

The Informational Theory of Legislative Committees: An Experimental Analysis*

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Abstract

We experimentally investigate the informational theory of legislative committees first proposed by Gilligan and Krehbiel [1987, 1989]. Two committees provide policy-relevant information to a legislature under two different procedural rules. Under the open rule, the legislature is free to make any decision; under the closed rule, the legislature is constrained to choose between a committee's proposal and an exogenous status quo. Our experiment shows that even in the presence of conflicts of interests, legislative committees help improve the legislature's decision by providing useful information. We further obtain evidence in support of three theoretical predictions: the *Outlier Principle*, according to which more extreme preferences of the committees reduce the extent of information transmission; the *Distributional Principle*, according to which the open rule is more distributionally efficient than the closed rule; and the *Restrictive-rule Principle*, according to which the closed rule better facilitates the informational role of legislative committees. We, however, obtain mixed evidence for the *Heterogeneity Principle*, according to which more information can be extracted in the presence of multiple committees with heterogeneous preferences. Our experimental findings provide overall support for the equilibrium predictions of Gilligan and Krehbiel [1989], some of which have been controversial in the literature.

Keywords: Legislative Committees; Strategic Information Transmission; Laboratory Experiment

JEL classification: C72, D82, D83

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1 Introduction

The informational theory of legislative committees first proposed by Gilligan and Krehbiel [1987, 1989] is one of the most influential theories of legislative organization. At its core, there is the idea that lawmakers are ignorant of the key variables affecting policy outcomes and legislative committees may help by providing information on these variables. The informational theory provides a formal framework to study why committees have incentives to perform this function, despite the fact that its members may have a conflict of interest with the decision makers and so an incentive to manipulate their decisions. Most importantly, the theory provides a framework to understand the impacts of legislative procedural rules on the effectiveness of the legislative process: explaining why it may be optimal to have the same bill referred by multiple committees; and why it may be optimal to adopt restrictive rules that delegate power to the committees.

Despite the theoretical success of the informational theory, empirical research on legislative rules has been limited. Two approaches have been attempted. First, the informational theory has been justified with historical arguments and case studies (Krehbiel [1990]). Second, there have been attempts to test some indirect, but empirically testable, implications of the theory. In particular, researchers have studied the extent to which committees are formed by preferences outliers, since it is predicted that such committees may not be able to convey information properly (see, e.g., Weingast and Marshall [1987], Krehbiel [1991], and Londregan and Snyder [1994]). Other researchers have studied the relationship between the presence of restrictive procedural rules and the composition of the committee, since in some versions of the theory more restrictive rules are predicted to be associated with committee specialization, heterogeneity of preferences within the committee, and less extreme biases (see, e.g., Sinclair [1994], Dionne and Huber [1996, 1997], and Krehbiel [1997a, 1997b]). None of these attempts, however, directly studied the *behavioral implications* of the informational theory. What makes it difficult to directly test the theory is the fact that behavior can be properly evaluated only with knowledge of individuals' private information: field data is typically not sufficiently rich nor even available.

The lack of direct behavioral evidence is problematic. First, existing empirical findings present conflicting evidence, and so it is not fully conclusive on the validity of the theoretical predictions. Second, and perhaps more importantly, the existing evidence is not sufficiently detailed to contribute to a better understanding of some important open theoretical questions. Informational theories are typically associated with multiple equilibria:

while some predictions are common to all equilibria, other equally important predictions are not. A key question in studying legislative organization is whether restrictive rules can facilitate the informational role of committees. The answer to this question, however, depends on which equilibrium to be selected and so is unanswerable by theory alone.

In this paper, we make the first attempt to gain insight into the informational role of legislative committees. Using a laboratory experiment, we test the predictions of the seminal works by Gilligan and Krehbiel [1989], who first proposed the informational theory, and by Krishna and Morgan [2001], who further developed on Gilligan and Krehbiel's [1989] framework. In their models, policies are chosen by the median voter of a legislature, who is uninformed about the state of the world. Two legislative committees with heterogeneous preferences observe the state and send recommendations to the legislature. Committees have biases of the same magnitude but of opposite signs: relative to the legislature's ideal policy, one committee would prefer a higher policy and the other a lower policy.

Two legislative rules are considered. Under the *open rule*, the legislature listens to the recommendations and is free to choose any policy. Under the *closed rule*, the legislature can only choose between the policy recommended by one of the committees or a given status quo policy; the other committee's recommendation plays only an informational role. For each of the two rules, we conducted two treatments: one in which the magnitude of the committees' biases is large (the high bias), and one in which the magnitude is small (the low bias). As a benchmark, we also investigated the case of only one committee (the *homogeneous rule*); in this case too, we conducted two treatments with two levels of bias.

Our experiment provides clear evidence that, even in the presence of conflicts of interests, committees improve the legislature's decision by providing useful information, as predicted by the informational theory of legislative committees. Perhaps more importantly, our experiment provides a first close look at which features underlying the informational theory are supported by laboratory evidence, and which are more problematic and in need of further theoretical works.

The first prediction of the informational theory that was supported by our experimental findings is the *Outlier Principle*, the idea that more extreme preferences of the committees reduce the extent of information transmission in equilibrium. While this principle appears intuitive and has been highlighted in the literature (see, e.g., Krehbiel [1992], who coined the term), from a theoretical point of view, it is controversial. The existence of an equilibrium featuring the outlier principle has been first proven by Gilligan and Krehbiel [1989]. Krishna

and Morgan [2001], however, have shown that a more efficient equilibrium exists in which the outlier principle is not valid. The two works differ in the criterion used for equilibrium selection: the first focuses on equilibria with simpler strategies, whereas the second focuses on the welfare property of equilibria. In our experiment, we found support for Gilligan and Krehbiel’s [1989] prediction: for both the open rule and the close rule, we found that a reduction in the committees’ bias resulted in a statistically significant increase in the legislature’s payoff.

The second set of predictions that our data supported is what we may call the *Distributional Principle* and the *Restrictive-rule Principle*. Gilligan and Krehbiel [1989] defined two measures of inefficiency: *distributional inefficiency*, as measured by the divergence between the expected equilibrium outcome and the legislature’s ideal policy; and *informational inefficiency*, as measured by the residual variance left in the policy outcome. A key finding in Gilligan and Krehbiel [1989] is that, compared to the open rule, the closed rule is less distributionally efficient (the distributional principle) but more informationally efficient (the restrictive-rule principle). Krishna and Morgan [2001] pointed out, however, that this result is not a feature of all equilibria: there exists at least another equilibrium under the open rule that is more informationally efficient than any equilibrium under the closed rule, and there are equilibria under the closed rule that achieves the maximal possible distributional efficiency. In this case too, our experimental evidence supported Gilligan and Krehbiel’s [1989] predictions. We found significant distributional inefficiency under the closed rule for both levels of bias, but found no significant inefficiency under the open rule. Regarding informational inefficiency, we also found that the open rule was more inefficient than the closed rule, though results here were less clear-cut: the difference in informational inefficiency was statistically significant only for the small bias.

There is another important prediction of the informational theory, however, for which we found mixed evidence: the *Heterogeneity Principle*, the idea that more information can be extracted by the legislature in the presence of multiple committees with heterogeneous preferences than in the case of one (homogeneous) committee. Supported both by Gilligan and Krehbiel [1989] and by Krishna and Morgan [2001], this prediction is indeed quite intuitive since it seems natural that increasing the number of informed committees should not hurt the legislature. However, this property is not supported by our experiment, highlighting an interesting behavioral phenomenon that has *not* been previously documented. For both levels of bias we did not find any statistically significant difference in the legislature’s welfare between the open rules with two committees and with one committee: the only

exception was the special case of informational efficiency with the small bias, where the open rule with one committee was in fact significantly superior.

The reason why having more than one committee did not improve welfare as expected appears to be due to an interesting new phenomenon that we may call the *Confusion Effect*. When the legislature receives only one recommendation, the recommendation tends to be followed: since a committee's recommendation is typically correlated with the true state, this leads the legislature to avoid "bad" mistakes, i.e., not to correct for large shocks in the state variable. When the legislature receives two conflicting recommendations, on the contrary, the legislature tends to "freeze" and ignore both of them: this leads to situations in which the policy incorporates no information about the environment.

We further found that, for both levels of bias, the legislature's overall welfare under the closed rule was not significantly different than under the open rule. These insignificant differences do not support Gilligan and Krehbiel's [1989] nor Krishna and Morgan's [2001] predictions. While consistent with Gilligan and Krehbiel [1989] the open rule appeared less informationally efficient than the closed rule, the open rule itself was, in line with Krishna and Morgan [2001], significantly more informative than is predicted by Gilligan and Krehbiel [1989], resulting in only a small dominance of the closed rule over the open rule. Such a small dominance of the closed rule over the open rule in informational efficiency was offset by the significant dominance of the open rule in distributional efficiency, thus leaving the differences of the legislature's overall welfare, which comprises of the two efficiencies, insignificant under the two rules.

Our findings largely supported the equilibrium predictions of Gilligan and Krehbiel [1989]. The qualitative features of subjects' behavior, especially those under the closed rule, can also be well explained by the equilibria in Gilligan and Krehbiel [1989]. This may indeed be an expected experimental outcome, since Gilligan and Krehbiel's [1989] equilibria are based on simpler (off-equilibrium) strategies, which should have a better empirical appeal than the more involved specifications supporting Krishna and Morgan's [2001] equilibria. We note, however, that the rather ambiguous welfare findings supporting neither theory suggests that we should be cautious in using the welfare analysis in the informational theory as the only normative criterion for choosing the type of institutions for the U.S. legislative system.

Related literature. Apart from the literature on the informational theory of legislative committees discussed above, our study contributes to two other literatures. The first is

the experimental literature on cheap-talk games. The focus of the literature has been on games with one sender and one receiver communicating under a unidimensional state space. Examples include Dickhaut, McCabe, and Mukherji [1995], Blume, Dejong, Kim, and Sprinkle [1998, 2001], Gneezy [2005], Cai and Wang [2006], Sánchez-Pagés and Vorsatz [2007, 2009], Wang, Spezio, and Camerer [2010], and Chung and Harbaugh [2014]. Two recent studies that depart from this trend are Lai, Lim, and Wang [2015] and Vespa and Wilson [2016], who design games that feature multiple senders and multidimensional state spaces. They use the games to experimentally investigate Battaglini’s [2002] fully revealing equilibrium in multidimensional cheap talk. Battaglini and Makarov [2014], on the other hand, extends the boundary of the literature by considering multiple receivers. They design games that test the prediction of Farrell and Gibbons’ [1989] model, in which multiple receivers listen to a single sender.

To our knowledge, our study is the first that expands this literature by introducing multiple senders in the framework of Gilligan and Krehbiel [1989] which features a unidimensional state space. Minozzi and Woon [2016] also experiment on games with two senders and unidimensional state spaces. They, however, consider a different type of setup in which the senders’ biases are private information.

The other literature to which our paper contributes is the small experimental literature on delegation because the closed rule can be considered as a case in which the decision maker delegates to the proposing committee but retains a veto power. Lai and Lim [2012] report findings from experiments on delegation-communication games. In their games, an uninformed principal chooses whether to fully delegate her decision rights to an informed agent or to retain it and communicate with the agent via cheap talk to obtain decision-relevant information. Fehr, Herz, and Wilkening [2013] study motivational consequences of delegation in a setup inspired by Aghion and Tirole [1997]. Dominguez-Martinez, Sloof, and von Siemens [2014] experimentally study the use of strategic ignorance in delegating real authority within a firm.

The organization of the remainder of the paper is as follows. In Section 2 we present the theoretical framework and discuss the main predictions of the informational theory of legislative committees. In Section 3 we describe the experimental design and procedures. We discuss the experimental findings in Section 4. Section 5 concludes.

2 The Model

2.1 The Set-Up

We sketch the model on which our experimental design is based and discuss its equilibrium predictions which form our experimental hypotheses. The model is a close variant of Gilligan and Krehbiel's [1989] model of *heterogeneous committees*, adapted for laboratory implementation.

There are three players, two senders (the committees), Sender 1 (S_1) and Sender 2 (S_2), and a receiver (the legislature). The two senders make bill proposals. Based on the proposals, the receiver (R) determines the action or the policy to be adopted, $a \in A \subseteq \mathbb{R}$. The senders are informed about the state of the world θ , commonly known to be uniformly distributed on $\Theta = [0, 1]$. The uniform prior suggests that θ has a mean of $\bar{\theta} = 1/2$. The receiver is uninformed. The players' payoffs are

$$\begin{aligned} U^{S_i} &= -(a - (\theta + b_i))^2, \quad i = 1, 2, \quad \text{and} \\ U^R &= -(a - \theta)^2, \end{aligned} \tag{1}$$

where $b_1 = b = -b_2 > 0$ are parameters measuring the misaligned interests between the senders and the receiver.¹ Sender i has an ideal state-contingent action $a_i^*(\theta) = \theta + b_i$. The receiver's ideal action is also state contingent, equalling to $a^*(\theta) = \theta$. Interests are misaligned because for every $\theta \in [0, 1]$ each sender prefers the receiver to take an action that is b_i higher than the receiver's ideal action.

The timing of the game is as follows. First, nature draws and privately reveals θ to both senders. Second, the senders send messages (i.e., propose bills) to the receiver according to the different legislative rules to be discussed below. Third, the receiver chooses an action according to the rule under consideration.

Two different rules for the heterogenous committees are considered: the *open rule* and the *closed rule*. Both rules allow Sender 1 and Sender 2 to send messages, $m_1 \in M_1$ and $m_2 \in M_2$, respectively.² The messages are sent independently and simultaneously. In the

¹Our set-up is slightly different from that in Gilligan and Krehbiel [1989]. For example, the state of the world θ enters into their payoff functions with a positive sign. Our set-up corresponds to the uniform-quadratic framework of Crawford and Sobel [1982]. We adopt this set-up as we view it as providing a more intuitive experimental environment for subjects to make decisions. The two setups are otherwise completely equivalent from a theoretical point of view, modulo a reinterpretation of the variables.

²Our experimental design implements message spaces analogous to $M_1 = M_2 = [0, 1]$ for the open rule.

open rule, the receiver is free to choose any action $a \in A$ after receiving the messages. In the closed rule, the receiver is constrained to choose from the set $\{m_1, SQ\}$, where $SQ \in [0, 1]$ is an exogenously given *status quo* action. As a benchmark, we also consider the case of *homogeneous committee*, in which a single sender sends message to the receiver under the open rule. Note that this benchmark reduces to the well-known model of cheap talk by Crawford and Sobel [1982].

A behavioral strategy for Sender i , $i = 1, 2$, $m_i : [0, 1] \rightarrow \Delta M_i$, specifies a distribution of messages he sends for each state of the world. A behavioral strategy for the receiver, $a : M_1 \times M_2 \rightarrow \Delta A$ (open rule) or $a : M_1 \times M_2 \rightarrow \Delta\{m_1, SQ\}$ (closed rule), specifies a distribution of feasible actions for each pair of received messages. Finally, a belief function of the receiver, $\mu : M_1 \times M_2 \rightarrow \Delta[0, 1]$, specifies the receiver's posterior beliefs. The solution concept is the perfect Bayesian equilibrium, where the receiver takes an action that maximizes expected payoff given beliefs, each sender chooses m_i to maximize payoff given the receiver's strategy, and beliefs are derived from Bayes' rule whenever possible.

2.2 Equilibrium Predictions

Two papers have studied the equilibria of the game described above: Gilligan and Krehbiel [1989] who have introduced the game and present the first analysis; and Krishna and Morgan [2001] who have presented an alternative analysis based on a different selection of equilibria. The equilibria characterized in these two papers bring out the interesting features of the two legislative rules, and the different characterizations found in them present a somewhat controversial picture that invites experimental inputs.

Accordingly, we use the two sets of equilibria characterized in Gilligan and Krehbiel [1989] and Krishna and Morgan [2001] as the theoretical benchmarks for evaluating our experimental findings. Table 1 summarizes their results by reporting the equilibrium expected payoffs characterized in both papers. Table 1 also reports, for the purpose of comparative statics with respect to the number of senders, the payoffs in the case in which there is only one sender under the open rule, i.e., the case of homogeneous committee.

As anticipated in the introduction, the theoretical predictions of the game can be divided into two groups. The first group includes the basic insights of the informational theory.

For the closed rule, it remains the case that $M_1 = [0, 1]$, but we follow the model of Gilligan and Krehbiel [1989] by implementing M_2 to be the set of all closed intervals in $[0, 1]$. See Section 3 for the details of our experimental design.

Table 1: Expected Payoffs over Rules

	Heterogeneous Committees				Homogeneous Committee
	Gilligan and Krehbiel [1989]		Krishna and Morgan [2001]		Crawford and Sobel [1982]
	Open Rule	Closed Rule	Open Rule	Closed Rule	Open Rule
R	$-\frac{16b^3}{3}$	$-\frac{16b^3}{3} - b^2(1 - 8b)$	0	$-\frac{4b^3}{3}$	$-\frac{1}{12N_{CS}(b)^2} - \frac{b^2(N_{CS}(b)^2 - 1)}{3}$
S_1	$-\frac{16b^3}{3} - b^2$	$-\frac{16b^3}{3}$	$-b^2$	$-\frac{4b^3}{3} - b^2$	$-\frac{1}{12N_{CS}(b)^2} - \frac{b^2(N_{CS}(b)^2 + 2)}{3}$
S_2		$-\frac{16b^3}{3} - 4b^2(1 - 4b)$			

Note: $N_{CS}(b) = \left\lceil -\frac{1}{2} + \frac{1}{2}\sqrt{1 + \frac{2}{b}} \right\rceil$, where $\lceil z \rceil$ denotes the smallest integer greater than or equal to z .

These results are uncontroversial and are characteristics of both the equilibria in Gilligan and Krehbiel [1989] and Krishna and Morgan [2001]. The first result is the *outlier principle*:

Result 1. *Both in Gilligan and Krehbiel [1989] and in Krishna and Morgan [2001], the receiver's and the senders' expected payoffs are non-increasing in the bias b :*

- *For the open rule, payoffs are strictly decreasing in the bias for $b \in [0, 1/4]$ in Gilligan and Krehbiel [1989]; in Krishna and Morgan [2001], while the senders' payoffs are strictly decreasing, the receiver's payoff is constant for $b \in [0, 1/4]$.*
- *For the closed rule, all three players' payoffs are strictly decreasing in the bias for $b \in [0, 1/4]$ in both Gilligan and Krehbiel [1989] and Krishna and Morgan [2001].*

In Krishna and Morgan [2001], the receiver's payoff under the open rule is independent of the bias, because their equilibrium achieves full revelation when $b \leq 1/4$; the action adopted coincides with the receiver's ideal action and so is independent of b . In all the other cases, information transmission is imperfect and depends on the extent of misaligned interests as measured by b .

The second result shared by the analyses in both Gilligan and Krehbiel [1989] and Krishna and Morgan [2001] is the *heterogeneity principle*: heterogeneity in the preferences of the senders allows the receiver to extract more information. In the appendix, we prove:

Result 2. *Compared to the case where there is only one sender under the open rule, the players are always better off when there are two senders with heterogeneous preferences (under either the open rule or the closed rule), and this is true in both Gilligan and Krehbiel [1989] and Krishna and Morgan [2001].*

Result 2 highlights the fact that the receiver can exploit the conflicts of interests between the senders themselves to extract more information. The equilibria in Gilligan and Krehbiel [1989] and in Krishna and Morgan [2001] differ in the way incompatible messages are interpreted, which will be elaborated below. We only note here that Krishna and Morgan [2001] construct equilibria in which the receiver extracts more information, so the expected benefit of having a heterogeneous committee (relative to having a homogeneous committee) is higher in their paper than in Gilligan and Krehbiel [1989].

