The Selective Disclosure of Evidence: An Experiment

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Abstract

We conduct a systematic test of the theory of selective disclosure. An informed sender seeks to influence an uninformed receiver by disclosing pieces of evidence. While the disclosed evidence is verifiable, the sender may select it from a larger pool of available evidence, known only to her. Our experimental design exploits the rich comparative-static predictions that result from varying the quantity of evidence available to the sender and how much of it can be disclosed to the receiver. Our findings corroborate the key qualitative predictions of the theory, thereby offering empirical support for selective disclosure as a significant force in communication. We also uncover two quantitative departures from the theory: Some senders persistently communicate more than predicted, and receivers partially neglect that the disclosed evidence is selected.

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1 Introduction

This paper presents the results of an experimental analysis of selective disclosure, a pervasive force in communication. In many situations, an informed sender seeks to influence the actions of an uninformed receiver by selecting which pieces of evidence, among many, to disclose. For instance, a journalist may choose what news events to report on depending on how they reflect on a political candidate; a defense lawyer may choose which evidence to present in court to increase the chance of her client's acquittal; a manager may choose which specific financial metrics to include in the company's annual report to shareholders.[1] These settings share two key features. The disclosed evidence is *verifiable* (i.e., the sender cannot fabricate it), but it may be *selected* from a larger pool, known only to the sender. Thus, even though the evidence is verifiable, its interpretation depends on the context—e.g., the sender' objective, or how much evidence was available—which ultimately determines the selection process.

Our experimental analysis is informed by a theory of selective disclosure that provides rich comparative statics, varying the quantity of evidence available to the sender and how much of it can be disclosed to the receiver. These comparative statics allow for a systematic test of selective disclosure. Relative to existing experiments, we shift the focus away from the well-studied question of *whether* evidence is disclosed, to the less explored question of *which* evidence is disclosed. Specifically, we analyze which evidence senders choose to disclose, how receivers respond to potentially selected evidence, and how selection impacts the overall informativeness of communication. Our results corroborate the key qualitative predictions of the theory, but also uncover two quantitative departures: First, some senders persistently communicate more than predicted, in contrast with most of the existing literature on disclosure; Second, receivers partially neglect selection, despite having ample learning opportunities. These results may inform policy, suggesting that mandating disclosure can be ine ective, and possibly detrimental, when selection opportunities are large.

Our model, which builds on Milgrom (1981), features a sender who privately observes the realization of a binary state of the world and has access to N independent signals, which are informative about the state. The sender can verifiably disclose up to K of these signals to a receiver. Thus, N represents how much evidence is available to the sender, and K represents the communication capacity of the environment. The receiver observes the disclosed signals and takes an action. Her payo is quadratic in the distance between her action and the realized state. The sender's payo , instead, is state-independent and increases with a; i.e., she wishes to

[1] In political economy, selective disclosure is considered one of the principal sources of media slant, where it is known as filtering or fact bias (see, e.g., Prat and Strömberg, 2013; Gentzkow et al., 2015).

persuade the receiver to take a higher action. Because the set of signal realizations is ordered and their distribution satisfies the monotone likelihood-ratio property, a higher signal realization is "more favorable" in the sense that, everything else being equal, it leads the receiver to take a higher action. Milgrom (1981) shows that, in this setting, there is a sequential equilibrium in which the sender discloses the K most favorable signals she observes. Under a suitable refinement—which relates to neologism proofness (Farrell, 1993)—we show that this equilibrium is also unique.

Our model makes several comparative-static predictions in K and N, which inspire our experimental design. In terms of players' behavior, the sender should disclose signals that appear more favorable as N increases and less favorable as K increases. Due to this positive selection, receivers should become more skeptical of any message as N increases or K decreases. Our main aggregate predictions concern the informativeness of the equilibrium, defined as the correlation between the state and the receiver's action. This measure captures how much information is transferred between the sender and the receiver. Fixing N, the informativeness should increase in K. Fixing K, the informativeness may display a non-monotonic relation with N, but necessarily decreases to zero as N grows large. These last predictions stem from a balance between the following two forces. On the one hand, a larger N allows the sender to be more selective, which decreases equilibrium informativeness. On the other, it also improves the sender's ability to communicate the state, which can increase informativeness. Thus, changing K and N allows us to span models in between the tradition of 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 often been analyzed separately by the experimental literature, leading to contrasting findings that our hybrid setting can help reconcile.

Our experimental treatments follow a 2x3-factorial, between-subject design, which only varies K and N, leaving all the other model ingredients unchanged. We consider two values for K—i.e., 1 or 3—and three values for N—i.e., K, 10, or 50. These treatments allow us to test the full range of predictions discussed above. Most notably, when $K = 1$, informativeness declines monotonically in N, while it is nonmonotone (first increasing, then decreasing) when $K = 3$. Furthermore, for both values of K, the equilibrium is essentially uninformative when $N = 50$.

We begin by establishing several patterns in the senders' data that are consistent with the key qualitative predictions of the theory. Specifically, we present two sets of positive findings. First, we find that which evidence senders disclose is largely consistent with the qualitative predictions of the theory: Senders disclose more favorable signals as N increases or as K decreases. Second, we analyze how informative senders' strategies are, net of mistakes receivers may make. In all cases, the average senders' informativeness changes across treatments in ways that are consistent with the comparative-statics predictions in N and K. These complex predictions narrow down the alternative theories that could explain all these observed patterns, providing a systematic test for our model.

Although the theory explains the qualitative patterns in the senders' data, we find two main quantitative deviations. First, senders sometimes disclose less favorable signals despite having more favorable ones available, showing a "modesty" bias. Second, senders' strategies are more informative than predicted, i.e., they overcommunicate. The latter finding contrasts with most existing experiments on verifiable disclosure, both in the lab and in the field, which find evidence of undercommunication.[2] To explain these deviations, we analyze senders' behavior at the individual level. While the majority of senders behave almost exactly as predicted by the theory, we identify a minority who persistently display behavior that we call "deception averse:" In the high state, they disclose the most favorable signals available; In the low state, however, they consistently fail to do so. This behavior can be interpreted as a particularly strong form of lying aversion: When the state is low, deception-averse senders refrain from disclosing signals that, despite having verifiably realized, may deceive the receiver. These senders are thus responsible for the modesty bias discussed above and, as their state-dependent behavior inflates the overall senders' informativeness, they explain overcommunication.

Finally, we analyze receivers' data. Our main positive finding is that receivers respond to the fact that the evidence they receive is selected, especially when N is larger or K is smaller. As predicted by the theory, when conditioning on the message's content, we find that receivers' guesses are on average lower as N increases or K decreases. That is, receivers become more skeptical of more selected evidence. While qualitatively these results corroborate the theory, we also find some departures from it. First, in all treatments receivers tend to be overly optimistic: Their guesses are higher than the optimal guess given senders' behavior. Second, this positive gap is larger in treatments with large N and, therefore, receivers underestimate the impact of selection, leading them to insu ciently discount good news in settings with large N. We attribute this unpredicted treatment e ect to selection neglect, a bias documented, for instance, by Enke (2020).

[2] In the models typically studied in this literature, the theory predicts full disclosure. Thus, it is impossible to find evidence of overcommunication in those settings. An exception is the work by de Clippel and Rozen (2020).

1.1 Related Literature

The central result in the early literature on verifiable disclosure is the unraveling principle, which states that, when the sender can verifiably disclose the state of the world, any equilibrium features full information transmission (see, e.g., Grossman, 1981; Milgrom, 1981). Disclosure models have been used to study a variety of applications such as quality disclosure by a privately informed seller or the disclosure of financial information by a firm (e.g., Verrecchia, 1983; Dye, 1985; Gal-Or, 1985). Milgrom (2008) and Dranove and Jin (2010) survey this literature.

The basic structure of the model we study dates back to Milgrom (1981). He shows that, for a generic K, there is a maximally selective equilibrium. Fishman and Hagerty (1990), build on Milgrom's model. They show that when $K = 1$ and N is large the equilibrium is uninformative. They then provide results that relate to the value of discretion in communication. In a related setting, Di Tillio et al. (2021) provide conditions under which observing the K most favorable signals out of N is more informative than observing K chosen at random. They show that in experiments with additive noise, increasing N increases (decreases) informativeness if and only if the reverse hazard function of the noise distribution is log-concave (log-convex). In contrast, in our environment with discrete signals and full support, informativeness must eventually decrease for all distributions, and we highlight a non-monotonicity result. Haghtalab et al. (2021) consider a model in which a sender can choose to send one signal out of N. One important difference in their setting is that the sender must choose one of the N signals and cannot choose to be silent.[3]

Our paper relates to a large body of experimental literature on cheap talk, which has been recently surveyed by Blume et al. (2020). In particular, Cai and Wang (2006) vary preference alignment between the sender and the receiver; they find that senders overcommunicate relative to the predictions of the cheap talk model and that receivers are overly trusting.[4] In contrast to experiments on cheap talk, experiments on the disclosure of verifiable information consistently find that senders under-communicate relative to the theoretical predictions. For instance, Jin et al. (2021) find that receivers are insufficiently skeptical when senders do not provide any information, which in turn leads senders to under-communicate.[5] This result has been

[3] Shin (2003), Dziuda (2011), and Hoffmann et al. (2020) study richer settings that also feature selective disclosure. Regarding equilibrium selection, Bertomeu and Cianciaruso (2018), Gieczewski and Titova (2024), and Gao (2024) propose equilibrium refinements for games with verifiable disclosure that, like ours, build on the tradition of neologism or announcement proofness.

[4] See also 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).

[5] See also Forsythe et al. (1989), King and Wallin (1991), Dickhaut et al. (2003), Forsythe et al. (1999),

confirmed by several papers, that modify the information environment. In particular, the literature has allowed for vagueness of the messages (Li and Schipper, 2020; Deversi et al., 2021), multidimensional states (Farina and Leccese, 2024), subjects' communication or more realistic contexts (Montero and Sheth, 2021), different preference alignments (Hagenbach and Perez-Richet, 2018) and partial commitment power for the sender (Fréchette et al., 2022).

Jin et al. (2022) and de Clippel and Rozen (2020) find evidence for strategic obfuscation of verifiable evidence. Information unraveling has also been studied in the field. For instance, Mathios (2000) and Jin and Leslie (2003) document the failures of information unraveling for food nutrition labels and hygiene grade cards in restaurants.

There is limited experimental evidence on partial verifiability of information. Li and Schipper (2018) studies a setting in which the receiver is unaware of the amount of evidence available to the sender. Burdea et al. (2023) designs an experiment to empirically test the predictions from Glazer and Rubinstein (2004) and Glazer and Rubinstein (2006). An informed sender sends a two-dimensional message to a receiver. The verifiability of the message depends on the treatment: either it is pure cheap talk, or only one dimension is verifiable. In the last case, the paper looks at two different treatments in which the dimension to verify is either chosen by the sender or by the receiver. Brown and Fragiadakis (2019) investigates receiver's understanding of the value of strategically selected information by comparing a setting in which the disclosure is exogenously mandated to one in which the sender can choose to disclose self-serving attributes. Penczynski et al. (2022) studies a setting in which the sender can selectly disclose verifiable information, as in our setting, but the main focus of the paper is to investigate the effect of competition on the effectiveness of communication.

In contemporaneous work, Ispano (2024) studies the selective disclosure of noisy evidence within an experimental framework that shares many similarities with ours. We highlight the three main differences relative to our design. First, his design does not allow for a test of the nonmonotonicity of informativeness in N. Second, he does not explore treatments with large N, which approximate a cheap talk setting. Third, his design assumes binary evidence, which simplifies the sender's problem. Net of these differences, the main results in Ispano (2024) appear to be qualitatively consistent with ours.[6]

Benndorf et al. (2015), Hagenbach et al. (2014) and Hagenbach and Perez-Richet (2018).

[6] Degan et al. (2023) experimentally tests the predictions from Di Tillio et al. (2017). An informed sender can disclose one of two signals but can only observe one of them. They compare a treatment in which of the two signals is disclosed is randomly determined with a treatment in which the sender can strategically select the signal to disclose (which they call manipulation). They report experimental results that are qualitatively in line with the theory. In particular, they find that there are instances where manipulated disclosure leads to higher welfare for the receiver.

2 Theory

2.1 Model

The 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 that are informative about the state. She can verifiably disclose up to K of these signals 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 $\Theta \subset \mathbb{R}$. The state is distributed according to a common prior distribution $\pi \in \Delta(\Theta)$ that has full support. The sender privately observes $N \geq 1$ conditionally independent and identically distributed signals $(s_1, \ldots, s_N)$, which are informative about θ. Each signal s belongs to a finite and ordered set S and is distributed according to $f(\cdot|\theta) \in \Delta(S)$. We assume that f satisfies the monotone likelihood ratio property, meaning that $\frac{f(s|\theta')}{f(s|\theta)}$ is monotone increasing in s for all $\theta' > \theta$.

