# Dynamic Evidence Disclosure: Delay the Good to Accelerate the Bad*

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**Abstract**

We analyze the dynamic tradeoff between generating and disclosing evidence. Agents are tempted to delay investing in a new technology in order to learn from information generated by the experiences of others. This informational free-riding is collectively harmful as it slows down learning and innovation adoption. A welfare-maximizing designer can delay the disclosure of previously generated information in order to speed up adoption. The optimal policy transparently discloses bad news and delays good news. This finding resonates with regulation demanding that fatal breakdowns be reported promptly. The designer's intervention makes all agents better off.

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# 1 Introduction

Society is constantly presented with opportunities to adopt new technologies, from groundbreaking medical treatments to innovative devices or software. Early stages of new technologies carry significant uncertainty about quality or viability. This uncertainty is reduced only as agents adopt and experience the new technology. However, the information generated by early adopters only benefits those who choose later, leading agents to adopt new technologies at a slower pace than socially optimal, slowing down learning and reducing potential benefits to society.[1]

This paper studies the dynamic tradeoff between evidence *generation* and *disclosure*. Fast evidence disclosure tomorrow creates free-riding incentives by increasing the value of waiting – slowing down evidence generation today. To explore the optimal balance between generation and disclosure, we introduce a designer who can control what type of evidence is disclosed at what time, and we analyze welfare-maximizing policies. We show that it is optimal to slow down disclosure of some evidence to speed up generation. Specifically, favorable news about the technology is delayed to encourage earlier investment and faster evidence generation while negative news is disclosed immediately to prevent inefficient investments.

We study a game in continuous time between a designer and a continuum of agents. Each agent chooses the time at which he makes an irreversible investment, if ever. Agents differ in discount rates. Each agent's net payoff at the time of investment is positive or negative, depending on an unknown state of the world, which can be good or bad. A fully revealing piece of evidence about the state is generated at a rate proportional to the mass of agents investing at that instant.

The designer commits to a public disclosure policy to maximize the expected discounted welfare of the agents. A disclosure policy specifies when and what type of evidence to disclose. Evidence is hard in that prior generation is necessary for disclosure, the designer cannot fake or manipulate evidence. Anticipating future disclosures, agents have an incentive to delay investment for informational free-riding, which causes welfare loss. For a non-trivial problem, some agent must be

[1] Take the case of COVID-19 vaccines. Surveys indicated that only 30% planned to get a vaccine soon after becoming available (see Schaffer DeRoo, Pudalov, and Fu, 2020).

willing to invest first, so we assume the prior about the state is high enough that immediate investment is optimal myopically, i.e. if no evidence was ever disclosed.

To examine the adoption equilibrium under a given disclosure policy, note that the agents' optimal investment behavior after the disclosure of fully revealing evidence is trivial: all agents who have not invested previously invest immediately after good news and never invest after bad news. Therefore, non-trivial investment dynamics occur while no evidence has been disclosed yet. Unless stated otherwise, the following descriptions refer to the behavior in the absence of evidence disclosure and we say an agent *experiments* if he invests without observing evidence. For any disclosure policy, the investment cycle of the new technology is partitioned into successive phases, corresponding to the time interval during which agents with the same discount rate experiment. In any equilibrium, all agents who are less patient must have invested before more patient agents start to experiment.

Consider the transparent benchmark where evidence is disclosed immediately when generated. Agents experiment gradually and each agent is indifferent between experimenting at his time and waiting for an additional instant. The speed of experimentation is increasing in the current belief that the state is good and in the discount rate of the agent that currently experiments; optimism about the state and impatience increase the opportunity cost of waiting. The belief is updated continuously as agents experiment and no evidence arrives. If the lack of evidence is more likely in the bad state than in the good state, the belief gradually decreases and experimentation slows down within each phase. In this no-news is bad-news case, if the overall mass of agents is large enough, the no-news belief decreases toward the myopic indifference threshold and investment dries out before all agents have experimented. Thus, in this case both the *amount* and the *rate* of experimentation are inefficiently low under transparency.

Our main result (Theorem 1) presents a simple welfare-maximizing policy: disclose negative evidence transparently as soon as it arrives, and delay positive evidence until some fixed time at which it is disclosed if available. There is no benefit from hiding bad news while it is optimal to delay good news to speed up generation. The simple policy characterized in Theorem 1 is always optimal.

Further, any optimal policy shares its key features: timely disclosure of bad news and delayed good news (Proposition 2).

Bad and good news are treated differently because bad news is decision relevant on the *action margin* —whether or not to invest— while good news is relevant on the *timing margin* —when to invest. Speeding up bad news by delaying good news is optimal because the action margin is relatively more important than the timing margin for the later agents who observe previously generated evidence.

For bad news, to correctly interpret the result that transparent disclosure is optimal, observe that delaying bad evidence *can* speed up generation as agents invest faster.[2] However, fixing any good-news process, it is impossible to disclose more of the generated bad news than under a transparent bad-news policy. Consider the agent's expected payoff from experimenting at some time $t$. Fixing the overall probability of disclosing bad evidence before time $t$, the agent's payoff is independent of the exact disclosure time of bad evidence prior to $t$. This is because bad news is *not* decision relevant on the *timing margin*: given that the agent plans to wait until $t$, it does not matter how much before $t$ he learns that he should not invest. Conversely, increasing the probability of disclosing bad evidence by time $t$ increases the payoff from waiting until $t$ because bad news is decision relevant on the *action margin*: agents experiment only if investment is myopically optimal at the current belief. Observing bad news changes the optimal action and guards agents against the wrong investment choice.

Good news, by contrast, is decision relevant only on the timing margin. While agents experiment, positive evidence does not change the myopically optimal action, but observing it earlier increases the expected payoff because the return of investment accrues earlier. Nonetheless, Proposition 2 shows that good evidence should be delayed at least until the experimentation time of the last type to experiment. Hiding good evidence speeds up experimentation because waiting becomes more costly; first because of the missing benefit of future good news and second because agents are more optimistic absent disclosure. This maximizes the speed at which bad evidence, which guards the agents against the wrong investment

[2] At the extreme, if no evidence is ever disclosed, all agents invest immediately.

choice, can be generated and disclosed.

If the lack of evidence is sufficiently more likely in the bad state than in the good state, investment eventually becomes myopically suboptimal in the absence of generated evidence. Then, good news becomes decision relevant on the action margin, and any optimal policy must disclose good evidence at one time (if generated). At this time, everyone invests if positive evidence is disclosed, or agents become so pessimistic absent evidence that nobody invests. The good-news disclosure is delayed to incentivize experimentation strictly earlier rather than waiting for a positive probability of good evidence.

The optimal disclosure policy leads to a Pareto improvement over transparency, and both the amount and the rate of experimentation are higher. Interestingly, with sufficient potential for positive evidence generation, the optimal policy can result in over-experimentation, surpassing even the first-best amount of experimentation. This over-experimentation is tied to the delays, which arise in any equilibrium but are absent in the first best. Since the optimal policy hides good news until the end, the agents' no-news belief is increasing and waiting becomes more costly. Letting more agents experiment can reduce the necessary delay of the good-evidence disclosure.

Endogenous learning through sufficient experience of early adopters is a crucial factor in the roll-out of any new technology[3] or practice, for example elective medical treatments or legislative changes in different states and countries.[4] When planning for a novel vaccination program, public hesitancy is a major concern. The optimal policy shares some features of so-called "confirmatory clinical trials with intention to treat." These trials verify the efficacy and safety of a new treat-

[3]PwC's "Global Artificial Intelligence" study estimates that AI could contribute up to $15.7 trillion to the global economy by 2030. The UK government's 2023 white paper on artificial intelligence (AI) states "[I]ndustry repeatedly emphasised that consumer trust is key to the success of innovation economies." and "By building trust, we can accelerate the adoption of AI across the UK to maximise the economic and social benefits." See https://pwc.co.uk/industries/financial-services/understanding-regulatory-developments/ai-in-financial-services-navigating-the-risk-opportunity-equation.html and https://gov.uk/government/publications/ai-regulation-a-pro-innovation-approach/white-paper.

[4]Consider the 2021 decriminalization of hard drugs in Oregon, known as Measure 110. After the increase in the volume of drug trade and drug-related crimes, other states have become less enthusiastic about adopting similar policies.

ment during a pre-specified horizon at the end of which the collected evidence is published to validate the benefits. Adverse effects, however, have to be reported immediately. Our findings support such reporting mandates: even though the prospect of prompt reporting may encourage individuals to postpone, hiding bad news would not improve welfare in our model.[5]

## 1.1 Related literature

This paper is related to the growing literature on dynamic information design. Dynamic persuasion of myopic agents is the focus of Ely (2017), Kremer, Mansour, and Perry (2014), Renault, Solan, and Vieille (2017), Che and Hörner (2017), and Arieli, Babichenko, Shaiderm (2024) among others. Here, our paper is most closely related to Kremer et al. (2014) and Che and Hörner (2017), as the designer persuades agents to experiment. By contrast, agents in our model are forward looking, leading to substantially different strategic forces. For instance, the tension between generation today and disclosure in the future is absent with myopic agents.[6] Hiding good news is never optimal in Che and Hörner (2017), but is beneficial in our setting to deter agents from waiting.

Dynamic information design with a forward-looking receiver is studied in Ball (2023), Ely and Szydlowski (2020), Orlov, Skrzypacz, and Zryumov (2020), and Zhao, Mezzetti, Renou, and Tomala (2024), among others.[7] The most important differences to these papers are that our designer does not know the true state and needs to generate evidence endogenously through the receivers' experimentation. Additionally, we focus on welfare-maximizing public disclosure to a heterogeneous population, while the papers above consider a single receiver who has a conflict of interest with the sender.[8] In the related work above, the promise of future

[5]There are natural reasons to immediately report adverse effects that are beyond the scope of our model. In particular, the duty of care owed by medical professionals would likely impede the censorship of indications of a health threat in order to accelerate testing. Our results lend additional support to such transparency rules.

[6]Additionally, the designer in our model cannot fake evidence that has not arrived, which is possible in Kremer et al. (2014) and Che and Hörner (2017).

[7]For information-design with exogenous generation and a single receiver facing a stopping problem, see Au (2015), Che, Kim, and Mierendorff (2023), Knoepfle (2020), Hébert and Zhong (2022), Koh and Sanguanmoo (2024), and Koh, Sanguanmoo, and Zhong (2024).

[8]We discuss private disclosures in Section 5. Contributions on public disclosure to multiple

information is used as a reward to incentivize the designer's preferred action, whereas the carrot effect in our paper entails *not* revealing information too fast to make investment today more attractive.

Halac, Kartik, and Liu (2017) and Ely, Georgiadis, and Rayo (2023) study optimal feedback- and contest design with pure good news.[9] In Ely et al. (2023), there is no learning, so feedback informs agents only about their standing among competitors. Our paper studies feedback from the opposite perspective: there is no competition, so feedback informs only about the technology. Halac et al. (2017) study quality uncertainty. Their optimal policy trades off agents' optimism about the competition versus optimism about the technology.[10]

Dynamic disclosure of verifiable evidence is studied in Acharya, DeMarzo, and Kremer (2011), Guttman, Kremer, and Skrzypacz (2014), Gratton, Holden, and Kolotilin (2018), Chatterjee, Das, and Dong (2024), and Zhou (2024). They study disclosure without commitment and without effect on generation.

Finally, social experimentation by forward-looking agents without information design is the focus of Rob (1991), Frick and Ishii (2024), Laiho and Salmi (2023), and Laiho, Murto, and Salmi (2024a). The transparency benchmark in our model is most closely related to the equilibria in Frick and Ishii (2024) and Laiho and Salmi (2023). Frick and Ishii (2024) show that increasing the potential of *generating* negative evidence beyond a saturation point has no impact on welfare. We show that interventions that speed up the *disclosure* of negative evidence can increase welfare.[11] In addition, experimentation is closely related to observational learning with timing decisions: Chamley and Gale (1994),

receivers include Laclau and Renou (2017) and Inostroza and Pavan (2024).

[9]See also Goltsman and Mukherjee (2011) and Aoyagi (2010). Smolin (2021) and Ely, Georgiadis, Khorasani, and Rayo (2022) study feedback to a single agent in dynamic moral hazard. Cetemen, Hwang, and Kaya (2020) consider blended feedback about quality and aggregate effort in a team-production problem.

[10]The equal-sharing contest, featuring no competition, makes hiding breakthroughs optimal to keep agents optimistic about quality. We demonstrate an additional benefit of hiding breakthroughs when agents decide to invest now or later: decreasing the value of waiting.

[11]The main analysis in Frick and Ishii (2024) establishes the welfare neutrality with homogeneous agents. They illustrate a negative welfare effect when agents have heterogeneous discount rates. Laiho, Murto, and Salmi (2024b) find a negative effect on equilibrium learning under direct network externalities. In a less related environment, Board and Meyer-ter Vehn (2024) find that a fixed observation lag may improve experimentation.

Murto and Välimäki (2011), and Wagner (2018). To the best of our knowledge, the only paper studying optimal information policies in this class of environments is the contemporaneous work by Chen, Eraslan, Ishida, and Yamashita (2024). They analyze an information design problem under payoff heterogeneity with a finite investment deadline and consider pure bad news and pure good news separately. Their designer crucially exploits her ability to "fake" news to reveal partial information. The focus of our paper is on the *timing* dimension as the designer can only delay the disclosure of fully revealing evidence but cannot manipulate or fabricate it.

# 2 Model

**Environment.** Time $t \geq 0$ is continuous. There is a continuum of agents indexed by $\theta \in [0, F_n]$ and one designer. Each agent chooses the time of an irreversible investment, with investment time $t = \infty$ if the agent never invests. The designer controls evidence disclosure as described shortly. If an agent invests at time $t$, the game ends for this agent and he collects a payoff $v_\omega$, which depends on the unknown state of the world $\omega \in \{G, B\}$. Payoffs satisfy $v_G > 0 > v_B$ and capture the cost and the benefit of the investment. The common prior is $x_0 = \Pr[\omega = G]$. The sequence of events in an instant $[t, t + \mathrm{d}t)$ can informally be described as follows. First, evidence is disclosed according to the policy. Then, each agent who remains in the game chooses whether to invest, and finally, evidence is generated.

**Evidence generation.** Evidence is generated as agents invest. Let the right-continuous process $q = (q_t)_{t\geq 0}$ denote the cumulative mass of agents who have invested by time $t$. If $\dot{q}_t$ is the flow of investments at instant $t$, then a piece of good evidence is generated at Poisson rate $\lambda_G \dot{q}_t$ if the state is good ($\omega = G$), and a piece of bad evidence is generated at Poisson rate $\lambda_B \dot{q}_t$ if the state is bad ($\omega = B$). The process $q$ may not be continuous.[12] In general, the probability that at least one piece[13] of $\omega$-evidence was generated by time $t$ is $1 - e^{-\lambda_\omega q_t}$. Parameters $\lambda_G > 0$

[12] We denote left limits by $q_{t-} = \lim_{s \nearrow t} q_s$ and $\dot{q}_t$ denotes the right derivative of $q$.

[13] Note that only the first piece of fully revealing good or bad evidence carries relevant information about the state. Henceforth, generation and disclosure refer to the first instance.

and $\lambda_B > 0$ determine the relative potential for good and bad evidence generation.