The more controversial issue, on which the predictions of the two papers differ, concerns the welfare under the open rule and the closed rule for the case of two senders. To highlight the difference, it is useful to introduce two measures of inefficiency. Define the equilibrium outcome function as a random variable $X(\theta) = a(\theta) - \theta$. The expected payoff of the receiver can be written as:

$$EU^R = - \underbrace{Var(X(\theta))}_{\text{informational}} - \underbrace{(EX(\theta))^2}_{\text{distributional}}. \quad (2)$$

The first part, $VarX(\theta)$, represents the *informational inefficiency* of the equilibrium: it measures the residual volatility in the outcome after information transmission. The second part, $(EX(\theta))^2$, represents the *distributional inefficiency*: it measures the systematic bias from the receiver's ideal action that remains after information transmission. In the full information case in which the receiver observes the state, both inefficiencies would be zero. Table 2 reports, for the two levels of bias ($b = 0.1$ and $b = 0.2$) adopted in our experiment, the values of $-VarX(\theta)$ and $-(EX(\theta))^2$ as predicted by Gilligan and Krehbiel [1989] and Krishna and Morgan [2001]. These negative values are interpreted respectively as the informational and the distributional *efficiencies*. The receiver's payoffs are also reported in the table.

Gilligan and Krehbiel [1989] is the first to study the impacts of the legislative rules on informational and distributional efficiencies. Their analysis leads them to the *restrictive-rule principle* and the *distributional principle*. In the following, we summarize these two principles together with a comparative statics of how the two efficiencies change with respect to $b \in [0, 1/4]$:

Result 3. *In Gilligan and Krehbiel [1989], informational efficiency is greater in the closed rule than in the open rule (the restrictive-rule principle). Furthermore, the efficiency is decreasing in $b \in [0, 1/4]$ under both rules. Distributional efficiency, on the contrary, is greater in the open rule than in the closed rule (the distributional principle): in the open*

Table 2: Predicted Efficiencies and Receiver's Payoff

Theory	Dist. Eff. $-(EX(\theta))^2$	Info. Eff. $-Var(X(\theta))$	Receiver's Payoff	Dist. Eff. $-(EX(\theta))^2$	Info. Eff. $-Var(X(\theta))$	Receiver's Payoff
	Closed Rule ($b = 0.1$)			Open Rule ($b = 0.1$)		
GK [1989]	-36.00×10^{-4}	-37.33×10^{-4}	-73.33×10^{-4}	0	-53.33×10^{-4}	-53.33×10^{-4}
KM [2001]	0	-13.33×10^{-4}	-13.33×10^{-4}	0	0	0
	Closed Rule ($b = 0.2$)			Open Rule ($b = 0.2$)		
GK [1989]	-16.00×10^{-4}	-170.67×10^{-4}	-186.67×10^{-4}	0	-426.67×10^{-4}	-426.67×10^{-4}
KM [2001]	0	-106.67×10^{-4}	-106.67×10^{-4}	0	0	0

Note: GK and KM stand for, respectively, Gilligan and Krehbiel [1989] and Krishna and Morgan [2001]. For distribution efficiency (Dist. Eff.) and informational efficiency (Info. Eff.), a less negative number indicates a higher level of efficiency, i.e., less inefficiency.

rule $(EX(\theta))^2 = 0$ for any $b \in [0, 1/4]$, while in the closed rule $(EX(\theta))^2$ is positive and increasing in $b \in [0, 1/4]$.

Krishna and Morgan [2001] select the most informative equilibrium, both for the open rule and the closed rule, and find:

Result 4. *In Krishna and Morgan [2001], informational efficiency is greater in the open rule than in the closed rule: in the open rule, full information transmission is possible for any $b \in [0, 1/4]$, while all the equilibria of the closed rule are informationally inefficient. Distributional efficiency is the same in the open rule and the closed rule: in both cases $(EX(\theta))^2 = 0$ for any $b \in [0, 1/4]$.*

To see why the theoretical analyses in these papers arrive at different conclusions, it is useful to review the respective equilibrium constructions. Consider first the open rule. In the equilibrium constructions of both Gilligan and Krehbiel [1989] and Krishna and Morgan [2001], if the senders' messages reveal the same state of the world, the receiver infers that both senders are telling the truth and adopts the corresponding ideal action; when the senders' messages are incompatible because they reveal different states, beliefs cannot be derived by Bayes' rule, and an arbitrary posterior belief is assigned for the receiver.

The two papers differ in the way these out-of-equilibrium beliefs are assigned. Gilligan and Krehbiel [1989] choose a particularly simple out-of-equilibrium belief: they essentially assume that the incompatible messages convey no information so that the expected state is the mean according to the prior, i.e., $\bar{\theta} = 1/2$.³ Consequently, the receiver's optimal action

³In Gilligan and Krehbiel [1989], the senders use mixed strategies. The randomizations, however, do

following message disagreements is $E(\theta|m_1, m_2) = 1/2$, independent of the messages. The “threat” of this action is sufficient to induce the senders to fully reveal the state when it is sufficiently low ($\theta \leq \bar{\theta} - 2b$) or sufficiently high ($\theta \geq \bar{\theta} + 2b$). When, instead, $\theta \in (\bar{\theta} - 2b, \bar{\theta} + 2b)$, no information is revealed, and so the action is constant at $1/2$. This equilibrium construction is illustrated in Figure 1(a), where we represent the equilibrium action as a function of the state.

Krishna and Morgan [2001], on the contrary, exploit the freedom to choose out-of-equilibrium beliefs to design a mechanism that optimally punishes a deviation: in this case the out-of-equilibrium beliefs (and the associated optimal actions) are functions of the messages. This more complicated specification of out-of-equilibrium beliefs allows Krishna and Morgan’s [2001] equilibrium to achieve full information transmission. This equilibrium is illustrated in Figure 1(b).

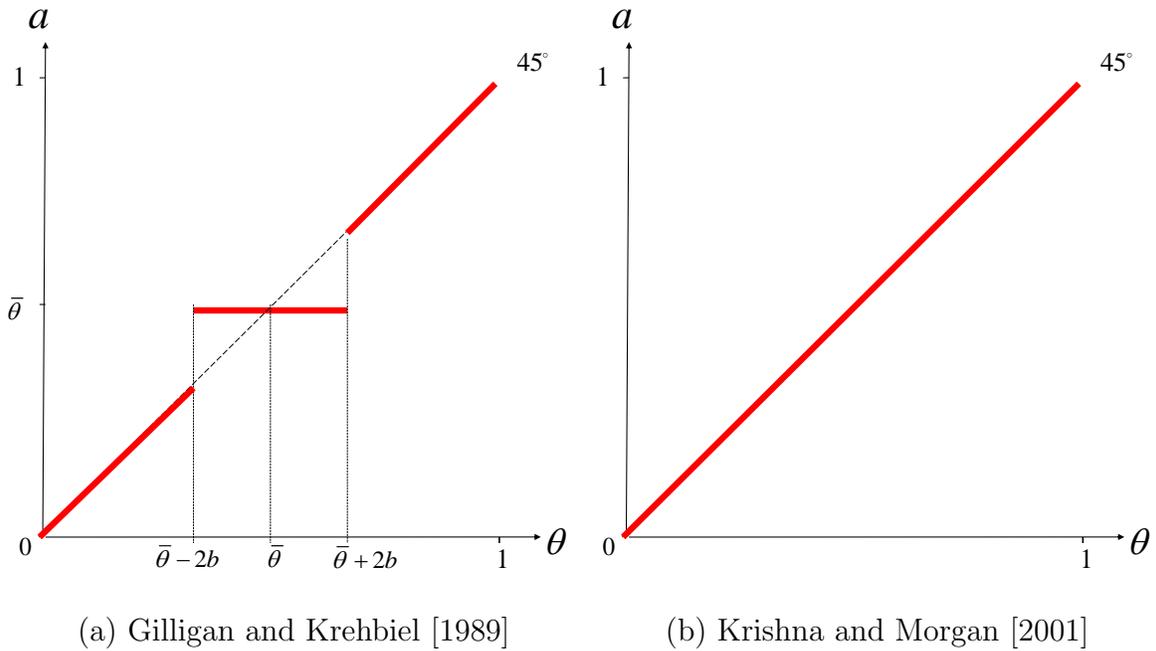


Figure 1: Equilibrium Actions – Open Rule

These two constructions for the open rule both have virtues and disadvantages. The construction in Gilligan and Krehbiel [1989] is parsimonious, since it corresponds to the assumption that when the messages are inconsistent with expected behavior, the receiver ignores them. However, it is reasonable to expect that out-of-equilibrium beliefs would depend on the actual messages received. Other than being an intuitive way of reacting

not have full support on the message spaces. Accordingly, there are still out-of-equilibrium beliefs.

to messages, there is also a theoretical basis for why we should expect the receiver not to ignore the messages even when they are incompatible. A standard way to select equilibrium beliefs for out-of-equilibrium events is to assume that they are derived from a perturbed model in which the players commit mistakes with small probabilities (in which case all events are possible and Bayes' rule can always be applied). In the current setting, when the probability of mistakes converges to zero, the probability that both senders commit a mistake converges to zero faster than the probability that only one of the two has committed a mistake: this implies that there is valuable information in the messages that the receiver will try to use. It follows that the receiver's action is generally a function of the messages.

The construction of Krishna and Morgan [2001] is theoretically very appealing, since it allows them to select equilibria according to a consistent criterion (i.e., choosing the most informative equilibrium). It also has the property that out-of-equilibrium beliefs are functions of the messages. The resulting construction, however, is rather complicated, which may appear to be empirically implausible.

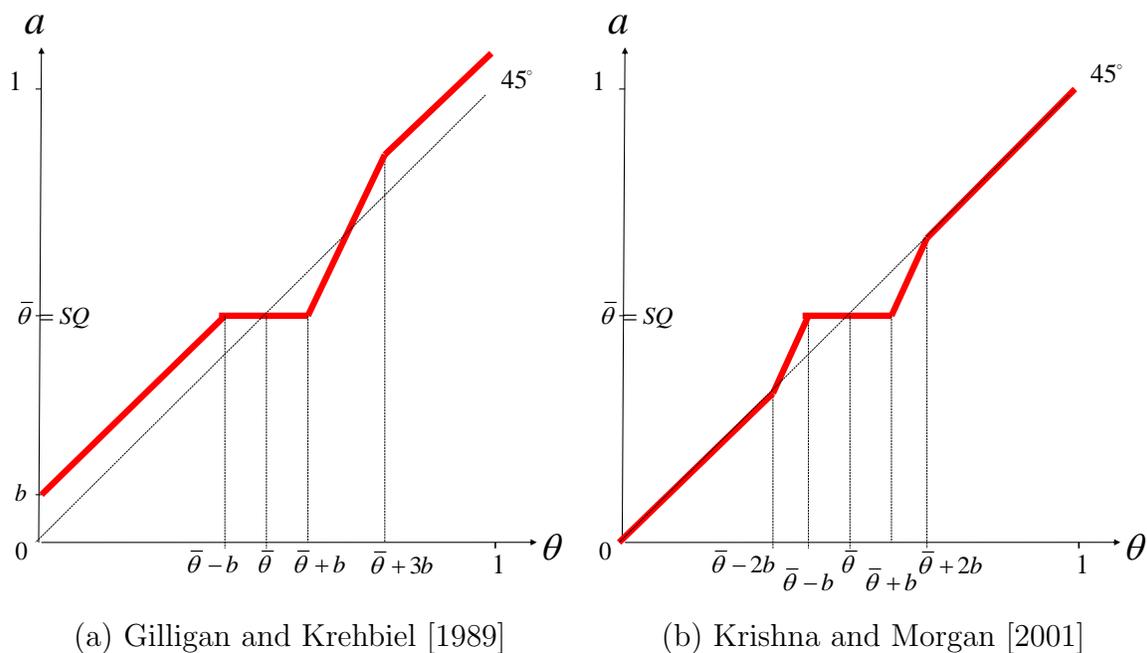


Figure 2: Equilibrium Outcomes – Closed Rule

Consider next the closed rule. In the equilibrium constructions of both Gilligan and Krehbiel [1989] and Krishna and Morgan [2001], if the senders' messages "agree" with each other, the receiver follows Sender 1's message, the proposed bill, as stipulated by the closed rule. Otherwise, the bill is rejected in favor of the status quo action.

While under the closed rule different specifications of off-equilibrium beliefs have no impact on the action taken in case of “disagreements,” the two papers differ in terms of what constitutes an “agreement.” In Gilligan and Krehbiel [1989], an agreement is defined as when Sender 1’s and Sender 2’s messages are such that $m_1 - m_2 = b$. Based on this definition, Gilligan and Krehbiel [1989] construct an equilibrium in which Sender 1 manages to exploit his proposal power to impress a bias on the equilibrium outcome so that $(EX(\theta))^2 > 0$. Although Sender 1 proposes his ideal action for a majority of the states, an interesting feature of the equilibrium is that there also exists a range, $(\bar{\theta} + b, \bar{\theta} + 3b)$, for which Sender 1 proposes “compromise” bills. From Sender 1’s perspective, the threat of disagreement from Sender 2 is particularly strong for $\theta \in (\bar{\theta} + b, \bar{\theta} + 3b)$. For these states, Sender 1 compromises—not proposing his ideal action—in order to make Sender 2 indifferent between his proposed bill and the status quo action. Sender 2 supports the bill under the indifference, sending an agreeing message. The receiver adopts the bill accordingly. This equilibrium construction is illustrated in Figure 2(a).

Krishna and Morgan [2001] define an agreement as the case where $m_1 - m_2 = 0$. Based on this definition, they construct an equilibrium where Sender 1 cannot impress a bias on the outcome so that, as in the open rule, $(EX(\theta))^2 = 0$. They also show that no closed-rule equilibrium can achieve full information transmission and be more efficient than the most informative equilibrium they characterize for the open rule. Note that even though “compromise” bills are also a feature of Krishna and Morgan’s [2001] equilibrium, the bills are proposed by Sender 1 for two disconnected ranges of state that are symmetric, $(\bar{\theta} - 2b, \bar{\theta} - b)$ and $(\bar{\theta} + b, \bar{\theta} + 2b)$. This equilibrium construction is illustrated in Figure 2(b).

3 Experimental Design and Procedures

We design a laboratory environment to be as faithful to the theoretical counterpart as possible. Within the confine of the experimental software (z-tree by Fischbacher [2007]), we implement the state space, the message space, and the action space with the interval $[0.00, 100.00]$ that contains two-decimal numbers.⁴ Subjects’ preferences are induced to capture the incentive structure of the quadratic payoffs in (1).

⁴One difference between our design and the set-up of the model is therefore that we consider an action space that coincides with the state space. Our bounded action space will slightly change the theoretical prediction of Gilligan and Krehbiel [1989] for the closed rule: in Figure 2(a), the optimal action will be flat when it hits the upper bound of the action space.

We conduct six treatments, two for the open rule with two senders, two for the closed rule with two senders, and two for the open rule with one sender. For each legislative rule, we implement two levels of bias, $b = 10$ (corresponding to $b = 0.1$ in the model) and $b = 20$ (corresponding to $b = 0.2$ in the model). These bias levels are chosen so that they provide reasonable variations within the coverage of the theoretical predictions. Table 3 summarizes our treatments.

Table 3: Experimental Treatments

$b = 10 / b = 20$	Two Senders (Heterogeneous Committees)	Single Sender (Homogeneous Committee)
Open Rule	<i>O-2</i>	<i>O-1</i>
Closed Rule	<i>C-2</i>	N/A

The experiment was conducted in English at The Hong Kong University of Science and Technology Experimental Lab. *Between-subject* design and *random matching* were used. Four sessions were conducted for each of *O-2* and *C-2* treatments, and a session was participated by five groups of three. Two sessions were conducted for each of *O-1* treatments, and a session consisted of two independent matching groups each participated by five groups of two. Using sessions or matching groups as units for independent observations, we thus have four observations for each of the six treatments. A total of 350 subjects, who had no prior experience in our experiment and were recruited from the undergraduate population of the university, participated in 20 sessions.

Upon arrival at the laboratory, subjects were instructed to sit at separate computer terminals. Each was given a copy of the experimental instructions. Instructions were read aloud and supplemented by slide illustrations. In each session, subjects first participated in one practice round and then 30 official rounds.

We illustrate the instructions for treatment *O-2* with $b = 20$.⁵ At the beginning of each session before the practice round, one third of the subjects were randomly assigned as Member A (Sender 1), one third as Member B (Sender 2) and the remaining one third as Member C (the receiver). These roles remained fixed throughout the session. Subjects

⁵The full instructions for *O-2* with $b = 20$ can be found in Appendix C, which also contains sample instructions for *C-2*.

formed groups of three, with one Member A, one Member B, and one Member C.

At the beginning of each round, the computer randomly drew a two-decimal number from the state interval $[0.00, 100.00]$.⁶ This state variable was revealed (only) to Members A and B in the following manner. Both members were presented with a line on their screens. The left end of the line started at $0 - b = -20$ and extended to the right end at $100 + b = 120$. The state variable was displayed as a green ball on the line, where the exact numerical value was also displayed separately. Also displayed was a blue ball, which indicated the member’s state-contingent ideal action.⁷

With this information on their screens, Members A and B then each sent a message to the paired Member C. The decisions were framed as asking Member A and Member B to report to Member C what the state variable was. Members A and B chose their messages, each represented by a two-decimal number from the interval $[0.00, 100.00]$, by clicking on the line. A red ball would be displayed on the line, which indicated the chosen message. The members could adjust their clicks until they arrived at their desired messages. The two messages were then displayed simultaneously on a similar line on Member C’s screen as a green ball (Member A’s message) and a white ball (Member B’s message), where the exact numerical values of the messages were also displayed separately. Member C then chose an action in two decimal places from the interval $[0.00, 100.00]$ by clicking on the line. Similar to the message choices of Members A and B, a red ball was displayed indicating the action choice, and Member C could adjust the action until he/she arrived at the desired choice.

We pause to comment on a different message space design for treatments *C-2*. In those treatments, Member B sent an interval message instead. This is to follow the original closed-rule setting in Gilligan and Krehbiel [1989], in which Sender 2 makes a speech in the form of “the state is in $[a, b]$.” We implemented the interval messages by allowing Member B to click on the line two times to pinpoint the interval they intended as the message.⁸

⁶The number was drawn “almost uniformly”: each two-decimal number in $[0.00, 100.00]$ except 0.00 and 100.00 was drawn with probability $1/10000$, while 0.00 and 100.00 are each drawn with probability $1/20000$. To avoid a convoluted explanation and given that the difference is practically non-existent (the numbers 0.00 and 100.00 were never drawn in any of the experimental sessions), in the experimental instructions we simply state that each possible number has equal chance to be selected.

⁷The extension of the line beyond the state interval $[0.00, 100.00]$ was to allow for the display of ideal actions when the state variable was realized to be above 80 or below 20.

⁸This adherence to Gilligan and Krehbiel’s [1989] model sacrifices consistency in the design of Member B’s message spaces across the open-rule and the close-rule treatments. As an antidote, we conducted two robustness-check sessions for the closed rule, one for each level of bias, in which Member B’s message was also a single point in $[0.00, 100.00]$. Thirty out of the 350 subjects participated in these two sessions. The findings from these two sessions showed little difference from the findings when Member B’s messages are interval messages. The analysis of the data from these two sessions is available upon request.

The round was concluded by Member C’s input of the action choice, after which a summary for the round would be provided to all members. The summary included the state variable, the messages sent, the chosen action, the distance between a member’s ideal action and Member C’s chosen action, and a member’s earning from the round.

We randomly selected three rounds for payments. A subject was paid the average amount of the experimental currency unit (ECU) he/she earned in the three selected rounds at the exchange rate of 10 ECU = 1 HKD.⁹ A session lasted for about one and a half hour, and subjects on average earned HKD\$117.32 (\approx US\$15.04) including a show-up fee.¹⁰

4 Experimental Findings

This section comprises three subsections. The first two subsections concern the observed information transmission outcomes, evaluated by the relationship between states and actions, the receivers’ payoffs, and the two measures of efficiencies. In Section 4.1, we report these outcome measures *separately* for the open-rule and the closed-rule treatments with two senders, *O-2* and *C-2*. In Section 4.2, we *compare* the receivers’ payoffs and the efficiencies under the two procedural rules, in which we also bring in the findings from the one-sender treatments, *O-1*, for comparison. In Section 4.3, we examine subjects’ behavior in treatments *O-2* and *C-2*, highlighting the departures from equilibrium predictions that lead to the observed outcomes.