The sender can verifiably disclose up to $K \leq N$ of the N signals. We refer to the vector of disclosed signals, listed in decreasing order, as the sender's message, denoted by m. We denote a message that contains no signal by $\emptyset$. Information is verifiable, meaning the sender can only disclose signals among those that have indeed been realized. The sender cannot fabricate new signals. We denote by M the set of all messages and by $M(\bar{s}) \subseteq M$ the set of messages that can be sent given $\bar{s}$.[7] Finally, the receiver observes m and chooses an action $a \in A = co(\Theta)$. 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 $\sigma_S : \Theta \times S^N \to \Delta(M)$, subject to the verifiability requirement $m \in M(\bar{s})$, for all $\bar{s}$ and $m \in supp\, \sigma_S(\theta, \bar{s})$. A strategy for the receiver is a mapping $\sigma_R : M \to \Delta(A)$. As in prior literature, (e.g., see Okuno-Fujiwara et al., 1990), we focus on Perfect Bayesian equilibria (PBE) in which the sender's strategy is pure. In addition, we restrict attention to sender's strategies that are independent of θ. Thus, a sender's strategy is a map $\sigma_S : S^N \to M$.

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. This contrasts with most of the literature on information disclosure, which assumes a sender can

[7] Formally, the message space is $M := \{\emptyset\} \cup \{\{\bar{s} \in S^k \mid 1 \leq k \leq K \text{ and } \bar{s}_i \geq \bar{s}_j \text{ for } i \leq j\}\}$. The set of messages that can be sent given $\bar{s}$ is $M(\bar{s}) := \{m' \in M \mid \text{if } m' \neq \{\emptyset\}, \exists\, 1 \leq k \leq K \text{ and an injective } \rho : \{1, \ldots, k\} \to \{1, \ldots, N\} \text{ s.t. } m' = (\bar{s}_{\rho(1)}, \ldots, \bar{s}_{\rho(k)})\}$.

verifiably reveal the state if desired. This is a key feature of our setting, as it leads to a failure of the unraveling principle (Okuno-Fujiwara et al., 1990): That is, no equilibrium is fully informative of the state, and changes in K and N give rise to nontrivial comparative statics in equilibrium informativeness.

In our model, N is exogenous, not chosen by the sender. Although in many applied settings the sender may influence N, this modeling choice allows us to focus our attention on the selection problem—which pieces of evidence the sender chooses to disclose—abstracting from the distinct problem of evidence generation. The selection of evidence, rather than its concealment, becomes a primary force in the model only when $K < N$. Such a situation reflects exogenous communication constraints, such as the receiver's inability to process too many signals, or institutional constraints that prevent the sender from disclosing all available evidence.

Our communication model has two key features. First, the disclosed evidence is verifiable, i.e., the sender cannot fabricate it. As such, this model falls in the tradition of disclosure models (e.g., Milgrom, 1981; Grossman, 1981). Second, when $K < N$, the disclosed evidence may be selected from a larger pool of evidence that only the sender can observe. As such, its interpretation depends on the context, a property that is reminiscent of cheap talk (e.g., Crawford and Sobel, 1982). As we will show, changing K and N allows us to span models in between these two classical traditions.

2.2 Equilibrium Predictions

Our setting can feature multiple equilibria. While this is common in many communication games, it is not typical in games of verifiable information disclosure, which typically feature a unique equilibrium outcome with full information transmission. Our analysis focuses on a natural equilibrium class in which the sender is maximally selective: Her strategy consists of disclosing the K highest available signals.

Definition 1. Fix N and K. A sender's strategy $s : S^N \to M$ is *maximally selective* if, for each $\bar{s}$, the message $m = s(\bar{s})$ contains the K highest signals in $\bar{s}$.

We focus on maximally selective equilibria for several reasons. First, this is the natural counterpart of the full disclosure result that obtains when senders possess verifiable evidence that is fully revealing. Second, this selection has a theoretical foundation. Indeed, the maximally selective equilibrium is unique among equilibria that are neologism-proof (Farrell (1993)). We discuss the details of this refinement in Appendix A. Third, this selection has empirical support. As we will see, many features of senders' behavior are consistent with the maximally selective strategy. Moreover, the empirical best response to receivers' observed strategies is indeed to disclose the K-highest signals. Finally, the maximally selective equilibrium is the unique sequential equilibrium when $K = N$ (Proposition 7 Milgrom, 1981); it is useful to focus on this equilibrium when $K < N$ to allow a simple contrast between these two cases.

The model offers several predictions regarding the behavior of senders and receivers that are simple but crucial features of behavior with selective disclosure. We summarize these predictions in the following remark and then offer some discussion.

Remark 1. Predictions regarding players' behavior:

1. (Sender's Behavior). Fix K. As N increases, there is a first-order stochastic increase in the distribution of disclosed signals. Conversely, fix N. As K increases, there is a first-order stochastic decrease in the distribution of disclosed signals. Finally, the number of disclosed signals increases with K and is independent of N.

2. (Receiver's Behavior). Fix any on-path message m. The receiver's guess decreases in N and in K.

Regarding sender's behavior, the model makes a prediction 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. Regarding receiver's 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 q, the sender's best K signals are likely to be better. Thus, when N increases, the same message m should be perceived more skeptically by the receiver. Likewise, fixing N, note that when K is higher, the same message m implies more signals have been concealed. Missing signals should be interpreted by the receiver as the worst signals, making the receiver more skeptical.

A key set of aggregate predictions of our model concerns the relation between the parameters K and N and the amount of information the sender transmits to the receiver. We define equilibrium informativeness as the correlation between the state q and the receiver's action a, which we denote by $I(K,N)$. The larger is $I(K,N)$, the more effectively the receiver learns about the state q through the messages disclosed by the sender.[8]

As illustrated by the next result, changes in K and N generate rich comparative statics in the equilibrium informativeness, which we exploit in our experimental analysis.

[8] This measure is a monotone transformation of the receiver's ex-ante expected payoff. See Appendix C for more details.

Proposition 1. As K and N vary, equilibrium informativeness $I(K,N)$ changes as follows:

1. Fixing N, $I(K,N)$ increases in K.
2. Fixing $K = N$, $I(K,N)$ increases in N.
3. Fix K and suppose that, for all θ, $f(\cdot|\theta)$ has full support. $I(K,N)$ converges to zero as $N \to \infty$. Moreover, $I(K,N)$ need not be monotonic in N.

We briefly discuss the intuition for these results. First, when N is fixed and K increases, 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 uncertainty about the state. Second, when $K = N$, the maximally selective equilibrium involves disclosing all available signals. This means the sender discloses signals that are not selected. Thus, as N grows, more i.i.d. signals are disclosed to the receiver, which increases equilibrium informativeness. Third, as the number of available signals approaches infinity, the full support assumption implies that for every θ, state with probability close to one, the sender can disclose the most favorable message. This implies that there is no separation among different θ's in equilibrium and, consequently, no possibility for the receiver to learn.

The intuition behind the non-monotonicity in the last result of Proposition 1 is perhaps more subtle. An increase in N generates two contrasting effects that can change informativeness in opposite directions. On the one hand, it is more likely that the sender has the best signal available, no matter the state θ. This leads to more pooling and, thus, lower informativeness. We can think of this as the "imitation effect." On the other hand, a higher N increases the probability that higher states can separate themself, making worse signals stronger evidence that the state is low. This increases equilibrium informativeness. We can think of this as a "separation effect." When $f(\cdot|\theta)$ is full support, these effects are present simultaneously, and which one prevails determines how the amount of information transmitted is affected by N. In Appendix D, we present a simple example that isolates the imitation and separation effects, providing intuition as to why, in general, equilibrium informativeness need not be monotone in N.[9]

[9] Di Tillio et al. (2021) characterize sufficient conditions on f under which one effect or the other dominates and, thus, equilibrium informativeness $I(K,N)$ is monotone in N. Their setting is close to ours but differs in that they assume S is infinite.

	Ball Label			
Urn Color	$s = A$	$s = B$	$s = C$	$s = D$
Yellow ($q = 0$)	10%	20%	25%	45%
Red ($q = 1$)	45%	25%	20%	10%

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

3 Experimental Design

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

In the laboratory, we implement a simple 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., $q = 1$) or yellow (i.e., $q = 0$) with equal probability. They both contain balls labeled with four different letters, $S = \{A, B, C, D\}$, representing the possible signal realizations. The composition of each urn depends on its color, as shown in Table 1. As in the theory, the distribution $f(s|q)$ has full support and satisfies MLRP, furthermore it is symmetric.

The interaction between the sender and the receiver unfolds as follows. The sender privately observes the color of the urn and a set of N balls drawn randomly from the urn with replacement. She then discloses up to K of these balls to the receiver. In the second stage, the receiver observes the balls selected 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 q. The probability of winning 100 points increases with the accuracy of her guess, incentivizing the receiver to truthfully report her subjective belief that $q = 1$. The details of this belief elicitation are described below.

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 Appendix F.2 and F.1). They are 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 available to the sender, the message, the receiver's guess, and their respective payoffs.

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})

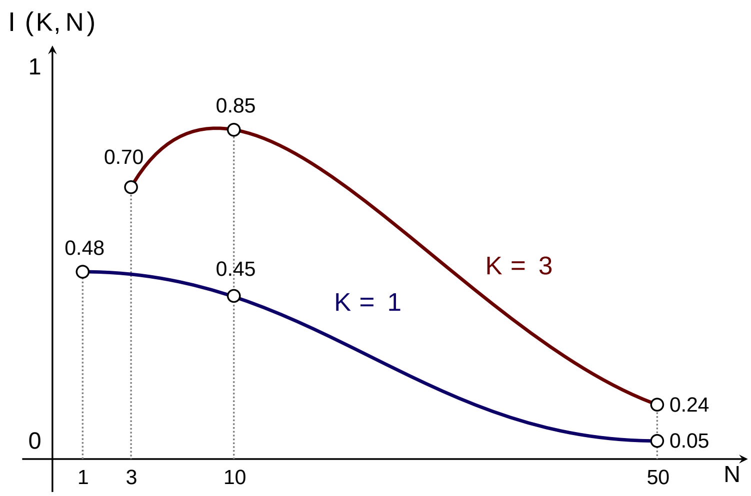

Figure 1: Equilibrium Informativeness

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 K, 10, or 50. Figure 1 reports the specific treatment predictions of $I(K, N)$ under this implementation. Notice that this choice of treatments allows us to test all the predictions listed in Proposition 1.

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 one of them participating in a single treatment (a "between-subject" design). Subjects were students recruited from the undergraduate populations at Columbia University and New York University in Spring 2023. Two sessions per treatment were conducted at the laboratory facilities of each institution.[10]

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. During the experiment, subjects received a pay in points that were converted into cash at the end of the experiments. The conversion rate was $1.20 for 100 points for senders and $0.90 for 100 points for receivers. The different conversion rates aimed at minimizing the differences in expected

[10] 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).

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). Previous literature has shown that the quadratic scoring rule can lead to biased guesses in the lab when subjects are not risk-neutral. To avoid these well-known issues, we do not incentivize the receivers with a quadratic payoff but use instead a binarized scoring rule. This rule determines the likelihood that a receiver wins 100 points based on their guess and the realized state.[11]

Measuring Informativeness in the Data. The correlation between the realized state and the observed receiver's action combines both sender and receiver behavior. When appropriate, to isolate the informativeness of the senders' strategies—i.e., to net out receivers' mistakes—we compute the correlation between the state and the guess of an idealized Bayesian receiver who optimally responds to senders' average behavior in the session. We call the resulting measure the Bayesian informativeness of the senders' strategies and denote it by $I^B(K, N)$. An identical decomposition technique is used in Fréchette et al. (2022).

Statistical Tests and Predictions. Our data analysis focuses on the last 15 rounds to allow time for learning.[12] Unless stated otherwise, our tests include subject specific random effects and cluster standard errors at the session level (see Fréchette (2012) and Online Appendix A.4. of Embrey et al. (2018) for a discussion of issues related to hypothesis testing for experimental data). Additionally, when comparing data against theoretical predictions, we compute the predictions by taking into account the small-sample nature of our data. That is, the prediction consists of the behavior of an agent who plays the equilibrium strategy given the observed sample.

4 Results

We organize our results into two subsections. Section 4.1 focuses on senders' behavior. We study what evidence they select to disclose (Section 4.1.1), how much information they transmit to receivers (Section 4.1.2), and what strategies are played more often (Section 4.1.3). Section 4.2 focuses on receivers' behavior. We study how they respond to selected evidence (Section 4.2.1), we find selection neglect in high-N treatments (Section 4.2.2), and document its consequences for overall communication informativeness (Section 4.2.3).

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[11] Incentive compatibility of the binarized scoring rule is independent of a subject's risk attitude (Allen, 1987; McKelvey and Page, 1990; Schlag et al., 2015; Hossain and Okui, 2013). We use the implementation outlined in Wilson and Vespa (2018). See also Danz et al. (2022).

[12] See Fréchette et al. (2024) for a discussion of this choice, which is common in experimental economics.

4.1 Senders' Behavior

4.1.1 What Evidence Do Senders Disclose?

We begin by testing a key comparative static of our model: What evidence do senders disclose, and how does this disclosure change as K and N change? Remark 1 predicts that, for a fixed K, the evidence disclosed should appear more favorable as N increases. Conversely, for a fixed N, the evidence disclosed should appear less favorable as K increases. The former prediction is driven by the fact that, when N is larger, the sender can choose K pieces of evidence from a larger pool. This opportunity allows the sender to be more selective, resulting in messages that appear more favorable. The latter prediction is driven by the fact that when K is larger, the sender must disclose more evidence. This forces the sender to become less selective, resulting in messages that appear less favorable.

