The Selective Disclosure of Evidence: An Experiment

Agata Farina — Princeton University
Guillaume R. Fréchette — New York University
Alessandro Ispano — Université Paris Dauphine
Alessandro Lizzeri — Princeton University
Jacopo Perego — Columbia University

September 3, 2024

Abstract

We conduct an experimental analysis of selective disclosure in communication. In our 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 the rich comparative-statics predictions of this model, enabling a systematic test of the relative importance of evidence selection versus evidence concealment in communication. 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: A minority of senders overcommunicate relative to predictions, while some receivers partially neglect the selective nature of the evidence they observe.

This paper merges and replaces Farina et al. (2024) and Ispano (2024). We are thankful to Jonathan Glover, Navin Kartik, Yichuan Lou, Marco Ottaviani, Emanuel Vespa, Leeat Yariv, Sevgi Yuksel, and seminar participants at Bocconi University, Brown University, Columbia University, John Hopkins University, MIT, New York University, Northwestern University, Princeton University, and the University of Pittsburgh for helpful comments.

1 Introduction

This paper presents the results of 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 specific features of its product portfolio to advertise 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 evidence is a centerpiece of the economic analysis of the potential distortions caused by asymmetric information, with numerous applications to 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]

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

[1] Prat and Strömberg (2013) and Gentzkow et al. (2015) argue that selective disclosure is in practice one of the principal sources of media slant, which they refer to as "filtering" or "fact bias." Koehler and Mercer (2009) illustrate how mutual-fund companies selectively advertise 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.

sender's ability to *select* which evidence to disclose. This shift in focus may lead 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, while 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 concealment and selection of evidence shapes the strategic interaction between the sender and the receiver in our setting. Notably, their relative importance changes as we vary N and K. When $K = N$, evidence can only be concealed, not selected, which makes it similar to a classic disclosure setting. Conversely, when N is large relative to K, selection is likely to be the dominant distortion: The sender can disclose highly favorable evidence regardless of the state, which is reminiscent of a cheap-talk setting. Thus, by varying K and N, our model accommodates forces typical of two opposite communication paradigms: verifiable disclosure (e.g., Milgrom, 1981; Grossman, 1981) at one extreme and cheap talk (e.g., Crawford and Sobel, 1982) at the other. These extremes have been analyzed separately in the experimental literature, leading to contrasting findings that, as explained below, our hybrid setting can help reconcile.

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 both the sender and the 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, the informativeness should increase in K. Instead, holding K constant, the 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.

We begin the data analysis by documenting several 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, i.e., 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.

Next, we document the main quantitative deviations in senders' behavior. First, when $N = K$, we observe concealment of evidence, consistent with prior disclosure experiments. When $N > K$, however, senders rarely conceal evidence: In these cases, concealment is no longer the dominant distortion, as senders predominantly use selection to influence the receiver's behavior. Second, we find that senders' strategies are more informative than predicted—i.e., senders overcommunicate—especially when N is large. This is in contrast with 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 hybrid framework helps reconcile these seemingly divergent findings.[4] Overall, the fact that senders rarely conceal evidence and often overcommunicate suggests that, in settings with ample opportunities for selection, mandating disclosure may be ineffective or even harmful for receivers.

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 persis-

[4]Models studied in the experimental literature on disclosure typically predict full information transmission (i.e., unraveling), making it impossible to observe overcommunication (see de Clippel and Rozen (2024) for an exception). In contrast, models studied in the experimental literature on cheap talk do not typically predict full information transmission.

tently 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.

Finally, we analyze receivers' behavior. Consistent with the qualitative predictions of the theory, we find that receivers partially account for the fact that the evidence they see may be selected. Specifically, conditional on the received message, they become more skeptical (i.e., their guess decreases) as N grows relative to K. However, the magnitude of these treatment effects is smaller than predicted: In all treatments, receivers tend to be overly optimistic—namely, their guesses are suboptimally high. Additionally, their mistakes are greater in treatments with large N, i.e., those in which selection is predominant. In other words, receivers' behavior displays some degree of *selection neglect*: Receivers do not entirely account for the impact of selection, leading them to insufficiently discount favorable evidence in settings with large N. Selection neglect has been widely documented in the realm of decision problems.[5] Our findings highlight the significance of this bias in a strategic setting, where selection arises endogenously from the desire of the sender to manipulate the receiver's behavior.[6]

1.1 Related Literature

The basic structure of our model can be traced back to Milgrom (1981). He shows that, for any N and K, when the signal distribution is atomless, there exists a maximally selective equilibrium, i.e., one in which the sender discloses the K highest signals. An important, albeit technical, difference from Milgrom's model is that we assume signals to be discrete. This modeling choice simplifies the experimental design for the subjects but complicates the analysis, requiring a novel existence proof. In the simplest 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. We extend their results to settings with arbitrary K and non-binary signals. Di Tillio

[5] For instance, see Esponda and Vespa (2018), Enke (2020), Araujo et al. (2021), Barron et al. (2024).

[6] A priori, it is not obvious how selection neglect would transfer to a strategic setting. On the one hand, the presence of strategic uncertainty could exacerbate the bias by making the inference problem more difficult for the receiver. On the other hand, it could reduce the bias by making the selection forces more salient for the receiver, as they stem from a sender with clearly conflicting preferences.

et al. (2021) also allow for arbitrary K but, as in Milgrom (1981), 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.[7]

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, i.e., 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.[8] In stark contrast, the experimental literature on cheap talk typically finds that senders overcommunicate relative to the predictions and that receivers are overly trusting.[9] Cai and Wang (2006) ascribe this deviation to lying aversion. As discussed above, our hybrid setting helps us reconcile the apparent puzzle between over and undercommunication.

The 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 instead 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.

[7] 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.

[8] 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.

[9] 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).

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, 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 $k \leq K$ signals disclosed by the sender are placed at the beginning of m in decreasing order, whereas the remaining $K - k$ positions, representing the undisclosed signals, are filled with o. 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 $\bar{s} \in S^N$.[10] After 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 can disclose only a limited amount of noisy evidence. No message can verifiably reveal the payoff-relevant state θ. More-

[10] 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, her message is $m = (s_1, \ldots, s_k, o, \ldots, o)$, the first k components of which appear in $\bar{s}$ and are ordered in a decreasing way.

over, when $K < N$, no message can verifiably reveal $\bar{s}$. 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.[11] As a consequence, equilibria in our setting 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. We will exploit these variations in our experiment.

In the model, N and K are exogenous. Although, in some settings, the players may be able to influence N and K, our modeling choice is intended to focus our experimental analysis on the selection of evidence, abstracting from distinct aspects of the problem, such as the production of evidence or the costs of disclosure. Note that when $K < N$, the sender faces a communication constraint. This could be due, for instance, to limits on the number of columns a newspaper has available for a given topic, or the airtime for a TV show, or the amount of news the audience can assimilate in a given time span.

2.2 Equilibrium Predictions

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. More 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 $i \in \{1, \ldots, K\}$, $m_i \geq m'_i$. 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 $m \in \operatorname{supp}(\sigma_S(\cdot|\theta, \bar{s}))$ is a maximal element of $M(\bar{s})$ for each $(\theta, \bar{s}) \in \Theta \times S^N$.

Proposition 1. *(Existence) For all N and K, there exists a perfect Bayesian equilibrium in which the sender's strategy is maximally selective.*[12]

We focus on maximally selective equilibria for two reasons. First, this equilibrium has been

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

[12] This result extends (Milgrom, 1981, Proposition 7) to the case of a discrete set of signals S. Our modeling choice—which is meant to simplify the experimental design—complicates the analysis and requires a different, combinatorial proof. Fishman and Hagerty (1990) do not face these complications as they assume S is binary and $K = 1$.

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 more favorable messages.[13]

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.

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

1. Sender's Behavior. *The distribution of signals disclosed by the sender increases in a first-order stochastic sense with N and decreases with K. Moreover, the number of disclosed signals increases with K and is independent of N.*

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 sender's behavior, the model makes predictions on the *quantity* of signals disclosed by the sender—which should increase in K—as well as on their *quality*: better (i.e., higher) signals are disclosed when N is higher while worse signals are disclosed when K is higher. Intuitively, when N is larger, the sender can be more selective, resulting in messages that appear more favorable. 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. Regarding receivers' behavior, the model predicts that, fixing any message m, the receiver should become more skeptical as N increases. 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

[13]Specifically, in an evidence-monotone PBE, if $m' \geq m$, the receiver's action following message m' is higher than that following message m. See Appendix A for details. A feature of this refinement is that it is easily testable in the data: 95% of the time across all our treatments, a receiver' action following message m' is indeed higher than that following message m.

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:*

1. *Fixing N, $\mathcal{I}(K, N)$ increases in K.*
2. *Fixing $K = N$, $\mathcal{I}(K, N)$ increases in N.*
3. *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 briefly discuss the intuition for these results. First, we fix N and increase K, thereby relaxing the communication constraint on the sender. In this case, it is more likely that, for a given θ, the sender can send messages that lower-state senders cannot imitate, allowing for more separation. This implies that more information is transmitted in equilibrium, leaving the receiver less uncertain about the state. Second, we let $K = N$ and consider the effects of increasing N when all the available evidence can be disclosed. In this case, the sender discloses all the signals in a nonselective manner. Thus, as N increases, the receiver observes more i.i.d. signal realizations, which increases equilibrium informativeness. Third, holding N constant, as N approaches infinity the full support assumption on f implies that, for all θ, the sender can disclose the most favorable message with probability approaching one. This implies that there is no separation among different θ's in equilibrium and, consequently, no possibility for the receiver to learn.

The nonmonotonicity in the last bullet of Proposition 2 stems from a balance between two forces, which we explore in our experiment. On the one hand, an increase in N increases the probability that a low-state sender can disclose more favorable signals, since now she can afford to be more selective. This leads to more pooling and, thus, contributes to lower informativeness. On the other hand, a higher N also increases the probability that a high-state sender can disclose more favorable signals. This allows such a sender to separate herself from the low-state counterpart, contributing to higher informativeness.[15]

[14] This measure is a monotone transformation of the receiver's ex-ante expected payoff (see Online Appendix D).

[15] Online Appendix E presents a simple example with a binary state and signals that isolates these two contrasting forces, providing intuition as to why equilibrium informativeness need not be monotone in N. In general, which force prevails depends on the relative rate at which the above-mentioned probabilities increase in N, for each state. Characterizing these effects is demanding and beyond the scope of this paper See Fishman and Hagerty (1990) for the case where $K = 1$ and the state and signals are binary.

	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%

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

3 Experimental Design

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

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 G 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 differ in the values of K and N, with four sessions

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})

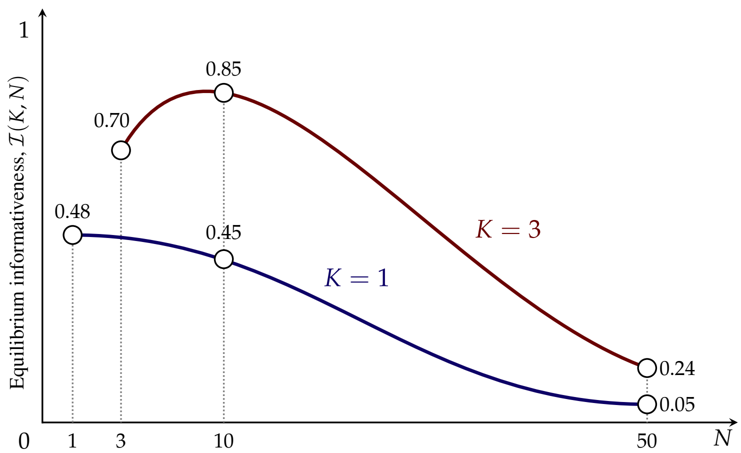


Figure 1: Predicted informativeness for the six treatments

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. An average of 17.25 subjects participated in each session, ranging from a minimum of 12 to a maximum 24. In total, 414 subjects participated in our experiment, with each participating 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 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 includes a \$10 show-up fee. Subjects accumulate 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

[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).

conversion rates aimed at minimizing 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 outlined in Wilson and Vespa (2018) (see also Danz et al. (2022)).

Discrete Signals and Observable States. Two design choices are worth emphasizing. First, our experiment features discrete signals. This allows for a design that does not require specifying probability densities. The choice of four possible signal realizations keeps the sender's problem nontrivial, as a potentially rich set of deviations from equilibrium can occur. Second, the sender observes the state θ. This enables a clearer comparison between treatments as we increase N: Potential differences in senders' behavior must originate from their greater ability to select (i.e., the focus of this study), rather than from having more information about the state. Incidentally, the discreteness of the signal space and the observability of the state are the two main theoretical differences relative to Milgrom (1981) and Di Tillio et al. (2021), requiring a new existence proof.

