opposite locked-report slack is

$$(2p_{\tau 1} - 1)(W_{CI} - W_{II} + \varepsilon_1) > 0. \tag{57}$$

The same terminal strategy is used after every message. The platform lottery then cancels from the expert's type posterior and from the deviation comparison. The construction is consequently a fully supported, policy-independent sequential equilibrium with strict truthful locked reports. It is nonmonotone: in particular, $h_H > h_L$ away from $t = 0$.

Finally, an interior disciplinary-silence policy requires

$$\varepsilon_2 < \varepsilon_2^{\text{policy}}(\zeta) = \frac{G_C^0(\zeta) - \eta_L G_I^0(\zeta)}{\eta_L - 1}, \tag{58}$$

where G_C^0 and G_I^0 are the noisy wage gaps under pure conflict revision. At $\zeta = 10^{-4}$,

$$\varepsilon_2^{\text{policy}} = 0.400177385298\ldots < 0.495597025155\ldots. \tag{59}$$

Every accuracy stake consistent with an interior disciplinary policy therefore admits the nonmonotone accuracy-offset equilibrium. Recording noise repairs the off-path-wage defect of full repetition but does not select the regular-monotone equilibrium from the unrestricted set.

B Formal assessment and analytical details

This section records the probability and deviation calculations that underlie the regular-monotone candidate. They are stated for the complete two-expert game rather than for a reduced form, since the locked-report constraints are the place where a reduced form would be most likely to conceal an error. Throughout, let

$$f_{\tau t}(s \mid \vartheta) = \begin{cases} p_{\tau t}, & s = \vartheta, \\ 1 - p_{\tau t}, & s \neq \vartheta, \end{cases} \tag{60}$$

and let $\mu_\pi(m \mid y, b)$ denote the platform's message kernel. The kernel is determined by (α, δ) as in the main text.

B.1 Likelihoods, beliefs, and sequential payoffs

For a reporting assessment σ, define A's type-conditional report likelihood by

$$L^\sigma_{A\tau}(r^2_A \mid \vartheta) = \sum_{s_{A1}, s_{A2}} f_{\tau 1}(s_{A1} \mid \vartheta) f_{\tau 2}(s_{A2} \mid \vartheta) \sigma_{A1}(r_{A1} \mid \tau, s_{A1}) \times \sigma_{A2}(r_{A2} \mid \tau, s^2_A, r_{A1}). \tag{61}$$

Conditional on A's locked report and the platform message, B's analogous likelihood is

$$L^\sigma_{B\tau}(r^2_B \mid y, m, \vartheta) = \sum_{s_{B1}, s_{B2}} f_{\tau 1}(s_{B1} \mid \vartheta) f_{\tau 2}(s_{B2} \mid \vartheta) \sigma_{B1}(r_{B1} \mid \tau, s_{B1}) \times \sigma_{B2}(r_{B2} \mid \tau, s^2_B, r_{B1}, m). \tag{62}$$

Bayes' rule therefore assigns the terminal wages

$$\rho_A = \frac{\omega L^\sigma_{AH}(r^2_A \mid \theta)}{\omega L^\sigma_{AH}(r^2_A \mid \theta) + (1-\omega) L^\sigma_{AL}(r^2_A \mid \theta)}, \tag{63}$$

$$\rho_B = \frac{\omega L^\sigma_{BH}(r^2_B \mid y, m, \theta)}{\omega L^\sigma_{BH}(r^2_B \mid y, m, \theta) + (1-\omega) L^\sigma_{BL}(r^2_B \mid y, m, \theta)}. \tag{64}$$

The other expert's report likelihood and the policy probability cancel from the relevant type odds. This is the formal likelihood version of the factorization lemma in the main text.

For completeness, the candidate probability of a public outcome $z = (r^2_A, r^2_B, m)$, conditional on state ϑ, is obtained by summing

$$\mu_\pi(m \mid r_{A1}, r_{B1}) \prod_{i \in \{A,B\}} \left[\omega_{\tau_i} f_{\tau_i 1}(s_{i1} \mid \vartheta) f_{\tau_i 2}(s_{i2} \mid \vartheta) \sigma_{i1}(r_{i1} \mid \tau_i, s_{i1})\right] \times \sigma_{A2}(r_{A2} \mid \tau_A, s^2_A, r_{A1}) \sigma_{B2}(r_{B2} \mid \tau_B, s^2_B, r_{B1}, m) \tag{65}$$

over $(\tau_A, \tau_B, s^2_A, s^2_B)$, where $\omega_H = \omega$ and $\omega_L = 1 - \omega$. Equation (65) is also the enumeration used by the classification and Blackwell programs.

