VERIFIABILITY IN COMMUNICATION AN EXPERIMENTAL ANALYSIS

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Introduction

Verifiability is a core ingredient in our theories of communication

- Cheap talk: no verifiability → large frictions in info transmission
- Disclosure: full verifiability → unravelling

These extreme paradigms often studied separately, with different goals

Our goal: Study how gradual changes in verifiability affect communication

- Model to flexibly vary verifiability (not all or nothing)
- Derive rich predictions to test in the lab

Our results (in progress):

- Complex qualitative predictions are broadly confirmed by the data
- Non standard deviations from quantitative predictions



- **1. Sender** privately observes the state $\theta \in \Theta = \{0,1\}$, $P(1) = \frac{1}{2}$
- 2. Given θ , Sender draws N i.i.d. signals from $S = \{A, B, C, D\}$
 - An exogenous information structure $f:\Theta \to \Delta(S)$, MLRP
- 3. Sender discloses up to K of the N drawn signals
- 4. Receiver observes the message, takes an action, payoff realizes
 - Receiver's action is $a \in [0, 1]$ and payoffs are:

$$u_S(\theta, a) = a$$
 $u_R(\theta, a) = 1 - (a - \theta)^2$

- Two states: a is the Receiver's belief that $\theta = 1$

Fix any $\theta \in \{0,1\}$ and assume N=3

Let f be

	Signal			
State	A	B	C	D
$\theta_L = 0$	10%	20%	25%	45%
$\theta_H = 1$	45%	25%	20%	10%

Assume that the Sender draws the signals $\{B, D, D\}$

If
$$K = 1$$

The Sender can send a message from the set $\{\varnothing,B,D\}$

Fix any $\theta \in \{0,1\}$ and assume N=3

Let f be

	Signal			
State	A	B	C	D
$\theta_L = 0$	10%	20%	25%	45%
$\theta_H = 1$	45%	25%	20%	10%

Assume that the Sender draws the signals $\{B, D, D\}$

If
$$K=3$$

The Sender can send a message from the set $\{\varnothing, B, D, BD, BDD\}$

When K = N, information is **fully verifiable**

► Sender can disclose all the signals → unraveling → no frictions

When K < N, information is partially verifiable

- Sender can only prove so much about herself → unraveling is unfeasible
- ► Scope for imitation via selective disclosure
- Even if they are verifiable, selection makes signals' meaning context dependent
 - \Rightarrow How persuasive a signal is depends on how selective the disclosure is

Hybrid framework between cheap-talk games and disclosure games

Theoretical Predictions

We study the effects of changing N and K on

- 1. Sender's behavior: disclosure strategy
 - How many signals?
 - Which signals?
- 2. Receiver's behavior: stated beliefs after a given message
 - How are beliefs affected by Sender's selection opportunities?
- 3. Informativeness of the communication
 - How effectively receiver learns state θ ?
 - We measure it in terms of Receiver's expected payoff

First, fix any (N, K)

Proposition Milgrom (1981)

There exists a perfect Bayesian equilibrium with maximal selective disclosure: Sender reports the K most favorable signals.

Observable Implications:

Sender's Behavior

- As K increases, the number of disclosed signals increases
- As N increases, the most favorable signal is sent with increasingly high probability

Receiver's Behavior

 $-\,$ As N increases the most favorable signal becomes increasingly less persuasive

Now fix any $N \geq 1$

How does an increase in K (verifiability) affect information transmission?

Proposition

Equilibrium informativeness increases in K.

Intuition: Easier to send messages that others cannot imitate \Rightarrow Less pooling \Rightarrow More information transmitted

Now fix any $K \geq 1$

How does an increase in N (selection) affect information transmission?

Proposition

When $N \to \infty$, equilibrium informativeness converges to zero.