**Evidence disclosure.** The designer controls what agents learn by committing to a public disclosure policy. We model information as *hard evidence*. The designer can delay or hide evidence, but she cannot manipulate or fabricate evidence.[14]

Formally, the designer chooses two families of cumulative distribution functions $G(\cdot|s)\colon [0,\infty] \to [0,1]$ and $B(\cdot|s)\colon [0,\infty] \to [0,1]$ such that, if good evidence is first generated at time $s \geq 0$, then the cdf $G(\cdot|s)$ defines the distribution over the delay $\Delta \geq 0$ until this piece of good evidence is publicly disclosed; and $B(\cdot|s)$ controls the disclosure delay of bad evidence analogously. The agents only care about the time evidence is disclosed, not when it is generated. It is convenient to represent the disclosure policy in terms of the cumulative hazard rates: the non-decreasing processes $\lambda_\omega z_t^\omega$ for $\omega \in \{G, B\}$. This way, $z = \left(z_t^G, z_t^B\right)_{t\geq 0}$ is expressed in the same units of measurement as $q$. Since evidence must be generated before disclosure, any policy must satisfy $z_t^\omega \leq q_{t-}$ for all $t \geq 0$ and $\omega \in \{G, B\}$.[15]

**Updating.** When evidence is disclosed, the agents' belief jumps either to 1 if good evidence or to 0 if bad evidence was disclosed. While no evidence has been disclosed, the agents update the belief about the state taking into account the relative disclosure probabilities. The no-news belief at time $t$ is

$$x_t = \frac{x_0 e^{-\lambda_G z_t^G}}{x_0 e^{-\lambda_G z_t^G} + (1 - x_0) e^{-\lambda_B z_t^B}}, \tag{1}$$

where $x_0 e^{-\lambda_G z_t^G}$ is the probability that the state is $G$ and no disclosure and $(1 - x_0) e^{-\lambda_B z_t^B}$ is the probability that the state is $B$ and no disclosure. The no-news belief can be increasing or decreasing, depending on whether $\lambda_G z_t^G - \lambda_B z_t^B$ is decreasing or increasing. Let $x(q) := \frac{x_0 e^{-\lambda_G q}}{x_0 e^{-\lambda_G q} + (1-x_0) e^{-\lambda_B q}}$ be the no-news belief based on the knowledge that no news was *generated* by $q$ investors.

**Payoffs.** The agent's index $\theta \in [0, F_n]$ determines his discount rate: $r(\theta) \in$

[14] We discuss more powerful information design tools in Section 5. In particular, private disclosures would enable the designer to implement the first best.

[15] We state the formal requirements on the measures and show how to construct the processes $(z^G, z^B)$ from the families of cdfs in Online Appendix B.1.

$\{r_1, \cdots, r_n\}$. Without loss, we order types such that $r_i > r_{i+1}$ for all $i$ and $r(\theta) \geq r(\theta')$ whenever $\theta \leq \theta'$. This implies that types with higher indices are more patient. Let $f_i$ denote the mass of agents with discount rate $r_i$ and define $F_i = \sum_{j=1}^{i} f_j$.[16] Let $V(x) = xv_G + (1-x)v_B$ denote the expected value from investing at belief $x$. In the absence of additional information (i.e. if $z_t^G = z_t^B = 0$ for all $t$), agents would invest immediately if and only if the belief is above the *myopic threshold* $x^{\text{myop}} := \frac{-v_B}{v_G - v_B}$. Assume the prior is above the threshold: $x_0 > x^{\text{myop}}$.[17]

Consider the problem of agent $\theta$ under some policy $z$. The optimal choice upon disclosure is trivial: invest immediately if good and never invest if bad news is disclosed. Absent disclosure, taking as given the processes $z_t^\omega$, agent $\theta$ solves

$$\sup_{\tau} \int_0^{\tau} e^{-r(\theta)t} x_0 v_G \mathrm{d}(1 - e^{-\lambda_G z_t^G}) + e^{-r(\theta)\tau} \left( x_0 v_G e^{-\lambda_G z_\tau^G} + (1-x_0) v_B e^{-\lambda_B z_\tau^B} \right). \quad (2)$$

The first term captures the event that good evidence is disclosed at some time $t \leq \tau$, i.e. before the agent experiments (invests absent disclosure). This (Stieltjes) integral includes disclosures arriving either at a rate or a jump.[18] The second term corresponds to the case of no disclosure by time $\tau$. It is easily verified that the term in parentheses equals $\left( x_0 e^{-\lambda_G z_\tau^G} + (1-x_0) e^{-\lambda_B z_\tau^B} \right) V(x_\tau)$, the probability that no evidence was disclosed times the conditional expected investment return. Notice that (2) has decreasing differences in $(\tau, r)$, which implies that more impatient agents invest weakly earlier than more patient agents under any disclosure policy.

We solve for the disclosure policy that maximizes the time-0 expected welfare. Before stating and solving the designer's problem formally in Section 4, we discuss two benchmarks.

[16]Formally, given the increasing mapping $r$, $F_i = \sup\{\theta : r(\theta) \leq r_i\}$ and $f_i = F_i - F_{i-1}$, with the convention $F_0 = 0$. While either the mapping $r$ or the distribution $F$ would suffice to specify the setup, having both objects drastically simplifies the statements.

[17]Without this assumption, no investment can be induced under any disclosure policy.

[18]For existence of the integral, note that $e^{-r(\theta)t} x_0 v_G$ is continuous and $z_t^G$ is monotone in $t$. At points of differentiability $\mathrm{d}(1 - e^{-\lambda_G z_t^G})$ reduces to the usual density term $e^{-\lambda_G z_t^G} \lambda_G \dot{z}_t^G \, \mathrm{d}t$.

# 3 First-best and transparent benchmarks

## 3.1 First best

The way the model is set up, all delays are due to strategic free-riding and inefficient. The social optimum calls for agents to experiment sequentially at infinite rate. Let agents invest in increasing order of $\theta$.[19] Then agent $\theta$ who has not invested can react to evidence generated by all previous agents $\theta' < \theta$. The first-best amount of experimentation $\theta^{\mathrm{FB}}$ solves

$$\max_{\theta \in [0,F_n]} \; x_0 v_G \left( F_n(1 - e^{-\lambda_G \theta}) + \theta e^{-\lambda_G \theta} \right) + (1 - x_0) v_B \int_0^{\theta} e^{-\lambda_B s} \, \mathrm{d}s. \tag{3}$$

If the state is good, then the payoff $v_G$ is enjoyed by all $F_n$ agents if good news arrives (probability $1 - e^{-\lambda_G \theta}$), or by the mass $\theta$ of experimenting agents if no good news arrives. If the state is bad, then the negative payoff $v_B$ is incurred by all agents who experiment before bad news arrives.

It is easily verified that social welfare (3) is increasing in $\theta$ for all $\theta \in [0, F_n]$ if and only if $x(F_n) \geq x^{\mathrm{myop}}$. In this case, which holds always when no news is good news ($\lambda_B \geq \lambda_G$), all agents should invest unless negative evidence is revealed, i.e. $\theta^{\mathrm{FB}} = F_n$. Conversely, if no news is bad news ($\lambda_B < \lambda_G$) and $F_n$ is large enough, then the lack of evidence leads the posterior to decrease below the myopic indifference threshold: $x(F_n) < x^{\mathrm{myop}}$. In that case, calling all agents to experiment is inefficient and we have $\theta^{\mathrm{FB}} < F_n$. However, due to the positive informational externality, the first-best amount of experimentation $\theta^{\mathrm{FB}}$ is such that $x(\theta^{\mathrm{FB}}) < x^{\mathrm{myop}}$ whenever $x(F_n) < x^{\mathrm{myop}}$. That is, the last agents to experiment receive a negative expected investment return.

## 3.2 Transparent disclosure

Consider the investment equilibrium under transparent disclosure, that is $z_t^{\omega} = q_{t-}$ for $\omega \in \{G, B\}$ and all $t$. To focus on building intuition, the formal derivations

[19] As agents invest at infinite rate, the order is irrelevant, the discount factor is 1 for all types. Increasing order of $\theta$ is in line with the order when agents freely time their investments.

are relegated to Appendix A.1.

Let $q_t^{\mathrm{TP}}$ denote the mass of agents who have experimented by time $t$ under transparency. Recall from the discussion of the agent problem (2) that agents invest in increasing order of patience. Under transparency, agents invest gradually, so the equilibrium process $q_t^{\mathrm{TP}}$ is continuous and the rate of investment, $\dot{q}_t^{\mathrm{TP}}$, must make the marginal agent indifferent between experimenting and waiting:[20]

$$r(q_t^{\mathrm{TP}})\,(x_t v_G + (1-x_t)v_B)^+ = (1-x_t)\lambda_B \dot{q}_t^{\mathrm{TP}}(-v_B). \tag{4}$$

The left-hand side gives the cost of waiting per unit of time. The right-hand side gives the expected gain per unit of time: the gain consists in avoiding the negative payoff $v_B$ in case bad news arrives, which occurs at rate $(1-x_t)\lambda_B \dot{q}_t^{\mathrm{TP}}$.

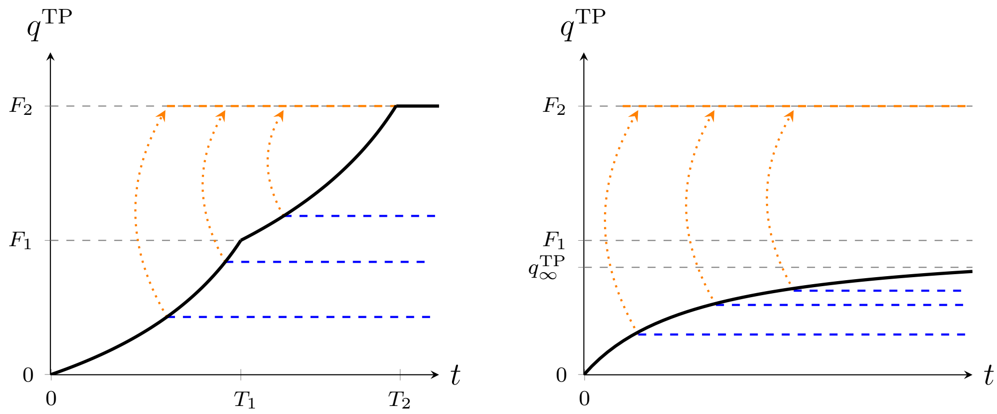


Figure 1: Investment process under transparency when $\lambda_G < \lambda_B$ (left) and when $\lambda_G > \lambda_B$ (right). The solid black curve depicts the mass of agents who have experimented. At all times, positive or negative evidence is generated and disclosed at a positive rate. If good evidence arrives, all agents invest immediately (orange arrows), if bad evidence arrives, no additional agents invest (blue lines).

Figure 1 depicts the experimentation dynamics under transparent disclosure when $n = 2$. In the left plot, no news is good news. Between times 0 and $T_1$, the impatient types $r_1$ experiment. Since agents become more optimistic, the rate of investment —and, thus, of disclosure— increases to keep agents with the same discount rate indifferent between investing and waiting. At time $T_1$, all

[20] We use $(V)^+ := \max\{0, V\}$. Note that $x_t$ is itself a function of $q_t^{\mathrm{TP}}$, so the indifference condition is a first-order ordinary differential equation (ODE). The solution to this ODE is provided in Appendix A.1.

agents with type $r_1$ have invested and the more patient agents with type $r_2$ start investing. Due to the lower cost of waiting ($r_2 < r_1$), the investment rate of the patient agents is initially lower and increases as the belief increases further. In the right plot, no news is bad news, so $\dot{q}^{\mathrm{TP}}$ is decreasing. In this example, $F_1$ is so large that $x(F_1) < x^{\mathrm{myop}}$. Then, $\dot{q}^{\mathrm{TP}}$ approaches 0 before all $r_1$-agents have experimented as the left-hand side of (4) approaches 0 as $x_t$ approaches $x^{\mathrm{myop}}$. Hence, $T_1 = \infty$ and the final amount of experimentation approaches $q_\infty^{\mathrm{TP}} < F_1$ that solves $x(q_\infty^{\mathrm{TP}}) = x^{\mathrm{myop}}$. This amount is inefficiently low. Agents disregard the social benefit from evidence generation and thus would never experiment when the expected return is negative.

# 4 Optimal disclosure policy

## 4.1 The designer's problem

Recall that a disclosure policy specifies two non-decreasing processes $z = \left(z_t^G, z_t^B\right)_{t\geq 0}$ such that each $z_t^\omega \leq q_{t-}$. Fixing a process $q$, we denote by $\tau(\theta)$ the time at which agent $\theta$ experiments. Formally, since (wlog) we let agents invest in increasing order of $\theta$, $\tau(\theta) = \inf\{t\colon q_t \geq \theta\}$. The designer's problem is

$$\begin{aligned}
\sup_{z,q:z_t^\omega \leq q_{t-}} \quad & \Bigg\{\int_0^{F_n}\Bigg[\int_0^{\tau(\theta)} e^{-r(\theta)s} x_0 v_G \mathrm{d}\Big(1-e^{-\lambda_G z_s^G}\Big) \\
& \qquad + e^{-r(\theta)\tau(\theta)}\Big(x_0 e^{-\lambda_G z^G_{\tau(\theta)}} v_G + (1-x_0) e^{-\lambda_B z^B_{\tau(\theta)}} v_B\Big)\Bigg]\mathrm{d}\theta \;\Bigg\}, \\
\text{such that,} \quad & \text{for all } \theta,\ \tau(\theta) \text{ is in} \\
\arg\max_{\tau\in[0,\infty]} \quad & \Bigg\{\int_0^{\tau} e^{-r(\theta)s} x_0 v_G \mathrm{d}\Big(1-e^{-\lambda_G z_s^G}\Big) + e^{-r(\theta)\tau}\Big(x_0 v_G e^{-\lambda_G z_\tau^G} + (1-x_0) v_B e^{-\lambda_B z_\tau^B}\Big)\Bigg\}.
\end{aligned} \tag{5}$$

We call a $(z, q)$ that solves (5) a *designer's solution* and the corresponding $z$ an *optimal policy*. Notice that the constraint on $\tau(\theta)$ requires the arg max to be non empty for all $\theta$ as part of the designer's problem, so that process $q$ is an equilibrium. The proof of Theorem 1 verifies existence under the optimal policy.

## 4.2 Optimal policy

Our first main result presents a simple optimal policy. Positive evidence is concealed up until some time $\bar{t} > 0$, and negative evidence is disclosed transparently as soon as it arrives.

**Theorem 1.** *There exists an optimal policy $z$ such that*

- *good evidence is disclosed at most once:* $z_t^G = \begin{cases} 0 & \text{if } t < \bar{t}, \\ q_{\bar{t}-} & \text{if } t \geq \bar{t}, \end{cases}$ *with* $\bar{t} \in (0, \infty]$,
- *bad evidence is disclosed immediately:* $z_t^B = q_{t-}$ *for all* $t$.

An outline of the proof of Theorem 1 is given in Section 4.4, followed by a characterization of all optimal policies. We first discuss the economic intuition and implied investment and learning dynamics (Section 4.3).

Theorem 1 shows that the gain from the informational intervention stems from withholding positive evidence. Requiring prompt reporting of breakdowns does not reduce welfare. Regulations governing medical trials with human subjects demand that severe adverse effects be disclosed immediately. For example, the EU regulation governing clinical trials[21] requires "the immediate cessation of any clinical trial in which there is an unacceptable level of risk" making reference to the principles outlined in the 1996 Declaration of Helsinki,[22] which states: "Physicians should cease any investigation if the hazards are found to outweigh the potential benefits." The optimality of immediately reporting bad evidence shows that these safeguarding measures do not conflict with informational interventions targeted at accelerating the initial uptake of new and experimental treatments.

Studying financial disclosures, Aboody and Kasznik (2000, p. 77) document that "top executives have compensation-related incentives to accelerate the disclosure of bad news and delay announcements of good news."[23] The common practice of compensating CEOs with stock options creates valuable disclosure incentives.

[21] See https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32014R0536.

[22] See https://www.wma.net/wp-content/uploads/2018/07/DoH-Oct1996.pdf.

[23] Other explanations for the finding that managers voluntarily disclose bad news early include reputational concerns and litigation risk minimization (Skinner, 1994).

