The Selective Disclosure of Evidence: An Experiment

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Abstract

We conduct an experimental analysis of selective disclosure in communication. In the model, an informed sender aims to influence a receiver by disclosing verifiable evidence that is selected from a larger pool of available evidence. Our experimental design leverages this model's rich comparative statics, allowing us to systematically quantify the effects of selection relative to concealment. Our findings confirm the key qualitative predictions of the theory, suggesting that selection, rather than concealment, is often the dominant distortion in communication. We also identify deviations from the theory: Some senders are "deception averse" and overcommunicate relative to predictions; receivers respond too optimistically to both concealed and selected evidence, with errors of similar magnitude. Yet selection generates greater overall distortion in receiver behavior because it is far more prevalent than concealment.

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1 Introduction

This paper presents an experimental analysis of *selective disclosure*. We study settings in which an informed sender seeks to influence the actions of an uninformed receiver by disclosing selected evidence. This form of selective communication is pervasive in practice. For instance, a journalist may select the news events to report depending on how they reflect on a political candidate; a defense lawyer may select the evidence to present in court in an attempt to increase the chance of acquittal; a firm may choose to advertise only some of the features of its products to customers.[1] These settings share the following characteristics: The evidence is verifiable (i.e., the sender cannot fabricate it) but possibly noisy (i.e., it is imperfectly informative); furthermore, it may be *selected* by the sender from a larger pool of available evidence. Thus, the interpretation of the disclosed evidence depends on the context—namely, how it was selected by the sender. This selection ultimately determines how effectively the sender and the receiver can communicate.

The disclosure of verifiable information is central to economic analyses of how asymmetric information can distort markets, with applications in financial economics, accounting, and industrial organization (for reviews, see Verrecchia (2001), Milgrom (2008), Dranove and Jin (2010), and Beyer et al. (2010)). The benchmark result in this literature—the *unraveling principle*—argues that if the sender can verifiably disclose the available evidence, she will do so, regardless of how favorable it is. According to this prediction, communication helps resolve the initial information asymmetry. The disclosure literature has largely focused on documenting and explaining a key deviation from this benchmark: The tendency of senders to conceal unfavorable evidence.[2] This behavior causes distortions, as senders undercommunicate relative to the unraveling benchmark, allowing the information asymmetry to persist. These distortions justify the adoption of disclosure mandates, which are common in many contexts.[3]

[1] Prat and Strömberg (2013) and Gentzkow et al. (2015) argue that selective disclosure—what they call "filtering" or "fact bias"—is in practice one of the principal sources of media slant. Their insight echoes the seminal work of Lippmann (1922), who observed that "every newspaper when it reaches the reader is the result of a whole series of selections as to what items shall be printed, in what position they shall be printed, how much space each shall occupy, what emphasis each shall have. There are no objective standards here." Analogous patterns arise in advertising. For example, Koehler and Mercer (2009) show that mutual fund companies selectively promote their better-performing funds.

[2] Starting from Dye (1985), several theoretical models have explained why concealment might occur in equilibrium. In the empirical literature, excessive concealment has been documented both in the field and the laboratory (see, e.g., Mathios, 2000; Jin and Leslie, 2003; Bertomeu et al., 2020; Jin et al., 2021).

[3] In the United States, for instance, regulations may require restaurants to display sanitary grades and calorie counts, publicly traded companies to disclose financial statements, and real estate sellers to reveal specific property conditions.

In this paper, we shift the emphasis away from distortions caused by the concealment of evidence and focus instead on a less-studied aspect of the problem: distortions arising from the sender's ability to *select* which evidence to disclose. This shift in focus leads to a corresponding change in policy recommendations. Our experimental analysis is informed by a theory of selective disclosure that provides rich comparative statics, whereby we vary the quantity of evidence available to the sender and how much of it can be disclosed to the receiver. These comparative statics results enable a systematic test of the strategic forces driving selective disclosure.

Our model, building on Milgrom (1981), features a sender who privately observes the state of the world and the realization of N independent signals (or evidence), which are informative about the state. The sender can verifiably disclose up to K of these signals to a receiver. In this context, N represents how much evidence is available to the sender, and K represents the communication capacity of the environment (e.g., the number of stories a newspaper can print). The receiver observes the disclosed signals and takes an action. The receiver's objective is to match her action to the state, whereas the sender wishes to persuade the receiver to take a higher action, regardless of the state. We show that in our setting, an equilibrium exists in which the sender discloses the K highest signals among those she observes. This equilibrium reflects the sender's incentives to be selective and disclose the most favorable evidence at her disposal.

The interplay between evidence concealment and selection shapes the strategic interaction between the sender and the receiver. Notably, their relative importance changes as we vary N and K. When $K = N$, evidence can only be concealed, not selected, similar to a classic disclosure setting. Conversely, when N is large relative to K, evidence can also be selected. The ability to capture both concealment and selection is a key feature of our experimental design. It allows us to quantify the effects of selection—the novel distortion we aim to study—relative to those of concealment, which are well understood and central to the disclosure literature.

Our experimental analysis is guided by the rich comparative static predictions that arise from varying K and N. As N increases relative to K, the sender should disclose more favorable evidence. This endogenous selection should make receivers more skeptical of any message as N increases or K decreases. The behavior of senders and receivers jointly determines the informativeness of the equilibrium, which we define as the correlation between the state and the receiver's action. Holding N constant, informativeness should increase in K. Instead, holding K constant, informativeness may be nonmonotone in N, but it should necessarily decrease to zero as N becomes large. These predictions stem from a balance between two forces, which we explore in our experiment: On the one hand, a larger N allows the sender to be more selective, decreasing equilibrium informativeness; on the other hand, it gives the sender more latitude to effectively communicate the state, potentially increasing informativeness.

In our experimental treatments, we vary K and N, leaving all the other parameters unchanged. We consider two values for K (namely, 1 and 3) and three values for N (namely, K, 10, and 50), for a total of six treatments. These treatments allow us to test the full range of predictions outlined above, providing a sharp and systematic evaluation of the theory. Although each individual treatment is informative on its own, our main focus is on the comparative statics across treatments, which allow us to isolate and quantify the role of selection and its implications.

We begin the data analysis by documenting several key patterns in senders' behavior that are consistent with the key qualitative predictions of the theory. First, we find that senders disclose more favorable signals as N increases relative to K. Indeed, a large number of senders play the exact equilibrium strategies most of the time. We then discuss senders' informativeness, that is, the amount of information contained in senders' strategies. We find that, for all treatment variations of K and N, senders' informativeness moves in the directions predicted by the theory, although, in some cases, these movements are not statistically significant. Therefore, selective disclosure appears to be an important force driving sender behavior in our data.

Next, we document the main quantitative deviations in senders' behavior. First, when $N = K$, we observe that senders often conceal unfavorable evidence, consistent with prior disclosure experiments. When $N > K$, however, concealment is no longer the dominant distortion, as senders predominantly use selection to influence the receiver's behavior. In other words, as favorable signals become more abundant, senders shift from concealing evidence to selectively disclosing it. Second, we find that senders' strategies are more informative than predicted—that is, senders overcommunicate—especially when N is large. This is in contrast to most of the prior experimental literature on verifiable disclosure, which finds undercommunication. Instead, it is consistent with findings from a different experimental literature, that on cheap talk (see, e.g., Cai and Wang (2006)). Our framework helps reconcile these seemingly divergent findings.

To understand these departures from the theory, we analyze senders' behavior at the individual level by performing a clustering analysis. In all treatments, the predominant cluster plays strategies that are close to equilibrium. However, we identify a minority cluster that persistently displays behavior that we call *deception averse*: When the state is high, these senders disclose the most favorable signals available; when the state is low, however, they consistently fail to do so. This behavior can be interpreted as a particularly stark form of lying aversion:

When the state is low, deception-averse senders refrain from disclosing high signals that could deceive the receiver into thinking that the state is high. These senders are thus responsible for overcommunication because their state-dependent behavior increases the average informativeness of senders' strategies.

We then discuss receivers' behavior. Our data corroborate a central qualitative prediction of the theory: Receivers' responses decrease in N, i.e., they become more skeptical as the extent of selection increases. Moreover, for fixed N and a fixed set of disclosed signals, receiver skepticism increases with K. These patterns indicate that receivers recognize that the evidence they observe is selected to varying degrees across treatments, thus showing that the thrust of the theory is valid even though, as the literature amply documents, receivers often deviate from Bayesian behavior.

We then analyze receivers' main quantitative deviations from the theory. As a baseline, we show that receivers are overly optimistic in all our treatments—namely, their guesses are suboptimally high—thus replicating a central finding of the previous literature. We go beyond this result by showing that the presence and extent of over-optimism vary systematically across treatments and types of evidence. We find that receivers perform comparably well when responding to non-selected evidence, whereas they make larger mistakes of similar magnitude when responding to either concealed or selected evidence. Nonetheless, the overall distortion created by receivers' mistakes in response to selected evidence is greater, because selection is far more prevalent than concealment. Finally, we argue that the patterns we uncover are far from arbitrary: A straightforward extension of our model—allowing for a simple form of receiver naïveté—offers a unified explanation for all the observed behavioral deviations in receiver behavior.

The paper concludes with a discussion of the policy implications of our analysis. We first revisit the widespread policy of mandated disclosure, which aims to prevent distortions caused by concealment by requiring senders to disclose exactly K signals. We observe that such policies are largely ineffective when N is large relative to K, as concealment is virtually absent in those settings. Even when $K = N$, our counterfactual simulations indicate that mandating disclosure can have ambiguous effects due to the presence of deception-averse senders, who use concealment in an informative way. We then turn to policies designed to discourage selection. Because selection is inherently more difficult to detect, any attempt to prohibit it directly is unlikely to be enforceable. We therefore discuss several natural policies that could indirectly discourage selection, while emphasizing that each of these interventions carries potential unintended consequences and may backfire.

1.1 Related Literature

Our paper contributes to the large body of experimental literature on the verifiable disclosure of evidence. One robust finding in this literature is that senders undercommunicate relative to the theoretical predictions, that is, the failure of the unraveling principle. For instance, in the laboratory, Jin et al. (2021) find that receivers are insufficiently skeptical when senders do not provide any information, which in turn leads senders to undercommunicate by concealing unfavorable evidence. In the field, Mathios (2000) and Jin and Leslie (2003) find excessive concealment in the context of food nutrition labels and hygiene grade cards in restaurants.[4] In stark contrast, the experimental literature on cheap talk typically finds that senders overcommunicate relative to the predictions and that receivers are overly trusting.[5] Cai and Wang (2006) ascribe this deviation to lying aversion.

Experimental research on selective disclosure is in its early stages. The studies most closely related to our work are Brown and Fragiadakis (2019) and Degan et al. (2023), who compare a treatment in which evidence is strategically selected to one in which it is selected randomly. These studies do not explore treatment variations in K and N, which are central to our approach. Further from our work is Penczynski et al. (2023), who investigate how competition among senders affects which evidence they disclose. Finally, Burdea et al. (2023) examine a scenario where a sender transmits a two-dimensional message to a receiver, but only one dimension can be verified. Their main treatment variation (inspired by Glazer and Rubinstein (2004, 2006)) involves changing who controls which of the two dimensions is verified—the sender or the receiver.

The basic structure of our model can be traced back to Milgrom (1981), who shows that, for any N and K, there exists a maximally selective equilibrium—that is, one in which the sender discloses the K highest signals. Our model differs from Milgrom's in several ways, as discussed at the end Section 2.1. These differences do not substantively alter the thrust of the theory, but they are important as they enable a cleaner experimental design—albeit at the cost of requiring a novel existence proof. In a setting where $K = 1$ and signals are binary, Fishman and Hagerty (1990) show that the informativeness of the maximally selective equilibrium need not be monotone in N and provide conditions under which it eventually converges to zero.

[4] Forsythe et al. (1989), King and Wallin (1991), Dickhaut et al. (2003), Forsythe et al. (1999), Benndorf et al. (2015), Hagenbach and Perez-Richet (2018), Deversi et al. (2021), Jin et al. (2022), Fréchette et al. (2022), Farina and Leccese (2024), and Hagenbach and Saucet (2024) also document instances of excessive concealment of evidence relative to theoretical predictions, although their primary focus varies.

[5] Blume et al. (2020) review this literature. Influential papers include Dickhaut et al. (1995), Blume et al. (1998), Forsythe et al. (1999), Blume et al. (2001), Sánchez-Pagés and Vorsatz (2007), Wang et al. (2010), and Wilson and Vespa (2020).

We extend their results to settings with arbitrary K and nonbinary signals. Di Tillio et al. (2021) also allow for arbitrary K but their signals take a continuum of realizations. They provide conditions on the signal distribution under which the informativeness of the maximally selective equilibrium is monotone in N. Their results do not apply to our setting due to the discreteness of the signal space.[6]

2 Theory

2.1 Model

Our model closely builds on Milgrom (1981). We examine the interaction between a privately informed sender and an uninformed receiver. The sender observes an underlying state of the world and N signals realizations, which are informative about the state. She can verifiably disclose up to K of these signals realizations to the receiver, who then chooses an action affecting the payoff of both players.

Formally, the sender privately observes a state θ, which belongs to a finite subset $\Theta \subseteq \mathbb{R}$. The state is distributed according to a distribution $p \in \Delta(\Theta)$, which has full support. The sender also privately observes the realization of N conditionally independent signals $\bar{s} = (\bar{s}_1, \ldots, \bar{s}_N)$. Each signal $\bar{s}_i$ belongs to a finite and ordered set S and is distributed according to a distribution $f(\cdot|\theta) \in \Delta(S)$, which has full support. We assume that f satisfies the monotone likelihood ratio property (MLRP), namely, $\frac{f(s|\theta')}{f(s|\theta)}$ is strictly increasing in $s \in S$ for all $\theta' > \theta$.

The sender can verifiably disclose up to $K \leq N$ of the N signals. The vector of disclosed signals forms the sender's message, denoted by m. We assume that the receiver does not observe the original positions of the disclosed signals in $\bar{s}$. Given this assumption, it is expositionally convenient to define m as a decreasing vector of length K: The $k \leq K$ disclosed signals are placed in the first k positions of message m, sorted in decreasing order, and the remaining $K - k$ entries in m, representing undisclosed signals, are denoted by o's. Let $\mathcal{M}$ be the set of all messages and $M(\bar{s}) \subseteq \mathcal{M}$ be the set of messages that can be sent given $\bar{s} \in S^N$.[7] After

[6] Shin (2003), Glazer and Rubinstein (2004), Glazer and Rubinstein (2006), Dziuda (2011), Hoffmann et al. (2020), Haghtalab et al. (2024), and Gao (2024) also study models with selective disclosure, although in settings more distant from ours.

[7] Formally, the message space is $\mathcal{M} := \{\bar{s} \in S^k \times \{o\}^{K-k} \mid 0 \leq k \leq K \text{ and } \bar{s}_i \geq \bar{s}_j \text{ for } i \leq j\}$. Given $\bar{s}$, the set of messages that can be sent is $M(\bar{s}) := \{o\}^K \cup \{m \in \mathcal{M} \mid \exists\ 1 \leq k \leq K \text{ and injective } \rho : \{1, ..., k\} \to \{1, ..., N\} \text{ s.t. } m_i = \bar{s}_{\rho(i)} \text{ for } i \leq k \text{ and } m_i = o \text{ for } i > k\}$. For instance, if the sender discloses no signals, her message is $m = (o, \ldots, o)$. This message is always available to the sender. If instead the sender discloses $k < K$ signals from $\bar{s}$, her message is $m = (s_1, \ldots, s_k, o, \ldots, o)$, the first k components of which appear in $\bar{s}$ and are

observing the message m, the receiver chooses an action $a \in A := \mathbb{R}$. The sender's payoff is $v(\theta, a) = a$, and the receiver's payoff is $u(\theta, a) = -(a - \theta)^2$.

A strategy for the sender is a mapping $\sigma : \Theta \times S^N \to \Delta(\mathcal{M})$, subject to the verifiability requirement $m \in M(\bar{s})$ for all $\bar{s}$. A strategy for the receiver is a mapping $\xi : \mathcal{M} \to \Delta(A)$. The relevant solution concept is perfect Bayesian equilibrium (PBE).

Discussion. The model describes situations in which the sender knows more than what she can verifiably prove. That is, no message can verifiably reveal the payoff-relevant state θ, nor the entire signal vector $\bar{s}$ when $K < N$. This contrasts with most of the literature on information disclosure, in which it is typically assumed that a sender can verifiably reveal her private information if desired.[8] The assumption that the sender knows more than she can verifiably prove is descriptive of many real-world communication settings, including the three examples discussed in the opening paragraph of the Introduction. As a consequence of this assumption, equilibria are partially informative of the state. This is a key feature of our setting since it implies that changes in K and N give rise to nontrivial comparative statics in how informative the equilibrium is, which we exploit in our experiment.

The case $K < N$ represents the most novel part of our experiment, as it will give rise to selective disclosure. We interpret $K < N$ as a communication constraint, which may stem from the receiver's inability to assimilate multiple signals or from the sender's inability to verify all of them.[9] Such constraints are pervasive in practice. Journalists, for instance, must report under strict limits on column space or airtime, leading to a series of selections about what to include. Similarly, advertisers must decide which product features to highlight to consumers. These features are often verifiable, yet firms retain discretion over which attributes to emphasize. They operate under a communication constraint, since advertising space is scarce and costly and consumer attention is limited. Finally, many college application systems restrict what information can be disclosed by imposing guidelines on length, format, and supporting materials—for example, limits on the number of recommendation letters.

We briefly comment on two important assumptions of our model. First, N and K are assumed to be common knowledge. In many real-world applications, however, K—and especially N—may be known to the sender but not to the receiver. This assumption is deliberate

listed in a decreasing order.

[8] Okuno-Fujiwara et al. (1990) show that such an assumption is needed for complete information transmission.

[9] A common justification for the verifiability of signals is that a regulator can impose penalties if the sender is found ex post to have lied. This justification, however, presupposes an infrastructure for verification, which itself requires resources. It is therefore natural to expect limits to verification capacity. For example, a third party may verify at most $K < N$ signals, and the sender must decide which of her signals to submit for verification.

and aims at maintaining tighter experimental control: Our model is intended to serve the experiment, where it is crucial to control subjects' beliefs about N in order to avoid confounding factors. When N is common knowledge, our experiment can identify frictions in communication that arise purely from selective disclosure, such as receiver overoptimism or selection neglect, ruling out alternative explanations based on incorrect beliefs about N. Therefore, any observed deviation from equilibrium is more likely to reflect a deeper behavioral mechanism.[10] Second, we assume that N and K are exogenous. While in some settings the sender may be able to choose N and K, our modeling choice is meant to focus the experimental analysis on the selection of evidence, abstracting away from other aspects such as the production of evidence (when N is chosen) or the cost of disclosure (when K is chosen).

Finally, it useful to note that our setting differs from Milgrom (1981) in three ways: The sender observes the state θ and not just the signal realizations; the signal space S is finite; and the receiver observe only the values of the disclosed signals, not their original position in the vector $\bar{s} = (\bar{s}_1, \ldots, \bar{s}_N)$. These modeling choices serve the important goal of enabling a cleaner experimental design (see discussion in Section 3). From a theoretical perspective, however, they complicate the analysis, requiring a novel proof for the existence of a maximally selective equilibrium (Proposition 1). Indeed, when S is finite and signal positions are unobserved, one must account for all permutations of $\bar{s}$ consistent with a given message, including the possibility of ties—i.e., multiple signal realizations taking the same value.

2.2 Equilibrium Predictions

Unlike in the typical disclosure setting, the constraints on the sender's ability to verifiably disclose her private information lead to the existence of multiple equilibria. Our analysis focuses on a class of equilibria in which the sender discloses the most favorable evidence available. In these equilibria, which we call *maximally selective*, the sender discloses the K-highest available signals, unless any of these signals is the lowest element in S; in that case, the sender may either disclose or conceal any of them, with both choices consistent with this class of equilibria.[11] In response to this sender's strategy, the receiver holds skeptical beliefs: On the equilib-

[10]Section E.5 in the Online Appendix presents an extension of our theoretical results to the case in which N is a random integer larger than K. Its realization is observed by the sender but not by the receiver. In the simple setting where states and signals are binary and $K = 1$, we show that our main comparative-static results continue to hold. Thus, in this setting, the randomness of N does not alter the key forces at play in the experiment.

[11]Formally, we extend the order on S to the set $S \cup \{o\}$, by assuming that $\min S$ and o are minimal elements in such a set. Then, we endow $\mathcal{M}$ with the partial order $m \geq m'$ if component-wise $m_i \geq m'_i$ for each $i \in \{1, \ldots, K\}$. Notice that, for each $\bar{s}$, $M(\bar{s})$ has at least one maximal element (in fact, it is a lattice). A sender's strategy is maximally selective if, for all $(\theta, \bar{s})$ and $m \in \text{supp}\,(\sigma_S(\cdot|\theta, \bar{s}))$, m is a maximal element of $M(\bar{s})$.

rium path, she believes that any undisclosed signal is no higher than the lowest among the disclosed ones (and equal to the worst possible one in case of concealment); off the equilibrium path, she believes that any undisclosed signal is equal to the worst possible one.

Proposition 1. *(Existence) For all N and K, there exists a perfect Bayesian equilibrium in which the sender's strategy is maximally selective.*

We focus on maximally selective equilibria for two reasons. First, this equilibrium has been the focus of several influential papers (see, e.g., Milgrom (1981), Fishman and Hagerty (1990), and Di Tillio et al. (2021)). Second, for any K, this equilibrium is unique in the class of "evidence-monotone" PBEs, namely, equilibria in which the receiver responds more favorably to messages that are more favorable.[12] Absent this refinement, the model admits other equilibria. These include equilibria in which the sender discloses fewer than K signals, or in which the sender's strategy depends on the state θ. These alternative, and to some extent, less intuitive equilibria are discussed in Online Appendix A.1.

The model offers several predictions regarding the behavior of senders and receivers. Some of these predictions immediately follow from the fact that the sender employs a maximally selective strategy. We summarize these in the following remark and then offer some discussion.

To state the remark, we first introduce a useful statistic of the sender's behavior. In a maximally selective equilibrium, the sender always reveals the K highest signal realizations—either directly, by disclosing them, or indirectly, by concealing a subset of the least favorable signals. We now ask: what is the "composition" of the sender's messages, and how does it change with N and K? To study this, imagine picking uniformly at random one of the signals that the sender reveals. The CDF of this random signal—denoted $G_{K,N}$—is the *distribution of disclosed signals* in a maximally selective equilibrium and, thus, captures the composition of the sender's messages.[13]

Remark 1. *Main predictions regarding players' behavior:*

1. Sender's Behavior. *The distribution of disclosed signals, namely, $G_{K,N}$, increases in a first-order stochastic dominance (FOSD) sense with N and decreases with K.*

[12] Specifically, in an evidence-monotone PBE, if $m' > m$, the receiver's action following message m' is higher than that following message m (see Appendix A for details). This refinement is directly testable with our data: In 90% of the cases, across treatments and observed message pairs where $m' > m$, the average receivers' action following m' is higher than that following m. Gordon et al. (2023) propose a related refinement for cheap-talk games.

[13] More formally, for $i \geq 1$, let $s_{(i:N)}$ denote the i-th highest order statistic of the vector $(s_1, \ldots, s_N)$, and let $F_{(i:N)}$ be its cumulative distribution function (CDF). Note that $G_{K,N}(s) = \frac{1}{K}\sum_{i=1}^{K} F_{(i:N)}(s)$.

2. Receiver's Behavior. *Fix K and consider any message on the equilibrium path for both N and N', with $N < N'$. The receiver's response to such a message is higher in N than in N'.*

Regarding the sender's behavior, the model predicts that the composition of the sender's messages improves as N increases and deteriorates as K increases. Intuitively, when N is larger, the sender can be more selective, resulting in messages that appear more favorable, thus increasing in a FOSD sense the distribution of disclosed signals. Conversely, when K is larger, the sender is compelled to disclose more signals to avoid the negative inference the receiver would make about signals the sender did not disclose. This forces the sender to become less selective, resulting in messages that appear less favorable, thus decreasing in a FOSD sense the distribution of disclosed signals. Regarding the receiver' behavior, the model predicts that, fixing any message m, the receiver's response decreases as N increases, i.e., she becomes more skeptical. To gain intuition, fix K and note that, as N increases, for any realization of the state θ, the sender's best K signals are likely to be higher. Thus, when N increases, the same message m should be perceived more skeptically by the receiver.

The behavior of the sender and the receiver jointly determines how informative the equilibrium is. We define *equilibrium informativeness* as the correlation between the state θ and the receiver's action a, which we denote by $\mathcal{I}(K, N)$. The greater the value of $\mathcal{I}(K, N)$, the more effectively the receiver learns about the state θ from the messages disclosed by the sender.[14] Changes in K and N generate rich comparative statics in the equilibrium informativeness, which we exploit in our experimental analysis.

Proposition 2. *As K and N vary, equilibrium informativeness $\mathcal{I}(K, N)$ changes as follows:*

i. Fixing N, $\mathcal{I}(K, N)$ increases in K.

ii. Fixing $K = N$, $\mathcal{I}(K, N)$ increases in N.

iii. For any given K, $\mathcal{I}(K, N)$ converges to zero as N increases. Moreover, $\mathcal{I}(K, N)$ need not be monotonic in N.

We now briefly discuss the intuition behind these results. Fix N and suppose that K increases to a higher value K'. In equilibrium, the receiver's inference is consistent with the sender revealing the K'-highest signals among those she privately observes. The resulting information

[14] Equilibrium informativeness is a monotone transformation of the receiver's ex ante expected payoff (see Online Appendix E.3).

Table 1: The distribution $f(s|\theta)$ used in the experiment.

	Composition of the Urns			
	$s = A$	$s = B$	$s = C$	$s = D$
$\theta = 0$ (Yellow Urn)	10%	20%	25%	45%
$\theta = 1$ (Red Urn)	45%	25%	20%	10%

partition is finer than the partition induced by revealing only the K-highest signals. Consequently, the receiver obtains more information under the higher K', making the equilibrium more informative. Second, let $K = N$ and consider the effects of increasing N. In this case, the sender reveals all the signals. Thus, as N increases, the receiver observes more i.i.d. signal realizations, which increases equilibrium informativeness. Third, holding K constant, as N approaches infinity the full support assumption on f implies that, for all θ, the sender will send the most favorable message with a probability approaching one. This implies that the equilibrium informativeness—namely, the correlation between the receiver's action and the underlying state θ—must converge to zero.