Intuition: When N grows, "highest" message available to every $\theta \Rightarrow \mathrm{All}$ types pool

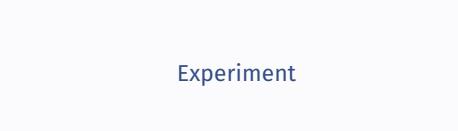
INCREASING N

When N is small, an increase in N generates two contrasting effects

- Information Effect. Sender has more evidence to prove her type
- Selection Effect. Sender is more selective, making "higher" signals less informative

Our approach so far: **compute** comparative statics within the parametric setting of the game actually implemented in the lab





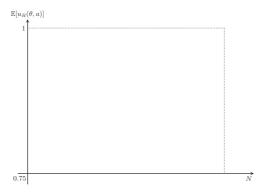
Subjects play the communication game for 30 rounds

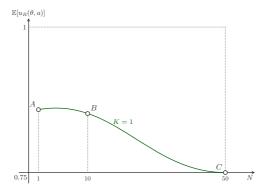
f is

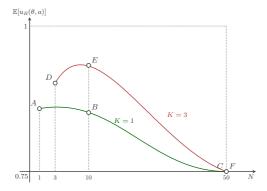
	Signal			
State	A	В	C	D
$\theta_L = 0$	10%	20%	25%	45%
$\theta_H = 1$	45%	25%	20%	10%

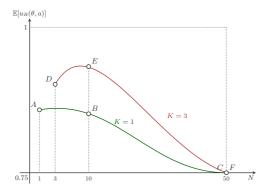
Six treatments:

	N = 1	N=3	N = 10	N = 50
K = 1	A		B	C
K = 3		D	E	F









Test 1. As N increases, informativeness decreases (selection effect)

$$B > C$$
 $E > F$

Test 2. As N increases, informativeness increases (information effect)

Test 3. As K increases, informativeness increases (more verifiability)



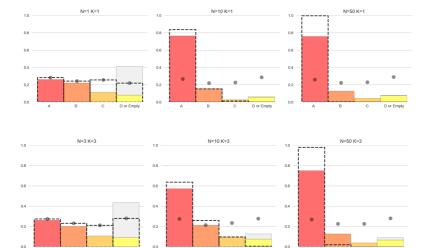
1. Sender's disclosure choices

- How many signals?
- Which signals?
- 2. Receiver's beliefs given the disclosed message
 - Do subjects account for the strategic selection in their guesses?
- 3. Informativeness: Receiver's expected payoff
 - Are the comparative statics in K and N confirmed in the data?
 - If not, what causes the theory-data gap?

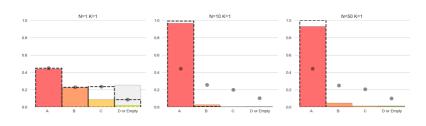
Focus on the last 20 rounds

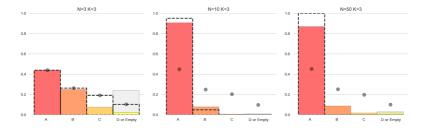
Sender's Behavior

Signals in Sender's Message: Observed Distribution (Bars) vs Theoretical Distribution (Dashed Bars) vs Random Distribution (Dots)

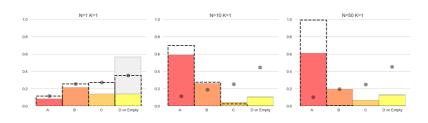


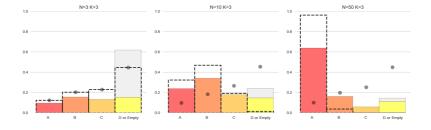
Signals in Sender's Message | H: Observed Distribution (Bars) vs Theoretical Distribution (Dashed Bars) vs Random Distribution (Dots)





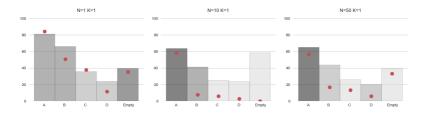
Signals in Sender's Message | L: Observed Distribution (Bars) vs Theoretical Distribution (Dashed Bars) vs Random Distribution (Dots)