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 session. 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.,

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

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 from the behavior of agents who plays the equilibrium strategies but taking into account the finite sample of realized signals $\bar{s}$ from the sessions. This ensures better comparability with the data.

Robustness to an Alternative Design. Online Appendix H presents the results from an alternative design that is complementary to the one just described. This alternative design considers a setting with a nonbinary state and a binary signal, instead of a binary state and a nonbinary signal. Additionally, beliefs are elicited in a different manner. There are three between-subject treatments, varying K and N, each with 5 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.[18]

4 Results

We organize our results into 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), focusing in particular on the extent to which they account for selection (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

[18]This alternative design originally appeared in Ispano (2024). As mentioned in our acknowledgments, the two projects have now been merged.

Table 3: The average number of signals disclosed. Notice that 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 parenthesis.

	$N = K$	$N = 10$	$N = 50$
$K = 1$	0.66	1	1
	$[0.78, 1]$	$[1, 1]$	$[1, 1]$
$K = 3$	1.89	2.85	2.92
	$[2.19, 3]$	$[2.98, 3]$	$[3, 3]$

number of disclosed signals 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 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. In these cases, mandating disclosure would likely be ineffective.

The first-order questions should then concern *which* evidence senders select to disclose and how informative it is. We will address these questions in this and the next subsections. We begin by showing that several qualitative patterns in the data are consistent with Remark 1 and, therefore, senders for the most part select to disclose the most favorable evidence available. This result predicts that, holding K constant, senders should disclose increasingly higher signals as N increases, since they can cherrypick their signals more effectively. Conversely, holding N constant, senders should disclose increasingly lower signals as K increases. This is because equilibrium forces compel senders to disclose more evidence, which requires 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.[19]

[19]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

Table 4: MGPA induced by senders' messages. Predicted values in parenthesis. For reference, a senders disclosing K signals at random who generate a MGPA of 2.50 in all treatments.

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

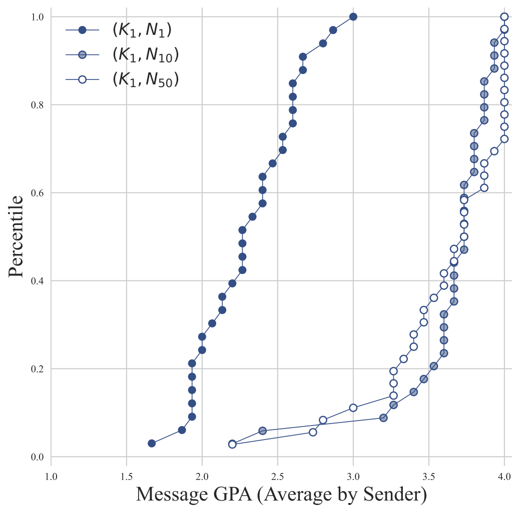
Table 4 reports the mean GPA (MGPA) computed at the treatment level. As predicted, holding K constant, we observe sizable increases in MGPA when N rises; conversely, holding N constant, the MGPA decreases as K increases. The same patterns hold when we look at sender-level data, as opposed to treatment averages. Figure 2 reports the cumulative distribution function (CDF) of sender-level MGPAs. We document a large first-order stochastic dominance (FOSD) increase in the CDF of sender-level MGPAs when N increases from $N = K$ to $N > K$ (p-value < 0.01).[20] 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 $N = 50$).

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). Additionally, the distributions reveal that senders' behavior is more heterogeneous than predicted.[21] We

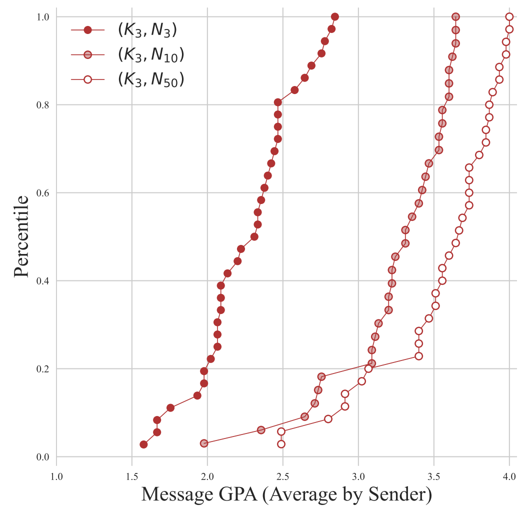
2.67. The results we present in this section are robust to other conventions: For example, coding a missing signal as a 2.5 (i.e., the expected grade given prior belief) or as a 0 (i.e., a grade strictly lower than D). Additionally, our results also hold if we do not use summary measures such as the GPA: Appendix F.2 reports the entire distribution of disclosed signals and how it changes in K and N.

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

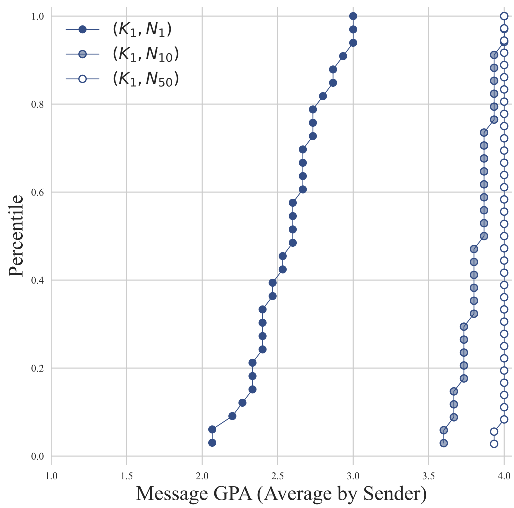
[21] Note that the predictions in the bottom panels of Figure 2 display some heterogeneity. This is due to the randomness of $\bar{s}$, the vector of signals available to each sender. Given any finite sample, two senders playing the



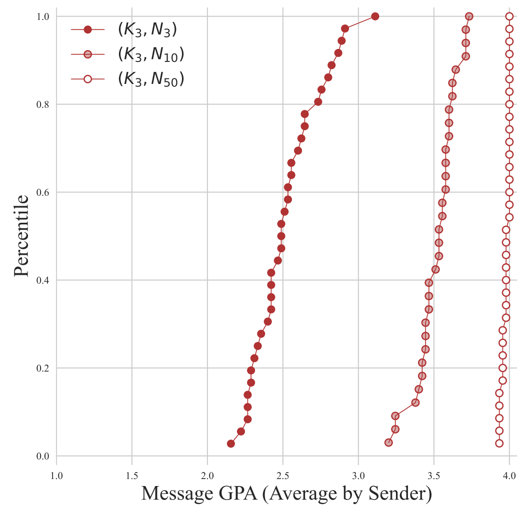
(a) $K = 1$, Data



(b) $K = 3$, Data



(c) $K = 1$, Predictions



(d) $K = 3$, Predictions

Figure 2: CDFs of Senders' Message GPAs: Data and Predictions

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

---

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 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.[22]

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, instead, is only weakly significant (p-value of the one-sided test < 0.10).

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, instead, 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, there is a notable quantitative deviation: Senders often *overcommunicate*, i.e., their informativeness is higher than predicted, especially for large N. This contrasts with prior results in the literature on disclosure—both from the laboratory and the field—that find

[22]The statistical tests reported in this subsection are performed by computing correlations at the sender's level and by clustering at the session level. We confirmed the robustness of these results by using an alternative bootstrapping procedure: For each treatment, we generate 1000 random subsamples, compute the senders' correlations in each of them, and use standard t-tests to compare the bootstrapped samples of correlations.

[23]The minor discrepancies between the predictions in Table 5 and those in Figure 1 stem from the fact that the former are calculated by imposing equilibrium behavior on the finite samples observed in the experiment (i.e., the θ's and the $\bar{s}$'s). This ensures a better comparability with the actual data.

Table 5: Senders' informativeness $\mathcal{I}^B(K, N)$ and predicted values.[23]

		$N = K$	$N = 10$	$N = 50$
$K = 1$	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

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 from 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. 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, over 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 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. These challenges both complicate the inference of the sender's strategy from the observed data and the comparisons

[24] de Clippel and Rozen (2024) also features partial information transmission, though their model differs from ours in both structure and goals. While their focus is not on informativeness, their findings do suggest instances of overcommunication by senders.

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

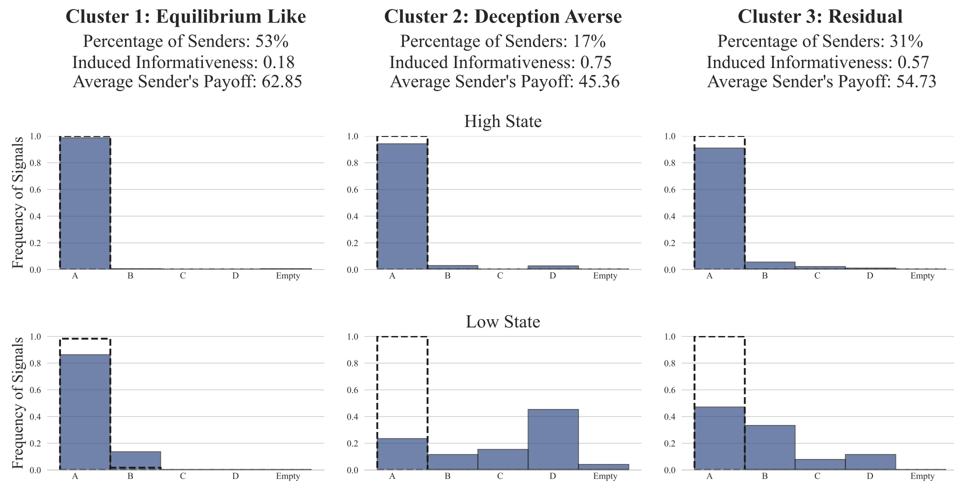


Figure 3: Sender's Clustering for Treatment (K_1, N_{50}). Equilibrium values shown as dashed bars.

across treatments.

To address these challenges, we introduce the GPA *gap*: This is the difference between the GPA of the message sent by the sender and the GPA of the equilibrium message, given the realized $\bar{s}$. For each sender, we calculate the conditional average gap, a two-dimensional vector that features the average gap conditional on each state (high or low). Then, using a k-means algorithm, we cluster the senders' conditional average gaps. 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, these measures are only partially affected by the randomness of the available signals because the conditional average gap 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.

We cluster senders' strategies into three groups. We interpret the clusters as representing different styles of play. For each cluster, we compute the average frequency with which each signal is sent conditional on the state. These averages represent the typical strategy played in this cluster. For each cluster, we also compute the average senders' informativeness as well as the corresponding senders' average payoff. Overall, this provides a comprehensive overview of senders' behavior: what strategies they play, how informative they are, and how much money they make.

Figures 3 and 4 report the outcome of our clustering analysis for treatment (K_1, N_{50}) and (K_3, N_{50}), respectively. The patterns emerging from these two treatments are broadly representative of what we find in the other treatments (see Online Appendix F.2). Our emphasis on large-N treatments is motivated by the fact that the deviations documented so far manifest

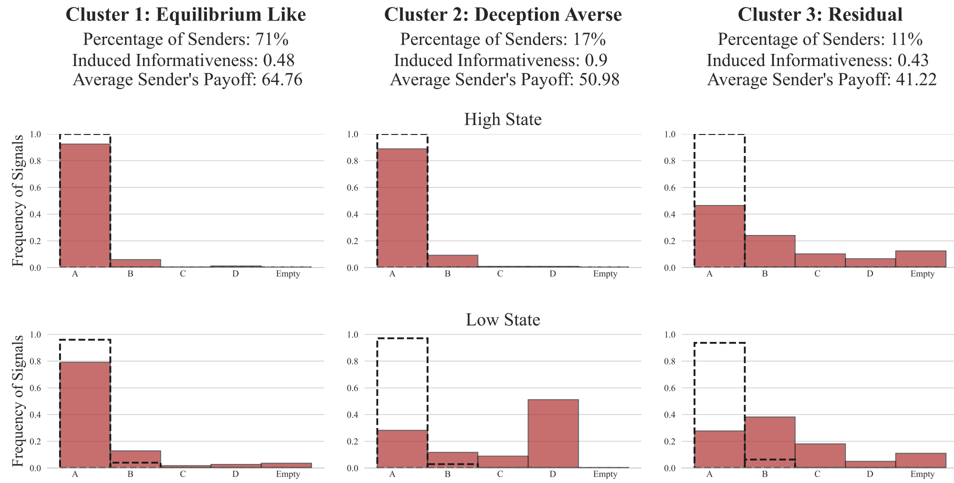


Figure 4: Sender's Clustering for Treatment (K_3, N_{50}). Equilibrium values shown as dashed bars.

more starkly for these treatments.

In both treatments, the majority of senders belong to Cluster #1. Senders in this cluster display behavior that is highly consistent with equilibrium: They overwhelmingly disclose the best available signals in both states. These senders earn the highest payoff and induce an informativeness that is closest to equilibrium.