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 single number, its implied grade point average (GPA). Just as in the case of school transcripts, we assign a numerical value to each signal that is disclosed and average them. In particular, we assign $A = 4$, $B = 3$, $C = 3$, and $D = 1$. Consistent with equilibrium reasoning, we assign a missing signal the value of 2. For example, when $K = 3$, a message $m = ABC$ would result in a GPA of 3.[13]

In Table 3, we report the mean GPA (MGPA) computed at the treatment level. In Figure 2, we report the cumulative distribution function (CDF) of sender-level MGPAs. Both also report the associated theoretical predictions. We emphasize the following three results.

First, as predicted, the MGPA increases in N for each K. When $K = 1$, the treatment-level MGPA increases from 2.31 for $N = 1$ to 3.61 for $N = 50$. Similarly, when $K = 3$, the treatment-level MGPA increases from 2.27 for $N = 3$ to 3.54 for $N = 50$. Both increases are significant at the 1% level. These treatment effects also hold across the distribution of MGPA computed at the sender's level, rather than at the treatment level. Figures 2a and 2b show a first-order stochastic dominance increase in the distribution of sender-level MGPAs when N increases from K to either 10 or 50. For both K's, the differences between $N = 10$ and $N = 50$ are small; these differences are also predicted by the theory to be relatively small (see Figures

[13] By mapping messages into GPAs we reduce the high-dimensional and partially-ordered set of messages into the real line. This is especially convenient for treatments with $K = 3$. The choice of coding a missing signal as a 1 is somewhat arbitrary. Our results are robust to alternative coding choices: for example, coding it as a 0 (i.e., a grade lower than a D) or as a 2.5 (i.e., the prior grade). The qualitative results presented in this subsection hold beyond the GPA. Appendix E.1 reports the full distribution of signals disclosed and how it changes in K and N.

Table 3: Mean GPA induced by senders' messages (predicted values shown in parenthesis)

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

2c and 2d).

Second, as predicted, the MGPA decreases in K for $N = 10$. As reported in Table 3, the treatment-level MGPA decreases from 3.63 to 3.24 as K increases from 1 to 3 (p-value $<$ 0.01). Additionally, by comparing Figures 2a and 2b, we see a first-order stochastic dominance decrease in the distribution of sender-level MGPAs between these two treatments.

Overall, these first two sets of results corroborate the theory and are a manifestation of selective disclosure. As N increases, senders can cherrypick their signals, leading to higher MGPAs. Conversely, as K increases, equilibrium forces compel senders to disclose more evidence, reducing their ability to be selective and resulting in lower MGPAs.

The third result is that there are some sizable quantitative differences between the theoretical predictions and the quality of evidence senders disclose in our data. Across all treatments, we find that senders induce MGPAs that are lower than those predicted by the theory. This is true both at the treatment level (Table 3) and at the sender level (Figures 2). We call this underreporting a *modesty bias*. Additionally, the distributions reveal that senders' behavior is more heterogeneous than predicted.[14] We will discuss this in more detail below.

[14] Note that the predictions in the bottom panels of Figure 2 display some heterogeneity. This is due to the randomness of the senders' available signals. Therefore, given any finite sample, two senders playing the equilibrium strategy may not induce the same MGPAs.

(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

Before proceeding, we briefly discuss the last prediction in the first bullet of Remark 1, which describes an immediate implication of the maximally-selective equilibrium: In theory, the number of disclosed signals should increase in K and be independent of N. Table 4 reports the average number of signals disclosed by the senders in the various treatments. We emphasize two aspects of this table. First, in treatments (K_1, N_1) and (K_3, N_3), the number of signals disclosed is significantly smaller than K (p-value < 0.01). This result is in line with one of the prominent findings from the existing experimental literature on verifiable disclosure (e.g., Jin et al., 2021): When there are no selection opportunities, i.e., $K = N$, senders do conceal evidence, especially when it is unfavorable, in contrast with the equilibrium predictions. The second aspect that we would like to emphasize is that the number of disclosed signals increases

Table 4: Average number of signals disclosed (predicted values shown in parenthesis)

	$N = K$	$N = 10$	$N = 50$
$K = 1$	0.66	1	1
	(1)	(1)	(1)
$K = 3$	1.89	2.85	2.92
	(3)	(3)	(3)

in N (p-value < 0.01 for the changes from $N = K$ to $N > K$; changes between $N = 10$ and $N = 50$ are not statistically significant). That is, selection trumps concealment: When selection opportunities are large, the concealment of evidence virtually disappears.

4.1.2 How Much Information Do Senders Transmit?

Next, we discuss how much information senders transmit. As discussed in Section 3, we quantify this in terms of the Bayesian informativeness $I^B(K, N)$, which is the correlation between the state and the guess of an idealized Bayesian receiver.

Table 5 reports the average $I^B(K, N)$ for all treatments.[15] We find that, for all treatment variations of K and N, the average Bayesian informativeness moves in the directions predicted by the theory. Next, we highlight the most important comparisons.

First, Proposition 1(a) and Figure 1 predict that, when fixing N, increasing K from 1 to 3 should increase Bayesian informativeness and that 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 non statistically significant one for $N = 50$, from 0.38 to 0.39.

Second, as predicted by Proposition 1(b), we find that Bayesian informativeness significantly increases from 0.46 in (K_1, N_1) to 0.73 in (K_3, N_3) (p-value < 0.01).

Third, Proposition 1(c) predicts that an increase in N should eventually decrease Bayesian informativeness for both K's. Accordingly, the average Bayesian 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).

[15] The values reported in Table 5 are derived by computing the correlation between the state and the guess of an idealized Bayesian receiver at the treatment level. To perform the statistical tests reported in the section we use, instead, correlations computed at the sender's level.

Table 5: Bayesian informativeness $I^B(K,N)$ of senders' strategies (predicted values shown in parenthesis)

	$N = K$	$N = 10$	$N = 50$
$K = 1$	0.46 (0.44)	0.43 (0.38)	0.38 (0.06)
$K = 3$	0.73 (0.69)	0.82 (0.84)	0.39 (0.22)

Finally, the theory predicts that informativeness should not be monotonic in N if $K = 3$. Accordingly, we find that increasing N from 1 to 10 decreases the average Bayesian informativeness from 0.46 to 0.43 for $K = 1$ but increases it from 0.73 to 0.82 for $K = 3$. Although the point estimates move in the direction predicted by the theory, these changes are not always statistically significant. In particular, the decrease when $K = 1$ is not significant, while the increase when $K = 3$ is significant at the 5% level, although the p-value of this test is sensitive to the exact specification.[16] To summarize, there is no case in which the prediction of the theory is rejected, and in the majority of cases, the predictions are in line with the theory.

To summarize, our findings indicate that senders transmit information in ways that qualitatively align with the theory's predictions. This alignment suggests that the theory effectively captures the key tensions in how selective disclosure shapes senders' behavior. However, quantitatively, we observe a substantial deviation from the theory, with senders **over**communicating, especially for large N. This contrasts with prior results in the literature on disclosure, both in the lab and in the field, that find that senders undercommunicate.[17] These prior results show that the unraveling principle often fails: senders communicate less than the theory predicts. One important difference from our setting is that, in these papers, informativeness is predicted to be maximal, i.e., using our notation, $I(K,N) = 1$. This is due to the rich evidence structure used by these studies. As such, these studies cannot uncover overcommunication, since any departure from the theory (even noisy behavior) would lead to undercommunication. In contrast, in our setting, full information transmission is not an equilibrium outcome. This is because the evidence structure available to senders is constrained: for example, when $K < \infty$, senders cannot communicate q, even if they want to. This constraint leads to an interior prediction for

[16] The robustness of these results is confirmed through a bootstrapping procedure. For each treatment, we generate 1000 random subsamples and we compute the Bayesian informativeness in each of them. This allows us to compare the resulting vectors of correlation through a standard t-test procedure and assess whether a significant difference can be detected.

[17] For instance, see Forsythe et al. (1989), Jin and Leslie (2003) Jin et al., 2021, Fréchette et al. (2022). An exception is de Clippel and Rozen (2020), who also find evidence of over-communication.

$I(K, N)$, allowing for the possibility of observing either over- or under-communication, depending on the sender's behavior. This feature is crucial as it enables nontrivial comparative statistics and allows the theoretical predictions to fail in both directions

4.1.3 Explaining Senders' Overcommunication

The previous section documents either average behavior close to equilibirum or overcommunication, depending on the treatment. Such behavior could be representative of individual behavior, or could hide systematic heterogeneous behavior where some subjects under or over-communicate. In this section, we analyze the heterogeneity in senders' behavior and relate it to the deviations 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 signals available. We do not observe what message would have been disclosed had the sender obtained a different set of available signals.[18] Third, some key features of behavior often vary across treatments: for instance, in some treatments, concealment is important, while in others it is not; furthermore, selection only matters if $N > K$. These challenges both complicate the inference of the sender's strategy from the observed data and the comparisons across treatments.

To address these challenges, we introduce the GPA gap the difference between the GPA of the message sent by the sender and the GPA of the equilibrium message. For each sender, we calculate the conditional mean gap, i.e., the mean gap conditional on the state (high or low). Then, using a k-means algorithm, each sender's strategy is classified along two dimensions: the high-state conditional mean gap and the low-state conditional mean gap. This approach allows us to bypass the issues discussed above. First, the sender's strategy is summarized in a much lower dimension, namely, the mean GPA gap conditional on each state. Second, these measures are only partially affected by the randomness of the signals because the gap is computed by using a benchmark, the equilibrium GPA, which also depends on the realized signals. Lastly, the procedure can be applied consistently for all treatments.[19]

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

[18] Eliciting the sender's strategy using the “strategy method” is impractical in this setting.

[19] As a robustness check, we can cluster senders strategies directly on the strategy space. This approach leads to qualitatively similar results. This procedure, however, is rather data-intensive and leads to less stable estimates, especially for treatments with low N.

Figure 3: Sender's Clustering for the Treatment (K_1, N_{50})

Figure 4: Sender's Clustering for the Treatment (K_3, N_{50})

signal is sent, conditional on the state.[20] These averages represent the typical strategy played in this cluster. For each cluster, we also compute the average Bayesian informativeness as well as the associated payoff that senders playing such strategies earned in the experiment. Overall, this provides a comprehensive view of senders' behavior: what strategies they played, and how informative and profitable they were.

Figure 3 reports the outcome of our clustering analysis for treatments with $N = 50$. The patterns emerging from these two treatments are broadly representative of what we find in the other treatments (see Appendix E). Our emphasis on large-N treatments is motivated by

[20] Specifically, for each cluster, the average frequency of disclosing signal s in state q is computed as follows. For each strategy in the cluster, we count the number of signals s that have been disclosed and divide it by K, namely, the number of disclosable signals. We then average the resulting number across all strategies in the cluster. This procedure provides us with a distribution of disclosed signals for each cluster. This is a convenient way of summarizing the typical strategy in the cluster.

the fact that the deviations documented in Sections 4.1.1 and 4.1.2 appear strongest for those treatments.

In both treatments, the largest cluster, capturing about 58% and 71% of the senders, respectively, displays behavior that is close to equilibrium. Strategies in this cluster overwhelmingly disclose the best available signals in both states. In both treatments, senders in this cluster earn the largest payoff and induce a low informativeness.[21]

Although many senders play strategies consistent with equilibrium behavior, a minority deviate from it. There is one type of deviation that appears in all treatments. In Figure 3, this deviation is represented by cluster #3, which captures about 17% of the senders in both treatments. This cluster displays behavior that we interpret as *deception-averse*. These senders disclose the best available signal in the high state, but fail to do so in the low state. Instead, in those cases, they predominantly disclose the worst signal, i.e., D. In both treatments, senders in this cluster induce the highest informativeness. The differences from the equilibrium-like cluster are particularly stark. For example, in treatment $(K = 1, N = 50)$, the Bayesian informativeness is 0.177 in the equilibrium cluster, whereas it is 0.746 in the deception-averse cluster. Additionally, senders in the deception-averse cluster earn a payoff that is 22% to 27% lower than that earned by senders in the equilibrium-like cluster. These qualitative patterns hold in the other treatments as well.

Deception aversion is related to lying aversion. However, there are some important differences. For instance, in our setting, senders cannot lie: Since disclosed signals are verifiable, all the information they convey to the receivers is true. However, they can choose to vary the type of signals they disclose (or not) depending on the realization of the state, thereby potentially conveying more information than is predicted in equilibrium.

The third cluster (middle panel) is best thought of as a residual cluster. It presents behavior that varies somewhat between treatments. In some treatments, such as those displayed in Figure 3, the behavior is somewhere between equilibrium and deception aversion. These senders disclose the best signals in the high state but intermediate signals in the low state. Senders in this residual cluster earn payoffs and induce Bayesian informativeness that are in between those of the other two clusters.[22]

[21] In the data as a whole, 24% of senders play exact equilibrium strategies in all of the last fifteen rounds, while 56% of the senders do so in at least 80% of these rounds.

[22] In other treatments, this cluster seems to represent senders whose behavior appears to display some degree of confusion.

4.1.4 Summary and Interpretation of Senders' Behavior

In summary, we find strong evidence that the senders engage in selective disclosure. This behavior affects what evidence they disclose and how informative their strategies are in ways that are qualitatively consistent with the theory.