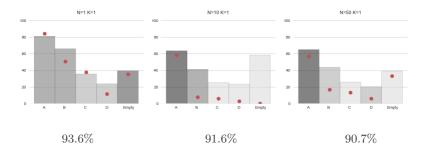


Receiver's Behavior

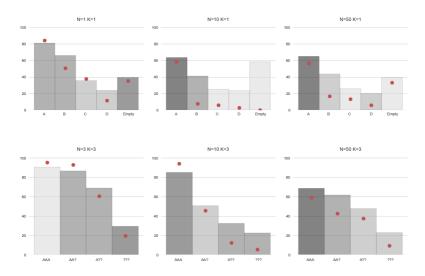
Receiver's Elicited Beliefs (Bars) vs Empirical Beliefs (Red Dots)



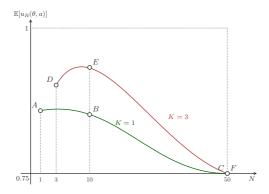
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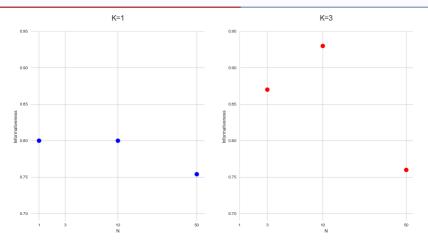


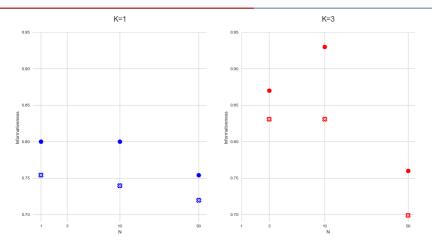
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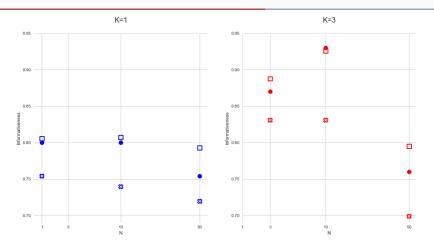












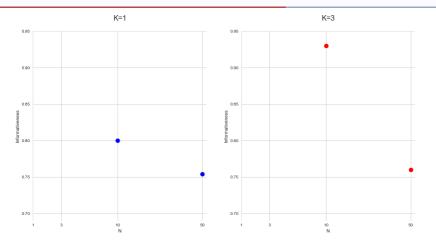


CONCLUSIONS

Flexible framework that introduces variations in verifiability and allows to derive rich comparative statics in informativeness

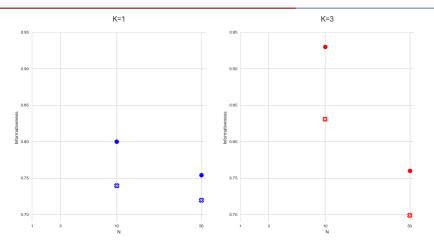
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 - Evidence of nuanced lying aversion
- 2. Receivers' beliefs are monotonic but over-optimistic
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- Informativeness is lower than predicted, but most comparative statics are confirmed
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 - Receivers do not not account for the informative value of selection





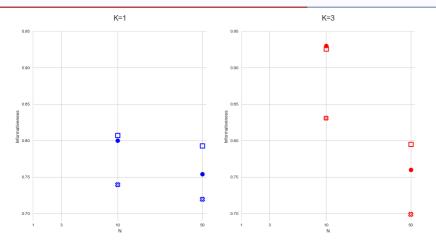
Test 1. As N increases, informativeness decreases (selection effect)

- Observed data:
- Bayesian data:



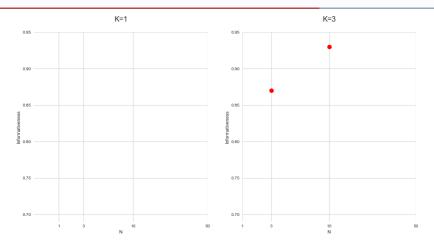
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- Bayesian data:



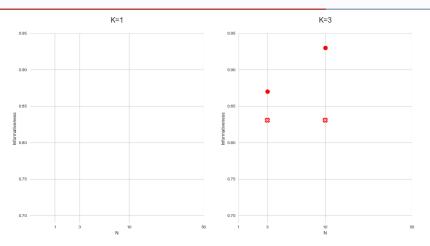
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- Observed data: not detected for K=1; detected for K=3
- Bayesian data: **not detected for** K = 1**; detected for** K = 3



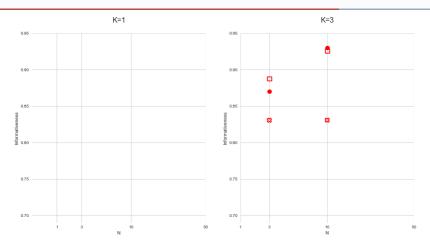
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- Observed data:
- Bayesian data:



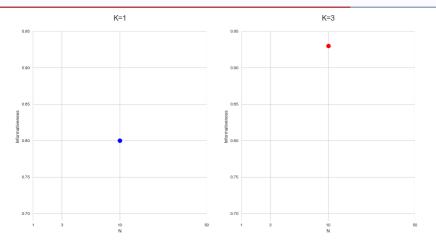
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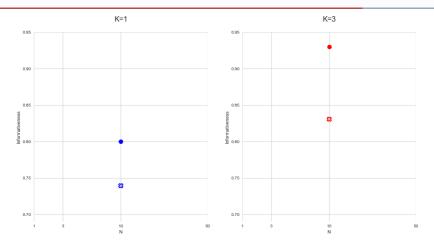
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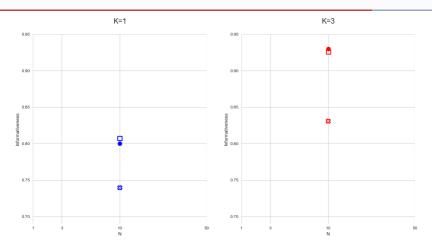
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- Observed data:
- Bayesian data:



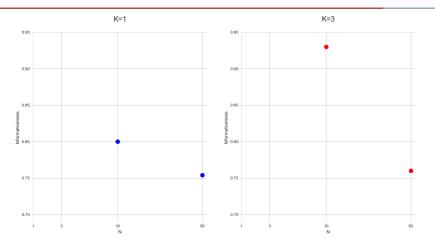
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- Observed data: detected
- Bayesian data:



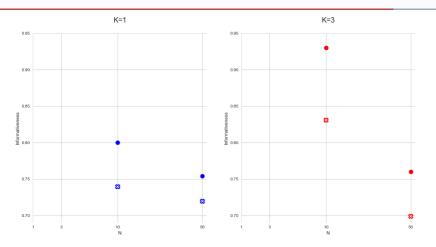
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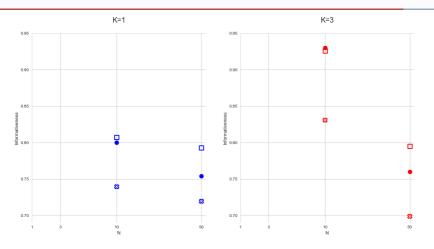
Test 4. The change in informativeness due to K decreases with N

- Observed data:
- Bayesian data:



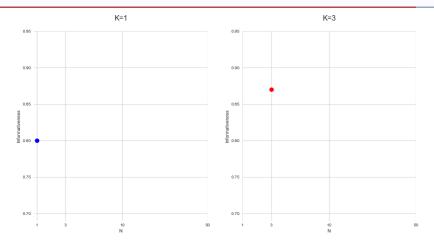
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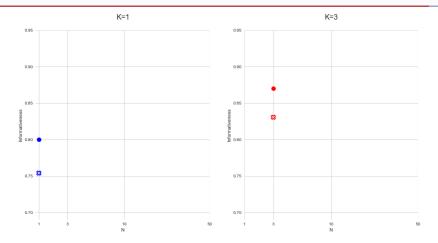
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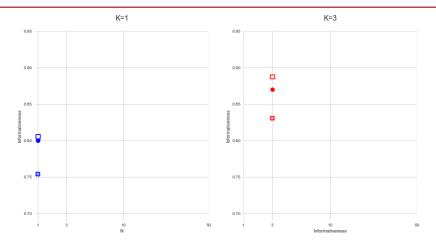
Test 5. If K = N, informativeness increases with N (full verifiability)