B.2 Correctness patterns and the cutoff map

Suppose locked reports are truthful. At a fixed positive-probability message branch, both types repeat after confirmation, the high type uses the second signal after a conflict, and the low type

repeats her locked report with probability h. The high-type correctness-pattern likelihoods are

$$\ell_H^{CC}(h) = p_{H1}p_{H2}, \qquad \ell_H^{CI}(h) = p_{H1}(1-p_{H2}), \tag{66}$$

$$\ell_H^{IC}(h) = (1-p_{H1})p_{H2}, \qquad \ell_H^{II}(h) = (1-p_{H1})(1-p_{H2}). \tag{67}$$

The low-type likelihoods are

$$\ell_L^{CC}(h) = p_{L1}\{p_{L2} + (1-p_{L2})h\}, \qquad \ell_L^{CI}(h) = p_{L1}(1-p_{L2})(1-h), \tag{68}$$

$$\ell_L^{IC}(h) = (1-p_{L1})p_{L2}(1-h), \qquad \ell_L^{II}(h) = (1-p_{L1})\{(1-p_{L2}) + p_{L2}h\}. \tag{69}$$

Substitution into

$$W_\chi(h) = \frac{\omega\ell_H^\chi(h)}{\omega\ell_H^\chi(h) + (1-\omega)\ell_L^\chi(h)} \tag{70}$$

gives the four wages used throughout the paper.

At $h = 0$, define

$$d_t = \frac{\kappa_{Ht}}{\kappa_{Lt}}, \qquad O = \frac{\omega}{1-\omega}\frac{(1-p_{H1})(1-p_{H2})}{(1-p_{L1})(1-p_{L2})}. \tag{71}$$

The posterior odds of type H, in the order II, CI, IC, CC, are O, d_1O, d_2O, d_1d_2O. Direct subtraction of the associated posterior probabilities yields

$$Q_0 = \frac{(1+d_1O)(1+d_1d_2O)}{d_1(1+O)(1+d_2O)}. \tag{72}$$

The monotonicity and domain of the endogenous cutoff can now be verified directly. As h rises, the low-type likelihoods of CC and II rise strictly, whereas those of CI and IC fall strictly. Hence W_{CC} and W_{II} fall, while W_{CI} and W_{IC} rise. It follows that

$$G_C(h) = W_{CC}(h) - W_{CI}(h) \qquad \text{falls strictly,} \tag{73}$$

$$G_I(h) = W_{IC}(h) - W_{II}(h) \qquad \text{rises strictly.} \tag{74}$$

Both gaps are positive at zero. As $h \uparrow 1$, W_{CI} tends to one while $W_{CC} < 1$, so there is a unique $h^\dagger \in (0,1)$ satisfying $G_C(h^\dagger) = 0$. Therefore

$$Q(h) = \frac{G_I(h)}{G_C(h)} : [0, h^\dagger) \longrightarrow [Q_0, \infty) \tag{75}$$

is continuous, strictly increasing, and onto.

If a message supplies likelihood ratio λ in favour of B's locked report, the posterior odds in favour of that report are λ/η_τ after a private conflict and $\lambda\kappa_{\tau 1}\kappa_{\tau 2}$ after confirmation. Comparing

repetition with reversal therefore gives

$$\text{conflict: } \frac{\lambda G_C(h) - \eta_\tau G_I(h)}{\lambda + \eta_\tau}, \tag{76}$$

$$\text{confirmation: } \frac{\lambda \kappa_{\tau 1}\kappa_{\tau 2} G_C(h) - G_I(h)}{1 + \lambda \kappa_{\tau 1}\kappa_{\tau 2}}. \tag{77}$$

Thus the relevant low-type branch conditions are

branch	conflict condition	confirmation condition
revealed agreement	$Q(h^{\mathsf{F}}) = \gamma/\eta_L$	$\gamma\kappa_{L1}\kappa_{L2} > Q(h^{\mathsf{F}})$
revealed disagreement	$\gamma\eta_L > 1/Q_0$	$\kappa_{L1}\kappa_{L2}/\gamma > Q_0$
silence	$Q(h_N) = \lambda_N/\eta_L$ if $\lambda_N > \bar{\lambda}$	$\lambda_N\kappa_{L1}\kappa_{L2} > Q(h_N)$

(78)

When $\lambda_N \le \bar{\lambda}$, the silent-conflict action is pure use of the second signal and $h_N = 0$; it is weak at equality. The corresponding high-type conflict inequalities are strict when $\eta_H > \eta_L$.