Positive evidence is decision relevant on the *timing margin* as it leads the agent to invest earlier by confirming the myopically optimal action. Conversely, negative evidence is decision relevant on the *action margin* as it changes the optimal action from investing to not investing. The bad-news part of Theorem 1 may be surprising in light of this and the indifference condition (4), which shows that it is the expected gain from bad news that creates incentives to delay under transparency. The intuition behind the result is that postponing bad news could lead to faster information generation only if no evidence in excess of the transparent policy is ever disclosed. We formalize this intuition in Section 4.5.

To build intuition for the good-news part, notice that delaying good news leads to faster experimentation, and generation, through two channels: first, without the prospect of good evidence triggering investment before time $t$, the expected payoff from waiting until $t$ decreases; second, agents are more optimistic absent evidence, increasing the cost of delays. However, there is a cost associated with delaying good evidence: hiding evidence decreases investments if good news is generated as good evidence that would trigger immediate investment is not disclosed. To see why the benefit outweighs the cost, consider the most impatient agents with discount rate $r_1$. Since the first agent must be willing to invest at time $t = 0$, any disclosure process must keep this type indifferent. The more patient types who invest later strictly benefit from accelerating negative disclosures by delaying positive disclosures: these agents care relatively more about avoiding the wrong action than about investing early. That is, more patient agents care more about the action margin and less about the timing margin.

One implication of the discussion above is that all agents are better off under the optimal policy in Theorem 1 than under full transparency. The most impatient agents are left indifferent and the later types strictly benefit from the intervention.

**Corollary 1.** *The disclosure policy described in Theorem 1 results in a Pareto improvement relative to transparent disclosure.*

The designer does not have to trade off potential winners and losers from the intervention, significantly fostering the acceptance of any proposed measure.

## 4.3 Equilibrium dynamics under the optimal policy

We discuss the investment and belief dynamics under the policy in Theorem 1. Figures 2 and 3 illustrate the amount of experimentation and the no-news belief under the optimal policy and under transparency, separately for the no news is good news and no news is bad news case. Beliefs are depicted in log-likelihood ratios, $\ell_t = ln(x_t/(1-x_t))$, to better illustrate the evolution.

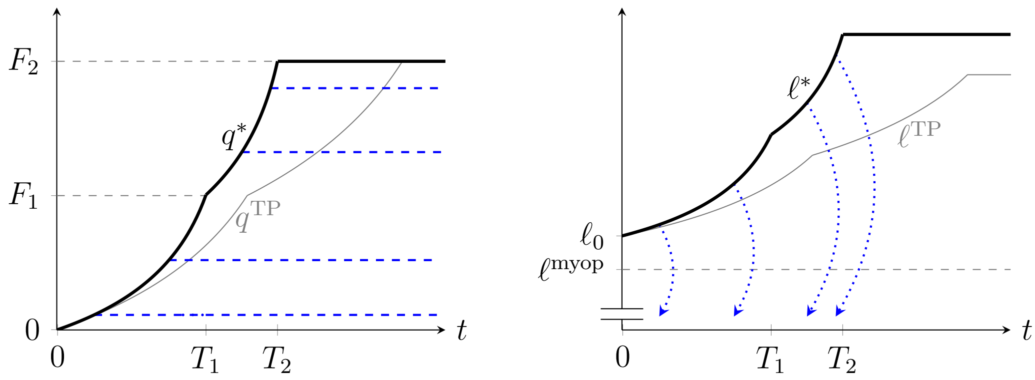


Figure 2: Experimentation $q_t$ and no-news belief $\ell_t = ln(x_t/(1-x_t))$ when $\lambda_B > \lambda_G$. At all times prior to $T_2$, negative evidence is disclosed at a positive rate. If negative evidence is disclosed, there is no further investment (left plot, dashed blue lines) and the belief jumps to 0, i.e. the log-likelihood ratio jumps to $-\infty$ (right plot, blue arrows).

In Figure 2, we have $\lambda_B > \lambda_G$, so the no-news belief increases under both the optimal policy and transparency. The belief increases faster under the optimal policy because of two reasons: censored good news and faster investments.

In Figure 3, we have $\lambda_B < \lambda_G$, so the no-news belief would decrease under transparency. However, the optimal policy censors good news before time $\bar{t}$, so the no-news belief is increasing. The figure depicts an example with $F_1$ large enough so that $x(F_1) < x^{\mathrm{myop}}$. This means that the posterior belief drops below the myopic threshold once we learn that the investment by all agents with type $r_1$ failed to generate evidence. Under transparency, not all high-type agents would invest absent news. The total amount of investment under transparency approaches the level at which the no-news belief equals the myopic indifference threshold. In contrast, the optimal policy delays good news so that all type-$r_1$ agents experiment. Eventually, the designer discloses all generated good evidence

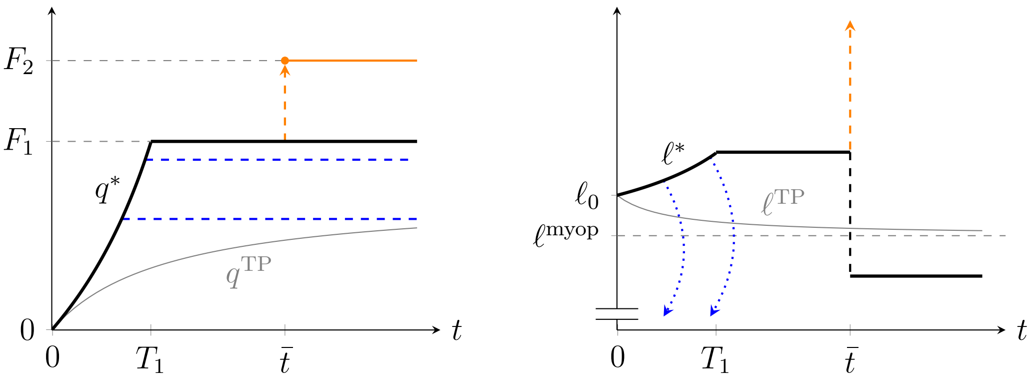


Figure 3: Experimentation and no-news belief when $\lambda_B < \lambda_G$ and $x(F_1) < x^{\text{myop}}$. Any time prior to $T_1$, negative evidence is disclosed at a positive *rate*. Between $T_1$ and $\bar{t}$, nobody invests and no evidence is disclosed. At time $\bar{t}$, positive evidence is disclosed with positive *probability*. If positive evidence is disclosed, the belief jumps to 1 and all agents invest (orange arrow). If no positive evidence is disclosed, the no-news belief jumps below the indifference threshold and no further agents invest.

at time $\bar{t}$, at which the remaining agents invest if good news is disclosed. To deter type-$r_1$ agents from waiting, the disclosure time $\bar{t}$ must be sufficiently large. Since there is a strictly positive probability of disclosure at time $\bar{t}$, there is a period $(T_1, \bar{t}\ )$ during which no one experiments and no information is disclosed.

Next, consider the total amount of experimentation, $q^*_\infty := \lim_{t\to\infty} q^*_t$ under the optimal policy. When $x(F_n) \geq x^{\text{myop}}$ as in Figure 2, everyone eventually experiments. In this case, the transparent benchmark and the optimal policy yield the same amount of total experimentation, although the timing is different.

However, if $x(F_n) < x^{\text{myop}}$, not all agents experiment under transparency. In the optimal policy, the designer can increase the amount of experimentation by delaying good news. To understand the designer's tradeoff when choosing how much to experiment, take an amount $\bar{q} > q^{\text{TP}}_\infty$ of experimentation and consider the disclosure policy from Theorem 1, denoting the disclosure time $\bar{t} = T + \Delta$, where $T$ is the time at which the last agent experiments and $\Delta$ is the necessary delay to deter this agent from waiting until $\bar{t}$. Agent $\bar{q}$ is willing to invest at $T$ if[24]

$$x_T v_G + (1 - x_T) v_B \geq e^{-r(\bar{q})\Delta} x_T (1 - e^{-\lambda_G \bar{q}}) v_G. \tag{6}$$

[24] The inequality $\bar{q} > q^{\text{TP}}_\infty$ implies that $x(\bar{q}) < x^{\text{myop}}$ and hence the agent invests at $T + \Delta$ only if good news arrives.

Increasing $\bar{q}$ may increase or decrease the necessary delay. On one hand, a higher discount rate of the marginal agent and a higher probability of good evidence increase the required $\Delta$. On the other hand, under the optimal policy $x_T$ increases with experimentation as only negative evidence is disclosed before $T$. If the marginal agent is more optimistic, he is less tempted to wait, and the delay can be reduced. This shows that the designer's tradeoff determining the amount of experimentation in the second-best policy differs starkly from the tradeoff in the first-best (Section 3.2), which trades off the cost of investment and the social value of information generation but features no delays. This additional tradeoff in the second best can induce a higher level of experimentation than the first best:

**Proposition 1.** *The amount of experimentation in any optimal policy*

- *may be above or below the first-best amount of experimentation,*
- *is above the transparent benchmark if* $x(F_{n-1}) < x^{myop}$.

The optimal policy in Theorem 1 may induce more experimentation than the first-best benchmark when no news is sufficiently bad news because the necessary delay $\Delta$ in (6) may decrease in $\bar{q}$, providing a benefit of over experimentation that is absent in the social optimum.

## 4.4 Proof sketch for Theorem 1

We prove Theorem 1 by deriving necessary conditions for an optimal policy. Then, we show that for any policy that satisfies the necessary conditions, there exists another policy of the form in Theorem 1 that guarantees each type the same expected payoff. Finally, the formal proof in Appendix A.7 verifies that an optimal policy always exists. The characterization in Proposition 2 highlights the importance of Theorem 1 by confirming that prompt reporting of bad news and delayed disclosure of good news are necessary for optimality.

Define, for a given process $q$, the last type that would ever experiment as

$$\bar{n} = \max\{i \leq n \colon \lim_{t \to \infty} q_t \leq F_i\}.$$

For $i < \bar{n}$, define the time at which agents of type $i+1$ start to experiment as

$$T_i = \inf\{t \geq 0 \colon q_t > F_i\}.$$

Since types $i \geq \bar{n}+1$ never experiment, let $T_{\bar{n}} = \sup\{t \geq 0 \colon q_t < q_\infty\}$ be the time of the last experimentation. $T_{\bar{n}}$ may not be finite.

We first show that it is never optimal to disclose positive evidence in the interior of any phase $(T_{i-1}, T_i)$ corresponding to types $i < \bar{n}$.

**Lemma 1.** *Under any optimal policy, $z_t^G$ is constant for all $t \in (T_{i-1}, T_i)$ if $i \leq \min\{\bar{n}, n-1\}$.*

Lemma 1 states that positive evidence that has not been disclosed at the beginning of the phase corresponding to agents of type $i$, will not be disclosed before all agents of type $i$ have invested. In particular, positive evidence generated by the investments of types $i$ will only be disclosed to later types.

To build intuition, take any type $i < \bar{n}$ and suppose good evidence is disclosed with positive probability in $(T_{i-1}, T_i)$. Let the random variable $\tilde{t}$ be the disclosure time of positive evidence conditional on lying in $(T_{i-1}, T_i]$.[25] For an agent of type $i$, the expected discounted payoff from this disclosure is $v_G\, \mathbb{E}\left[e^{-r_i \tilde{t}}\, \mathbb{1}\{\tilde{t} \in (T_{i-1}, T_i]\}\right]$. Consider a utility-preserving contraction of time $\tilde{t}$ to a deterministic time $\hat{T}_i$ satisfying $e^{-r_i \hat{T}_i}\, \mathbb{P}[\tilde{t} \in (T_{i-1}, T_i]] = \mathbb{E}\left[e^{-r_i \tilde{t}}\, \mathbb{1}\{\tilde{t} \in (T_{i-1}, T_i]\}\right]$. Such a contraction increases welfare due to the agents' different risk preferences over time lotteries. More patient agents have a less convex discount factor as a function of time, making them relatively more risk averse over time lotteries. Thus, pooling the time of the release of positive evidence in a way that leaves type $i$ indifferent strictly benefits more patient types $k > i$, and it preserves the incentives of more impatient types $j < i$ to invest earlier since delaying their investment beyond $T_{i-1}$ becomes less attractive. The formal proof is in Appendix A.2.

Building on Lemma 1, we show that any optimal policy must disclose the generated bad evidence before the next type of agents start to invest:

[25] Note that the latter interval also includes the disclosure probability at $T_i$.

**Lemma 2.** *Under any optimal policy, $z^B_{T_i} \geq F_i$ for all $i < \bar{n}$.*

We prove Lemma 2 in Appendix A.3 by showing that if not all bad news is revealed at $T_i$, there is a strict improvement to give out the remaining bad evidence at some new time $\hat{T}_i$ in a way that agents with type $r_i$ are indifferent. This makes later types with $r_k < r_i$ strictly better off without inducing earlier types with $r_j > r_i$ to postpone investment. The alternative scheme is feasible because the additional information comes out of the "storage" $F_i - z^B_{T_i}$, which means that even if type $i+1$ postpones investment until the additional bad news is disclosed, there is enough generated information.

Lemma 2 implies that whenever bad news is decision relevant, it should be revealed. Why is it not necessary to also give out bad news immediately at times $t \in (T_{i-1}, T_i)$? Theorem 1 shows that it does not harm to give out bad news immediately also between $T_{i-1}$ and $T_i$. However, each agent of type $i$ gets the same expected payoff as the first type-$i$ agent to experiment. Hence, the designer cannot make the current marginal type better off. There is no strict benefit, and hence transparency within phases is not part of the necessary conditions.

The following two lemmas follow from Lemma 2 (the proofs are in Appendix A.4):

**Lemma 3.** *Under any optimal policy, the no-news belief $x_t$ crosses $x^{myop}$ at most once.*

**Lemma 4.** *Under any optimal policy, a) $\bar{n} = n$ if $x(F_{n-1}) > x^{myop}$, and b) $\bar{n} < n$ if $x(F_{n-1}) < x^{myop}$.*

Lemma 4 formalizes the discussion on the amount of experimentation in Section 4.3: the designer lets all agents experiment if and only if the lack of evidence is not too indicative of the bad state.

Next, we provide a converse of Lemma 2 for optimal good-news disclosure:

**Lemma 5.** *Under any optimal policy, $z^G_{T_i} = 0$ for all $i < \bar{n}$.*

Committing to disclose good news has two effects on welfare: 1) it enables more patient types to invest faster, increasing welfare; 2) it increases the incentive to wait because agents are more pessimistic absent news, decreasing welfare. To get Lemma 5, we show that the former dominates the latter. See Appendix A.5.

Lemma 5 implies that whenever good news is not decision relevant for the current marginal type, it should not be disclosed. Once we show that decision-relevant good news must be disclosed, but potentially with a delay, we get a characterization of the necessary conditions for an optimal policy, as summarized by the following proposition (proof in Appendix A.6):

**Proposition 2.** *Suppose $(z, q)$ is a designer's solution. Let $\bar{n}$ be the last type who invests if no news is revealed. Then we must have*

- $z_t^B \geq F_i$ *for all* $t > T_i$ *and* $i < \bar{n}$,
- $z_t^G = 0$ *for all* $t < T_{\bar{n}-1}$, *and, if* $\bar{n} < n$, *there exists* $\bar{t} > T_{\bar{n}-1}$ *such that* $z_t^G = 0$ *for all* $t < \bar{t}$ *and* $z_t^G = q_{\bar{t}-}$ *for all* $t \geq \bar{t}$.