4.1 Information Transmission Outcomes: Open Rule and Closed Rule with Two Senders

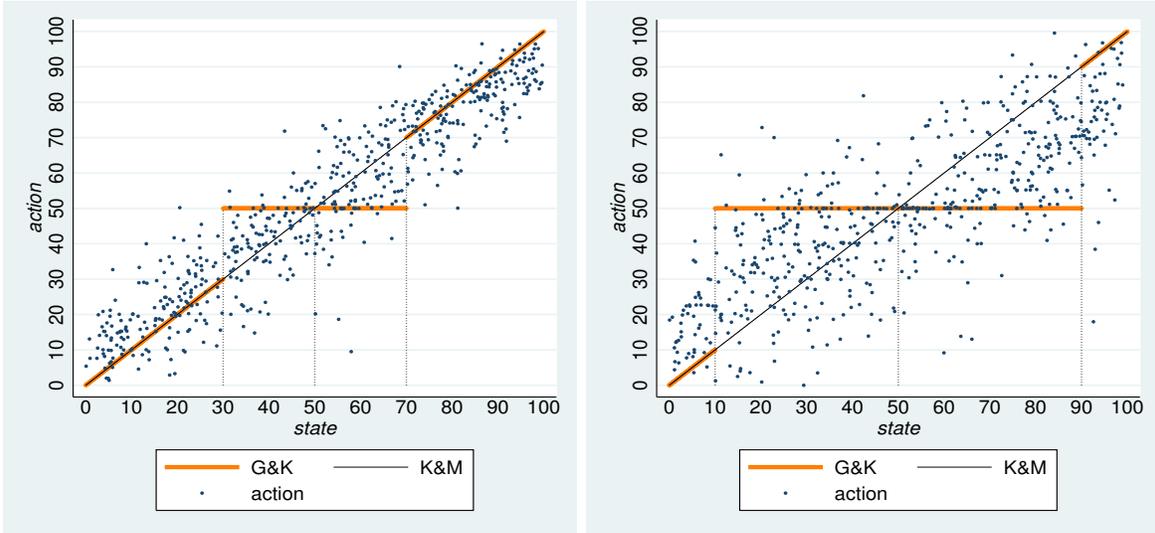
Treatments *O-2*. For the two treatments of open rule with two senders, *O-2* with $b = 10$ and with $b = 20$, Figure 3 illustrates the relationship between the realized θ and the chosen a .¹¹ We also include in the figure the theoretical predictions by Gilligan and Krehbiel [1989] (G&K; the bold line) and by Krishna and Morgan [2001] (K&M; the 45-degree, fine line).

Two features of the data clearly emerged from both treatments. First, we observed a

⁹The number of ECU a subject earned in a round was determined by a reward formula that was used to induce the quadratic preferences. Refer to the sample instructions in Appendix C for the details.

¹⁰Under the Hong Kong’s currency board system, the HK dollar is pegged to the US dollar at the rate of 1 USD = 7.8 HKD.

¹¹In this subsection, we will refer to the “open rule with two senders” as simply the “open rule.”

(a) $b = 10$ (b) $b = 20$ Figure 3: Relationship between States and Actions: Treatments $O-2$

positive correlation between the state and the action. This feature was in line with Krishna and Morgan’s [2001] equilibrium, who indeed predict that the state is equal to the action. We formally confirm the positive correlation by running a random-effect GLS regression with panel data, in which a is the dependent variable and θ is the independent variable: the coefficient predicted by Krishna and Morgan [2001] is one; the regression coefficients are 0.851 for $b = 10$ ($p < 0.0001$) and 0.598 for $b = 20$ ($p < 0.0001$), with constant terms 7.282 for $b = 10$ and 18.205 for $b = 20$, both significantly different from zero ($p < 0.0001$).¹²

The second feature apparent from Figure 3 was the evidence of pooling for states close to $E(\theta) = 50$, especially for $b = 20$: subjects appeared to have a tendency to choose 50 when the true state was close to 50, a behavior that was in line with Gilligan and Krehbiel [1989], who predict that 50 is chosen when $\theta \in [50 - 2b, 50 + 2b]$ (i.e. $[30, 70]$ for $b = 10$ and $[10, 90]$ for $b = 20$).¹³ A similar regression with an additional dummy variable for the states in $[50 - 2b, 50 + 2b]$ and an interaction term of this dummy with the state confirms the case for $b = 20$: the coefficient for the dummy variable is positive at 5.783 ($p = 0.019$),

¹²In fact, Gilligan and Krehbiel [1989] also predict a positive correlation between the state and the action: when $b = 10$ the correlation is $\frac{3\sqrt{65}}{25} = 0.9674$ and when $b = 20$ the correlation is $\frac{\sqrt{61}}{5\sqrt{5}} = 0.6985$. This observation implies that the positive correlation observed in the entire range of the state space should be combined with the analysis we have in the next paragraph on the middle pooling interval to draw a meaningful conclusion.

¹³For $b = 20$, 31.4% and 17.6% of actions are in $[49, 51]$ respectively for $\theta \in [40, 60]$ and for $\theta \in [20, 80]$. For $b = 10$, 15.2% and 10.7% of actions are in $[49, 51]$ respectively for $\theta \in [40, 60]$ and for $\theta \in [30, 70]$.

indicating that the fitted line for the states in $[10, 90]$ has a significantly greater intercept than that of the fitted line for all states; the coefficient of the interaction term is negative at -0.0988 ($p = 0.010$), indicating that the fitted line for $[10, 90]$ has a smaller slope. Insignificantly signed coefficients are, however, obtained for $b = 10$.¹⁴ Our data analysis thus suggests that a higher level of bias resulted in a qualitative change of the information transmission outcome from that predicted by Krishna and Morgan [2001] to that by Gilligan and Krehbiel [1989]. We summarize our first set of findings:

Finding 1. *In treatments O-2, the receivers' action was positively correlated with the state as in both Gilligan and Krehbiel [1989] and Krishna and Morgan [2001]. There was, however, evidence of pooling for states near $E(\theta)$ as predicted by Gilligan and Krehbiel [1989], especially for $b = 20$.*

Table 4: Observed Efficiencies and Receivers' Payoffs

Session/ Matching Group	Dist. Eff. $-(EX(\theta))^2$	Info. Eff. $-Var(X(\theta))$	Receivers' Payoffs	Dist. Eff. $-(EX(\theta))^2$	Info. Eff. $-Var(X(\theta))$	Receivers' Payoffs	Dist. Eff. $-(EX(\theta))^2$	Info. Eff. $-Var(X(\theta))$	Receiver's Payoffs
	<i>C-2 (b = 10)</i>			<i>O-2 (b = 10)</i>			<i>O-1 (b = 10)</i>		
1	-27.29	-42.20	-69.49	-0.03	-100.80	-100.83	-5.50	-82.61	-88.10
2	-30.16	-49.48	-79.64	-0.58	-121.40	-121.97	-17.30	-131.35	-148.65
3	-22.91	-52.76	-75.67	-1.02	-70.41	-71.43	-1.15	-205.85	-207.00
4	-30.83	-44.38	-75.21	-2.56	-80.89	-83.45	-14.14	-78.58	-92.73
Mean	-27.80	-47.20	-75.00	-1.05	-93.37	-94.42	-9.52	-124.60	-134.12
	<i>C-2 (b = 20)</i>			<i>O-2 (b = 20)</i>			<i>O-1 (b = 20)</i>		
1	-31.08	-449.05	-480.13	-5.18	-280.71	-285.89	-10.50	-335.38	-345.43
2	-13.68	-287.98	-301.66	-8.30	-243.57	-251.87	-7.64	-518.19	-525.83
3	-118.33	-190.54	-308.87	-0.07	-398.26	-398.33	-0.00	-334.95	-334.95
4	-57.36	-256.85	-314.21	-12.96	-280.55	-293.51	-5.21	-320.90	-326.11
Mean	-55.11	-296.11	-351.22	-6.63	-300.77	-307.40	-5.72	-377.36	-383.08

Krishna and Morgan [2001] construct a fully revealing equilibrium, in which the equilibrium outcome $X(\theta) = a(\theta) - \theta = 0$ (i.e., the receiver's action coincides with the state) and is independent of the state for both $b = 10$ and $b = 20$. Gilligan and Krehbiel [1989], on the contrary, predicts that a reduction in the bias translates into a reduction in the variance of the equilibrium outcome and an increase in the receiver's payoff. Table 4 shows that Gilligan and Krehbiel's prediction was confirmed by the data. A reduction in the bias from $b = 20$ to $b = 10$ resulted in a significantly lower informational inefficiency: the average $Var(X(\theta))$ decreased from 300.77 when $b = 20$ to 93.37 when $b = 10$ (one-sided $p = 0.0143$, Mann-Whitney test). It also resulted in a lower, though not significant, distributional inefficiency: the average $(EX(\theta))^2$ decreased from 6.63 when $b = 10$ to 1.05

¹⁴For $b = 10$, the dummy variable coefficient is -0.501 ($p = 0.850$) and the interaction term coefficient is 0.0091 ($p = 0.857$).

when $b = 20$ (one-sided $p = 0.1$, Mann-Whitney test). The consequence of this is that the receivers' average payoff was higher with $b = 10$ (-94.92) than with $b = 20$ (-307.4), and the difference was statistically significant ($p = 0.0143$, Mann-Whitney test). This result is consistent with Gilligan and Krehbiel [1989] but not with Krishna and Morgan [2001].¹⁵ The following summarizes this finding:

Finding 2. *In treatments O-2, a reduction in the bias from $b = 20$ to $b = 10$ resulted in:*

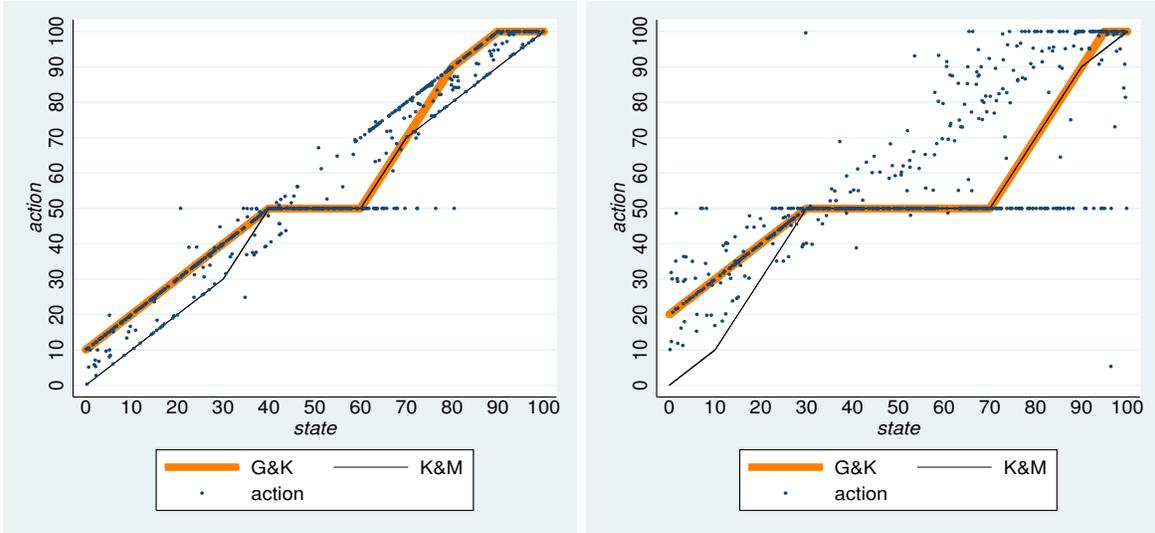
- *A statistically significant increase in the receivers' average payoff, a finding consistent with Gilligan and Krehbiel [1989] but not with Krishna and Morgan [2001];*
- *A statistically significant reduction in informational inefficiency, a finding consistent with Gilligan and Krehbiel [1989] but not with Krishna and Morgan [2001];*
- *No statistically significant change in distributional inefficiency, a finding consistent with both Gilligan and Krehbiel [1989] and Krishna and Morgan [2001].*

Treatments C-2. For the two treatments of closed rule with two senders, C-2 with $b = 10$ and with $b = 20$, Figure 4 illustrates the relationship between the realized θ and the chosen a .¹⁶ We also include in the figure the theoretical predictions by Gilligan and Krehbiel [1989] (G&K; the bold line) and by Krishna and Morgan [2001] (K&M; the fine line).

In this case too, two facts emerged from the figure. First, as predicted by both Gilligan and Krehbiel [1989] and Krishna and Morgan [2001], there was evidence that the receivers chose the status quo action for “intermediate” states (the theories predict that $a = 50$ is chosen for states between 40 and 60 when $b = 10$ and for states between 30 and 70 when $b = 20$) and adopted Sender 1s' proposals for more “extreme” states. When $b = 10$, the receivers' actions mostly coincided with Sender 1s' ideal actions ($\theta + b = \min\{\theta + 10, 100\}$), except for states between 40 and 60 where the status quo action was chosen. Note that when the states were in $[60, 80]$, the receivers' actions did not appear to be in pure strategy, since we observed concentrations of actions at both Sender 1s' proposals $\theta + 10$ and the status quo 50. When $b = 20$, the receivers' action matched Sender 1s' ideal actions ($\theta + b = \min\{\theta + 20, 100\}$) when the state was below 30 and became 50 beyond that, except when

¹⁵Consistent with the use of $(EX(\theta))^2$ and $Var(X(\theta))$, we report the receivers' payoffs by computing $[-Var(X(\theta)) - (EX(\theta))^2]$ as stated in (2). In the experiment, in order to provide subjects with proper rewards with minimal chance of zero payment, the actual subject payoffs were linear transformations of the reported payoffs. Refer to the sample instructions in Appendix C for the details regarding the subjects' reward formula.

¹⁶In this subsection, we will refer to the “closed rule with two senders” as simply the “closed rule.”



(a) $b = 10$

(b) $b = 20$

Figure 4: Information Transmission in $C-2$

the state was above 90 (where 100 was chosen). Similar to the case of $b = 10$, there was evidence that the receivers randomized: we observed concentrations of actions at 50 and 100 when the state was in $[75, 95]$, for which a Sender 1 who proposed his/her ideal action would propose 100 or something close.

To formally evaluate the theoretical predictions, we run a piecewise linear regression for the relationship between the realized θ and the chosen a , with breakpoints set according to the predicted relationship. Figures 19 and 20 in Appendix D illustrate the estimation results.¹⁷ We first divide the state space into four or five segments according to the prediction in Gilligan and Krehbiel [1989]: $[0, 50 - b)$, $[50 - b, 50 + b)$, $[50 + b, 50 + 3b)$, $[50 + 3b, 50 + 4b)$, and $[50 + 4b, 100]$ for $b = 10$; $[0, 50 - b)$, $[50 - b, 50 + b)$, $[50 + b, 95)$, and $[95, 100]$ for $b = 20$.

The baseline case is $\theta \in [0, 50 - b)$ and, for $b = 10$, $\theta \in [50 + 3b, 50 + 4b)$ as well. For this baseline case, the estimated coefficients of the state are close to one and the estimated intercepts are in the neighborhood of b : the state coefficients are 0.973 for $b = 10$ (the 95% confidence interval is $[0.949, 0.997]$) and 0.916 for $b = 20$ (the 95% confidence interval is $[0.693, 1.138]$); the intercepts are 8.93 for $b = 10$ (the 95% confidence interval is $[7.832, 10.018]$) and 22.17 for $b = 20$ (the 95% confidence interval is $[17.855, 26.494]$).

¹⁷In running the regression for the case of $b = 20$, we dropped one outlier in which a very low action ($a < 10$) was taken in a state close to 100 ($\theta > 95$), implying that the Sender 1 in that observation proposed a very low action for a very high state and the proposal was adopted by the receiver. This outlier can be seen in the bottom right corner of Figure 4(b).

The coefficients of the dummy variable for $\theta \in [50 - b, 50 + b)$ are significantly positive: 26.559 for $b = 10$ ($p < 0.001$) and 10.643 for $b = 20$ ($p = 0.007$). Furthermore, the interaction term of the dummy with the state are significantly negative: -0.656 for $b = 10$ ($p < 0.001$) and -0.456 for $b = 20$ ($p < 0.001$). These together indicate that, compared to the baseline case, the fitted lines for the states in $[50 - b, 50 + b)$, one for each value of b , have significantly greater intercepts and smaller slopes.

There remain two line segments, $[50 + b, 50 + 3b)$ and $[50 + 4b, 100]$ for $b = 10$ and $[50 + b, 95)$ and $[95, 100]$ for $b = 20$. For the first segment, the coefficients of the dummy variables are significantly negative: -47.843 for $b = 10$ ($p < 0.001$) and -35.330 for $b = 20$ ($p = 0.005$); the coefficients of the interaction term are positive with significance only for $b = 10$: 0.622 for $b = 10$ ($p < 0.001$) and 0.177 for $b = 20$ ($p = 0.346$). These together indicate that, compared to the baseline case, the fitted lines for the states in $[50 + b, 50 + 3b)$ or $[50 + b, 95)$ have smaller intercepts and higher slopes, all with significance except for the case of slope for $b = 20$. For the second segment, the coefficients of the dummy variables are positive with significance only for $b = 10$: 80.034 for $b = 10$ ($p = 0.002$) and 54.181 for $b = 20$ ($p = 0.733$); the coefficients of the interaction term are negative with again significance only for $b = 10$: -0.867 for $b = 10$ ($p < 0.001$) and -0.748 for $b = 20$ ($p = 0.646$). These together indicate that, compared to the baseline case, the fitted lines for the states in $[50 + 4b, 100]$ or $[95, 100]$ have larger intercepts and smaller slopes but with significance only for $b = 10$.

We further note that adding additional dummies for the prediction in Krishna and Morgan [2001] yield only insignificant results. This is perhaps not surprising, since the two theories generate similar qualitative predictions, the difference of which may be too subtle to be picked up by laboratory behavior. Our regression analysis provides formal evidence for the following:

Finding 3. *In the closed rule:*

- *Sender 1s' proposals were adopted in more extreme states, $\theta \in [0, 40) \cup (60, 100]$ for $b = 10$ and $\theta \in [0, 30) \cup (75, 100]$ for $b = 20$;*
- *The status quo 50 was chosen in intermediate states, $\theta \in [40, 60]$ for $b = 10$ and $\theta \in [30, 75]$ for $b = 20$;*
- *For states $\theta \in [60, 80]$ for $b = 10$ and $\theta \in [75, 95]$ for $b = 20$, the receivers mixed between Sender 1s' proposals and the status quo.*

The key difference between Gilligan and Krehbiel [1989] and Krishna and Morgan [2001] lies in their prediction for the size of the distributional inefficiency. While Krishna and Morgan [2001] predict that distributional inefficiency is zero, Gilligan and Krehbiel [1989] predict that Sender 1 will be able to take advantage of the closed rule and impose a positive bias, so that $(EX(\theta))^2 > 0$. As can be verified from Table 4, we obtained evidence in favor of Gilligan and Krehbiel [1989]: when $b = 10$, the average $(EX(\theta))^2$ was 27.8; when $b = 20$, the average $(EX(\theta))^2$ was 55.11; both were significantly larger than zero (one-sided $p = 0.0625$, the lowest possible p -value for four observations from the Wilcoxon signed-rank tests). This suggests that Sender 1s' ideal actions were often chosen, which is evident in Figure 4.

Finding 4. *As predicted by Gilligan and Krehbiel [1989], the observed distributional inefficiencies were positive under the closed rule.*

For the comparative statics with respect to b under the closed rule, the two theories both predict that there is less informational inefficiency with $b = 10$ than with $b = 20$. They, however, disagree regarding distributional inefficiency. Specifically, Gilligan and Krehbiel [1989] predict that there is also less distributional inefficiency with $b = 10$ than with $b = 20$, while Krishna and Morgan [2001] predict $EX(\theta)^2 = 0$ regardless of b .