We documented three main departures from the theory. First, senders show a modesty bias, i.e., they disclose worse evidence than predicted. Second, they overcommunicate, i.e., they convey more information than predicted. Third, our clustering analysis reveals 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 three departures are connected. In particular, the deception-averse senders drive the modesty bias, as they fail to disclose the highest available evidence when the state is low, thus lowering the average MGPA. Moreover, the state-dependent nature of the deception-averse strategy implies that these senders communicate more information than predicted, leading to overcommunication.

4.2 Receivers' Behavior

4.2.1 How Do Receivers Respond to Selected Evidence?

We now discuss receivers' behavior, starting with a key prediction. For any fixed message m, the receiver's guess should decrease as N increases. This is because receivers should anticipate 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 start with a simple test. A receiver who observes message $m = A$ in treatments with $K = 1$ should respond more skeptically when $N = 50$ than when $N = 1$. To quantify this comparison, we introduce the *empirical optimal guess*, which is the receiver's best response to the senders' observed strategies.[23] We use the empirical optimal guess as the benchmark against which to evaluate the observed receivers' guesses. Due to senders' selective disclosure, the empirical optimal guess decreases from 83.9 in treatment (K_1, N_1) to 57.2 in treatment (K_1, N_{50}). The observed receivers' guess shows a similar qualitative pattern: On average, there is a large decrease from 82.0 in (K_1, N_1) to 64.5 in (K_1, N_{50}) (p-value < 0.01).

To provide more systematic evidence of the receivers' responses to changes in N, we esti-

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[23] Specifically, the empirical optimal guess given a message m is $E(q|m) = Pr(1|m)$, i.e. the fraction of times message m was sent when $q = 1$ 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 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)	(2.55)
$D_{N_{10}}$	18.67	29.22	24.72	30.92
	(2.69)	(1.91)	(2.95)	(2.91)
$D_{N_{50}}$	17.04	25.84	28.16	43.12
	(2.20)	(1.43)	(3.00)	(3.28)
Constant	19.08	2.91	6.28	25.92
	(1.98)	(2.50)	(5.18)	(5.81)
Obs	1,545	1,545	1,560	1,560
Subjects	103	103	104	104

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

mate the following regression model:

$$a_{i,m} = b_0 + b_1 GPA_m + b_2 D_{N_{10}} + b_3 D_{N_{50}} + \epsilon_{i,m}, \tag{1}$$

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 $K = 3$. The dummy coefficients capture how much the receivers' guess decreases compared to the benchmark case of $N = K$. 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 asymmetrically so across treatments. The GPA circumvents this issue.[24]

Table 6 reports the results of the regression. For both K, the dummy coefficients are strongly significant. As N increases, receivers become more skeptical of messages with the same GPA, as predicted by the theory. For $K = 1$, the average guess decreases by 18.67 points from $N = 1$

[24] 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). Additionally, we obtain qualitatively similar results if we use a nonparametric approach to estimate the receivers' responses. See Appendix E.2.1 for details.

to $N = 10$ and by 17.04 points from $N = 1$ to $N = 50$. For $K = 3$, it decreases by 24.72 points from $N = 3$ to $N = 10$ and by 28.16 points from $N = 3$ to $N = 50$. These effects are significant at the 1% level.

Table 6 also reports the treatment effects that we should have observed had receivers best responded to our senders. We do so by replacing the dependent variable in the regression model of Equation 1 with the empirical optimal guess. Comparing the estimated coefficients of these regressions with those discussed before, we conclude that, while receivers become more skeptical as predicted, they do not correct their responses as much as they should have. We will come back to this point in the next subsection.

A second key prediction about receivers' behavior consists of stuyding how they respond to messages with the same GPA when we fix N and increase K (rather than the opposite). To fix ideas, consider receving a message with a GPA of 4 in treatments (K_1, N_{10}) and (K_3, N_{10}). Intuitively, messages are more selected in the former treatment than in the latter. Therefore, receivers should be less skeptical of a message with the same GPA as K increases. To test this, for each $N \in \{10, 50\}$, we regress the receiver's guess on a constant, the GPA of the observed message, and a dummy variable D_{K_3} that 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)). Our data align qualitatively with these predictions. 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 some key qualitative predictions of the theory and demonstrate that receivers account, at least directionally, for the fact that the evidence they observe is differentially selected across the different treatments. Quantitatively, however, we also documented that receivers do not adjust as much as they should to changes in K and N. 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, response gaps are significantly positive across the treatments (p-value < 0.01, except for

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	31.81	16.09	19.72
	(3.34)	(3.67)	(1.62)	(0.75)
D_{K_3}	8.40	17.96	3.43	1.66
	(4.77)	(3.08)	(2.55)	(0.72)
Constant	30.71	71.14	0.702	23.87
	(13.08)	(14.56)	(5.22)	(2.91)
Obs	1,005	1,005	1,065	1,065
Subjects	67	67	71	71

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

(K_3, N_{10}), whose p-value is 0.09). This finding aligns with previous experimental results that show receivers are often overly optimistic.[25] Considering the complexity of the receiver's task, the magnitudes of these gaps appear moderate, although they conceal substantial heterogeneity (as we will discuss shortly).

Second, response gaps are small when N is small and increase as N rises, indicating greater overoptimism with larger N. This is, perhaps, counterintuitive, as the receiver's task becomes arguably simpler as N grows. For instance, in treatment (K_1, N_{50}), a receiver observes the same message ($m = A$) about 75% of the time over 30 rounds, and learns the outcomes ex-post at the end of each round. This should in principle facilitate learning and reduce the response gap relative to treatment (K_1, N_1), where the most common message ($m = ?$) is only observed 33% of the time ($m = A$ is observed roughly 25% of the time).

To investigate this unpredicted treatment effect, we regress the response gap on the same covariates used in Equation 1. Table 8b reports the estimated coefficients. For all K, the response gap increases with N, conditional on messages with the same GPA. These effects are significant at the 1% level. We identify similar effects when comparing the CDF of receiver-level response gaps between treatments with $N = K$ and those with $N = 50$, while controlling for the message distribution in treatments with $N = 50$. Figure 5 shows that, for all K, the

[25] E.g., see Cai and Wang (2006) and Jin et al. (2021). Section 1.1 reports a broader overview of the literature.

Table 8: Comparison of Treatment Effects

(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

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

response-gap CDFs increase in a first-order stochastic sense as N increases from K to 50, indicating that receivers become increasingly overoptimistic with larger N.

We attribute this unpredicted treatment effect to selection neglect, a bias documented, for instance, by Enke (2020). Our results show that receivers are unable to fully account for the fact that disclosed evidence becomes more selected as N increases. This leads receivers to be insufficiently skeptical, as reflected by the response gap increasing in N.

To summarize, we provided evidence of selection neglect in a strategic communication setting, where selection plays a crucial role. This bias persists despite ample learning opportunities for receivers in our treatments. Although existing literature has documented selection neglect in non-strategic decision problems, our findings highlight its significance in a strategic setting. Notice that, 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 harder for the receiver. On the other hand, it could ameliorate the bias by making the selection forces more salient for the receiver, as they stem from a sender with clearly conflicting preferences.

(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

4.2.3 How Much Information Do Receivers Absorb?

We conclude by discussing how the overall informativeness of the communication between the senders and the receivers changes across treatments. Recall that, in Section 4.1.2, we focused on Bayesian informativeness $I^B(K, N)$, i.e., the correlation between the realized state and the empirical optimal guess. This measure isolated the extent to which the senders transmit information to the receivers, net of the mistakes the latter may make in responding to it. In this section, instead, we focus on overall informativeness, denoted by $I(K, N)$. This is computed as the correlation between the realized state and the actual receiver's guess. The 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 main goal is to test whether the documented presence of receivers' mistakes invalidates the comparative statics discussed in Section 4.1.2.

Table 9 reports the treatment-level informativeness across treatments. This table should be compared with Table 5, discussed earlier.[26] Predictably, $I(K, N) \leq I^B(K, N)$: receivers' mistakes only decrease overall informativeness relative to its Bayesian counterpart, because these mistakes add noise that decreases the correlation with the state.

We emphasize three aspects of our findings from Table 9. First, for a fixed N, increasing K should increase overall informativeness (Proposition 1(a)). The increase should be large for

[26] Again, the values reported in Table 9 are derived by computing the correlation between the state and the guess at the treatment level. To perform the statistical tests reported in the section we use, instead, correlations computed at the receiver's level.

Table 9: Informativeness $I(K, N)$ in the data (predicted values shown in parenthesis)

		$N = K$	$N = 10$	$N = 50$
$K = 1$	$I(K, N)$	0.31	0.26	0.23
		(0.44)	(0.38)	(0.06)
	$I^B(K, N)$	0.46	0.43	0.38
$K = 3$	$I(K, N)$	0.59	0.62	0.15
		(0.69)	(0.84)	(0.22)
	$I^B(K, N)$	0.73	0.82	0.39

$N = 10$ and small for $N = 50$. Accordingly, the data shows a large increase for $N = 10$, from 0.26 to 0.62 (p-value < 0.01). For $N = 50$, the direction is the opposite of the one predicted by theory and there is a non statistically significant decrease from 0.23 to 0.15.

Second, in line with Proposition 1(b), overall informativeness increases from $N = K = 1$, when it is 0.31, to $N = K = 3$, when it is 0.59 (p-value < 0.01).

Third, as predicted by Proposition 1(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 $K = 1$. However, while the first effect is significant at the 1% level, the latter is not.

Finally, when $K = 3$, the overall informativeness increases from $N = 3$ to $N = 10$ (from 0.59 to 0.62) but, in contrast with the prediction, the increase is never significant. Therefore, despite senders transmitting more information (as discussed in Section 4.1.2), receivers do not fully take advantage of it.

References

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

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. and D. Cianciaruso (2018): "Verifiable Disclosure," *Economic Theory*, 65(4), 1011–1044.

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?" .

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 (2020): "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. Srensen (2017): “Persuasion bias in science: can economics help?” The Economic Journal, 127, F266–F304.

——— (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 certi cation: 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 nitely 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.

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

Farrell, J. (1993): “Meaning and credibility in cheap-talk games,” Games and Economic Behavior, 5, 514–531.

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

Gal-Or, E. (1985): "Information sharing in oligopoly," Econometrica: Journal of the Econometric Society, 329–343.

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.

Gieczewski, G. and M. Titova (2024): "Coalition-Proof Disclosure," Working Paper.

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.

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., F. Koessler, and E. Perez-Richet (2014): "Certifiable pre-play communication: Full disclosure," Econometrica, 82, 1093–1131.

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

Haghtalab, N., N. Immorlica, B. Lucier, M. Mobius, and D. Mohan (2021): "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," Working Paper.

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.

Li, Y. and B. C. Schipper (2018): "Disclosure under unawareness: An experiment," University of California, Davis.

Li, Y. X. and B. C. Schipper (2020): "Strategic reasoning in persuasion games: An experiment," Games and Economic Behavior, 121, 329–367.

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.

Montero, M. and J. D. Sheth (2021): "Naivety about hidden information: An experimental investigation," Journal of Economic Behavior & Organization, 192, 92–116.

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 (2022): "Disclosure of verifiable information under competition: An experimental study," Available at SSRN 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.

Verrecchia, R. E. (1983): "Discretionary disclosure," Journal of accounting and economics, 5, 179–194.

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.

A Equilibrium Refinement

In this section, we formally define our main equilibrium concept, show that this can lead to multiple equilibria, and then present our refinement that predicts a unique equilibrium outcome.

First, we define a pure-strategy, state-independent PBE in our framework. To do so, we show that, when focusing on state-independent sender's strategies, the receiver's equilibrium strategy can be pinned down by her beliefs on $\bar{s}$. To see this, note that if $\mu(\cdot|m) \in \Delta(S^N)$ is the receiver's belief about the vector $\bar{s}$ conditional on observing message m, her posterior belief $\pi(\cdot|m) \in \Delta(\Theta)$ about the underlying state is

$$\pi(\theta|m) = \frac{\pi(\theta)\sum_{\bar{s}}\mu(\bar{s}|m) f(\bar{s}|\theta)}{\sum_{\theta'}\pi(\theta')\sum_{\bar{s}}\mu(\bar{s}|m) f(\bar{s}|\theta')} \qquad \forall\theta.$$

Moreover, given m and the associated belief $\mu(\cdot|m)$, the receiver's optimal action is unique and deterministic, i.e the expectation of θ under $\pi(\cdot|m)$:

$$\sigma_R(m) = \arg\max_{a\in A}\sum_{\theta} u(a,\theta)\pi(\theta|m) = \sum_{\theta}\theta\pi(\theta|m).$$

Denote by $q(\bar{s}) := \sum_{\theta}\pi(\theta) f(\bar{s}|\theta)$ be the total probability of $\bar{s}$ and, for any nonempty set $Q \subseteq S^N$, let $q(\bar{s}|Q)$ be the conditional probability of $\bar{s}$ given that it belongs to Q, namely:

$$q(\bar{s}|Q) := \begin{cases} \frac{q(\bar{s})}{\sum_{\bar{s}'\in Q} q(\bar{s}')} & \bar{s}\in Q, \\ 0 & \text{else.} \end{cases}$$

Finally, for all θ and $\bar{s}$, let $E(\theta|\bar{s}) := \sum_{\theta}\theta\pi(\theta|\bar{s})$. Therefore, given m and belief $\mu(\cdot|m)$, the receiver's optimal action is $\sum_{\bar{s}'}\mu(\bar{s}'|m)E(\theta|\bar{s}')$.