Together with Lemma 4, Proposition 2 implies that if there is potential for the belief process to cross the myopic threshold before the last type starts investing, i.e. if $x(F_{n-1}) < x^{\text{myop}}$, any optimal policy reveals positive evidence exactly once (for generic type distributions). Finally, Theorem 1 follows once we verify that for any policy $\hat{z}_t$ that satisfies the necessary conditions for optimality in Proposition 2, there exists another policy $z_t$ that gives the same expected payoff for each type and takes the following form: $z_t^B = q_{t-}$ for all $t$, $z_t^G = 0$ for all $t < \bar{t}$, and $z_t^G = q_{\bar{t}-}$ for all $t \geq \bar{t}$ where $\bar{n}$ is the last type who invests under $\hat{z}_t$ if no news is revealed. The details of the argument are in Appendix A.7.

## 4.5 Different approach to the optimality of transparent breakdowns

The result that it is optimal to disclose all bad evidence instantaneously is counter-intuitive from the perspective that it is precisely the prospect of observing bad news that makes agents wait in the transparent benchmark. To better understand the key forces behind the result, we illustrate a stronger argument in favor of transparently disclosing bad news in an environment where the good news process is fixed exogenously. This alternative perspective helps to disentangle the limits of disclosure policies from the impact of welfare maximization. We show that it is never possible to speed up bad-news learning beyond full transparency.

Let good news arrive according to a continuous exogenous process $(z_t^G)_{t\geq 0}$.[26] We start by characterizing the endogenous bad news process under transparent breakdowns $z_t^B = q_{t-}$. This case is analogous to the transparent benchmark in Section 3 but with exogenous $z_t^G$. In the equilibrium, the stock of investment under transparent breakdowns, denoted by $q_t^{\mathrm{TB}}$, follows:

$$\dot{q}_t^{\mathrm{TB}} = \frac{r(q_t^{\mathrm{TB}})}{\lambda_B} \frac{(x_t v_G + (1-x_t)v_B)^+}{(1-x_t)(-v_B)},$$

where process $x_t$ now depends on both $q_t^{\mathrm{TB}}$ and $z_t^G$. Note that $\dot{q}_t^{\mathrm{TB}} > 0$ for all $t$ with $q_t^{\mathrm{TB}} < F_n$ if $\lambda_B q_t^{\mathrm{TB}} \geq \lambda_G z_t^G$ for all $t$, i.e. if bad news dominates. If $\lambda_B q_t^{\mathrm{TB}} < \lambda_G z_t^G$, $x_t$ decreases at time $t$ and may decrease below the myopic indifference threshold. In that case, the remaining agents invest only after good news.

By restricting the disclosure of bad evidence, i.e., $z_t^B < q_t^{\mathrm{TB}}$, the designer can implement faster information generation relative to the transparent breakdowns. However, we show that it is not possible to reveal the additional information faster than under transparency because agents would delay their investment:

**Proposition 3.** *Any incentive compatible bad-evidence disclosure policy $z^B$ satisfies $z_t^B \leq q_t^{TB}$ for all $t$.*

Proposition 3 implies that the designer cannot reveal a larger total amount of bad news in the future by hiding some bad news today. The proof in Appendix A.9 consists of showing that if the revelation of bad news is faster than under transparency, there always exist agents who want to deviate to wait.

Proposition 3 sheds light on why full transparency of breakdowns is part of the optimal policy in Theorem 1: the designer would like to provide more bad news learning because it is decision relevant but cannot do so by promising to delay it.

[26] The continuity of $z^G$ is not necessary for the result below, but imposed here for a cleaner characterization of the transparent breakdowns benchmark $q^{\mathrm{TB}}$.

Hence, the best the designer can do is to use the good news policy to speed up information generation and then disclose bad evidence as it arrives. Notice that we have a partly stronger result in Proposition 2 showing that it is *necessary* for optimality to disclose all bad news at least as often as the type changes. In the limit with a continuum of heterogeneous types ($n \to \infty$ and each $f_i \to 0$), this implies that only full transparency of bad news is optimal.

# 5 Discussion

## 5.1 Homogeneous agents and other forms of heterogeneity

Since the payoff of the first agent to invest is independent of future disclosures, the disclosure policy affects welfare only if agents are heterogeneous. However, the homogeneous-agent case can be insightful when the objective is different from welfare maximization. We present one example, the speed of learning all potential evidence, in Online Appendix B.2. Notice that Proposition 3 holds independent of the designer's objective and applies to homogeneous agents as well.

We consider heterogeneity in discount rates for three reasons. First, the fundamental inefficiency in the transparent benchmark and the second-best policy consists of delays, and we analyze optimal disclosure policies when individuals differ precisely in how much delays affect them. Second, discounting heterogeneity has the analytical advantage that the myopic indifference threshold is the same for everyone, which implies that whether each type of evidence is decision relevant or not is the same for all agents. Third, the discount rates also capture differences in the rate at which the investment opportunity becomes unavailable or obsolete for different agents, e.g., a vaccine becomes useless when the agent gets infected by a virus before being vaccinated. Other forms of heterogeneity, or a combination of them, are also natural in other applications. Here, we present the two most obvious alternatives and then discuss how our results extend to them.[27]

[27] One can also consider heterogeneity in information generation where some agents are experts whose experience is more informative about the quality of the innovation. This kind of heterogeneity alone is not enough to break welfare neutrality. Our results generalize to the case where the agents differ in both informativeness and discount rates.

**Payoff heterogeneity.** Consider a model otherwise identical to the main model but suppose that the types $1, \ldots, n$ differ in their investment payoffs such that $v^i_\omega \geq v^{i+1}_\omega$ for all $i$ and $\omega$. This leads to investment dynamics similar to the main model where types with lower indices always invest earlier.

**Different arrival times.** For another form of heterogeneity consider (identical) agents who arrive in separate cohorts. To fix ideas, suppose that type $i$ specifies the arrival time in $\{t_1, \ldots, t_n\}$ with $t_i < t_{i+1}$. Now, if $t_{i+1} - t_i$ is short enough, not all cohort $i$ agents invest before cohort $i+1$ arrives under transparency.[28]

The strengthened bad-news result in Proposition 3 extends to both alternatives above. The argument in the proof of Proposition 3 builds on showing that the marginal agents' incentive compatibility cannot be satisfied if there is more information than under transparency *at any future time*. As the argument does not involve a comparison with any other types, the same logic applies when agents differ across different dimensions.

## 5.2 Manipulating evidence

In our setup, the designer cannot manipulate or fabricate evidence but decides when to disclose hard evidence. In comparison to more permissive information design tools where the sender can send any messages based on what she has learned, we believe that choosing the timing at which available evidence is released requires less commitment power. Furthermore, considering a hard evidence model without freedom over what messages can be sent helps to focus on the question of *when* information should be revealed. However, it may also be interesting to ask what happens if the designer can manipulate evidence.

The standard Bayesian-persuasion approach would lead to a trivial result regarding welfare maximization: if the designer can perfectly condition the messages on the true state of the world, there is no reason to hide any information. Even if the designer needs to learn the state through endogenous experimentation, she can

[28] In the other case, $t_{i+1} - t_i$ is sufficiently large for all $i$, there is no scope for the disclosure policy to affect welfare.

implement the first best if she has full control over the information environment, including the ability to send private messages. First, by committing to disclose no information to the agent after a certain time, the designer can always eliminate his incentive to wait. Further, the designer can implement the first best by sending personalized recommendations to invest in a way that the agent's expected investment return when observing the recommendation is positive.

The case when the designer needs to learn the state endogenously and can send any messages but publicly is more closely related to our problem. The full analysis of optimal public evidence manipulation is beyond the scope of the present paper, but we discuss some potential avenues.

There are two potential ways the designer may want to manipulate evidence. She may sometimes want to send "fake bad" or "fake good news," i.e., send a message that increases the belief that a certain type of evidence has been generated without fully certifying the corresponding state. Faking good news, called "spamming" in Che and Hörner (2017), is most promising when no news is bad news and the belief can decrease below the myopic threshold. In that case, splitting the belief both above and below the myopic threshold may be feasible. This splitting is beneficial because the designer's value has a convex kink at the myopic threshold. Above the threshold, the value is concave, and hence it may be beneficial to have a smaller upward jump with a larger probability than jumping all the way to 1 with a smaller probability. This kind of split can be achieved by sending a message that pools the case when good evidence has been generated with spamming, i.e., sending the good signal with some probability even without evidence.

There is no similar opportunity if no news is good news. Faking bad news is not optimal in our environment. If the designer terminates the game with some probability by sending out a bad message even if no evidence has arrived, she can incentivize faster investment. However, for all remaining potential investors the cost of an early termination is larger than the benefit of faster learning.[29]

[29] Chen et al. (2024) find that faking bad news may be optimal, but this result relies on the finite investment horizon: faking bad news may help when there is not enough time for everyone to invest in the transparent equilibrium.

## 5.3 Concluding remarks

This paper seeks to answer the question of whether the generated data should be disclosed to the public as it arrives or only after more information has been collected. We address this question in the important case where individuals are forward-looking and information is generated endogenously.

The main applied takeaway of our paper is that information revealing bad quality should be disclosed transparently, while good news may be censored to encourage experimentation. This finding resonates with regulation demanding that fatal breakdowns be reported promptly. On the contrary, it may be wise to keep collecting more data before releasing a potential breakthrough. If the public is expecting to get to know about breakthroughs fast, they may choose to wait until one occurs and become pessimistic if it does not.

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# A Proofs

## A.1 Transparent benchmark

Take some type $r_i$ and some time $t \in [T^b_{i-1}, T^b_i)$. Recall that $V(x_t) = x_t v_G + (1 - x_t)v_B$ is the expected payoff from investing at time $t$ when the current no-news belief is $x_t$. Type $r_i$ has to be indifferent between stopping immediately at $t$ or waiting for small duration $\Delta$ and stop at time $t + \Delta$ if no bad news have arrived during $[t, t + \Delta)$. The expected time-$t$ payoff from the latter strategy is

$$x_t \left(1 - e^{-\lambda_G \dot{q}^{\mathrm{TP}}_t \Delta}\right) v_G + (x_t e^{-\lambda_G \dot{q}^{\mathrm{TP}}_t \Delta} + (1 - x_t) e^{-\lambda_B \dot{q}^{\mathrm{TP}}_t \Delta}) e^{-r_i \Delta} V(x_{t+\Delta}).$$

Noting that $x_{t+\Delta} = \frac{x_t e^{-\lambda_G \dot{q}^{\mathrm{TP}}_t \Delta}}{x_t e^{-\lambda_G \dot{q}^{\mathrm{TP}}_t \Delta} + (1-x_t) e^{-\lambda_B \dot{q}^{\mathrm{TP}}_t \Delta}}$ and $1 - x_{t+\Delta} = \frac{(1-x_t) e^{-\lambda_B \dot{q}^{\mathrm{TP}}_t \Delta}}{x_t e^{-\lambda_G \dot{q}^{\mathrm{TP}}_t \Delta} + (1-x_t) e^{-\lambda_B \dot{q}^{\mathrm{TP}}_t \Delta}}$, the above payoff is equal to

$$x_t \left(1 - e^{-\lambda_G \dot{q}^{\mathrm{TP}}_t \Delta}\right) v_G + e^{-r_i \Delta} (x_t e^{-\lambda_G \dot{q}^{\mathrm{TP}}_t \Delta} v_G + (1 - x_t) e^{-\lambda_B \dot{q}^{\mathrm{TP}}_t \Delta} v_B).$$

The above payoff from waiting must equal the payoff from investing at $t$ immediately. Forming the Taylor approximation and taking the limit as $\Delta \to 0$ from that indifference condition yields (4) in the main text.

Since $x_t$ is itself a function of $q^{\mathrm{TP}}_t$, the indifference condition above is a first-order ordinary differential equation (ODE). The solution to this ODE for each sub-interval $t \in [T^b_{i-1}, T^b_i)$ gives

$$q^{\mathrm{TP}}_t - q^{\mathrm{TP}}_{T^b_{i-1}} = \frac{1}{\lambda_B - \lambda_G} \log \left( \frac{(1 - x_{T^b_{i-1}})(-v_B) e^{r_i (t - T^b_{i-1}) \frac{\lambda_G}{\lambda_B}}}{x_{T^b_{i-1}} v_G e^{r_i (t - T^b_{i-1}) \frac{\lambda_G}{\lambda_B}} - V(x_{T^b_{i-1}}) e^{r_i (t - T^b_{i-1})}} \right).$$

## A.2 Proof of Lemma 1

*Proof.* Take some $(z, q)$ that is feasible in (5). Consider fist the case $i < \bar{n}$. Recall that $T_i = \inf\{t \geq 0 \colon q_t > F_i\}$ is the time at which agents of type $i + 1$ start experimenting under this policy. Suppose, contrary to the property in Lemma 1, that $z^G_{s'} > z^G_s$ for some $T_{i-1} < s < s' < T_i$. We construct a new process $(\hat{z}, \hat{q})$ that increases the expected welfare and has $\hat{z}^G$ constant on $[T_{i-1}, \hat{T}_i)$, where $\hat{T}_i$ is the time at which the new policy discloses all evidence that was disclosed in $(T_{i-1}, T_i]$ under the original policy. And time $\hat{T}_i$ is chosen such that agents with type $r_i$ get the same expected payoff from waiting until time $T_i$ under the original and from waiting until time $\hat{T}_i$ under the modified policy. Given a value $\hat{T}_i$, defined formally below, construct the modified $\hat{z}$ as

$$\hat{z}_t^\omega = \begin{cases} z_t^\omega & \text{for } t \leq T_{i-1}, \\ z_{T_{i-1}}^\omega & \text{for } t \in (T_{i-1}, \hat{T}_i), \\ z_{t+(T_i-\hat{T}_i)}^\omega & \text{for } t \geq \hat{T}_i, \end{cases} \qquad \text{for } \omega \in \{G, B\}.$$

The steps in the proof below will ensure that all agents invest earlier under the modified policy, guaranteeing feasibility.

The new disclosure time $\hat{T}_i$, is the time of an expected-utility-preserving contraction of all possible disclosures on $(T_{i-1}, T_i]$. Let the amounts of disclosed evidence in this interval under the original policy be $\hat{z}_i^G \equiv z_{T_i}^G - z_{T_{i-1}}^G > 0$ and $\hat{z}_i^B \equiv z_{T_i}^B - z_{T_{i-1}}^B \geq 0$. These amounts of evidence are disclosed at $\hat{T}_i$ under the new policy.[30] Time $\hat{T}_i$ is chosen such that agents of type $i$ get the same expected utility from waiting until time $\hat{T}_i$ under the new policy as they got from waiting until time $T_i$ under the original policy. Let $W(i)$ denote the continuation utility from the original policy of type $i$ at time $T_i$ if no evidence has been disclosed by time $T_i$. By construction, the new policy gives the same continuation problem at time $\hat{T}_i$ as the original policy at time $T_i$. Thus, $W(i)$ will also be the time-$\hat{T}_i$ continuation utility under the new policy. Formally, $\hat{T}_i$ satisfies

$$\begin{aligned} & e^{-r_i(\hat{T}_i - T_{i-1})} \left[ x_{T_{i-1}} v_G \left(1 - e^{-\lambda_G \hat{z}_i^G}\right) + \left( x_{T_{i-1}} e^{-\lambda_G \hat{z}_i^G} + (1 - x_{T_{i-1}}) e^{-\lambda_B \hat{z}_i^B} \right) W(i) \right] \\ = & \int_{T_{i-1}}^{T_i} e^{-r_i(t - T_{i-1})} x_{T_{i-1}} v_G \, \mathrm{d} \left( 1 - e^{-\lambda_G (z_t^G - z_{T_{i-1}}^G)} \right) \\ & + e^{-r_i(T_i - T_{i-1})} \left( x_{T_{i-1}} e^{-\lambda_G \hat{z}_i^G} + (1 - x_{T_{i-1}}) e^{-\lambda_B \hat{z}_i^B} \right) W(i). \end{aligned}$$

[30] That is, the probability of disclosing $G$-evidence at time $\hat{T}_i$ in state $\omega = G$ and conditional on no previous disclosure is $1 - e^{-\lambda_G \hat{z}_i^G}$, and analogously for $B$-evidence.