B.3 Locked-report deviations

Let $c(a, \vartheta) = C$ if $a = \vartheta$ and I otherwise, and write

$$\chi(a_1, a_2; \vartheta) = \big(c(a_1, \vartheta), c(a_2, \vartheta)\big). \tag{79}$$

By label symmetry, it suffices to condition on first signal one. Under sealing, A's truthful and deviation values can be written

$$V_{A\tau}^{T,\mathsf{S}} = \sum_{\vartheta, s_2} f_{\tau 1}(1 \mid \vartheta) f_{\tau 2}(s_2 \mid \vartheta) \sum_{r_2} \widehat{\sigma}_{A2}^{\mathsf{S}}(r_2 \mid \tau, (1, s_2), 1) W_{\chi(1, r_2; \vartheta)}(h^{\mathsf{S}}), \tag{80}$$

$$V_{A\tau}^{D,\mathsf{S}} = \sum_{s_2} \max_{r_2} \sum_{\vartheta} f_{\tau 1}(1 \mid \vartheta) f_{\tau 2}(s_2 \mid \vartheta) W_{\chi(0, r_2; \vartheta)}(h^{\mathsf{S}}). \tag{81}$$

The maximization in (81) both evaluates a lie and specifies a sequentially optimal continuation after it.

For B, let

$$g_q(y \mid \vartheta) = \begin{cases} q, & y = \vartheta, \\ 1 - q, & y \neq \vartheta. \end{cases} \tag{82}$$

Using the candidate message-contingent strategy and wage, her corresponding values are

$$V_{B\tau}^{T,\pi} = \sum_{\vartheta,s_2,y,m} f_{\tau 1}(1 \mid \vartheta) f_{\tau 2}(s_2 \mid \vartheta) g_q(y \mid \vartheta) \mu_\pi(m \mid y, 1) \times \sum_{r_2} \widehat{\sigma}_{B2}^{\pi}(r_2 \mid \tau, (1, s_2), 1, m) \widetilde{W}^{\pi}_{\chi(1,r_2;\vartheta)}(m, y, 1), \tag{83}$$

$$V_{B\tau}^{D,\pi} = \sum_{s_2,m} \max_{r_2} \sum_{\vartheta,y} f_{\tau 1}(1 \mid \vartheta) f_{\tau 2}(s_2 \mid \vartheta) g_q(y \mid \vartheta) \mu_\pi(m \mid y, 0) \times \widetilde{W}^{\pi}_{\chi(0,r_2;\vartheta)}(m, y, 0). \tag{84}$$

In particular, the lie in (84) is allowed to change whether the locked reports agree and hence to change the feedback lottery. The four incentive slacks used in the main text are

$$\Delta_{A\tau}^{\mathsf{S}} = V_{A\tau}^{T,\mathsf{S}} - V_{A\tau}^{D,\mathsf{S}}, \qquad \Delta_{B\tau}^{\pi} = V_{B\tau}^{T,\pi} - V_{B\tau}^{D,\pi}. \tag{85}$$

Finally, in the sealed benchmark, the high type's terminal report has accuracy p_{H2}, whereas the low type's unconditional terminal-report accuracy is

$$\mathbb{P}(r_2 = \theta \mid L) = p_{L2} + h(p_{L1} - p_{L2}). \tag{86}$$

The distortion therefore concerns the use of new information; its effect on terminal accuracy depends on which private signal is more precise.

C Exact-profile selective-disclosure equilibrium and benchmark gains

Fix the four signal precisions at

$$p_{L1} = \frac{11}{20}, \qquad p_{L2} = \frac{5}{8}, \qquad p_{H1} = \frac{33}{40}, \qquad p_{H2} = \frac{19}{20}. \tag{87}$$

Writing $\kappa_{\tau t} = p_{\tau t}/(1 - p_{\tau t})$, these precisions imply

$$\eta_L = \frac{15}{11}, \qquad \eta_H = \frac{133}{33}, \qquad \eta_H - \eta_L = \frac{8}{3}. \tag{88}$$