- Observed data:
- Bayesian data:



Test 5. If K = N, informativeness increases with N (full verifiability)

- Observed data: detected
- Bayesian data:



Test 5. If K = N, informativeness increases with N (full verifiability)

- Observed data: detected
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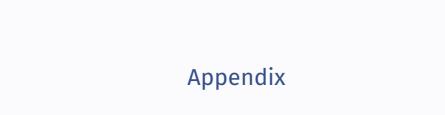


CONCLUSIONS Conclusions

Flexible framework that introduces variations in verifiability and allows to derive rich comparative statics in informativeness

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Rich experimental literature on communication

Disclosure:

- ▶ Jin, Luca and Martin (2022, AEJ: Micro) failure of unravelling and why
- ► Hagenbach and Perez-Richet (2018, GEB) preference alignment
- ► Li and Schipper (2020, GEB) vague disclosure

Cheap Talk:

► Cai and Wang (2006, GEB) – overcommunication wrt the theory

Partially Verifiable Disclosure

- ▶ Burdea, Montero, Sefton (2022) test of Glazer, Rubinstein ('04, '06)
- ▶ Li and Schipper (2018) asymmetric info on amount of evidence
- ▶ Penczynski, Koch and Zhang (2021) private acquisition of evidence

Closest in the approach:

► Frechette, Lizzeri and Perego (2022, Ecma) – Persuasion

Closest papers that feature partially verifiable information, $\bar{\omega} \notin M(\bar{\omega})$

The Basic Setting:

- ▶ Milgrom (1981, Bell), example to showcase MLRP
- Fishman and Hagerty (1990, QJE), optimal amount of discretion
- Di Tillio, Ottaviani and Sorensen (2021, Ecma), effect of selection on information transmission

Mechanism-Design Approach:

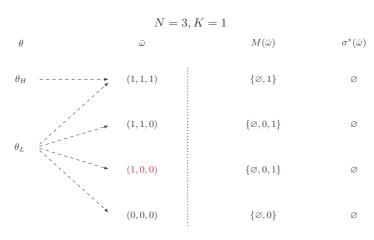
- ▶ Glazer and Rubinstein (2004, Ecma) Receiver's Verification, K=1
- ► Glazer and Rubinstein (2006, TE) Sender's verification

Richer Settings: Uknown N or Endogenous K

- ► Shin (2003, Ecma)
- Dziuda (2011, JET)

Unlike classic disclosure games, SE outcome not unique when K < N

Off-path beliefs can support other equilibrium outcome



REFINEMENTS

Multiplicity is a serious (albeit common) challenge for experiments

▶ Data will provide guidance as to which equilibrium is played

The selective-disclosure outcome is the only one that survives certain refinements:

- ► Refinements for signalling games (e.g., Cho-Kreps '87, Banks-Sobel '87) have no force here
- Refinements for cheap talks: Farrel (1993)'s Neologism Proofness, Matthews, Okuno-Fujiwara, Postelwite (1991), and some weaker versions



We refine off-path beliefs via Neologism Proofness (Farrel, 1993)

A **neologism** is a a pair (m, C) such that $C \subseteq \tilde{C}(m)$.

Literal meaning of $(m,C) \leadsto \text{"My type } \bar{\omega} \text{ belongs to } C$ "

Definition

A neologism (m,C) is **credible** relative to equilibrium (σ^*,μ^*) if

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

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

The equilibrium is **neologism proof** if no neologism is credible

Remark (Existence, again)

Our equilibrium is Neologism Proof.