The common prediction for informational inefficiency shared by both theories was confirmed with statistical significance: $Var(X(\theta))$ was significantly lower when $b = 10$ than when $b = 20$ (47.2 vs. 296.11; one-sided $p = 0.0143$, Mann-Whitney test). The difference in distributional inefficiency was not statistically significant, thus statistically supporting Krishna and Morgan [2001]). Nevertheless, the observed sign of the insignificant difference was consistent with what Gilligan and Krehbiel [1989] predict: $(EX(\theta))^2$ was lower when $b = 10$ than when $b = 20$ (27.8 vs. 55.1; one-sided $p = 0.1714$, Mann-Whitney test). These differences translated into a significantly higher receivers' average payoff when $b = 10$ than when $b = 20$ (-75 vs. -351.22, one-sided $p = 0.0143$, Mann-Whitney test), confirming both theories. We summarize these findings, which conclude this subsection:

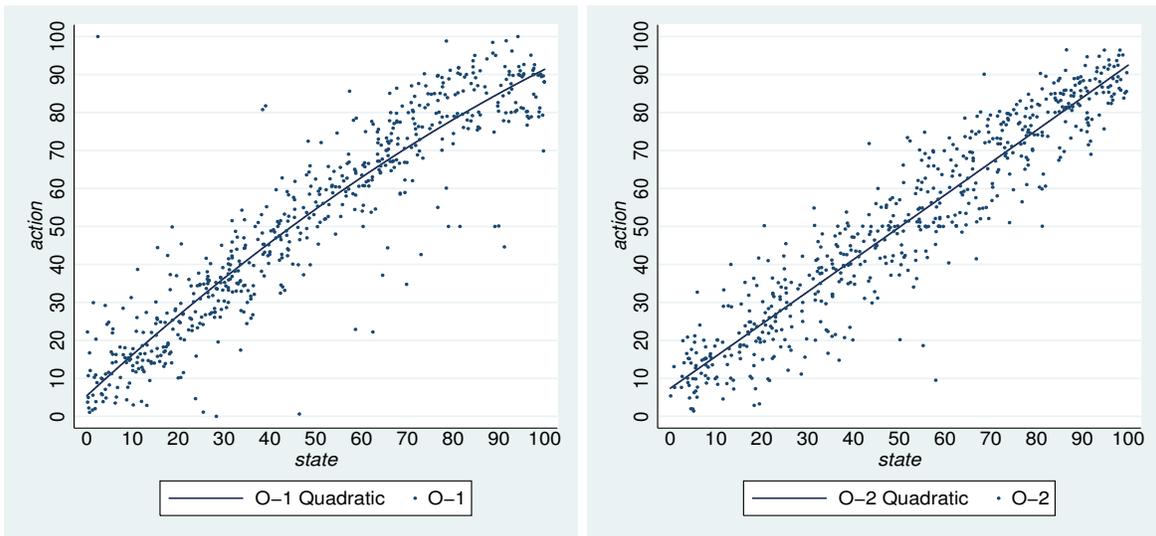
Finding 5. *In treatments C-2, a reduction in the bias from $b = 20$ to $b = 10$ resulted in:*

- *A statistically significant increase in the receivers' average payoff, a finding consistent with both Gilligan and Krehbiel [1989] and Krishna and Morgan [2001];*
- *A statistically significant reduction in informational inefficiency, a finding consistent with both Gilligan and Krehbiel [1989] and Krishna and Morgan [2001];*

- No statistically significant change in distributional inefficiency, a finding consistent with Krishna and Morgan [2001] but not with Gilligan and Krehbiel [1989].

4.2 One-Sender Treatments and Welfare Comparisons

Treatments O-1. Before we proceed to the welfare comparisons, we first report the findings from the two treatments of open rule with one sender, O-1 with $b = 10$ and with $b = 20$, which will also be included in the comparisons.



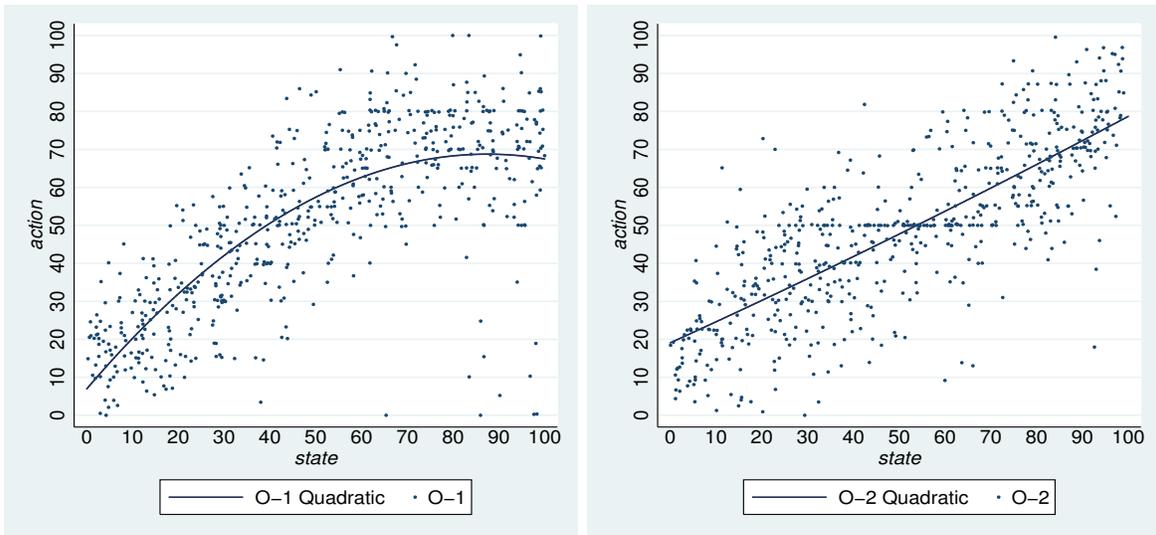
(a) O-1

(b) O-2

Figure 5: Information Transmission in O-2 and O-1 for $b = 10$

Figures 5(a) and 6(a) illustrate the relationship between the realized θ and the chosen a in these two treatments. For both levels of bias, there is a clear evidence of an overall positive correlations between the state and the action. At the same time, there is some evidence of pooling at the upper ends of the state spaces, $[80, 100]$ for $b = 10$ and $[60, 100]$ for $b = 20$. To confirm these observations formally, we run random-effect GLS regressions allowing for *quadratic relationship*. The fitted lines, which are also shown in the two figures, are quadratic for both levels of bias ($p < 0.001$ for the coefficients of the term θ^2).

Recall that the open rule with one sender is equivalent to the cheap-talk model advanced by Crawford and Sobel (1982). Crawford and Sobel show that, unless the sender and the receiver share common interests, all equilibria are partitional; information transmission is partial, and the action correlates with the state only limitedly. The positive correlations

(a) $O-1$ (b) $O-2$ Figure 6: Information Transmission in $O-2$ and $O-1$ for $b = 20$

observed between the realized θ and the chosen a therefore suggest that *overcommunication*, a common, robust finding in the experimental literature on one-sender communication games, also occurred in our $O-1$ treatments.¹⁸

Comparison between $O-2$ and $O-1$. Both Gilligan and Krehbiel [1989] and Krishna and Morgan [2001] offer the equilibrium predictions that the open rule with two senders yields a higher receiver’s payoff than does the open rule with one sender.

The last two sets of columns in Table 4 provide the relevant comparisons between $O-2$ and $O-1$. When $b = 10$, both distributional and informational inefficiencies were greater in $O-1$ than in $O-2$ (9.52 and 124.6 vs. 1.05 and 93.37), although only the latter was statistically significant (one-sided $p = 0.2429$ for distributional inefficiency and one-sided $p = 0.0286$ for informational inefficiency, Mann-Whitney tests). When $b = 20$, informational inefficiency was greater in $O-1$ than in $O-2$ (377.36 vs. 300.77), but unlike the case for $b = 10$ there was less distributional inefficiency in $O-1$ than in $O-2$ (5.72 vs. 6.63). Both differences were, however, not statistically significant (one-sided $p \geq 0.1$, Mann-Whitney tests). This leads to a rather surprising result that, for each of $b = 10$ and $b = 20$, the receivers’ payoffs in $O-2$ (−94.42 and −307.4) were not significantly higher than those in $O-1$ (−134.12 and −383.08; one-sided $p \geq 0.1$, Mann-Whitney tests):

¹⁸For overcommunication observed in the laboratory, see, e.g., Blume et al. [1998, 2001], Cai and Wang [2006], Sánchez-Pagés and Vorsatz [2007, 2009], and Wang, Spezio, and Camerer [2010].

Finding 6. *In the open rule, there was no significant difference in the receivers' payoffs between the cases of two senders and one sender.*

Finding 6 is a consequence of two facts. On one hand, we observed the common finding of overcommunication in our *O-1* treatments with one sender as discussed above. On the other hand, there was a significant level of noise in the information transmission outcomes in our *O-2* treatments with two senders, much higher than the theoretical predictions. One wanes while the other waxes, these two findings together drove the results that the receivers' payoffs were not significantly different when the number of sender increases from one to two.

We note, however, that Finding 6 does not imply that the observed behavior or outcome was the same in *O-1* and *O-2*. Figures 5(b) and 6(b) show, for the two *O-2* treatments, the fitted lines from similar random-effect GLS regressions allowing for *quadratic relationship*, which are visually different from the corresponding fitted lines in Figures 5(a) and 6(a) for the *O-1* treatments; the lines for the two-sender cases are linear for both levels of bias ($p \geq 0.543$ for the coefficients of the term θ^2).

An interesting phenomenon observed in the data that may explain why two senders were not much better than one was that, with two senders, when messages were in conflict, the receiver might decide to ignore them (as predicted by Gilligan and Krehbiel [1989]); with one sender, instead, the receiver rarely ignored the message, which was in line with the overcommunication we observed. This phenomenon, which we may call the *confusion effect*, can be most clearly seen in Figure 6(b) for the case of *O-2*: when θ was in [30, 75] we observed a significant fraction of actions equal to 50, the optimal action when the messages are ignored; such a concentration of action at 50 was not observed in *O-1* [Figure 6(a)]. A similar concentration is also observed in Figure 5(b), though to a much smaller extent with the lower $b = 10$.

To formally confirm this observation, we run a random-effect probit regression, regressing a dummy dependent variable for $a \in [49, 51]$ on two independent variables, the state θ and a dummy variable for treatment *O-1*.¹⁹ The coefficient for the treatment dummy is negative and significant for $b = 20$: -0.411 ($p = 0.021$). For $b = 10$, the coefficient is negative but at most marginally significant: -0.441 ($p = 0.095$). We summarize this

¹⁹The use of the range $a \in [49, 51]$ rather than the point $a = 50$ for the dummy dependent variable is to account for the fact that subjects were rarely able to precisely click at $a = 50$ on the screen using their mouse even when it was their intention to choose an action as close to 50 as possible. Our definition for the dummy dependent variable is meant to allow for a small amount of such "tremble."

observation as another finding:

Finding 7. *In the open rule, the status quo action $EX(\theta)$ was chosen more often with two senders than with one sender, suggesting that two conflicting messages may have led the receivers to ignore them which resulted in a lower degree of information aggregation.*

This finding suggests that there may be an implicit cost in increasing the number of experts in an advising situation that has not been recognized before in the theoretical literature: conflicting out-of-equilibrium messages may drastically reduce welfare by inducing the receiver to shut down updating and go for the prior.

Comparison between C-2 and O-1. Gilligan and Krehbiel [1989] and Krishna and Morgan [2001] commonly predict that the closed rule with two senders is less informationally inefficient than the open rule with one sender. They, however, differ in their prediction for distributional inefficiency: Gilligan and Krehbiel [1989] predict that the closed rule with two senders is more distributionally inefficient than the open rule with one sender, while, having characterized an equilibrium for the closed rule with two senders with $(E(\theta))^2 = 0$, Krishna and Morgan [2001] predict the opposite.

Consistent with Gilligan and Krehbiel's [1989] prediction, Table 4 indicates that the closed rule had greater distributional inefficiency: for both levels of bias, the average $(EX(\theta))^2$ was significantly higher in C-2 than in O-1 (27.8 vs. 9.52 for $b = 10$ and 55.11 vs. 5.72 for $b = 20$; one-sided $p = 0.0143$, Mann-Whitney tests). For informational inefficiency, the prediction was confirmed with statistical significance only for one level of bias: for $b = 10$, the average $Var(X(\theta))$ was significantly lower in C-2 than in O-1 (47.2 vs. 124.6; one-sided $p = 0.0143$, Mann-Whitney test); for $b = 20$, the average $Var(X(\theta))$ was lower, but not significantly, in C-2 than in O-1 (296.11 vs. 377.36; one-sided $p = 0.1$, Mann-Whitney test). Overall, these differences were sufficient to result in a significantly higher receivers' payoffs in C-2 than in O-1 for $b = 10$ (-75 vs. -134.12; one-sided $p = 0.0143$, Mann-Whitney test) but not so for $b = 20$ (-351.22 vs. -383.08; one-sided $p = 0.1$, Mann-Whitney test). We summarize:

Finding 8. *Receivers' average payoff was significantly higher in C-2 than in O-1 only for $b = 10$.*

Similar to Finding 6, Finding 8 is due to the fact that with two senders we still had a significant level of noise in the outcome. However, there was less noise under the closed rule, making two senders better than one for $b = 10$. A comparison between Figures 4,

5(a), and 6(a) makes the differences clear. Similar to the case of *O-2* and *O-1*, the fact that the receivers' payoffs in *C-2* and *O-1* were not significantly different does not imply that behavior was similar; the receivers in the closed rule treatments may also choose to ignore the messages and chose action under the prior if the messages are inconsistent. This confusion effect under the closed rule is clearly evident in Figure 4(b), where the status quo action 50 was chosen much more frequently than is predicted by the theory: according to both theories the status quo action 50 should not be taken for states larger than 70 or less than 25, but we obtained a cluster of observations in these ranges. Similar observations were also present when $b = 10$: we obtained cases of action 50 taken for states larger than 60 and less than 40, although the theories predict this should not be the case.

Finding 9. *Even for the closed rule, the status quo action was chosen for states in which the theory predicts a fully or partially revealing equilibrium, suggesting that two conflicting messages may have led the receivers to ignore them which resulted in a lower degree of information aggregation.*

Comparison between *O-2* and *C-2*. We conclude this subsection by addressing the choice between the open rule and the closed rule, the fundamental policy question that motivates the work by Gilligan and Krehbiel [1989] and Krishna and Morgan [2001]. Gilligan and Krehbiel [1989] predict that the open rule provides a higher distributional efficiency but a lower informational efficiency than does the closed rule. Krishna and Morgan [2001] construct equilibria in which the open rule is as distributionally efficient as the closed rule but superior in terms of informational efficiency.

Table 4 provides clear evidence in support of Gilligan and Krehbiel's prediction for distributional efficiency. For both levels of bias, the average $(EX(\theta))^2$ was significantly lower in *O-2* than in *C-2* (1.05 vs. 27.8 for $b = 10$ and 6.63 vs. 55.11 for $b = 20$; one-sided $p = 0.0143$, Mann-Whitney tests):

Finding 10. *The closed rule was more distributionally inefficient than the open rule.*

The results for informational efficiency are somewhat less clear cut. When $b = 10$, the average $Var(X(\theta))$ was significantly lower in *C-2* than in *O-2* (47.2 vs. 93.37; one-sided $p = 0.0143$, Mann-Whitney test); when $b = 20$, the average $Var(X(\theta))$ was lower in *C-2* than in *O-2* but not significantly (296.11 vs. 300.77; one-sided $p = 0.5571$, Mann-Whitney test):

Finding 11. *The open rule was more informationally inefficient than the closed rule, but the differences were less striking than what Gilligan and Krehbiel [1989] predict.*

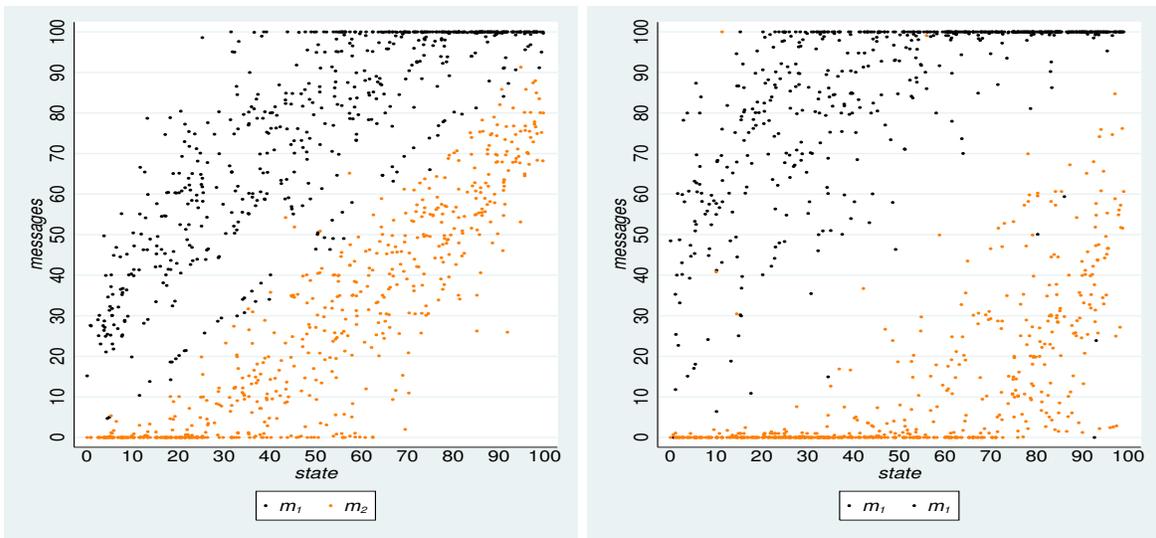
Given these results it is not surprising that the welfare comparison between the two rules is ambiguous. For both levels of bias, the average receivers' payoffs in *C-2* and *O-2* were not significantly different (-75 vs. -94.42 for $b = 10$ and -351.22 vs. -307.4 for $b = 20$; two-sided $p = 0.2$, Mann-Whitney tests):

Finding 12. *The receivers' payoff differences between the open and the closed rules were not statistically significant.*

4.3 Strategies in Two-Sender Treatments

In this subsection, we examine subjects' behavior in treatments *O-2* and *C-2*. We investigate what observed behavior of the senders and the receivers contributed to the information transmission outcomes analyzed in Section 4.1, in which we observed imperfect compliance with the predictions of Gilligan and Krehbiel [1989].

Treatments O-2. Figure 7 presents the relationship between the senders' message and the realized state in the two treatments of *O-2*. At least two sets of discrepancies between the data and the theoretical predictions appear clear.