Set $\omega = 2/5$. The peer accuracy, peer likelihood ratio, truthful wage cutoff, and silent-pressure threshold are

$$q = \frac{33}{50}, \qquad \gamma = \frac{33}{17}, \qquad Q_0 = \frac{202419}{394279}, \qquad \bar{\lambda} = \frac{3036285}{4337069}. \tag{89}$$

Direct substitution verifies that

$$\frac{1}{\eta_L Q_0} < \gamma < \frac{\kappa_{L1}\kappa_{L2}}{Q_0}. \tag{90}$$

Clearing the positive denominators in the sealed and revealed-agreement mixing equations gives

$$P^{\mathsf{S}}(h) = 11390625h^3 - 8262000h^2 - 8143395h + 2113774, \tag{91}$$

$$P^{\mathsf{F}}(h) = 114665625h^3 - 129012750h^2 - 55925895h + 49565984. \tag{92}$$

The monotonicity of Q selects a unique relevant root. Exact rational evaluation gives

$$0.2243083281662 < h^{\mathsf{S}} < 0.2243083281663, \tag{93}$$

$$0.5379129780400 < h^{\mathsf{F}} < 0.5379129780401. \tag{94}$$

Under the disciplinary-silence policy, disagreement is never revealed and agreement is revealed with probability

$$\alpha^* = \frac{1-\bar{\lambda}}{q-(1-q)\bar{\lambda}}. \tag{95}$$

Using eq. (89),

$$\alpha^* = \frac{2032475}{2859576} \approx 0.710760965961387. \tag{96}$$

The silent-message likelihood ratio satisfies the exact identity

$$\frac{1-q\alpha^*}{1-(1-q)\alpha^*} = \bar{\lambda}. \tag{97}$$

Hence $h_N = 0$ makes the low type indifferent at a silent conflict. The high type strictly uses the second signal.

For completeness, the remaining terminal strictness conditions can be certified without decimals. The differences between the relevant posterior odds and wage cutoffs are

$$\bar{\lambda}\kappa_{L1}\kappa_{L2} - Q_0 = \frac{359856}{394279}, \quad \gamma\eta_L - Q_0^{-1} = \frac{141536}{202419}, \quad \frac{\kappa_{L1}\kappa_{L2}}{\gamma} - Q_0 = \frac{17117776}{31936599}. \tag{98}$$

Every term is positive. They verify, respectively, confirmation after silence, revision after a revealed disagreement, and confirmation when the peer opposes the two private signals.

The factorization result in the main text makes A's first-report problem identical to the sealed benchmark, independently of the policy. Let $\Delta^{\mathsf{S}}_{A\tau}$ denote her truthful-report value less her best first-report deviation value. Exact interval evaluation gives

$$\Delta^{\mathsf{S}}_{AL} > 0.019311962160434, \qquad \Delta^{\mathsf{S}}_{AH} > 0.149521073327309. \tag{99}$$

Following a first-report lie, both types of A optimally set $r_{A2} = s_{A2}$. The smallest payoff advantages of that terminal action over the alternative are

$$\text{type } L :> 0.035493075864379, \qquad \text{type } H :> 0.057924699810662. \tag{100}$$

Thus A's on- and off-path conditions are strict.

The generic finite sums in eqs. (83) and (84) explicitly allow B's locked-report lie to alter the feedback lottery and then select an optimal terminal report following every resulting (s_2, m). Exact interval evaluation at π^* gives

$$\Delta_{BL}^{\pi^*} > 0.020509853706241, \qquad \Delta_{BH}^{\pi^*} > 0.156047076876312. \tag{101}$$

Thus both types of B strictly lodge their first signals at the exact-profile policy. Together with eq. (99), this verifies all four strict first-report constraints, in addition to the continuation conditions required for membership in Π^{RM}.

Enumerating the complete outcomes $z = (r_{A1}, r_{A2}, r_{B1}, r_{B2}, m)$ and integrating over both types and all signals gives the following certified state-classification intervals:

policy	classification-accuracy interval
S	$(0.778346976214800, 0.778346976214828)$
F	$(0.789032094987011, 0.789032094987031)$
π^*	$(0.792048902955015, 0.792048902955033)$

(102)

Equivalently, for the posterior call value at $k = 1/2$,

comparison	gain interval
$C^* - C^{\mathsf{S}}$	$(0.006850963370093, 0.006850963370116)$
$C^* - C^{\mathsf{F}}$	$(0.001508403983991, 0.001508403984011)$

(103)

All lower endpoints are strictly positive. At the exact-profile policy, the smallest nonzero absolute state-likelihood gap among public outcomes is bounded as follows:

$$\min_{z:\, \widehat{P}_1^{\pi^*}(z) \neq \widehat{P}_0^{\pi^*}(z)} |\widehat{P}_1^{\pi^*}(z) - \widehat{P}_0^{\pi^*}(z)| > 0.001221358846864. \tag{104}$$

These strict margins will also be used for the open-set argument.