Cluster 2 in our clustering analysis reveals one type of nonequilibrium play that appears in all treatments. Senders in this cluster—approximately 17% of the sender population—display behavior that we interpret as *deception-averse*: In the high state, they disclose the best available signal, as prescribed by the equilibrium; However, in the low state, they consistently fail to do so and, in fact, disclose the worst signal most of the time. Deception-averse senders induce the highest informativeness, as their behavior strongly correlates with the state. Thus, this cluster of senders contribute to the overcommunication documented in the previous section. Furthermore, they earn a payoff that is 22% to 27% lower than the amount earned by senders in the equilibrium-like cluster. These qualitative patterns hold in the other treatments as well (see Online Appendix F.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.[26] Our deception-averse senders appear reluctant to disclose evidence that might mislead receivers into believing the state is high when it is not. One noteworthy aspect of these senders' behavior

[26] 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.

is that, when the state is low, they do not exclusively disclose D-signals—despite this being feasible and, arguably, the most effective way to help receivers guess the state. Instead, on average, senders in this cluster disclose D-signals only 40% to 50% of the time. Although it is clear that the behavior of these senders leads to more information transmission, and is thus less deceptive, the reason they do not always send the worst possible message is less clear. Perhaps, they trade off their aversion to deception with a lower payoff. Their behavior could stem from a reluctance to be "excessively" deceptive (i.e., sending B's and C's instead of A's), a counterpart in a disclosure setting of the findings by Gneezy et al. (2018). Alternatively, this behavior could be the result of *unselective* disclosure: Deception-averse senders may want to disclose a representative sample of K signals drawn from $\bar{s}$. This would result in disclosing D-signals about 45% of the time (see Table 1).

Deception-averse senders represent a key difference 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. This observation may help clarify an apparent puzzle in the literature: Experiments on cheap talk often find overcommunication whereas those on disclosure often find undercommunication. In our experiment, deception-averse behavior (which increases informativeness) counterbalances the more classic finding that some senders conceal evidence (which lowers informativeness). In previous disclosure experiments, this balancing is impossible. It is instead possible in cheap talk experiments, due to lying aversion. Our hybrid setting accommodates both types of behavior, suggesting that when N is large, concealment practically disappears, and selection effects dominate.[27]

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 that the theory effectively captures the key tensions in how selective disclosure shapes senders' communication. We also documented two main departures from the theory. First, 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 com-

[27]We consider Cluster #3 as a residual of the k-means clustering algorithm, capturing behavior that varies across treatments. In some cases, like Figure 3, it reflects behavior between equilibrium and deception aversion. In others, like Figure 4, it is small and harder to interpret, possibly indicating confusion.

municate 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. This is because receivers should understand that senders become 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 between these treatments shows a similar qualitative pattern: 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 $K = 3$.[28] The dummy coefficients capture how much the receivers' guess decreases 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 $K = 3$, 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 coeffi-

[28] We report the OLS 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). Appendix F.3.1 shows the nonparametric estimates of receiver's 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)	(2.48)	(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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

cients 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.[29] 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 is 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 increase K, 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' guess should increase in K controlling for messages with the same GPA. To test this prediction, we estimate

[29]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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

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 the fact that the evidence they observe is differentially selected across the treatments. Quantitatively, however, they do not fully account for this selection. The next subsection explores why.

4.2.2 The Failure to Fully Account for Selection

To better understand how receivers deviate from the theory, we compute the *response gap*, which is the difference between a receiver's guess and the empirical optimal guess. A positive response gap indicates that the receiver has overestimated the state, while a negative gap indicates underestimation.

Table 8a reports the average response gap by treatment. Two patterns stand out. First, re-

Table 8: Receivers' Response Gaps

(a) Average Response Gaps by Treatment

	$K = 1$	$K = 3$
$N = K$	6.63	5.24
$N = 10$	11.73	5.25
$N = 50$	10.04	12.09

(b) OLS on Response Gaps

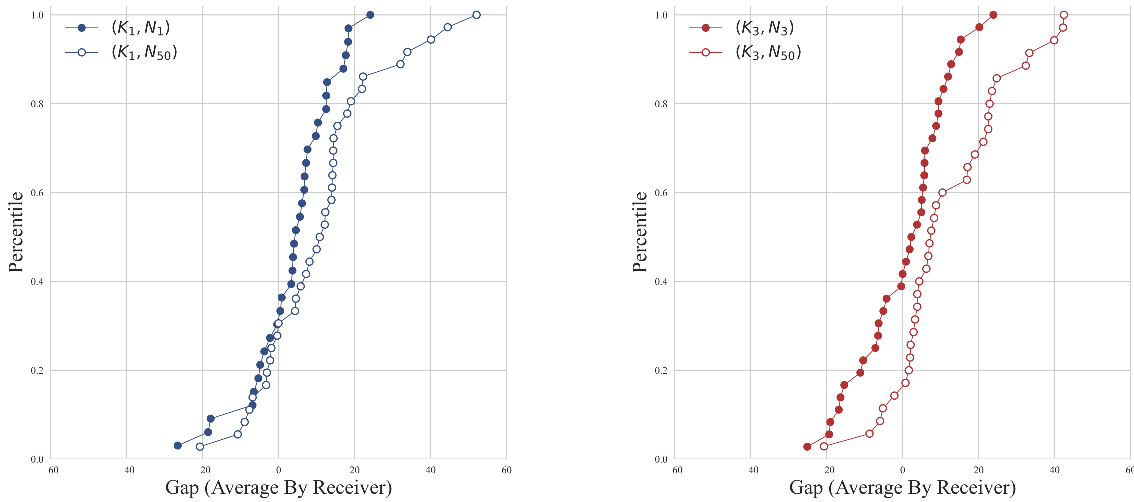
	$K = 1$	$K = 3$
	Gap	Gap
GPA	-4.13^{***}	-6.33^{***}
	(1.34)	(1.20)
$D_{N_{10}}$	10.56^{***}	6.18^{***}
	(2.47)	(2.15)
$D_{N_{50}}$	8.81^{***}	14.92^{***}
	(2.65)	(2.17)
Constant	16.18^{***}	19.57^{***}
	(2.94)	(2.84)
Obs	$1,545$	$1,560$
Subjects	103	104

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

sponse gaps are significantly positive across all treatments (p-value < 0.01, except for (K_3, N_{10}), whose p-value is 0.09). This finding aligns with previous experimental results that show receivers are often overly optimistic (e.g., Cai and Wang, 2006; Jin et al., 2021). Considering the complexity of the receiver's task, the magnitudes of these gaps appear small, although they conceal substantial heterogeneity. Second, response gaps increase with N, indicating greater overoptimism with larger N. This may seem counterintuitive, as the receiver's task arguably becomes simpler as N grows: For instance, in treatment (K_1, N_{50}), receivers observe the same message ($m = A$) about 75% of the time, and are provided with detailed feedback at the end of each round. This should facilitate learning and, thus, reduce the response gap relative to treatments such as (K_1, N_1), where, for example, $m = A$ is observed only 25% of the time.

To investigate the statistical significance of this unpredicted treatment effect, we regress the response gap on the same covariates used in Equation 1.[30] Table 8b reports the estimated

[30]Controlling for GPA is important 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.



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

Figure 5: CDF of Receivers' Response Gaps

coefficients. We find that, for both values of K, the increase in the response gap as we move from low to high values of N is significant (p-value < 0.01). The same patterns hold when we look at receiver-level effects, as opposed to average effects. Figure 5 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.

We interpret these results as follows. Receivers' behavior shows some degree of *selection neglect*: Receivers do not entirely account for the impact of selection, leading them to insufficiently discount favorable evidence in settings with large N. Perhaps surprisingly, this bias persists despite ample learning opportunities for receivers in our treatments. Recall, indeed, that our analysis focuses on the last 15 rounds of each session, and the fact that receivers are provided with detailed feedback at the end of each round. Selection neglect has been extensively studied in decision-making contexts (e.g., Esponda and Vespa, 2018; Enke, 2020; Araujo et al., 2021; Barron et al., 2024). Our findings highlight its significance in a strategic setting where selection arises endogenously from the desire of the sender to manipulate the receiver's behavior. A priori, it is not clear how selection neglect would transfer to a strategic setting. On one hand, strategic uncertainty could amplify the bias by complicating the receiver's inference process. On the other hand, it might mitigate the bias by making the selection pressures more apparent to the receiver, given that they originate from a sender with a clearly conflicting objective.

Table 9: 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, $\mathcal{I}^B(K, N)$: This is the correlation between the realized state and the empirical optimal guess and it 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 9 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 9. 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 $N = 50$. Accordingly, the data shows a large increase for $N = 10$ (p-value < 0.01) and a statistically-insignificant treatment effect 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 directionally 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 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 identified deviations from the theory: A form of deception aversion causes some senders to overcommunicate, while receivers tend to partially neglect the selective nature of the disclosed evidence.

Deception aversion is reminiscent of lying aversion, a well-documented phenomenon in cheap-talk experiments that improves information transmission in those experiments. Nonetheless, making information verifiable leads to even more transmission, even if the increase is less than predicted in theory. Hence, to this point, the available empirical evidence suggests that policy could resolve issues of information transmission in the presence of misaligned preferences by making information verifiable and imposing disclosure mandates. What our theory and experiment highlight is that this may not be sufficient.

Indeed, we have argued that when selection is the main distortion in communication, disclosure mandates—the typical policy response to excessive concealment of evidence—are ineffective. To address this issue, an effective policy must target the root of selection, which stems from the disparity between the amount of available evidence (N) and the communication capacity of the environment (K). Although increasing the communication capacity is always beneficial, as illustrated by our experiment, this approach may be costly or impractical. An alternative that may warrant further experimental investigation is the role of measures that aggregate the available evidence, such as summary ratings or other sufficient statistics. If these measures could be made verifiable and easily interpretable by receivers, they would ameliorate the problems created by selection. For instance, the "Nutrition Facts" labels mandated by the FDA summarize detailed nutritional data into key, easily interpretable statistics. Digital platforms that rely on user-generated reviews often summarize a large set of past experiences into key statistics, such as the average rating. Effective regulation and business strategies must focus on designing mechanisms that minimize the potential for senders to bias the information consumers receive through selective disclosure. It seems valuable to investigate whether summary measures can be effective on their own, whether they would coexist with direct evidence disclosure, and how these different forms of evidence disclosure might interact.

References

Abeler, J., D. Nosenzo, and C. Raymond (2019): "Preferences for Truth-Telling," *Econometrica*, 87, 1115–1153.

Allen, F. (1987): "Discovering personal probabilities when utility functions are unknown," *Management Science*, 33, 542–544.

Araujo, F. A., S. W. Wang, and A. J. Wilson (2021): "The Times They Are A-Changing: Experimenting with Dynamic Adverse Selection," *American Economic Journal: Microeconomics*, 13, 1–22.

Barrett, G. F. and S. G. Donald (2003): "Consistent tests for stochastic dominance," *Econometrica*, 71, 71–104.

Barron, K., S. Huck, and P. Jehiel (2024): "Everyday Econometricians: Selection Neglect and Overoptimism When Learning from Others," *American Economic Journal: Microeconomics*, 16, 162–98.

Benndorf, V., D. Kübler, and H.-T. Normann (2015): "Privacy concerns, voluntary disclosure of information, and unraveling: An experiment," *European Economic Review*, 75, 43–59.

Bertomeu, J., P. Ma, and I. Marinovic (2020): "How Often Do Managers Withhold Information?" *The Accounting Review*, 95, 73–102.

Beyer, A., D. A. Cohen, T. Z. Lys, and B. R. Walther (2010): "The financial reporting environment: Review of the recent literature," *Journal of Accounting and Economics*, 50, 296–343.

Blume, A., D. V. DeJong, Y.-G. Kim, and G. B. Sprinkle (1998): "Experimental evidence on the evolution of meaning of messages in sender-receiver games," *The American Economic Review*, 88, 1323–1340.

——— (2001): "Evolution of Communication with Partial Common Interest," *Games and Economic Behavior*, 37, 79–120.

Blume, A., E. K. Lai, and W. Lim (2020): "Strategic information transmission: A survey of experiments and theoretical foundations," *Handbook of experimental game theory*, 311–347.

Bock, O., I. Baetge, and A. Nicklisch (2014): "hroot: Hamburg registration and organization online tool," *European Economic Review*, 71, 117–120.

Brier, G. W. (1950): "Verification of forecasts expressed in terms of probability," *Monthly weather review*, 78, 1–3.

Brown, A. L. and D. E. Fragiadakis (2019): "Benign vs. Self-Serving Information Reduction: Do Individuals Understand the Difference?" *Working Paper*.

Burdea, V., M. Montero, and M. Sefton (2023): "Communication with partially verifiable information: an experiment," *Games and Economic Behavior*, 142, 113–149.