The nonmonotonicity in Proposition 2.(iii) arises from the interplay between two forces that affect informativeness in opposite directions. The first force is intuitive. As N increases, a lower–state sender has a greater chance of disclosing higher signals, since she selects them from a larger sample. Higher signals are therefore disclosed more frequently. This increased pooling toward the upper end of the signal space reduces the dispersion in the distribution of disclosed signals, which contributes to lowering the equilibrium informativeness. We refer to this as the *imitation effect*. The second force is more subtle. As N increases, lower signals are disclosed less frequently. Consequently, when such signals are disclosed, they become more indicative of a low state. This force raises equilibrium informativeness, and we refer to it as the *revelation effect*. In general, both effects operate simultaneously: increasing N lowers the frequency of low signals (reducing informativeness) but also makes those low signals more diagnostic (increasing informativeness).[15]

3 Experimental Design

This section describes the laboratory implementation of our model and our design choices.

[15] To illustrate these two contrasting forces, Online Appendix E.4 presents a simple example with a binary state and binary signals.

The experiment implements an instance of the model described in Section 2.1 with a binary state and four possible signal realizations. We use unframed and nontechnical language. There is an urn that can be red (i.e., $\theta = 1$) or yellow (i.e., $\theta = 0$) with equal probability. Each urn contains balls labeled with four different letters—A, B, C, or D—representing the possible signal realizations. The composition of each urn depends on its color, as shown in Table 1: This represents the distribution $f(s|\theta)$ used in the experiment.

The interaction between the sender and the receiver unfolds in two stages. In the first stage, the sender privately observes the color of the urn (i.e., the state) and the letters on N balls drawn randomly from the urn with replacement (i.e., the realizations of the signals). She then discloses up to K of these balls to the receiver. In the second stage, the receiver observes which balls have been disclosed by the sender, and takes an action $a \in [0, 1]$, which we refer to as the receiver's guess. The sender and the receiver earn points that are converted into cash at the end of the experiment. Given a, the sender earns $100a$ points. The receiver, instead, earns either 0 points or 100 points, depending on her guess a and the underlying state θ. As explained below, the probability the receiver wins 100 points increases with the accuracy of her guess a, incentivizing her to truthfully report her subjective belief that $\theta = 1$.

At the beginning of each session, instructions are read aloud and the recruited subjects play two practice rounds to familiarize themselves with the game and the graphical interface (see Online Appendix F for screenshots of the interface). Subjects are then randomly assigned a fixed role—sender or receiver—and play 30 rounds of the game in that role. Sender and receiver pairs are randomly rematched in each round. At the end of every round, subjects are presented with the same feedback: the state, the signals that were available to the sender, the message sent, the receiver's guess, and their respective payoff.

We conducted six treatments that only differed in the values of K and N, with four sessions per treatment. The chosen combinations of K and N are reported in Table 2: K is either 1 or 3 and, for each K, N is either equal to K, 10, or 50. Figure 1 reports the specific treatment predictions of $\mathcal{I}(K, N)$ under this implementation. This choice of treatments allows us to test the full range of the predictions outlined in Proposition 2.

Population. In each session, an average of 17.25 subjects participated; the number of subjects ranged from a minimum of 12 to a maximum of 24. In total, 414 subjects participated in our experiment: each one participated in a single treatment (a between-subjects design). Subjects were students recruited from the undergraduate populations at Columbia University and New York University in 2023. Two sessions per treatment were conducted at the laboratory facilities

Table 2: Our 2x3-factorial design and the treatments' denominations.

	$N = K$	$N = 10$	$N = 50$
$K = 1$	(K_1, N_1)	(K_1, N_{10})	(K_1, N_{50})
$K = 3$	(K_3, N_3)	(K_3, N_{10})	(K_3, N_{50})

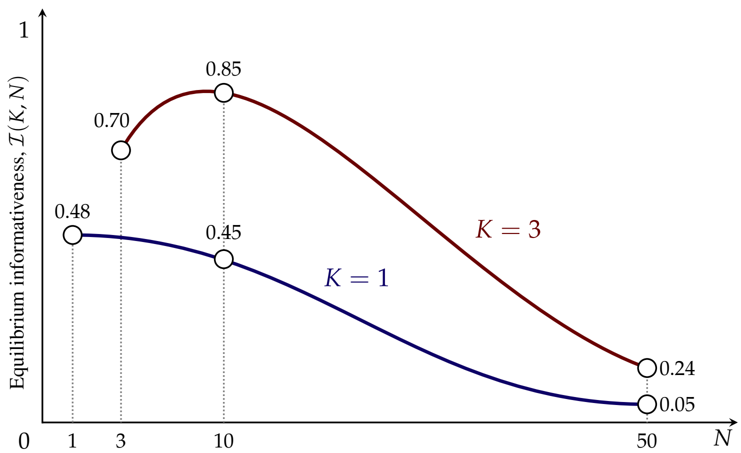


Figure 1: Predicted informativeness for the six treatments.

of each institution.[16]

Earnings. On average, a session lasted 75 minutes and each subject earned \$30.51 (from a minimum of \$18.41 to a maximum of \$37.66), which included a \$10 show-up fee. Subjects accumulated points that were converted into cash at the end of the experiment. The conversion rate was \$1.20 for 100 points for senders and \$0.90 for 100 points for receivers. The different conversion rates aimed to minimize the differences in expected payoffs between the two roles.

Belief Elicitation. Since the state is binary, the receiver's quadratic payoff makes her task equivalent to a belief elicitation via the quadratic scoring rule (Brier, 1950). This is implemented in the experiment using the binarized scoring rule (Allen, 1987; McKelvey and Page, 1990; Schlag et al., 2015; Hossain and Okui, 2013). This rule determines the likelihood that a receiver wins 100 points based on their guess and the realized state; and is robust to risk preferences. We follow the implementation procedure outlined in Wilson and Vespa (2018) and our choices are in line with the recommendations in Healy and Leo (2024) (see also Danz et al.

[16] The experimental interface was designed with the software oTree (Chen et al., 2016). Subjects were recruited at New York University using *hroot* (Bock et al., 2014) and at Columbia using *ORSEE* (Greiner, 2015).

(2022)).

Observable State and Discrete Signals. We note two design choices, which are reflected in our model. First, the sender observes the state θ, allowing for a clearer comparison between treatments as we increase N. This ensures that any differences in senders' behavior must originate from their greater ability to select (which is the focus of this study) rather than from having more information about the state due to the observation of additional signals. Second, signals are discrete. This allows for a design that does not require specifying probability densities. We chose four possible signal realizations to keep the sender's problem nontrivial, as a potentially rich set of deviations from equilibrium can occur in this case. It is worth noting that many real-world contexts feature discrete signals. For example, credit-rating agencies assign discrete ratings to the debt of firms and governments, and restaurant hygiene cards—as well as energy-efficiency certifications for buildings—often take the form of letter grades.

Measuring Informativeness in the Data. We measure the informativeness of communication as the correlation between the realized state and the observed receiver's action. This measure combines the behavior of both senders and receivers. In our analysis, it will sometimes be useful to isolate the informativeness of the senders' strategies—i.e., to net out receivers' mistakes. We do so by computing the correlation between the state and the guess of an idealized Bayesian receiver who optimally responds to senders' average behavior in the treatment. We refer to the resulting measure as the informativeness of the senders' strategies, or simply the senders' informativeness, denoted $\mathcal{I}^B(K,N)$. An identical decomposition technique is used in Fréchette et al. (2022).

Statistical Tests and Predictions. Our analysis focuses on data from the last 15 rounds of each session, to allow enough time for subjects to learn their environment.[17] Unless stated otherwise, our statistical tests are performed as regressions with subject-specific random effects and clustered standard errors at the session level (see Fréchette (2012) and Embrey et al. (2018, Appendix A.4) for a discussion of issues related to hypothesis testing for experimental data). Additionally, when comparing outcomes in our data against theoretical outcomes, such as informativeness, we take into account the finite nature of our dataset. That is, the theoretical outcome is computed for the realized signals $\bar{s}$ in the experiment. This ensures better comparability with the data.

Robustness to an Alternative Design. Online Appendix D presents the results from an alter-

[17] Appendix C.1 illustrates that there are trends in behavior over the course of the sessions. In many treatments, senders become more selective and receivers become more skeptical. For a discussion on the rationale behind focusing on later rounds in experimental economics, see Fréchette et al. (2024).

Table 3: The average number of signals disclosed as a fraction of K.

		$N = K$	$N = 10$	$N = 50$
$K = 1$	Data	66%	100%	100%
	Predictions	[78%, 100%]	[100%, 100%]	[100%, 100%]
$K = 3$	Data	63%	95%	97%
	Predictions	[73%, 100%]	[99%, 100%]	[100%, 100%]

Equilibrium predictions do not uniquely specify what a sender should do if a D signal is among the K-highest elements in $\bar{s}$. This gives rise to a range of predictions, as reported in the table.

native design that is complementary to the one just described. This alternative design considers a setting with a nonbinary state and binary signals, instead of a binary state and nonbinary signals. Additionally, beliefs are elicited in a different manner, i.e., by using the quadratic scoring rule. There are three between-subject treatments, varying K and N, each with five sessions. Despite these differences, the conclusions drawn from this alternative design are, in the dimensions that are comparable, very similar to those that we describe in the following section.

4 Results

We organize our results in two parts. Section 4.1 focuses on senders' behavior: We study what evidence senders disclose (Section 4.1.1), how much information they transmit to receivers (Section 4.1.2), and the strategies they play (Section 4.1.3). Section 4.2 focuses on receivers' behavior: We study how receivers respond to the disclosed evidence (Section 4.2.1) and document their deviations from the theory (Section 4.2.2). We conclude by evaluating the consequence of their behavior on the overall informativeness of communication (Section 4.2.3).

4.1 Senders' Behavior

4.1.1 What Evidence Do Senders Disclose?

In this section, we test simple but consequential comparative static predictions that are inspired by Remark 1: How much and which evidence do senders disclose, and how does it change with K and N?

To begin, we examine *how much* evidence senders disclose. Table 3 shows the average number of disclosed signals as a fraction of K in each treatment. We emphasize two aspects of this table. First, in treatments with $N = K$, i.e., those without selection opportunities, the number of disclosed signals is significantly smaller than predicted (p-value < 0.01). That is, senders conceal some of the evidence and, thus, the unraveling principle fails. This result is consistent with one of the central distortions documented by the existing experimental literature on disclosure (e.g., see Jin et al. (2021)). Mandating disclosure—namely, requiring that the sender discloses exactly K signals—would resolve this distortion. However, notice that the number of disclosed signals increases in N (p-value < 0.01 for the changes from $N = K$ to $N > K$). When N is large, indeed, senders rarely conceal evidence.

The first-order questions should then concern *which* evidence senders select to disclose and how informative it is. We begin by showing that several qualitative patterns in the data are consistent with Remark 1 and, therefore, senders for the most part disclose the most favorable evidence available. This result predicts that, holding K constant, senders should disclose increasingly higher signal realizations as N increases, since they can cherry-pick their signals more effectively. Conversely, holding N constant, senders should disclose increasingly lower signal realizations as K increases because equilibrium forces compel senders to disclose more evidence, requiring them to be less selective.

There are several ways in which we can test these predictions. A particularly convenient one, both analytically and for data visualization, is to map each message into a real number, its implied grade point average (GPA). Just as in the case of school transcripts, we assign a numerical value to each signal in a message and average them. In particular, we assign $A \to 4$, $B \to 3$, $C \to 2$, and $D \to 1$. Consistent with equilibrium reasoning, we assign any missing signal the value of a D signal.[18]

Table 4 reports the mean GPA (MGPA) computed at the treatment level. As predicted, holding K constant, we observe sizable increases in MGPA going from treatments with $N = K$ to treatments with $N > K$ (p-value < 0.01); conversely, holding N constant, the MGPA decreases as K increases. As predicted, this effect is large and statistically significant when $N = 10$ (p-value < 0.01) and small and not significant when $N = 50$. The same patterns hold when we look at sender-level data, as opposed to treatment averages. Figure 2 reports the cumulative distribution function (CDF) of sender-level MGPAs. We document a large first-order

[18] For instance, when $K = 3$, message $m = (A, B, C)$ has a GPA of 3, and message $m = (A, B, o)$ has a GPA of 2.67. The results we present in this section are robust to other conventions; for example, coding a missing signal as a 2.5 (i.e., the expected grade given prior belief) or as a 0 (i.e., a grade strictly lower than D). Additionally, our results also hold if we do not use summary measures such as GPA. Figure C.5 (Online Appendix C.2) reports the distribution of disclosed signals and how it changes in K and N.

Table 4: Mean grade point average (MGPA) induced by senders' messages.

		$N = K$	$N = 10$	$N = 50$
$K = 1$	Data	2.31	3.63	3.61
	Predictions	2.57	3.83	4.00
$K = 3$	Data	2.27	3.24	3.54
	Predictions	2.52	3.52	3.98

For reference, an "unselective" sender who discloses K signals at random would generate an MGPA of 2.50 in all treatments.

stochastic dominance (FOSD) increase in the CDF of sender-level MGPAs when N increases from $N = K$ to $N > K$ (p-value < 0.01).[19] For both values of K, the differences between $N = 10$ and $N = 50$ are small; the theory also predicts these differences to be relatively small (see Figures 2c and 2d), because senders already have ample opportunity for selection when $N = 10$. Additionally, the comparison between Figures 2a and 2b reveals, holding N constant, the CDF of sender-level MGPAs decreases (in a FOSD sense) as K increases (p-value < 0.01 for $N = 10$ and p-value < 0.1 for $N = 50$).

The main force driving a sender to switch from concealment (when N is small) to selection (when N is large) is the greater availability of high signals in the sender's sample. One way to assess this is to regress the number of disclosed signals on the GPA of the K-highest signals available to the sender and a constant. This regression is meaningful only in treatments with a non-trivial degree of concealment, since otherwise the dependent variable is constant. As shown by Table 3, this excludes (K_1, N_{10}) and (K_1, N_{50}). In all other treatments, we find a positive and statistically significant coefficient (p-values < 0.01).

These results corroborate the qualitative predictions of Remark 1 and are a manifestation of the fact that senders predominantly engage in selective disclosure. Quantitatively, we find that, across all treatments, 24% of senders play in a way that is *exactly* consistent with maximally selective strategies in all of the last 15 rounds, while 56% of the senders do so in at least 80% of these rounds. Nonetheless, there are meaningful quantitative differences between the predictions and the data. For all treatments, senders induce MGPAs that are lower than predicted. This is true both at the treatment level (Table 4) and at the sender level (Figure 2). Addition-

[19] All the FOSD tests reported in the paper follow the procedure in Barrett and Donald (2003). For the implementation, we follow Lee and Whang (2024). Note however that this procedure does not account for the correlation between subject-level and session-level data.

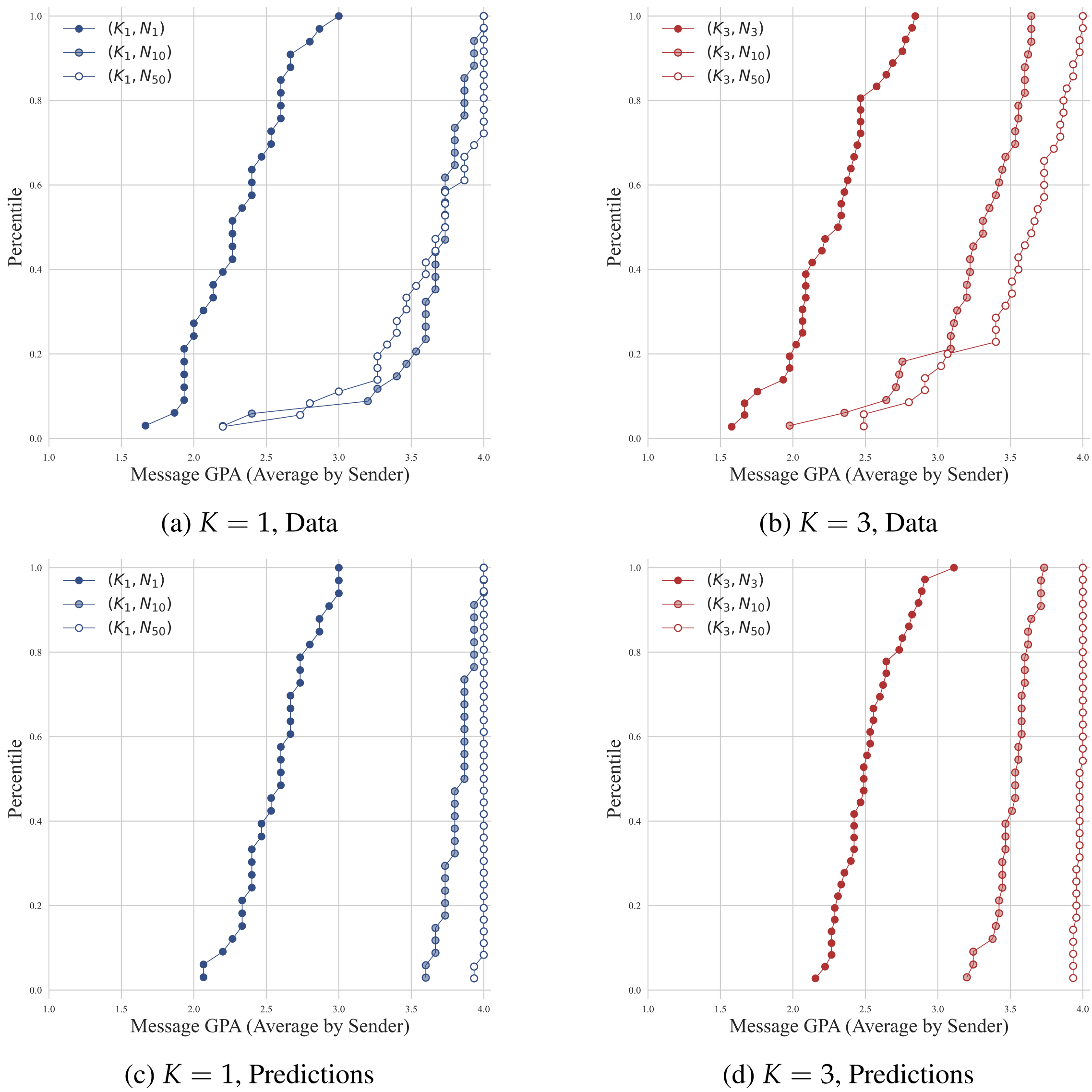


Figure 2: CDFs of senders' message GPAs: data and predictions

ally, the distributions reveal that senders' behavior is more heterogeneous than predicted.[20] We will address these quantitative deviations and further analyze senders' heterogeneity in Section 4.1.3.

4.1.2 How Much Information Do Senders Transmit?

Next, we discuss how much information senders transmit. As discussed in Section 3, we define senders' informativeness, denoted by $\mathcal{I}^B(K, N)$, as the correlation between the state and the

[20]Note that the predictions in the bottom panels of Figure 2 display some heterogeneity due to the randomness of $\bar{s}$, the vector of signals available to each sender. Given any finite sample, two senders playing the equilibrium strategy may not induce the same MGPAs. However, there is clearly more heterogeneity in senders' behavior than what can be explained by such randomness.

Table 5: Senders' informativeness $\mathcal{I}^B(K,N)$ and predicted values.[22]

		$N = K$	$N = 10$	$N = 50$
$K = 1$	Senders' Informativeness	0.46	0.43	0.38
	Predictions	0.44	0.38	0.06
$K = 3$	Senders' Informativeness	0.73	0.82	0.39
	Predictions	0.69	0.84	0.22

guess of an idealized Bayesian receiver who optimally responds to senders' average behavior in the treatment.

Table 5 reports the average $\mathcal{I}^B(K,N)$ for each treatment. We find that, for *all* treatment variations of K and N, the average senders' informativeness moves in the directions predicted by the theory. Next, we highlight the most important comparisons.[21]

First, Proposition 2(a) and Figure 1 predict that, holding N constant, increasing K should increase senders' informativeness. Quantitatively, this increase should be large for $N = 10$ and small for $N = 50$. Accordingly, the data exhibit a large and significant increase for $N = 10$, from 0.43 to 0.82 (p-value < 0.01), while only a statistically insignificant one for $N = 50$, from 0.38 to 0.39.

Second, as predicted by Proposition 2(b), we find that when senders can disclose all the evidence (i.e., when $K = N$), increasing N significantly increases senders' informativeness, from 0.46 to 0.73 (p-value < 0.01).

Third, Proposition 2(c) predicts that an increase in N should eventually decrease senders' informativeness for both values of K. Accordingly, the average senders' informativeness decreases from 0.73 to 0.39 for $K = 3$ and from 0.46 to 0.38 for $K = 1$. The former treatment effect is significant at the 1% level. The latter effect is only weakly significant (p-value of the one-sided test < 0.10).

[21]The statistical tests reported in this subsection are performed by computing correlations at the sender's level and by clustering at the session level. The robustness of these results is confirmed by using an alternative bootstrapping procedure: For each treatment, we generate $1,000$ random subsamples, compute the senders' correlations in each of them, and use standard t-tests to compare the bootstrapped samples of correlations.

[22]The minor discrepancies between the predictions in Table 5 and those in Figure 1 stem from the fact that the former are calculated for the realized θ's and $\bar{s}$'s rather than in expectation. This ensures a better comparability with the data.

Finally, the theory predicts that informativeness should decrease in N if $K = 1$ but display a nonmonotonicity if $K = 3$. Accordingly, we find that increasing N from K to 10 increases senders' informativeness from 0.73 to 0.82 if $K = 3$, but decreases it from 0.46 to 0.43 if $K = 1$. The former treatment effect is significant at the 5% level, although the p-value of this test is sensitive to the exact specification. The latter effect is not significant.

To summarize, despite the richness of our predictions, there is no case in which the theory is rejected, and in the majority of cases, the predicted changes are statistically significant. These findings suggest that the theory effectively captures the key tensions in how selective disclosure shapes the informativeness of senders' strategies.

Nonetheless, we observe a notable quantitative deviation: senders often *overcommunicate*, particularly when N is large. By overcommunication we mean that the informativeness of senders' strategies exceeds that predicted by the equilibrium. This contrasts with prior results in the literature on disclosure—both from the laboratory and the field—that find that senders *undercommunicate*. This preceding literature shows that senders often conceal evidence and communicate less than predicted—a failure of the unraveling principle. The key difference relative to our setting is that, due to the unraveling argument, informativeness in these papers is predicted to be maximal. Any departure from equilibrium behavior would lead to undercommunication. As such, these studies cannot uncover overcommunication.[23] In contrast, in our setting, informativeness is never predicted to be maximal (see discussion in Section 2.1). This is a key feature of our design as it enables the rich comparative statistics discussed above and allows the theoretical predictions to potentially fail in either directions—overcommunication and undercommunication.[24]

4.1.3 Understanding Senders' Heterogeneity and Overcommunication

In this subsection, we analyze the heterogeneity in senders' behavior and relate it to the deviations from the theory that we have identified so far.

There are challenges in studying senders' heterogeneity, especially in a way that can be easily visualized. First, the sender's strategy space is large. Second, we only observe part of the senders' strategy, namely what message is sent given the realized signals $\bar{s}$, which are

[23] One exception is de Clippel and Rozen (2025), which also features partial information transmission. Although their model and focus differ from ours, their findings suggest instances of overcommunication by senders.

[24] When $N = K$, overcommunication is possible only because the sender observes the state, and it is necessarily achieved through state-dependent concealment strategies. Thus, concealment can sometimes *increase* informativeness. By contrast, when $N > K$, overcommunication may arise even without concealment and if the sender does not observe θ.

random.[25] Third, some key features of behavior often vary across treatments; for instance, in some treatments, concealment is important, while in others it is not.

To address these challenges, we first reduce the dimensionality of senders' strategies and then apply a simple clustering algorithm to group them into three representative categories, each capturing a distinct behavior. Specifically, we proceed as follows. We define the *GPA gap* as the average difference between the GPA of the messages sent by a sender and the GPA of the message that would have been sent under the equilibrium strategy. For each sender, we compute two versions of this GPA gap: one conditional on the state being high and one conditional on the state being low. This yields a two-dimensional vector for each sender, summarizing key aspects of their behavior in the game. We then apply a k-means algorithm to cluster the senders in three groups based on these two conditional GPA gaps.[26] This approach allows us to partially overcome the challenges discussed above. First, the sender's strategy is summarized into a much lower dimensional space. Second, the conditional GPA gap is only partially affected by the randomness of the available signals because it is computed relative to a benchmark—the equilibrium GPA—that similarly depends on this randomness. Lastly, the procedure can be applied consistently for all treatments.

To visually represent each cluster, we compute the within-cluster average frequency with which each signal is sent conditional on the state. Moreover, we compute the average informativeness of the strategies in each cluster, as well as their corresponding average payoff. Overall, this approach provides a comprehensive yet structured overview of senders' behavior, summarizing the strategies they play, their informativeness, and the corresponding payoffs.[27]

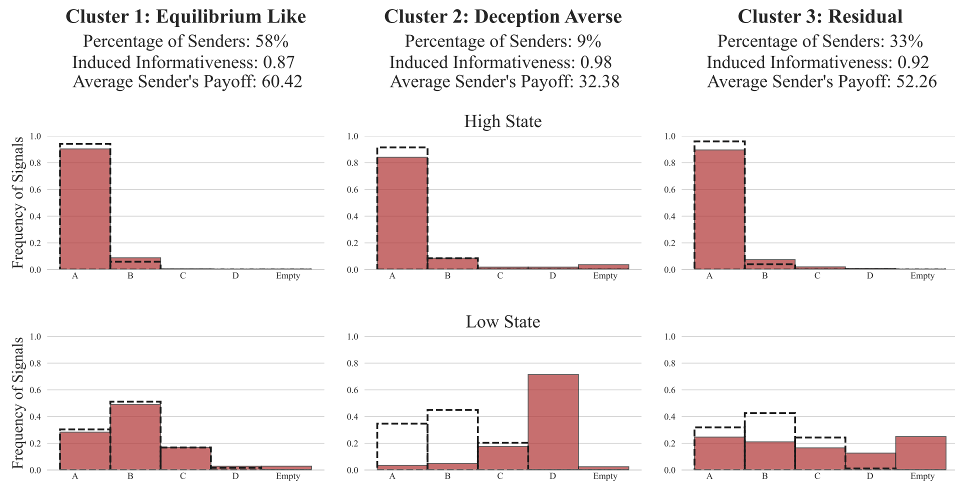
To keep the presentation concise, Figure 3 reports results for only two of our treatments, (K_3, N_{10}) and (K_3, N_{50}). We focus on these two treatments because they provide the most informative and conceptually rich contrasts in our design. The patterns we observe are broadly representative of the results across the other treatments, which are presented in Online Appendix C.2.