Definition A.1. A pure-strategy, state-independent PBE is a pair $(\sigma^*: S^N \to M; \mu^*: M \to \Delta(S^N))$ such that

1. For all $\bar{s}\in S^N$ and $m'\in M(\bar{s})$, $\sum_{\bar{s}'}\mu^*(\bar{s}'|\sigma^*(\bar{s}))E(\theta|\bar{s}') \geq \sum_{\bar{s}'}\mu^*(\bar{s}'|m')E(\theta|\bar{s}')$;
2. For all $m\in\sigma^*(S^N)$, $\mu^*(\bar{s}|m) = q(\bar{s}|\sigma^{*-1}(m))$ for all $\bar{s}$.

Any pair (σ,μ) induces an outcome $x: S^N \to A$ for the game, which is defined as

$$x(\bar{s}) := \sum_{\bar{s}'}\mu(\bar{s}'|\sigma(\bar{s}))E(\theta|\bar{s}') \qquad \forall\bar{s}.$$

Despite the presence of verifiable information, the game can admit multiple PBE outcomes. We provide two simple examples to show that it is possible to identify two pairs (a, m) that induce different outcomes but that both satisfy Definition A.1.

Equilibrium 1. (Maximally selective equilibrium) Let $N = 2$, $K = 1$. Assume $Q = \{0, 1\}$ (with equal probability), $S = \{0, 1\}$, $f(1|1) = p > \frac{1}{2}$ and $f(1|0) = q < \frac{1}{2}$. We can show that there is an equilibrium in which the sender always discloses the most favorable realization of $\bar{s}$.

$\bar{s}$	$m = s(\bar{s})$	$a = x(\bar{s})$
1, 1	1	$a(1)$
1, 0	1	$a(1)$
0, 1	1	$a(1)$
0, 0	0	$a(0)$

where $a(1) = E[q|m = 1] = \frac{p^2 + 2p(1-p)}{p^2 + 2p(1-p) + q^2 + 2q(1-q)} > \frac{1}{2}$ and $a(0) = \frac{(1-p)^2}{(1-p)^2 + (1-q)^2} < \frac{1}{2}$. This equilibrium is sustained by any $a(\varnothing) = 0$. Notice that $a(1)$ and $a(0)$ are computed using receiver's beliefs consistent with Definition A.1, while the equilibrium conditions do not constrain the choice of $a(\varnothing)$.

Equilibrium 2. (No disclosure equilibrium) Let $N = 2$, $K = 1$. Assume $Q = \{0, 1\}$ (with equal probability), $S = \{0, 1\}$, $f(1|1) = p > \frac{1}{2}$ and $f(1|0) = q < \frac{1}{2}$. We can show that there is an equilibrium in which the sender always discloses $m = \varnothing$, no matter the realization of $\bar{s}$.

$\bar{s}$	$m = s(\bar{s})$	$a = x(\bar{s})$
1, 1	$\varnothing$	$a(\varnothing)$
1, 0	$\varnothing$	$a(\varnothing)$
0, 1	$\varnothing$	$a(\varnothing)$
0, 0	$\varnothing$	$a(\varnothing)$

where $a(\varnothing) = \frac{1}{2}$. This equilibrium is sustained by $a(1) = a(0) = 0$. Notice that $a(\varnothing)$ is computed using beliefs that are consistent with Definition A.1, while $a(1)$ and $a(0)$ are not constrained by any equilibrium condition.

Such multiplicity can constitute a challenge in our empirical analysis. For this reason, we refine the set of PBEs using a notion of neologism proofness (see Farrell, 1993) that we adapt to our setting with partially verifiably information. For any $m \in M$, define $M^{-1}(m) = \{\bar{s} \in S^N : m \in M(\bar{s})\}$, i.e. the set of signal realizations in S^N that would allow the sender to disclose message m.

Definition A.2 (Refinement) Let (σ^*, μ^*) be a pure-strategy, state-independent perfect Bayesian equilibrium. A neologism is a pair (m, C) with $m \in M$ and $C \subseteq M^{-1}(m)$. A neologism (m, C) is credible if

(i) $\sum_{\bar{s}'} q(\bar{s}'|C) E(q|\bar{s}') > \sum_{\bar{s}'} \mu^*(\bar{s}'|\sigma^*(\bar{s})) E(q|\bar{s}')$ for all $\bar{s} \in C$,

(ii) $\sum_{\bar{s}'} q(\bar{s}'|C) E(q|\bar{s}') \leq \sum_{\bar{s}'} \mu^*(\bar{s}'|\sigma^*(\bar{s})) E(q|\bar{s}')$ for all $\bar{s} \notin C$,

The equilibrium is neologism proof if no neologism is credible.

This refinement is a direct application of Farrell (1993)'s neologism proofness, adapted to capture the fact that our setting features verifiable information.[27] The literal meaning of the neologism (m, C) is: "I am a sender who can send message m and my $\bar{s}$ belongs to C." Verifiability requires that C must be a subset of signals $\bar{s}'$ that are compatible with m, namely $C \subseteq M^{-1}(m)$.[28] A neologism (m, C) is credible relative to the equilibrium if it is precisely the types in C who benefit (strictly) from this neologism being believed over what they would get in the putative equilibrium.

Next, we introduce a sender's strategy that will play an important role in the equilibrium characterization. Under this strategy, the sender discloses the K highest signals among those that are available.

Definition A.3. Fix N and K. A sender's strategy $\sigma : S^N \to M$ is maximally selective if, for each $\bar{s}$, $\sigma(\bar{s})$ selects the K highest signals in $\bar{s}$.

We can show that all neologism-proof equilibria induce the same outcome, which is the one induced by a maximally selective sender's strategy.

Proposition 2 (Existence and Uniqueness). For all N and $1 \leq K \leq N$, there exists a pure-strategy, state-independent perfect Bayesian equilibrium in which the sender plays a maximally selective strategy. The outcome of this equilibrium is the unique one induced by a neologism-proof equilibrium. We refer to this equilibrium as the maximally selective equilibrium.

[27] Remember that, when $K < N$, our game features an element of cheap-talk communication. Like in cheap-talk games, refinements such as the intuitive criterion or divinity have no force in our setting. These refinements aim to discipline out-of-equilibrium beliefs. However, any equilibrium outcome in a cheap talk game can be achieved with strategies that assign a positive probability to all messages, thereby leaving no room for restricting beliefs. A similar challenge arises in our game, that can be equivalently formalized as one in which the sender sends at most K verifiable messages and at least $N - K$ unverifiable ones.

[28] For instance, if $K = 1$ and $N = 2$, $\bar{s} = (1, 2)$ is not compatible with $m = 3$.

B Proofs

Definition B.1. A collection of sets $\{S_i\}_{i=1}^{N} \subseteq S$ satisfies Property A if, for every i and every $s', s'' \in S_i$, $\{s \in S | s' < s < s''\} \subseteq S_i$.

Lemma B.1. Let $\{S_i\}_{i=1}^{N} \subseteq S$ and $\{S'_i\}_{i=1}^{N} \subseteq S$ satisfy Property A. If $\max S'_i \geq \max S_i$ and $\min S'_i \geq \min S_i$ for all i, then

$$E(q | s \in S'_1 \times \dots \times S'_N) \geq E(q | s \in S_1 \times \dots \times S_N).$$

Proof. Let $\{S_i\}_{i=1}^{N} \subseteq S$ and $\{S'_i\}_{i=1}^{N} \subseteq S$ satisfy Property A. We shall denote $S_{-i} := \prod_{j \neq i} S_j$. The proof can be organized in N steps. In the first step, we fix an arbitrary index $i \in \{1, \dots, N\}$ and show that $E(q | s_{-i} \in S'_{-i}, s_i \in S'_i) \geq E(q | s_{-i} \in S'_{-i}, s_i \in S_i)$.

To do so, fix $\hat{s}_{-i} \in S_{-i}$. We begin by showing that $E(q | s_{-i} = \hat{s}_{-i}, s_i \in S'_i) \geq E(q | s_{-i} = \hat{s}_{-i}, s_i \in S_i)$. There are two cases to consider. If $\max S_i \leq \min S'_i$, then

$$\begin{aligned}
E(q | s_{-i} = \hat{s}_{-i}, s_i \in S'_i) &= \sum_{\hat{s}_i \in S'_i} Pr(\hat{s}_i | S'_i) E(q | s_{-i} = \hat{s}_{-i}, s_i = \hat{s}_i) \\
&\geq \sum_{\hat{s}_i \in S'_i} Pr(\hat{s}_i | S'_i) E(q | s_{-i} = \hat{s}_{-i}, s_i = \min S'_i) \\
&= E(q | s_{-i} = \hat{s}_{-i}, s_i = \min S'_i) \\
&\geq \sum_{\hat{s}_i \in S_i} Pr(\hat{s}_i | S_i) E(q | s_{-i}, s_i = \hat{s}_i) \\
&= E(q | s_{-i}, s_i \in S_i)
\end{aligned}$$

If $\max S_i > \min S'_i$, instead, let $C = S_i \cap S'_i$. By Property A, $C \neq \emptyset$. Moreover, since $\max S'_i \geq \max S_i$, $\max C = \max S_i$ and since $\min S'_i \geq \min S_i$, $\min C = \min S'_i$. Therefore, $\max S_i \setminus C \leq \min C \leq \max C \leq \min S'_i \setminus C$. By similar steps as above, we have that $E(q | s_{-i} = \hat{s}_{-i}, s_i \in S'_i \setminus C) \geq E(q | s_{-i} = \hat{s}_{-i}, s_i \in C)$ and, thus,

$$\begin{aligned}
& E(q | s_{-i} = \hat{s}_{-i}, s_i \in S'_i) \\
= \; & Pr(S'_i \setminus C | S'_i) E(q | s_{-i} = \hat{s}_{-i}, s_i \in S'_i \setminus C) + Pr(C | S'_i) E(q | s_{-i} = \hat{s}_{-i}, s_i \in C) \\
\geq \; & E(q | s_{-i} = \hat{s}_{-i}, s_i \in C).
\end{aligned}$$

A similar argument leads to $E(q | s_{-i} = \hat{s}_{-i}, s_i \in C) \geq E(q | s_{-i} = \hat{s}_{-i}, s_i \in S_i)$. Therefore,

$E(q|s_{-i} = \hat{s}_{-i}, s_i \in S'_i) \geq E(q|s_{-i} = \hat{s}_{-i}, s_i \in S_i)$. Moreover, since $\hat{s}_{-i} \in S'_{-i}$ was arbitrary:

$$\begin{aligned} E(q|s_{-i} \in S'_{-i}, s_i \in S'_i) &= \Pr(s_{-i} \in S'_{-i}|S'_{-i})E(q|s_{-i} = \hat{s}_{-i}, s_i \in S'_i) \\ &\geq \Pr(s_{-i} \in S'_{-i}|S'_{-i})E(q|s_{-i} = \hat{s}_{-i}, s_i \in S_i) \\ &= E(q|s_{-i} \in S'_{-i}, s_i \in S_i). \end{aligned}$$

This completes the first step of the proof. The remaining $N-1$ steps follow the same logic.

Lemma B.2. Given posterior belief $m(\cdot|m) \in \Delta(S^N)$, there is a unique posterior belief $p(\cdot|m) \in \Delta(Q)$ defined as

$$p(q|m) = \sum_{\bar{s} \in M^{-1}(m)} p(q|\bar{s})m(s|m) \quad \forall q.$$

Proof. Fix q and m. Then

$$\begin{aligned} p(q|m) &= \sum_{\bar{s} \in M^{-1}(m)} p(q|\bar{s})m(s|m) \\ &= \sum_{\bar{s} \in M^{-1}(m)} \frac{p(q)f(\bar{s}|q)}{m(\bar{s})} \frac{m(\bar{s})s(m|\bar{s})}{\sum_{\bar{s}' \in M^{-1}(m)} m(\bar{s}')s(m|\bar{s}')} \\ &= \frac{p(q)\sum_{\bar{s} \in M^{-1}(m)} f(\bar{s}|q)s(m|\bar{s})}{\sum_{\bar{s}' \in M^{-1}(m)} \sum_q p(q)f(\bar{s}'|q)s(m|\bar{s}')} \\ &= \frac{p(q)\sum_{\bar{s}} f(\bar{s}|q)s(m|\bar{s})}{\sum_{q'} p(q')\sum_{\bar{s}'} f(\bar{s}'|q')s(m|\bar{s}')} =: p(q|m) \end{aligned}$$

The use of this result is that we can then define the equilibrium in terms of $s(\cdot|m)$ rather than $p(\cdot|m)$.

Proposition 3. For all N and $1 \leq K \leq N$, there exists a pure-strategy Perfect Bayesian Equilibrium in which the sender plays the maximal selective strategy.