Cai, H. and J. T.-Y. Wang (2006): "Overcommunication in strategic information transmission games," *Games and Economic Behavior*, 56, 7–36.

Chen, D. L., M. Schonger, and C. Wickens (2016): "oTree—An open-source platform for laboratory, online, and field experiments," *Journal of Behavioral and Experimental Finance*, 9, 88–97.

Crawford, V. P. and J. Sobel (1982): "Strategic information transmission," *Econometrica: Journal of the Econometric Society*, 1431–1451.

Danz, D., L. Vesterlund, and A. J. Wilson (2022): "Belief elicitation and behavioral incentive compatibility," *American Economic Review*, 112, 2851–2883.

de Clippel, G. and K. Rozen (2024): "Communication, perception, and strategic obfuscation," Tech. rep., Working Paper.

Degan, A., M. Li, and H. Xie (2023): "An experimental investigation of persuasion through selective disclosure of evidence," *Canadian Journal of Economics/Revue canadienne d'économique*, 56, 1490–1516.

Deversi, M., A. Ispano, and P. Schwardmann (2021): "Spin doctors: An experiment on vague disclosure," *European Economic Review*, 139, 103872.

Di Tillio, A., M. Ottaviani, and P. N. Sørensen (2021): "Strategic sample selection," *Econometrica*, 89, 911–953.

Dickhaut, J., M. Ledyard, A. Mukherji, and H. Sapra (2003): "Information management and valuation: an experimental investigation," *Games and Economic Behavior*, 44, 26–53.

Dickhaut, J. W., K. A. McCabe, and A. Mukherji (1995): "An experimental study of strategic information transmission," *Economic Theory*, 6, 389–403.

Dranove, D. and G. Z. Jin (2010): "Quality disclosure and certification: Theory and practice," *Journal of economic literature*, 48, 935–963.

Dye, R. A. (1985): "Disclosure of nonproprietary information," *Journal of accounting research*, 123–145.

Dziuda, W. (2011): "Strategic argumentation," *Journal of Economic Theory*, 146, 1362–1397.

Embrey, M., G. R. Fréchette, and S. Yuksel (2018): "Cooperation in the finitely repeated prisoner's dilemma," *The Quarterly Journal of Economics*, 133, 509–551.

Enke, B. (2020): "What you see is all there is," *The Quarterly Journal of Economics*, 135, 1363–1398.

Esponda, I. and E. Vespa (2018): "Endogenous sample selection: A laboratory study," *Quantitative Economics*, 9, 183–216.

Farina, A., G. R. Fréchette, A. Lizzeri, and J. Perego (2024): "The Selective Disclosure of Evidence: An Experiment," *SSRN Working Paper*, 4870035.

Farina, A. and M. Leccese (2024): "Hiding a Flaw: A Lab Experiment on Multi-Dimensional Information Disclosure," *Available at SSRN 4785923*.

Fishman, M. J. and K. M. Hagerty (1990): "The optimal amount of discretion to allow in disclosure," *The Quarterly Journal of Economics*, 105, 427–444.

Forsythe, R., R. M. Isaac, and T. R. Palfrey (1989): "Theories and tests of" blind bidding" in sealed-bid auctions," *The Rand Journal of Economics*, 214–238.

Forsythe, R., R. Lundholm, and T. Rietz (1999): "Cheap talk, fraud, and adverse selection in financial markets: Some experimental evidence," *The Review of Financial Studies*, 12, 481–518.

Fréchette, G. R. (2012): "Session-effects in the laboratory," *Experimental Economics*, 15, 485–498.

Fréchette, G. R., A. Lizzeri, and J. Perego (2022): "Rules and commitment in communication: An experimental analysis," *Econometrica*, 90, 2283–2318.

Fréchette, G. R., E. Vespa, and S. Yuksel (2024): "Repeated Games," *Working Paper*.

Gao, Y. (2024): "Inference from Selectively Disclosed Data," *Working Paper*.

Gentzkow, M., J. M. Shapiro, and D. F. Stone (2015): "Media bias in the marketplace: Theory," in *Handbook of media economics*, Elsevier, vol. 1, 623–645.

Glazer, J. and A. Rubinstein (2004): "On optimal rules of persuasion," *Econometrica*, 72, 1715–1736.

——— (2006): "A game theoretic approach to the pragmatics of debate: An expository note," in *Game Theory and Pragmatics*, Springer, 248–262.

Gneezy, U., A. Kajackaite, and J. Sobel (2018): "Lying Aversion and the Size of the Lie," *American Economic Review*, 108, 419–53.

Greiner, B. (2015): "Subject pool recruitment procedures: organizing experiments with ORSEE," *Journal of the Economic Science Association*, 1, 114–125.

Grossman, S. J. (1981): "The informational role of warranties and private disclosure about product quality," *The Journal of Law and Economics*, 24, 461–483.

Hagenbach, J. and E. Perez-Richet (2018): "Communication with Evidence in the Lab," *Games and Economic Behavior*, 112, 139–165.

HAGENBACH, J. AND C. SAUCET (2024): "Motivated Skepticism," *Review of Economic Studies*, rdae058.

HAGHTALAB, N., N. IMMORLICA, B. LUCIER, M. MOBIUS, AND D. MOHAN (2024): "Persuading with anecdotes," Tech. rep., National Bureau of Economic Research.

HOFFMANN, F., R. INDERST, AND M. OTTAVIANI (2020): "Persuasion through selective disclosure: Implications for marketing, campaigning, and privacy regulation," *Management Science*, 66, 4958–4979.

HOSSAIN, T. AND R. OKUI (2013): "The binarized scoring rule," *Review of Economic Studies*, 80, 984–1001.

ISPANO, A. (2024): "Selective Disclosure," *SSRN Working Paper*, 4793394.

JIN, G. Z. AND P. LESLIE (2003): "The effect of information on product quality: Evidence from restaurant hygiene grade cards," *The Quarterly Journal of Economics*, 118, 409–451.

JIN, G. Z., M. LUCA, AND D. MARTIN (2021): "Is no news (perceived as) bad news? An experimental investigation of information disclosure," *American Economic Journal: Microeconomics*, 13, 141–173.

——— (2022): "Complex disclosure," *Management Science*, 68, 3236–3261.

KING, R. R. AND D. E. WALLIN (1991): "Market-induced information disclosures: An experimental markets investigation," *Contemporary Accounting Research*, 8, 170–197.

KOEHLER, J. J. AND M. MERCER (2009): "Selection neglect in mutual fund advertisements," *Management Science*, 55, 1107–1121.

LEE, K. AND Y.-J. WHANG (2024): "PySDTest: a Python Package for Stochastic Dominance Tests," *arXiv preprint arXiv:2307.10694*.

MATHIOS, A. D. (2000): "The impact of mandatory disclosure laws on product choices: An analysis of the salad dressing market," *The Journal of Law and Economics*, 43, 651–678.

MCKELVEY, R. D. AND T. PAGE (1990): "Public and private information: An experimental study of information pooling," *Econometrica: Journal of the Econometric Society*, 1321–1339.

MILGROM, P. (2008): "What the seller won't tell you: Persuasion and disclosure in markets," *Journal of Economic Perspectives*, 22, 115–131.

MILGROM, P. R. (1981): “Good news and bad news: Representation theorems and applications,” *The Bell Journal of Economics*, 380–391.

MILGROM, P. R. AND R. J. WEBER (1982): “A theory of auctions and competitive bidding,” *Econometrica: Journal of the Econometric Society*, 1089–1122.

OKUNO-FUJIWARA, M., A. POSTLEWAITE, AND K. SUZUMURA (1990): “Strategic information revelation,” *The Review of Economic Studies*, 57, 25–47.

PENCZYNSKI, S., C. KOCH, AND S. ZHANG (2023): “Disclosure of verifiable information under competition: An experimental study,” *SSRN Working Paper*, 4130449.

PRAT, A. AND D. STRÖMBERG (2013): *The Political Economy of Mass Media*, Cambridge University Press, 135–187, Econometric Society Monographs.

SÁNCHEZ-PAGÉS, S. AND M. VORSATZ (2007): “An experimental study of truth-telling in a sender–receiver game,” *Games and Economic Behavior*, 61, 86–112.

SCHLAG, K. H., J. TREMEWAN, AND J. J. VAN DER WEELE (2015): “A penny for your thoughts: A survey of methods for eliciting beliefs,” *Experimental Economics*, 18, 457–490.

SHIN, H. S. (2003): “Disclosures and asset returns,” *Econometrica*, 71, 105–133.

SOBEL, J. (2020): “Lying and deception in games,” *Journal of Political Economy*, 128, 907–947.

VERRECCHIA, R. E. (2001): “Essays on disclosure,” *Journal of Accounting and Economics*, 32, 97–180.

WANG, J. T.-Y., M. SPEZIO, AND C. F. CAMERER (2010): “Pinocchio’s pupil: using eyetracking and pupil dilation to understand truth telling and deception in sender-receiver games,” *American economic review*, 100, 984–1007.

WILSON, A. AND E. VESPA (2018): “Paired-uniform scoring: Implementing a binarized scoring rule with non-mathematical language,” Tech. rep., Working paper.

WILSON, A. J. AND E. VESPA (2020): “Information transmission under the shadow of the future: An experiment,” *American Economic Journal: Microeconomics*, 12, 75–98.

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 Online Appendix C 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 $(\theta, \bar{s}) \in \Theta \times S^N$. An 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.*

B Proofs

We first we need to introduce some additional notation. 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 $f(\bar{s}|\theta) = \prod_i f(s_i|\theta)$ and $f(s_i|\theta)$. Define the n-th order statistics of $\bar{s}$ as $\bar{s}_{(n)}$ and consider the following random variables:

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

To ease the notation, in what follows we will use y_i in place of $y_i(\bar{s})$ and y for a generic vector $(y_1, \ldots, y_n)$. From this definition, it follows that $y_i \geq y_j$ for any $i \geq j$.

The joint probability of $(\theta, y) \in \Theta \times S^N$ is given by:

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

- $p(\theta) f(y|\theta)$ 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.*

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

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

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 $\bar{y}, \bar{y}' \in S^N$

$$h(\bar{y} \vee \bar{y}')h(\bar{y} \wedge \bar{y}') \geq h(\bar{y})h(\bar{y}'). \tag{2}$$

If at least one between y and y' is not weakly decreasing, $h(y)h(y') = 0$, and thus the affiliation inequality of Equation 2 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. □

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

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

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. □

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

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

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.

Proof of Proposition 2. The proof is divided into three sections, each corresponding to a different part of the statement.

1. Fix N and let $(\sigma^{'*}, \mu^{'*})$ and (σ^*, μ^*) be the maximally selective equilibria for K' and K, respectively.

   We first show that if $K' > K$, then $(\sigma^{'*}, \mu^{'*})$ is Blackwell more informative than (σ^*, μ^*). Let $\mathcal{P}' = \{\sigma^{'*-1}(m)\}_{m \in \sigma'^*(S^N)}$ and $\mathcal{P} = \{\sigma^{-1}(m)\}_{m \in \sigma^*(S^N)}$.

   Note that $\mathcal{P}' = \{B(m)\}_{m \in \mathcal{M}^{K'}}$ and $\mathcal{P} = \{B(m)\}_{m \in \mathcal{M}^K}$ where

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

   and $\mathcal{M}^K = \{m \in \mathcal{M} : \ell(m) = K\}$.

   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 $X' = B(m')$. Define $m = (m'_1, \ldots, m'_K) \in \mathcal{M}^K$ and $X = B(m)$. Clearly, $B(m') \subseteq B(m)$ and, thus, $X' \subseteq X$. Moreover, if $m' \neq \min S^{K'}$, $B(m') \subsetneq B(m)$.

   By the Blackwell theorem, we can conclude that $\mathcal{I}(K', N) > \mathcal{I}(K, N)$. □

2. Fix $K = N$ and $K' = N'$ and let $(\sigma^{'*}, \mu^{'*})$ 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 $\mu^{'*}$ and μ^* are degenerate distributions.

   We want to show that if $N' > N$, $(\sigma^{'*}, \mu^{'*})$ 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. $\square$

Online Appendix (For Online Publication Only)

C Equilibrium Multiplicity

In this section, we provide three examples of PBEs that are not maximally selective and hence induce a different equilibrium outcome. Throughout, we suppose that $\Theta = \{0, 1\}$, with each state equally likely, and we fix $N = 2$ and $K = 1$. Also, 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.

Example 1. (*Nondisclosure equilibrium*) Suppose $S = \{A, B\}$, $f(A|1) \in (0, 1)$ and $f(A|0) \in (0, f(A|1))$. There exists an equilibrium in which the sender never discloses, i.e., always sends $m = \{o\}$ regardless of her type θ and the realization of the signals $\bar{s}$.