Figure 3 shows that, in both treatments, the majority of senders belong to Cluster 1: Senders

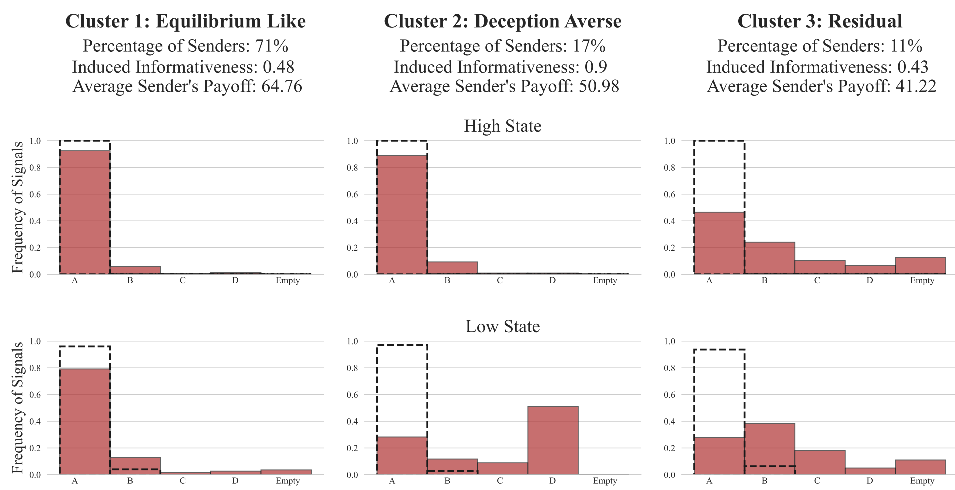
[25] We do not observe which message would have been chosen had the sender obtained a different set of available signals. Eliciting the sender's strategy using the *strategy method* is impractical in this setting.

[26] Fréchette et al. (2022) employ the same algorithm for the same purpose, namely that of classifying senders' behavior by reducing the high dimensionality of their strategies.

[27] To assess the robustness of the results we present in this subsection, we conducted the clustering analysis in several other ways: using an alternative specification based on the sender-specific conditional distribution of disclosed signals (an eight-dimensional vector), varying the number of clusters (2, 3, or 4), changing the initial seed, and altering the amount of data from the experiment (last 15, 20, or 25 rounds). In all cases, the results tell a consistent story: while the majority of senders play equilibrium-like strategies, there is a non-negligible minority who do not and, in particular, exhibit behavior consistent with deception aversion.



(a) Treatment (K_3, N_{10})



(b) Treatment (K_3, N_{50})

Figure 3: Sender's clustering across treatments. Equilibrium predictions shown as dashed bars.

in this cluster exhibit behavior that is highly consistent with the maximally selective equilibrium, represented by the dashed bars. These senders overwhelmingly disclose the best available signals in both states. It is particularly revealing to observe how closely sender behavior in treatment (K_3, N_{10}) aligns with the equilibrium, even conditional on the low state, despite the equilibrium prescribing substantial disclosure of B and C signals. Finally, compared to the other clusters, senders in Cluster 1 achieve the highest payoffs.

Cluster 2 reveals a type of nonequilibrium behavior that consistently appears across all treatments. Senders in this cluster display behavior that we interpret as *deception-averse*. In the high state, they overwhelmingly disclose the best available signals, as prescribed by the equilibrium. However, in the low state, they systematically fail to do so and, in fact, often disclose the worst signals. As a consequence of this state-dependent behavior, deception-averse senders induce the highest levels of informativeness and, thus, contribute to the overcommunication documented in the previous section. Moreover, they earn substantially lower payoffs than senders in Cluster 1 (the equilibrium-like cluster). These qualitative patterns are robust across the other treatments as well (see Online Appendix C.2).

Deception aversion is related to lying aversion, but with a key distinction. In our setting, senders cannot lie, as the evidence is verifiable. Yet, they can deceive through selection. Deception-averse senders appear reluctant to disclose evidence that might mislead receivers into believing the state is high when it is not. The presence of deception-averse senders marks a notable departure from previous experiments on disclosure. In those experiments, evidence typically fully reveals the state, and equilibrium predicts full disclosure, leaving no room for deception aversion to manifest empirically.[28] This observation may help clarify two contrasting results from the literature: Experiments on cheap talk often find overcommunication whereas those on disclosure often find undercommunication. In our experiment, both types of deviations are present at the same time: deception aversion (which increases informativeness) counterbalances the more classic finding that some senders conceal evidence (which reduces informativeness).

Turning now to Cluster 3, it should be interpreted as the residual outcome of the k-means clustering algorithm. It captures patterns of behavior that vary across treatments. In some cases, such as in Figure 3a, it reflects intermediate behavior that lies between equilibrium play and deception aversion. In these instances, using only two clusters would already capture the main behavioral regularities, and the third cluster simply subdivides an existing one into finer, in-between categories. In other cases, such as in Figure 3b, Cluster 3 is relatively small and less interpretable, possibly reflecting noisy or inconsistent play. In these cases, specifying three clusters helps isolate the two main behavioral types while absorbing residual heterogeneity into a third, less structured group.

4.1.4 Summary and Interpretation of Senders' Behavior

In summary, we find that the senders overwhelmingly engage in selective disclosure. Their behavior is qualitatively consistent with the theoretical predictions of our model. This indicates

[28] Sobel (2020) discusses the theoretical distinction between lying and deception in communication. Abeler et al. (2019) conduct a metastudy of the existing experimental literature and document the prevalence of lying aversion in cheap-talk settings. Choi et al. (2025) and Elmshauser et al. (2025) aim to disentangle deception aversion from lying aversion in cheap talk (see also, Sutter, 2009).

that the theory effectively captures the key tensions in how selective disclosure shapes senders' communication. We also document two main departures from the theory. First, on average senders overcommunicate, i.e., they convey more information than predicted. Second, our clustering analysis reveals that a group of senders is deception-averse. They disclose the best available signals in the high state but refrain from doing so in the low state. These departures are connected. In particular, by sending different messages in different states, the deception-averse senders communicate more information than predicted, leading to overcommunication in the aggregate.

4.2 Receivers' Behavior

4.2.1 How Do Receivers Respond to Selected Evidence?

We now discuss receivers' behavior. We begin by testing a key prediction from Remark 1: For any fixed message m, the receiver's guess should decrease as N increases, because receivers should understand that senders are more selective with larger N.

This prediction is strongly borne out in the data. Before diving into a structured analysis of this prediction, we first provide a simple illustration. Consider a receiver observing message $m = A$ in a treatment with $K = 1$. This receiver should respond more skeptically if $N = 50$ than if $N = 1$. As predicted, the average receivers' guess aligns with this prediction: it decreases from 0.82 when $N = 1$ to 0.64 when $N = 50$ (p-value < 0.01).

To provide more systematic evidence of the receivers' responses to changes in N, we estimate the following regression model:

$$a_{i,m} = \beta_0 + \beta_1 \mathrm{GPA}_m + \beta_2 D_{N_{10}} + \beta_3 D_{N_{50}} + \varepsilon_{i,m}, \tag{1}$$

where $a_{i,m}$ is the guess of receiver i to message m, GPA_m is the induced GPA of the message, and $D_{N_{10}}$ and $D_{N_{50}}$ are dummies that equal 1 if $N = 10$ or $N = 50$, respectively. We estimate this model separately for $K = 1$ and $K = 3$.[29] The dummy coefficients capture how much the receivers' guesses decrease compared to the benchmark cases of $N = K$. Remark 1 predicts that these dummy coefficients should be negative. Note that we control for the GPA of a message rather than the messages themselves. We do so because, for treatments with $K = 3$,

[29] We report the OLS (with random effects) estimates here for ease of exposition; however, the results are robust to considering different regression models (i.e., Tobit) and specifications (e.g., replacing the GPA with the message as a regressor). Online Appendix C.3 shows the nonparametric estimates of receivers' guesses on message GPA by treatment.

Table 6: Regression results of receivers' responses for each K

	$K=1$		$K=3$	
	(1) Receiver's Guess	(2) Empirical Optimal Guess	(3) Receiver's Guess	(4) Empirical Optimal Guess
GPA	15.33^{***}	19.46^{***}	26.59^{***}	32.94^{***}
	(0.91)	(0.96)	(2.21)	(2.54)
$D_{N_{10}}$	-18.67^{***}	-29.21^{***}	-24.72^{***}	-30.92^{***}
	(2.69)	(1.93)	(2.95)	(2.90)
$D_{N_{50}}$	-17.04^{***}	-25.84^{***}	-28.16^{***}	-43.13^{***}
	(2.20)	(1.44)	(3.00)	(3.27)
Constant	19.08^{***}	2.91	-6.28	-25.93^{***}
	(1.98)	(2.47)	(5.18)	(5.80)
Obs	1,545	1,545	1,560	1,560
Subjects	103		104	

(1) and (3) with subject random effects, (2) and (4) without.
Standard errors clustered at the session level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

some messages are only rarely used and the frequency of such messages is different across treatments. The GPA circumvents this issue.

Table 6 reports the results of these regressions (columns 1 and 3). For both values of K, the dummy coefficients are negative and strongly significant, as predicted. That is, as N increases, receivers become more skeptical of messages with the same GPA. To understand whether these treatment effects are quantitatively in line with the predictions, Table 6 also reports the coefficients that would have obtained if receivers had best responded to the senders (columns 2 and 4). This calculation is performed by replacing the dependent variable in the regression model of Equation (1) with the *empirical optimal guess*: This is the guess of an idealized receiver who best responds to the senders' observed strategies. We use it as the benchmark against which to evaluate the receivers' actual behavior.[30] Comparing the estimated coefficients of these regressions (columns 2 and 4) with those discussed before (columns 1 and 3), we conclude that, although receivers become more skeptical, they do not adjust their responses as much as would

[30]Specifically, the empirical optimal guess given a message m is $\mathbb{E}(\theta|m) = \Pr(1|m)$, i.e. the fraction of times message m was sent when $\theta = 1$ by any sender. We compute this by using data at the treatment level. Our results in this section are robust to computing the empirical optimal guess at the session level.

Table 7: Regression results of receivers' responses for $N = 10$ and $N = 50$

	$N = 10$		$N = 50$	
	(1) Receiver's Guess	(2) Empirical Optimal Guess	(3) Receiver's Guess	(4) Empirical Optimal Guess
GPA	23.90^{***}	31.73^{***}	16.09^{***}	19.75^{***}
	(3.34)	(3.70)	(1.62)	(0.75)
D_{K_3}	8.40^{*}	17.93^{***}	3.43	1.66^{*}
	(4.77)	(3.09)	(2.55)	(0.72)
Constant	-30.71^{**}	-70.83^{***}	-0.702	-23.97^{***}
	(13.08)	(14.70)	(5.22)	(2.90)
Obs	$1,005$	$1,005$	$1,065$	$1,065$
Subjects	67		71	

(1) and (3) with subject random effects, (2) and (4) without.
Standard errors clustered at the session level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

be required to fully account for selection. We discuss this point further in the next subsection.

A complementary test consists of studying how receivers respond to messages with the same GPA as K increases, holding N constant. To fix ideas, consider receiving a message with a GPA of 4 in treatments (K_1, N_{10}) and (K_3, N_{10}). Intuitively, this message is more selected in the former treatment than in the latter. Therefore, fixing $N \in \{10, 50\}$, receivers' guesses should increase in K controlling for messages with the same GPA. To test this prediction, we estimate a regression model that is similar to that of Equation (1) with a dummy variable D_{K_3}, which equals 0 if $K = 1$ and 1 if $K = 3$. Table 7 shows that the treatment effects are predicted to be large for $N = 10$ and small for $N = 50$ (see columns 2 and 4). The data are in line with these predictions (see columns 1 and 3): For $N = 10$, the predicted treatment effect is positive and significant at the 10% level. For $N = 50$, this effect is small and insignificant.

Overall, these results corroborate a key qualitative prediction of the theory: receivers recognize that the evidence they observe is differentially selected across treatments and respond accordingly. This shows that the thrust of the theory remains valid even though, as the literature amply shows, receivers often do not behave as Bayesians. Yet, from a quantitative perspective, receivers' mistakes do create a wedge between the theory and the data, which we document and explain in the next subsection.

Table 8: Average response gaps by treatment and type of message

		$K = N$		$K < N$			
		(K_1, N_1)	(K_3, N_3)	(K_1, N_{10})	(K_1, N_{50})	(K_3, N_{10})	(K_3, N_{50})
(i)	All messages	6.63^{***}	5.24^{***}	11.73^{***}	10.04^{***}	5.25^{*}	12.09^{***}
		(495)	*(540)*	*(510)*	*(540)*	*(495)*	*(525)*
(ii)	Length-K messages	4.95^{***}	-3.34	11.64^{***}	10.14^{***}	4.68	11.33^{***}
		(327)	*(154)*	*(509)*	*(538)*	*(456)*	*(500)*
(iii)	Empty messages	9.89^{***}	14.64^{***}	—	—	—	—
		(168)	*(39)*	*(1)*	*(2)*	*(10)*	*(2)*

The observation count is shown in parentheses. The response gap conditional on empty messages for treatments with $K < N$ is not reported, as concealement is virtually absent in those treatments.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

4.2.2 Receiver Optimism

To better understand how receivers deviate from the theory, we introduce the receiver *response gap*, defined as the difference between a receiver's actual guess and the empirically optimal guess. A positive response gap indicates that the receiver overestimates the state and is thus overly optimistic.

In this subsection, we document how the receiver's response gap varies systematically across treatments and types of disclosed evidence. Table 8 reports the average response gaps under various conditions. We discuss four key patterns that stand out from this table.

First, row (i) in Table 8 shows that the average response gap is positive and significant in all treatments (p-value < 0.01, except for (K_3, N_{10}), which has a p-value of 0.09). This baseline observation indicates that receivers are, on average, overly optimistic, replicating a central finding of the previous literature (e.g., Cai and Wang, 2006; Jin et al., 2021).

Second, we study whether receivers make more mistakes when responding to *concealed* evidence or *nonselected* evidence. To do so, we focus on treatments (K_1, N_1) and (K_3, N_3). In these treatments, because $K = N$, a message of length K is, by construction, nonselected. Table 8 shows that the response gaps to an empty message (9.89 and 14.64, respectively) are significantly higher than the response gaps to a length-K message (4.95 and -3.34, respectively), with p-values below 0.01 in both treatments.

Third, we study whether receivers make more mistakes when responding to *concealed* evidence or *selected* evidence. To do so, we compare the response gap conditional on empty messages in treatments with $K = N$—which best isolate the receiver's response to concealed evidence—with the response gap conditional on messages of length K in treatments with $K < N$—which best isolate the receiver's response to selected evidence. We find that receivers' mistakes when responding to concealed versus selected evidence are of comparable magnitude.[31]

Fourth, we find that although receivers make mistakes of similar magnitude when responding to concealed versus selected evidence, the overall distortion created by selection is greater because selection is far more prevalent than concealment. Specifically, row (i) of Table 8 shows that for each K the average response gaps increase with N. This indicates larger mistakes in treatments where selection is the dominant distortion. This finding is explained by noting that, while receivers make mistakes of similar magnitude when responding to concealed versus selected evidence, in treatments with large N selected evidence is pervasive, whereas in treatments with $K = N$ the receiver encounters concealed evidence only about one third of the time (see Table 3). To investigate the statistical significance of this fourth finding, we regress the response gap on the same covariates used in Equation (1). Table 9 reports the estimated coefficients. We find that, for both values of K, the increase in the response gap as we move from $N = K$ to $N > K$ is significant (p-value < 0.01).[32]

Overall, these four findings provide the first direct quantitative comparison between two kinds of receiver deviations documented in separate strands of the experimental literature. The failure to update correctly in response to concealed evidence has been studied in the literature on verifiable disclosure, while the failure to update correctly in response to selected evidence has been examined in the literature on selection neglect.[33] Our results show that these two kinds of biases produce mistakes of similar magnitude but with different aggregate implications.

[31] In all but one comparison, the response gap to concealed evidence does not differ significantly from the response gap to selected evidence. The only exception is the comparison between (K_3, N_3) and (K_3, N_{10}), where the difference is statistically significant.

[32] In the regression, it is important to control for the GPA because an increase in N produces two effects: first, a message may take on a different meaning as it becomes more selected; second, the frequency with which a message is received may change. The response gap averages mistakes across different messages, so if some messages cause more mistakes, changes in their frequency can create a spurious effect on the response gap. This fourth finding can also be shown by examining receiver-level response gaps rather than treatment averages (see Online Appendix C.4.2).

[33] See, for example, Esponda and Vespa (2018), Enke (2020), Araujo et al. (2021), and Barron et al. (2024). Note that the selection-neglect literature has thus far predominately focused on decision-making settings. In contrast, we document selection neglect in a strategic communication setting, where selection arises endogenously from the sender's desire to influence the receiver's behavior. Ali et al. (2021) also studies selection neglect in a strategic setting, in the context of a two-player simultaneous voting game with asymmetrically informed voters.

Table 9: OLS on receivers' response gaps

	$K = 1$	$K = 3$
	Response gap	Response gap
GPA	-4.13^{***}	-6.33^{***}
	(1.34)	(1.20)
$D_{N_{10}}$	10.56^{***}	6.18^{***}
	(2.47)	(2.15)
$D_{N_{50}}$	8.81^{***}	14.92^{***}
	(2.65)	(2.17)
Constant	16.18^{***}	19.57^{***}
	(2.94)	(2.84)
Obs	$1,545$	$1,560$
Subjects	103	104

With random effects at the subject level.
Standard errors clustered at the session level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Our work also shows that these biases coexist within the same experimental framework, suggesting they are likely not entirely distinct phenomena and may share a common explanation. Indeed, they can be rationalized by a simple extension of our model. In this richer model, the receiver is either sophisticated or naïve, with probabilities that are constant across treatments. The sophisticated receiver behaves as in our baseline model, as does the sender. The naïve receiver, instead, takes both concealed and selected evidence at "face value": she neglects selection when evidence is disclosed and draws no inference when evidence is concealed. This captures the behavior of a receiver who is still Bayesian but has wrong beliefs about the sender's strategy. In such a model, sophisticated receivers never contribute to the response gap (by construction). In contrast, naïve receivers contribute positively, as they fail to recognize that the evidence they see (or do not see) has been strategically disclosed to inflate their responses. On average, this model generates response gaps that vary with treatment and type of evidence in a way consistent with the empirical patterns reported above (see Online Appendix C.4.1 for details).

In summary, the results in this subsection shed new light on receiver optimism, highlighting its systematic patterns across treatments and types of evidence and showing that a relatively simple form of receiver naïveté offers a unified explanation for the observed deviations in behavior.

Table 10: Overall informativeness, senders' informativeness, and theoretical predictions

		$N = K$	$N = 10$	$N = 50$
$K = 1$	Overall Informativeness	0.31	0.26	0.23
	Senders' Informativeness	0.46	0.43	0.38
	Theory	0.44	0.38	0.06
$K = 3$	Overall Informativeness	0.59	0.62	0.15
	Senders' Informativeness	0.73	0.82	0.39
	Theory	0.69	0.84	0.22

4.2.3 How Much Information Do Receivers Absorb?

We conclude by discussing how the informativeness of communication between senders and receivers changes across treatments. Recall that, in Section 4.1.2, we focused on *senders*' informativeness, $\mathcal{I}^B(K, N)$, which is the correlation between the realized state and the empirical optimal guess and which measures the informativeness of the senders' strategies. In this section, instead, we focus on *overall* informativeness, denoted by $\mathcal{I}(K, N)$. This is computed as the correlation between the realized state and the actual receiver's guess. Thus, overall informativeness provides us with a comprehensive measure that tracks the amount of information that is transmitted by the sender and absorbed by the receiver. Our final task in this section is to evaluate how the receivers' mistakes documented so far affect the comparative statics predictions of the model.

Table 10 reports overall informativeness at the treatment level, along with the senders' informativeness and the theoretical predictions (already reported in Table 5). Note that, by definition, $\mathcal{I}(K, N) \leq \mathcal{I}^B(K, N)$. Indeed, overall informativeness cannot be higher than senders' informativeness as receivers' mistakes add noise that can only decrease the correlation between the state and the guess.

We emphasize three aspects of Table 10. First, for a fixed N, increasing K should increase overall informativeness (Proposition 2(a)). The increase should be large for $N = 10$ and small for $N = 50$. The data shows a large increase for $N = 10$ (p-value < 0.01) and a statistically insignificant treatment effect (with a wrong sign) for $N = 50$.

Second, as predicted by Proposition 2(b), we find that when senders can disclose all the evidence (i.e., when $K = N$) increasing N significantly increases overall informativeness from 0.31 to 0.59 (p-value < 0.01).

Third, as predicted by Proposition 2(c), increasing N from K to 50 reduces informativeness from 0.59 to 0.15 when $K = 3$ and from 0.31 to 0.23 when $K = 1$. Although the first effect is significant at the 1% level, the latter is not significant. Finally, when $K = 3$, the overall informativeness increases from $N = 3$ to $N = 10$ (from 0.59 to 0.62) but this increase is not significant. Therefore, in this case, despite senders transmitting more information, receivers do not use it to their advantage.

To summarize, receivers' mistakes do introduce noise into the data, making it harder to detect the treatment effects predicted by the model's rich comparative statics. Nonetheless, despite these challenges, there is no case in which the theory is rejected, and in the majority of instances, the predicted changes remain statistically significant.

5 Policy Implications

In this final section, we discuss the policy implications of our results. We begin with policies aimed at discouraging concealment and then turn to those intended to reduce selection.

5.1 Policies To Discourage Concealment: Mandatory Disclosure

In our setting, mandatory disclosure refers to a policy that prevents concealment by requiring the sender to reveal exactly K signals. Such policies play a prominent practical role, as noted in the introduction, because they are used to mitigate the distortionary effects of concealment. In applications of the standard disclosure setting, mandatory disclosure is beneficial to the receiver. In our richer setting, however, our results show that it can be ineffective in some cases and even harmful in others.[34]

To begin, in treatments with $K < N$, mandatory disclosure would be largely ineffective because senders rarely conceal evidence in the first place (see Table 3). As noted earlier, the main distortion in these treatments arises from selection rather than concealment and is therefore unaffected by a mandatory-disclosure policy. We discuss policies that target selection

[34] Other papers document that mandated disclosure can backfire. For example, Dranove et al. (2003) find that cardiac surgery report cards induced providers to avoid high-risk patients, leading to worse overall outcomes for sicker patients. This moral-hazard effect is fundamentally different from the mechanism we highlight.

later.

In treatments with $K = N$, by contrast, mandatory disclosure has more bite. At a high level, it influences senders' behavior in two ways. First, it prevents low-type senders from manipulating naïve receivers by concealing unfavorable evidence. This force is also present in the standard disclosure setting—where the sender knows her type and can choose whether to fully reveal it. In this standard setting, concealment provides no benefit to receivers and often harms them. This is the classic rationale for mandatory disclosure, which remains valid in our environment. Second, in our richer setting, mandatory disclosure affects senders' behavior in a different way. Because senders cannot fully reveal their type, when disclosure is voluntary they can sometimes use concealment informatively—for example, by withholding favorable evidence when the state is low. This is best illustrated by our cluster of deception-averse senders, whose behavior increases the informativeness of communication. Mandatory disclosure blocks this channel of informative concealment, thereby harming receivers.

Therefore, in our setting the effect of mandatory disclosure on senders' informativeness is ex ante ambiguous: On the one hand, mandatory disclosure prevents senders from concealing unfavorable evidence, which benefits receivers; on the other, it can disrupt the informative use of concealment, which harms receivers.[35] Table 10 shows that these opposing forces roughly balance out, with mandatory disclosure mildly suppressing senders' informativeness. To see this, recall that the theory predicts full disclosure by the sender (or an equivalent strategy). Comparing this theoretical benchmark with the senders' observed informativeness, we find that mandatory disclosure would reduce the informativeness of their strategies by about two percentage points in (K_1, N_1) and four percentage points in (K_3, N_3).

So far, we have evaluated mandatory disclosure through the lens of senders' informativeness—a measure that isolates the informational content of their strategies by assuming receivers are Bayesian. If all receivers were Bayesians, this would conclude the analysis of mandatory disclosure. However, as documented in Section 4.2.2, receivers are often non-Bayesian. This introduces a third potential effect of mandatory disclosure, one that concerns receivers' behavior. In treatments with $K = N$, receivers may respond more effectively when disclosure is mandated, because the evidence they observe would then be non-selected and require no strategic inference. Indeed, as shown in Section 4.2.2, receivers perform better when responding to non-selected evidence than to concealed evidence.

To evaluate the overall impact of mandated disclosure on receiver welfare—taking into ac-

[35] As above, we assume that the sender communicates only through verifiable disclosure and cannot supplement this with cheap-talk messages.

count the three effects discussed above—we simulate a simple model of players' behavior and then consider a counterfactual with mandatory disclosure. For simplicity, we restrict the analysis to treatment (K_1, N_1). Using the same procedure described in Section 4.1.3, we cluster senders into three groups: 55% are classified as equilibrium types, 18% as deception-averse types, and 27% belong to a residual cluster, which in this case represents a hybrid between the former and the latter (see Figure C.6 in Online Appendix C.2). For each group of senders, we compute their "average" strategy, represented as a probabilistic mapping from the state θ to the messages sent. The receiver's guess in response to any message is modeled as a truncated normal distribution (with support on $[0, 1]$), with message-specific mean and variance chosen to match the data. The resulting overall informativeness (the correlation between the state and the simulated receiver's guess) is 0.32. This value is very close to what we obtain from the data (0.31, see Table 10), suggesting that our simulation captures the key features of the data-generating process.[36]

We then compare this value with the outcome of a counterfactual exercise in which disclosure is mandated. Specifically, we modify the strategies of the three sender clusters by imposing that whatever signal a sender observes must be disclosed. We consider two versions of this counterfactual. In the first, the receiver's behavior remains exactly as described above. Under this scenario, overall informativeness is essentially unchanged at 0.32. Thus, in this case, mandatory disclosure has no effect. In the second version of the counterfactual simulation, we change receivers' behavior to account for the possibility that it is easier for them to respond to non-selected evidence. Specifically, we assume that, conditional on any message, the receiver's guess is drawn from a truncated normal with mean equal to the correct Bayesian response to that message. The variance parameter, instead, is left unchanged as described above, to capture the fact that receivers will still make some mistakes in their guesses. Under this counterfactual, the overall informativeness increases to 0.34. In other words, mandatory disclosure has a modest positive effect. More generally, the magnitude and direction of the impact of mandated disclosure depend on the prevalence of the cluster of deception-averse senders. If their proportion were higher than in our experiment, informativeness would also be higher, reducing the appeal of mandatory disclosure. Conversely, if their proportion were lower, the appeal of mandatory disclosure would increase.