Moreover, Neologism Proofness delivers outcome uniqueness

An equilibrium (σ, μ) induces an outcome $x: \Omega^N \to A$,

$$x(\bar{\omega}) = \sum_{\bar{\omega}'} \mu(\bar{\omega}' | \sigma(\bar{\omega})) \mathbb{E}(\theta | \bar{\omega}') \quad \forall \bar{\omega}.$$

Proposition (Uniqueness)

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

Let
$$M(\bar{\omega}):=\left\{m\in\Omega^k\mid k\leq K \text{ and } \exists \text{ injective} \right.$$

$$\rho:\left\{1,...,k\right\}\rightarrow\left\{1,...,N\right\} \text{ s.t. } m=\left(\omega_{\rho(1)},...,\omega_{\rho(k)}\right)\right\}\cup\{\varnothing\}.$$

Denote $\mathcal{M} = \bigcup_{\bar{\omega} \in \Omega^N} M(\bar{\omega})$ the space of all messages

Sender's Strategy

pure and θ -independent

 $-\sigma:\Omega^N\to\mathcal{M}$ s.t. $\sigma(\bar{\omega})\in M(\bar{\omega})$, for all $\bar{\omega}$

Receiver's Beliefs and Strategy

- $-\mu:\mathcal{M}\to\Delta(\Omega^N)$
- $-a:\mathcal{M}\to\Delta(A)$

Given μ , receiver's optimal strategy given by

$$a(m) := \arg\max_{a} \mathbb{E}(-(a-\theta)^{2}|m) = \mathbb{E}(\theta|m) = \sum_{\bar{\omega}} \mu(\bar{\omega}|m)\mathbb{E}(\theta|\bar{\omega})$$
 $\forall m$

Definition:

A Sequential Equilibrium is a pair (σ^*, μ^*) s.t.

1. For all $\bar{\omega} \in \Omega^N$, $\sigma^*(\bar{\omega}) \in M(\bar{\omega})$ and

$$\sum_{\bar{\omega}'} \mu^*(\bar{\omega}'|\sigma^*(\bar{\omega})) \mathbb{E}(\theta|\bar{\omega}') \ge \sum_{\bar{\omega}'} \mu^*(\bar{\omega}'|m') \mathbb{E}(\theta|\bar{\omega}') \qquad m' \in M(\bar{\omega})$$

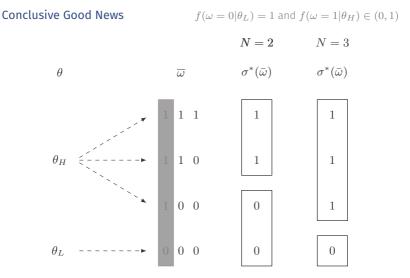
2. For all m, supp $\mu^*(\cdot|m) \subseteq \tilde{C}(m)$. In particular, if $m \in \sigma^*(\Omega^N)$,

$$\mu^*(\bar{\omega}|m) = \mathbf{q}(\bar{\omega}|\sigma^{\star^{-1}}(m)) \quad \forall \bar{\omega}$$

Notation:

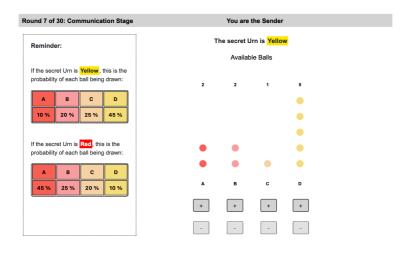
 $\tilde{C}(m):=\{ar{\omega}\in\Omega^N:m\in M(ar{\omega})\};$ types that could have sent m

Total Prob: $q(\bar{\omega}) = \sum_{\theta} p(\theta) f(\bar{\omega}|\theta)$; Conditional Prob: $q(\bar{\omega}|K)$



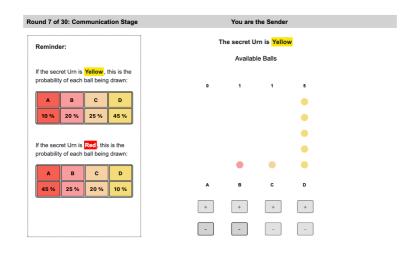
 $N \uparrow \leadsto$ less likely that θ_H can separate from $\theta_L \leadsto$ informativeness \uparrow