$\bar{s}$	$m = \sigma^*(\bar{s}, \theta)$	$a = \mu^*(m)$
A, A	o	$1/2$
A, B or B, A	o	$1/2$
B, B	o	$1/2.$

This equilibrium is sustained, for instance, by the belief that $\mu^*(A) = \mu^*(B) = 0$, i.e., that any disclosed signal is sent by the low type.

Example 2. (*Uninformative disclosure equilibrium*) Suppose $S = \{A, B\}$, $f(A|1) \in (1/2, 1)$ and $f(A|0) = 1 - f(A|1)$. There exists an equilibrium in which the sender discloses if and only if the two signals differ, in which case she selects which of the two realizations to disclose with some type-independent randomization.

$\bar{s}$	$m = \sigma^*(\bar{s}, \theta)$	$a = \mu^*(m)$
A, A	o	$1/2$
A, B or B, A	A with prob $\epsilon \in (0, 1)$, B with prob $1 - \epsilon$	$1/2$
B, B	o	$1/2.$

In this equilibrium, all feasible messages are on the equilibrium path, but the receiver's beliefs do not move given the symmetry of the information structure and of the sender's strategy.

Example 3. (*Non-monotone disclosure equilibrium*) Suppose $S = \{A, B, C\}$, $f(A|1) = 14/20$, $f(B|1) = 5/20$, $f(C|1) = 1/20$, $f(A|0) = 2/20$, $f(B|0) = 1/20$, and $f(C|0) =$

17/20. Note that f satisfies the monotone likelihood ratio property since $f(A|1)/f(A|0) = 7$, $f(B|1)/f(B|0) = 5$, and $f(C|1)/f(C|0) = 1/17$. There exists an equilibrium, described here below, in which the receiver's action is non-monotone in the favorableness of the disclosed signal in that $\mu^*(B) > \mu^*(A) > \mu^*(C)$.

$\bar{s}$	$m = \sigma^*(\bar{s}, \theta)$	$a = \mu^*(m)$
A, A	A	$28/37$
A, B or B, A	B	$175/214$
A, C or C, A	A	$28/37$
B, B	B	$175/214$
B, C or C, B	B	$175/214$
C, C	C	$1/290$

The receiver's beliefs upon any disclosed signal is pinned-down by Bayes' rule, i.e.,

$$\mu^*(B) = \frac{2\frac{1}{20}\frac{5}{20} + \left(\frac{5}{20}\right)^2 + 2\frac{5}{20}\frac{14}{20}}{\left(2\frac{1}{20}\frac{5}{20} + \left(\frac{5}{20}\right)^2 + 2\frac{5}{20}\frac{14}{20}\right) + \left(2\frac{1}{20}\frac{17}{20} + \left(\frac{1}{20}\right)^2 + 2\frac{1}{20}\frac{2}{20}\right)} = \frac{175}{214} \cong 0.82$$

$$\mu^*(A) = \frac{2\frac{1}{20}\frac{14}{20} + \left(\frac{14}{20}\right)^2}{\left(2\frac{1}{20}\frac{14}{20} + \left(\frac{14}{20}\right)^2\right) + \left(2\frac{2}{20}\frac{17}{20} + \left(\frac{2}{20}\right)^2\right)} = \frac{28}{37} \cong 0.76$$

$$\mu^*(C) = \frac{\left(\frac{1}{20}\right)^2}{\left(\frac{1}{20}\right)^2 + \left(\frac{17}{20}\right)^2} = \frac{1}{290} \cong 0.005,$$

while upon nondisclosure one can take any $\mu^*(o) \leq \mu^*(C)$. Intuitively, this equilibrium exists because signal A is not much better news than signal B, while signal C is really bad news, and given the sender's strategy, the probability that the remaining signal is equal to C is higher when A is observed than when B is observed.

D 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:

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

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 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 provide an intuition for this result by introducing two effects, the imitation and the selection effect. The following example illustrates more in detail both effects and how their interaction is the key determinant in the shape of $\mathcal{I}(K, N)$.

We first relax the assumption that f has full support and study two extreme cases.

Let $\Theta = \{0, 1\}$, $p(1) = \frac{1}{2}$, $S = \{A, B\}$ and suppose that $f(A|1) = \gamma > \frac{1}{2}$ and $f(A|0) = \eta < \frac{1}{2}$. Finally, assume that $K = 1$. Given the parameters, the set of possible messages is $\mathcal{M} = \{A, B, o\}$. A maximally selective sender's strategy discloses $m = A$ if A is available and otherwise discloses $m \in \{B, o\}$. This implies that, after observing $m \in \{B, o\}$, the receiver will place probability one over a vector of signals $\bar{s}$ with $\bar{s}_i = B$ for all $i \in \{1, ..., N\}$. Let's denote this vector of signals by $\bar{s}_B$. Formally, after $m \in \{B, o\}$, $\mu^*(\bar{s}_B|m) = 1$ and $\mu^*(\bar{s}|m) = 0$ for all $\bar{s} \neq \bar{s}_B$. On the other hand, after seeing $m = A$, the receiver places positive probability on every $\bar{s} \in S$ such that $s_i = A$ for at least one $i \in \{1, ..., N\}$. Formally, after observing $m =$

A, $\mu^*(\bar{s}|m) = q(\bar{s}|S \setminus \{\bar{s}_B\})$, while $\mu^*(\bar{s}_B|m) = 0$. Given this premise, it is easy to see that

$$p\left(1|m \in \{B,o\}\right) = \frac{\frac{1}{2}(1-\gamma)^N}{\frac{1}{2}(1-\gamma)^N + \frac{1}{2}(1-\eta)^N} = \frac{(1-\gamma)^N}{(1-\gamma)^N + (1-\eta)^N}$$

$$p\left(1|m = A\}\right) = \frac{\frac{1}{2}\left(1-(1-\gamma)^N\right)}{\frac{1}{2}\left(1-(1-\gamma)^N\right) + \frac{1}{2}\left(1-(1-\eta)^N\right)} = \frac{1-(1-\gamma)^N}{2-(1-\gamma)^N-(1-\eta)^N}$$

Since θ is binary, the optimal action of the receiver coincides with the posterior beliefs we derived above. Her expected payoff given message m as

$$\mathbb{E}_\theta\left[u\left(\theta, \sigma_R(m)\right)|m\right] = -\frac{p(1|m)p(0|m)}{2}.$$

From this, we can get the ex-ante receiver's expected payoff as

$$\mathbb{E}_m\left[\mathbb{E}_\theta\left[u\left(\theta, \sigma_R(m)\right)|m\right]\right] = -\frac{(1-\gamma)^N\left(1-(1-\gamma)^N\right) + (1-\eta)^N\left(1-(1-\eta)^N\right)}{2\left((1-\gamma)^N + (1-\eta)^N\right)\left(2-(1-\gamma)^N-(1-\eta)^N\right)} =$$

$$-\frac{1}{2}\left[1 - \frac{\left(1-(1-\gamma)^N\right)^2}{2-(1-\gamma)^N-(1-\eta)^N} - \frac{(1-\gamma)^{2N}}{(1-\gamma)^N+(1-\eta)^N}\right]$$

According to our definition, the equilibrium informativeness is equal to

$$\mathcal{I}(K,N) = \frac{1}{4} - \mathbb{E}_m\left[\mathbb{E}_\theta\left[u\left(\theta, \sigma_R(m)\right)|m\right]\right]$$

Let us consider the extreme case of *perfect good news*, i.e. the case in which $\eta = 0$ and $\gamma < 1$. Under these conditions, $m = A$ perfectly reveals that $\theta = 1$. This implies that

$$\mathcal{I}(K,N) = \frac{1}{4} - \frac{(1-\gamma)^N}{2\left(1+(1-\gamma)^N\right)}$$

It is easy to verify that $\mathcal{I}(K,N)$ is strictly increasing in N. Hence, an increase in N always leads to more information 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 disclose $m = A$. In addition, as a consequence of the previous fact, when N grows, a disclosure of $m \in \{B,o\}$ makes the receiver more confident of $\theta = 0$. These two channels together are responsible of the fact that more available signals lead to more information transmitted in equilibrium: We refer to this as *separation effect*.

Let us now consider the other extreme case of *perfect bad news*, i.e. the case in which $\eta > 0$ and $\gamma = 1$. Under these conditions, $m \in \{B, o\}$ perfectly reveals that $\theta = 0$. Under this parametrization, we have that

$$\mathcal{I}(K, N) = \frac{1}{4} - \frac{1 - (1 - \eta)^N}{2\,(2 - (1 - \eta)^N)}$$

It is easy to show that when $\gamma = 1$, $I(K, N)$ is 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-signal. Thus, disclosing the fully-revealing message $m \in \{B, o\}$ becomes less likely and, at the same time, $m = A$ becomes weaker evidence of $\theta = 1$. This decrease in separation opportunities leads to less information transmitted in equilibrium: We refer to this as *imitation effect*.

Finally, we consider the case in which f has full support, i.e. we have both $\eta > 0$ and $\gamma < 1$. It is possible to show that for every pair (γ, η), $\mathcal{I}(K, N)$ increases moving from $N = 1$ to $N = 2$. However, as $N \to \infty$, $\mathcal{I}(K, N)$ converges to zero. This suggests that equilibrium informativeness is non-monotonic in N. Intuitively, in this case, both the separation 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.

Hence, the example discussed above allows us to illustrate that the effect of a change in N on $\mathcal{I}(K, N)$ is the result of multiple forces given by the interaction of players' strategic incentives and available messages. The exact parametrization of the model pins down what are the cases in which the *separation effect* dominates over the *imitation effect*. However, as N becomes extremely large, the negative effect on information transmitted prevails, making communication fully ineffective.

F Additional Figures and Results

F.1 Behavior Over Rounds

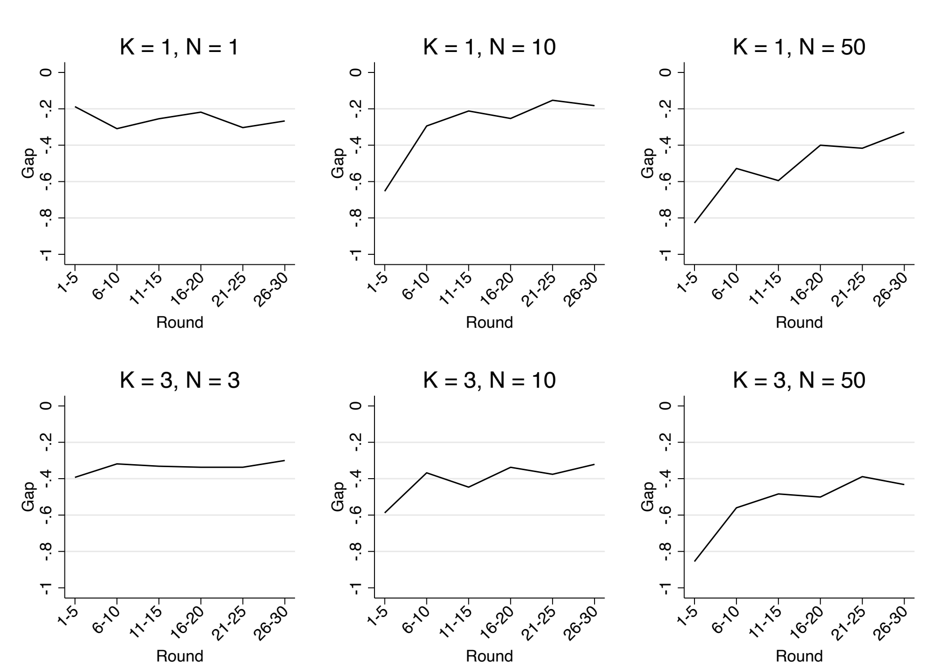


Figure 6: MGPA of Messages Over Rounds

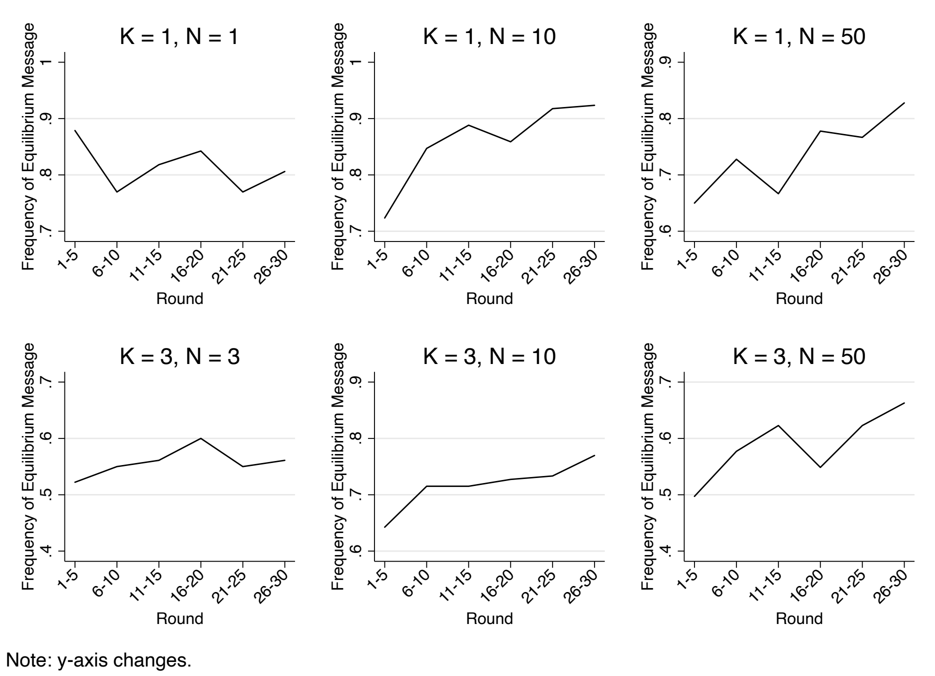


Figure 7: Equilibrium Messages Over Rounds

We present summary figures of the evolution of behavior along, 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 6 plots the evolution of the gap between the equilibrium message and 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 7 displays the fraction of messages that exactly correspond to the equilibrium prediction. Across all treatments, the majority of messages are consistent with the equilibirum; 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.