Proof. For any message $m \in M$, denote its length by $\ell(m) \in \mathbb{N}$. We construct an equilibrium in which the sender's strategy $s : S^N \to M$ reports the K most favorable signals in $\bar{s}$. That is,

$$s(\bar{s}) \in \{m \in M(\bar{s}) \mid \ell(m) = K \text{ and } |\{\bar{s}_i \in \{\bar{s}_1, \ldots, \bar{s}_N\} : s_i \geq m_K\}| \geq N - K + 1\}.$$

In our candidate equilibrium, upon observing a message m, the receiver assigns a positive probability to the following lists of signals:

$$C(m) = \{\bar{s} \in S^N \mid \exists \text{ an injective } \rho : \{1, \dots, \ell(m)\} \to \{1, \dots, N\} \text{ s.t. } \text{if } i \in \rho(\{1, \dots \ell(m)\}),\ \bar{s}_i = m_{\rho^{-1}(i)}; \text{if } i \notin \rho(\{1, \dots \ell(m)\}),\ \bar{s}_i \le h(m)\},$$

where

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

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 equilibrium beliefs $\mu^* : M \to \Delta(S^N)$ are given by

$$\mu^*(\bar{s}|m) = \pi(\bar{s}|C(m))$$

and they pin down the optimal action[29]

$$a^*(m) = \sum_\theta \theta \frac{\pi(\theta) \sum_{\bar{s}} \mu^*(\bar{s}|m) f(\bar{s}|\theta)}{\sum_{\theta'} \pi(\theta') \sum_{\bar{s}} \mu^*(\bar{s}|m) f(\bar{s}|\theta')} = E(\theta|\bar{s} \sim \mu^*(\cdot|m)) = E(\theta|\bar{s} \in C(m))$$

We want to show that the pair (σ^*, μ^*) is a perfect Bayesian equilibrium. Conditions (2) of Definition A.1 is satisfied by construction. Therefore, we only need to check condition (1). Specifically, we need to show that, for all $\bar{s}$,

$$E(\theta|\bar{s} \in C(\sigma^*(\bar{s}))) \ge E(\theta|\bar{s} \in C(m')) \quad \forall m' \in M(\bar{s}). \tag{2}$$

To do so, it is convenient to first translate this problem into the space of ordered vectors $O = \{\bar{s} \in S^N \mid \bar{s}_1 \ge \dots \ge \bar{s}_N\}$. We show that restricting attention to O is without loss of generality. We begin by specializing the definition of $C(m)$ to O:

$$\bar{C}(m) = \{\bar{s} \in O \mid \forall i \le \ell(m)\ \bar{s}_i = m_i \text{ and } \forall i > \ell(m)\ \bar{s}_i \le h(m)\}.$$

Given any vector $\bar{s} \in S^N$, denote the set of its permutations by

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

Note that, for every m, the collection $\{B(\bar{s})\}_{\bar{s} \in \bar{C}(m)}$ partitions $C(m)$. Indeed, it is easy to see

[29] See Lemma B.2.

that, for every $\bar{s}, \bar{s}' \in \bar{C}(m)$ s.t. $\bar{s} \neq \bar{s}'$, $B(\bar{s}) \cap B(\bar{s}') = \emptyset$ and $C(m) = \bigcup_{\bar{s} \in \bar{C}(m)} B(\bar{s})$. With this, we can define the restriction of distribution f onto the subset of ordered vectors O. For any $\bar{s} \in O$, let

$$\bar{f}(\bar{s}|\theta) = \sum_{\bar{s}' \in B(\bar{s})} f(\bar{s}'|\theta) = |B(\bar{s})| f(\bar{s}|\theta)$$

where the second equality follows from the exchangeability of f. Since

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

we have that

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

Therefore, the equilibrium condition in Equation 2 holds if and only if

$$E(\theta|\bar{C}(\sigma(\bar{s}))) \geq E(\theta|\bar{C}(m')) \quad \forall \bar{s} \in S^N, m' \in M(\bar{s}).$$

To show this latter condition, fix $\bar{s} \in S^N$ and denote $m = \sigma(\bar{s})$. Let $m' \in M(\bar{s})$ and, to avoid trivial cases, assume $m' \neq m$. That is, m' does not contain the K-highest signals. Note that this implies that,

$$m_i \geq m'_i \quad \text{for all} \quad i \leq \ell(m'). \tag{3}$$

Indeed, if there was $i \leq \ell(m)$ such that $m'_i > m_i$, then we could construct m'' from m and m' such that $\ell(m'') = K$ and $m''_i \geq m_i$, with at least one strict inequality, a contradiction.

Given m, define $\{S_i\}_{i=1}^N$, such that $S_i = \{m_i\}$ for all $i \leq K$ and $S_i = \{s \in S | s \leq m_K\}$ for $i > K$. Similarly, given m', define $\{S'_i\}_{i=1}^N$, such that $S'_i = \{m'_i\}$ for all $i \leq \ell(m')$ and $S_i = \{s \in S | s \leq h(m')\}$ for $i > \ell(m')$. Note that $E(\theta|\bar{A}(m)) = E(\theta|s_1 \in S_1, \ldots, s_N \in S_N)$ and $E(\theta|\bar{A}(m')) = E(\theta|s_1 \in S'_1, \ldots, s_N \in S'_N)$. Therefore, the equililibrium condition in (2) is equivalent to

$$E(\theta|s_1 \in S_1, \ldots, s_N \in S_N) \geq E(\theta|s_1 \in S'_1, \ldots, s_N \in S'_N).$$

To prove this inequality, we will invoke Lemma B.1 after showing that its premises apply here. Fix $i \in \{1, \ldots, N\}$ and note that S_i is either a singleton or is $\{s \leq h(m)\}$. In either case, if

$s', s'' \in S_i$, then $\{s' < s < s''\} \subseteq S_i$. Therefore, $\{S_i\}_{i=1}^N$ has Property A and, for a similar argument, so does $\{S'_i\}_{i=1}^N$.

Moreover, $\max S_i \geq \max S'_i$ for all i. To show this, we consider two cases. First, suppose $\ell(m') < K$. If $i \leq \ell(m')$, $S'_i = \{m'_i\}$ and $S_i = \{m_i\}$. By (3), $m_i \geq m'_i$ and thus $\max S_i \geq \max S'_i$. If $i > \ell(m')$, then $S'_i = \{\min S\}$ and, thus, $\max S_i \geq m_K \geq \min S = \max S'_i$. Next, suppose that $\ell(m') = K$. For all $i \leq K$, $S'_i = \{m'_i\}$ and $S_i = \{m_i\}$. By (3), $m_i \geq m'_i$ and thus $\max S_i \geq \max S'_i$. If $i > K$, then $\max S'_i = m'_K$ and $\max S_i = m_K$. By (3), $m_K \geq m'_K$ and thus $\max S_i \geq \max S'_i$. Similar steps as above can be followed to show that $\min S_i \geq \min S'_i$ for all i.

Therefore, we can invoke Lemma B.1 to conlcude that

$$
\begin{aligned}
E(q|\bar{C}(s_1(\bar{s}))) &= E(q|s_1 \in S_1, \ldots, s_N \in S_N) \\
&\geq E(q|s_1 \in S'_1, \ldots, s_N \in S'_N) \\
&= E(q|\bar{C}(m')).
\end{aligned}
$$

Since $\bar{s}$ and $m' \in M(\bar{s})$ were arbitrary, this concludes the proof that there exists a perfect Bayesian equilibrium in which the sender plays the maximal selective strategy.

Remark 2. Our equilibrium is neologism proof.

Proof. Fix N and K and denote our equilibrium by (σ^*, μ^*). For a message m of length k, we denote by $B(m)$ the set of types $\bar{s}$ whose k-best facts are those in m. Formally,

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

Let's denote with M^K the set of messages that have length K. It is easy to show that $\{B(m)\}_{m \in M^K}$ partitions S^N.

Observe that, if $m \in \sigma^*(S^N)$, $\sigma^{*-1}(m) = B(m)$ and $\ell(m) = K$. Moreover, if $\bar{s} \in B(m)$,

$$
\sum_{\bar{s}'} \mu^*(\bar{s}'|\sigma^*(\bar{s})) E(q|\bar{s}') = \sum_{\bar{s}'} q(\bar{s}'|B(m)) E(q|\bar{s}') =: E(q|B(m)).
$$

Our equilibrium induces an order on $M^K = \sigma^*(S^N)$ where

$$
m^i \succ m^j \quad \text{if} \quad E(q|B(m^i)) > E(q|B(m^j))
$$

We want to show that no neologism is credible. Fix $m \in M$ and $C \subseteq M^{-1}(m)$ and suppose by contradiction it is credible. Trivially,[30] there exists an $m^* \in M^K$ such that $C \cap B(m^*) \neq \emptyset$ and, for all other $m' \in M^K$, such $m^* \neq m'$ and $C \cap B(m') \neq \emptyset$, we have $E(q|B(m^*)) > E(q|B(m'))$.

Define the set

$$
\begin{aligned}
D(m, m^*) = \{\bar{s} \in S^N | \exists \text{ an injective } r : \{1, ..., N\} \to \{1, ..., N\} \text{ s.t. } \bar{s}_1 \leq \dots \leq \bar{s}_N, \\
\forall i \leq K \ \bar{s}_i \leq m^*_i \text{ and } \forall i > K \ \bar{s}_i \leq m^*_K\} \cap M^{-1}(m)
\end{aligned}
$$

The following result characterizes C.

Claim 1. $C = D(m, m^*)$.

$\subseteq$ direction. Let $\bar{s} \in C$ but $\bar{s} \notin D(m, m^*)$. By definition of neologism, $\bar{s} \in M^{-1}(m)$ given $C \subseteq M^{-1}(m)$. This implies that for $\bar{s} \notin D(m, m^*)$ it must be that

$$
\begin{aligned}
\bar{s} \notin \{\bar{s} \in S^N | \exists \text{ an injective } r : \{1, ..., N\} \to \{1, ..., N\} \text{ s.t. } \bar{s}_1 \leq \dots \leq \bar{s}_N, \\
\forall i \leq K \ \bar{s}_i \leq m^*_i \text{ and } \forall i > K \ \bar{s}_i \leq m^*_K\}
\end{aligned}
$$

This implies that for at least one $i \in \{1, .., N\}$, $s_i > m^*_1$. This means that is there is $\bar{m} > m^*$ such that $\bar{s} \in B(\bar{m}) \cap C$. However, this contradicts the definition of m^*. Therefore, $\bar{s} \in D(m, m^*)$.

$\supseteq$ direction. Let $\bar{s} \in D(m, m^*)$ and suppose $\bar{s} \notin C$. This implies that $\bar{s} \in M^{-1}(m)$. Moreover, by the partition property, there is $\bar{m} \in M^K$ such that $\bar{s} \in B(\bar{m}) \cap M^{-1}(m)$. Since

$$
\begin{aligned}
\bar{s} \in \{\bar{s} \in S^N | \exists \text{ an injective } r : \{1, ..., N\} \to \{1, ..., N\} \text{ s.t. } \bar{s}_1 \leq \dots \leq \bar{s}_N, \\
\forall i \leq K \ \bar{s}_i \leq m^*_i \text{ and } \forall i > K \ \bar{s}_i \leq m^*_K\}
\end{aligned}
$$

it must be that $E(q|B(m^*)) \geq E(q|B(\bar{m}))$. By Definition A.2 part (i), we must have

$$
E(q|C) > E(q|B(m^*)) \geq E(q|B(\bar{m}))
$$

since we are assuming that the neologism is credible.

However $\bar{s} \notin C$ and $\bar{s} \in M^{-1}(m)$ leads to a contradiction of part (ii) of Definition A.2. This would imply that the neologism cannot be credible. Therefore, $\bar{s} \in C$.

[30] Because of the partition argument and the fact that messages are totally ordered.

The final step of the proof consists of showing this Claim:

Claim 2. $E(q|B(m^*)) \geq E(q|C)$.

To show this we use the previous Claim to replace C with $D(m, m^*)$ and then we use Lemma B.1. To see why the Claim is true it is sufficient to note that

$$B(m^*) = \{s_1 = m_1, \ldots, s_K = m_K, s_{K+1} \leq m_K, \ldots, s_N \leq m_K\}$$

whereas $D(m, m^*)$ has previously defined as containing only $\bar{s}$ that "do not exceed" m^*, i.e. whose ordered components are all weakly below the components of m^*. Invoking Lemma B.1 concludes the proof of Claim 2.

Given Claim 2, we can immediately conclude that part (i) of Definition A.2 fails: (m, C) is not credible and we reach a contradiction. This implies that our equilibrium is neologism proof.

Lemma B.3. Let $M_K := \{m \in M | \ell(m) = K\}$, $m_1 = \max M_K$ and

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

For all $m \in M_K$,

$$\sum q(\bar{s}'|M^{-1}(m))E(q|\bar{s}') \leq \sum q(\bar{s}'|M^{-1}(m_1))E(q|\bar{s}') = \sum q(\bar{s}'|B(m_1))E(q|\bar{s}').$$

Proof. Let us begin by proving the equality. To so, we argue that $M^{-1}(m_1) = B(m_1)$. First, note that

$$B(m_1) = \{\bar{s}|m_1 \in M(\bar{s}),\ \ell(m_1) = K \text{ and } m_1 > m\ \forall\ m \in M(\bar{s}) \text{ s.t. } \ell(m) = K\}$$

and

$$M^{-1}(m_1) = \{\bar{s}|m_1 \in M(\bar{s})\}$$

Direction $\subseteq$. Suppose $\bar{s} \in B(m_1)$. Then $m_1 \in M(\bar{s})$, and thus $\bar{s} \in M^{-1}(m_1)$.