[36]For more details about the simulation exercise described in this section, see Section C.5 of the Online Appendix.

5.2 Policies To Discourage Selection

Mandatory disclosure is a relatively straightforward policy to implement (e.g., restaurants can be required to display hygiene cards). By contrast, correcting the distortions created by selection is inherently more difficult. The challenge is that identifying selection requires either direct evidence of the sender's intent (such as auditing the disclosure protocol, where feasible) or statistical inference from repeated observations to show that the disclosed evidence reflects a systematic reporting bias rather than mere randomness. In what follows, we discuss three approaches to mitigating selection (see also Di Tillio et al. (2017, 2021)).

First, it may sometimes be feasible to require the sender to disclose specific dimensions of her private information. For example, a recruiter could require candidates to report particular aspects of their previous work experience, rather than allowing them to choose which ones to emphasize. This approach effectively reduces N and thus the sender's discretion in selecting which evidence to disclose (see also Fishman and Hagerty (1990)). Both our theory and our experimental results indicate that such a policy of decreasing N can have ambiguous effects on receiver welfare, as it may reduce informativeness and thereby harm receivers (see, e.g., Proposition 2.(iii) and Table 5).

Second, selection could also be mitigated by requiring senders to disclose more evidence, thereby increasing K relative to N. For example, a recruiter could require candidates to submit two letters of recommendation rather than only one. Both our theoretical and experimental results show that increasing K is always beneficial for the receiver (see Proposition 2.(ii) and Tables 5 and 10).

However, the practical desirability of such a policy depends on the source of the friction that limits communication capacity. For example, if K is low relative to N because of limited receiver attention, increasing K could reduce welfare. In such cases, the regulator might instead try to mitigate selection by requiring the sender to provide evidence in a "compressed" format. The "Nutrition Facts" labels mandated by the FDA, for instance, condense detailed nutritional data into a few key statistics, and bond rating agencies distill vast financial information into grades designed to capture creditworthiness.[37] Such compressed measures, however, inevitably involve information loss and must themselves be verifiable, creating scope for further regulatory intervention.

[37] See Bernstein et al. (2023) for a discussion of the birth of such agencies and their impact on credit markets.

6 Concluding Remarks

This paper presented an experimental analysis of selective disclosure in communication. Using an experimental design informed by a broad set of theoretical comparative statics, we systematically assessed the relative importance of selected versus concealed evidence. Our findings largely support the key qualitative predictions of the theory, revealing that selection is a significant friction in communication. Specifically, when the amount of available evidence is large, senders rarely conceal evidence, and selection emerges as the dominant distortion, consistent with the theoretical predictions.

We also document systematic deviations from the theoretical predictions. Unlike most prior studies on verifiable disclosure, we find that senders' strategies are, on average, more informative than predicted. This pattern is driven by a small group of deception-averse senders who, in low states, refrain from disclosing high signals that could mislead receivers. Receivers, in turn, are overly optimistic: their guesses are systematically too high, with the extent of bias varying across treatments and types of evidence. They perform well when responding to non-selected evidence but make larger, comparable errors under concealment and selection. Since selection is far more prevalent than concealment, it generates greater overall distortion.

Mandatory disclosure—the typical policy response to evidence concealment—can be ineffective in our setting, and in some cases even harmful. The most prevalent distortion arises from selection, yet existing policies aimed at curbing it also appear insufficient. An effective policy should address the root cause of selection—the disparity between the amount of available evidence and the communication capacity of the environment—while remaining simple and enforceable. Designing and testing such policies warrants further empirical investigation.

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Appendix

A Equilibrium Refinement

This section introduces our equilibrium refinement and shows it leads to a unique equilibrium outcome. First, let us provide a formal definition of PBE for our framework. To this end, note that the receiver's equilibrium strategy is pinned down by her belief on θ following any message, which we denote by $\mu(\theta|m) \in \Delta(\Theta)$. Given such belief, for any $m \in \mathcal{M}$, the receiver's optimal action is unique and deterministic, i.e., it is equal to the expectation of θ under $\mu(\cdot|m)$:

$$\xi = \arg\max_{a \in A} \sum_{\theta} u(a,\theta)\mu(\theta|m) = \sum_{\theta} \theta\mu(\theta|m) = \mathbb{E}(\theta|m).$$

Definition A.1. *A Perfect Bayesian equilibrium (PBE) is a pair* $(\sigma^* : \Theta \times S^N \to \Delta(\mathcal{M})$*;* $\mu^* : \mathcal{M} \to \Delta(\Theta))$ *such that*

1. *For all* $\theta \in \Theta$*,* $\bar{s} \in S^N$*,* $m \in supp\,(\sigma^*(\cdot|\theta,\bar{s}))$ *and* $m' \in M(\bar{s})$*,*

$$\mathbb{E}(\theta|m) = \sum_{\theta \in \Theta} \theta\mu^*(\theta|m) \geq \sum_{\theta \in \Theta} \theta\mu^*(\theta|m') = \mathbb{E}(\theta|m');$$

2. *If* $m \in supp\,(\sigma^*(\cdot|\theta,\bar{s}))$ *for some* $\theta \in \Theta$ *and* $\bar{s} \in S^N$

$$\mu^*(\theta|m) = \frac{p(\theta)\sum_{\bar{s}} \sigma^*(m|\theta,\bar{s}) f(\bar{s}|\theta)}{\sum_{\theta'} p(\theta')\sum_{\bar{s}} \sigma^*(m|\theta',\bar{s}) f(\bar{s}|\theta')} \qquad \forall \theta \in \Theta.$$

   Otherwise, $\mu^*(\cdot|m) \in \Delta(\Theta)$*.*

Any PBE (σ^*, μ^*) induces an equilibrium *outcome* $x^* : \Theta \times S^N \to A$ defined as

$$x^*(\theta,\bar{s}) := \sum_{m \in M(\bar{s})} \sigma^*(m|\theta,\bar{s}) \sum_{\theta' \in \Theta} \theta'\mu^*(\theta'|m) \qquad \forall (\theta,\bar{s}) \in \Theta \times S^N$$

Despite the presence of verifiable information, the game admits multiple equilibrium outcomes (see Section A.1 for examples). We refine the set of PBEs by imposing a monotonicity requirement on how the receiver responds to evidence. Formally, we extend the order on S to the set $S \cup \{o\}$, by assuming that $\min S$ and o are minimal elements in such a set. The set of messages $\mathcal{M}$ is then endowed with the following partial order: $m \geq m'$ if, for each

$i \in \{1, \ldots, K\}$, $m_i \geq m'_i$. Our refinement requires that, if $m' \geq m$, the receiver's guess following message m' is higher than that following message m.

Definition A.2 (Evidence Monotone)**.** *A PBE* (σ^*, μ^*) *is* evidence monotone *if for all* $m, m' \in \mathcal{M}$ *such that* $m' > m$, $\mathbb{E}_{\mu^*}(\theta \mid m') > \mathbb{E}_{\mu^*}(\theta \mid m)$.

Recall that a sender's strategy is maximally selective if $m \in \text{supp}\,(\sigma_S(\cdot|\theta, \bar{s}))$ is a maximal element of $M(\bar{s})$ for each $(\theta, \bar{s}) \in \Theta \times S^N$. A maximally-selective equilibrium is a PBE in which the sender's strategy is maximally selective.

Proposition 3 (Uniqueness)**.** *All evidence-monotone PBEs induce the same equilibrium outcome. This outcome is the same as the one induced by any maximally-selective equilibrium.*

A.1 Equilibrium Multiplicity

We provide four examples of PBEs that are not maximally selective and, hence, induce a different equilibrium outcome than the one we studied in the paper. All these examples are not "Evidence Monotone," and thus fail our refinement.

Throughout, let $\Theta = \{0, 1\}$, with each state equally likely, and fix $N = 2$ and $K = 1$. Also, we use notation $\mu(m) \triangleq \mu(\theta = 1|m)$ to refer to the receiver's belief that $\theta = 1$, which also coincides with the optimal guess given such belief.

Example 1. (*Uninformative equilibrium with no disclosure*) Suppose $S = \{A, B\}$, with $f(A|\theta) \in (0, 1)$ and $f(A|1) > f(A|0)$. An equilibrium exists in which the sender never discloses any evidence—i.e., the sender always sends message $m = \{o\}$ regardless of the state θ and the realized signals $\bar{s}$. On the equilibrium path, the receiver's posterior is $\mu^*(m = o) = \frac{1}{2}$, so her action is $a = \frac{1}{2}$. This equilibrium is sustained, for instance, by off-path beliefs such that $\mu^*(m = A) = \mu^*(m = B) = 0$. That is, if the sender were to disclose any signal, the receiver would infer that the state is $\theta = 0$ and respond with action $a = 0$. $\triangle$

Example 2. (*Partially-Selective Equilibria*) Using the same logic as in Example 1, one can construct equilibria in which the sender discloses only the highest K' signals, for some $1 \leq K' < K$. These equilibria are sustained by pessimistic off-path beliefs: if the sender deviates by disclosing more than K' signals, the receiver infers that the state is $\theta = 0$, as in the example above. $\triangle$

It is useful to note that the kind of equilibria discussed in Example 1 and 2 above do not arise in standard disclosure games (e.g., Milgrom (1981)). The crucial difference is that, in our setting, the sender knows more than she can verifiably communicate. Specifically, the sender observes both the state θ and the vector of signal realizations $\bar{s}$ (i.e., the evidence), but since $N < \infty$, there exists no message that can verifiably prove the true state θ. In standard disclosure games, instead, the sender can verifiably reveal θ, so a sender observing a high state would strictly prefer to separate and would be able to do so. That logic breaks down in our setting: a sender observing the highest state cannot credibly reveal it. She can at best disclose the most favorable message (i.e., a message consisting of K signals equal to $\max S$). But since $f(\cdot|\theta)$ has full support for all θ, this message is compatible with any state. Therefore, off the equilibrium path, the receiver can rationally believe that a sender who discloses the highest message (or any message for what matters) must have observed the lowest state.

Example 3. (*Uninformative equilibrium with disclosure*) Suppose $S = \{A, B\}$, $f(A|1) \in (1/2, 1)$ and $f(A|0) = 1 - f(A|1)$. An equilibrium exists in which the sender strategy is as follows. If the two realized signals are identical—i.e., if $\bar{s} = (s_1, s_2)$ with $s_1 = s_2$—the sender conceals the evidence and sends the empty message $m = \{o\}$. If the signals differ—i.e., $s_1 \neq s_2$—the sender sends $m = \{s_1\}$ with probability ϵ, and $m = \{s_2\}$ with probability $1 - \epsilon$, independently of the state. In this equilibrium, all feasible messages are on the equilibrium path. The receiver's equilibrium belief is $\mu^*(m) = \frac{1}{2}$ for all m and, thus, the equilibrium is uninformative. △

Example 4. (*State-dependent uninformative equilibrium*). Denote $f(A \mid 1) = \gamma$, $f(A \mid 0) = \eta$, with $1 > \gamma > \eta > 0$. Consider a candidate equilibrium in which the sender's strategy is as follows. When the sender has at least one A to disclose, she does so with probability $\lambda_\theta \in (0, 1)$, and does not disclose otherwise. When instead the sender has no A to disclose, she discloses a B with probability $\sigma_\theta \in (0, 1)$, and does not disclose otherwise. These probabilities may depend on the state θ. Note that all feasible messages $\{A, B, o\}$ are observed on the equilibrium path, so beliefs are pinned down by Bayes' rule. We now compute those beliefs. Let $p_1 \triangleq 1 - (1 - \gamma)^2$ and $p_0 \triangleq 1 - (1 - \eta)^2$ denote the probability that $\bar{s}$ contains at least one A given $\theta = 1$ and $\theta = 0$, respectively. Similarly, let $q_1 \triangleq (1 - \gamma)^2$ and $q_0 \triangleq (1 - \eta)^2$ denote the probability that $\bar{s} = (B, B)$ given $\theta = 1$ and $\theta = 0$, respectively. Then the receiver's posterior beliefs and optimal guesses conditional on the feasible messages are:

$$a(A) = \frac{p_1 \lambda_1}{p_1 \lambda_1 + p_0 \lambda_0}, \quad a(B) = \frac{q_1 \sigma_1}{q_1 \sigma_1 + q_0 \sigma_0}, \quad a(o) = \frac{1 - q_1 \sigma_1 - p_1 \lambda_1}{2 - q_1 \sigma_1 - p_1 \lambda_1 - q_0 \sigma_0 - p_0 \lambda_0}.$$

For the sender's strategy to be sequentially rational, it must be that $a(B) = a(A) = a(o) = \frac{1}{2}$, which implies:

$$\frac{\lambda_0}{\lambda_1} = \frac{(2-\gamma)\gamma}{(2-\eta)\eta} > 1, \quad \text{and} \quad \frac{\sigma_0}{\sigma_1} = \frac{(1-\gamma)^2}{(1-\eta)^2} < 1.$$

Thus, for any $1 > \gamma > \eta > 0$, it is possible to find values $(\lambda_\theta, \sigma_\theta)$ for which the strategy described above constitutes an equilibrium. This equilibrium relies on the counterintuitive behavior that, conditional on observing the same signal realizations, a low-state sender is more likely to disclose a higher signal than a high-state sender, in order to "undo" the MLRP. Moreover, it is easy to verify that the existence of this equilibrium does not depend on θ being uniformly distributed. $\triangle$

B Proofs

B.1 Existence

We begin by introducing some additional notation that will be useful in the proofs. Consider the random vector $(\theta, \bar{s}) \in \Theta \times S^N$, which is distributed according to the probability mass function $f(\theta, \bar{s}) := p(\theta) f(\bar{s}|\theta)$, where $f(\bar{s}|\theta) = \prod_i f(s_i|\theta)$. Denote the n-th order statistics of $\bar{s}$ as $\bar{s}_{(n)}$ and consider the following random variables

$$y_1(\bar{s}) = \bar{s}_{(N)}; y_2(\bar{s}) = \bar{s}_{(N-1)}; \ldots; y_N(\bar{s}) = \bar{s}_{(1)}.$$

For instance, $y_1(\bar{s})$ represents the highest realization in $\bar{s}$. To ease the notation, in what follows we will use y_i in place of $y_i(\bar{s})$. Notice that $y_i \geq y_j$ for any $i \leq j$. We write y to denote a generic vector $(y_1, \ldots, y_n)$. The joint probability of $(\theta, y) \in \Theta \times S^N$ is given by:

$$g(\theta, y) = p(\theta) f(y|\theta) B(y) \mathbb{1}_{\{y_1 \geq \ldots \geq y_N\}},$$

where

- $p(\theta) f(y|\theta)$ is the joint probability of (θ, y), ignoring that the signal realizations $y = (y_1, \ldots, y_n)$ have been reordered;
- $B(y)$ is the multinomial coefficient of vector y, which counts the number of distinct permutations of such vector. For each $s \in S$, let $q_s(y)$ be the number of elements in

$(y_1, \ldots, y_n)$ that are equal to s. Note that,

$$B(y) = \frac{n!}{\prod_s q_s(y)!};$$

- $\mathbb{1}_{\{y_1 \geq \ldots \geq y_N\}}$ is an indicator function that takes the value 1 if and only if the vector y is weakly decreasing.

Lemma B.1. *The random variables $(\theta, y_1, \ldots, y_n)$ are affiliated. That is, their joint distribution g is such that*

$$g(z \vee z')g(z \wedge z') \geq g(z)g(z')$$

for any $z, z' \in \Theta \times S^N$.

The proof of this result is relegated to Online Appendix E.

Proof of Proposition 1. For any message $m \in \mathcal{M}$, denote by $\ell(m) \in \{0, \ldots, N\}$ the number of disclosed signals in m, i.e. the components that are different from o. We construct an equilibrium in which the sender plays a maximally selective strategy. In particular, we focus on the maximally selective strategy in which the sender discloses the K most favorable signals, i.e. for which $\ell(m) = K$ for every on-path message. It is straightforward to see that for any $\bar{s} \in S^N$ there exists a $m \in M(\bar{s})$ which is a maximal element and satisfies this definition. Additionally, such strategy is pure and independent of θ, so it can be described as $\sigma^* : S^N \to \mathcal{M}$.

In our candidate equilibrium, the disclosed message only provides the receiver with information about the possible realizations of $\bar{s} \in S^N$. In particular, upon observing message m the receiver assigns a positive probability to $\bar{s}$ belonging to $C(m)$, where

$$\begin{aligned} C(m) := \{\bar{s} \in S^N | \exists \text{ an injective } \rho : \{1, ..., \ell(m)\} \to \{1, ..., N\} \text{ s.t.} \\ \text{if } i \in \rho(\{1, \ldots \ell(m)\}),\ \bar{s}_i = m_{\rho^{-1}(i)}; \text{if } i \notin \rho(\{1, \ldots \ell(m)\}),\ \bar{s}_i \leq h(m)\}, \end{aligned} \quad (2)$$

and

$$h(m) = \begin{cases} m_K & \ell(m) = K, \\ \min S & \text{else.} \end{cases}$$

By construction, when $\ell(m) = K$, $C(m) = {\sigma^*}^{-1}(m)$. Instead, when $\ell(m) < K$, m is off the equilibrium path. In this case $C(m)$ only contains the most pessimistic $\bar{s}$'s compatible with the observed m. Given this, the receiver's equilibrium belief $\mu^* : \mathcal{M} \to \Delta(\Theta)$ is

$$\mu^*(\theta|m) = \frac{p(\theta)\sum_{\bar{s}\in C(m)} f(\bar{s}|\theta)}{\sum_{\theta'\in\Theta} p(\theta')\sum_{\bar{s}\in C(m)} f(\bar{s}|\theta')}.$$

This equilibrium uniquely pins down the receiver's optimal action given m, namely

$$a^*(m) = \sum_{\theta} \theta\mu^*(\theta|m) = \mathbb{E}(\theta|\bar{s} \in C(m)).$$

We want to show that the pair (σ^*, μ^*) is a perfect Bayesian equilibrium (Definition A.1). Condition (2) of such definition holds by construction. For Condition (1) to hold, we need to show that, for all $\bar{s}$, and $m' \in M(\bar{s})$,

$$a^*(\sigma^*(\bar{s})) = \mathbb{E}(\theta|C(\sigma^*(\bar{s}))) \geq \mathbb{E}(\theta|C(m')) = a^*(m'). \tag{3}$$

To do so, it is convenient to first translate this problem into the space of ordered vectors $Y = \{\bar{s} \in S^N | \bar{s}_1 \geq \ldots \geq \bar{s}_N\}$. To distinguish between any $\bar{s} \in S^N$ and the ones whose components are ordered in a weakly decreasing way, we indicate the vectors in Y as y. By definition, $y_1 \geq \ldots \geq y_N$. We show that restricting attention to Y is without loss of generality. We begin by specializing the definition of $C(m)$ to Y:

$$\bar{C}(m) = \{y \in Y | \forall i \leq \ell(m)\ y_i = m_i \text{ and } \forall i > \ell(m)\ y_i \leq h(m)\}.$$

Given any vector $y \in Y$, denote the set of its permutations by

$$\mathcal{B}(y) = \{\bar{s}' \in S^N | \exists \text{ an injective } \rho : \{1, ..., N\} \to \{1, ..., N\} \text{ s.t. } \bar{s}'_i = y_{\rho(i)}\}$$

Note that, for every m, the collection $\{\mathcal{B}(y)\}_{y\in\bar{C}(m)}$ partitions $C(m)$, that is, for every $y, y' \in \bar{C}(m)$ s.t. $y \neq y'$, $\mathcal{B}(y) \cap \mathcal{B}(y') = \varnothing$ and $C(m) = \bigcup_{y\in\bar{C}(m)} \mathcal{B}(y)$. Next, we define the restriction of distribution f onto the subset of ordered vectors Y. For any $y \in Y$, let

$$\bar{f}(y|\theta) = \sum_{y\in\mathcal{B}(y)} f(y|\theta) = |\mathcal{B}(y)| f(y|\theta) = B(y) f(y|\theta)$$

where the second equality follows from the exchangeability of f and the third one from the definition of $B(y)$ as the multinomial coefficient of the vector y. More generally, we can define the distribution $\bar{f}(\cdot|\theta)$ as

$$\bar{f}(y|\theta) = B(y)f(y|\theta)\mathbb{1}_{\{y_1 \geq \ldots \geq y_N\}}$$

to account for the fact that the vectors in the support need to be ordered in a weakly decreasing way. Since

$$\sum_{\bar{s}\in C(m)} f(\bar{s}|\theta) = \sum_{\bar{s}\in \bigcup_{y\in\bar{C}(y)} B(y)} f(\bar{s}|\theta) = \sum_{y\in\bar{C}(m)} \sum_{\bar{s}\in B(y)} f(\bar{s}|\theta) = \sum_{y\in\bar{C}(m)} \bar{f}(y|\theta)$$

we have that

$$\begin{aligned} \mathbb{E}(\theta|C(m)) &= \textstyle\sum_\theta \theta \frac{p(\theta)\sum_{\bar{s}\in C(m)} f(\bar{s}|\theta)}{\sum_{\theta'\in\Theta} p(\theta')\sum_{\bar{s}\in C(m)} f(\bar{s}|\theta)} \\ &= \textstyle\sum_\theta \theta \frac{p(\theta)\sum_{y\in\bar{C}(m)} \bar{f}(y|\theta)}{\sum_{\theta'\in\Theta} p(\theta')\sum_{y\in\bar{C}(m)} \bar{f}(y|\theta')} \\ &= \mathbb{E}(\theta|\bar{C}(m)) \end{aligned}$$

Under this redefinition of the problem, after observing a message $m = (m_1, \ldots, m_K)$, the receiver will take action

$$\begin{aligned} \mathbb{E}[\theta|\bar{C}(m)] &= \mathbb{E}[\theta|y_1 = m_1, \ldots, y_K = m_K, y_{K+1} \leq m_K, \ldots, y_N \leq m_K] \\ &= \sum_{\theta\in\Theta} \theta \frac{p(\theta)\bar{f}(y_1 = m_1, \ldots, y_K = m_K, y_{K+1} \leq m_K, \ldots, y_N \leq m_K|\theta)}{\sum_{\theta\in\Theta} p(\theta)\bar{f}(y_1 = m_1, \ldots, y_K = m_K, y_{K+1} \leq m_K, \ldots, y_N \leq m_K|\theta)}. \end{aligned}$$

At this point, we can argue that all the assumptions needed to apply Theorem 5 from Milgrom and Weber (1982) are satisfied. First, we can apply Lemma B.1, to show that the random variables $(\theta, y_1, \ldots, y_N)$ are affiliated. Second, we can define the function $H(\theta, y_1, \ldots, y_n) = \theta$ and easily see that such function is non-decreasing. We can then rewrite $\mathbb{E}[\theta|\bar{C}(m)]$ as

$$q(m_1, \ldots, m_K) = \mathbb{E}[\theta|y_1 = m_1, \ldots, y_K = m_K, \underline{s} \leq y_{K+1} \leq m_K, \ldots, \underline{s} \leq y_n \leq m_K]$$

where $\underline{s} = \min S$. Theorem 5 allows us to conclude that $q(\cdot)$ is nondecreasing in all of its arguments. Under the assumption that the sender is playing a maximally selective strategy, it must be true that $\sigma^*(m) = m \geq m'$ for all $m' \in M(\bar{s})$. This directly implies that $q(m_1, \ldots, m_K) \geq q(m'_1, \ldots, m'_K)$ and so that

$$a^*(\sigma^*(\bar{s})) = \mathbb{E}(\theta|C(\sigma^*(\bar{s}))) \geq \mathbb{E}(\theta|C(m')) = a^*(m').$$

Condition (1) of Definition A.1 is satisfied. This completes the proof that there exists an equilibrium in which the sender plays a maximally selective strategy. $\square$

B.2 Uniqueness

Remark 2. *All the maximally selective equilibria induce the same equilibrium outcome.*

Proof. For any message $m \in \mathcal{M}$, denote by $\ell(m) \in \{0, \ldots, K\}$ the number of disclosed signals in m that are different from o. Denote by $\bar{x} : \Theta \times S^N \to A$ the outcome of the maximally selective equilibrium in Proposition 1 and by $x^* : \Theta \times S^N \to A$ the outcome of any other maximally selective equilibrium.

First, we consider the case in which the sender's maximally selective strategy is type-independent, namely, the strategy $\sigma^* : S^N \to \Delta(\mathcal{M})$ always discloses a maximal element in $\mathcal{M}(\bar{s})$ and does not depend on θ. This implies that

$$\text{supp}\,(\sigma^*(\cdot|\bar{s})) \in \bar{M}(\bar{s}) = \{m \in \mathcal{M}(\bar{s}) \mid m \geq m' \text{ for all } m' \in \mathcal{M}(\bar{s})\}.$$

Given this definition, if there exists $m \in \bar{M}(\bar{s})$ such that $m_i > \min S$ for all $i \leq K$, such element will be unique and $\text{supp}\,(\sigma^*(\cdot|\bar{s})) = \bar{M}(\bar{s}) = \{m\}$. Instead, if there exists $m \in \bar{M}(\bar{s})$ such that $m_i = \min S$ for some given $i \in \{1, \ldots, K\}$, there must also exist a $m' \in \bar{M}(\bar{s})$ such that $m'_i = o$. This implies that $|\bar{M}(\bar{s})| > 1$. Instances with $|\bar{M}(\bar{s})| > 1$ are the only ones in which the sender's maximally selective strategy may differ from the one considered in Proposition 1 by assigning a positive probability to messages that contain some elements equal to o (in place of $\min S$). Note that, since the candidate equilibrium is independent of θ, for the on-path messages, the receiver forms a posterior belief only conditioning on the information available on $\bar{s}$. Let us denote by $\tilde{\mathcal{M}}$ the set of messages such that $m_i > \min S$ for all $i \leq K$. Given the maximally selective strategy, each of these messages is sent with positive probability in equilibrium, and for each $m \in \tilde{\mathcal{M}}$ the receiver believes that $\bar{s} \in C(m)$, where $C(m)$ is defined as in Proposition 1:

$$\begin{aligned} C(m) := \{\bar{s} \in S^N | \exists \text{ an injective } \rho : \{1, ..., K\} \to \{1, ..., N\} \text{ s.t.} \\ \text{if } i \in \rho(\{1, \ldots K\}),\ \bar{s}_i = m_{\rho^{-1}(i)}; \text{if } i \notin \rho(\{1, \ldots K\}),\ \bar{s}_i \leq m_K)\}. \end{aligned}$$

This implies that, upon observing message $m \in \tilde{\mathcal{M}}$, the receiver's posterior belief is the same as the one computed in Proposition 1. Hence, it must be that $\bar{x}(\theta, \bar{s}) = x^*(\theta, \bar{s})$ for all $\theta \in \Theta$ and $\bar{s} \in \bigcup_{m \in \tilde{\mathcal{M}}} C(m)$.