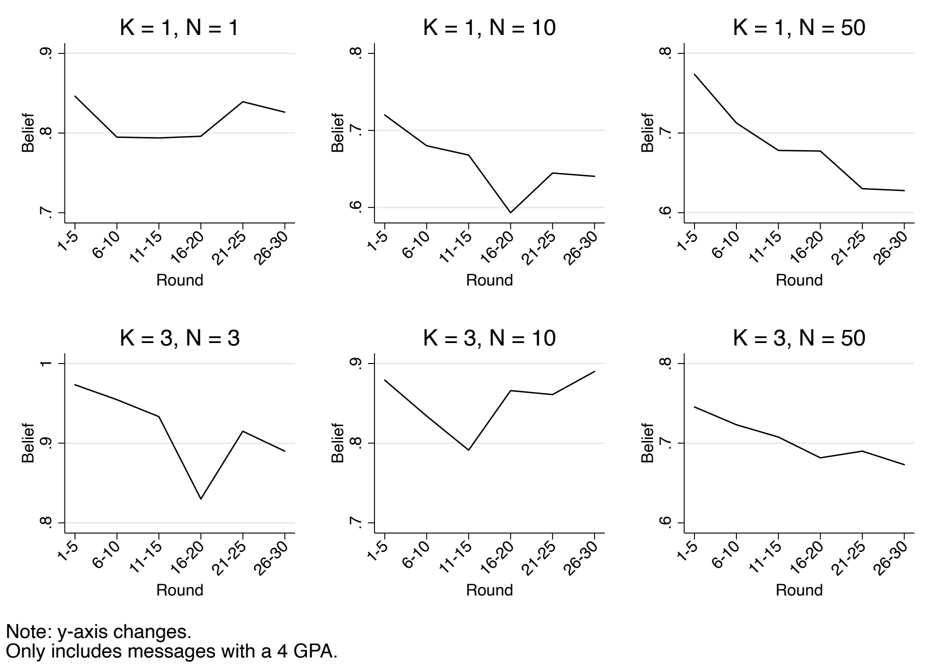


Figure 8: Average Belief Over Rounds

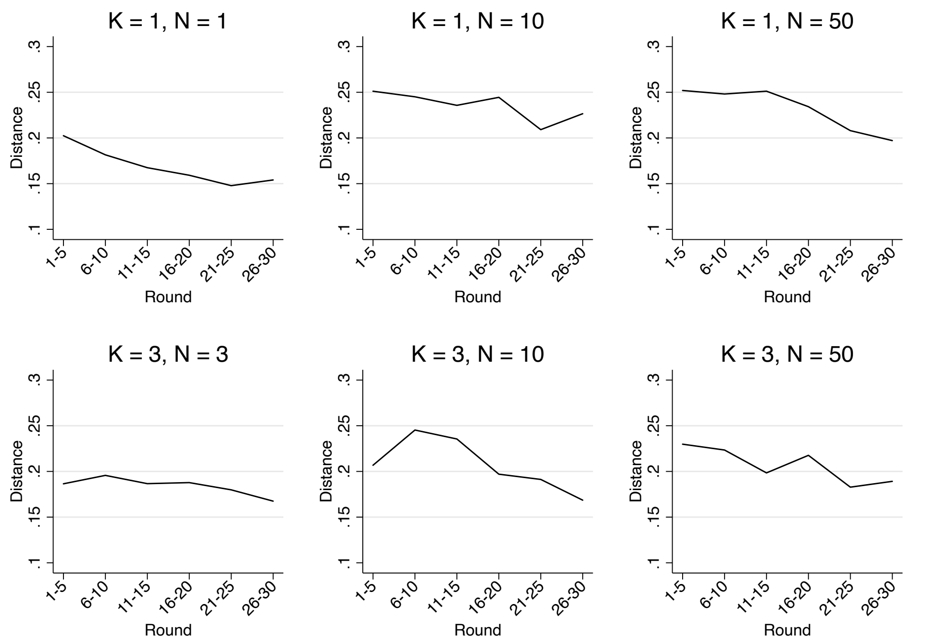
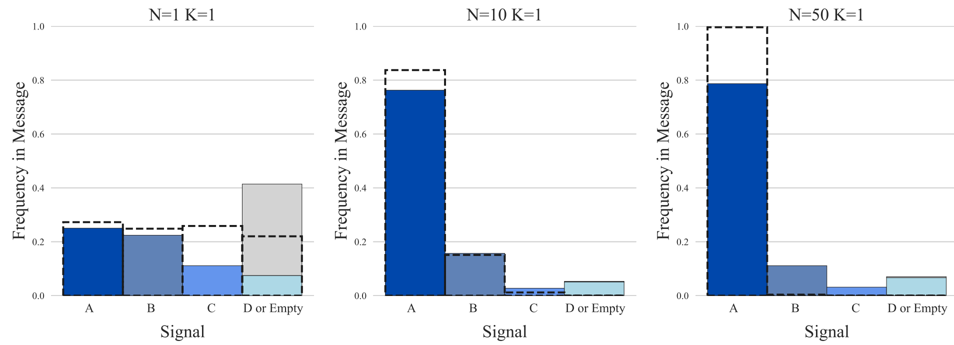


Figure 9: Accuracy Over Rounds

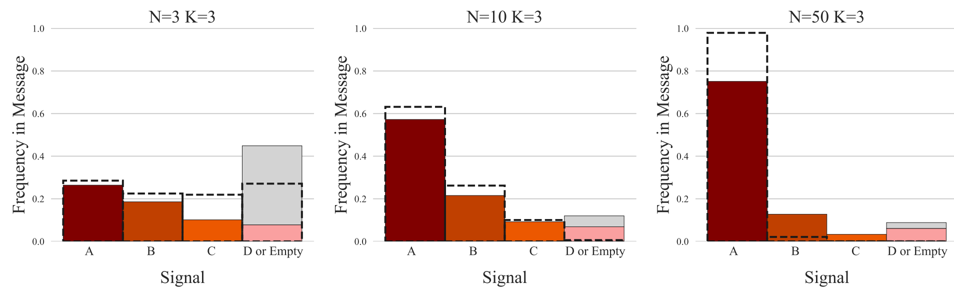
On the receiver side, the first figure shows the average belief for messages with a GPA of 4 (overall the most common GPA corresponding to 46% of the sample). The figure illustrates the fact that in most treatments, receivers become more skeptical of messages that have the same GPA. In some treatments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

Figure 9 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.

F.2 k-means Clustering in the Treatments with $N < 50$



(a) Signal Distribution for $K = 1$



(b) Signal Distribution for $K = 3$

Figure 10: Signal Distributions

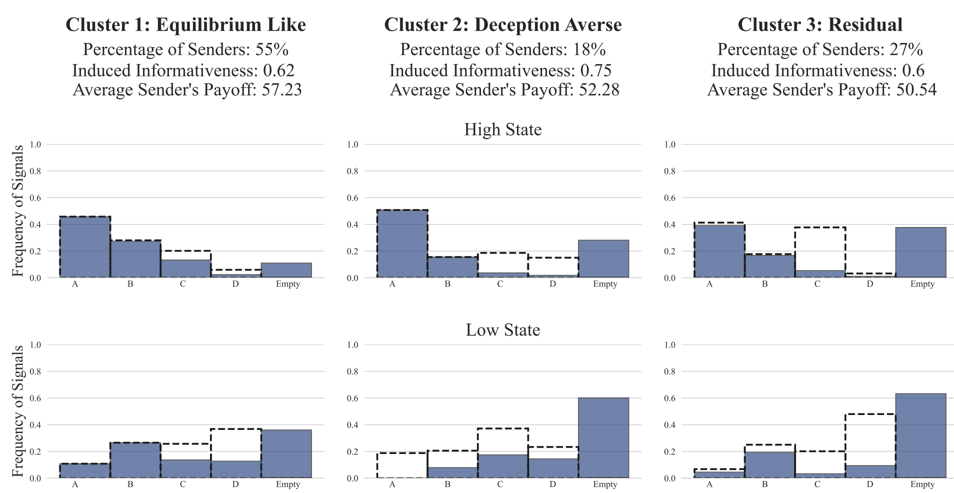


Figure 11: Sender's Clustering for the Treatment (K_1, N_1)

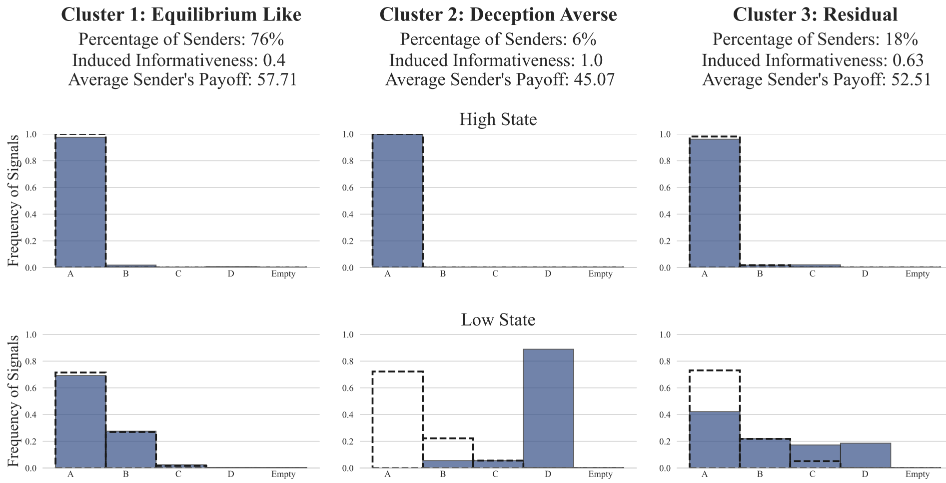


Figure 12: Sender's Clustering for the Treatment (K_1, N_{10})

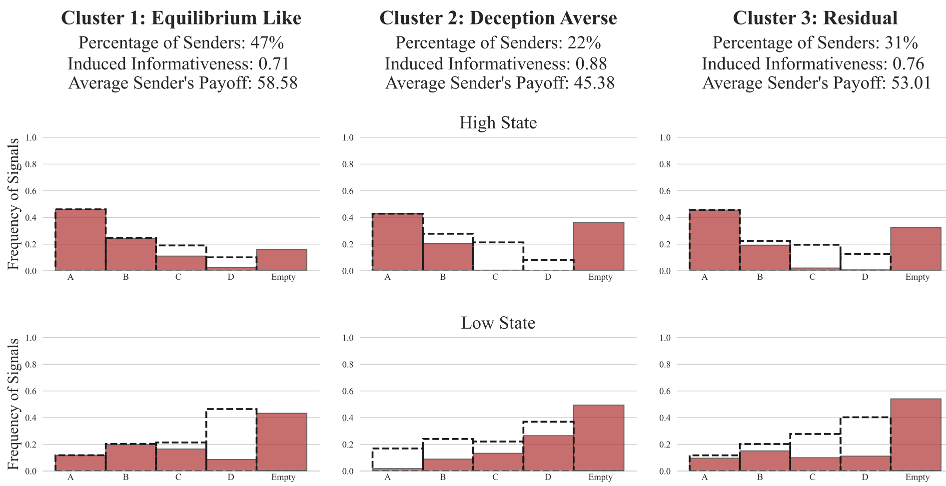


Figure 13: Sender's Clustering for the Treatment (K_3, N_3)