The left-hand side is the expected utility under the new policy and the right-hand side under the original policy. Under the original policy, agents of type $i$ were (weakly) willing to invest at time $T_{i-1}$ rather than waiting until $T_i$. Thus, the choice of $\hat{T}_i$ above ensures that those agents are still willing to invest at time $T_{i-1}$. This also implies that more impatient types $j < i$ are not waiting longer under the new policy than under the original policy, ensuring that the new policy is feasible.

We now verify that the new policy strictly increases welfare. Divide both sides of the indifference condition above by the term in squared brackets to get

$$\begin{aligned} e^{-r_i\hat{T}_i} =& \frac{x_{T_{i-1}} v_G \int_{T_{i-1}}^{T_i} e^{-r_i t}\,\mathrm{d}\left(1-e^{-\lambda_G(z_t^G - z_{T_{i-1}}^G)}\right)}{x_{T_{i-1}} v_G\left(1-e^{-\lambda_G \hat{z}_i^G}\right) + \left(x_{T_{i-1}} e^{-\lambda_G \hat{z}_i^G} + (1-x_{T_{i-1}})e^{-\lambda_B \hat{z}_i^B}\right) W(i)} \\ &+ e^{-r_i T_i}\frac{\left(x_{T_{i-1}} e^{-\lambda_G \hat{z}_i^G} + (1-x_{T_{i-1}})e^{-\lambda_B \hat{z}_i^B}\right) W(i)}{x_{T_{i-1}} v_G\left(1-e^{-\lambda_G \hat{z}_i^G}\right) + \left(x_{T_{i-1}} e^{-\lambda_G \hat{z}_i^G} + (1-x_{T_{i-1}})e^{-\lambda_B \hat{z}_i^B}\right) W(i)}. \end{aligned}$$

Below we make use of the fact that the term on the right-hand side is decreasing in the continuation utility $W(i)$, which holds because $\int_{T_{i-1}}^{T_i} e^{-r_i t}\,\mathrm{d}\left(1-e^{-\lambda_G(z_t^G - z_{T_{i-1}}^G)}\right) > e^{-r_i T_i}\left(1-e^{-\lambda_G \hat{z}_i^G}\right)$.

For all later types $k > i$, the ex-ante expected utility from waiting until time $\hat{T}_i$ and then behaving optimally under the new policy strictly exceeds the payoff this type got from waiting until time $T_i$ and then behaving optimally under the original policy. This is the case if and only if

$$\begin{aligned} e^{-r_k\hat{T}_i} >& \frac{x_{T_{i-1}} v_G \int_{T_{i-1}}^{T_i} e^{-r_k t}\,\mathrm{d}\left(1-e^{-\lambda_G(z_t^G - z_{T_{i-1}}^G)}\right)}{x_{T_{i-1}} v_G\left(1-e^{-\lambda_G \hat{z}_i^G}\right) + \left(x_{T_{i-1}} e^{-\lambda_G \hat{z}_i^G} + (1-x_{T_{i-1}})e^{-\lambda_B \hat{z}_i^B}\right) W(k)} \\ &+ e^{-r_k T_i}\frac{\left(x_{T_{i-1}} e^{-\lambda_G \hat{z}_i^G} + (1-x_{T_{i-1}})e^{-\lambda_B \hat{z}_i^B}\right) W(k)}{x_{T_{i-1}} v_G\left(1-e^{-\lambda_G \hat{z}_i^G}\right) + \left(x_{T_{i-1}} e^{-\lambda_G \hat{z}_i^G} + (1-x_{T_{i-1}})e^{-\lambda_B \hat{z}_i^B}\right) W(k)}. \end{aligned} \tag{7}$$

Note for the first term on the right-hand side that $\frac{\int_{T_{i-1}}^{T_i} e^{-r_k t}\,\mathrm{d}(1-e^{-\lambda_G(z_t^G - z_{T_{i-1}}^G)})}{1-e^{-\lambda_G \hat{z}_i^G}} = \mathbb{E}\left[e^{-r_k\tilde{t}} \mid \tilde{t} \in (T_{i-1}, T_i]\right]$, for the random arrival time of good news $\tilde{t}$. Use $r_k < r_i$ and the concavity of the function $(\cdot)^{r_k/r_i}$ to apply Jensen's inequality to this term.

This shows that the right-hand side in (7) is smaller[31] than

$$\left(\frac{x_{T_{i-1}}v_G\int_{T_{i-1}}^{T_i} e^{-r_it}\,\mathrm{d}\left(1-e^{-\lambda_G(z_t^G-z_{T_{i-1}}^G)}\right)}{x_{T_{i-1}}v_G\left(1-e^{-\lambda_G\hat{z}_i^G}\right)}\right)^{r_k/r_i}$$

$$\times\frac{x_{T_{i-1}}v_G\left(1-e^{-\lambda_G\hat{z}_i^G}\right)}{x_{T_{i-1}}v_G\left(1-e^{-\lambda_G\hat{z}_i^G}\right)+\left(x_{T_{i-1}}e^{-\lambda_G\hat{z}_i^G}+(1-x_{T_{i-1}})e^{-\lambda_B\hat{z}_i^B}\right)W(k)}$$

$$+\left(e^{-r_iT_1}\right)^{r_k/r_i}\frac{\left(x_{T_{i-1}}e^{-\lambda_G\hat{z}_i^G}+(1-x_{T_{i-1}})e^{-\lambda_B\hat{z}_i^B}\right)W(k)}{x_{T_{i-1}}v_G\left(1-e^{-\lambda_G\hat{z}_i^G}\right)+\left(x_{T_{i-1}}e^{-\lambda_G\hat{z}_i^G}+(1-x_{T_{i-1}})e^{-\lambda_B\hat{z}_i^B}\right)W(k)}$$

Since the above is a weighted average of two terms, each elevated by an exponent smaller than 1, we can apply Jensen's inequality again to conclude that the previous term is smaller than

$$\left(\frac{\int_{T_{i-1}}^{T_i} e^{-r_it}x_{T_{i-1}}v_G\,\mathrm{d}\left(1-e^{-\lambda_G(z_t^G-z_{T_{i-1}}^G)}\right)}{x_{T_{i-1}}v_G\left(1-e^{-\lambda_G\hat{z}_i^G}\right)}\right.$$

$$\times\frac{x_{T_{i-1}}v_G\left(1-e^{-\lambda_G\hat{z}_i^G}\right)}{x_{T_{i-1}}v_G\left(1-e^{-\lambda_G\hat{z}_i^G}\right)+\left(x_{T_{i-1}}e^{-\lambda_G\hat{z}_i^G}+(1-x_{T_{i-1}})e^{-\lambda_B\hat{z}_i^B}\right)W(k)}$$

$$\left.+\,e^{-r_iT_1}\frac{\left(x_{T_{i-1}}e^{-\lambda_G\hat{z}_i^G}+(1-x_{T_{i-1}})e^{-\lambda_B\hat{z}_i^B}\right)W(k)}{x_{T_{i-1}}v_G\left(1-e^{-\lambda_G\hat{z}_i^G}\right)+\left(x_{T_{i-1}}e^{-\lambda_G\hat{z}_i^G}+(1-x_{T_{i-1}})e^{-\lambda_B\hat{z}_i^B}\right)W(k)}\right)^{r_k/r_i}$$

Note that $W(k)\geq W(i)$ because $e^{-r_kt}>e^{-r_it}$, so the more patient $r_k$-agents can ensure at least the same continuation payoff as $r_i$-agents. We have confirmed that the term in parentheses above is decreasing in the continuation utility. Thus, the above expression is bounded above by the equivalent term where $W(k)$ is replaced by $W(i)$, which equals $\left(e^{-r_i\hat{T}_i}\right)^{r_k/r_i}=e^{-r_k\hat{T}_i}$ by construction.

Hence, following the same strategy as under the original policy, all agents with types $r_k<r_i$ get a strictly higher utility (i) because their expected payoff from receiving good news disclosed in $(T_{i-1},T_i]$ under the original policy is increased by pooling the disclosures on time $\hat{T}_i$, and (ii) because $\hat{T}_i<T_i$ so that the no-news continuation payoff $W(k)$ accrues earlier.

[31] Strictly smaller because $\hat{z}_i^G>0$.

Finally, consider type $i = \bar{n}$ when $\bar{n} < n$. That is, $i < n$ being the last type to experiment. Recall that $T_{\bar{n}}$ is the time at which the last agent experiments. We will show a stronger result than stated in the lemma: there is at most one time $\bar{t} \in (T_{\bar{n}-1}, \infty)$ at which positive evidence can be disclosed.[32] Formally, we show that there exists $\bar{t}$ such that $z^G_{\bar{t}-} = z^G_{T_{\bar{n}-1}+}$ and $z^G_{\bar{t}+} = z^G_{\infty}$.

We follow similar steps as in the previous case with the difference that now all information that the original policy discloses on $(T_{\bar{n}-1}, \infty)$ is pooled on time $\bar{t}$. Time $\bar{t}$ is chosen such that the agents of type $\bar{n}$ are indifferent between investing at $T_{\bar{n}}$ under the original policy and waiting until $\bar{t}$ under the new policy. Since the modified policy discloses no information beyond $\bar{t}$, the continuation utility at time $\bar{t}$ is $V(\hat{x}_{\bar{t}})^+$ for any agent who waits until $\bar{t}$. Further $\bar{n} < n$ requires that under the original policy $\lim_{t\to\infty} V(x_t) \leq 0$. Since all information that was ever disclosed under the original policy will be disclosed at $\bar{t}$ under the new policy we conclude that $V(\hat{x}_{\bar{t}})^+ = (\lim_{t\to\infty} V(x_t))^+ = 0$. Thus, we choose $\bar{t}$ to satisfy

$$e^{-r_{\bar{n}}\bar{t}} x_{T_{\bar{n}-1}} v_G\Big(1 - e^{-\lambda_G \overset{\infty}{z}{}^G_{\bar{n}}}\Big) = x_{T_{\bar{n}-1}} v_G \int_{T_{\bar{n}-1}}^{T_{\bar{n}}} e^{-r_{\bar{n}}t} \mathrm{d}\Big(1 - e^{-\lambda_G (z^G_t - z^G_{T_{\bar{n}-1}})}\Big) + e^{-r_{\bar{n}}T_{\bar{n}}}\Big(x_{T_{\bar{n}-1}} e^{-\lambda_G \hat{z}^G_{\bar{n}}} + (1 - x_{T_{\bar{n}-1}}) e^{-\lambda_B \hat{z}^B_{\bar{n}}}\Big) W(\bar{n}), \tag{8}$$

where $\overset{\infty}{z}{}^\omega_{\bar{n}} \equiv z^\omega_\infty - z^\omega_{T_{\bar{n}-1}}$, and $\hat{z}^\omega_{\bar{n}} = z^\omega_{T_{\bar{n}}} - z^\omega_{T_{\bar{n}-1}}$.

As in the previous case, the maintained willingness of agents of type $\bar{n}$ to invest at $T_{\bar{n}-1}$ implies that more impatient agents are not induced to wait longer by the modification, ensuring feasibility.

We show that, with $\bar{t}$ in (8), the more patient types $k > \bar{n}$ are strictly better off waiting forever under the new policy than waiting forever under the original policy. This is equivalent to

$$e^{-r_k \bar{t}} > \frac{\int_{T_{\bar{n}-1}}^{\infty} e^{-r_k t} \, \mathrm{d}\left(1 - e^{-\lambda_G (z^G_t - z^G_{T_{\bar{n}-1}})}\right)}{\left(1 - e^{-\lambda_G \overset{\infty}{z}{}^G_{\bar{n}}}\right)}, \quad \text{for all } k > \bar{n}. \tag{9}$$

[32] Stronger because we may have that $\bar{t} > T_{\bar{n}}$ so that $z^G$ is flat on a strictly larger interval than stated in the lemma.

By (8), $e^{-r_k \bar{t}}$ is equal to

$$\Bigg(\frac{x_{T_{\bar{n}-1}} v_G \int_{T_{\bar{n}-1}}^{T_{\bar{n}}} e^{-r_{\bar{n}} t} \mathrm{d}\Big(1 - e^{-\lambda_G (z_t^G - z_{T_{\bar{n}-1}}^G)}\Big)}{x_{T_{\bar{n}-1}} v_G \Big(1 - e^{-\lambda_G \overset{\infty}{z}{}^G_{\bar{n}}}\Big)} + \frac{e^{-r_{\bar{n}} T_{\bar{n}}} \Big(x_{T_{\bar{n}-1}} e^{-\lambda_G \hat{z}_{\bar{n}}^G} + (1 - x_{T_{\bar{n}-1}}) e^{-\lambda_B \hat{z}_{\bar{n}}^B}\Big) W(\bar{n})}{x_{T_{\bar{n}-1}} v_G \Big(1 - e^{-\lambda_G \overset{\infty}{z}{}^G_{\bar{n}}}\Big)}\Bigg)^{r_k / r_{\bar{n}}}$$

Once time $T_{\bar{n}}$ is reached, agents of type $\bar{n}$ always have the option to wait forever, thus their continuation utility satisfies $W(\bar{n}) \geq x_{T_{\bar{n}}} v_G \int_{T_{\bar{n}}}^{\infty} e^{-r_{\bar{n}}(t - T_{\bar{n}})} \,\mathrm{d}\left(1 - e^{-\lambda_G (z_t^G - z_{T_{\bar{n}}}^G)}\right)$. Hence, $e^{-r_k \bar{t}}$ is at least

$$\Bigg(\frac{x_{T_{\bar{n}-1}} v_G \int_{T_{\bar{n}-1}}^{T_{\bar{n}}} e^{-r_{\bar{n}} t} \mathrm{d}\Big(1 - e^{-\lambda_G (z_t^G - z_{T_{\bar{n}-1}}^G)}\Big)}{x_{T_{\bar{n}-1}} v_G \Big(1 - e^{-\lambda_G \overset{\infty}{z}{}^G_{\bar{n}}}\Big)} + \frac{\Big(x_{T_{\bar{n}-1}} e^{-\lambda_G \hat{z}_{\bar{n}}^G} + (1 - x_{T_{\bar{n}-1}}) e^{-\lambda_B \hat{z}_{\bar{n}}^B}\Big) x_{T_{\bar{n}}} v_G \int_{T_{\bar{n}}}^{\infty} e^{-r_{\bar{n}} t} \mathrm{d}\Big(1 - e^{-\lambda_G (z_t^G - z_{T_{\bar{n}}}^G)}\Big)}{x_{T_{\bar{n}-1}} v_G \Big(1 - e^{-\lambda_G \overset{\infty}{z}{}^G_{\bar{n}}}\Big)}\Bigg)^{r_k / r_{\bar{n}}}.$$

Note that $\left(x_{T_{\bar{n}-1}} e^{-\lambda_G \hat{z}_{\bar{n}}^G} + (1 - x_{T_{\bar{n}-1}}) e^{-\lambda_B \hat{z}_{\bar{n}}^B}\right) x_{T_{\bar{n}}} = x_{T_{\bar{n}-1}} e^{-\lambda_G \hat{z}_{\bar{n}}^G}$. Thus, $e^{-r_k \bar{t}}$ is at least $\left(\frac{x_{T_{\bar{n}-1}} v_G \int_{T_{\bar{n}-1}}^{\infty} e^{-r_{\bar{n}} t} \,\mathrm{d}\left(1 - e^{-\lambda_G (z_t^G - z_{T_{\bar{n}-1}}^G)}\right)}{x_{T_{\bar{n}-1}} v_G \left(1 - e^{-\lambda_G \overset{\infty}{z}{}^G_{\bar{n}}}\right)}\right)^{r_k / r_{\bar{n}}}$. Since $r_k / r_{\bar{n}} < 1$, Jensen's inequality implies that the above is greater than the right-hand side of (9). This proves that more patient agents are strictly better off.