We are now left to prove that the outcome is the same for all $\bar{s} \in S^N \setminus \bigcup_{m \in \tilde{\mathcal{M}}} C(m)$. Let us define $\underline{\mathcal{M}} = \mathcal{M} \setminus \tilde{\mathcal{M}}$ as the set of messages that contains at least one $m_i \in \{\min S, o\}$ for some $i \leq K$. For any on-path $m \in \underline{\mathcal{M}}$, the receiver believes that $\bar{s} \in \tilde{C}(m)$, where

$$\begin{aligned}\tilde{C}(m) :=& \{\bar{s} \in S^N | \exists \text{ an injective } \rho : \{1, ..., \ell(m)\} \to \{1, ..., N\} \text{ s.t. if } i \in \rho(\{1, \ldots K\}), \\ & \bar{s}_i = m_{\rho^{-1}(i)}; \text{if } i \notin \rho(\{1, \ldots \ell(m)\}),\ \bar{s}_i = \min S)\} \cap \{\bar{s} \in S^N : \sigma^*(m|\bar{s}) > 0\} \\ =& C(m) \cap \{\bar{s} \in S^N : \sigma^*(m|\bar{s}) > 0\}.\end{aligned}$$

Given the possibility of mixed strategies, we also need to define the probability that the receiver assigns to any $\bar{s} \in \tilde{C}(m)$:

$$Prob(\bar{s}|\tilde{C}(m)) = \frac{\sum_{\theta \in \Theta} f(\bar{s}|\theta)\sigma^*(m|\bar{s})}{\sum_{\bar{s}' \in \tilde{C}(m)} \sum_{\theta \in \Theta} f(\bar{s}'|\theta)\sigma^*(m|\bar{s})}.$$

It is straightforward that any $\bar{s} \in C(m)$ would induce the same $\mathbb{E}(\theta|\bar{s})$. Indeed, by definition, all $\bar{s} \in C(m)$ are one permutation of the other, but they contain the same number of $\bar{s}_i$ for each $\bar{s}_i \in S$. By the law of iterated expectations, it is necessarily true that $\mathbb{E}(\theta|\bar{s}) = \mathbb{E}(\theta|C(m)) = \mathbb{E}(\theta|\tilde{C}(m))$ for all $\bar{s} \in C(m)$.

Note that, in the expression, $C(m)$ is defined as in Proposition 1 for each $m \in \underline{\mathcal{M}}$. Consistently with the maximally selective equilibrium, a component equal to o is interpreted by the receiver as $\min S$. This implies that, for any m and m' such that $\ell(m) = K > \ell(m')$, $m_i = m'_i$ for all $i \leq \ell(m')$ and $m_i = \min S$ for all $i > \ell(m')$, $C(m) = C(m')$. Given this argument, for any $m \in \underline{\mathcal{M}}$ with $\ell(m) < K$ we can replace $C(m)$ with $C(m^K)$, where m^K is such that $m_i = m_i^K$ for all $i \leq \ell(m)$ and $m_i^K = \min S$ for all $i > \ell(m)$. For each $m^K \in \underline{\mathcal{M}}$, define $\underline{\mathcal{M}}(m^K)$ as the set of messages $m \in \underline{\mathcal{M}}$ such that $C(m^K) = C(m)$. Three facts are straightforward:

1. For any $m^K \neq m^{K'}$, $C(m^K) \cap C(m^{K'}) = \emptyset$;
2. $C(m^K) = \bigcup_{m \in \underline{\mathcal{M}}(m^K)} \tilde{C}(m)$;
3. $\bigcup_{m \in \tilde{\mathcal{M}}, m^K \in \underline{M}} C(m) = S^N$.

Hence, it must be that $\bar{x}(\theta, \bar{s}) = x^*(\theta, \bar{s})$ for all $\theta \in \Theta$ and $\bar{s} \in \bigcup_{m^K \in \underline{\mathcal{M}}} C(m^K)$, which implies that $\bar{x}(\theta, \bar{s}) = x^*(\theta, \bar{s})$ for all $\theta \in \Theta$ and $\bar{s} \in S^N$.

Now, let us focus on an equilibrium in which a maximally selective strategy that depends on θ is played. That is, there exist at least a $\bar{s} \in S^N$ and two distinct types θ and θ' such that $\sigma^*(\cdot|\theta, \bar{s})$ and $\sigma^*(\cdot|\theta', \bar{s})$ differ. Given that the strategy is maximally selective, it must be that $|\bar{M}(\bar{s})| > 1$. Indeed, if $M(\bar{s})$ has a unique maximal element the strategies $\sigma^*(\cdot|\theta,\bar{s})$ and $\sigma^*(\cdot|\theta',\bar{s})$ would need to be pure and would necessarily coincide. This would make the argument from the first part of the proof still valid to argue the equivalence in outcomes. Hence, we just need to prove that $\bar{x}(\theta,\bar{s}) = x^*(\theta,\bar{s})$ for all $\theta \in \Theta$ and $\bar{s} \in \{s \in S^N : |\bar{M}(s)| > 1\}$.

Fix any $\tilde{s} \in \{s \in S^N : |\bar{M}(s)| > 1\}$ for which the conditions above are satisfied. For the candidate strategy to be an equilibrium, it must be that for each $m \in \text{supp}(\sigma^*(\cdot|\theta,\tilde{s})) \cup \text{supp}(\sigma^*(\cdot|\theta',\tilde{s}))$, $\mathbb{E}(\theta|m)$ is the same, otherwise the sender would have a profitable deviation. Letting $\bar{a} = \mathbb{E}(\theta|m)$ denote such constant value, we need to show that $\bar{a} = \mathbb{E}(\theta|C(m))$, where $m \in \bar{M}(\tilde{s})$, $m_i \neq o$ for all $i \leq K$ and $C(m)$ is defined as in Proposition 1. As argued before, $C(m)$ contains all the permutations of $\tilde{s}$ and by the law of iterated expectations it must be that for any $C \subset C(m)$, $\mathbb{E}(\theta|C)$ is constant and equal to $\mathbb{E}(\theta|C(m))$. In particular, $\mathbb{E}(\theta|C(m)) = \mathbb{E}(\theta|\tilde{s})$. First, assume that $\bar{a} < \mathbb{E}(\theta|\tilde{s})$. Then, it must be that there exists $m' \in \bar{M}(\tilde{s})$ but $m' \notin \text{supp}(\sigma^*(\cdot|\theta,\tilde{s})) \cup \text{supp}(\sigma^*(\cdot|\theta',\tilde{s}))$ such that $\mathbb{E}(\theta|m') > \bar{a}$, which contradicts the optimality of the sender's strategy. Now assume that $\bar{a} > \mathbb{E}(\theta|\tilde{s})$. Then, there must exist $m' \in \bar{M}(\tilde{s})$ that is used in equilibrium, again making the sender's strategy suboptimal. Hence, it must be that $\bar{a} = \mathbb{E}(\theta|\tilde{s})$. Since the choice of $\bar{s}$ was arbitrary, it must be that $\bar{x}(\theta,\bar{s}) = x^*(\theta,\bar{s})$ for all $\theta \in \Theta$ and $\bar{s} \in \{s \in S^N : |\bar{M}(s)| > 1\}$.

We can conclude that the set of outcomes induced by a maximally selective equilibrium is a singleton, i.e. it only contains x^*. □

Remark 3. *Any evidence-monotone PBE is a maximally selective equilibrium.*

Proof. Let (σ^*, μ^*) be an evidence-monotone PBE. We need to show that the sender's strategy needs to be maximally selective. Suppose by contradiction that the sender's strategy is not maximally selective. Then, there exist a $(\theta,\bar{s}) \in \Theta \times S^N$ and $m \in M(\bar{s})$ such that $m \in \text{supp}\,(\sigma^*(\cdot|\theta,\bar{s}))$ but m is not a maximal element of $M(\bar{s})$. Denote by $\bar{m} \in M(\bar{s})$ a maximal element of the set. Since m is not maximal, it must be that $\bar{m} > m$. Due to evidence monotonicity, it must be that $\mathbb{E}_{\mu^*}(\theta \mid \bar{m}) > \mathbb{E}_{\mu^*}(\theta \mid m)$. Since $\bar{m}$ is a feasible message, this violates sender's optimality in the definition of PBE.

We are only left to argue that an evidence monotone PBE always exists, i.e. that there is a maximally selective equilibrium in which for all $m > m'$, $\mathbb{E}_{\mu^*}(\theta \mid m) > \mathbb{E}_{\mu^*}(\theta \mid m')$. This directly follows from the strict MLR property of f, that makes the function $q(\cdot)$ in Proposition 1 strictly increasing in all of its arguments. □

Proof of Proposition 3. It directly follows from Remark 2 and Remark 3.

B.3 Comparative Statics

Proof of Proposition 2. The proof is divided into three sections, each corresponding to a different part of the statement. Without loss of generality, throughout we focus on the maximally selective strategy that prescribes to always disclose K signals.

1. Fix N and let (σ'^*, μ'^*) and (σ^*, μ^*) be the maximally selective equilibria for K' and K, respectively. We first show that, if $K' > K$, the information structure induced by the equilibrium (σ'^*, μ'^*) is Blackwell more informative than the information structure induced by the equilibrium (σ^*, μ^*). We have that $\sigma'^* : S^N \to \mathcal{M}$ and $\sigma^* : S^N \to \mathcal{M}$. Let $\mathcal{P}' = \{\sigma'^{*-1}(m)\}_{m \in \sigma'^*(S^N)}$ and $\mathcal{P} = \{\sigma^{-1}(m)\}_{m \in \sigma^*(S^N)}$ be the partitions on S^N that are induced by σ'^* and σ^*, respectively. Let $\mathcal{M}^K = \{m \in \mathcal{M} : \ell(m) = K\}$ be the set of messages of length K. Note that $\mathcal{P}' = \{C(m)\}_{m \in \mathcal{M}^{K'}}$ and $\mathcal{P} = \{C(m)\}_{m \in \mathcal{M}^K}$, where $C(m)$ (previously defined in Equation (2) from the Proof of Proposition 1) is the subset of signal vectors in S^N for which the K-highest elements are those in m. We want to show that $\mathcal{P}' \subseteq \mathcal{P}$, meaning the partition induced by σ'^* is finer than that induced by σ^*. Fix any $X' \in \mathcal{P}'$. We want to show there is $X \in \mathcal{P}$ such that $X' \subseteq X$, with at least one strict inequality. By definition, there is $m' \in \mathcal{M}^{K'}$ such that $X' = C(m')$. Define $m = (m'_1, \ldots, m'_K) \in \mathcal{M}^K$ and $X = C(m)$. Clearly, $C(m') \subseteq C(m)$ and, thus, $X' \subseteq X$. Moreover, if $m' \neq \min S^{K'}$, $C(m') \subsetneq C(m)$. By Blackwell (1953), we can conclude that the ex-ante expected payoff of the receiver under $\mathcal{P}'$ is higher than that under $\mathcal{P}'$. Since $\mathcal{I}(K, N)$ is a monotone transformation of the receiver's ex-ante expected payoff (see Online Appendix E.3), we have $\mathcal{I}(K', N) \geq \mathcal{I}(K, N)$. □

2. Fix $K = N$ and $K' = N'$ and let (σ'^*, μ'^*) and (σ^*, μ^*) be the maximally selective equilibria for N' and N, respectively. In both equilibria all the available signals are disclosed. This implies that the beliefs μ'^* and μ^* are degenerate distributions. We want to show that if $N' > N$, (σ'^*, μ'^*) is Blackwell more informative then (σ^*, μ^*). Given the structure of the equilibrium, it is enough to show that $f(\cdot|\theta) \in \Delta(S^N)$ is a garbling of $f'(\cdot|\theta) \in \Delta(S^{N'})$. Let's define garbling function $g : S^{N'} \to \Delta(S^N)$ such that for any $\bar{s} \in \Delta(S^N)$ and $\bar{s}' \in \Delta(S^{N'})$

$$g(\bar{s}|\bar{s}') = \begin{cases} 1 & \text{if } \bar{s}' = (\bar{s}, s) \text{ for } s \in S \\ 0 & \text{otherwise} \end{cases}$$

Notice that for all $\bar{s} \in S^N$

$$f(\bar{s}|\theta) = \sum_{\bar{s}' \in \Delta(S^{N'})} g(\bar{s}|\bar{s}') f'(\bar{s}'|\theta) = \sum_{s \in S} f'((\bar{s}, s)|\theta)$$

At this point, we can apply the Blackwell's theorem to conclude that $\mathcal{I}(K', N') > \mathcal{I}(K, N)$. □

3. Fix K and let $(\sigma^{'*}, \mu^{'*})$ the maximally selective equilibrium of our game. As in the proof of Proposition 3, we can induce an order on $\mathcal{M}^K$. Given the full support assumption, as $N \to \infty$, $Prob\left(\sigma^{*-1}(m_1) \neq S\right) \to 0$. This implies that $p(\theta|m_1) \to p(\theta)$ for all $\theta \in \Theta$ and so $\mathbb{E}_m\left[\mathbb{E}_\theta\left[u(\theta, \sigma_R(m))|m\right]\right] \to Var[\theta]$. We can then conclude that $\mathcal{I}(K, N) \to 0$. For the non-monotonicity, see the example in Appendix E.4. □

Online Appendix for

The Selective Disclosure of Evidence: An Experiment

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Jacopo Perego — Columbia University

Contents

C Additional Figures and Results

C.1 The Dynamics of Subjects Behavior

We present summary figures of the evolution of behavior, two for senders and two for receivers. In all cases, the variable of interest is plotted for each treatment against blocks of five rounds.

On the sender side, Figure C.1 plots the evolution of the gap between the GPA of the equilibrium message and that of the actual message. In all but one treatment, the final gap is smaller than the starting one: consistent with messages being more selected and less concealed. However, this evolution is substantial only in the treatments where selection is the main force.

Figure C.2 displays the fraction of messages that exactly correspond to the equilibrium prediction. Across all treatments, the majority of messages are consistent with the equilibrium; and by the end more than 75% of the messages in four of the six treatments correspond to equilibrium. Again, the evolution is most noticeable in treatments where selection is the dominant force. By the end, the treatment with the lowest rate of equilibrium messages is K_3, N_3. The deviations in that treatment are driven by some senders concealing lower signals.

On the receiver side, Figure C.3 shows the average belief for messages with a GPA of 4 (overall the most common GPA corresponding to 46% of the sample). The figure illustrates the fact that in most treatments, receivers become more skeptical of messages that have the same GPA. In some treatments the magnitude of these changes is large.

Figure C.4 shows that receivers are learning to better guess the probability of the red urn with experience. The y-axis is the absolute difference between the probability of a red urn, given the GPA of a message, and the guess. Accuracy tends to increase with experience, but overall subjects seem more accurate in treatments with lower N.

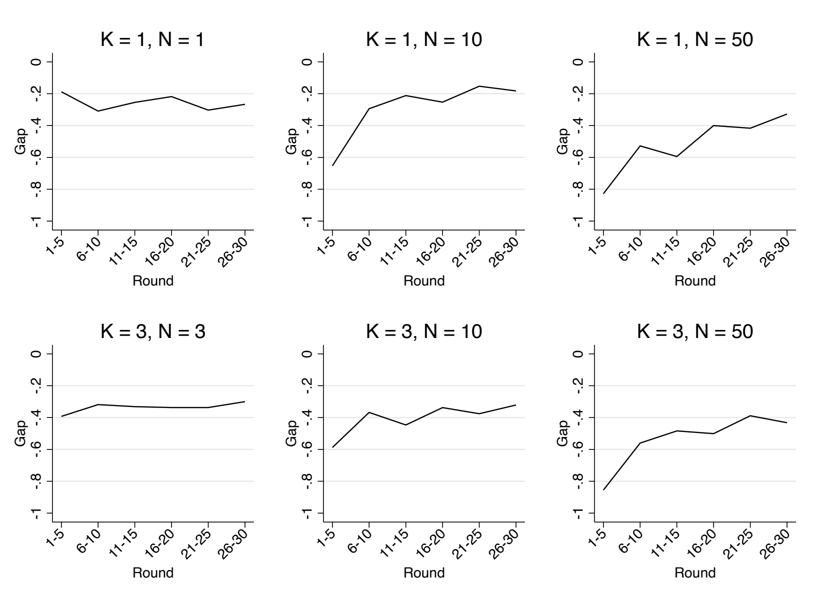


Figure C.1: MGPA of Messages Over Rounds

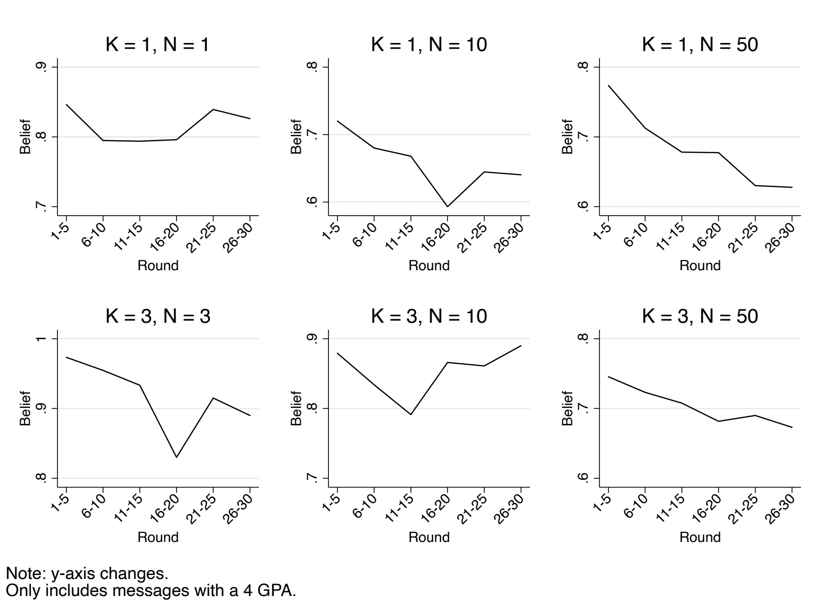


Figure C.3: Average Belief Over Rounds

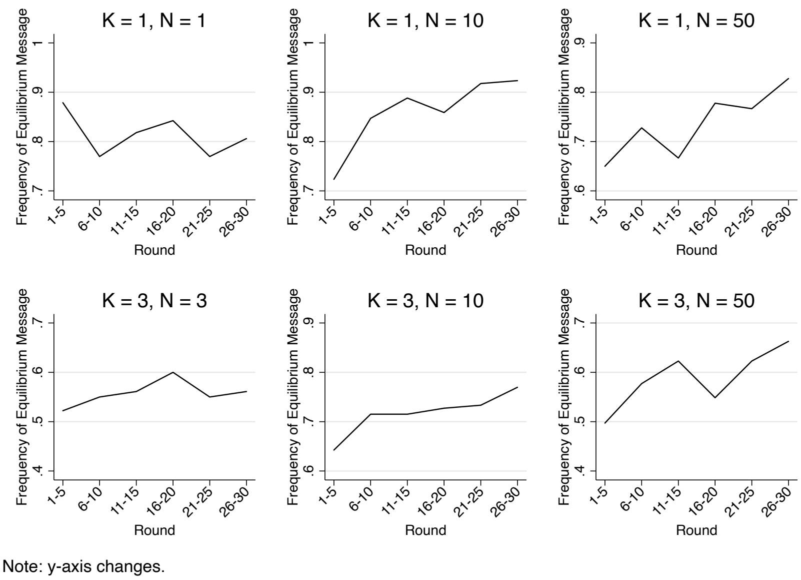


Figure C.2: Equilibrium Messages Over Rounds

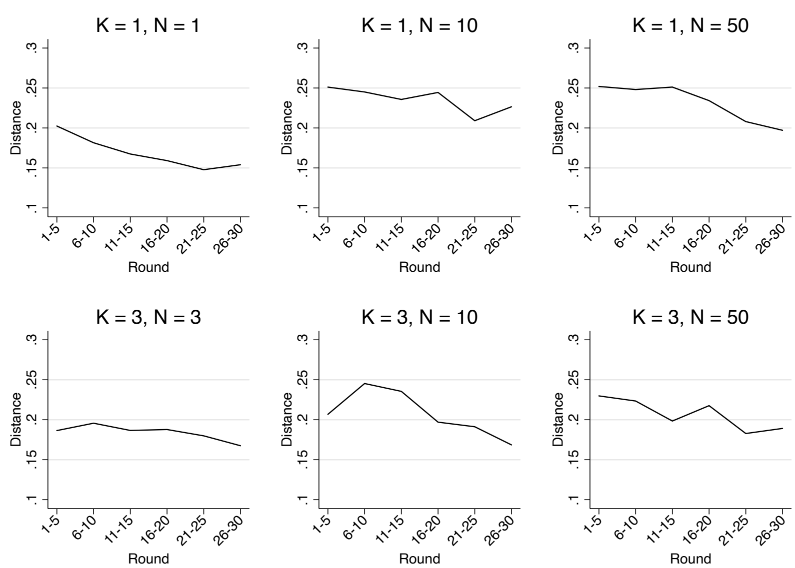
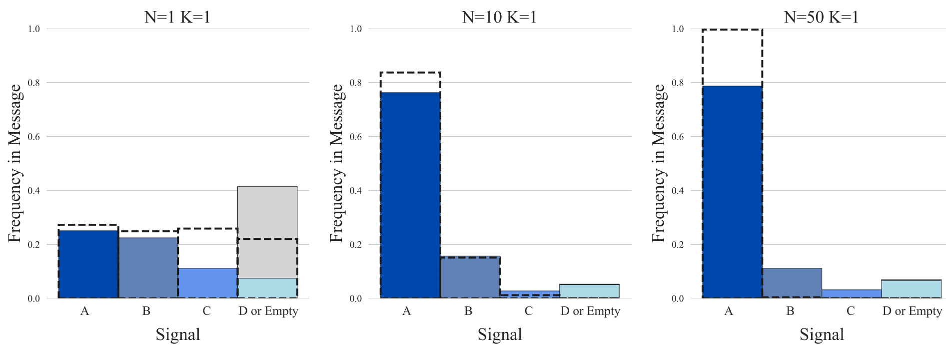
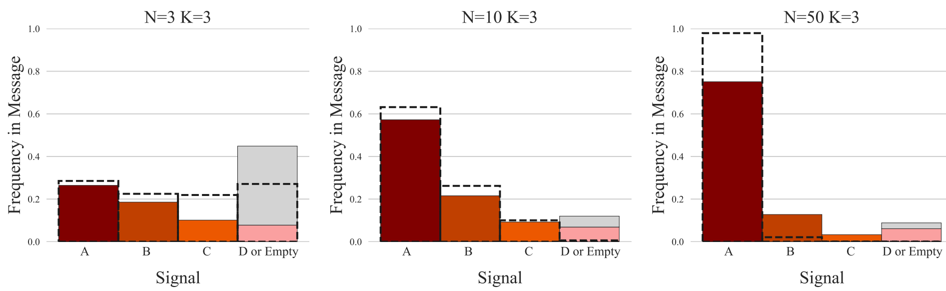


Figure C.4: Accuracy Over Rounds

C.2 Additional Results for Senders



(a) Signal Distribution for $K = 1$



(b) Signal Distribution for $K = 3$

Figure C.5: Signal Distributions

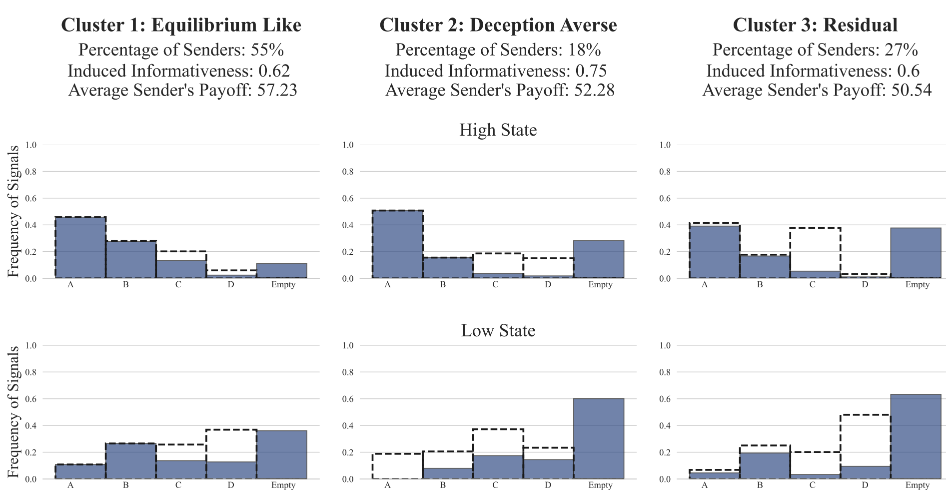


Figure C.6: Sender's Clustering for the Treatment (K_1, N_1)

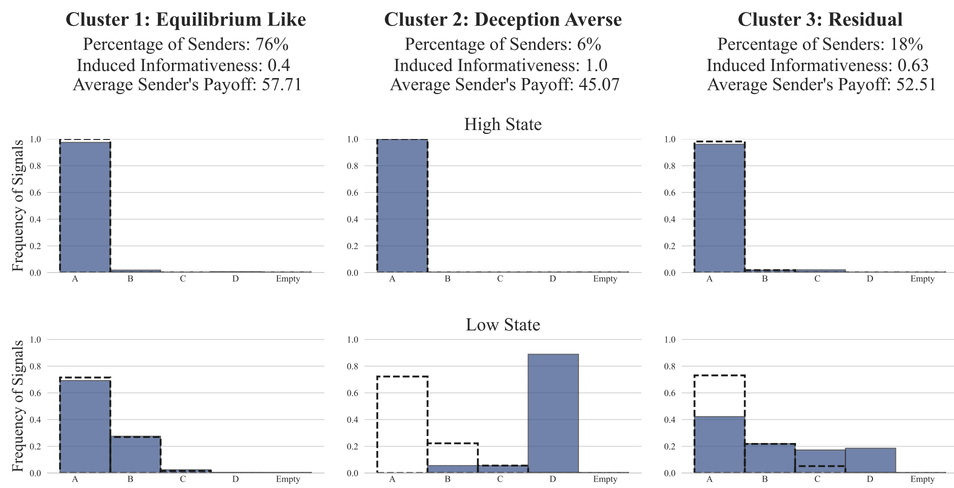


Figure C.7: Sender's Clustering for the Treatment (K_1, N_{10}).