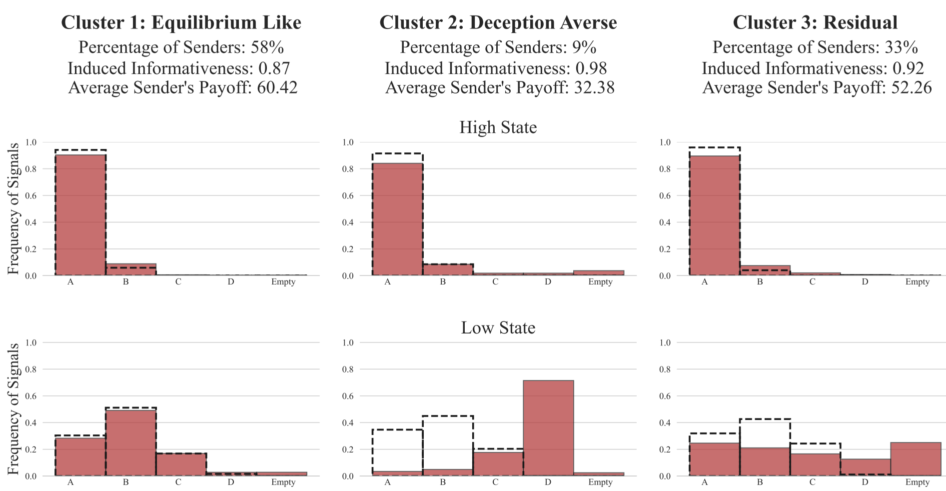


Figure 14: Sender's Clustering for the Treatment (K_3, N_{10})

F.3 Receiver' Behavior

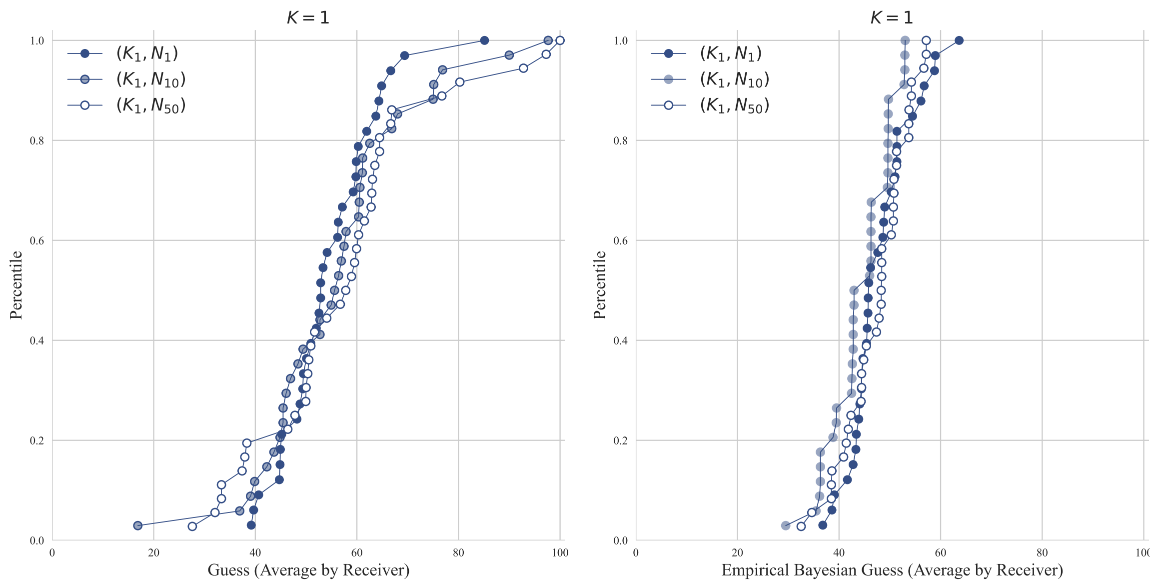


Figure 15: Cumulative Distribution Functions of Receivers' Guesses for $K = 1$

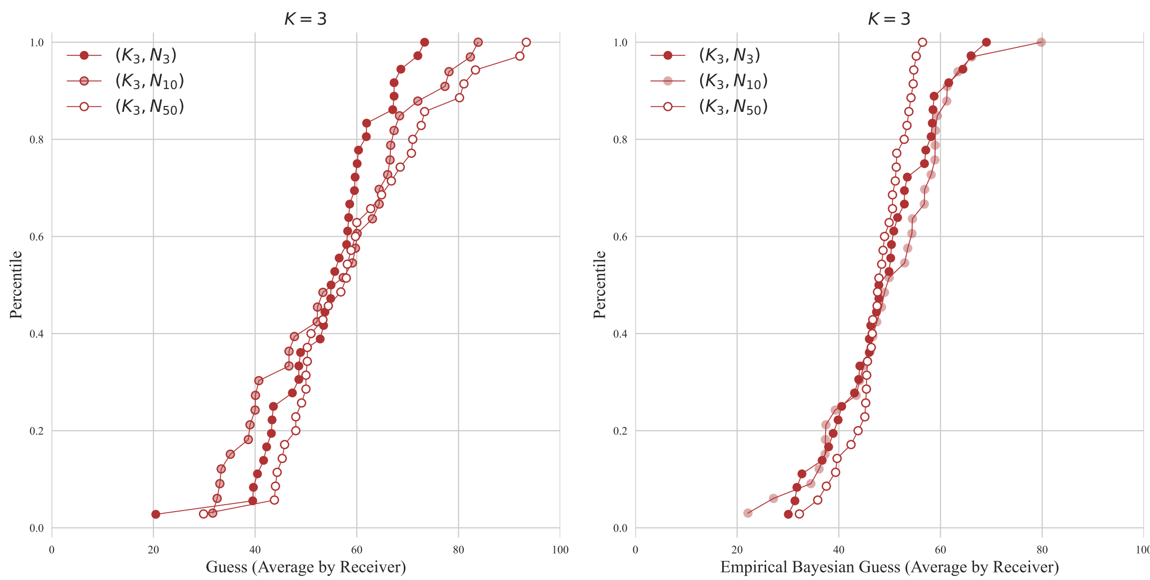
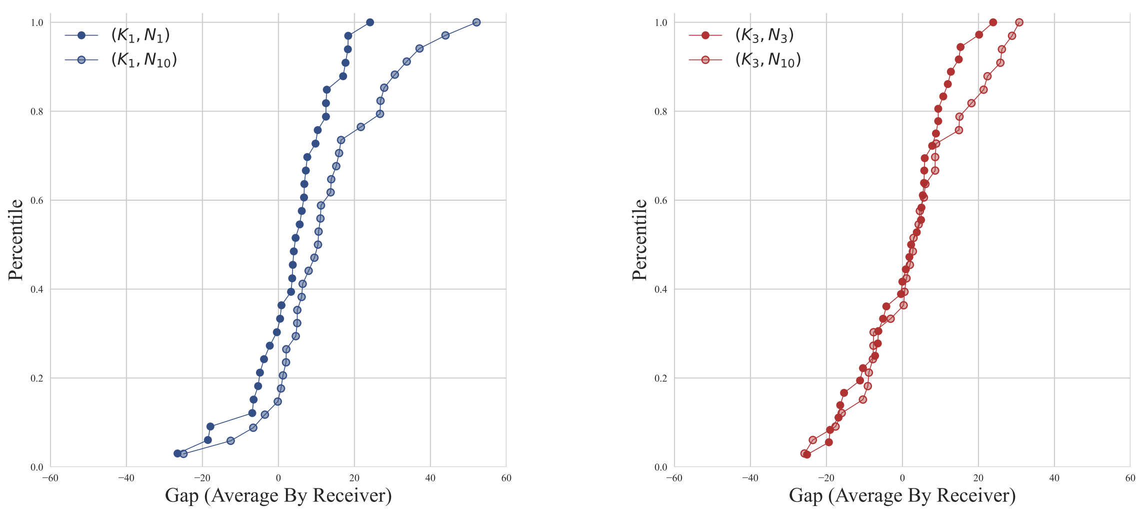


Figure 16: Cumulative Distribution Functions of Receivers' Guesses for $K = 3$

Table 10: Receivers' Responses for each K - Tobit Results

	$K = 1$		$K = 3$	
	(1) Receiver's Guess	(2) Empirical Optimal Guess	(3) Receiver's Guess	(4) Empirical Optimal Guess
GPA	16.94^{***}	19.48^{***}	33.48^{***}	43.20^{***}
	(0.93)	(0.98)	(3.83)	(4.02)
$D_{N_{10}}$	-20.53^{***}	-29.26^{***}	-30.18^{***}	-45.86^{***}
	(3.15)	(1.95)	(3.91)	(5.16)
$D_{N_{50}}$	-17.73^{***}	-25.87^{***}	-35.53^{***}	-59.08^{***}
	(3.64)	(1.44)	(4.82)	(6.18)
Constant	15.95^{***}	2.86	-20.96^{**}	-49.97^{***}
	(1.87)	(2.52)	(8.80)	(9.11)
Obs	1,545	1,545	1,560	1,560
Subjects	103	103	104	104

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



(a) (K_1, N_1) and (K_1, N_{10}) (b) (K_3, N_3) and (K_3, N_{10})

Figure 17: CDF of Receivers' Response Gaps: Comparisons with $N = 10$

Table 11: Receivers' Responses for $N = 10$ and $N = 50$ - Tobit Results

	$N = 10$		$N = 50$	
	(1) Receiver's Guess	(2) Empirical Optimal Guess	(3) Receiver's Guess	(4) Empirical Optimal Guess
GPA	30.07^{***}	37.77^{***}	18.61^{***}	20.79^{***}
	(6.12)	(7.89)	(1.63)	(1.16)
D_{K_3}	12.12^{*}	15.91^{***}	3.53	1.09
	(6.59)	(3.39)	(4.19)	(0.72)
Constant	-52.02^{**}	-92.89^{***}	-7.56	-27.74^{***}
	(23.07)	(30.00)	(6.17)	(4.35)
Obs	1,005	1,005	1,065	1,065
Subjects	67	67	71	71

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

F.3.1 Response to Selected Evidence: Additional Results

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 this Section, 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.

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.

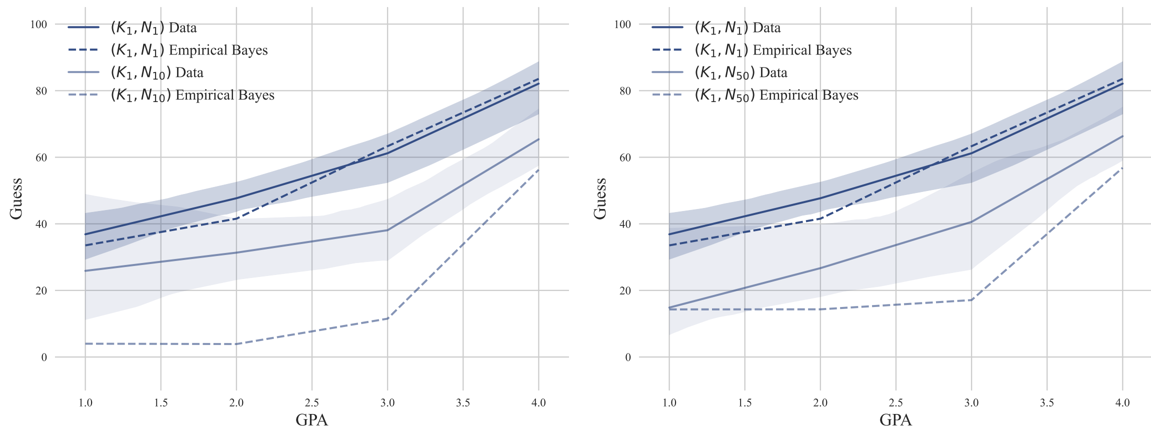


Figure 18: Receivers' Average Guesses for $K = 1$

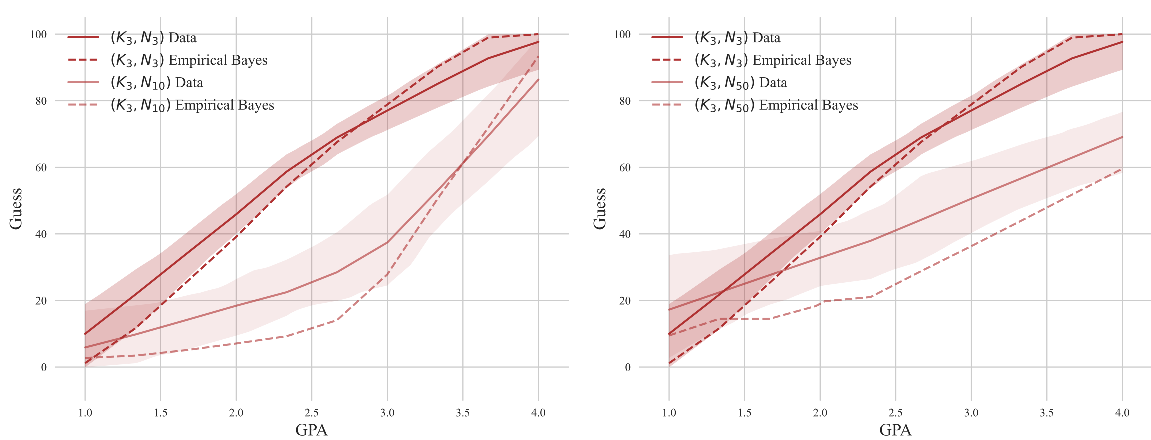


Figure 19: Receivers' Average Guesses for $K = 3$

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.