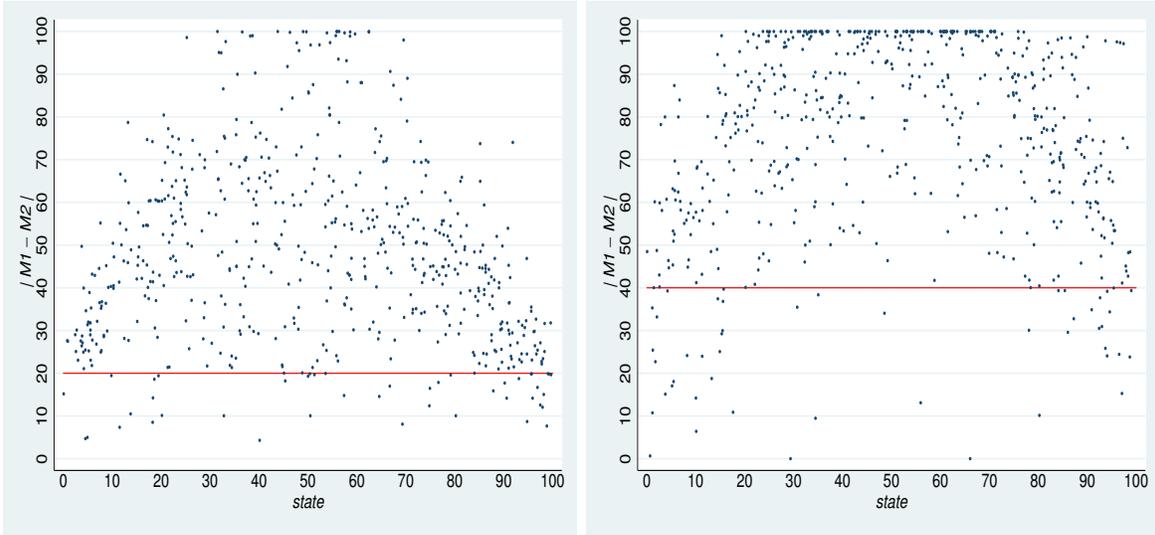


(a) $b = 10$

(b) $b = 20$

Figure 7: Senders' Messages in *O-2*

First, we observed a lot more noise in the data than predicted by the theory in regions in which full revelation is predicted, and too little in regions in which no information revelation is predicted. Consider the full revelation cases first. Gilligan and Krehbiel [1989] predict



(a) $b = 10$

(b) $b = 20$

Figure 8: Distance of Messages $|m_1 - m_2|$ in *O-2*

full revelation in states $\theta \in [0, 30) \cup (70, 100]$ for $b = 10$ and $\theta \in [0, 10) \cup (90, 100]$ for $b = 20$, while Krishna and Morgan [2001] predict full information revelation in all states. In both theories, full revelation is achieved in equilibria with fully separating strategies in which $|m_1 - m_2|$ is constant and equal to $2b$. As can be seen from Figure 7, subjects did not appear to follow these strategies in the respective relevant intervals. This point is further confirmed by Figure 8, which presents the distribution of $|m_1 - m_2|$: the relationship between the two messages appeared to be characterized by a degree of randomness that is inconsistent with full revelation, suggesting that most messages should be seen, at least under the lens of the two equilibria, as “out of equilibrium.” The prevalence of “out-of-equilibrium” messages may provide further support for the confusion effect discussed in Section 4.1, in which the receivers responded to messages that cannot be reconciled with each other by ignoring them and choosing action based on the prior.

Consider next the case with no information revelation in Gilligan and Krehbiel’s [1989] equilibrium, i.e., $\theta \in [30, 70]$ for $b = 10$ and $\theta \in [10, 90]$ for $b = 20$. Here we expect a constant policy. Figure 3 in Section 4.1, however, shows that in this range too the policy on average reflects the state of the world, especially for $b = 10$, suggesting that the messages are partly informative. The evidence supporting a constant policy (at least for some receivers) is nonetheless stronger for $b = 20$.

The second discrepancy is more specifically connected to the senders’ behavior. Figure

7 suggests, perhaps consistently with the failure of full information revelation, that the senders tended to use extreme messages (at the boundaries of the message space).²⁰ Sender 1s tended to pool at the boundary message $m_1 = 100$ when the state was higher than 40 for $b = 10$ and 30 for $b = 20$; similarly, Sender 2s tended to pool at the boundary message $m_2 = 0$ when the state was lower than 60 for $b = 10$ and 70 for $b = 20$. This is perhaps consistent with a situation in which Sender 1s (Sender 2s) believe that the higher (the lower) their messages the more they will be able to bias the receivers' actions toward their ideal actions.

The third discrepancy has to do with how the receivers respond to “out-of-equilibrium messages,” which may explain the observed behavior by the senders. Both of our reference theories model out-of-equilibrium beliefs in such a way that senders have no incentives to send extreme “out-of-equilibrium” messages: in Gilligan and Krehbiel [1989], out-of-equilibrium action is constant and independent of the senders' messages; in Krishna and Morgan [2001], out-of-equilibrium beliefs are specifically designed to optimally punish deviations so that out-of-equilibrium action is not constant and dependent upon the senders' messages.

Neither approach, however, seems to be fully supported by the data. Figures 5 and 6 show that Gilligan and Krehbiel's [1989] prediction of a message-independent out-of-equilibrium belief is not verified: the receiver tended to extract information out of the messages, even when the messages are not “fully revealing” (i.e., $|m_1 - m_2| = 2b$ in Figure 7). To verify Krishna and Morgan's prediction, consider the incentive compatibility constraints that guarantee full revelation in their equilibrium. A deviation is unprofitable if two sets of inequalities are satisfied:

$$\begin{aligned} U^{S_1}(a(m_1, m_2) - (\theta + b)) &\leq U^{S_1}(b) \\ U^{S_2}(a(m_1, m_2) - (\theta - b)) &\leq U^{S_2}(b) \end{aligned}$$

for all $\theta \in \Theta$, $m_1, m_2 \in M$, where $U^{S_i}(\cdot) = -(\cdot)^2$, $i = 1, 2$, and $a(m_1, m_2)$ denotes the action induced by the off-path message pair (m_1, m_2) .

The first condition guarantees that Sender 1 is unwilling to deviate if Sender 2 reports truthfully (up to a constant); the second condition guarantees that Sender 2 is unwilling

²⁰Interestingly, for the case with $b = 10$ we also observed cases in which messages were “truthful,” i.e., were equal to the realized state: this can be seen from the concentration of the state-message pairs on or close to the 45 degree line in Figure 7. The evidence of truthful messages was almost absent for $b = 20$.

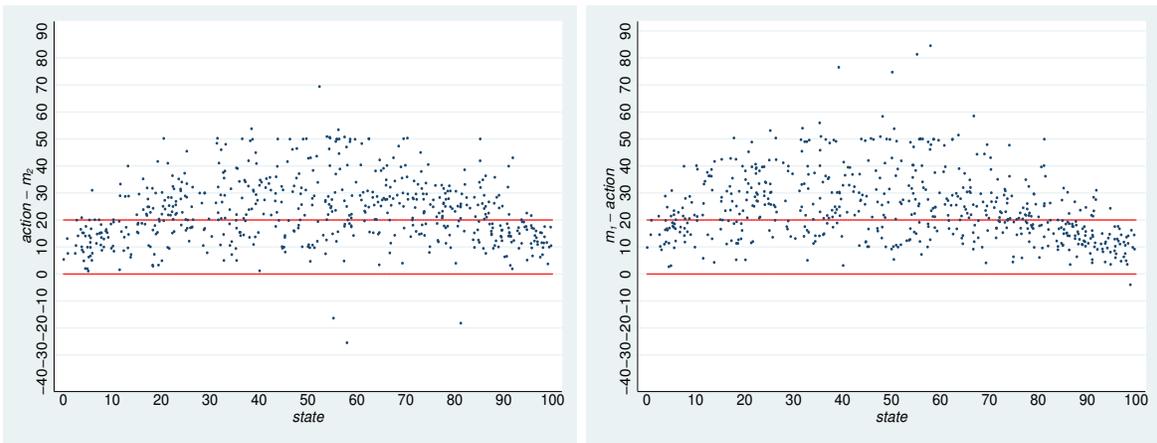
to deviate if Sender 1 reports truthfully. After some rearrangement, the inequalities boil down to

$$a(m_1, m_2) - m_2 \notin (0, 2b) \tag{3}$$

and

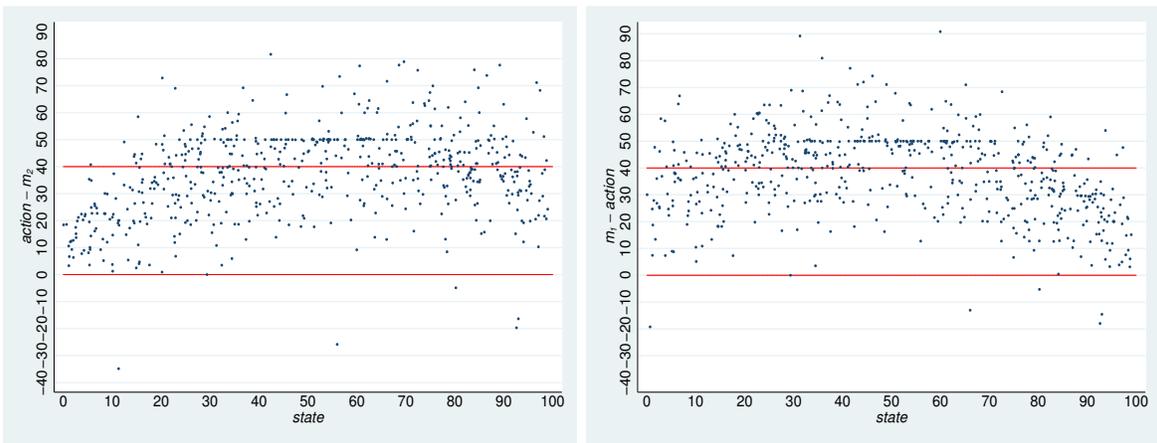
$$m_1 - a(m_1, m_2) \notin (0, 2b). \tag{4}$$

In words, these inequalities make sure that no unilateral deviation is profitable and are satisfied if $(a - m_2)$ is not in $(0, 2b)$ (first inequality) and if $(m_1 - a)$ is not in $(0, 2b)$ (second inequality).



(a) For Sender 1's Incentive Compatibility (b) For Sender 2's Incentive Compatibility

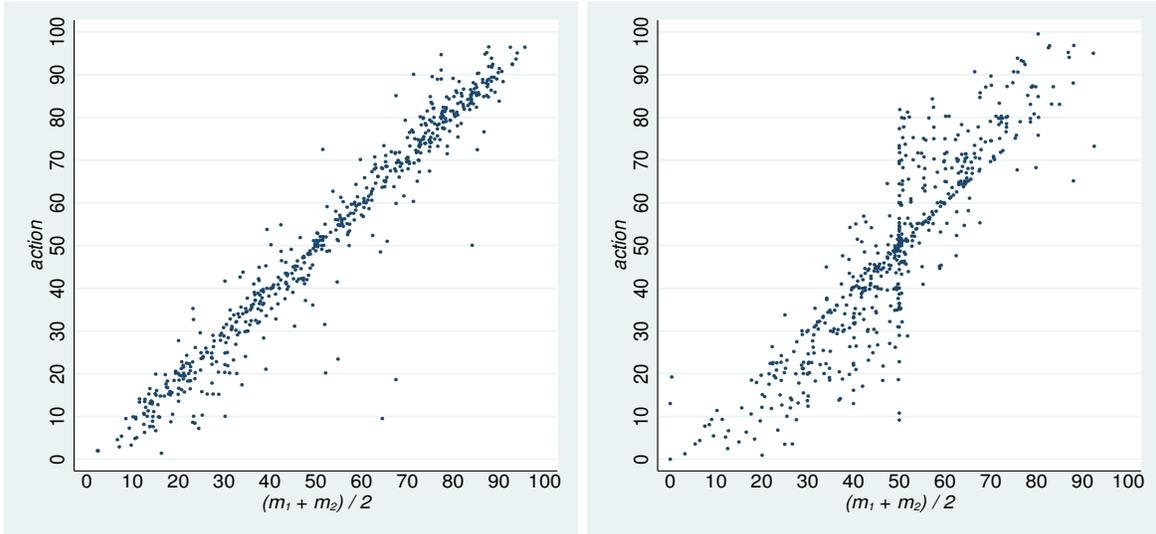
Figure 9: Observed Distances between Actions and States in $O-2$ ($b = 10$)



(a) For Sender 1's Incentive Compatibility (b) For Sender 2's Incentive Compatibility

Figure 10: Observed Distances between Actions and States in $O-2$ ($b = 20$)

Figures 9 and 10 present the observed distances $(a - m_2)$ and $(m_1 - a)$ across different states. In each figure, the two horizontal lines at 0 and $2b$ represent the incentive compatibility constraint: if the observed distance in question is within the bounds, the receiver’s response will not be punishing. In this case too, the figures show that the constraints were respected only roughly half the time and mostly for states close to 50.



(a) $b = 10$

(b) $b = 20$

Figure 11: Receivers’ Actions as a Function of Average Messages in *O-2*

More than following a constant rule as in Gilligan and Krehbiel [1989] or efficient punishing strategies as in Krishna and Morgan [2001], receivers appeared to follow a more “naive” rule of choosing a policy close to the average of the messages. Figure 11 presents the relationship between the receivers’ observed actions and the average messages: actions were taken around the 45-degree line, suggesting that, in deciding what action to take, the receivers formed beliefs that were based on some forms of convex combination of the two messages. This reaction function is problematic from an “equilibrium” point of view because, if correctly understood, it is susceptible to easy manipulation by the senders. While we did indeed see some behavior consistent with this (i.e. the senders sending messages at the extremes of the action space), the data suggested that the senders could exploit this naive reaction function if they were fully expecting it.²¹

Treatments C-2. Several qualitative features of our strategy data from the closed-rule treatments can be explained by the theoretical predictions of Gilligan and Krehbiel [1989].

²¹As a contribution to rationalize the observed behavior under the open rule, we develop a non-equilibrium, level- k model of behavior, which is available in Appendix B.

Three figures help illustrate. Figure 12 presents Sender 1s’ messages (proposals) and the lower bounds of Sender 2s’ interval messages (speeches). Figure 13 presents the receivers’ acceptance rate of Sender 1s’ proposals. Figure 14 reports the receivers’ acceptance rate of Sender 1s’ proposals in $(50 + 2b, 50 + 4b)$, conditioned on different ranges of differences between Sender 1s’ proposals and the lower bounds of Sender 2s’ speeches.²²

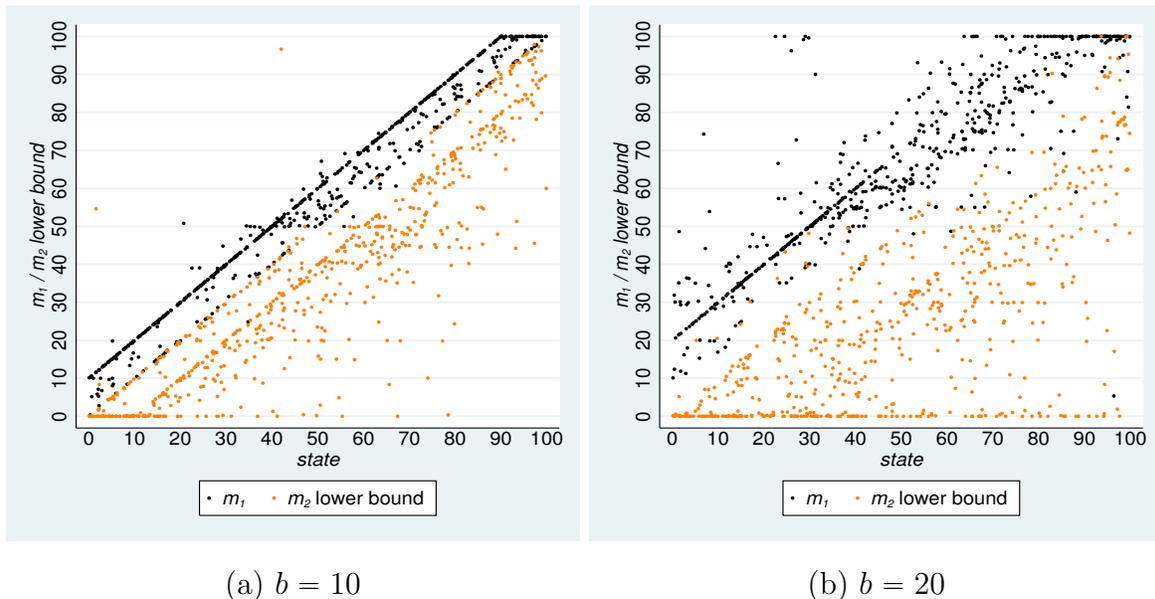


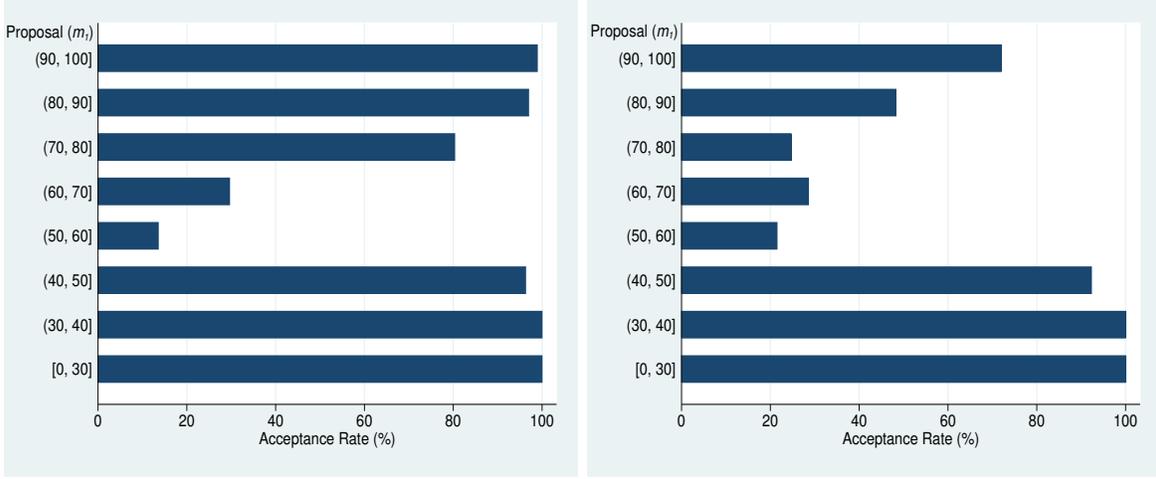
Figure 12: Sender 1s’ Proposals and the Lower Bounds of Sender 2s’ Interval Messages in $C-2$

Consider first the senders’ behavior. Figure 12 indicates that, for lower states, Sender 1s typically proposed their ideal action, i.e., $m_1(\theta) = \theta + b$. For higher states, there tended to be more proposals from Sender 1s that were strictly below their ideal actions. This was in line with a key feature of Gilligan and Krehbiel’s [1989] equilibrium, in which “compromise” bills from Sender 1s are sent for relatively higher states. Since Sender 2’s ideal action is $a_2^*(\theta) = \theta - b$, for higher states the status quo action is more attractive to Sender 2s. This appeared to have contributed to the observed compromise of Sender 1s, consistent with the rationale behind the equilibrium construction. This observation suggests that the receivers may reject a bill based on certain notion of “agreement” between Sender 1 and Sender 2.²³

Consider next the receivers’ behavior. As Figure 13 indicates, the receivers followed Sender 1s’ proposals for $m_1 < 50$, took the status quo action 50 for $m_1 \in [50, 50 + 2b]$,

²²In the case where $50 + 4b \geq 100$ (i.e., when $b = 20$), the proposal interval used for reporting the receivers’ acceptance rate becomes $(50 + 2b, 100)$.

²³For Sender 2s’, we observed some clustering of messages around their ideal actions, $a_2^*(\theta) = \theta - b$, even though the messages were more dispersed than predicted.

(a) $b = 10$ (b) $b = 20$ Figure 13: Receivers' Acceptance Rate of Sender 1s' Proposals in $C-2$

and gradually converged back to follow the proposals for $m_1 > 50 + 2b$. The almost 100% acceptance rate for $m_1 \notin [50, 50 + 4b]$, independent of Sender 2s' speeches, is consistent with the equilibrium prediction of Gilligan and Krehbiel [1989]. Given the observed strategy of Sender 1s, $m_1(\theta) = \theta + b < 100$, the receivers accept the proposal if and only if

$$\underbrace{-b^2}_{\text{accepting } m_1} > \underbrace{-(50 - m_1 + b)^2}_{\text{rejecting } m_1} \Leftrightarrow m_1 \notin [50, 50 + 2b],$$

and Sender 2s prefer m_1 over the status quo if and only if

$$\underbrace{-(2b)^2}_{\text{from } m_1} > \underbrace{-(50 - m_1 + 2b)^2}_{\text{status quo}} \Leftrightarrow m_1 \notin [50, 50 + 4b].$$

The above analysis implies that, for $m_1 \notin [50, 50 + 4b]$, both Sender 1s and Sender 2s prefer m_1 over the status quo 50, so there is no incentive for generating any disagreement. Knowing this, the receivers ignoring Sender 2s' speeches and adopting $m_1 \notin [50, 50 + 4b]$ are a best response.