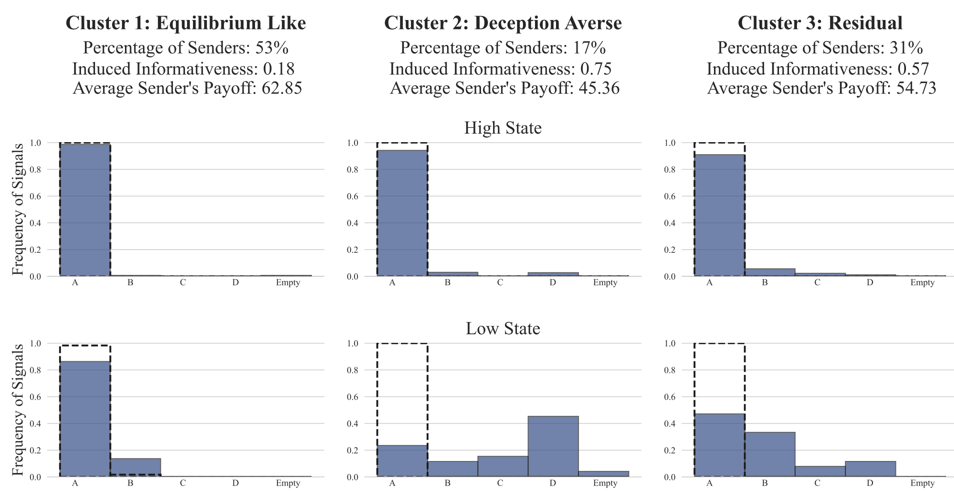


Figure C.8: Sender's Clustering for the Treatment (K_1, N_{50})

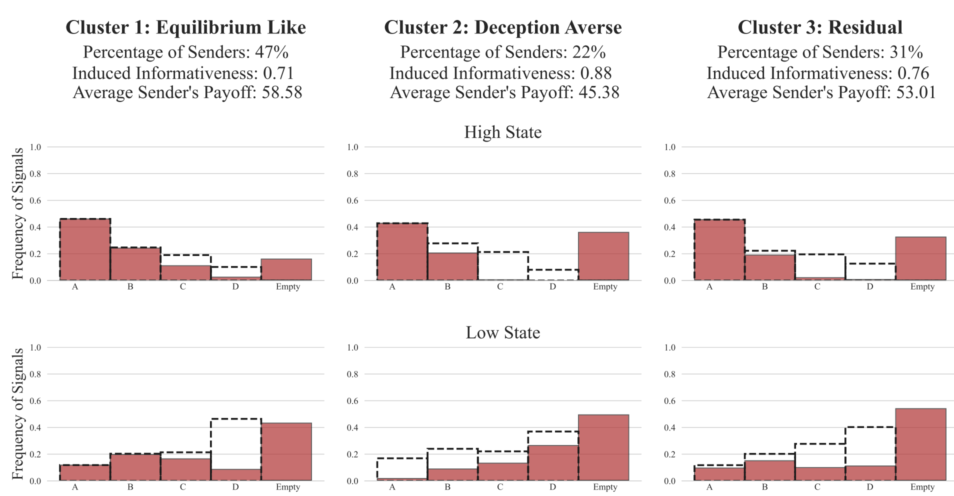


Figure C.9: Sender's Clustering for the Treatment (K_3, N_3)

C.3 Additional Results for Receivers

We study how, on average, the guesses made by the receivers respond to the message GPA. Our theoretical predictions suggest that keeping fixed a value of the GPA, receivers should become more skeptical as N increases, leading to lower guesses for any given GPA. Indeed, a higher value of N allows for more selection on the part of the sender, making favorable messages less informative about the type being high and unfavorable messages more informative about the type being low. In Figures C.10 and C.11, we plot polynomial fits of the actual receivers' guesses and of the guesses of an idealized Bayesian receiver as a function of the message GPA.

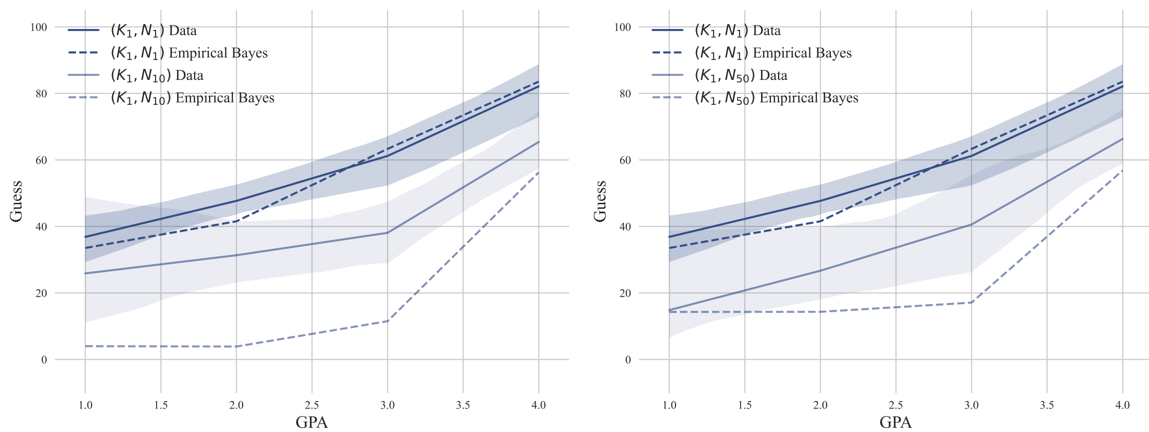


Figure C.10: Receivers' Average Guesses for $K = 1$

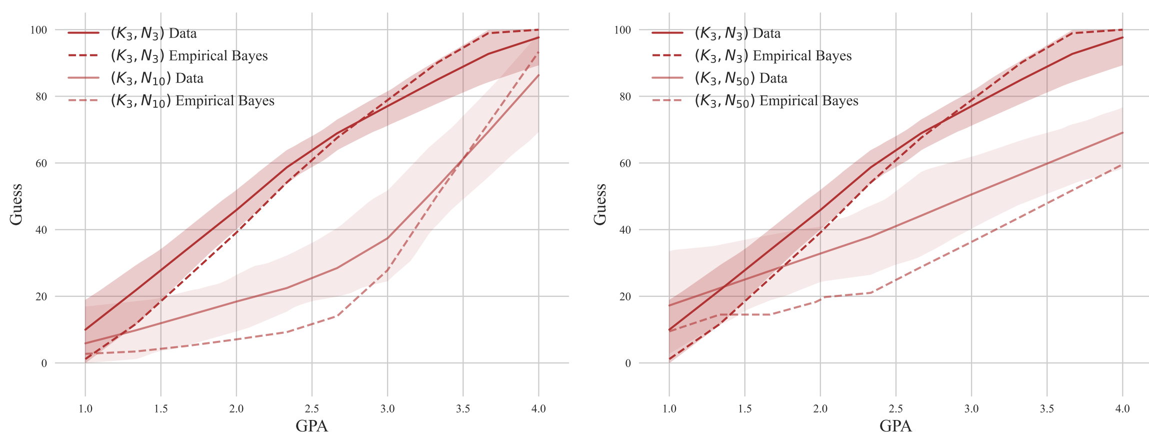


Figure C.11: Receivers' Average Guesses for $K = 3$

The first pattern we can observe is that receivers' guesses are higher when the disclosed information becomes more favorable. The second notable pattern that we can observe in the figure emerges from the comparison between $N = K$ and $N > K$: the receivers' guesses decrease in N for each message GPA and the decrease is particularly pronounced for higher values of the GPA. The only exception is the comparison between (K_3, N_{10}) and (K_3, N_3), where the guesses are similar for high values of the GPA. This suggests that receivers account for the fact that evidence is more selected when N is larger and they adjust their guesses accordingly.

Comparing the guesses of an idealized Bayesian receiver with the behavior of receivers in the data, we note that the qualitative patterns are similar. However, the receivers do not adjust their guesses enough when moving from $N = K$ to $N > K$. When N is large, subjects tend to overguess for every value of the GPA (except for the $N = K = 3$ treatment in which receivers tend to underguess). As discussed in Section 4.2.1, this behavior is in line with the bias of *selection neglect*: when making inferences given the disclosed information receivers may fail to account for the nature of the undisclosed information.

C.4 Additional Material on Receiver Optimism

C.4.1 A Behavioral Model

In this subsection, we present a simple behavioral model and discuss how it can rationalize the empirical findings presented in Section 4.2.2.

In the model, there is a sender and a receiver. The receiver is either sophisticated or naïve, with probabilities that are constant across treatments. The sophisticated receiver and the sender behave as in the theory of Section 2.1. Namely, the sender plays a maximally selective strategy and the sophisticated receiver best responds to it. The naïve receiver, by contrast, takes both concealed and selected evidence at *face value*: she neglects selection when evidence is disclosed and draws no inference when evidence is concealed.

In the discussion below, we argue how this simple model explains the facts reported in Section 4.2.2. For conciseness, we present the arguments for $K = 1$; the case $K = 3$ follows similar logic.

We begin by explaining the first finding. Note that sophisticated receivers never contribute to the response gap (by construction). In contrast, naïve receivers always contribute positively, as the sender plays a maximally selective strategy and they fail to recognize that the evidence they see (or do not see) has been strategically disclosed to inflate their responses. Therefore, in all treatments the average response gap is strictly positive.

Let us now focus on the second finding. Consider treatment (K_1, N_1). By construction, a sophisticated receiver always guesses correctly for all m, and thus never contributes to the response gap. Conversely, a naïve receiver makes no mistakes when $m \neq o$ (response gap is zero), but is overly optimistic when $m = o$ (response gap is positive). Indeed, in this latter case, the naïve receiver's guess equals the unconditional expectation of the state, $\mathbb{E}(\theta)$, whereas the sophisticated receiver would guess a strictly lower value, recognizing that the sender conceals only relatively low signal realizations. As a consequence, the response gap is strictly positive if $m = o$ and it is zero otherwise. Therefore, the response gap conditional on $m = o$ is larger than the response gap when $m \neq o$.

We now explain the third finding. In treatment (K_1, N_1), the response gap conditional on $m = o$ is a convex combination of 0 (the response gap of a sophisticated receiver) and $\mathbb{E}(\theta) - \mathbb{E}(\theta|D) > 0$ (the response gap of a naïve receiver).[2] By contrast, in treatment (K_1, N_{50}), with probability close to 1 the realized message is $m = A$. Conditional on $m = A$, the response gap is a convex combination of 0 (sophisticated receiver) and approximately $\mathbb{E}(\theta|A) - \mathbb{E}(\theta)$ (naïve receiver). Indeed, upon observing $m = A$, the naïve receiver guesses $\mathbb{E}(\theta|A)$, whereas the sophisticated receiver (recognizing selection) guesses approximately $\mathbb{E}(\theta)$, since N is large relative to K. Because in our setting the prior is uniform and f is symmetric, we obtain $\mathbb{E}(\theta|A) - \mathbb{E}(\theta) = \mathbb{E}(\theta) - \mathbb{E}(\theta|D)$. Hence, the response gap in these two cases is the same.

Finally, we explain the fourth finding. Note that $m = A$ occurs almost with probability 1 in (K_1, N_{50}). From Fact 1 we know that the response gap in treatment (K_1, N_1) is entirely explained by responses to message $m = o$, which happens with probability strictly smaller than 1. From Fact 3, we know that the response gap conditional on $m = o$ in (K_1, N_1) is approximately equal to the response gap conditional on $m = A$ in treatment (K_1, N_{50}). Therefore, the average response gap in (K_1, N_1) must be smaller than the average response gap in (K_1, N_{50}).

This model can further explain an additional empirical finding about receiver optimism that we did not report in the main text. Fix $K = 1$ and consider treatments with $K < N$. The response gap conditional on message $m \in \mathcal{M}$ is positive for all m, is non-monotonic in m, and is maximal for the second-highest message, $m = B$ (see Table C.1).[3] This fact highlights a particular pattern that emerges when we study receiver optimism within the same treatment but across different messages (in this respect, it is similar to the exercise we performed for the second finding). We now argue that our behavioral model explains this peculiar pattern. Consider again treatment (K_1, N_{50}). Under our experimental parameters, a naïve receiver would guess approximately 0.81, 0.55, 0.44, and 0.18 after observing messages A, B, C, and D, respec-

[2] Recall that $\mathbb{E}(\theta|s) = p(\theta)f(s|\theta) / \sum_{\theta'} p(\theta')f(s|\theta')$, for all $s \in S$.

[3] Recall that when $K = 1$, the message space $\mathcal{M} = \{A, B, C, D, o\}$ is totally ordered. Performing the same exercise for $K = 3$ is challenging, as there are many more possible messages and fewer data points for each message.

Table C.1: Response gaps by message for (K_1, N_{10}) and (K_1, N_{50})

	$m = A$	$m = B$	$m = C$	$m = D$
$N = 10$	6.47	32.18	18.93	21.81
	389 obs	*80 obs*	*14 obs*	*26 obs*
$N = 50$	7.31	25.63	12.35	15.19
	425 obs	*60 obs*	*17 obs*	*36 obs*

tively. By contrast, a sophisticated receiver would guess approximately $\mathbb{E}(\theta) = \frac{1}{2}$ when $m = A$ and 0 when $m \neq A$. Hence, the response gap is non-monotonic in m and is largest at $m = B$.

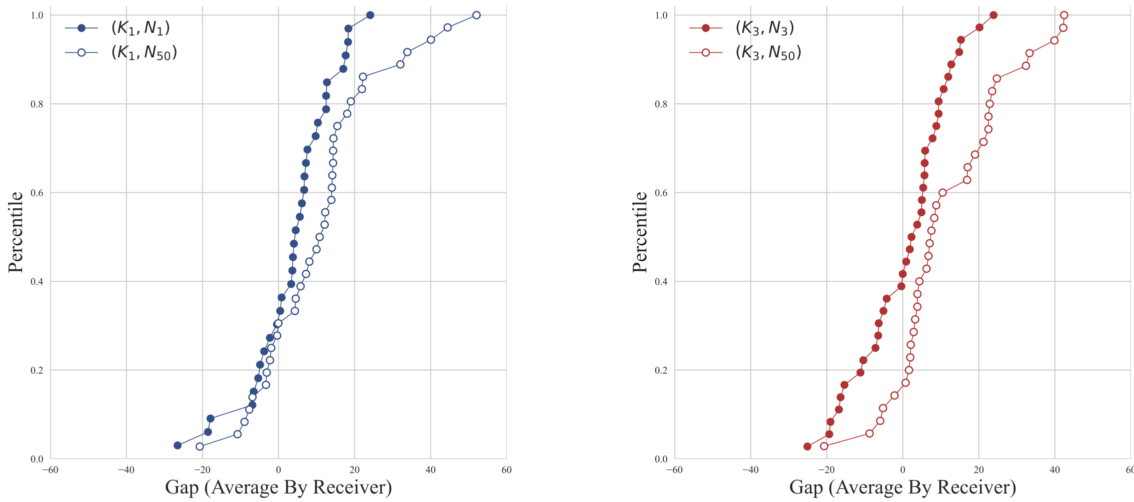
C.4.2 Receiver Optimism Increases with Selection

In Section 4.2.2, we established that the response gap increases in N. That is, receivers make larger mistakes in treatments where selection is the dominant distortion. We investigated the statistical significance of this finding in the regression model of Table 9. In this appendix, we present a robustenss exercise. We show that the same results hold when we look at receiver-level effects as opposed to average effects. Figure C.12 reports the CDF of the receiver-level response gaps, controlling for the message distribution. It shows that, for both values of K, these CDFs increase in a FOSD sense as N increases from K to 50 (p-value < 0.05 for $K = 1$ and p-value < 0.01 for $K = 3$). This indicates that, percentile by percentile, receivers make more mistakes when N is large.

C.5 Mandated Disclosure Simulation

We start by describing our baseline simulation. Assume $K = N = 1$. We use the same procedure discussed in Section 4.1.3 to cluster senders into three groups: 55% are classified as equilibrium types, 18% as deception-averse types, and 27% belong to a residual cluster, which in this case represents a hybrid between the former and the latter (see Figure C.6 in Online Appendix C.2). For each group of senders, we compute their "average" strategy in the form of a probabilistic mapping from the state θ to the messages sent. We then compute the average receiver's guess conditional on each message, as well as the variance of these guesses.

We use these numbers to simulate the play of 100,000 interactions (200,000 subjects). This proceeds along the following steps: 1) Randomly generate θ and one signal s. Independently



(a) (K_1, N_1) and (K_1, N_{50}) (b) (K_3, N_3) and (K_3, N_{50})

Figure C.12: CDF of receivers' response gaps

of (θ, s), generate the sender's behavioral type (one of the three clusters identified above). 2) Randomly generate a message, $m \in \{o, s\}$, according to the average sender strategy estimated above. 3) Given m, generate a random guess from a truncated normal (between 0 and 1). The variance of the truncated normal is determined so that the average guess conditional on the message comes closest to the estimated guessing strategy from above, while the overall variance of guesses matches that observed in the data. 4) Compute the correlation between the state and the guess.

When simulating mandated disclosure, we impose that whatever signal a sender has must be sent. In the text we discuss two cases. One where the behavior of receivers is unchanged. In the other, since mandated disclosure makes it clear how messages relate to evidence, we assume that, on average, receivers correctly estimate the probability that the state is high given the message. However, they still make mistakes in their guesses, and those are simulated following the same process as in our baseline, namely: a truncated normal distribution with the same standard deviation as in step 3 above. We then compute the correlation between the state and those guesses.

D Robustness to an Alternative Design

This section covers an additional experiment with an alternative design to the one presented in the paper.[4] After a brief description (section D.1), we replicate the key tables using this new data set (section D.2). In the dimensions that are comparable to our main design, the results are qualitatively consistent. The only exception is that we find that senders do not overcommunicate, and we explain how some design features are likely to limit this possibility.

D.1 Experimental Design

The experiment featured a disclosure game very similar to the one considered in the paper. The sender observes a randomly drawn number $\theta \in \{1,2,...99\}$, where each number is equally likely. She also observes N draws with replacement from a (virtual) urn containing 100 balls, of which θ are white and the rest are black. Thus, θ is also the percentage probability of drawing a white ball. For each ball she observes, she must decide whether to show it to the receiver, and she can show a maximum of K balls in total. The receiver observes the shown balls, if any, displayed in a random order, and makes a guess a about θ. The payoffs of the sender and the receiver are $3 + 8a/100$ and $10 - 8(\frac{\theta - a}{100})^2$, respectively.

The design consisted of three treatments that varied K and N, as summarized in Table D.2. Theoretical predictions on equilibrium informativeness are in Figure D.13.[5] Each subject participated in only one treatment and was randomly assigned the role of sender or receiver for the entire experiment. She played fifteen rounds of the game with a randomly selected participant in the opposite role in each round. At the end of the round, both subjects observed the sender's type θ, the receiver's guess a, and the payoffs, but the receiver did not learn the color of the undisclosed balls. More details about the design can be found in Ispano (2024).

The experiment was completely computerized and implemented with O-tree. All experimental sessions were conducted at the LEEM experimental laboratory of Montpellier in 2023. Each of the fifteen sessions, five per treatment, had an average of 18.5 participants and lasted about one hour, including reading of instructions and payment. The average payment, including a 5€ show-up fee, was 15.74€, and earnings ranged from 10.29€ to 18.84€. The experiment was pre-registered on AsPredicted.org (#144222).

[4] This alternative design originally appeared in Ispano (2024). As mentioned in our acknowledgments, that paper is now merged into the current one.

[5] For the sake of precision, these predictions obtain when θ is drawn from a continuous uniform distribution, in which case the equilibrium informativeness takes a simple closed form for any K and N.

	$N = K$	$N = 6$
$K = 2$	(K_2, N_2)	(K_2, N_6)
$K = 6$	(K_6, N_6)	

Table D.2: Treatments' Denominations

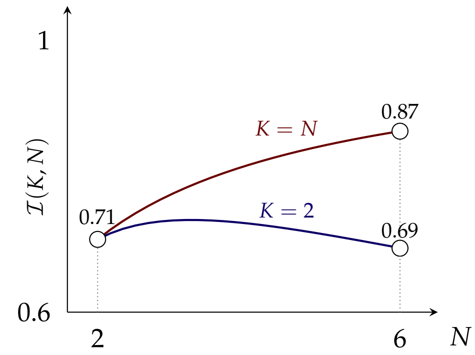


Figure D.13: Predicted Informativeness

D.2 Results

In the analysis, we use the same specifications and statistical tests as in the main body of the paper. Likewise, we focus on the second half of the rounds, i.e., from round 9 to 15.

D.2.1 Senders' Behavior

What Evidence Do Senders Disclose?

Mirroring Table 3, Table D.3 reports the average number of disclosed signals as a fraction of K in each treatment. In each treatment, the number of disclosed signals is significantly lower than K (p-value < 0.01), and increases with selection opportunities, i.e., it is significantly higher in (K_2, N_6) than in (K_2, N_2) (p-value < 0.01). Likewise, mirroring Table 4, Table D.4 reports the MGPA of the senders' messages. In computing the GPA, a disclosed white ball has a value of 4, while a disclosed black ball and a concealed ball have a value of 1. The MGPA increases significantly in N, i.e., from (K_2, N_2) to (K_2, N_6) (p-value < 0.01), and decreases significantly in K, i.e., from (K_2, N_6) to (K_6, N_6) (p-value < 0.01). Also, the MGPA is not significantly different between the two treatments in which $N = K$. Finally, in all treatments, the MGPA is significantly lower than the theoretically predicted one (p-value < 0.01).

How Much Information Do Senders Transmit?

As can be seen in Table D.5, which mirrors Table 10, for all treatment variations of K and N, the average senders' informativeness moves in the directions predicted by the theory. The increase in senders' informativeness from (K_2, N_6) to (K_6, N_6) is significant (p-value < 0.05), and so is the increase from (K_2, N_2) to (K_6, N_6) (p-value < 0.05). The decrease from (K_2, N_2) to (K_2, N_6) is not, which is however predicted to be small and insignificant even by the the-

Table D.3: The average number of signals disclosed as a fraction of K.

		$N = K$	$N = 6$
$K = 2$	Data	59.8%	80.8%
	Predictions	[48.8%, 100%]	[81.6%, 100%]
$K = 6$	Data	54.1%	
	Predictions	[53.1%, 100%]	

Table D.4: Mean grade point average (MGPA) induced by senders' messages.

		$N = K$	$N = 6$
$K = 2$	Data	2.24	3.05
	Predictions	2.46	3.45
$K = 6$	Data	2.22	
	Predictions	2.59	

Table D.5: Overall Informativeness, Senders' Informativeness, and Theoretical Predictions

		$N = K$	$N = 6$
$K = 2$	Overall Informativeness	0.42	0.21
	Senders' Informativeness	0.64	0.57
	Predictions	0.69	0.67
$K = 6$	Overall Informativeness	0.48	
	Senders' Informativeness	0.69	
	Predictions	0.85	

ory. Finally, the senders' informativeness is not significantly different from the theoretical informativeness in treatments (K_2, N_2) and (K_2, N_6), while it is significantly lower in treatment (K_6, N_6) (p-value < 0.05). That is, in this treatment, senders undercommunicate. These results contrast with those of the main experiment, where overcommunication is found for treatments with large N. Among design differences that may explain this discrepancy, e.g., equilibrium informativeness is lower to begin with for large N and a higher number of rounds may facilitate communication, we suspect that the richness of the message space relative to the type space also plays a role. Indeed, as argued in the paper, deception aversion is responsible for overcommunication. With only two types, a low type can easily separate by sending the lowest signal, especially when N is large. Such a strategy has no clear counterpart in this setting.

Evidence of Deception Aversion. Table D.6 reports the results of a basic test of deception aversion along the lines of the analysis of section 4.1.3. Namely, in each treatment, the GPA is regressed on the sender's type after controlling for the favorableness of signals as measured by

Table D.6: GPA as a Function of Type Controlling for Theoretical GPA

	(K_2, N_2)	(K_2, N_6)	(K_6, N_6)
	(1)	(2)	(3)
	GPA	GPA	GPA
Theoretical GPA	0.824***	0.732***	0.682***
	(0.0324)	(0.104)	(0.138)
Sender type	0.00258**	0.00735*	0.00405
	(0.00112)	(0.00379)	(0.00472)
Constant	0.0864	0.143	0.235**
	(0.0554)	(0.110)	(0.102)
Observations	322	343	308
Subjects	46	49	44

Notes: * $(p < 0.1)$, ** $(p < 0.05)$, *** $(p < 0.01)$. Standard errors, in parentheses, are clustered at the session level.

the maximum GPA that senders could generate, i.e., the theoretically predicted one. Contrary to theoretical predictions and consistent with deception aversion, in treatments (K_2, N_2) and (K_2, N_6) the GPA increases significantly with the type.

D.2.2 Receivers' Behavior

How Do Receivers Respond to Selected Evidence?

Mirroring Tables 6 and 7, Tables D.7 and D.8 examine how receivers' guesses and the empirical optimal guesses vary with N for fixed K, and with K for fixed N, respectively, while controlling for the GPA of the message. Consistent with the theory, guesses decrease with N and increase with K, even though, unlike in the main experiment, the effect of N for receivers' guesses is not statistically significant, possibly due to the smaller variation in N in this setting. As in the main experiment, comparing the two columns in each table shows that receivers adjust their guesses less than they should.

Receiver Optimism

Mirroring Table 8, Table D.9a reports the average response gap, i.e., the difference between the receiver's guess and the empirical optimal guess. As in the main experiment, when considering

Table D.7: Regression Results of Receivers' Responses for $K = 2$

	$K = 2$	
	(1)	(2)
	Guess	Optimal Guess
GPA	8.648***	13.46***
	(1.130)	(0.587)
D_{N_6}	-2.389	-6.236***
	(1.937)	(0.767)
Constant	30.32***	17.50***
	(2.544)	(1.336)
Observations	665	665
Subjects	95	

Notes: * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$). Standard errors, in parentheses, are clustered at the session level. Regression (2) does not include random effects.

Table D.8: Regression Results of Receivers' Responses for $N = 6$

	$N = 6$	
	(1)	(2)
	Guess	Optimal Guess
GPA	10.51***	14.28***
	(1.934)	(1.030)
D_{K_6}	9.404***	12.12***
	(2.294)	(1.167)
Constant	22.26***	8.754**
	(5.931)	(3.290)
Observations	651	651
Subjects	93	

Notes: * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$). Standard errors, in parentheses, are clustered at the session level. Regression (2) does not include random effects.

all messages the response gap is positive in each treatment, although here it statistically different from zero only in treatment (K_2, N_2) (p-value < 0.05). This difference may reflect that treatments with large N relative to K are not considered, so receivers encounter less favorable evidence overall, and that binary signals simplify equilibrium reasoning about undisclosed evidence. These features also blur the distinction between selection and concealment. Combined with receivers updating too conservatively even when messages are maximally favorable, this may explain why patterns are less clear when focusing on messages of length K or on empty messages only. Response gaps are largest for empty messages in treatments (K_2, N_2) and (K_2, N_6), and for messages of length K, the gap is not significantly negative only in treatment (K_2, N_6). Besides, mirroring Table 9, Table D.9b documents how, as in the main experiment, the response gap increases significantly with N when fixing K and controlling for the GPA.