D Global candidate-value optimality in the reveal-or-silence class

The concealment-ray theorem in the main text reduces the candidate-value comparison over the policy square to full disclosure and the two boundaries $\delta = 0$ and $\alpha = 0$. This section certifies the remaining one-dimensional comparisons for symmetric state classification. Equilibrium feasibility is verified separately by the first-report calculations above.

On $\delta = 0$, the silent-message likelihood ratio is

$$\lambda(\alpha) = \frac{1 - q\alpha}{1 - (1-q)\alpha}. \tag{105}$$

While the silent branch has an interior root h, its candidate-continuation condition is $\lambda(\alpha) = \eta_L Q(h)$. Solving for the policy parameter gives

$$\alpha(h) = \frac{1 - \eta_L Q(h)}{q - (1-q)\eta_L Q(h)}, \qquad 0 < h < h^{\mathsf{S}}. \tag{106}$$

The parameter falls from α^* to zero as h rises from zero to h^{S}.

On $\alpha = 0$, silence becomes increasingly favourable to the old report as the disagreement-disclosure probability δ rises. Solving the corresponding equilibrium condition gives

$$\delta(h) = \frac{\eta_L Q(h) - 1}{q\eta_L Q(h) - (1-q)}, \qquad h^{\mathsf{S}} < h < h^{\mathsf{F}}. \tag{107}$$

For each public outcome z, the state-likelihood gap at $k = 1/2$ is bilinear in the boundary policy parameter and the silent mixing root. Substitution of eqs. (106) and (107) makes the complete call value a rational function of h. After differentiation and clearing the positive denominator, the derivative numerator is a polynomial of degree 12. A Sturm sequence counts its roots exactly.

The computation encloses h^{S} and h^{F} by the rational brackets in eqs. (93) and (94). Conditional history probabilities and the derivative numerator are bilinear in these two roots, so their extrema over each bracket rectangle occur at its four corners.

We also certify the action selected inside every absolute-value term. For each of the 48 public-outcome labels, write the state-likelihood gap after boundary substitution as

$$G_z(h) = P_1(z) - P_0(z) = \frac{N_z(h)}{D(h)}, \qquad D(h) > 0. \tag{108}$$

Twenty-four gaps vanish identically. Eight revealed-outcome numerators contain the policy numerator as a factor; it has the unique sealed root h^{S}, with Sturm variation $4 \to 3$. Four silent-outcome gaps factor as $(h - h^{\mathsf{S}})R_z(h)$, and an exact derivative enclosure makes this root simple. On $\alpha = 0$, eight numerators also contain the unit-policy factor, which has the unique full-disclosure root h^{F}, again with variation $4 \to 3$. After removing these structural factors, every residual polynomial has zero Sturm roots on the enlarged interval at all four root-bracket corners. Hence exactly twelve gaps are positive throughout each economically relevant open interval, and the downstream action selected after each public outcome does not switch there.

With those action regions fixed, the derivative Sturm calculation gives

boundary	root interval	sign(dC/dh)
$\delta = 0$	$(0, h^{\mathsf{S}})$	$-$
$\alpha = 0$	$(h^{\mathsf{S}}, h^{\mathsf{F}})$	$+$

(109)

Each of the eight corner derivative polynomials has zero Sturm roots on the relevant interval and the displayed strict sign.

Because $\alpha(h)$ falls with h, the first row shows that value rises strictly as α moves from zero to α^*. For $\alpha \geq \alpha^*$, silent behaviour is fixed at $h_N = 0$. Each outcome likelihood is affine in α, so the optimized decision value is convex. Its maximum on $[\alpha^*, 1]$ is at an endpoint, and eq. (103) shows that α^* beats $\alpha = 1$, which is full disclosure.

On $\alpha = 0$, $\delta(h)$ rises with h. The second row shows that the best point is full disclosure, which is strictly below the exact-profile policy by eq. (103). The concealment-ray reduction then proves unique global candidate-value optimality over the full (α, δ) square, that is, over Π^{RS}. Since the continuation checks and the four strict locked-report constraints place π^* in Π^{RM}, the candidate-to-equilibrium corollary in the main text transfers this conclusion to the regular-monotone equilibrium over Π^{RM}.