□

## A.3 Proof of Lemma 2

*Proof.* Suppose that $(z, q)$ satisfies the IC constraint in (5), $z_t^G$ is constant for all $t \in (T_{i-1}, T_i)$ if $i < \bar{n}$ as in Lemma 1, and, contrary to the claim, $z_{T_i}^B < F_i$ for some $i < \bar{n}$. We show that there exists another process $(\hat{z}, \hat{q})$ that satisfies the IC constraint, has $z_{T_i}^B \geq F_i$ for all $i < \bar{n}$, and leads to strictly higher expected welfare.

We apply an induction argument. First, we show that if the original policy does not disclose all bad evidence at $T_{\bar{n}-1}$, there is a strict improvement that does.

Then, we show for all $i < \bar{n}$ that there is a strict improvement if not all bad evidence is disclosed at $T_{i-1}$ but all bad evidence is disclosed at $T_i$.

Let $\lim_{t\to\infty} z_t^\omega =: z_\infty^\omega$. As a preliminary step, notice that if $z_\infty^B < F_{\bar{n}}$, $\bar{n} < n$, and $\frac{x_0 e^{-\lambda_G z_\infty^G}}{x_0 e^{-\lambda_G z_\infty^G} + (1-x_0)e^{-\lambda_B F_{\bar{n}}}} \geq x^{\text{myop}}$, then it would be a strict improvement to disclose the additional available bad news at some time $t$ chosen such that types $\bar{n}+1$ are willing to invest at $t$ without inducing more impatient agents to wait until $t$. Hence, we focus on the cases where either $\bar{n} = n$ or $\frac{x_0 e^{-\lambda_G z_\infty^G}}{x_0 e^{-\lambda_G z_\infty^G} + (1-x_0)e^{-\lambda_B F_{\bar{n}}}} < x^{\text{myop}}$.

Suppose that $z_{T_{\bar{n}-1}}^B < F_{\bar{n}-1}$. We suggest an alternative policy $\hat{z}$ that is otherwise the same as the original but has $\hat{z}_t^B = F_{\bar{n}-1}$ for all $t \in [\hat{T}_{\bar{n}-1}, T_{\bar{n}})$, where time $\hat{T}_{\bar{n}-1} > T_{\bar{n}-1}$ is chosen such that type $\bar{n}-1$ is indifferent between investing at $T_{\bar{n}-1}$ and waiting until the additional bad evidence is disclosed at $\hat{T}_{\bar{n}-1}$. The fact that type $r_{\bar{n}-1}$ is indifferent implies that more patient agents $\bar{n}$ are strictly better off waiting until $\hat{T}_{\bar{n}-1}$ and all less patient agents $r > r_{\bar{n}-1}$ strictly prefer investing at time $T_{\bar{n}-1}$ or earlier. As the incentives of the less patient agents remain unchanged, it remains incentive compatible to have $\hat{z}_t = z_t$ for all $t \leq T_{\bar{n}-1}$, and hence, the expected payoff of types $i < \bar{n}$ remains unchanged. Type $\bar{n}$ is strictly better off.

To complete the first step, we need to check that the modified policy implements the same good news process as the original policy. If $\bar{n} = n$, any good news released after $T_{\bar{n}-1}$ is irrelevant because all remaining agents are willing to invest also absent good news. Hence, we focus on $\bar{n} < n$. Let $\bar{t} := \inf\{t > T_{\bar{n}-1} : z_t^G > z_{T_{\bar{n}-1}}^G\}$ be the earliest time after $T_{\bar{n}-1}$ at which the original policy discloses good news. The amount of good news generated by $\bar{t}$ under the original policy will also be available under the modified policy if $\hat{T}_{\bar{n}-1} \leq \bar{t}$ because, by construction, agents of type $\bar{n}$ prefer investing at $\hat{T}_{\bar{n}-1}$ to waiting beyond $\bar{t}$ To see this, recall that types $\bar{n}$ weakly prefer investing at $T_{\bar{n}-1}$ to waiting until $\bar{t}$ under the original scheme, and investing at $\hat{T}_{\bar{n}-1}$ under the alternative scheme is strictly better for them.

Hence, we are left to verify that $\hat{T}_{\bar{n}-1} \leq \bar{t}$, This is immediate if $\bar{t} = \infty$. For the case of $\bar{t} < \infty$, we know from the proof of Lemma 1 that a one-time disclosure of good news is strictly better than multiple disclosures also after $T_{\bar{n}-1}$, which implies that we can focus on the case where $z_\infty^G = z_{\bar{t}}^G$.[33] This tells us that $x^{\text{myop}} >$

[33] There always exists a policy that is otherwise identical to the original policy but pools

$\frac{x_0 e^{-\lambda_G z_\infty^G}}{x_0 e^{-\lambda_G z_\infty^G}+(1-x_0)e^{-\lambda_B F_{\bar{n}}}} \geq \frac{x_0 e^{-\lambda_G z_{\bar{t}}^G}}{x_0 e^{-\lambda_G z_{\bar{t}}^G} + (1-x_0)e^{-\lambda_B F_{\bar{n}-1}}}$, which implies that $x_0 e^{-\lambda_G z_{\bar{t}}^G} v_G + (1-x_0)e^{-\lambda_B F_{\bar{n}-1}} v_B < 0$.

As investing at $T_{\bar{n}-1}$ is incentive compatible under the original scheme, we have

$$V(x_{T_{\bar{n}-1}}) \geq e^{-r_{\bar{n}}(\bar{t}-T_{\bar{n}-1})} x_{T_{\bar{n}-1}} \left(1 - e^{-\lambda_G \hat{z}_{\bar{n}}^G}\right) v_G, \tag{10}$$

where $\hat{z}_{\bar{n}}^G := z_{\bar{t}}^G - z_{T_{\bar{n}-1}}^G$. By the construction of $\hat{T}_{\bar{n}-1}$, we also have

$$V(x_{T_{\bar{n}-1}}) < e^{-r_{\bar{n}}(\hat{T}_{\bar{n}-1}-T_{\bar{n}-1})} \left(x_{T_{\bar{n}-1}} v_G + (1 - x_{T_{\bar{n}-1}})e^{-\lambda_B \hat{z}_{\bar{n}}^B} v_B\right), \tag{11}$$

where $\hat{z}_{\bar{n}}^B := F_{\bar{n}-1} - z_{T_{\bar{n}-1}}^B$. Combining (10) and (11) and rearranging gives

$$e^{-r_{\bar{n}}(\bar{t}-\hat{T}_{\bar{n}-1})} < \frac{x_{T_{\bar{n}-1}} e^{-\lambda_G \hat{z}_{\bar{n}}^G} v_G + (1 - x_{T_{\bar{n}-1}})e^{-\lambda_B \hat{z}_{\bar{n}}^B} v_B}{x_{T_{\bar{n}-1}} \left(1 - e^{-\lambda_G \hat{z}_{\bar{n}}^G}\right) v_G} + 1,$$

where the first term on the RHS is negative by $x_0 e^{-\lambda_G z_{\bar{t}}^G} v_G + (1-x_0)e^{-\lambda_B F_{\bar{n}-1}} v_B < 0$. Hence, $\hat{T}_{\bar{n}-1} < \bar{t}$.

The second step of the induction argument is almost identical. Suppose no full revelation of bad news at $T_{i-1}$ but full revelation of bad news at $T_i$. Again, define an alternative policy that disclose all bad evidence from agents with $r \geq r_{i-1}$ at time $\hat{T}_{i-1} \in (T_{i-1}, T_i)$ such that type $i-1$ is indifferent between investing at $T_{i-1}$ and waiting until $\hat{T}_{i-1}$. All more patient types are now better off as they strictly prefer waiting, and the incentives and expected payoff for all more impatient types remain unchanged. To see that $\hat{T}_{i-1} < T_i$, recall that we assume full bad news revelation at $T_i$. Hence, there is more information available at $T_i$ than at $\hat{T}_{i-1}$. Since the original scheme is incentive compatible, $i-1$ must prefer investing at $T_{i-1}$ over waiting until $T_i$, which then gives that waiting until $\hat{T}_{i-1}$ under the alternative scheme must be a better option than waiting until $T_i$, which is only possible if $\hat{T}_{i-1} < T_i$. □

all good-news disclosure times after $T_{\bar{n}-1}$ and gives an upper bound for the welfare under the original policy.

## A.4 Proofs of Lemmas 3 and 4

### Proof of Lemma 3

*Proof.* Suppose not. Then it must be that $x_t < x^{\text{myop}}$ for some $t < T_{\bar{n}-1}$, where $\bar{n}$ is the last type who invests if no news is revealed. Since for $i < \bar{n}$ good news are only revealed at times $t = T_i$ for some $i$ (Lemma 5), this requires $x_{T_i} < x^{\text{myop}}$ for some $i < \bar{n}$. From Lemma 2, we fur)ther know that $z^B_{T_i} = F_i$ for all $i < \bar{n}$. But then no further agent is willing to invest given the current belief, and, since all generated bad news has been disclosed already, it is impossible to have $x_t \geq x^{\text{myop}}$ for any $t > T_i$. The fact that $x_t < x^{\text{myop}}$ for all $t > T_i$ contradicts $i < \bar{n}$. □

### Proof of Lemma 4

*Proof.* Part (a) is an immediate consequence of Lemmas 1 and 2 as with the condition $x(F_{n-1}) > x^{\text{myop}}$ they imply that under any optimal policy $x_t > x^{\text{myop}}$ for all $t \in [0, T_{n-1}]$, and at least some agents with type $i = n$ invests absent news.

We prove part (b) by arguing that it is strictly better to reveal all good news at $T_{n-1}$ rather than hiding enough good news to make type $n$ willing to invest absent news. Recall that all agents with type $n$ receive the same expected payoff as the first of them to invest. Hence, fixing disclosure and investment choices prior to $T_{n-1}$, the question of optimality boils down to maximizing type $n$'s welfare at time $T_{n-1}$. Suppose, contrary to statement, that there is an optimal policy such that $x_{T_{n-1}} \geq x^{\text{myop}}$. We suggest that there is a strict improvement to reveal all good news with a long enough delay, $\Delta$, chosen so that type $n-1$ is indifferent between investing at $T_{n-1}$ and waiting until the revelation of good news at $T_n + \Delta$.[34] If $n-1$ is indifferent, agents with type $r_n < r_{n-1}$ must strictly prefer to wait for the good news at $T_n + \Delta$ and is hence strictly better off than under the original policy. Thus no policy featuring $\bar{n} = n$ is optimal when $x(F_{n-1}) < x^{\text{myop}}$. □

[34] Such a $\Delta$ must exist because we must have $x_{T_{n-2}} > x^{\text{myop}}$ since type $n-1$ would not be willing to experiment at $T_{n-2}$ if $x_{T_{n-2}} \leq x^{\text{myop}}$. This is obvious for $x_{T_{n-2}} < x^{\text{myop}}$. For $x_{T_{n-2}} = x^{\text{myop}}$ is follows from the fact that any optimal policy reveals all bad news, so that $x_{T_{n-2}} = x^{\text{myop}}$ and $x_{T_{n-1}} \geq x^{\text{myop}}$ only if some good news are revealed in the meantime and the agent would be better off waiting for good news rather than investing with a payoff of $V(x^{\text{myop}}) = 0$.

## A.5 Proof of Lemma 5

*Proof.* In ant adoption equilibrium all agents with the same discount rate must get the same expected payoff as the agent with that discount rate who experiments first. Therefore, we can rewrite the designer's problem (5) using the investment time $T_{i-1}$ to compute the expected payoff of all type-$i$ agents and specify the amount of disclosed evidence only at times in $\{T_i\}_{i\geq 0}$. The incentive compatibility constraints simplify to requiring that agents of type $i < \bar{n}$ weakly prefer investing at time $T_{i-1}$ to waiting until time $T_i$, and agents of type $\bar{n}$ prefer investing at $T_{\bar{n}-1}$ to waiting until $\bar{t}$, where $\bar{t} := \inf\{t > T_{\bar{n}-1} : z_t^G > z_{T_{\bar{n}-1}}^G\}$ is the earliest time at which good news is disclosed after $T_{\bar{n}-1}$. By Lemma 1t there is no good-news disclosure within a phase. Lemma 2 implies that $z_{T_i}^B = F_i$. Hence, the value of the designer's problem can be determined by the following finite-dimensional problem, where the maximization is over the last experimenting type $\bar{n}$, the times $\{T_i\}_{i=1}^{\bar{n}-1}$ and $\bar{t}$, and the amount of good news disclosed at those times $\{z_i^G\}_{i=1}^{\bar{n}}$:

$$
\begin{aligned}
\max \Bigg\{ & \sum_{i=1}^{\bar{n}-1} x_0 v_G \Big(e^{-\lambda_G z_{i-1}^G} - e^{-\lambda_G z_i^G}\Big) \sum_{j=i+1}^{n} f_j e^{-r_j T_i} + \Big(e^{-\lambda_G z_{\bar{n}-1}^G} - e^{-\lambda_G z_{\bar{n}}^G}\Big) \sum_{j=\bar{n}+1}^{n} f_j e^{-r_j \bar{t}} \\
& + \sum_{i=1}^{\bar{n}} f_i e^{-r_i T_{i-1}} \Big(x_0 v_G e^{-\lambda_G z_{i-1}^G} + (1-x_0) v_B e^{-\lambda_B F_{i-1}}\Big) \Bigg\} \\
& \text{such that } \forall i \leq \bar{n}\text{: } z_{i-1}^G \leq z_i^G \leq F_i, \text{ and } \forall i < \bar{n}, \\
& e^{-r_i T_{i-1}} \Big(x_0 v_G e^{-\lambda_G z_{i-1}^G} + (1-x_0) v_B e^{-\lambda_B F_{i-1}}\Big) \\
& \geq e^{-r_i T_i} \Big[x_0 v_G (e^{-\lambda_G z_{i-1}^G} - e^{-\lambda_G z_i^G}) + \Big(x_0 v_G e^{-\lambda_G z_i^G} + (1-x_0) v_B e^{-\lambda_B F_i}\Big)^+\Big] \\
\text{and } & e^{-r_{\bar{n}} T_{\bar{n}-1}} \Big(x_0 v_G e^{-\lambda_G z_{\bar{n}-1}^G} + (1-x_0) v_B e^{-\lambda_B F_{\bar{n}-1}}\Big) \\
& \geq e^{-r_{\bar{n}} \bar{t}} \Big[x_0 v_G (e^{-\lambda_G z_{\bar{n}-1}^G} - e^{-\lambda_G z_{\bar{n}}^G}) + \Big(x_0 v_G e^{-\lambda_G z_{\bar{n}}^G} + (1-x_0) v_B e^{-\lambda_B F_{\bar{n}}}\Big)^+\Big].
\end{aligned} \tag{12}
$$

Recall the convention that $T_0 = z_0^G = 0$. Define for ease of exposition $\tilde{V}_i \equiv x_0 v_G e^{-\lambda_G z_{i-1}^G} + (1-x_0) v_B e^{-\lambda_B F_{i-1}}$ and $\hat{V}_i \equiv x_0 v_G e^{-\lambda_G z_{i-1}^G} + (1-x_0) v_B e^{-\lambda_B F_i}$ for the terms on the left- and on the right-hand side of the IC constraints, respectively. Note that these values differ from $V$ because they are ex-ante expected values whereas $V(x_{T_{i-1}})$ is *conditional* on reaching time $T_{i-1}$ without evidence. The value $\tilde{V}_i$ considers all evidence disclosed at $T_{i-1}$ whereas $\hat{V}_i$ also takes into account the (lack of) bad evidence to be disclosed at $T_i$.