Direction $\supseteq$. Let $\bar{s} \in M^{-1}(m_1)$. Then $m_1 \in M(\bar{s})$. However, $m_1 = \max M^K$ and thus m_1 will also be the highest message in $M(\bar{s})$ with length K. So $\bar{s} \in B(m_1)$.

Therefore, $M^{-1}(m_1) = B(m_1)$. Next, we prove the inequality. Fix $m \in M_K$ and let

$k = \ell(m)$. Note that,

$$M^{-1}(m_1) = \{\bar{s} : s_1 = m_{11}, \ldots, s_K = m_{1K}, s_i \in S \;\forall i > K\}$$

$$M^{-1}(m) = \{\bar{s} : s_1 = m_1, \ldots, s_k = m_k, s_i \in S \;\forall i > k\}$$

Since m_1 is maximal and $k \leq K$, it is easy to check that the conditions of Lemma B.1 are satisfied and therefore the claimed inequality holds.

Proposition 4 (Uniqueness) Let (σ^*, μ^*) our equilibrium and (σ, μ) any other NP equilibrium. Let x^* and x be their respective outcomes. Then, $x^* = x$.

Proof. Fix N and K. Let (σ^*, μ^*) be our equilibrium and (σ, μ) be any other NP equilibrium. Denote by x^* and x their respective outcomes. Let $\mathcal{M}_K := \{m \in \mathcal{M} \mid \ell(m) = K\}$. Note that, for all $m \in \mathcal{M}_K$, $\sigma^{-1}(m) \neq \emptyset$, that is, m is sent with positive probability. We begin by introducing an order on $\mathcal{M}_K$. For any $m, m' \in \mathcal{M}_K$, denote $m \succeq m'$ if

$$\sum_{\bar{s}'} \mu(\bar{s}'|m) E(q|\bar{s}') \geq \sum_{\bar{s}'} \mu(\bar{s}'|m') E(q|\bar{s}').$$

We can order the messages $m_1 \succeq m_2 \succeq \ldots \succeq m_L$, where L is finite, since $\mathcal{M}_K$ is finite.

Define

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

It is easy to see that $\{B(m)\}_{m \in \mathcal{M}_K}$ partitions S.

Step 1. We want to show that $\forall \bar{s} \in B(m_1)$, $x(\bar{s}) = x^*(\bar{s})$.

We can argue that that $m_1 = \max \mathcal{M}_K$. Assume by contradiction that this is not the case but there exists $\hat{m} > m_1$, i.e. $\hat{m}_i \geq m_{1i}$ with at least one strict inequality. By Lemma B.1

$$\sum_{\bar{s}'} \mu(\bar{s}'|\hat{m}) E(q|\bar{s}') > \sum_{\bar{s}'} \mu(\bar{s}'|m_1) E(q|\bar{s}')$$

contradicting the order we defined.

We begin by showing that $x(\bar{s}) \leq x^*(\bar{s})\ \forall \bar{s} \in B(m_1)$. Suppose not, i.e., there is $\bar{s} \in B(m_1)$ such that $x(\bar{s}) > x^*(\bar{s})$. Let $\hat{s} \in \arg\max_{\bar{s} \in S^N} x(\bar{s})$ and $\hat{m} = \sigma(\hat{s})$. That is, $\hat{s}$ is the type that induces the highest receiver's action in equilibrium (σ, μ). Therefore, $x(\hat{s}) \geq x(\bar{s}) > x^*(\bar{s})$.

Because $\hat{m}$ is the first best, each $\bar{s} \in M^{-1}(\hat{m})$ must send $\hat{m}$ in equilibrium. Thus,

$$x(\hat{s}) = \sum q(\bar{s}'|M^{-1}(\hat{m}))E(\theta|\bar{s}') > \sum q(\bar{s}'|B(m_1))E(\theta|\bar{s}') = x^*(\bar{s}).$$

However, by Lemma B.3, we know that, for all $m \in M$, and in particular for $m = \hat{m}$,

$$\sum q(\bar{s}'|M^{-1}(\hat{m}))E(\theta|\bar{s}') \leq \sum q(\bar{s}'|M^{-1}(m_1))E(\theta|\bar{s}') = \sum q(\bar{s}'|B(m_1))E(\theta|\bar{s}').$$

This is a contradiction. We conclude that $x(\bar{s}) \leq x^*(\bar{s})$ $\forall \bar{s} \in B(m_1)$.

To establish the equality in the claim of this step, we need to show that $x(\bar{s}) \geq x^*(\bar{s})$ $\forall \bar{s} \in B(m_1)$. Suppose not, that $\exists \bar{s} \in B(m_1)$ such that $x(\bar{s}) < x^*(\bar{s})$. There are two possible cases to consider.

- Suppose there is $\hat{s} \in B(m_1)$ such that $x(\bar{s}) < x(\hat{s}) = x^*(\bar{s})$.[31] Denote by $\hat{m} = \sigma(\hat{s})$ the equilibrium message sent by $\hat{s}$. Clearly, $\hat{m} \notin M(\bar{s})$, otherwise $\bar{s}$ would have a profitable deviation and (σ, μ) would not be an equilibrium. Moreover, $\hat{m} \neq m_1$, since $\bar{s} \in B(m_1) \Rightarrow m_1 \in M(\bar{s})$. By the previous step of this proof, we know that $x(\hat{s})$ is the highest action that can be induced in (σ, μ). Therefore, every $\bar{s} \in M^{-1}(\hat{m})$ sends $\hat{m}$. Since $\hat{m} \neq m_1$, $M^{-1}(\hat{m}) \neq M^{-1}(m_1) = B(m_1)$. Therefore, by Lemma B.3, for all $m \in M$, and in particular for $m = \hat{m}$

$$\begin{aligned} x(\hat{s}) = \sum q(\bar{s}'|M^{-1}(\hat{m}))E(\theta|\bar{s}') &< \sum q(\bar{s}'|M^{-1}(m_1))E(\theta|\bar{s}') \\ &= \sum q(\bar{s}'|B(m_1))E(\theta|\bar{s}') = x^*(\hat{s}) \end{aligned}$$

  The inequality is strict for $m = \hat{m}$ since $M^{-1}(\hat{m}) \neq M^{-1}(m_1)$.

- Therefore, it must be that $x(\bar{s}) < x^*(\bar{s})$, $\forall \bar{s} \in B(m_1)$. However, in this case, there is a credible neologism $(m_1, B(m_1))$. By assumption, all $\bar{s} \in B(m_1)$ strictly gain if the neologism is believed, since $x(\bar{s}) < x^*(\bar{s})$. Moreover, $B(m_1) = M^{-1}(m_1)$ and thus no other type can send m_1. Therefore, (σ, μ) is not a NP equilibrium, a contradiction.

Step k. Suppose that for all $1 \leq k' < k$ and $\bar{s} \in B(m^{k'})$, $x(\bar{s}) = x^*(\bar{s})$. We want to show that, $\forall \bar{s} \in B(m^k)$, $x(\bar{s}) = x^*(\bar{s})$.

The previous steps show that for all $k' < k$, all $s \in B(m^{k'})$ achieve the same outcome in the maximally selective equilibrium and in any neologism-proof equilibrium. Consider the set $S_k = S^N \setminus \bigcup_{l=1}^{k-1} B(m^l)$. We can argue that, for any $s \in S_k$, $m^i \notin M(s)$ for all $i < k$. Indeed,

[31] Note that $x^*(\hat{s}) = x^*(\bar{s})$, since x^* is constant within $B(m)$ for all m.

assume by contradiction that there exists $s \in S_k$ such that $m^i \in M(s)$ for $i < k$. By the ordering defined at the beginning of the proof

$$\sum_{\bar{s}'} \mu(\bar{s}'|m^i) E(q|\bar{s}') > \sum_{\bar{s}'} \mu(\bar{s}'|m^k) E(q|\bar{s}')$$

implying that s has a profitable deviation and (s^*, m^*) is not an equilibrium.

Given this observation, we can denote the new message space $M_K^k = M_K \setminus \{m_1, ..., m_{k-1}\}$ where the previously defined order implies

$$m_k \succ m_{k+1} \succ ... m_L.$$

In addition, applying the same argument from Step 1, we can argue that $m_k = \max M_K^k$.

Given this premise, we can apply the same argument we used in Step 1 to show that $x(\bar{s}) = x^*(\bar{s})$ for any $s \in B(m_k)$.

Since $\{B(m)\}_{m \in M_K}$ partitions S^N, we can conclude that any neologism proof equilibrium generates the same outcome as the maximally selective equilibrium.

Proof of Proposition 2. It directly follows from Proposition 3, Remark 2 and Proposition 4.

Proof of Proposition 1. The proof is divided into three sections, each corresponding to a different part of the statement.

1. Fix N and let $(s^{*\prime}, m^{*\prime})$ and (s^*, m^*) be the maximally selective equilibria for K' and K, respectively.

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

   Note that $P' = \{B(m)\}_{m \in M_{K'}}$ and $P = \{B(m)\}_{m \in M_K}$ where

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

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

   Fix any $X' \in P'$. We want to show there is $X \in P$ such that $X' \subseteq X$, with at least one strict inequality. By definition, there is $m' \in M_{K'}$ such that $X' = B(m')$. Define $m = (m'_1, \ldots, m'_K) \in M_K$ 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 $I(K', N) \geq I(K, N)$.

2. Fix $K = N$ and $K' = N'$ and let (σ', μ') and (σ, μ) be the maximally selective equilibria for N' and N, respectively. In both equilibria all the available signals are disclosed. This implies that the beliefs m' and m are degenerate distributions.

   We want to show that if $N' > N$, (σ', μ') is Blackwell more informative then (σ, μ). Given the structure of the equilibrium, it is enough to show that $f(\cdot|\theta) \in \Delta(S^N)$ is a garbling of $f'(\cdot|\theta) \in \Delta(S^{N'})$. Let's define garbling function $g : S^{N'} \to \Delta(S^N)$ such that for any $\bar{s} \in \Delta(S^N)$ and $\bar{s}' \in \Delta(S^{N'})$

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

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

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

   At this point, we can apply the Blackwell's theorem to conclude that $I(K', N') \geq I(K, N)$.

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

Online Appendix (For Online Publication Only)

C 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 3. Consider any PBE of our game. Fix the message $m \in M$, the receiver's strategy $\sigma_R : M \to A$, the sender's strategy $\sigma_S : S^N \to M$ and the receiver's posterior belief $p(\cdot|m) \in \Delta(\Theta)$. The correlation between the state θ and the receiver's action induced by σ_R is a monotonic transformation of the ex-ante expected payoff of the receiver.

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

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

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

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

At this point notice that

$$Prob(m, \theta) = Prob(\theta) \cdot Prob(m|\theta) = p(\theta) \cdot \frac{p(\theta|m) \sum_{\theta'} p(\theta') \sum_{s \in \sigma_S^{-1}(m)} f(s|\theta')}{p(\theta)}$$

where

$$p(\theta|m) = \frac{p(\theta) \sum_{s \in \sigma_S^{-1}(m)} f(s|\theta)}{\sum_{\theta' \in \Theta} p(\theta') \sum_{s \in \sigma_S^{-1}(m)} f(s|\theta')}.$$

Rearranging the expression we get

$$E_{\theta,m}[u_R(\theta, \sigma_R(m))] = -\sum_{m \in M} \sum_{\theta' \in \Theta} p(\theta') \sum_{s \in \sigma_S^{-1}(m)} f(s|\theta') \cdot \left(E[\theta|m] - \theta'\right)^2.$$

A few algebraic steps allow us to show that

$$E_{\theta,m}[u_R(\theta, s_R(m))] = -\sum_{m \in M} \text{Prob}(m) Var[\theta|m] = -E_m[Var[\theta|m]]$$

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 $E_m[Var[\theta|m]]$ is monotonic transformation of $Corr(\theta, \alpha)$, where α is the random variable generated by $s_R(\cdot)$ and

$$Corr(\theta, \alpha) = \frac{E[\theta \alpha] - E[\theta]E[\alpha]}{\sqrt{Var[\theta]Var[\alpha]}} = \frac{E_m[E_\theta[\theta \, s_R(m)|m]] - E[\theta]E_m[s_R(m)]}{\sqrt{Var[\theta]Var_m[s_R(m)]}}$$

Notice that:

- $E_m[s_R(m)] = E[\theta]$;
- $E_m[E_\theta[\theta \, s_R(m)|m]] = E_m\left[s_R(m)^2\right]$ since $E_\theta[\theta|m] = s_R(m)$;
- $Var_m[s_R(m)] = E_m\left[s_R(m)^2\right] - E[\theta]^2$.

This implies that

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

Given that $E_m[Var[\theta|m]] = E_m\left[E[\theta|m]^2\right] - E_m\left[E\left[\theta^2|m\right]\right] = E[\alpha^2] - E[\theta^2]$, we can derive the following relation:

$$E_m[Var[\theta|m]] = Var[\theta] - Corr(\theta, \alpha)^2 \, Var[\theta].$$

This argument allows us to conclude that both $E_m[Var[\theta|m]]$ and $Corr(\theta, \alpha)$ 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.

D Examples of the Non-Monotonicity of $I(K, N)$

As stated in Proposition 1, $I(K, N)$ 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 $I(K,N)$.