As a separate check on the kink, exact one-sided derivative intervals with respect to α at α^* are

$$\begin{aligned} \left.\frac{dC}{d\alpha}\right|_{\alpha^*-} &\in (0.015534406550318, 0.015534406550319), \\ \left.\frac{dC}{d\alpha}\right|_{\alpha^*+} &\in (-0.005215077518895, -0.005215077518893). \end{aligned} \tag{110}$$

D.1 Robustness margins

The nonzero outcome gaps in eq. (104), the one-sided slopes in eq. (110), the four first-report slacks in eqs. (99) and (101), and the benchmark gains in eq. (103) are all strict. The mixing roots vary continuously with the five primitives because $Q'(h) > 0$ at the relevant roots. The gap factorizations above preserve the local action classification, while the strict derivative signs preserve the peak at the recalibrated disciplinary threshold. Finally, outside any small neighborhood of that threshold, compactness and the exact strict global comparison provide a uniform value gap. These facts yield the open neighborhood stated in the main text's robustness proposition.

E One-at-a-time sensitivity diagnostics

The baseline row inherits the separate exact global certificate. Each remaining row uses exact-arithmetic root isolation and interval evaluation to establish continuation feasibility, strict locked-report incentives, strict gains over both polar policies, and the signs of the local one-sided derivatives. The non-baseline rows do not establish global optimality over the policy square.

Each row varies one primitive while holding the other four at the exact profile. The policy is recalculated as $\pi^{\mathrm{DS}} = (\alpha^{\mathrm{DS}}, 0)$. Gains are reported in percentage points, and the slack column is the minimum across both types of both experts.

Table 3: One-at-a-time sensitivity diagnostics

profile	α^{DS}	accuracy	gain vs. S	gain vs. F	min. slack	local peak
baseline	0.710761	0.792049	1.370	0.302	0.019312	yes
$\omega = 0.35$	0.851159	0.771297	1.633	0.160	0.017331	yes
$\omega = 0.45$	0.559412	0.812319	1.064	0.440	0.021120	yes
$p_{L1} = 0.53$	0.692432	0.785665	1.197	0.358	0.012692	yes
$p_{L1} = 0.57$	0.725436	0.798867	1.534	0.248	0.024407	yes
$p_{L2} = 0.60$	0.821858	0.780110	1.674	0.154	0.017390	yes
$p_{L2} = 0.65$	0.567488	0.805664	0.987	0.517	0.021244	yes
$p_{H1} = 0.80$	0.600090	0.791209	0.949	0.429	0.017753	yes
$p_{H1} = 0.85$	0.811470	0.793264	1.866	0.186	0.021005	yes
$p_{H2} = 0.925$	0.669009	0.787448	1.003	0.282	0.021873	yes
$p_{H2} = 0.975$	0.753724	0.795698	1.899	0.315	0.015579	yes

Across these perturbations, the disciplinary policy remains feasible and strictly improves on both polar protocols, but its disclosure probability is sensitive: α^{DS} ranges from approximately 0.56 to 0.85. The gain over full disclosure remains modest, ranging from approximately 0.15 to 0.52 percentage points. These calculations support the local mechanism and the qualitative open-set proposition; they are not a substitute for a global certificate away from the baseline.

F Blackwell incomparability of sealing and full disclosure

For a cutoff $k \in (0,1)$, the posterior call value is

$$C^{\mathsf{P}}(k) = \frac{1}{2} \sum_{z} \left[(1-k) P_1^{\mathsf{P}}(z) - k P_0^{\mathsf{P}}(z) \right]_+, \qquad \mathsf{P} \in \{\mathsf{S}, \mathsf{F}\}. \tag{111}$$

This is the value of a binary state-decision problem: action 1 pays $1-k$ in state 1 and $-k$ in state 0, while action 0 pays zero.

Exact rational interval evaluation of the complete public experiments gives

k	$C^{\mathsf{F}}(k) - C^{\mathsf{S}}(k)$
1/10	$(-0.002333574526653, -0.002333574526575)$
1/2	$(\ 0.005342559386091,\ \ 0.005342559386115)$

(112)

The ranking crosses between two ordinary binary decision problems. If either complete experiment Blackwell dominated the other, its value would be weakly higher in every decision problem. The crossing therefore proves incomparability.

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