Similarly, the low acceptance rate for $m_1 \in (50, 50 + 2b]$, independent of Sender 2s' speeches, is also consistent with Gilligan and Krehbiel's [1989] prediction. For $m_1 \in (50, 50 + 2b]$, the preferences of Sender 1s and Sender 2s are totally misaligned so that it is impossible for them to reach an agreement. Knowing this, the receivers ignoring Sender 2s' speeches and rejecting $m_1 \in (50, 50 + 2b]$ in favor of the status quo are a best response.

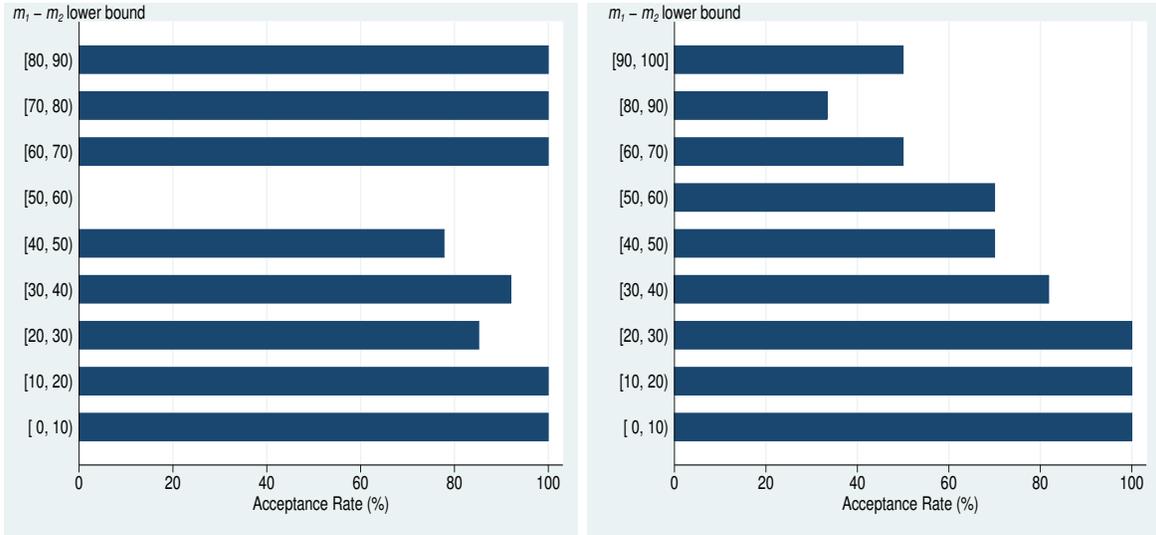
(a) $b = 10$ (b) $b = 20$

Figure 14: Receivers' Acceptance Rate of Sender 1s' Proposals in $(50 + 2b, 50 + 4b)$ Conditioned on Different Ranges of $(m_1 - \text{Lower Bound of } m_2)$ in $C-2$

It remains to account for the exceptionally high acceptance rate for $m_1 \in (50 + 2b, 50 + 4b)$. As revealed by Figure 12, a high proportion of proposals in this range were “compromise” bills, which should be readily accepted by the receivers given the absence of sizable disagreements.²⁴

There nevertheless existed some discrepancies between the observed behavior and the behavior predicted by Gilligan and Krehbiel's [1989] equilibrium, which may well be attributed to the usual noisier behavior in the laboratory. Other than the senders' behavior being noisier than predicted, we observed a rather strong propensity for the receivers to accept Sender 1s' proposals, even for states in which the status quo is predicted to be chosen (the acceptance rate was at least 13.5% for $b = 10$ and 21.5% for $b = 20$ and was often well above 30%). For the rejections of the proposals, Figure 14 reveals that the receivers also did not respond to disagreements in the messages for the states in which the theory predicts that only compromise bills should be accepted.²⁵

²⁴The relatively high acceptance rate for $m_1 = 100$ can be explained by the fact that the action space in our experiment is bounded above so that most observed proposals at 100 must be “compromise” bills.

²⁵See Appendix B for a non-equilibrium, level- k model for the closed rule.

5 Conclusion

In this paper, we have provided the first experimental investigation of the informational theories of legislative committees with heterogeneous committees. We have focused on two legislative rules: the open rule, in which the decision maker is free to take any action after hearing the committees recommendations; and the closed rule, in which the decision maker is forced to choose between one of the committees' recommendations and an exogenous status quo. The experimental approach allows us to directly observe subjects' behavior under these two rules, exploring whether they are consistent with the equilibrium strategies characterized in the theoretical work.

We found clear evidence that even in the presence of conflict, committees can help improve the legislature's decisions by credibly communicating valuable information. More specifically, the experimental evidence supports two of the key lessons from informational theories first suggested by Gilligan and Krehbiel [1989]: the *outlier principle*, according to which information transmission is inversely proportional to the preference bias of the committees; and the *efficiency principle*, according to which the open rule is more distributionally efficient than the closed rule. We also obtained evidence that supports the *restrictive-rule principle*, according to which the closed rule is more informationally efficient than the open rule, although the evidence was weaker. Finally, we did not find evidence for the *heterogeneity principle*, according to which more information can be extracted by the legislature in the presence of multiple committees with heterogeneous preferences.

These deviations from the theoretical predictions are due to a number of behavioral phenomena that are highlighted by the experimental data. In our experiment, the receivers seem to follow one of two rules: either they react to the committees messages by choosing a weighted combination of them; or they completely disregard the messages and choose the expected optimal policy. Because of this, we observe less information transmission than predicted for subsets of states in which the theories predict full information transmission, and more information transmission than predicted when the theories predict no information transmission.

These non-equilibrium findings, obtained in a highly controlled environment with repetitions, show convincingly that the theoretical optimality of the open rule does not translate into its empirical optimality. This suggests that in order to achieve the efficient outcome of the open rule in practice, the institutional designer may have to ensure that the participants have a good understanding of the functioning of the legislative rule; otherwise, the

design and study of optimal legislative rules may have to take into account various possible behavioral biases. Our study, which expands our knowledge on the types of sub-optimal behavior of human subjects under different legislative rules, helps shed light on what kind of behavioral biases may arise and what properties a behaviorally optimal institution should possess.

Our laboratory analysis of the informational theories of legislative committees has been focused on the case with multiple heterogeneous committees. For this reason, we have ignored other important insights that have been explored by the theoretical literature: for example, how legislative organization (open rule vs. closed rule) affects communication with just one committee; and how legislative organization affects the incentives to acquire information for a committee. We leave the experimental investigations of these cases to future work.

References

- [1] Aghion, P., Tirole, J. (1997): “Formal and real authority in organizations.” *Journal of Political Economy*, 105 (1), 1–29.
- [2] Battaglini, M. (2002): “Multiple Referrals and Multidimensional Cheap Talk.” *Econometrica*, 50, 1431-1451.
- [3] Battaglini, M., and U. Makarov (2014): “Cheap Talk with Multiple Audiences: An Experimental Analysis.” *Games and Economic Behavior*, 83, 147–164.
- [4] Blume, A., D. V. Dejong, Y.-G. Kim, and G. B. Sprinkle (1998): “Experimental Evidence on the Evolution of the Meaning of Messages in Sender-Receiver Games.” *American Economic Review*, 88, 1323–1340.
- [5] Cai, H., and J. T.-Y. Wang (2006): “Overcommunication in Strategic Information Transmission Games.” *Games and Economic Behavior*, 56, 7–36.
- [6] Chung, W. and R. Harbaugh (2014): “Biased Recommendations.” mimeo.
- [7] Crawford, V. (2003): “Lying for Strategic Advantage: Rational and Boundedly Rational Misrepresentation of Intentions.” *American Economic Review*, 93(1), 133–149.
- [8] Crawford, V., and N. Iriberri (2007a): “Level-k Auctions: Can a Nonequilibrium Model of Strategic Thinking Explain the Winner’s Curse and Overbidding in Private-Value Auctions?” *Econometrica*, 75(6), 1721–1770.
- [9] Crawford, V., and N. Iriberri (2007b): “Fatal Attraction: Salience, Naïveté, and Sophistication in Experimental “Hide-and-Seek” Games.” *American Economic Review*, 97(5), 1731–1750.
- [10] Crawford, V., and J. Sobel (1982): “Strategic information transmission.” *Econometrica*, 50, 1431–1452.
- [11] Dion, D., Huber, J. (1996): “Procedural choice and the house committee on rules.” *Journal of Politics*, 58, 25–53.
- [12] Dion, D., Huber, J. (1997): “Sense and sensibility: the role of rules.” *American Journal of Political Science*, 41, 945–958.

- [13] Dominguez-Martinez, S., Sloof, R., von Siemens, F. A. (2014): “Monitored by your friends, not your foes: Strategic ignorance and the delegation of real authority.” *Games and Economic Behavior*, 85, 289-305
- [14] Farrell, J., and R. Gibbons (1989): “Cheap Talk with Two Audiences.” *American Economic Review*, 79, 1214-1223.
- [15] Fehr, Ernst, Holger Herz, and Tom Wilkening (2013): “The Lure of Authority: Motivation and Incentive Effects of Power.” *American Economic Review*, 103(4): 1325-59.
- [16] Gilligan, T.W., Krehbiel, K. (1987) “Collective decision-making and standing committees: an informational rationale for restrictive amendment procedures,” *Journal of Law, Economics and Organization*, 3, 287–335.
- [17] Gilligan, T.W., Krehbiel, K. (1989): “Asymmetric information and legislative rules with a heterogeneous committee,” *American Journal of Political Science*, 33, 459–490.
- [18] Kartik, N. (2009): “Strategic communication with lying costs.” *Review of Economic Studies*, 76(4), 1359–1395.
- [19] Kartik, N., M. Ottaviani, and F. Squintani (2007): “Credulity, lies, and costly talk.” *Journal of Economic theory*, 134(1), 93–116.
- [20] Krehbiel, K. (1990): “Are congressional committees composed of preference outliers?,” *American Political Science Review*, 84, 149–163.
- [21] Krehbiel, K. (1991): *Information and Legislative Organization*. University of Michigan Press, Ann Arbor.
- [22] Krehbiel, K. (1997a): “Restrictive rules reconsidered,” *American Journal of Political Science*, 41, 929–944.
- [23] Krehbiel, K. (1997b): “Rejoinder to sense and sensibility,” *American Journal of Political Science*, 41, 958–964.
- [24] Krehbiel, K. (2001): “Plausibility of signals by a heterogeneous committee,” *American Political Science Review*, 95, 453–456.
- [25] Krishna, V., Morgan, J. (2001): “Asymmetric information and legislative rules,” *American Political Science Review*, 95, 435–452.

- [26] Lai, E. K. and Lim, W. (2012): “Authority and communication in the laboratory.” *Games and Economic Behavior*, 74, 541–560.
- [27] Lai, E. K., Lim, W., and Wang, J. T. (2015): “An experimental analysis of multidimensional cheap talk.” *Games and Economic Behavior*, 91, 114–144.
- [28] Londregan J. and J. Snyder (1994): “Comparing Committee and Floor Preferences,” *Legislative Studies Quarterly*, 19:2, 223–266.
- [29] Minozzi, W., and J. Woon (2016): “Competition, preference uncertainty, and jamming: A strategic communication experiment.” *Games and Economic Behavior*, 96, 97–114.
- [30] Sánchez-Pagés, S., and M. Vorsatz (2007): “An experimental study of truth-telling in sender-receiver game.” *Games and Economic Behavior*, 61, 86–112.
- [31] Sinclair, B. (1994): “House special rules and the institutional design controversy,” *Legislative Studies Quarterly*, 19:4, 477–494.
- [32] Vespa, E., and A. J. Wilson (2016): “Communication with multiple senders: an experiment.” *Quantitative Economics*, 7, 1–36.
- [33] 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.
- [34] Weingast, B.R., Marshall, W.J. (1988): “The industrial organization of congress or why legislatures like firms are not organized as market,” *Journal of Political Economy*, 96, 132–163.

Appendix A – Proof of Result 2

We only need to show that the open and closed rules with heterogeneous committees are better than the homogeneous rule in the equilibrium of Gilligan and Krehbiel [1989], since the median voter's payoff in the equilibrium by Krishna and Morgan [2001] is even higher. We proceed in two steps.

Step 1. Consider the open rule first. We have: $EU_O^R(b) = -\frac{b^2}{3} \cdot 16b \geq -\frac{4}{3}b^2$, since $b < 1/4$. There are three cases to consider. If $N(b) > 2$ then $EU_{CS}^R(b) = -\frac{1}{12N(b)^2} - \frac{b^2(N(b)^2-1)}{3} < -\frac{b^2}{3}(N(b)^2-1) < -\frac{8}{3}b^2 < -\frac{4}{3}b^2$. If $N(b) = 2$ then $EU_{CS}^R(b) = -\frac{1}{12 \cdot 4} - b^2$. So we have $EU_{CS}^R(b) < EU_O^R(b)$ if $\frac{1}{12 \cdot 4} + b^2 > \frac{16b^3}{3}$. This inequality is verified for $b < 1/4$. Finally, if $N(b) = 1$, $EU_{CS}^R(b) = -\frac{1}{12} < -\frac{4}{3}b^2$. The result for the senders follows immediately.

Step 2. Consider now the closed rule. Let's start from the receiver's payoff. We have:

$$EU_C^R(b) = -\frac{1}{12}(4b)^3(1-3b) - (b(1-4b))^2 > -\frac{1}{12}\left(1 - \frac{3}{4}\right) = -2.0833 \times 10^{-2},$$

where the inequality follows from the fact that $\frac{dEU_C^R(b)}{db} < 0$ when $b < 1/4$. There are two cases to consider. If $N(b) \leq 2$, then $EU_{CS}^R(b) < -\frac{1}{48} < EU_C^R(b)$. If $N(b) > 2$, then $EU_{CS}^R(b) < -\frac{8}{3}b^2$. So the result is proven if:

$$\frac{1}{12}(4b)^3(1-3b) + (b(1-4b))^2 < \frac{8}{3}b^2$$

This inequality is always verified when $b < 1/4$.

Consider now Sender 1's payoff. $EU_C^{S1}(b) = -\frac{1}{12}(4b)^3(1-3b) - (b(1-4b))^2 > -1/48$. Here too, we have two cases to consider. If $N(b) \leq 2$, then $EU_{CS}^{S1}(b) < -1/48 - b^2 < EU_C^{S1}(b)$. If $N(b) > 2$, then $EU_{CS}^{S1}(b) < -\frac{8}{3}b^2 - b^2 = -\frac{11}{3}b^2$. So the result is proven if:

$$\frac{1}{12}(4b)^3(1-3b) + 16b^4 < \frac{11}{3}b^2$$

This condition is always verified for $b < 11/16$.

Finally, consider Sender 2's payoff. $EU_C^{S2}(b) = -\frac{1}{12}(4b)^3(1-3b) - (2b(1-2b))^2 > -\frac{1}{12 \cdot 4}$. There are two cases to consider. If $N(b) \leq 2$, then $EU_{CS}^{S2}(b) < -\frac{1}{12 \cdot 4} - b^2 < EU_C^{S2}(b)$. If $N(b) > 2$, then $EU_{CS}^{S2}(b) < -\frac{8}{3}b^2 - b^2 = -\frac{11}{3}b^2$. So the result is proven if:

$$\frac{1}{12}(4b)^3(1-3b) + (2b(1-2b))^2 < \frac{11}{3}b^2$$

This condition is always verified for $b < 1/4$. ■

Appendix B – Level- k Models

In this appendix, we construct two level- k models, one for the open rule and one for the closed rule. As the anchoring point of the model, we assume, consistent with the convention in the literature, that level-0 senders tell the truth so that $m_1(\theta) = m_2(\theta) = \theta$ and that level-0 receiver credulously adopts the senders' proposal.²⁶ For the open rule, this means that level-0 receiver takes an action that is equal to the average of the two messages so that $a(m_1, m_2) = \bar{m} = \frac{m_1 + m_2}{2}$.²⁷ For the closed rule, we assume that level-0 receiver adopts Sender 1's proposal so that $a(m_1, m_2) = m_1$, since the receiver can only choose between adopting Sender 1's proposal and taking the *status quo* action.

We further assume that level- k Sender i , $i = 1, 2$ and $k = 1, \dots, K$, best responds to level- k Sender $j \neq i$ and level- $(k - 1)$ receiver, while level- k receiver best responds to level- k senders.²⁸ Since the games in question are communication games, in addition to the standard assumptions for level- k models such as the specification of level-0 behavior, we need to make further assumptions regarding how the receiver responds to unexpected (off-path) messages. For both level- k models, we assume that level- k receiver, $k = 1, \dots, K$, takes $a = 50$, the optimal action under the prior, when messages not expected from level- k senders are received. For the close rule, this is to say that the receiver will take the *status quo* action under these scenarios. Note that this assumption parallels that in Gilligan and Krehbiel [1989] regarding how the receiver responds to out-of-equilibrium messages. We adopt the assumption out of simplicity concern, a guiding principle for our modeling choice.

Open Rule. Under our specification, level-1 senders' strategies are $m_1(\theta) = \min\{2(\theta + b), 100\}$ and $m_2(\theta) = \max\{2(\theta - b) - 100, 0\}$. To illustrate that these are best responses to level-0 receiver and level-1 other sender, suppose that the realized $\theta = 20$ and the bias is $b = 10$. Sender 1 sends $m_1 = 60$, and Sender 2 sends $m_2 = 0$. The level-0 receiver takes action $a = \bar{m} = 30$. Since this is the ideal action of Sender 1, he has no incentive to deviate. Given that Sender 2's ideal action is 10, he would want to send a lower message. But since zero is the lowest possible message, $m_2 = 0$ is the best response.²⁹

²⁶The use of truthful senders and credulous receivers as the anchoring level-0 types can be traced back to Crawford [2003]. Such a specification is adopted by the experimental literature (e.g, Cai and Wang [2006], Wang, Spezio, and Camerer [2010], and Crawford and Irreberri [2007a, b]) and the theoretical work on lying aversion (e.g., Kartik [2006] and Kartik, Ottaviani, and Squintani [2007]).

²⁷For expositional convenience, we now use $m_1(\cdot)$, $m_2(\cdot)$ and $a(\cdot, \cdot)$ to denote pure strategies.

²⁸Unlike most level- k models have at most two player roles choosing simultaneously and have level- k players best respond to level- $(k - 1)$, we have three player roles with the receiver choosing after seeing senders' messages. Hence, we follow Wang, Spezio and Camerer [2010]'s asymmetric sender-receiver level- k model to have the level- k receiver best respond to level- k senders, but have level- k senders best respond to each other, as well as the level- $(k - 1)$ receiver.

²⁹For the bias parameters we adopt in the experiment, the detailed cases of level-1 senders' strategies

Best responding to the beliefs derived from the level-1 senders' strategies, level-1 receiver's on-path response rule is

$$a(m_1, m_2) = \begin{cases} \max\{\bar{m} - b, 0\}, & \bar{m} < 50, \\ \bar{m}, & \bar{m} = 50, \\ \min\{\bar{m} + b, 100\}, & \bar{m} > 50. \end{cases}$$

Suppose that the bias is $b = 10$ and the receiver receives on-path messages $m_1 = 60$ and $m_2 = 0$. This is the case where $\bar{m} = 30 < 50$, and the receiver takes $a = 30 - 10 = 20$. Level-1 Sender 2 sends $m_2 = 0$ only for $\theta \leq 60$. The message thus contains only coarse information. On the other hand, level-1 Sender 1 sends $m_1 = 60$ only when $\theta = 20$, and the precise information in m_1 makes Sender 2's message effectively useless. The receiver updates beliefs accordingly and takes $a = 20$, her ideal action for $\theta = 20$. Similarly, if the two on-path messages are such that $\bar{m} > 50$, the receiver follows Sender 2's message given that Sender 1 will then be providing coarse information. If $m_1 = 100$ and $m_2 = 0$ so that $\bar{m} = 50$, combining the two messages the receiver believes that $\theta \in [40, 60]$ (note that Sender 1 sends $m_1 = 100$ only for $\theta \geq 40$). Given the uniform prior, the receiver takes $a = 50$, which equals the conditional expected value of $\theta \in [40, 60]$.