How Much Information Do Receivers Absorb?

Finally, Table D.5 above also reports the overall informativeness resulting from the interaction between senders and receivers. As in the main experiment, by construction, overall infor-

Table D.9: Receivers' Response Gaps

(a) Average Response Gaps by Treatment

		$K = N$		$K < N$
		(K_2, N_2)	(K_6, N_6)	(K_2, N_6)
(i)	All messages	2.05^{**}	2.43	1.99
		(322 obs)	*(308 obs)*	*(343 obs)*
(ii)	Length-K	-2.87^{**}	-2.30^{**}	-1.29
		(133 obs)	*(54 obs)*	*(258 obs)*
(iii)	Empty	8.01^{**}	-4.90	8.02^{**}
		(70 obs)	*(42 obs)*	*(47 obs)*

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

(b) OLS on Response Gaps

	$K = 2$
	Gap
GPA	-4.828***
	(0.916)
D_{N_6}	3.861**
	(1.940)
Constant	12.86***
	(2.131)
Observations	665
Subjects	95

Notes: * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$). Standard errors, in parentheses, are clustered at the session level.

mativeness is lower than senders' informativeness. Moreover, overall informativeness moves in the directions predicted by the theory. The increase in informativeness from (K_2, N_6) to (K_6, N_6) is significant (p-value < 0.01), as is the increase from (K_2, N_2) to (K_6, N_6) (p-value < 0.05). Interestingly, even the decrease from (K_2, N_2) to (K_2, N_6), which is predicted to be insignificant by the theory, is significant (p-value < 0.05), which is consistent with selection neglect by receivers.

E Supplementary Proofs, Examples and Extensions

E.1 Proof of Lemma B.1

***Proof of Lemma** B.1.* [6] Denote by $z = (\theta, y_1, \ldots, y_n)$ a generic realization of these random variables. To show that the random variables $(\theta, y_1, \ldots, y_n)$ are affiliated, we need to show that, for any $z, z' \in \Theta \times S^N$,

$$g(z \vee z')g(z \wedge z') \geq g(z)g(z'),$$

[6] For this proof, we refer to the notation introduced at the beginning of Section B.1.

where $z \vee z'$ and $z \wedge z'$ are the component-wise max and min of the two vectors (Theorem 24 in Milgrom and Weber, 1982). $\Theta \times S^n$ is a lattice, thus the operations $\vee$ and $\wedge$ are well-defined. Additionally, letting $z = (\theta, y)$ and $z' = (\theta', y')$, if y and y' are weakly decreasing, $z \vee z'$ and $z \wedge z'$ are also weakly decreasing.

Since the product of affiliated functions is affiliated (Theorem 1(ii) in Milgrom and Weber, 1982), it is enough to show that the functions $p(\theta)f(y|\theta)$ and $B(y)\mathbb{1}_{\{y_1 \geq \ldots \geq y_n\}}$ are affiliated.

For the former, fixing $z = (\theta, y)$ and $z = (\theta', y')$, we need to show that

$$p(\theta \vee \theta')f(y \vee y'|\theta \vee \theta')p(\theta \wedge \theta')f(y \wedge y'|\theta \wedge \theta') \geq p(\theta)f(y|\theta)p(\theta')f(y'|\theta').$$

Dividing by $p(\theta)p(\theta')$ and using the fact that $f(y|\theta) = \prod_i f(y_i|\theta)$, the expression above becomes

$$\prod_i f(y_i \vee y_i'|\theta \vee \theta') \prod_i f(y_i \wedge y_i'|\theta \wedge \theta') \geq \prod_i f(y_i|\theta) \prod_i f(y_i'|\theta').$$

It suffices to show that, for all $i \in \{1 \ldots, n\}$,

$$f(y_i \vee y_i'|\theta \vee \theta')f(y_i \wedge y_i'|\theta \wedge \theta') \geq f(y_i|\theta)f(y_i'|\theta').$$

This holds thanks to a simple application of the MLRP.

For the latter, letting $h(y) = B(y)\mathbb{1}_{\{y_1 \geq \ldots \geq y_n\}}$, we need to show that for all $\bar{y}, \bar{y}' \in S^N$

$$h(\bar{y} \vee \bar{y}')h(\bar{y} \wedge \bar{y}') \geq h(\bar{y})h(\bar{y}'). \tag{4}$$

If at least one between y and y' is not weakly decreasing, $h(y)h(y') = 0$, and thus the affiliation inequality of Equation (4) holds because $h(y) \geq 0$ for any y. Therefore, assume both y and y' are weakly decreasing. We need to show that

$$B(y \vee y')B(y \wedge y') \geq B(y)B(y') = \frac{n!}{\prod_s q_s(y \vee y')!} \frac{n!}{\prod_s q_s(y \wedge y')!} \geq \frac{n!}{\prod_s q_s(y)!} \frac{n!}{\prod_s q_s(y')!} \implies$$

$$\prod_s q_s(y)! \prod_s q_s(y')! \geq \prod_s q_s(y \vee y')! \prod_s q_s(y \wedge y')! \implies$$

$$\prod_s q_s(y)!\, q_s(y')! \geq \prod_s q_s(y \vee y')!\, q_s(y \wedge y')!$$

It suffices to show that, for each $s \in S$,

$$q_s(y)!\, q_s(y')! \geq q_s(y \vee y')!\, q_s(y \wedge y')!$$

To this end, we first prove two properties of q_s.

Claim 1. *If y and y' are weakly decreasing and $s \in S$,*

$$\min\{q_s(y), q_s(y')\} \leq q_s(y \vee y') \leq \max\{q_s(y), q_s(y')\},$$

$$\min\{q_s(y), q_s(y')\} \leq q_s(y \wedge y') \leq \max\{q_s(y), q_s(y')\},$$

and

$$q_s(y) + q_s(y') = q_s(y \vee y') + q_s(y \wedge y').$$

Proof of Claim 1. Fix $s \in S$. Fix y and y', both weakly decreasing. Let $\underline{\iota} = \min\{i : y_i = s\}$, the position of the first appearance of s in y. Let $\bar{\iota} = \max\{i+1 : y_i = s\}$, the position following the last appearance of s in y. If s never appears in y, let $\underline{\iota} = \bar{\iota} = \min\{i : y_i < s\}$ if there exists some i such that $y_i < s$, and let $\underline{\iota} = \bar{\iota} = n$ if $y_i > s$ for all i. By definition, $\bar{\iota} \geq \underline{\iota}$. Note that, since y is weakly decreasing, $q_s(y) = \bar{\iota} - \underline{\iota}$. Define $\bar{\iota}'$ and $\underline{\iota}'$ for y' accordingly. It is straightforward to show that

$$q_s(y \vee y') = \max\{\bar{\iota}, \bar{\iota}'\} - \max\{\underline{\iota}, \underline{\iota}'\}, \qquad q_s(y \wedge y') = \min\{\bar{\iota}, \bar{\iota}'\} - \min\{\underline{\iota}, \underline{\iota}'\}.$$

Given these alternative definitions, it becomes easy to show that the first two inequalities in the Claim hold. In particular, they can be simplified to be

$$\min\{\bar{\iota} - \underline{\iota}, \bar{\iota}' - \underline{\iota}'\} \leq \max\{\bar{\iota}, \bar{\iota}'\} - \max\{\underline{\iota}, \underline{\iota}'\} \leq \max\{\bar{\iota} - \underline{\iota}, \bar{\iota}' - \underline{\iota}'\}$$

$$\min\{\bar{\iota} - \underline{\iota}, \bar{\iota}' - \underline{\iota}'\} \leq \min\{\bar{\iota}, \bar{\iota}'\} - \min\{\underline{\iota}, \underline{\iota}'\} \leq \max\{\bar{\iota} - \underline{\iota}, \bar{\iota}' - \underline{\iota}'\}.$$

To show that both statements are true, we need to consider four cases.

1. $\max\{\bar{\iota}, \bar{\iota}'\} = \bar{\iota}$ and $\max\{\underline{\iota}, \underline{\iota}'\} = \underline{\iota} \implies \min\{\bar{\iota}, \bar{\iota}'\} = \bar{\iota}'$ and $\min\{\underline{\iota}, \underline{\iota}'\} = \underline{\iota}'$. Our two inequalities become

$$\min\{\bar{\iota} - \underline{\iota}, \bar{\iota}' - \underline{\iota}'\} \leq \bar{\iota} - \underline{\iota} \leq \max\{\bar{\iota} - \underline{\iota}, \bar{\iota}' - \underline{\iota}'\}$$

$$\min\{\bar{\iota} - \underline{\iota}, \bar{\iota}' - \underline{\iota}'\} \leq \bar{\iota}' - \underline{\iota}' \leq \max\{\bar{\iota} - \underline{\iota}, \bar{\iota}' - \underline{\iota}'\}$$

which are both trivially true;

2. $\max\{\bar{\iota},\bar{\iota}'\} = \bar{\iota}'$ and $\max\{\underline{\iota},\underline{\iota}'\} = \underline{\iota}' \implies \min\{\bar{\iota},\bar{\iota}'\} = \bar{\iota}$ and $\min\{\underline{\iota},\underline{\iota}'\} = \underline{\iota}$. The argument resembles point 1 and both inequalities are trivially true;

3. $\max\{\bar{\iota},\bar{\iota}'\} = \bar{\iota}$ and $\max\{\underline{\iota},\underline{\iota}'\} = \underline{\iota}' \implies \min\{\bar{\iota},\bar{\iota}'\} = \bar{\iota}'$ and $\min\{\underline{\iota},\underline{\iota}'\} = \underline{\iota}$. Our two inequalities become

$$\min\{\bar{\iota}-\underline{\iota},\bar{\iota}'-\underline{\iota}'\} \leq \bar{\iota}-\underline{\iota}' \leq \max\{\bar{\iota}-\underline{\iota},\bar{\iota}'-\underline{\iota}'\}$$

$$\min\{\bar{\iota}-\underline{\iota},\bar{\iota}'-\underline{\iota}'\} \leq \bar{\iota}'-\underline{\iota} \leq \max\{\bar{\iota}-\underline{\iota},\bar{\iota}'-\underline{\iota}'\}.$$

Notice that, under our assumptions, $\bar{\iota}-\underline{\iota} \geq \bar{\iota}'-\underline{\iota}'$ and we can further simplify the two inequalities to

$$\bar{\iota}'-\underline{\iota}' \leq \bar{\iota}-\underline{\iota}' \leq \bar{\iota}-\underline{\iota}$$

$$\bar{\iota}'-\underline{\iota}' \leq \bar{\iota}'-\underline{\iota} \leq \bar{\iota}-\underline{\iota}$$

which are both true due the fact that $\bar{\iota} \geq \bar{\iota}'$ and $\underline{\iota}' \geq \underline{\iota}$.

4. $\max\{\bar{\iota},\bar{\iota}'\} = \bar{\iota}'$ and $\max\{\underline{\iota},\underline{\iota}'\} = \underline{\iota} \implies \min\{\bar{\iota},\bar{\iota}'\} = \bar{\iota}$ and $\min\{\underline{\iota},\underline{\iota}'\} = \underline{\iota}'$. The argument resembles part 3 and both inequalities are satisfied.

The last equation in the Claim follows trivially from our definitions. Indeed

$$\begin{aligned} q_s(y)+q_s(y') =& (\bar{\iota}-\underline{\iota})+(\bar{\iota}'-\underline{\iota}') = (\bar{\iota}+\bar{\iota}')-(\underline{\iota}+\underline{\iota}') = \\ & (\max\{\bar{\iota},\bar{\iota}'\}+\min\{\bar{\iota},\bar{\iota}'\})-(\max\{\underline{\iota},\underline{\iota}'\}+\min\{\underline{\iota},\underline{\iota}'\}) = \\ & (\max\{\bar{\iota},\bar{\iota}'\}-\max\{\underline{\iota},\underline{\iota}'\})+(\min\{\bar{\iota},\bar{\iota}'\}-\min\{\underline{\iota},\underline{\iota}'\}) = \\ & q_s(y\vee y')+q_s(y\wedge y') \end{aligned}$$

$\triangle$

We now return to our target, which is to show $q_s(y)!\ q_s(y')! \geq q_s(y\vee y')!\ q_s(y\wedge y')!$ Without loss of generality, assume $a := q_s(y) \leq q_s(y') =: b$ and let $a+b=Z$. From Claim 1, we know that $q_s(y\vee y')+q_s(y\wedge y') = Z$, $a \leq q_s(y\vee y') \leq b$ and $a \leq q_s(y\wedge y') \leq b$. Given these results, we cab write the following chain of equations

$$q_s(y\vee y')!\ q_s(y\wedge y')! \leq \max_{\substack{c,d:\\ a\leq c,d\leq b\\ c+d=Z}} c!d! = a!b! = q_s(y)!\ q_s(y')!$$

The first inequality follows from Claim 1. The second inequality follows from the fact that the maximum of the product of two factorials is achieved when they take opposite extreme values.

This completes the proof and allows us to conclude that the random variables $(\theta, y_1, \ldots, y_n)$ are affiliated. $\square$

E.2 Proof of Remark 1

Proof of Remark 1, point 1. Denote the order statistics of the vector of signal realizations as $s_{(1:N)} \geq s_{(2:N)} \geq \ldots \geq s_{(N:N)}$, where $s_{(1:N)}$ denote the highest order statistic. Denote by $F_{(i:N)}$ the CDF of $s_{(i)}$, i.e. $F_{(i:N)}(s) = \mathbb{P}(s_{(i:N)} \leq s)$, for all $s \in S$. In any maximally selective equilibrium, the sender always reveals the K-highest signal realizations in $(s_1, \ldots, s_N)$. Let $g_{K,N}(s)$ be the probability that a signal drawn uniformly at random from the K-highest signal realizations revealed by the sender is equal to $s \in S$. That is,

$$g_{K,N}(s) \triangleq \frac{1}{K} \sum_{i=1}^{K} \mathbb{P}(s_{(i:N)} = s).$$

Thus, the CDF of the probability measure $g_{K,N}$ is

$$G_{K,N}(\hat{s}) \triangleq \sum_{s \leq \hat{s}} g_{K,N}(s) = \frac{1}{K} \sum_{i=1}^{K} \mathbb{P}(s_{(i:N)} \leq \hat{s}) = \frac{1}{K} \sum_{i=1}^{K} F_{(i:N)}(\hat{s}).$$

First, we want to show that for all N and $s \in S$, $G_{K,N+1}(s) \leq G_{K,N}(s)$ (with the rest of the argument holding by induction). This follows from the fact that, for all $i = 1, \ldots, N$ and s, $F_{(i,N)}(s) \geq F_{(i,N+1)}(s)$ (see, e.g., Shaked and Shanthikumar (2007, Corollary 1.C.38.), then use that the likelihood ratio order implies the FOSD order and that the latter is closed under mixtures). In particular, this holds for each $i \leq K$ and, therefore, $G_{K,N+1}(s) \leq G_{K,N}(s)$.

Second, we want to show that for all K and $s \in S$, $G_{K,N}(s) \leq G_{K+1,N}(s)$ (with the rest of the argument holding by induction). Using the definition above, we have that

$$\begin{aligned} G_{K+1,N}(s) &= \frac{1}{K+1} \sum_{i=1}^{K} F_{(i:N)}(s) + \frac{1}{K+1} F_{(K+1:N)}(s) \\ &= \frac{K}{K+1} \left(\frac{1}{K} \sum_{i=1}^{K} F_{(i:N)}(s) \right) + \frac{1}{K+1} F_{(K+1:N)}(s). \end{aligned}$$

Notice that $F_{(i:N)}(s) \leq F_{(j:N)}(s)$ for each $i < j$ and s. This follows directly from the fact that, by definition of the order statistics, $s_{(i:N)} \geq s_{(j:N)}$. Thus, $F_{(K+1:N)}(s) \geq \frac{1}{K}\sum_{i=1}^{K} F_{(i:N)}(s) = G_{K,N}(s)$. Thus, $G_{K+1,N}(s)$ is a convex combination of $G_{K,N}(s)$ and a greater term, and therefore $G_{K,N}(s) \leq G_{K+1,N}(s)$. $\square$

Proof of Remark 1, point 2. We want to show that in any maximally selective equilibrium, fixing any K and any on-the-equilibrium-path message m, the conditional expectation of θ given m is decreasing in N. Any such message reveals the K-highest signal realizations in $(s_1, \dots, s_N)$. Let $\tilde{s} = (s_1, \dots, s_K)$ denote the vector of the K-highest signal realizations revealed by m. By Milgrom (1981), a sufficient condition for such expectation to be decreasing in N is hence that $\frac{\mathbb{P}_N(\tilde{s}|\theta)}{\mathbb{P}_{N+1}(\tilde{s}|\theta)}$ is increasing in θ, where $\mathbb{P}_n(\tilde{s}|\theta)$ denotes the probability that the K-highest signal realizations out of n draws are those in $\tilde{s}$ conditional on θ. We have that

$$\mathbb{P}_N(\tilde{s} \mid \theta) = \begin{cases} \frac{N!}{(N-L)!\prod_{j=1}^{r-1} m_j!} \prod_{j=1}^{r-1} f(y_j \mid \theta)^{m_j} f(\min S \mid \theta)^{N-L} & \text{if } y_r = \min S \\ \sum_{n_r=m_j}^{N-L} \frac{N!}{(N-L-n_r)!\prod_{j=1}^{r-1} m_j! n_r!} \prod_{j=1}^{r-1} f(y_j \mid \theta)^{m_j} f(y_r \mid \theta)^{n_r} F(y_r^- \mid \theta)^{N-L-n_r} & \text{if } y_r > \min S \end{cases}$$

where:

- $\tilde{s} = (s_1, \dots, s_K)$ is the vector of the K-highest signal realizations revealed by m;
- $y(\tilde{s}) = (y_1, \dots, y_r)$ is the vector of the *distinct* values in $\tilde{s}$, with $y_r \triangleq \min\{\tilde{s}_i \in \tilde{s}\}$. Namely, $y(\tilde{s})$ differs from $\tilde{s}$ in that identical realizations are collapsed into single elements, and, moreover, the lowest of these elements, denoted by y_r, is arranged at the end;
- $y_r^- \triangleq \max\{s \in S \mid s < y_r\}$ denotes the largest signal in S that is strictly less than y_r;
- each element $y_j \in y(\tilde{s})$ has multiplicity m_j in $\tilde{s}$ and n_j in the *entire sample*;
- for each y_j with $j < r$, $n_j = m_j$, since realizations strictly higher than y_r cannot appear outside the top K. Thus, $L \triangleq \sum_{j=1}^{r-1} m_j$ denotes the total multiplicity of such realizations in the entire sample;
- as for y_r, if $y_r = \min S$, all realizations outside the top K must be equal to $\min S$ as well, so $n_r = N - L$, while if $y_r > \min S$, n_r varies from m_r to $N - L$.

First, we consider the case $y_r = \min S$. Then,

$$\frac{\mathbb{P}_N(\tilde{s}|\theta)}{\mathbb{P}_{N+1}(\tilde{s}|\theta)} = \frac{\frac{N!}{(N-L)!\prod_{j=1}^{r-1} m_j!} \prod_{j=1}^{r-1} f(y_j \mid \theta)^{m_j} f(\min S \mid \theta)^{N-L}}{\frac{(N+1)!}{(N+1-L)!\prod_{j=1}^{r-1} m_j!} \prod_{j=1}^{r-1} f(y_j \mid \theta)^{m_j} f(\min S \mid \theta)^{N+1-L}}$$

$$= \frac{N+1-L}{N+1} \frac{1}{f(\min S \mid \theta)}.$$

Thus, the result follows since, by the MLRP, $f(\min S \mid \theta)$ is decreasing in θ (the MLRP implies FOSD, i.e., $F(s \mid \theta') \leq F(s \mid \theta)$ for $\theta' > \theta$ and $s \in S$, which in particular holds at $s = \min S$).

Next, we consider the case $y_r > \min S$. Then,

$$\begin{aligned}
\frac{\mathbb{P}_N(\tilde{s}|\theta)}{\mathbb{P}_{N+1}(\tilde{s}|\theta)} &= \frac{\sum_{n_r=m_r}^{N-L} \frac{N!}{(N-L-n_r)!\, n_r!} f(y_r \mid \theta)^{n_r} F(y_r^- \mid \theta)^{N-L-n_r}}{\sum_{n_r=m_r}^{N+1-L} \frac{(N+1)!}{(N+1-L-n_r)!\, n_r!} f(y_r \mid \theta)^{n_r} F(y_r^- \mid \theta)^{N+1-L-n_r}} \\
&= \frac{N+1-L}{N+1} \frac{\sum_{n_r=m_r}^{N-L} \binom{N-L}{n_r} f(y_r \mid \theta)^{n_r} F(y_r^- \mid \theta)^{N-L-n_r}}{\sum_{n_r=m_r}^{N+1-L} \binom{N+1-L}{n_r} f(y_r \mid \theta)^{n_r} F(y_r^- \mid \theta)^{N+1-L-n_r}} \\
&= \frac{N+1-L}{N+1} \frac{(f(y_r \mid \theta) + F(y_r^- \mid \theta))^{N-L} \sum_{n_r=m_r}^{N-L} \binom{N-L}{n_r} p_\theta^{n_r} (1-p_\theta)^{N-L-n_r}}{(f(y_r \mid \theta) + F(y_r^- \mid \theta))^{N+1-L} \sum_{n_r=m_r}^{N+1-L} \binom{N+1-L}{n_r} p_\theta^{n_r} (1-p_\theta)^{N+1-L-n_r}} \\
&= \frac{N+1-L}{N+1} \frac{1}{F(y_r \mid \theta)} \frac{\mathbb{P}_{\text{Bin}(N-L,p_\theta)}(n_r \geq m_r)}{\mathbb{P}_{\text{Bin}(N+1-L,p_\theta)}(n_r \geq m_r)},
\end{aligned}$$

where the second equation obtains using that $\frac{N!}{(N-L-n_r)!\, n_r!} = \binom{N-L}{n_r} \frac{N!}{(N-L)!}$, in the third equation $p_\theta \triangleq \frac{f(y_r|\theta)}{f(y_r|\theta)+F(y_r^-|\theta)} = \frac{f(y_r|\theta)}{F(y_r|\theta)}$ and, in the forth equation, $\mathbb{P}_{\text{Bin}(N-L,p_\theta)}(n_r \geq m_r)$ is the right tail (i.e., the probability of at least m_r successes) of a binomial distribution with success probability p_θ and $N-L$ trials. By the MLRP, $F(y_r \mid \theta)$ is decreasing in θ while p_θ is increasing in θ (since the MLRP implies reverse hazard rate dominance). Hence, a sufficient condition for $\frac{\mathbb{P}_N(\tilde{s}|\theta)}{\mathbb{P}_{N+1}(\tilde{s}|\theta)}$ to be increasing in θ is that the ratio of right tails in the last equation is increasing in p_θ.

To see this, note that by a known Beta-Binomial identity, $\mathbb{P}_{\text{Bin}(N,p)}(n \geq x) = \frac{\text{B}(p;x,1+N-x)}{\text{B}(x,1+N-x)}$, where $\text{B}(.,.,.)$ and $\text{B}(.,.)$ are the incomplete and complete Beta functions, respectively. Thus, ignoring multiplicative constants,

$$R(p) \triangleq \frac{\mathbb{P}_{\text{Bin}(N,p)}(n \geq x)}{\mathbb{P}_{\text{Bin}(N+1,p_\theta)}(n \geq x)} \propto \frac{\int_0^p t^{x-1}(1-t)^{N-x}\, dt}{\int_0^p t^{x-1}(1-t)^{N+1-x}\, dt}$$

Defining $f(p) \triangleq \int_0^p t^{x-1}(1-t)^{N-x}\, dt$ and $h(p) \triangleq \int_0^p t^{x-1}(1-t)^{N+1-x}\, dt$, so that $R(p) \propto$

$\frac{f(p)}{h(p)}$, and using that $f'(p) = p^{x-1}(1-p)^{N-x}$ and $h'(p) = p^{x-1}(1-p)^{N+1-x}$,

$$R'(p) \propto \frac{p^{x-1}(1-p)^{N-x}\left[h(p)-(1-p)f(p)\right]}{h(p)^2}.$$

The sign of $R'(p)$ is hence determined by the sign of

$$\begin{aligned} h(p)-(1-p)f(p) &= \int_0^p t^{x-1}\left[(1-t)^{N+1-x}-(1-p)(1-t)^{N-x}\right]dt \\ &= \int_0^p t^{x-1}(1-t)^{N-x}(p-t)dt > 0. \end{aligned}$$

□

E.3 Informativeness

In this Section, we establish the link between the ex ante receiver's expected payoff and the expected variance of the state θ given the disclosed message.