To solve the above problem, note that by Lemma 3 and the definition of $\bar{n}$ we have that $x_t > x^{\text{myop}}$ for all $t \leq T_{\bar{n}-1}$, so that the last parenthesis on the right-hand side is positive. Thus,for $i < \bar{n}$ the right-hand side of the IC constraint is equal to $e^{-r_i T_i}[x_0 v_G e^{-\lambda z^G_{i-1}} + (1-x_0) v_B e^{-\lambda F_i}] = e^{-r_i T_i}\hat{V}_i$. For $i = \bar{n}$ the right-hand side of the constraint is equal to $e^{-r_{\bar{n}}\bar{t}} x_0 v_G (e^{-\lambda z^G_{\bar{n}-1}} - e^{-\lambda z^G_{\bar{n}}}) > 0$ whenever $\bar{n} < n$. We focus on the case $\bar{n} < n$. The proof for $\bar{n} = n$ is parallel. Assigning Lagrange-multiplier $\gamma_i$ to the IC constraint featuring $r_i$, the first-order condition (FOC) with respect to $\bar{t}$ is

$$x_0 v_G (e^{-\lambda_G z^G_{\bar{n}-1}} - e^{-\lambda_G z^G_{\bar{n}}}) r_{\bar{n}} \left[ - \sum_{j=\bar{n}+1}^{n} f_j \frac{r_j}{r_{\bar{n}}} e^{-r_j \bar{t}} + \gamma_{\bar{n}} e^{-r_{\bar{n}}\bar{t}} \right] = 0. \tag{13}$$

Since $r_j < r_{\bar{n}}$ for all $j > \bar{n}$, the FOC implies $\sum_{j=\bar{n}+1}^{n} f_j e^{-r_j \bar{t}} > \gamma_{\bar{n}} e^{-r_{\bar{n}}\bar{t}}$. The derivative with respect to $z_{\bar{n}}$ is $\left(x_0 v_G \lambda_G e^{-\lambda_G z^G_{\bar{n}}}\right) \left[\sum_{j=\bar{n}+1}^{n} f_j e^{-r_j \bar{t}} - \gamma_{\bar{n}} e^{-r_{\bar{n}}\bar{t}}\right]$. Therefore, $z_{\bar{n}}$ must be equal to $F_{\bar{n}}$.

Next, consider the derivative with respect to $z^G_{\bar{n}-1}$. This is $(x_0 v_G \lambda_G e^{-\lambda_G z^G_{\bar{n}-1}}) > 0$ multiplied with

$$- \sum_{j=\bar{n}+1}^{n} f_j e^{-r_j \bar{t}} + \sum_{j=\bar{n}}^{n} f_j e^{-r_j T_{\bar{n}-1}} - f_{\bar{n}} e^{-r_{\bar{n}} T_{\bar{n}-1}} - \gamma_{\bar{n}} (e^{-r_{\bar{n}} T_{\bar{n}-1}} - e^{-r_{\bar{n}} T_{\bar{n}}}). \tag{14}$$

We show first that this derivative is negative and then show by induction that the derivative with respect to $z^G_i$ is negative for all $i < \bar{n} - 1$.

For the first step $i = \bar{n} - 1$ we have

$$\gamma_{\bar{n}} = \sum_{j=\bar{n}+1}^{n} f_j \frac{r_j}{r_{\bar{n}}} \frac{e^{-r_j \bar{t}}}{e^{-r_{\bar{n}}\bar{t}}} > \sum_{j=\bar{n}+1}^{n} f_j \frac{e^{-r_j T_{\bar{n}-1}} - e^{-r_j \bar{t}}}{e^{-r_{\bar{n}} T_{\bar{n}-1}} - e^{-r_{\bar{n}}\bar{t}}},$$

where the equality follows from (13), and the inequality holds since $r_j < r_{\bar{n}}$ and the relation between the summation terms is equivalent to $\frac{e^{r_{\bar{n}}(\bar{t}-T_{\bar{n}-1})}-1}{r_{\bar{n}}} > \frac{e^{r_j(\bar{t}-T_{\bar{n}-1})}-1}{r_j}$.

For $i < \bar{n} - 1$, the derivative with respect to $z^G_i$ is $(x_0 v_G \lambda_G e^{-\lambda_G z^G_i} > 0$ times)

$$- \sum_{j=i+2}^{n} f_j e^{-r_j T_{i+1}} + \sum_{j=i+1}^{n} f_j e^{-r_j T_i} - f_{i+1} e^{-r_{i+1} T_i} - \gamma_{i+1} (e^{-r_{i+1} T_i} - e^{-r_{i+1} T_{i+1}}). \tag{15}$$

We show by induction that the derivative above is negative for all $i < \bar{n}-1$. That is, going from higher to lower $i$, we show that

$$\gamma_{i+1} > \sum_{j=i+2}^{n} f_j \frac{e^{-r_j T_i} - e^{-r_j T_{i+1}}}{e^{-r_{i+1} T_i} - e^{-r_{i+1} T_{i+1}}} \quad \text{implies} \quad \gamma_i > \sum_{j=i+1}^{n} f_j \frac{e^{-r_j T_{i-1}} - e^{-r_j T_i}}{e^{-r_i T_{i-1}} - e^{-r_i T_i}}. \quad (16)$$

The first-order condition with respect to $T_i$ for $i < \bar{n}-1$.

$$-x_0 v_G (e^{-\lambda_G z_{i-1}^G} - e^{-\lambda_G z_i^G}) \sum_{j=i+1}^{n} f_j r_j e^{-r_j T_i} - f_{i+1} r_{i+1} e^{-r_{i+1} T_i} \tilde{V}_{i+1}$$
$$+ \gamma_i r_i e^{-r_i T_i} \hat{V}_i - \gamma_{i+1} r_{i+1} e^{-r_{i+1} T_i} \tilde{V}_{i+1} = 0.$$

This is equivalent to $\gamma_i = x_0 v_G (e^{-\lambda_G z_{i-1}^G} - e^{-\lambda_G z_i^G}) \sum_{j=i+1}^{n} f_j \frac{r_j e^{-r_j T_i}}{r_i e^{-r_i T_i} \hat{V}_i} +$ $f_{i+1} \frac{r_{i+1} e^{-r_{i+1} T_i} \tilde{V}_{i+1}}{r_i e^{-r_i T_i} \hat{V}_i} + \gamma_{i+1} \frac{r_{i+1} e^{-r_{i+1} T_i} \tilde{V}_{i+1}}{r_i e^{-r_i T_i} \hat{V}_i}$. We have $\frac{\tilde{V}_{i+1}}{\hat{V}_i} = \frac{x_0 v_G e^{-\lambda_G z_i^G} + (1-x_0) v_B e^{-\lambda_B F_i}}{x_0 v_G e^{-\lambda_G z_{i-1}^G} + (1-x_0) v_B e^{-\lambda_B F_i}}$. Note that for $i < \bar{n}$, given that $\gamma_{i+1}$ satisfies the left part (16), the derivative with respect to $z_i^G$ is negative, so that $z_i^G = z_{i-1}^G$. This implies that the term above is equal to 1. Consequently, $\gamma_i$ satisfies the right part of (16) if

$$f_{i+1} \frac{r_{i+1} e^{-r_{i+1} T_i}}{r_i e^{-r_i T_i}} + \sum_{j=i+2}^{n} f_j \frac{e^{-r_j T_i} - e^{-r_j T_{i+1}}}{e^{-r_{i+1} T_i} - e^{-r_{i+1} T_{i+1}}} \frac{r_{i+1} e^{-r_{i+1} T_i}}{r_i e^{-r_i T_i}} \geq \sum_{j=i+1}^{n} f_j \frac{e^{-r_j T_{i-1}} - e^{-r_j T_i}}{e^{-r_i T_{i-1}} - e^{-r_i T_i}}.$$

This holds as, for the $j = i+1$ term we have again $(e^{r_i (T_i - T_{i-1})} - 1)/r_i > (e^{r_{i+1} (T_i - T_{i-1})} - 1)/r_{i+1}$, and for the terms $j \geq i+2$ we have[35]

$$\frac{e^{-r_j T_i} - e^{-r_j T_{i+1}}}{e^{-r_{i+1} T_i} - e^{-r_{i+1} T_{i+1}}} \frac{r_{i+1} e^{-r_{i+1} T_i}}{r_i e^{-r_i T_i}} > \frac{e^{-r_j T_{i-1}} - e^{-r_j T_i}}{e^{-r_i T_{i-1}} - e^{-r_i T_i}}.$$

It follows that any solution to the above problem has $z_i^G = 0$ for all $i < \bar{n}$; and, whenever $\bar{n} < n$, then $z_{\bar{n}}^G = F_{\bar{n}}$. □

[35] This inequality is equivalent to

$$\frac{e^{r_i (T_i - T_{i-1})} - 1}{r_i} \Big/ \frac{e^{r_j (T_i - T_{i-1})} - 1}{r_j} > \frac{1 - e^{-r_{i+1} (T_{i+1} - T_i)}}{r_{i+1}} \Big/ \frac{1 - e^{-r_j (T_{i+1} - T_i)}}{r_j}.$$

## A.6 Proof of Proposition 2

*Proof.* Proposition 2 follows from Lemma 2 and Lemma 5 once we show that $z_t^G = q_{t-}$ for all $t \geq T_{\bar{n}}$ if $\bar{n} < n$.

From Lemma 1, we know that good news revelation takes place only at one $t = T$ after $T_{\bar{n}-1}$. Let $z$ be the amount of good news revealed at $T$. Notice first that it is optimal to choose $z$ and $T$ such that type $\bar{n}$ is indifferent between investing at $T_{\bar{n}-1}$ and waiting until $T$ when investing only after good news. We let $T(z)$ denote the time that makes type $\bar{n}$ indifferent when $z$ is the amount of good news:

$$T(z): \quad x_{\bar{n}-1}v_G + (1 - x_{\bar{n}-1})v_B = e^{-r_{\bar{n}}(T(z)-T_{\bar{n}-1})}x_{\bar{n}-1}(1 - e^{-\lambda_G z})v_G.$$

The derivative with respect to $z$ is $T'(z) = \frac{\lambda_G e^{-\lambda_G z}}{r_{\bar{n}}(1-e^{-\lambda_G z})}$.

We show that it is optimal to maximize $z$, that is to set $z = F_{\bar{n}} - z^G_{T_{\bar{n}-1}}$. Notice that the way we have constructed $T(z)$ implies that no type $i \leq \bar{n}$ is affected. Hence, it is enough to maximize the expected payoff of types $i > \bar{n}$:

$$\max_z \sum_{i=\bar{n}+1}^{n} e^{-r_i(T(z)-T_{\bar{n}-1})}x_{\bar{n}-1}(1 - e^{-\lambda_G z})v_G,$$

with the first-order condition:

$$\sum_{i=\bar{n}+1}^{n} e^{-r_i(T(z)-T_{\bar{n}-1})}x_{\bar{n}-1}v_G(x_{\bar{n}-1}(\lambda_G e^{-\lambda_G z} - r_i T'(z)(1 - e^{-\lambda_G z})).$$

Once we plug in $T'(z)$, the first-order conditions becomes

$$\sum_{i=\bar{n}+1}^{n} e^{-r_i(T(z)-T_{\bar{n}-1})}x_{\bar{n}-1}v_G(x_{\bar{n}-1}\lambda_G e^{-\lambda_G z}(1 - \frac{r_i}{r_{\bar{n}}}),$$

which is strictly positive since $r_{\bar{n}} > r_i$ for all $i > \bar{n}$. Therefore, an optimal scheme must reveal all generated good news. □

## A.7 Proof of Theorem 1

*Proof.* The proofs of Lemmas 1-3 are constructed so that they show that if a policy does not satisfy a certain property, there exists another policy that satisfies the property and is strictly better. Therefore, we know that the designer's problem (5) is equivalent with the problem where we restrict to policies satisfying the properties of Lemmas 1-3. Importantly, this holds for the supremum in Problem (5), even when the maximum were not attained.

Combining the properties of Lemmas 1-3, gives that we can restrict to policies where $z_t^G$ changes only at some $T_i$, $z_t^B \geq F_i$ for all $t > T_i$ and $i < \bar{n}$, and the no-news belief crosses the myopic threshold at most once. Furthermore, any incentive compatible solution must be such that all agents of the same type get the same expected payoff. This leads to that (5) is equivalent with (12) in the proof of Lemma 5. We can then replace sup with max in the designer's problem as (12) is a continuous maximization problem over a compact domain.[36]

Then, we are left to show that for all policies that satisfy the necessary conditions, there exists a policy that takes the form described in Theorem 1, is incentive compatible, and achieves at least the same welfare. The good news part of the statement is trivial. As solution to (12) must have $z_{T_i}^G = 0$ for all $i < \bar{n}$ and $z_t^G = F_{\bar{n}}$ for all $t > T_{\bar{n}}$ if $\bar{n} < n$ by Proposition 2, one can use $T_{\bar{n}}$ as the $\bar{t}$ in the statement of Theorem 1. Recall $\lim_{t\to\infty} q_t = F_{\bar{n}}$. Furthermore, the possible good news revelation in $(T_{\bar{n}-1}, T_{\bar{n}})$, which does not make the no-news belief drop below the myopic threshold, does not affect the objective or the IC constraints in (12). Therefore, the designer can equally well set $z_t^G = 0$ also for $t \in (T_{\bar{n}-1}, T_{\bar{n}})$.

To show the bad news part of Theorem 1, we argue that in a policy that maximizes (12), $T_i - T_{i-1}$ is such that type $i$ is indifferent at $T_{i-1}$ for all $i < \bar{n}$. Suppose instead that type $i$ strictly prefers investing at $T_{i-1}$ rather than waiting until $T_i$. Then, it is a strict improvement to give out bad news already at $T_i - \epsilon$: type $i + 1$ is strictly better off and the IC for type $i$ is still satisfied if $\epsilon$ is small.

Since we know that each type $i < \bar{n}$ is indifferent between investing at $T_{i-1}$

[36]While $T_i$ could in principle take any values in $\mathbb{R}_+$, the relevant values of $\{T_i\}$ can easily be restricted to a sufficiently large compact set as the objective is decreasing in $T_i$.

and waiting until $T_i$ and we know that any optimal scheme reveals all bad news at the latest at $T_i$, the following holds:

$$x_{T_{i-1}} v_G + (1 - x_{T_{i-1}}) v_B = e^{-r_i (T_i - T_{i-1})} x_{T_{i-1}} v_G + (1 - x_{T_{i-1}}) e^{-\lambda_B f_i} v_B.$$

This is the same condition as under transparent bad news. Hence, the implied information process is the same at $T_i$ for all $i < \bar{n}$ under transparent bad news and under the original scheme. As all incentive compatible disclosure policies give the same expected welfare to all agents of each type, the exact disclosure time of bad news in $(T_{i-1}, T_i)$ does not affect welfare.

Finally, consider the last phase, $t \in (T_{\bar{n}-1}, T_{\bar{n}})$. If $\bar{n} = n$, the disclosure policy after $T_{\bar{n}-1}$ does not affect anyone's payoff, and hence transparent bad news is trivially optimal. Let $\bar{n} < n$. Then, $z^B_{T_{\bar{n}}} = z^G_{T_{\bar{n}}} \geq F_{\bar{n}}$ under any policy that maximizes (12). Since bad news is not decision relevant for $i > \bar{n}$, transparency does not affect their payoffs. Furthermore, it does not affect the IC of type $\bar{n}$ because the rate of investment adjusts so that type $\bar{n}$ remains indifferent.