Level-2 players' strategies follow a similar logic. Knowing that (in most cases) level-1 receiver discounts or adds on the average message by b , level-2 senders further bias their message and adopt strategies $m_1(\theta) = \min\{2(\theta + 2b), 100\}$ and $m_2(\theta) = \max\{2(\theta - 2b) - 100, 0\}$.³⁰ Given

are:

$$\begin{aligned} \text{for } b = 10, m_1(\theta) &= \begin{cases} 100, & \theta > 40, \\ 2(\theta + 10), & \theta \leq 40, \end{cases} \text{ and } m_2(\theta) = \begin{cases} 0, & \theta < 60, \\ 2(\theta - 10) - 100, & \theta \geq 60; \end{cases} \\ \text{for } b = 20, m_1(\theta) &= \begin{cases} 100, & \theta > 30, \\ 2(\theta + 20), & \theta \leq 30, \end{cases} \text{ and } m_2(\theta) = \begin{cases} 0, & \theta < 70, \\ 2(\theta - 20) - 100, & \theta \geq 70. \end{cases} \end{aligned}$$

Under these strategies and the level-0 receiver's action rule, Sender 1 obtains his ideal action for $\theta \leq 50 - b$, and Sender 2 obtains his for $\theta \geq 50 + b$. For $\theta \in (50 - b, 50 + b)$, in which the level-0 receiver's action is $a = 50$, Sender 1 (Sender 2) obtains an action that is closer to his ideal action than it is to Sender 2's (Sender 1's) when $\theta < 50$ ($\theta > 50$); when $\theta = 50$, they obtain an action that is of equal distance to their respective ideal actions.

³⁰For our adopted bias parameters, the detailed cases of the strategies are:

$$\begin{aligned} \text{for } b = 10, m_1(\theta) &= \begin{cases} 100, & \theta > 30, \\ 2(\theta + 20), & \theta \leq 30, \end{cases} \text{ and } m_2(\theta) = \begin{cases} 0, & \theta < 70, \\ 2(\theta - 20) - 100, & \theta \geq 70; \end{cases} \\ \text{for } b = 20, m_1(\theta) &= \begin{cases} 100, & \theta > 10, \\ 2(\theta + 40), & \theta \leq 10, \end{cases} \text{ and } m_2(\theta) = \begin{cases} 0, & \theta < 90, \\ 2(\theta - 40) - 100, & \theta \geq 90. \end{cases} \end{aligned}$$

Under these strategies and the level-1 receiver's action rule, Sender 1 obtains his ideal action for $\theta \leq 50 - 2b$, and Sender 2 obtains his for $\theta \geq 50 + 2b$. Note that even though for $\theta \leq 50 - 2b$, Sender 2 does not obtain a very desirable action, the action taken (i.e., Sender 1's ideal action) is closer to Sender 2's ideal action than is 50, the assumed response for off-path messages. Thus, Sender 2 has no incentive to create off-path messages by deviating from $m_2(\theta) = \max\{2(\theta - 2b) - 100, 0\}$. A similar argument applies for the symmetric case of Sender 1's absence of incentive to deviate when $\theta \geq 50 + 2b$. For $\theta \in (50 - 2b, 50 + 2b)$, in which the level-1 receiver's action is $a = 50$, Sender 1 (Sender 2) obtains an action that is closer to his ideal action

these level-2 senders' strategies, the best-responding level-2 receiver then discounts or adds on the average messages by $2b$:

$$a(m_1, m_2) = \begin{cases} \max\{\bar{m} - 2b, 0\}, & \bar{m} < 50, \\ \bar{m}, & \bar{m} = 50, \\ \min\{\bar{m} + 2b, 100\}, & \bar{m} > 50. \end{cases}$$

Higher level players' strategies are similarly derived by iterating on these best-responding processes.³¹

Closed Rule. Best responding to level-0 receiver, level-1 senders' strategies are $m_1(\theta) = \min\{\theta + b, 100\}$ and $m_2(\theta) = \max\{\theta - b, 0\}$, i.e., they are recommending their ideal actions.³² Given these strategies, the on-path response rule of level-1 receiver is

$$a(m_1, m_2) = \begin{cases} m_1, & m_1 \in [b, 50] \cup [50 + 2b, 100), m_2 = \max\{m_1 - 2b, 0\}, \\ m_1, & m_1 = 100, m_2 \in [100 - 2b, 100 - b], \\ 50, & m_1 \in (50, 50 + 2b), m_2 = m_1 - 2b. \end{cases}$$

Best responding to level-1 receiver, level-2 Sender 1's strategy coincides with that of level-1, i.e., $m_1(\theta) = \min\{\theta + b, 100\}$. For level-2 Sender 2, note that he strictly prefers the *status quo* $a = 50$ over $a = \min\{\theta + b, 100\}$ if $(\theta - b) \in [50, \min\{50 + 2b, 75\})$. Accordingly, level-2 Sender 2

than it is to Sender 2's (Sender 1's) when $\theta < 50$ ($\theta > 50$); when $\theta = 50$, they obtain an action that is of equal distance to their respective ideal actions. Note that since the on-path action is the same as the assumed response for off-path messages, the senders also have no incentive to deviate in this case.

³¹In particular, level- k senders' strategies, $k = 3, \dots, K$, are $m_1(\theta) = \min\{2(\theta + kb), 100\}$ and $m_2(\theta) = \max\{2(\theta - kb) - 100, 0\}$. Note that for $k \geq \frac{50}{b}$, the strategies coincide with the strategies in a babbling equilibrium in which $m_1(\theta) = 100$ and $m_2(\theta) = 0$. For level- k receiver, $k = 3, \dots, K$, the on-path response rule is

$$a(m_1, m_2) = \begin{cases} \max\{\bar{m} - kb, 0\}, & \bar{m} < 50, \\ \bar{m}, & \bar{m} = 50, \\ \min\{\bar{m} + kb, 100\}, & \bar{m} > 50. \end{cases}$$

Similarly, for $k \geq \frac{50}{b}$, the receiver's best response coincides with the babbling action $a(m_1, m_2) = 50$.

³²Given that level-0 receiver follows Sender 1's proposal, any message by Sender 2 is a best response. We adopt a natural choice so that Sender 1's and Sender 2's strategies are symmetric in the sense that they both recommend their ideal actions. For the bias parameters we adopt in the experiment, the detailed cases of the strategies are:

$$\begin{aligned} \text{for } b = 10, m_1(\theta) &= \begin{cases} 100, & \theta > 90, \\ \theta + 10, & \theta \leq 90, \end{cases} \text{ and } m_2(\theta) = \begin{cases} 0, & \theta < 10, \\ \theta - 10, & \theta \geq 10; \end{cases} \\ \text{for } b = 20, m_1(\theta) &= \begin{cases} 100, & \theta > 80, \\ \theta + 20, & \theta \leq 80, \end{cases} \text{ and } m_2(\theta) = \begin{cases} 0, & \theta < 20, \\ \theta - 20, & \theta \geq 20. \end{cases} \end{aligned}$$

will have an incentive to induce the off-path response if $\theta \in [50 + b, \min\{50 + 3b, 75 + b\})$. In this, Sender 2 will be indifferent between any messages that result in an unexpected message pair. We prescribe a message rule so that the resulting specification is as parsimonious as possible. We assume that level-2 Sender 2 sends the same message for all $\theta \in [50 + b, \min\{50 + 3b, 75 + b\})$ to induce unexpected message pairs, where such message will not create incentive for level-2 Sender 1 to deviate from $m_1(\theta) = \min\{\theta + b, 100\}$.³³ Any $m_2 \in [0, 50) \cup (100 - b, 100]$ will satisfy these requirements.³⁴ To pin down a message that will be used, we assume that level-2 Sender 2 will choose a message in $[0, 50)$. In particular, the strategy of level-2 Sender 2 is specified to be:

$$m_2(\theta) = \begin{cases} \max\{\theta - b, 0\}, & \theta \in [0, 50 + b) \cup [\min\{50 + 3b, 75 + b\}, 100], \\ 50 - b, & \theta \in [50 + b, \min\{50 + 3b, 75 + b\}). \end{cases}$$

Best responding to the beliefs derived from level-2 senders' strategies, the on-path response rule of level-2 receiver (stated as a function of m_1 only) coincides with that of level-1.³⁵ The difference lies in their off-path responses. Note first that when level-2 receiver receives $m_1 \in [50 + 2b, \min\{50 + 4b, 75 + 2b, 100\})$, she expects to receive $m_2 = 50 - b$ from Sender 2. When $b > 12.5$, she also expects to see $m_2 = 50 - b$ when $m_1 = 100$. Any other m_2 will induce

³³Recall that level-2 Sender 1 best responds to level-2 Sender 2 and level-1 receiver.

³⁴Note first that the message cannot be in $[50, \min\{50 + 2b, 75\})$, otherwise there will exist a $\theta \in [50 + b, \min\{50 + 3b, 75 + b\})$ at which Sender 2 cannot induce the off-path response. For $m_2 \in [100 - 2b, 100 - b]$, there exist some $\theta \in [50 + b, \min\{50 + 3b, 75 + b\})$ (e.g., $\theta = 75 + \varepsilon - b$) for which level-2 Sender 1 strictly prefers to send $m_1 = 100$ instead of $m_1 = \theta + b$ in order to induce $a = 100$. For $b \geq 12.5$, $50 + 2b \geq 75 \geq 100 - 2b$, and thus all $m_2 \in [50, 100 - b]$ are ruled out as candidates for Sender 2's off-path message. For $b < 12.5$, $50 + 2b < 75 < 100 - 2b$; when b is sufficiently small, there are messages close to $100 - 2b$ that will not create incentive for Sender 1 to deviate from $m_1(\theta) = \min\{\theta + b, 100\}$. The range $[0, 50) \cup (100 - b, 100]$ stated above, however, guarantees that there is no incentive for Sender 1 to deviate for any b .

³⁵Specifically, for $b \geq 12.5$, level-2 receivers choose (for $\theta \in [0, 50 - b]$, $(50 - b, 50 + b)$, $[50 + b, \min\{50 + 3b, 75 + b\})$, and $[\min\{50 + 3b, 75 + b\}, 100]$, respectively)

$$a(m_1, m_2) = \begin{cases} m_1, & m_1 \in [b, 50], m_2 = \max\{m_1 - 2b, 0\}, \\ 50, & m_1 \in (50, 50 + 2b), m_2 = m_1 - 2b, \\ m_1, & m_1 \in [50 + 2b, \min\{50 + 4b, 75 + 2b, 100\}), m_2 = 50 - b, \\ m_1, & m_1 = 100, m_2 = 50 - b \text{ or } m_2 \in [\max\{\min\{50 + 2b, 75\}, 100 - 2b\}, 100 - b]. \end{cases}$$

For $b < 12.5$, level-2 receivers choose (for $\theta \in [0, 50 - b]$, $(50 - b, 50 + b)$, $[50 + b, \min\{50 + 3b, 75 + b\})$, $[\min\{50 + 3b, 75 + b\}, 100 - b]$, and $[100 - b, 100]$, respectively)

$$a(m_1, m_2) = \begin{cases} m_1, & m_1 \in [b, 50], m_2 = \max\{m_1 - 2b, 0\}, \\ 50, & m_1 \in (50, 50 + 2b), m_2 = m_1 - 2b, \\ m_1, & m_1 \in [50 + 2b, \min\{50 + 4b, 75 + 2b, 100\}), m_2 = 50 - b, \\ m_1, & m_1 \in [\min\{50 + 4b, 75 + 2b, 100\}, 100), m_2 = \max\{m_1 - 2b, 0\}, \\ m_1, & m_1 = 100, m_2 \in [100 - 2b, 100 - b]. \end{cases}$$

an off-path response in these cases. Furthermore, level-2 receiver does not expect to receive $m_2 \in [50, \min\{50 + 2b, 75\})$; if she does, she will take the *status quo* action as off-path response regardless of what m_1 is.

The above implies that the strategies of higher-level Sender 1s remain the same as that of level-1.³⁶ For higher-level Sender 2s, the strategies are essentially the same as that of level-2, except that they need to use a different message to induce the off-path response. We specify, e.g., that level-3 Sender 2 adopts

$$m_2(\theta) = \begin{cases} \max\{\theta - b, 0\}, & \theta \in [0, 50 + b) \cup [\min\{50 + 3b, 75 + b\}, 100], \\ 50 - b - \varepsilon, & \theta \in [50 + b, \min\{50 + 3b, 75 + b\}). \end{cases}$$

for some $\varepsilon > 0$. The strategies of higher-level receivers will also coincide with that of level-1, except for what message combinations they consider to be off path.

³⁶Note that $m_2 = 50 - b$ is sent by level-2 Sender 2 for both $\theta = 50$ and $\theta = 50 + b$. Thus, $m_2 = 50 - b$ paired with $m_1 = 50 + b$ and $m_2 = 50 - b$ paired with $m_1 = 50 + 2b$ are both expected by level-2 receiver. The former message pair induces $a = 50$ while the latter induces $a = 50 + 2b$. Accordingly, level-3 Sender 1 has no strict incentive to deviate from $m_1(\theta) = \min\{\theta + b, 100\}$ when his ideal action is $50 + b$, i.e., when $\theta = 50$. Had for $\theta \in [50 + b, \min\{50 + 3b, 75 + b\})$ level-2 receiver expected level-2 Sender 2 to send $m_2 \in (50 - b, 50)$, say, $m_2 = 50 - b + \delta$, level-3 Sender 1 would have preferred to send $m_1 \in [50 + 2b, \min\{50 + 3b, 75 + b, 100\})$ instead of $50 + b + \delta$ when $\theta = 50 + \delta$. Our choice of $m_2 = 50 - b$ for level-2 Sender 2's strategy when $\theta \in [50 + b, \min\{50 + 3b, 75 + b\})$ is to maintain a simple specification where the strategies of higher-level Sender 1s remain the same as that of level-1.

Appendix C – Experimental Instructions

Instructions for Treatment O-2 with $b = 20$

Welcome to the experiment. This experiment studies decision making between three individuals. In the following two hours or less, you will participate in 30 rounds of decision making. Please read the instructions below carefully; the cash payment you will receive at the end of the experiment depends on how well you make your decisions according to these instructions.

Your Role and Decision Group

There are 15 participants in today’s session. One third of the participants will be randomly assigned the role of Member A, another one third the role of Member B, and the remaining the role of Member C. Your role will remain fixed throughout the experiment. In each round, three participants, one Member A, one Member B and one Member C, will be matched to form a group of three. The three members in a group make decisions that will affect their rewards in the round. Participants will be randomly rematched after each round to form new groups.

Your Decision in Each Round

In each round and for each group, the computer will randomly select a number with two decimal places from the range $[0.00, 100.00]$. Each possible number has equal chance to be selected. The selected number will be revealed to Member A and Member B. Member C, without seeing the number, will have to choose an action. In the rest of the instruction, we will call the randomly selected number X and Member C’s chosen action Y .

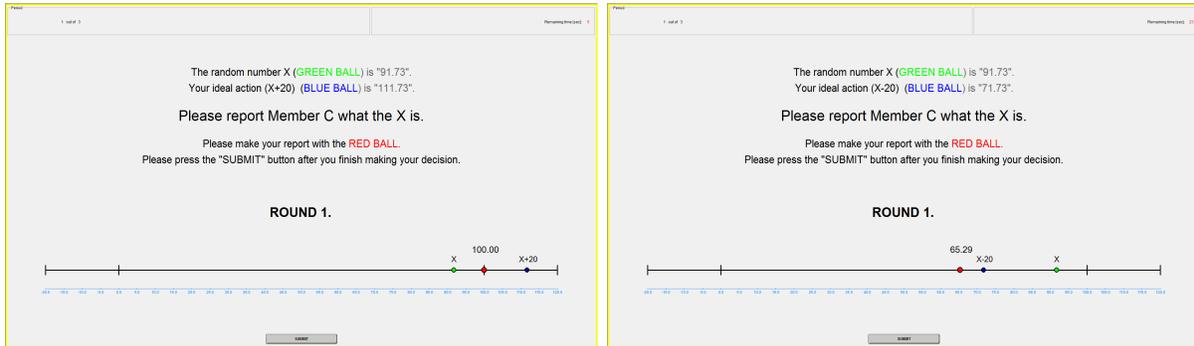
Member A’s and B’s Decisions

You will be presented with a line on your screen. The left end of the line represents -20.00 and the right end 120.00 . You will see a green ball on the line, which represents the randomly selected number X . There is another ball, a blue one, that represents your “ideal action,” which is equal to $X + 20$ (Member A) or $X - 20$ (Member B). This ideal action is related to your reward in the round, which will be explained below.

With all this information on your screen, you will be asked to report to Member C what X is. You do so by clicking on the line. A red ball, which represents your reported X , will move to

the point you click on. You can adjust your click until you arrive at the point/number you wish to report, after which you click the submit button. You are free to choose any point in the range $[0.00, 100.00]$ for your report; it is not part of the instructions that you have to tell the truth.

Once you click the submit button, your decision in the round is completed and your report will be transmitted to your paired Member C, who will then be asked to choose an action.



(a) Member A's Screen

(b) Member B's Screen

Figure 15: Screen Shots

Member C's Decision

You will be presented with a similar line on your screen. After seeing Member A's report represented by a green ball and Member B's report represented by a white ball on the line, you will be asked to make your action choice by clicking on the line. A red ball, which represents your action, will move to the point you click on. You can adjust your click until you arrive at the point/number you wish to choose, after which you click the submit button. The final position of the red ball will represent your action choice Y . You are free to choose any point in the range $[0.00, 100.00]$ for your action. Once you click the submit button, your decision in the round is completed.

Similar to Member A or Member B, you will have your "ideal action," which is equal to the X unknown to you. More details will be explained below.

Your Reward in Each Round

Your reward in the experiment will be expressed in terms of experimental currency unit (ECU). The following describes how your reward in each round is determined.

Member A's Reward

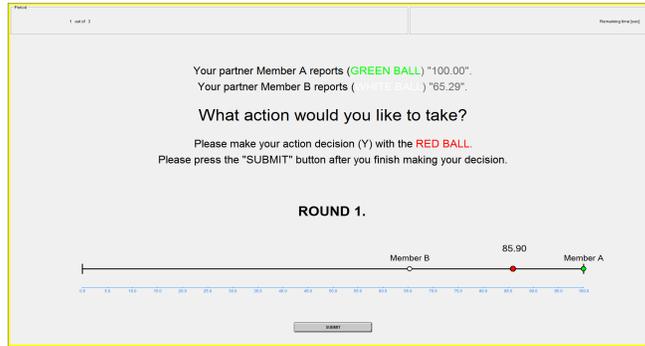


Figure 16: Member C's Screen

The amount of ECU you earn in a round depends on the distance between **your ideal action** $(X + 20)$ **and Member C's action choice** Y . In particular,

$$\text{Your reward in each round} = 100 - \frac{[(X+20)-Y]^2}{50}.$$

In case that this value is negative, you will get 0.

Here are some examples:

1. The computer selected the random number $X = 25$. (Thus, your idea action is $X + 20 = 45$.) Your reported X is 70. Member B reported X is 40. After the reports, Member C chooses action $Y = 55$. The distance between your ideal action $X+20$ and Y is **10**. Your earning in the round will be $100 - \frac{[10]^2}{50} = 98$ ECU.
2. The computer selected the random number $X = 25$. (Thus, your idea action is $X + 20 = 45$.) Your reported X is 70. Member B reported X is 40. After the reports, Member C chooses action $Y = 65$. The distance between your ideal action $X+20$ and Y is **20**. Your earning in the round will be $100 - \frac{[20]^2}{50} = 92$ ECU.
3. The computer selected the random number $X = 25$. (Thus, your idea action is $X + 20 = 45$.) Your reported X is 70. Member B reported X is 40. After the reports, Member C chooses action $Y = 75$. The distance between your ideal action $X+20$ and Y is **30**. Your earning in the round will be $100 - \frac{[30]^2}{50} = 82$ ECU.