Let $Q=\{0,1\}$, $p(1)=\frac{1}{2}$, $S=\{A,B\}$ and suppose that $f(A|1)=g>\frac{1}{2}$ and $f(A|0)=h<\frac{1}{2}$. Finally, assume that $K=1$. Given the parameters, the set of possible messages is $M=\{A,B,\emptyset\}$. A maximally selective sender's strategy discloses $m=A$ if A is available and otherwise discloses $m\in\{B,\emptyset\}$. This implies that, after observing $m\in\{B,\emptyset\}$, 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 $m\in\{B,\emptyset\}$, $\mu(\bar{s}_B|m)=1$ 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 $\bar{s}_i=A$ 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

$$p(1|m\in\{B,\emptyset\})=\frac{\frac{1}{2}(1-g)^N}{\frac{1}{2}(1-g)^N+\frac{1}{2}(1-h)^N}=\frac{(1-g)^N}{(1-g)^N+(1-h)^N}$$

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

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

$$E_q[u(q,s_R(m))|m]=-\frac{p(1|m)p(0|m)}{2}.$$

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

$$E_m[E_q[u(q,s_R(m))|m]]=-\frac{(1-g)^N\left(1-(1-g)^N\right)+(1-h)^N\left(1-(1-h)^N\right)}{2((1-g)^N+(1-h)^N)(2-(1-g)^N-(1-h)^N)}=$$

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

According to our definition, the equilibrium informativeness is equal to

$$I(K,N)=\frac{1}{4}-E_m[E_q[u(q,s_R(m))|m]]$$

Let's consider the extreme case of *perfect good news*, i.e. the case in which $h=0$ and

$g < 1$. Under these conditions, $m = A$ perfectly reveals that $q = 1$. This implies that

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

It is easy to verify that $I(K,N)$ 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 $q = 1$ 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 $m \in \{B, \emptyset\}$ makes the receiver more confident of $q = 0$. 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's now consider the other extreme case of *perfect bad news*, i.e. the case in which $h > 0$ and $g = 1$. Under these conditions, $m \in \{B, \emptyset\}$ perfectly reveals that $q = 0$. Under this parametrization, we have that

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

It is easy to show that when $g = 1$, $I(K,N)$ 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 $m \in \{B, \emptyset\}$ becomes less likely and, at the same time, $m = A$ becomes weaker evidence of $q = 1$. 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 h has full support, i.e. we have both $h > 0$ and $g < 1$. It is possible to show that for every pair (g, q), $I(K,N)$ increases moving from $N = 1$ to $N = 2$. However, as $N \to \infty$, $I(K,N)$ 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 $I(K,N)$ after an increase in N.

Hence, the example discussed above allows us to illustrate that the effect of a change in N on $I(K,N)$ 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 eect dominates over the imitation e ect. However, as N becomes extremely large, the negative eect on information transmitted prevails, making communication fully ineective.

E Additional Figures and Results

E.1 Senders' Behavior

(a) Signal Distribution for $K = 1$

(b) Signal Distribution for $K = 3$

Figure 6: Signal Distributions

Figure 7: Sender's Clustering for the Treatment (K_1, N_1)

Figure 8: Sender's Clustering for the Treatment (K_1, N_{10})

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

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

E.2 Receiver' Behavior

Figure 11: Cumulative Distribution Functions of Receivers' Guesses for K = 1

Figure 12: 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

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

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

Figure 13: CDF of Receivers' Response Gaps: Comparisons with $N = 10$

E.2.1 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

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

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

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

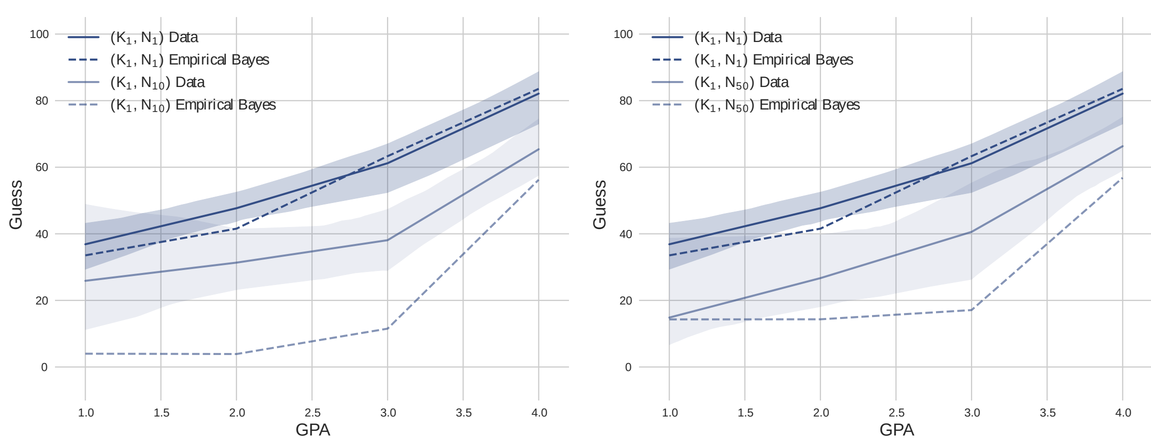

Figure 14: Receivers' Average Guesses for $K = 1$

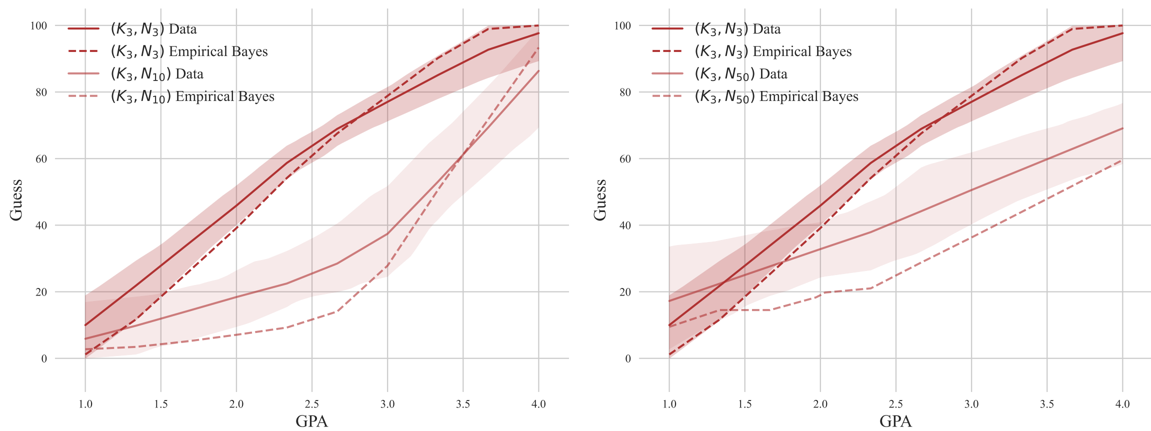

Figure 15: Receivers' Average Guesses for $K = 3$

decrease in N for each message GPA and the decrease is particularly pronounced for higher values of the GPA. The only exception is the comparison between (K_3, N_{10}) and (K_3, N_3), where the guesses are similar for high values of the GPA. This suggests that receivers account for the fact that evidence is more selected when N is larger and they adjust their guesses accordingly.

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

F Design

F.1 Graphical Interface

Figures 16, 17, 18 and 19 show the software interface of our experiment. More specifically, Figures 16 and 17 show the message choice of the sender (communication stage). Figure 18 shows the screen for the choice of the receiver's guess (guessing stage). Figure 19 shows the feedback screen, where all relevant information is reported to both players.

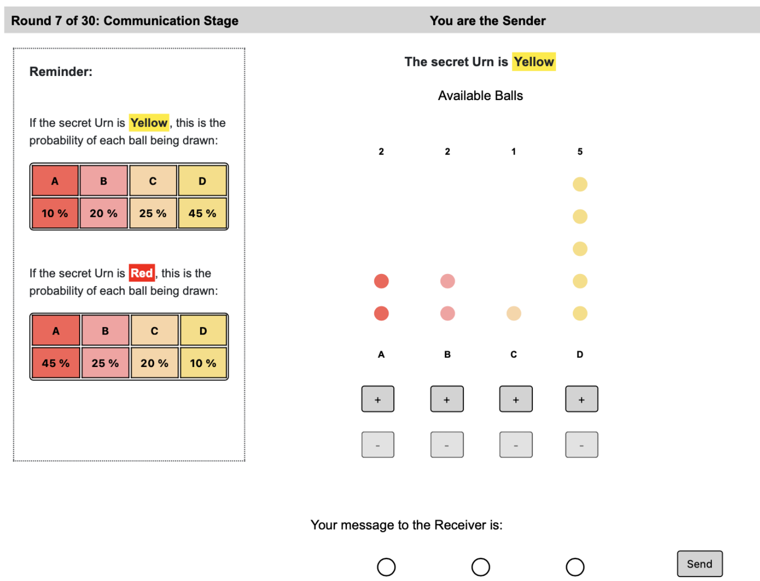

Figure 16: Sender's Interface Before the Message Choice

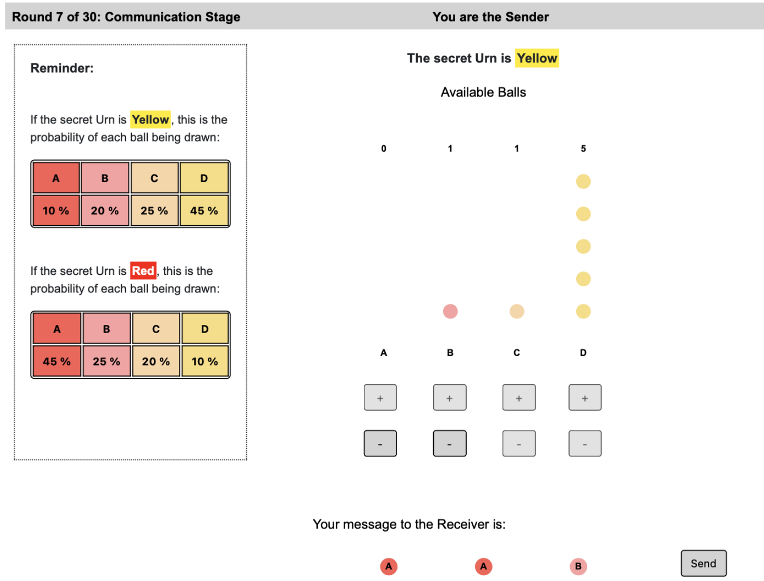

Figure 17: Sender's Interface After the Message Choice

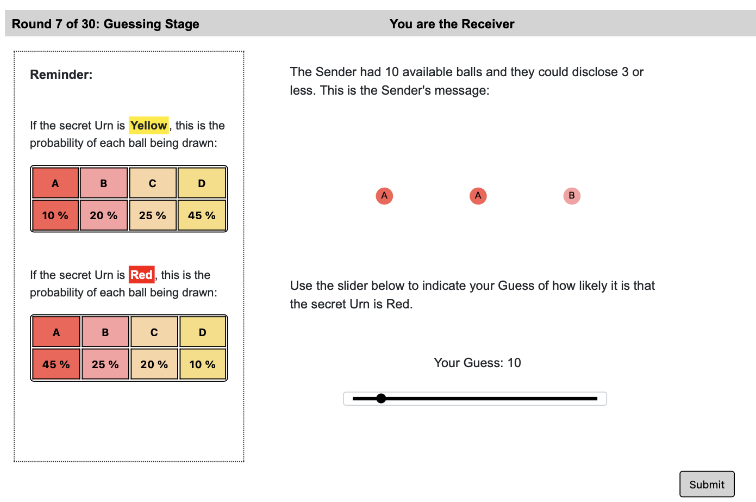

Figure 18: Receiver's Interface

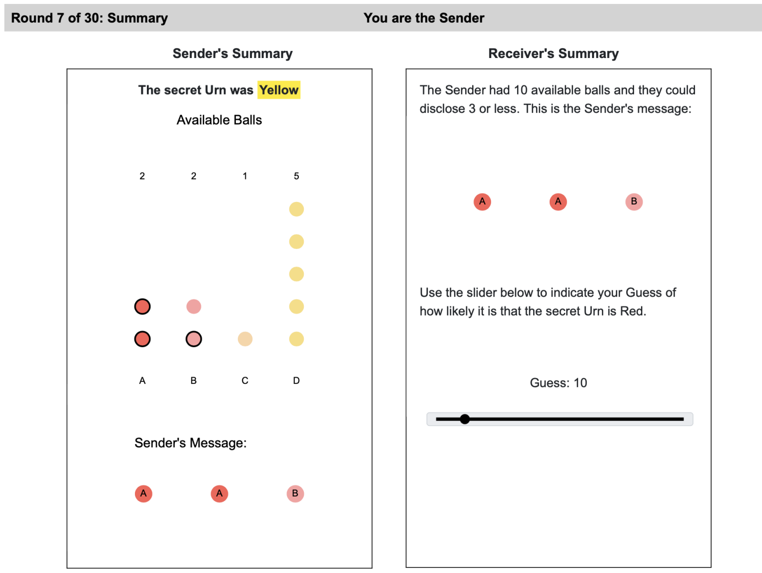

Figure 19: Feedback Interface

F.2 Sample Instructions

In this section, we reproduce instructions for one of our treatments, (K_3, N_{10}). These instructions were read out aloud so that everybody could hear. A copy of these instructions was handed out to the subject and available at any point during the experiment.

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