We conclude that for all optimal policies, there exists a policy that takes the form of the policy in the claim and gives the same expected payoff for each type as the original policy. Hence, the altered policy is also optimal. □

## A.8 Proof of Proposition 1

The first part, that the optimal policy implements weakly more experimentation than the transparency benchmark, is easily shown. Suppose $x(F_{n-1}) < x^{\text{myop}}$, and let $i < n$ be the smallest number such that $x(F_i) < x^{\text{myop}}$ holds. This implies that the amount of experimentation under transparency is strictly below $F_i$. To see that Proposition 2 implies that total experimentation is at least $F_i$ under any optimal scheme, notice first the public belief must be above the myopic threshold when all types with lower indices than $i$ have invested. Therefore, at least some $r_i$ type agents must invest under any optimal scheme. But as an optimal policy never reveals good news within a phase (Lemma 1), this implies that all type-$r_i$ agents must invest.

We prove the second part of the proposition by providing examples of both cases: one where the amount of investment is larger under the designer's policy than under the social optimum and another where the opposite holds. For simplicity, let $n = 2$ and $\lambda_B = 0$. Suppose that $F_1$ is such that $x(F_1) < x^{\text{myop}}$. Then, the designer's policy must be such that good evidence is revealed after all high type agents have invested but before low types start to invest.

Next, take derivative of the social value (3) with respect to $q$ when $\lambda_B = 0$:

$$(1 - x_0)v_B + x_0 e^{-\lambda_G q} v_G + x_0 \lambda_G e^{-\lambda_G q} v_G (F_1 + F_2 - q). \tag{17}$$

To see that the derivative (17) can be negative at $F_1$, notice that the third term goes to zero as $\lambda_G \to \infty$. The sum of the first two terms is negative for $q$ close to $F_1$ by $x(F_1) < x^{\text{myop}}$. Hence, the social optimum experiments less than the designer's solution when the potential of good news learning is high.

To see that the socially optimal investments can be strictly above $F_1$, notice that the third term in (17) goes to infinity as $F_2 \to \infty$ for any fixed $q$. Hence, the social optimum experiments more than the designer's solution when there are many patient agents. □

## A.9 Proof of Proposition 3

*Proof.* In the proof, we use $x_t$ and $q_t$ for the belief and the stock under $z_t^B$ and similarly $x_t^{\text{TB}}$ and $q_t^{\text{TB}}$ under transparent breakdowns. Suppose, contrary to the claim, that $z_t^B > q_t^{\text{TB}}$ for some $t$. Let $\hat{t} := \inf\{\tau \in \mathbb{R}_+ : z_\tau^B > q_\tau^{\text{TB}}\}$. Notice that $q_t^{\text{TB}}$ is continuous and hence $q_t^{\text{TB}} = q_{t-}^{\text{TB}}$. As a preliminary step, notice that $q_{t+} - q_{t-} > 0$ implies $z_{t-}^B = z_{t+}^B$ because otherwise investing at $t$ would not be incentive compatible. Hence, we have only two potential cases: either $q_{\hat{t}-} > q_{\hat{t}}^{\text{TB}}$ or $q_{\hat{t}-} = q_{\hat{t}}^{\text{TB}} = z_{t+}^B$.

First, assume that $q_{\hat{t}-} > q_{\hat{t}}^{\text{TB}}$. This implies that there exist type $r$ and times $t' < \hat{t}$ and $t'' \geq \hat{t}$ such that some agent $r$ stops at $t'$ under $z_t^B$ but waits until $t''$ under instantaneous revelation. Furthermore, $t'$ satisfies $z_{t'}^B \leq q_{t'}^{\text{TB}}$.

Since waiting is optimal under transparent breakdowns, we have

$$x_{t'}^{\text{TB}} v_G + (1 - x_{t'}^{\text{TB}}) v_B \le \int_{t'}^{t''} e^{-r(s-t')} x_{t'}^{\text{TB}} v_G \, \mathrm{d}\left(1 - e^{-\lambda_G (z_s^G - z_{t'}^G)}\right)$$
$$+ e^{-r(t''-t')} \left( x_{t'}^{\text{TB}} e^{-\lambda_G (z_{t''}^G - z_{t'}^G)} v_G + (1 - x_{t'}^{\text{TB}}) e^{-\lambda_B (q_{t''}^{\text{TB}} - q_{t'}^{\text{TB}})} v_B \right). \tag{18}$$

Since investing is optimal under $z_t^B$, we have

$$x_{t'} v_G + (1 - x_{t'}) v_B \ge \int_{t'}^{t''} e^{-r(s-t')} x_{t'} v_G \, \mathrm{d}\left(1 - e^{-\lambda_G (z_s^G - z_{t'}^G)}\right)$$
$$+ e^{-r(t''-t')} \left( x_{t'} e^{-\lambda_G (z_{t''}^G - z_{t'}^G)} v_G + (1 - x_{t'}) e^{-\lambda_B (z_{t''}^B - z_{t'}^B)} v_B \right). \tag{19}$$

When comparing (18) with (19), the only differences are that the beliefs at time $t'$ may be different such that $x_{t'}^{\text{TB}} \ge x_{t'}$ (because $z_{t'}^B \le q_{t'}^{\text{TB}}$) and that $z_{t''}^B - z_{t'}^B > q_{t''}^{\text{TB}} - q_{t'}^{\text{TB}}$, i.e. there is more information arriving between $t'$ and $t''$ under $z_t^B$. Therefore, (18) contradicts (19). (To obtain the contradiction, subtract (18) from (19). If $x_{t'} = x_{t'}^{\text{TB}}$, the only remaining term is a positive term on RHS. If $x_{t'} - x_{t'}^{\text{TB}} < 0$, divide both sides by it, and a direct comparison gives the result.)

Next, assume that $q_{\hat{t}-} = q_{\hat{t}}^{\text{TB}} = z_{\hat{t}+}^B$. Let $r' := \lim_{s \to_+ \hat{t}} r^{\text{TB}}(s)$ and $t'' := \min\{\sup(t : r^{\text{TB}}(t) = r'), \inf(t > \hat{t} : z_t^B < q_t^{\text{TB}})\}$. Notice that $t'' - \hat{t}$ is bounded away from zero because $q_t^{\text{TB}}$ is continuous.

By the definition of $\hat{t}$, for all $\epsilon > 0$, there exists time $t' < \hat{t} + \epsilon$ such that agent $r'$ weakly prefers to wait at time $t'$ until time $t''$ under instantaneous revelation. With these definitions, the optimality of waiting under the transparent benchmark (18) and the incentive compatibility of $z_t^B$ (19) must hold in this case, too. Next, take the limit as $\epsilon \to 0$, i.e. $t' \to \hat{t}$. Then, all other differences between (18) and (19) disappear, except the difference from $q_{t''}^{\text{TB}} < z_{t''}^B$, which then implies that the RHS of (18) is strictly smaller than the RHS of (19) for small $\epsilon$. Hence, we conclude that there always exists $\epsilon > 0$ such that it is not possible to satisfy both (18) and (19) in this case either. □

# B Online appendix

In this Online appendix we show the equivalence, from the perspective of the agents, of the representations of disclosure policies in terms of families of cdfs $B$ and $G$ and the processes $z_t^B$ and $z_t^G$ as introduced in the Model Section 2.

## B.1 Equivalent representation of disclosure policies

Fix any non-decreasing adoption process $q_t$. We will denote by $\tilde{\omega}$, the conditional probability measure and by $\omega$ its corresponding cdf. Formally, the sender commits to two (regular) conditional probabilities $\tilde{\omega} : \mathcal{B}(\mathbb{R}_+) \times \mathbb{R}_+ \to [0,1]$, such that for all $T \in \mathcal{B}(\mathbb{R}_+)$, the function $\tilde{\omega}(T|\cdot)$ is Borel measurable; and for any realized generation time $s \in \mathbb{R}_+$, the conditional distribution $\tilde{\omega}(\cdot|s)$ is a probability measure over disclosure delays.

Compute for any $\omega$-evidence policy specified above, i.e., given a family of conditional cdfs $\omega(\cdot|s)_{s\geq 0}$ the corresponding process $(z_t^\omega)_{t\geq 0}$. The probability that $\omega$-evidence is disclosed by time $t$ is[37]

$$\int_0^{t-} \omega(t-s|s)\,\mathrm{d}\left(1-e^{-\lambda_\omega q_s}\right),$$

where $1-e^{-\lambda_\omega q_s}$ is the probability that $\omega$-evidence has been generated by time $s$, and, for each $s<t$, $\omega(t-s|s)$ is the probability that the piece of $\omega$-evidence generated at $s$ is disclosed no later than at time $t$. The corresponding cumulative hazard rate $z^\omega$ is given by the identity

$$1-e^{-\lambda_\omega z_t^\omega} = \int_0^{t-} \omega(t-s|s)\,\mathrm{d}\left(1-e^{-\lambda_\omega q_s}\right),$$

or, equivalently

$$z_t^\omega = \frac{-1}{\lambda_\omega}\log\left(1-\int_0^{t-} \omega(t-s|s)\,\mathrm{d}\left(1-e^{-\lambda_\omega q_s}\right)\right).$$

[37]Right-continuity of cdf $\omega(\cdot|s)$ for all $s$ implies that $\lim_{s\nearrow t}\omega(t-s|s) = \lim_{s\nearrow t}\omega(0|s)$, so the disclosure of evidence generated just before $t$ is included in this term.

Note further that cdfs $\omega(t-s|s)$ are non-decreasing in $t$ for all $s$, the term on the right-hand side is non-decreasing in $t$. Further, if $\omega(t-s|s)=0$ for all $s<t$, then $z_t^\omega=0$; and if $\omega(t-s|s)=1$ for all $s<t$, then $z_t^\omega=\frac{-1}{\lambda_\omega}\log\left(e^{-\lambda_\omega q_{t-}}\right)=q_{t-}$.

Conversely, for any pair of generation and disclosure processes we can find a family of conditional distributions satisfying the relationship above. This follows from Theorem 1 ((i) $\Longrightarrow$ (v)) in Kamae, Krengel, and O'Brien (1977).

## B.2 Illustrative example of with homogenous agents

Here we illustrate that the main findings of the main paper do not hinge on discounting heterogeneity. To illustrate if and how the designer can speed up information generation by delaying disclosure, consider a simple example. Assume here that $F_n=1$ and let $n=1$ so that all agents share the same discount rate $r_1=r$. Let good news and bad news be equally likely, $\lambda_G=\lambda_B=:\lambda$. In this case, under transparency, the belief is constant and the adoption process is linear: $q_t^{\text{TP}}=\frac{r}{\lambda}\frac{x_0v_G+(1-x_0)v_B}{(1-x_0)(-v_B)}t$.

For illustration, consider a designer whose objective is to minimize the time at which all potential evidence has been revealed, i.e. find the smallest $T$ such that $z_T=(1,1)$. The example introduces some of our results and the way we approach the designer's problem in a simplified environment.

In this example with identical agents, a disclosure process $z$ is feasible if and only if agents are willing to invest at time 0 (as well as $z_t^\omega\leq 1$ for all $t$):

$$x_0v_G+(1-x_0)v_B\geq\int_0^t e^{-rs}x_0v_G\,\mathrm{d}\left(1-e^{-\lambda z_s^G}\right)+e^{-rt}\left(x_0v_Ge^{-\lambda z_t^G}+(1-x_0)v_Be^{-\lambda z_t^B}\right),\qquad\text{for all } t\geq 0. \tag{20}$$

In particular, it is necessary for information generation that agents are willing to invest at time 0 rather than waiting until time $T$:

$$x_0v_G+(1-x_0)v_B\geq\int_0^T e^{-rs}x_0v_G\mathrm{d}\left(1-e^{-\lambda z_s^G}\right)+e^{-rT-\lambda}(x_0v_G+(1-x_0)v_B). \tag{21}$$

Since any process $z^G$ satisfies $\int_0^T e^{-rs}\,\mathrm{d}(1-e^{-\lambda z_s^G}) \geq e^{-rT}(1-e^{-\lambda z_T^G})$ and $z_T^G = 1$ by definition, the inequality above gives a lower bound $T^*$ for the disclosure time $T$:

$$e^{-rT} \leq \frac{x_0 v_G + (1-x_0)v_B}{x_0 v_G + e^{-\lambda}(1-x_0)v_B} =: e^{-rT^*}. \tag{22}$$

Consider a disclosure policy where the designer commits to hide all news until time $T^*$: $z_t = (0,0)$ for all $t < T^*$ and $z_{T^*} = (1,1)$. Then, the constraint (20) is trivially satisfied for all $t < T^*$ and holds as an equality for $t = T^*$. Hence, the designer can implement the lower bound $T^*$ by postponing all disclosure.

Is fully postponing all disclosure necessary for implementation? Consider good news first. Observe that $\int_0^{T^*} e^{-rs}\,\mathrm{d}(1-e^{-\lambda z_s^G}) > e^{-rT^*}(1-e^{-\lambda z_{T^*}^G})$ if $z_t^G > 0$ for any $t < T^*$. This then implies that the right-hand side of the necessary condition (21) is strictly above $e^{-rT^*}(x_0 v_G + e^{-\lambda}(1-x_0)v_B)$, making the disclosure process infeasible, independent of the timing of bad news. Therefore, we conclude:

**Observation 1.** *Any disclosure policy that implements $z_{T^*} = (1,1)$ never discloses good evidence strictly before $T^*$: $z_t^G = 0$ for all $t < T^*$.*

Next, consider bad news. Fixing $z_T^B = 1$, the exact disclosure time of negative evidence before $T$ does not affect the necessary condition (21). However, if the disclosure is too fast, the constraint (20) may be violated for earlier times $t < T$. It is helpful to consider what happens if the designer discloses all bad news immediately: we say that an information policy has *transparent breakdowns* if $z_t^B = q_{t-}$ for all $t$. However, the evolution of $q_t$ depends on the good news policy and may hence differ from the transparent benchmark $q_t^{\mathrm{TP}}$.

Because we are interested in implementing full revelation at $T^*$ and since we know by Observation 1 that it requires hiding good news until $T^*$, consider transparent breakdowns under the assumption that good evidence is disclosed only at time $T^*$. The equilibrium investment process $q$ evolves such that all agents remain indifferent between experimenting and waiting. The indifference condition takes the same form as (4) under the fully transparent benchmark.[38] In contrast to (4),

[38]With homogeneous agents ($r$ instead of $r_i$) and with $\lambda_B = \lambda$.

however, the belief is now $x_t = x_0/(x_0+(1-x_0)e^{-\lambda q_t})$ because good evidence is not disclosed. Because $x_t > x_0$ for all $t \in (0, T^*)$, the investment $q$ evolves faster than under full transparency: hiding good news makes agents willing to experiment earlier.[39] The investment amount $q_t$ that solves the indifference condition with censored good news reaches 1 exactly at $t = T^*$. This confirms that transparent breakdowns implement full revelation at $T^*$. Because agents are indifferent at all $t \leq T^*$, the policy with transparent breakdowns also maximizes information revelation prior to time $T^*$, conditional on incentive compatibility and full revelation by time $T^*$:

**Observation 2.** *Among all disclosure policies that implement $z_{T^*} = (1, 1)$, transparent breakdowns, i.e. $z_t^B = q_{t-}$ for all $t$, maximizes $z_t^B$ at all times $t$.*

We find that the designer who seeks to maximize information revelation hides good evidence but reveals bad evidence. These observations are shared with the main model where the designer seeks to maximize the expected welfare of the agents under discounting heterogeneity. With homogeneous agents, the disclosure policy has no effect on welfare. Sharing the same discount rate, every agent gets the same expected payoff as the first investor. Observation 2 shows that censoring earlier bad evidence does not allow the designer to disclose more cumulative bad evidence at later times.[40]

[39]To see this note that the left-hand side of indifference condition (4) is decreasing in $x_t$ and the right-hand side is increasing. When the agent believes that the bad state is less likely he expects less negative evidence, decreasing the benefit of waiting; and his expected investment return is higher, increasing the cost of waiting.

[40]Note that this *does* work with good evidence. By Observation 1, the maximal feasible value of $z_{T^*}^G$ is strictly increased by delaying good news prior to $T^*$.