Remark 4. *Consider any PBE of our game. Fix the message $m \in \mathcal{M}$, the receiver's strategy $\xi : \mathcal{M} \to A$, the sender's strategy $\sigma : \Theta \times S^N \to \Delta(\mathcal{M})$ and the receiver's posterior belief $\mu(\cdot|m) \in \Delta(\Theta)$. The correlation between the state θ and the receiver's action induced by $\xi(\cdot)$ is a monotonic transformation of the ex ante expected payoff of the receiver.*

Proof. Consider any PBE of our game. Fix the message $m \in \mathcal{M}$, the receiver's strategy $\xi : \mathcal{M} \to A$, the sender's strategy $\sigma : \Theta \times S^N \to \Delta(\mathcal{M})$ and the receiver's posterior belief $\mu(\cdot|m) \in \Delta(\Theta)$. We have that

$$\mathbb{E}_\theta\left[u\left(\theta, \xi(m)\right)\right] = -\sum_{\theta' \in \Theta} \mu(\theta'|m)\left(\mathbb{E}\left[\theta|m\right]-\theta'\right)^2$$

Given this, we can derive the ex-ante expected payoff of the receiver as:

$$\begin{aligned} \mathbb{E}_{\theta,m}\left[u_R\left(\theta, \xi(m)\right)\right] &= -\sum_{m \in \mathcal{M}} Prob(m) \sum_{\theta' \in \Theta} \mu(\theta'|m)\left(\mathbb{E}\left[\theta|m\right]-\theta'\right)^2 \\ &\quad - \sum_{m \in \mathcal{M}} \sum_{\theta' \in \Theta} Prob(m,\theta')\left(\mathbb{E}\left[\theta|m\right]-\theta'\right)^2. \end{aligned}$$

At this point notice that

$$Prob(m,\theta) = Prob(m) \cdot \mu(\theta|m).$$

Rearranging the expression we get

$$\mathbb{E}_{\theta,m}\left[u_R\left(\theta,\xi(m)\right)\right] = -\sum_{m\in\mathcal{M}} Prob(m) \sum_{\theta'\in\Theta} \mu(\theta|m)\left(\mathbb{E}\left[\theta|m\right]-\theta'\right)^2$$

which implies

$$\mathbb{E}_{\theta,m}\left[u_R\left(\theta,\xi(m)\right)\right] = -\sum_{m\in\mathcal{M}} Prob(m) Var\left[\theta|m\right] = -\mathbb{E}_m\left[Var\left[\theta|m\right]\right]$$

This argument directly links the ex-ante expected payoff of the receiver with the variance of θ given the disclosed message. We can now show that $-\mathbb{E}_m\left[Var[\theta|m]\right]$ is monotonic transformation of $Corr(\theta,a)$, where a is the random variable generated by $\xi(\cdot)$ and

$$Corr(\theta,a) = \frac{\mathbb{E}\left[\theta\cdot a\right]-\mathbb{E}[\theta]\mathbb{E}[a]}{\sqrt{Var[\theta]Var[a]}} = \frac{\mathbb{E}_m\left[\mathbb{E}_\theta\left[\theta\cdot\xi(m)|m\right]\right]-\mathbb{E}[\theta]\mathbb{E}_m[\xi(m)]}{\sqrt{Var[\theta]Var_m[\xi(m)]}}$$

Notice that:

- $\mathbb{E}_m[\xi(m)] = \mathbb{E}[\theta]$;
- $\mathbb{E}_m\left[\mathbb{E}_\theta\left[\theta\cdot\xi(m)|m\right]\right] = \mathbb{E}_m\left[\xi(m)^2\right]$ since $\mathbb{E}_\theta[\theta|m] = \xi(m)$;
- $Var_m[\xi(m)] = \mathbb{E}_m\left[\xi(m)^2\right] - \mathbb{E}[\theta]^2$.

This implies that

$$Corr(\theta,a) = \frac{\sqrt{Var_m[\xi(m)]}}{\sqrt{Var[\theta]}} = \frac{\sqrt{\mathbb{E}[a^2]-\mathbb{E}[\theta]^2}}{\sqrt{Var[\theta]}}.$$

Given that $-\mathbb{E}_m[Var[\theta|m]] = \mathbb{E}_m\left[\mathbb{E}\left[\theta|m\right]^2\right] - \mathbb{E}_m\left[\mathbb{E}\left[\theta^2|m\right]\right] = \mathbb{E}[a^2]-\mathbb{E}[\theta^2]$, we can derive the following relation:

$$-\mathbb{E}_m[Var[\theta|m]] = Var[\theta]\cdot Corr(\theta,a)^2 - Var[\theta].$$

□

This argument allows us to conclude that both $-\mathbb{E}_m[Var[\theta|m]]$ and $Corr(\theta,a)$ can be used to study the level of information transmitted in equilibrium. Indeed, both measures provide the same comparative statics with respect to the main parameters of our model.

E.4 Examples of the Non-Monotonicity of $\mathcal{I}(K,N)$

As stated in Proposition 2, $\mathcal{I}(K,N)$ can be non-monotonic in N. In Section 2.2 we provided an intuition for this result by introducing two effects, the imitation and the revelation effect. The following example illustrates more in detail both effects and how their interaction is the key determinant of the shape of $\mathcal{I}(K,N)$.

Throughout, we suppose that $\Theta = \{0,1\}$, with each state equally likely, and we fix $K = 1$. Also, we assume $S = \{B, A\}$, with $f(A|1) = \gamma > \eta = f(A|0)$. Besides, we let $\mu(m) = \mu(1|m)$ denote the receiver's belief that $\theta = 1$, which also coincides with the optimal guess given such belief. Finally, among all possible maximally selective strategies of the sender, we focus on the one that prescribes to always disclose a signal, namely, send $m = A$ if an A is available and $m = B$ otherwise.

In equilibrium, the receiver's beliefs, hence actions, upon each disclosed signal are pinned down by Bayes' rule, i.e.,

$$a(B) = \mu(B) = \frac{(1-\gamma)^N}{(1-\gamma)^N + (1-\eta)^N}$$

$$a(A) = \mu(A) = \frac{1-(1-\gamma)^N}{2-(1-\gamma)^N-(1-\eta)^N}.$$

Thus, the receiver's expected utility in equilibrium is

$$\begin{aligned}
\mathbb{E}\left[u\left(\theta,a\right)\right] &= -\frac{1}{2}\left(\left(1-(1-\gamma)^N\right)(1-a(A))^2 + (1-\gamma)^N\left(1-a(B)\right)^2\right) \\
&\quad -\frac{1}{2}\left(\left(1-(1-\eta)^N\right)(a(A))^2 + (1-\eta)^N\left(a(B)\right)^2\right) \\
&= -\frac{(1-\gamma)^N\left(1-(1-\gamma)^N\right) + (1-\eta)^N\left(1-(1-\eta)^N\right)}{2\left((1-\gamma)^N+(1-\eta)^N\right)\left(2-(1-\gamma)^N-(1-\eta)^N\right)}.
\end{aligned}$$

According to our definition of equilibrium informativeness, $(\mathcal{I}(K,N))^2 = 1 + \mathbb{E}\left[u\left(\theta,a\right)\right]/Var[\theta]$ (see Section E.3). Hence, defining $\mathcal{I}^2(K,N) \triangleq (\mathcal{I}(K,N))^2$ and using that $Var[\theta] = 1/4$,

$$\mathcal{I}^2(K,N) = \frac{\left((1-\gamma)^N-(1-\eta)^N\right)^2}{\left(2-(1-\gamma)^N-(1-\eta)^N\right)\left((1-\gamma)^N+(1-\eta)^N\right)}.$$

To build intuition, we first relax the assumption that f has full support and study two extreme cases. Consider first the extreme case of *perfect good news*, i.e., the case in which $\eta = 0$ and

$\gamma < 1$. Under this parametrization, $m = A$ perfectly reveals that $\theta = 1$. Then,

$$\mathcal{I}^2(K, N) = \frac{1 - (1-\gamma)^N}{1 + (1-\gamma)^N},$$

which is strictly increasing in N. Hence, an increase in N always leads to more information being transmitted in equilibrium. The intuition behind this result is straightforward. Only $\theta = 1$ can draw a signal equal to A and, when this happens, the value of the state is fully revealed. The larger the number of available signals, the more likely it is that a high-type sender can send $m = A$. In addition, as a consequence of the previous fact, when N grows, observing $m = B$ makes the receiver more confident that $\theta = 0$. These two channels together are responsible for the fact that more available signals lead to more information being transmitted in equilibrium: We refer to this as the *revelation effect*.

Now consider the other extreme case of *perfect bad news*, i.e., the case in which $\eta > 0$ and $\gamma = 1$. Under this parametrization, $m = B$ perfectly reveals that $\theta = 0$. Then,

$$\mathcal{I}^2(K, N) = \frac{(1-\eta)^N}{2 - (1-\eta)^N},$$

which is strictly decreasing in N. That is, the amount of information transmitted in equilibrium decreases with the number of available signals. Again, the intuition is simple. As N grows, the low-type sender is increasingly more likely to draw at least one A. Thus, sending the fully-revealing message $m = B$ becomes less likely and, at the same time, $m = A$ becomes weaker evidence of $\theta = 1$. This leads to less information being transmitted in equilibrium: We refer to this as the *imitation effect*.

Finally, consider the case in which f has full support, i.e., in which both $\eta > 0$ and $\gamma < 1$. Intuitively, in this case, both the revelation and imitation effects play a role in how the information transmitted in equilibrium changes with the number of available signals. Which effect prevails determines the direction of the change in $\mathcal{I}(K, N)$ after an increase in N. We now show that when the signal has symmetric precision, i.e., $\gamma > 1/2$ and $\eta = 1 - \gamma$, informativeness always increases when moving from $N = 1$ to $N = 2$. Indeed,

$$\mathcal{I}^2(1, 2) - \mathcal{I}^2(1, 1) = \frac{(2\gamma - 1)^2}{1 - 4(1-\gamma)^2\gamma^2} - (2\gamma - 1)^2 > 0,$$

which is positive because the denominator of the first term is positive and less than one. Since $\mathcal{I}(K, N)$ always converges to zero in the limit as N goes to infinity, it is nonmonotonic in N.

Hence, the example discussed above allows us to illustrate that the effect of a change in N on informativeness is the result of positive and negative forces. The exact parametrization of the model pins down the overall effect. However, as N becomes extremely large, the negative force always prevails, making communication fully ineffective.

E.5 A Model with Random N

This section considers an extension of the theoretical predictions of Section 2.2 when N is not common knowledge. For simplicity we assume that the state and signals are binary, i.e., $\Theta = \{0, 1\}$ and $S = \{A, B\}$, and at most one signal can be disclosed, i.e., $K = 1$. This setting is similar to that analyzed in Section E.4. For ease of exposition, we also assume that the state is uniformly distributed and signals have symmetric precision, i.e., $f(A|1) = f(B|0) = \gamma \in (1/2, 1)$. All insights generalize to an arbitrary prior and likelihood function.

In contrast to the main model, we assume that N is a random variable. While its distribution is common knowledge, the realized value of N is observed only by the sender. Specifically, for a given $n \in \mathbb{N}$, we assume that $N = n$ with probability $\delta \in (0, 1)$ and $N = 1$ with complementary probability $1 - \delta$. This specification is not intended to be fully general, but we believe it captures the core features of a setting in which N is no longer common knowledge. We show that the comparative-static results with respect to N in Section 2.2 carry through in this variation with respect to δ and n.[7]

We begin by computing the unconditional probability that each message is sent, under the assumption that the sender plays the maximally selective strategy that consists of disclosing the highest signal available. Note that:

$$\begin{aligned}
\Pr(m = A) &= \frac{1}{2}\left[(1-\delta)\gamma + \delta(1-(1-\gamma)^n)\right] + \frac{1}{2}\left[(1-\delta)(1-\gamma) + \delta(1-\gamma^n)\right] \\
&= \frac{1}{2}\left[(1-\delta)(\gamma + 1 - \gamma) + \delta\left(2 - (1-\gamma)^n - \gamma^n\right)\right] \\
&= \frac{1}{2}\left[1 + \delta\left(1 - (1-\gamma)^n - \gamma^n\right)\right].
\end{aligned}$$

[7] As in our baseline model, we continue to assume that $\mathbb{P}(N \geq K) = 1$—that is, the receiver knows that N is at least as large as K. This is an important assumption. When it does not hold, the sender may have fewer than K signals to disclose, which introduces incentives to hide behind a veil of ignorance—a feature reminiscent of Dye (1985). In such cases, it is known that a maximally selective equilibrium may fail to exist.

Similarly,

$$\begin{aligned}
\Pr(m = B) &= \frac{1}{2}\left[(1-\delta)(1-\gamma) + \delta(1-\gamma)^n\right] + \frac{1}{2}\left[(1-\delta)\gamma + \delta\gamma^n\right] \\
&= \frac{1}{2}\left[(1-\delta)(1-\gamma+\gamma) + \delta\left((1-\gamma)^n + \gamma^n\right)\right] \\
&= \frac{1}{2}\left[1 - \delta\left(1 - (1-\gamma)^n - \gamma^n\right)\right].
\end{aligned}$$

Finally, since the sender always discloses either A or B, we have $\Pr(m = o) = 0$.

We now discuss the predictions of Remark 1. First, we note that the distribution of signals disclosed by the sender increases in a first-order stochastic sense with both δ and n. Since $K = 1$, this simply means that the probability of receiving message $m = A$ increases in both δ and n, while the probability of receiving message $m = B$ decreases in both δ and n. In other words, as δ or n increases, the message received appears more favorable, as predicted by Remark 1.1.

Next, we compute the receiver's optimal response to each message. We have:

$$\begin{aligned}
a(A) = \Pr(\theta = 1 \mid m = A) &= \frac{\Pr(\theta = 1)\Pr(m = A \mid \theta = 1)}{\Pr(m = A)} \\
&= \frac{(1-\delta)\gamma + \delta\left(1 - (1-\gamma)^n\right)}{1 + \delta\left(1 - (1-\gamma)^n - \gamma^n\right)}.
\end{aligned}$$

Similarly,

$$\begin{aligned}
a(B) = \Pr(\theta = 1 \mid m = B) &= \frac{\Pr(\theta = 1)\Pr(m = B \mid \theta = 1)}{\Pr(m = B)} \\
&= \frac{(1-\delta)(1-\gamma) + \delta(1-\gamma)^n}{1 - \delta\left(1 - (1-\gamma)^n - \gamma^n\right)}.
\end{aligned}$$

Since message $m = o$ is off-path, we assign to it the most pessimistic belief, which induces the lowest possible action, $a(o) = 0$. It can be verified that $a(A) > a(B) > a(o)$. Therefore, it is optimal for the sender to employ a maximally selective strategy, and a maximally selective equilibrium exists. This extends the result in Proposition 1 to the current setting.

Next, a direct computation of the derivative $\frac{d\,a(A)}{d\delta}$ shows that its sign is determined by the numerator:

$$\gamma(1-\gamma)^n - 2\gamma + \gamma^{n+1} - (1-\gamma)^n + 1 = 1 - 2\gamma - (1-\gamma)^{n+1},$$

which is negative for all $\gamma > \frac{1}{2}$. Therefore, $a(A)$ is decreasing in δ. Similarly, the derivative

$\frac{d\,a(B)}{d\delta}$ has numerator

$$\gamma(1-\gamma)^n - \gamma^n + \gamma^{n+1} = \gamma(1-\gamma)\left[(1-\gamma)^{n-1} - \gamma^{n-1}\right],$$

which is also negative for all $\gamma > \frac{1}{2}$. Thus, $a(B)$ is decreasing in δ. Together, these results imply that, for any n, as δ increases, the receiver becomes more skeptical of the messages received—responding with lower actions—regardless of whether A or B is observed. This is in line with the comparative statics of Remark 1.2.

Having derived the probabilities of each message and the receiver's best response, we can now compute the receiver's expected utility, which, as shown in Online Appenix E.3, is a monotone transformation of informativeness. The derivation is somewhat algebraically intensive, so we omit the intermediate steps and report the final expression directly. Letting $X \triangleq \gamma(1-\gamma)$, $W \triangleq \gamma^{n-1} + (1-\gamma)^{n-1}$, and $Z \triangleq \gamma^n + (1-\gamma)^n$, the receiver's expected utility in the maximally selective equilibrium simplifies to

$$\mathbb{E}[u_R] = -\frac{1}{2}\left(\frac{2X(1-\delta)\left[1-\delta(1-W)\right] + 2\delta^2 X^n + \delta(1-Z)\left[1-\delta(1-Z)\right]}{1-\delta^2(1-Z)^2}\right)$$

Figure E.14 plots the receiver's expected utility as a function of n for various values of δ. We highlight that the pattern mirrors the one observed in our baseline model (see Proposition 2 and Figure 1). Notably, as $n \to \infty$, the receiver's utility does not converge to the value it would attain under complete ignorance, namely -0.25 (the negative of the prior variance). This is because, in the current model, the sender's strategy remains partially informative, as $N = 1$ with probability $1-\delta$.

F Design

F.1 Graphical Interface

The figures in this section show the software interface of our main experiment, namely the one described in the main body of the paper. Figures F.15 and F.16 show the sender's screen at the time of selecting her message. Figure F.17 shows the receiver's screen at the time of making her guess. Figure F.18 shows the feedback screen.

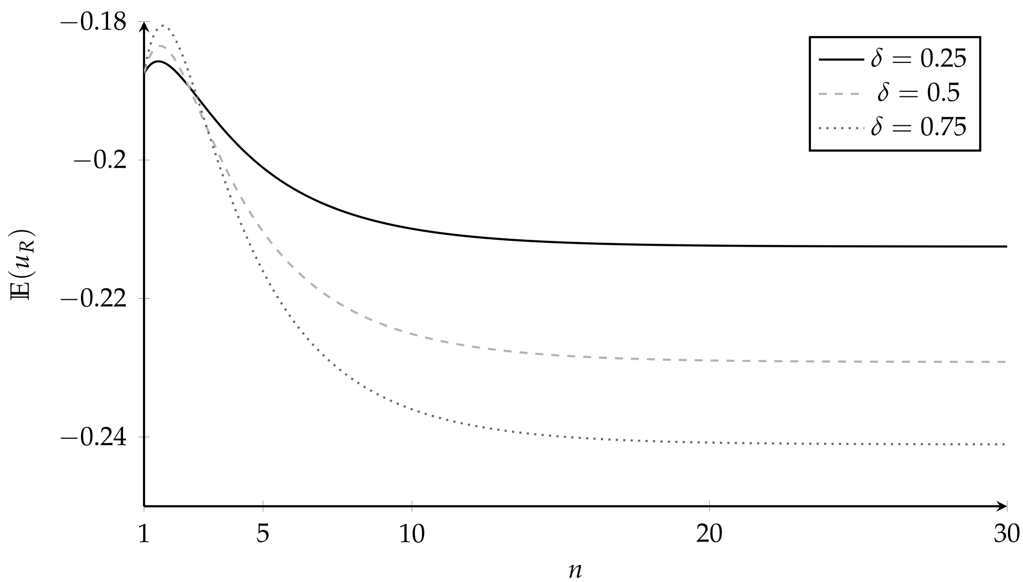


Figure E.14: Receiver's expected utility with random N. We set $\gamma = 0.75$ and let $\delta \in \{\frac{1}{4}, \frac{2}{4}, \frac{3}{4}\}$.

Figure F.15: Sender's Interface Before the Message Choice

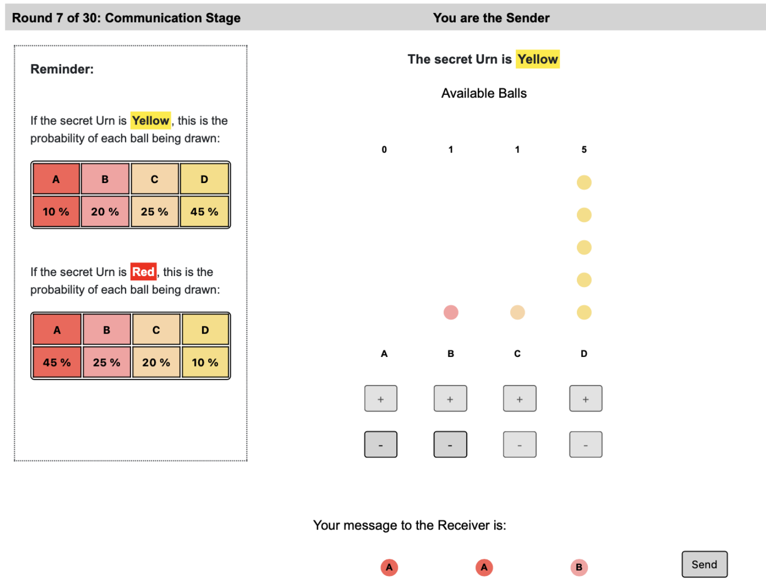


Figure F.16: Sender's Interface After the Message Choice

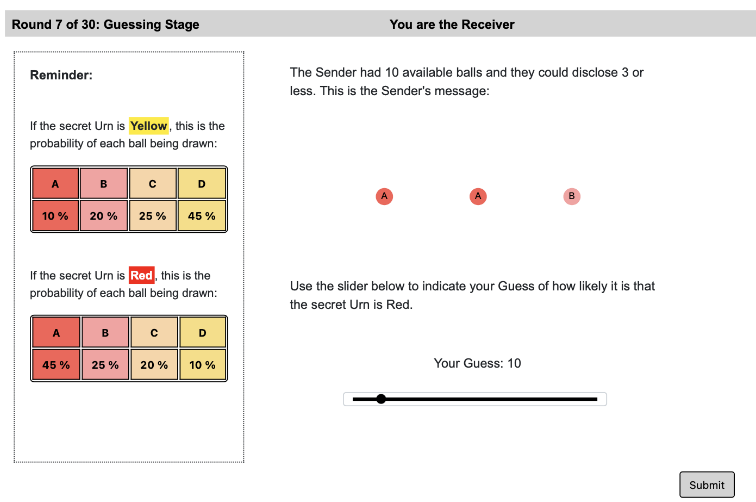


Figure F.17: Receiver's Interface

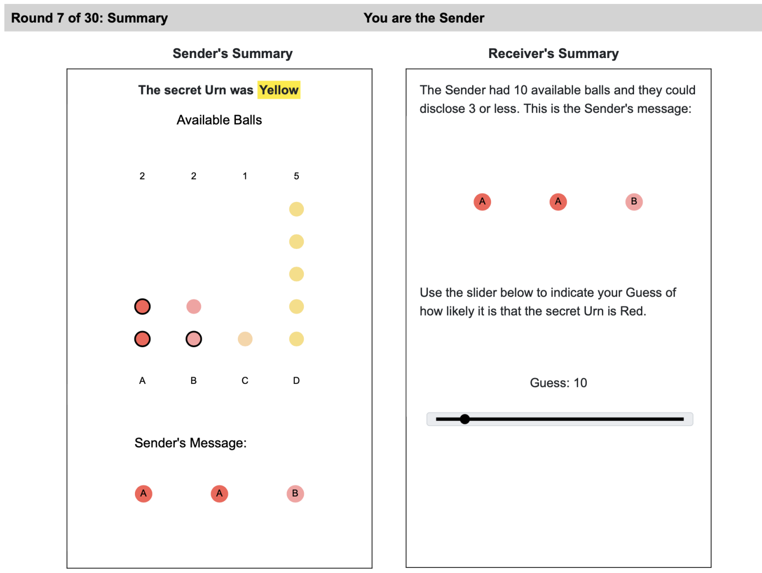


Figure F.18: Feedback Interface

F.2 Sample Instructions

We reproduce instructions for one of our treatments, (K_3, N_{10}). These instructions were read out aloud at the beginning of each session. Additionally, a copy of the instructions was handed out to the subject and it was available to them at any point during the experiment.

Welcome

You are about to participate in a session on decision-making, and you will be paid for your participation with cash vouchers (privately) at the end of the session. What you earn depends partly on your decisions, partly on the decisions of others, and partly on chance.

Please turn off phones and tablets now. Please close any program you may have open on the computer. The entire session will take place through computer terminals, and all interaction among you will take place through computers. Please do not talk or in any way try to communicate with other participants during the session.

We will start with a brief instruction period. During the instruction period you will be given a description of the main features of the session and will be shown how to use the computer interface. If you have any questions during this period, raise your hand and your question will be answered privately.

Instructions

You will play for 30 matches in either of two roles: **Sender** or **Receiver**. At the end of each round, you will be randomly paired with a new player.

There are two urns: one **Red** and one **Yellow**. Each urn contains four types of balls, labeled A, B, C, and D.

The Round

At the beginning of each round, the Computer randomly selects one of the two urns (we will refer to the selected urn as secret Urn). The secret Urn has a 50% chance of being Red and a 50% chance of being Yellow.

The Computer randomly draws 10 balls from the secret Urn. Depending on the color of the secret Urn, each ball has a chance of being drawn that is reported in the table below:

Urn	A	B	C	D
Red Urn	45%	25%	20%	10%
Yellow Urn	10%	20%	25%	45%

The 10 balls are drawn independently, meaning that the chance of drawing a ball is not affected by previous draws.

1. Communication Stage—Sender is Active

The sender observes the color of the secret Urn and sees the 10 balls that were drawn from it by the Computer.

The Sender can disclose to the Receiver up to 3 of these 10 balls. We call this the Sender's **Message**.

2. Guessing Stage—Receiver is Active

The Receiver observes the Sender's Message but does not observe the color of the secret Urn.

The Receiver must guess how likely it is that the secret Urn is Red. Specifically, the Receiver chooses a number from 0 to 100. We call this the Receiver's **Guess**.

For example, a Guess of 20 indicates that the Receiver believes there is a 20% chance that the secret Urn is Red. A Guess of 80, instead, indicates that the Receiver believes there is an 80% chance that the secret Urn is Red. More generally, a higher Guess indicates a greater chance that the secret Urn is Red.

3. Feedback

At the end of each round, both Sender and Receiver will see screens that summarize information from the Round. You will learn the color of the secret Urn; the balls that were available to the Sender; the Message sent by the Sender; the Receiver's Guess; and your payoff. You will also see a history of what happened in previous rounds.

How Payoffs Are Determined

In each round, you earn points that will be converted into cash at the end of the experiment.

Sender

The number of points the Sender earns in a round depends only on the Receiver's Guess and not on the color of the secret Urn. Specifically, the number of earned points is equal to the Receiver's Guess. Therefore, the higher the Receiver's Guess, the greater the number of points earned by the Sender.

Receiver

The number of points the Receiver earns depends on the Guess, on the color of the secret Urn, and on chance. Specifically, the number of earned points is determined as follows:

> The Computer randomly generates two numbers between 0 and 100, where each integer number is equally likely. Let's call them the *Computer's Random Numbers*.
>
> The Receiver earns 100 points if one of the following two things happens:
>
> - The secret Urn is Red and the Receiver's Guess is greater than or equal to the smallest of the two *Computer's Random Numbers*.
> - The secret Urn is Yellow and the Receiver's Guess is smaller than or equal to the largest of the two *Computer's Random Numbers*.
>
> The Receiver earns 0 points otherwise.

This compensation rule was designed so that the Receiver has the greatest chance of earning 100 points when they choose a Guess that equals their true belief that the secret Urn is Red.

Final Payments

At the end of the experiment, the total number of points you earned will be converted to dollars at the rate of:

- $0.012 per point ($1.20 per 100 points) if you are the Sender.
- $0.009 per point ($0.90 per 100 points) if you are the Receiver.

In addition, you will receive a flat participation fee of $10.

Practice Rounds:

The experiment will begin with 2 practice rounds, to make you familiar with the interface and the tasks of both Sender and Receiver. All the choices you make in the Practice Rounds are unpaid and do not affect in any way the rest of the experiment.

Summary

Before we start, let me remind you that:

- You will play 30 Rounds in the same role: Sender or Receiver. You will be assigned your role at the end of the Practice Rounds.
- The secret Urn has an equal chance of being Red or Yellow.
- The Computer randomly draws 10 balls from the secret Urn.
- The Sender can disclose to the Receiver up to 3 of these 10 balls.
- The Receiver has to guess how likely it is that the secret Urn is Red.
- The Receiver has the greatest chance of earning points when they choose a Guess that equals their true belief that the secret Urn is Red.
- The higher the Receiver's Guess, the greater the number of points earned by the Sender.
- At the end of each Round, you are randomly paired with a new participant.