Send

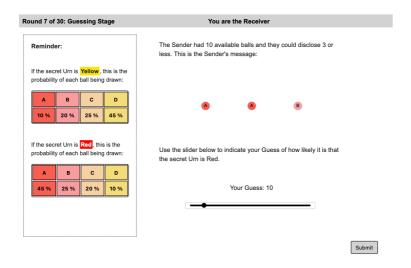


Your message to the Receiver is:

Send



Your message to the Receiver is:



Round 7 of 30: Payoff

You are the Sender

The secret Urn was Yellow

The Receiver's Guess was 10, so in this Round you earned 10 points.

Continue

Round 7 of 30: Payoff

You are the Receiver

The secret Urn was Yellow

In this Round you earned 100 points.

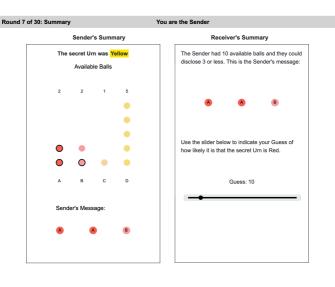
Continue

How were your points determined?

The secret Urn was Yellow, Your Guess was 10.

The two Computer's Random Numbers were 59 and 44.

Your Guess was smaller than or equal to the largest of the two Computer's Random Numbers, so you earned 100 points.



Round 7 of 30: History			You are the Sender	
Rou	nd	Secret Urn	Message	Guess
7		Yellow	A A B	10
6		Red	8 8 O	77
5		Red	A B B	77
4		Red	A A A	97
3		Red	66	87
2		Yellow	© © O	52
1		Red	000	0

Next

In the model, $u_R(\theta, a) = -(a - \theta)^2$

Since $\Theta = \{Y, R\}$, equilibrium $a^* = \Pr(\theta = R|m)$, Receiver's posterior belief

Effectively, a Quadratic Scoring Rule

In the lab, we use the **Binarized Scoring Rule**, robust to risk aversion and non-EU

Following Danz, Vesterlund and Wilson (2022) and Vespa and Wilson (2016), we implement the BSR "opaquely" (paired uniform)

Receiver's EU under the BSR is a linear transformation of the one in model. Thus, same theoretical predictions hold

Under QSR:

$$\mathbb{E}[u_R|m] = -Pr(\theta = 1|m)(1 - \mathbb{E}[\theta|m])^2 - Pr(\theta = 0|m)\mathbb{E}[\theta|m]^2$$

Under BSR:

$$\mathbb{E}[u_R|m] = 100 \cdot Pr(Winning) = 100 \cdot Pr(W)$$

where
$$Pr(W) = Pr(W|\theta=1)Pr(\theta=1|m) + Pr(W|\theta=0)Pr(\theta=0|m)$$

$$Pr(W|\theta = 1) = Pr(a \ge \min\{g_1, g_2\}), \text{ where } g_1, g_2 \sim \mathcal{U}[0, 1]$$

 $Pr(W|\theta = 1) = 1 - Pr(a < g_1)Pr(a < g_2) = 1 - (1 - a)^2$

$$Pr(W|\theta=0) = Pr(a \le \max\{g_1, g_2\})$$
, where $g_1, g_2 \sim \mathcal{U}[0, 1]$
 $Pr(W|\theta=0) = 1 - Pr(a > g_1)Pr(a > g_2) = 1 - a^2$

$$\Rightarrow Pr(W) = 1 - (1 - a)^2 Pr(\theta = 1|m) - a^2 Pr(\theta = 0|m)$$
$$\Rightarrow a^* = Pr(\theta = 1|m)$$

Under the BSR:

$$\mathbb{E}[u_R|m] = 100 \cdot \left[1 - (1-a)^2 Pr(\theta = 1|m) - a^2 Pr(\theta = 0|m)\right]$$

which is a linear transformation of the $\mathbb{E}[u_R|m]$ under the QSR