G Design

G.1 Graphical Interface

The figures in this section show the software interface of our experiment. More specifically, Figures 20 and 21 show the sender's screen at the time of selecting her message. Figure 22 shows the receiver's screen at the time of making her guess. Figure 23 shows the feedback screen.

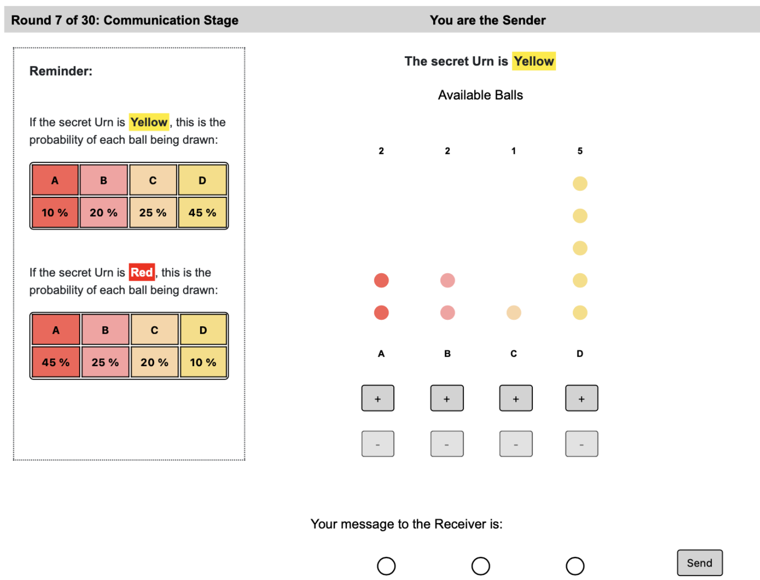


Figure 20: Sender's Interface Before the Message Choice

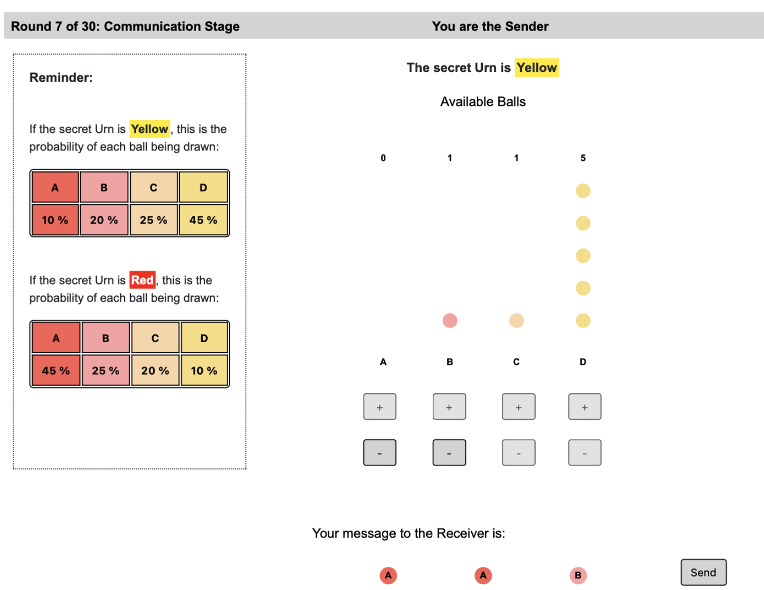


Figure 21: Sender's Interface After the Message Choice

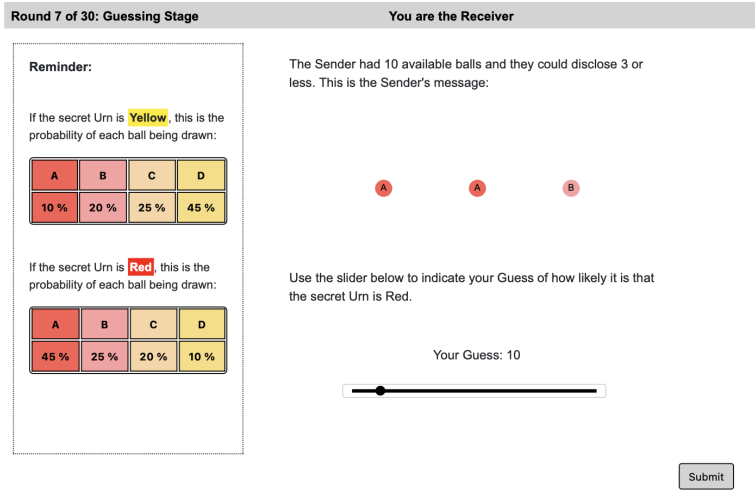


Figure 22: Receiver's Interface

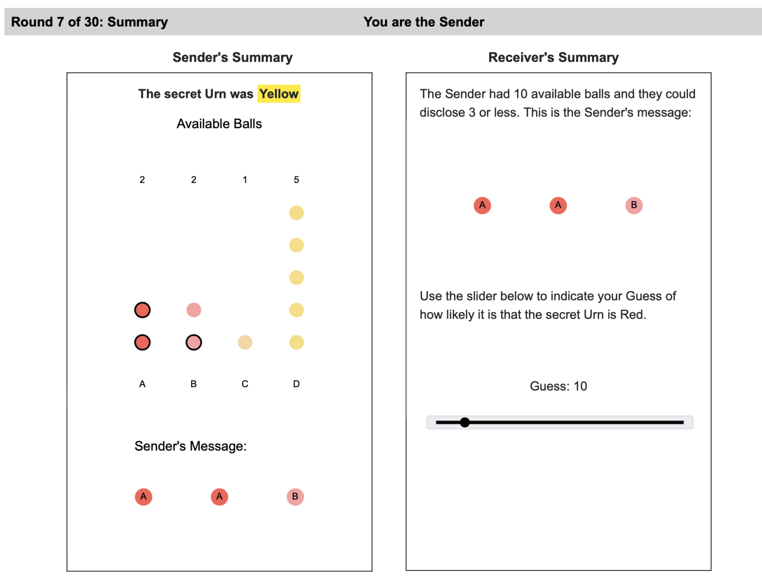


Figure 23: Feedback Interface

G.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.

H Robustness to an Alternative Design

This section covers an additional experiment with an alternative design to the one presented in the paper. After a brief description (section H.1), we replicate the key tables using this new data set (section H.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.

H.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 12. Theoretical predictions on equilibrium informativeness are in Figure 24.[31] 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).

[31] 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 12: Treatments' Denominations

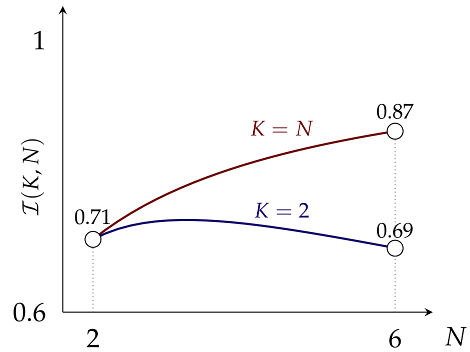


Figure 24: Predicted Informativeness

H.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 8 to 15.

H.2.1 Senders' Behavior

What Evidence Do Senders Disclose?

Mirroring Table 3, Table 13 reports the average number of disclosed signals in each treatment. All results carry through. In each of the two treatments in which $N = K$, the number of disclosed signals is significantly lower than K (p-value < 0.01). Also, selection trumps concealment in the sense that the number of disclosed signals is significantly higher in (K_2, N_6) than in (K_2, N_2) (p-value < 0.01).

Likewise, mirroring Table 4, Table 14 reports the mean GPA of the senders' messages in the three treatments. In computing the GPA, a disclosed white ball has a value of 4, while a disclosed black ball and an undisclosed, disclosable, ball have a value of 1. Again, all results carry through. The mean GPA 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_6, N_6) to (K_2, N_6) (p-value < 0.01). Also, the mean GPA is not significantly different between the two treatments in which $N = K$. Finally, in all treatments, the mean GPA is significantly lower than the theoretically predicted one (p-value < 0.01).

How Much Information Do Senders Transmit?

As can be seen in Table 15, which mirrors Table 9, for all treatment variations of K and N, the average senders' informativeness moves in the directions predicted by the theory. The increase

Table 13: Average Number of Disclosed Signals (predictions in parentheses)

	$N = K$	$N = 6$
$K = 2$	1.20	1.62
	$[0.98, 2]$	$[1.63, 2]$
$K = 6$	3.24	
	$[3.19, 6]$	

Table 14: Mean GPA Induced by Senders' Messages (predictions in parentheses)

	$N = K$	$N = 6$
$K = 2$	2.24	3.05
	(2.46)	(3.45)
$K = 6$	2.22	
	(2.59)	

Table 15: Overall Informativeness, Senders' Informativeness, and Theoretical Predictions

		$N = K$	$N = 6$
$K = 2$	Overall Informativeness	0.42	0.21
	Senders' Informativeness	0.64	0.56
	Theory	0.69	0.67
$K = 6$	Overall Informativeness	0.48	
	Senders' Informativeness	0.68	
	Theory	0.85	

in senders informativeness from (K_2, N_6) to (K_6, N_6) is significant (p-value < 0.10), and so is the increase from (K_2, N_2) to (K_6, N_6) (p-value < 0.10). 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 theory. 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. This result is in contrast to that of the main experiment, where overcommunication is found, especially 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 a major driver of overcommunication. With only two types, a low type that wants to separate can easily do so by sending the lowest signal, especially when N is large. Such a strategy has no clear counterpart in this setting.

Table 16: 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.

Evidence of Deception Aversion. Table 16 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 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.

H.2.2 Receivers' Behavior

How Do Receivers Respond to Selected Evidence?

Mirroring Table 6, Table 17 examines how, fixing K and controlling for the GPA of the message, the receivers' guesses, and the empirically optimal ones, vary with N. Consistent with the theory, for the same GPA, guesses decrease when N, although unlike the main experiment, the effect is not significant. This difference may be due to the smaller variation of N in this experiment. Nevertheless, results again provide evidence of selection neglect, since, as for the main experiment, a comparison of the two columns clarifies how the optimal guess should decrease in N.

Likewise, mirroring Table 7, Table 18 examines how, fixing N and controlling for the GPA of

Table 17: Regression Results of Receivers' Responses for $K = 2$

	$K = 2$	
	(1)	(2)
	Guess	Optimal Guess
GPA	8.648***	12.88***
	(1.130)	(0.424)
D_{N_6}	-2.389	-6.391***
	(1.937)	(0.652)
Constant	30.32***	20.40***
	(2.544)	(1.006)
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 18: Regression Results of Receivers' Responses for $N = 6$

	$N = 6$	
	(1)	(2)
	Guess	Optimal Guess
GPA	10.51***	14.49***
	(1.934)	(1.172)
D_{K_6}	9.404***	12.24***
	(2.294)	(1.205)
Constant	22.26***	9.090**
	(5.931)	(3.692)
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.

the message, the receivers' guesses, and the empirically optimal ones, vary with K. Consistent with the theory and the results from the main experiment, guesses increase with K. And again, a comparison of the two columns shows how receivers do not respond to this change as much as they should.

The Failure to Fully Account for Selection

Mirroring Table 8a, Table 19a reports the average response gap, i.e., the difference between the receiver's guess and the sender's type. As in the main experiment, the response gaps are positive in each treatment, although in this case they are not statistically different from zero. Concurrent explanations for this difference may be that, in this experiment, receivers observe evidence whose content is overall less favorable (since treatments with large N are not considered), and that the equilibrium reasoning required to make a correct inference about undisclosed evidence is simpler (since signals are binary). Nevertheless, mirroring Table 8b, Table 19b documents how, fixing K and controlling for the GPA, the response gap increases significantly with N as in the main experiment, providing further evidence of selection neglect.

Table 19: Comparison of Treatment Effects

(a) Average Gaps by Treatment

	$K=2$	K=6
$N=K$	0.439	1.492
$N=6$	1.003	

(b) OLS on Response Gaps

	$K=2$
	Gap
GPA	-4.239***
	(0.940)
D_{N_6}	4.005**
	(1.904)
Constant	9.931***
	(2.201)
Observations	665
Subjects	95

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

How Much Information Do Receivers Absorb?

Finally, in addition to the senders' informativeness and the theoretical one, Table 15 above also reports the overall informativeness resulting from the interaction between senders and receivers. As in the main experiment, naturally, the overall informativeness is lower than the senders' informativeness. Moreover, the 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 small by the theory, is significant (p-value < 0.05), which is consistent with selection neglect by receivers.