These examples demonstrate that the loss of earning from the first 10 distance is only 2 ECU whereas the loss of earning from the second and the third 10 distances are 6 ECU and 10 ECU respectively. In other words, the father away the action is from your ideal action, the higher the rate of loss. Table 5 provides an elaborate example regarding your earning and the distance between your ideal action and the action taken by Member C.

Member B's Reward

The amount of ECU you earn in a round depends on the distance between **your ideal action** $(X - 20)$ **and Member C's action choice** Y . In particular,

$$\text{Your reward in each round} = 100 - \frac{[(X-20)-Y]^2}{50}.$$

In case that this value is negative, you will get 0.

Member C's Reward

The amount of ECU you earn in a round depends on the distance between **your ideal action** X **and the action choice** Y . More precisely,

$$\text{Your reward in each round} = 100 - \frac{[X-Y]^2}{50}.$$

In case that this value is negative, you will get 0.

Here are some examples:

1. You choose action $Y = 30$. It turns out that the computer selected the random number $X = 20$. The distance between your ideal action X and your action choice Y is **10**. Then your earning in the round will be $100 - \frac{[10]^2}{50} = 98$ ECU.
2. You choose action $Y = 40$. It turns out that the computer selected the random number $X = 20$. The distance between your ideal action X and your action choice Y is **20**. Then your earning in the round will be $100 - \frac{[20]^2}{50} = 92$ ECU.
3. You choose action $Y = 50$. It turns out that the computer selected the random number $X = 20$. The distance between your ideal action X and your action choice Y is **30**. Then your earning in the round will be $100 - \frac{[30]^2}{50} = 82$ ECU.

These examples demonstrate that the loss of earning from the first 10 distance is only 2 ECU whereas the loss of earning from the second and the third 10 distances are 6 ECU and 10 ECU respectively. In other words, the farther away the action is from your ideal action, the higher the rate of loss. Table 5 provides an elaborate example regarding your earning and the distance between your ideal action and the action taken by Member C.

Information Feedback

Distance between (Your Ideal Action) and Y	0	10	20	30	40	50	60	70	>70
Your earning	100	98	92	82	68	50	28	2	0

Table 5: Your earnings

At the end of each round, the computer will provide a summary for the round: which number was selected and revealed to Member A and Member B, Member A’s report, Member B’s report, Member C’s action choice, distance between your ideal action and Member C’s action choice and your earning in ECU.

Your Cash Payment

The experimenter randomly selects 3 rounds out of 30 to calculate your cash payment. (So it is in your best interest to take each round seriously.) Your total cash payment at the end of the experiment will be the average amount of ECU you earned in the 3 selected rounds plus a HK\$40 show-up fee.

Quiz and Practice

To ensure your understanding of the instructions, we will provide you with a quiz and practice round. We will go through the quiz after you answer it on your own.

You will then participate in 1 practice round. The practice round is part of the instructions which is not relevant to your cash payment; its objective is to get you familiar with the computer interface and the flow of the decisions in each round. Once the practice round is over, the computer will tell you “The official rounds begin now!”

Adminstration

Your decisions as well as your monetary payment will be kept confidential. Remember that you have to make your decisions entirely on your own; please do not discuss your decisions with any other participants.

Upon finishing the experiment, you will receive your cash payment. You will be asked to sign your name to acknowledge your receipt of the payment. You are then free to leave.

If you have any question, please raise your hand now. We will answer your question individually. If there is no question, we will proceed to the quiz.

1. Which of the following is true?
 - (a) *Member A* and *Member B* must pay more to report to *Member C* a higher value of X .
 - (b) *Member A* and *Member B* must pay less to report to *Member C* a lower value of X .
 - (c) *Member A* and *Member B* are free to report to *Member C* any value of X in the range of $[0.00, 100.00]$. There is no direct cost of report.

2. Suppose you are assigned to be a *Member A*. Which of the following is true? What is your answer if you are assigned to be a *Member B* or *Member C*?
 - (a) Your reward is higher if the distance between $X + 20$ and Y is bigger.
 - (b) Your reward is higher if the distance between X and Y is bigger.
 - (c) Your reward is higher if the distance between $X + 20$ and Y is smaller.
 - (d) Your reward is higher if the distance between X and Y is smaller.
 - (e) Your reward is higher if the distance between $X - 20$ and Y is bigger.
 - (f) Your reward is higher if the distance between $X - 20$ and Y is smaller.

3. Suppose you are assigned to be a *Member A*. The computer chooses the random number $X = 25$. Which of the following is true?
 - (a) Both you and *Member B* know the chosen number X but *Member C* does not know the chosen number X .
 - (b) Neither you nor *Member B* knows the chosen number X .
 - (c) You are the only person in your group who knows the chosen number X .

Instructions for Treatment C-2 with $b = 20$

Welcome to the experiment. This experiment studies decision making among three individuals. In the following two hours or less, you will participate in 30 rounds of decision making. Please read the instructions below carefully; the cash payment you will receive at the end of the experiment depends on how well you make your decisions according to these instructions.

Your Role and Decision Group

There are 15 participants in today's session. One third of the participants will be randomly assigned the role of Member A, another one third the role of Member B, and the remaining the role of Member C. Your role will remain fixed throughout the experiment. In each round, three participants, one Member A, one Member B and one Member C, will be matched to form a group of three. The three members in a group make decisions that will affect their rewards in the round. Participants will be randomly rematched after each round to form new groups.

Your Decision in Each Round

In each round and for each group, the computer will randomly select a number with two decimal places from the range $[0.00, 100.00]$. Each possible number has equal chance to be selected. The selected number will be revealed to Member A and Member B. Member C, without seeing the number, will have to choose an action. In the rest of the instruction, we will call the randomly selected number X and Member C's chosen action Y .

Member A's Decisions

You will be presented with a horizontal line on your screen. The left end of the line represents 0.00 and the right end 120.00. You will see a green ball on the line, which represents the randomly selected number X . There is another blue ball that represents your "ideal action," which is equal to $X + 20$. This ideal action is related to your reward in the round, which will be explained below.

With all this information on your screen, you will be asked to make a proposal to Member C on what action to take. You do so by clicking on the line. A red ball, which represents your proposal, will move to the point you click on. You can adjust your click until you arrive at the point/number you desire, after which you click the submit button. You are free to choose any point in the range $[0.00, 100.00]$ for your proposal.

Once you click the submit button, your decision in the round is completed and your proposal will be transmitted to your paired Member C. With the additional information provided by Member B, Member C will then decide whether to accept your proposal or take a status quo action $SQ=50.00$.



(a) Member A's Screen

(b) Member B's Screen

Figure 17: Screen Shots

Member B's Decisions

You will be presented with a horizontal line on your screen. The left end of the line represents -20.00 and the right end 100.00 . You will see a green ball on the line, which represents the randomly selected number X . There is another blue ball that represents your “ideal action,” which is equal to $X - 20$. This ideal action is related to your reward in the round, which will be explained below.

With all this information on your screen, you will be asked to make a speech to Member C regarding where X is. You do so by positioning a Red Line and a Blue Line that cross the horizontal line, in which your speech takes the form “ X is between the Red Line and the Blue Line.” You position the lines by clicking on the horizontal line, with left click of the mouse determining the position of the Red Line and right click the position of the Blue Line. You can adjust your clicks until you arrive at the positions you desire, after which you click the submit button. You are free to choose any interval in the range $[0.00, 100.00]$ for your speech, including a degenerate one in which the Red Line and the Blue Line coincide.

Once you click the submit button, your decision in the round is completed and your speech will be transmitted to your paired Member C, who will then decide whether to accept Member A's proposal or take a status quo action $SQ=50.00$.

Member C's Decision

You will be presented with a similar horizontal line on your screen. After seeing Member A’s proposal represented by a green ball and Member B’s speech represented by the Red Line and Blue Line, you will be prompted to enter your choice of action. You must choose one of the two options: either to “TAKE the PROPOSAL” from Member A or to “TAKE the STATUS QUO” which is represented by a light blue ball (50.00) on the line. Once you click one of the buttons, your decision in the round is completed.

Similar to Member A or Member B, you will have your “ideal action,” which is equal to the X unknown to you. More details will be explained below.

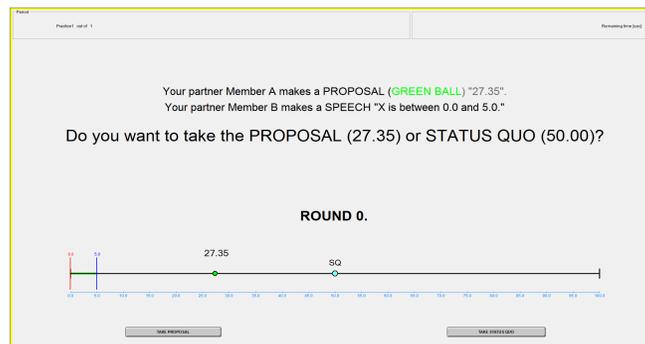


Figure 18: Member C’s Screen

Your Reward in Each Round

Your reward in the experiment will be expressed in terms of experimental currency unit (ECU). The following describes how your reward in each round is determined.

Member A's Reward

The amount of ECU you earn in a round depends on the distance between **your ideal action** $(X + 20)$ and **Member C's action choice** Y . In particular,

$$\text{Your reward in each round} = 100 - \frac{[(X+20)-Y]^2}{50}.$$

In case that this value is negative, you will get 0.

Here are some examples:

1. The computer selected the random number $X = 25$. (Thus, your idea action is $X + 20 = 45$.) You make a proposal "55". Member B made a speech " X is between 10 and 20." After the proposal and the speech, Member C chooses to take the proposal $Y = 55$. The distance between your ideal action $X+20$ and Y is **10**. Your earning in the round will be $100 - \frac{[10]^2}{50} = 98$ ECU.
2. The computer selected the random number $X = 25$. (Thus, your idea action is $X + 20 = 45$.) You make a proposal "65". Member B made a speech " X is between 10 and 20." After the proposal and the speech, Member C chooses to take the proposal $Y = 65$. The distance between your ideal action $X+20$ and Y is **20**. Your earning in the round will be $100 - \frac{[20]^2}{50} = 92$ ECU.
3. The computer selected the random number $X = 25$. (Thus, your idea action is $X + 20 = 45$.) You make a proposal "75". Member B made a speech " X is between 10 and 20." After the proposal and the speech, Member C chooses to take the proposal $Y = 75$. The distance between your ideal action $X+20$ and Y is **30**. Your earning in the round will be $100 - \frac{[30]^2}{50} = 82$ ECU.

These examples demonstrate that the loss of earning from the first 10 distance is only 2 ECU whereas the loss of earning from the second and the third 10 distances are 6 ECU and 10 ECU respectively. In other words, the farther away the action is from your ideal action, the higher the rate of loss. Table 6 provides an elaborate example regarding your earning and the distance between your ideal action and the action taken by Member C.

Member B's Reward

The amount of ECU you earn in a round depends on the distance between **your ideal action** $(X - 20)$ and **Member C's action choice** Y . In particular,

$$\text{Your reward in each round} = 100 - \frac{[(X-20)-Y]^2}{50}.$$

In case that this value is negative, you will get 0.

Member C's Reward

The amount of ECU you earn in a round depends on the distance between **your ideal action** X and **the action choice** Y . More precisely,

$$\text{Your reward in each round} = 100 - \frac{[X-Y]^2}{50}.$$

In case that this value is negative, you will get 0.

Here are some examples:

1. Member A makes a proposal "30" and Member B makes a speech "X is between 10 and 20." You choose to take the proposal $Y = 30$. It turns out that the computer selected the random number $X = 20$. The distance between your ideal action X and your action choice Y is **10**. Then your earning in the round will be $100 - \frac{[10]^2}{50} = 98$ ECU.
2. Member A makes a proposal "40" and Member B makes a speech "X is between 10 and 20." You choose to take the proposal $Y = 40$. It turns out that the computer selected the random number $X = 20$. The distance between your ideal action X and your action choice Y is **20**. Then your earning in the round will be $100 - \frac{[20]^2}{50} = 92$ ECU.
3. Member A makes a proposal "50" and Member B makes a speech "X is between 10 and 20." You choose to take the proposal $Y = 50$. It turns out that the computer selected the random number $X = 20$. The distance between your ideal action X and your action choice Y is **30**. Then your earning in the round will be $100 - \frac{[30]^2}{50} = 82$ ECU.

These examples demonstrate that the loss of earning from the first 10 distance is only 2 ECU whereas the loss of earning from the second and the third 10 distances are 6 ECU and 10 ECU respectively. In other words, the father away the action is from your ideal action, the higher the rate of loss. Table 6 provides an elaborate example regarding your earning and the distance between your ideal action and the action taken by Member C.

Distance between (Your Ideal Action) and Y	0	10	20	30	40	50	60	70	>70
Your earning	100	98	92	82	68	50	28	2	0

Table 6: Your earnings

Information Feedback

At the end of each round, the computer will provide a summary for the round: which number was selected and revealed to Member A and Member B, Member A’s proposal, Member B’s speech, Member C’s action choice, distance between your ideal action and Member C’s action choice and your earning in ECU.

Your Cash Payment

The experimenter randomly selects 3 rounds out of 30 to calculate your cash payment. (So it is in your best interest to take each round seriously.) Your total cash payment at the end of the experiment will be the average amount of ECU you earned in the 3 selected rounds plus a HK\$40 show-up fee.

Quiz and Practice

To ensure your understanding of the instructions, we will provide you with a quiz and practice round. We will go through the quiz after you answer it on your own.

You will then participate in 1 practice round. The practice round is part of the instructions which is not relevant to your cash payment; its objective is to get you familiar with the computer interface and the flow of the decisions in each round. Once the practice round is over, the computer will tell you “The official rounds begin now!”

Administration

Your decisions as well as your monetary payment will be kept confidential. Remember that you have to make your decisions entirely on your own; please do not discuss your decisions with any other participants.

Upon finishing the experiment, you will receive your cash payment. You will be asked to sign your name to acknowledge your receipt of the payment. You are then free to leave.

If you have any question, please raise your hand now. We will answer your question individually. If there is no question, we will proceed to the quiz.

1. Which of the following is true?
 - (a) *Member A* must pay more to propose to *Member C* a higher value of X .
 - (b) *Member A* must pay less to propose to *Member C* a lower value of X .
 - (c) *Member A* is free to propose to *Member C* any value of X in the range of $[0.00, 100.00]$. There is no direct cost of proposal.

2. Suppose you are assigned to be a *Member A*. Which of the following is true? What is your answer if you are assigned to be a *Member B* or a *Member C*?
 - (a) Your reward is higher if the distance between $X + 20$ and Y is bigger.
 - (b) Your reward is higher if the distance between X and Y is bigger.
 - (c) Your reward is higher if the distance between $X + 20$ and Y is smaller.
 - (d) Your reward is higher if the distance between X and Y is smaller.
 - (e) Your reward is higher if the distance between $X - 20$ and Y is bigger.
 - (f) Your reward is higher if the distance between $X - 20$ and Y is smaller.

3. Suppose you are assigned to be a *Member A*. The computer chooses the random number $X = 25$. Which of the following is true?
 - (a) Both you and *Member B* know the chosen number X .
 - (b) Neither you nor *Member B* knows the chosen number X .
 - (c) You are the only person in your group who knows the chosen number X .

Appendix D – Additional Figures

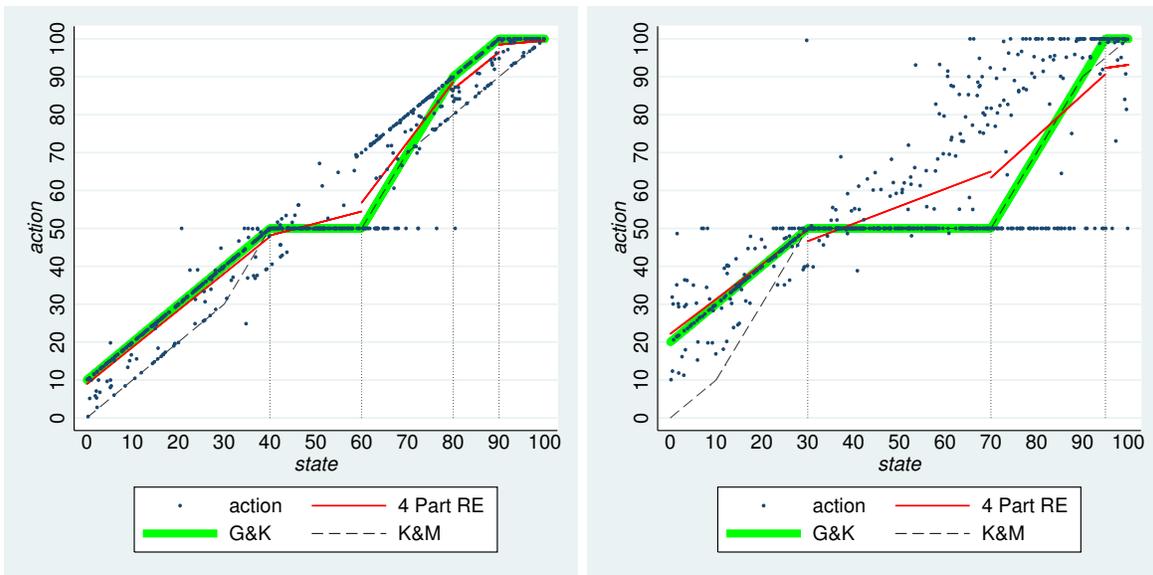


Figure 19: Information Transmission in $C-2$ with Four GK Segments

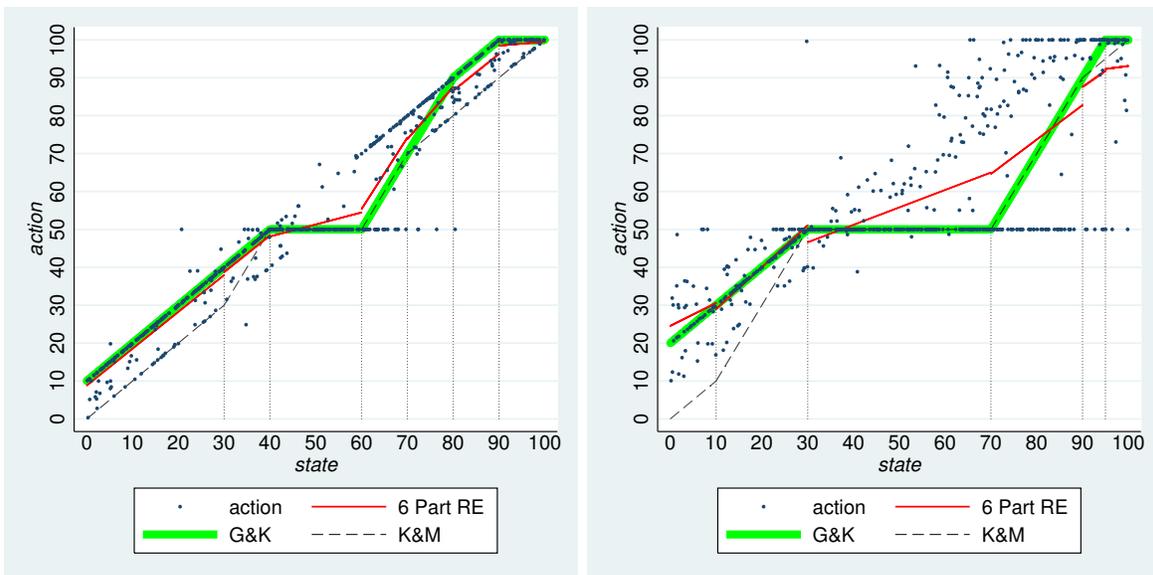


Figure 20: Information Transmission in $C-2$ with Six KM Segments