The Informational Theory of Legislative Committees: An Experimental Analysis*

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Abstract

We experimentally investigate the informational theory of legislative committees (Gilligan and Krehbiel 1989). Two committee members provide policy-relevant information to a legislature under alternative legislative rules. Under the open rule, the legislature is free to make any decision; under the closed rule, the legislature chooses between a member's proposal and a *status quo*. We find that even in the presence of biases the committee members improve the legislature's decision by providing useful information. We obtain evidence for two additional predictions: the *outlier principle*, according to which more extreme biases reduce the extent of information transmission; and the *distributional principle*, according to which the open rule is more distributionally efficient than the closed rule. When biases are less extreme, we find that the distributional principle dominates the *restrictive-rule principle*, according to which the closed rule is more informationally efficient. Overall, our findings provide experimental support for Gilligan and Krehbiel's informational theory.

Keywords: Legislative Committees; Informational Theory; Open Rule; Closed Rule; Laboratory Experiment

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1 Introduction

Scholars of the U.S. Congress have long recognized the importance of its committees as the center stage of the legislative process. A number of theories, both normative and positive, have therefore been developed to rationalize them and assess their welfare impact. These theories have emphasized the importance of legislative committees not only in the legislative process but also in preserving the balance of power between the House and the Senate and even in imposing party discipline.[1]

One of the most influential theories of legislative committees is the informational theory, first proposed by Gilligan and Krehbiel (1987, 1989). At its core, there is the idea that lawmakers are ignorant of the key variables affecting policy outcomes and that legislative committees may help by providing information on these variables. The informational theory provides a formal framework to study why committees, though having conflicts of interest, have incentives to perform this function. Most importantly, the theory provides a framework to understand the impacts of legislative procedural rules on the effectiveness of the legislative process: it explains why it may be optimal to have the same bill referred by multiple committee members 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 evaluate some indirect but 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 (e.g., Weingast and Marshall 1988; Krehbiel 1991; Londregan and

[1]A discussion of the alternative theories of legislative committees and how they relate to the informational theory is presented in Section 2.

Snyder 1994; Poole and Rosenthal 1997). Other researchers have studied the relationship between the presence of restrictive rules and the composition of committees since in some versions of the theory more restrictive rules are predicted to be associated with committee specializations, heterogeneity of preferences within committees, and less extreme biases (e.g., Sinclair 1994; Dion and Huber 1996; Krehbiel 1997a; 1997b). None of these attempts, however, directly examine the *behavioral implications* of the informational theory. What makes it difficult to directly test the theory is that behavior can be properly evaluated only with knowledge of individuals' private information: field data are typically not sufficiently rich nor even available.

The lack of direct behavioral evidence is problematic. First, existing empirical findings present conflicting evidence, and thus they are not fully conclusive on the validity of the theoretical predictions. Second, 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 committees is whether restrictive rules can facilitate the informational role of the committees. The answer to this question, however, depends on which equilibrium is selected and is therefore unanswerable by theory alone.

In this paper, we make the first experimental 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 propose the informational theory for heterogenous committees, and by Krishna and Morgan (2001), who further develop 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 committee members with heterogeneous preferences observe the state and each send a recommendation or a potentially binding proposal to the legislature. Committee members have biases of the same magnitude but of opposite signs: relative to the legislature's ideal policy, one committee prefers a higher policy and the other a lower policy.

Our experiment implements two legislative rules first studied by Gilligan and Krehbiel (1989) for heterogeneous committees. Under the *open rule*, the legislature listens to the committee members' recommendations and is free to choose any policy. Under the *closed rule*, the legislature can only choose between the policy proposed by a committee member and an exogenously given *status quo* policy. The other informed committee member sends a speech that, however, has only an informational role. As a benchmark, we also consider a baseline open rule with one committee member (the homogeneous committee), a case previously studied by Crawford and Sobel (1982) and Gilligan and Krehbiel (1987). For each of these rules, we consider two preference treatments: one in which there is a large misalignment of preferences between the legislature and the committee members (high bias) and one in which there is a small misalignment (low bias).[2]

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

The first prediction of the informational theory that our data speak to is the *outlier principle*, which involves comparisons *within* each legislative rule: under both the open and

[2]Gilligan and Krehbiel study other rules that we do not include in our experiment. For heterogeneous committees, Gilligan and Krehbiel (1989) also consider what they call the modified rule, under which both committee members propose and the legislature chooses between the two proposals and a given *status quo*; for homogeneous committees, Gilligan and Krehbiel (1987) consider a closed-rule model in which there is only one committee member without a speech-making right by a second member. Given that to study each rule we need several treatments (on alternative bias levels and subject-matching protocols), we have chosen to focus only on the open and the closed rules for heterogeneous committees and on the open rule for the homogeneous committee.

the closed rules, more extreme preferences of the committee members reduce the extent of information transmission. While this principle appears intuitive and has been highlighted in the literature (Krehbiel 1991), it is controversial from a theoretical point of view. The existence of equilibria featuring the outlier principle is first proved by Gilligan and Krehbiel (1989). With different selections of equilibria, Krishna and Morgan (2001) show that more informative equilibria exist: for the open rule, they construct a fully revealing equilibrium under which the outlier principle does not hold. Our data support Gilligan and Krehbiel (1989): under both legislative rules, we find that an increase in the committee members' biases results in a statistically significant decrease in the legislature's payoff.

The second set of predictions that our data speak to involves comparisons *between* the legislative rules, what we may call the *restrictive-rule principle* and the *distributional principle*. Gilligan and Krehbiel (1989) define two measures of inefficiency: *informational inefficiency*, which is measured by the residual variance in the equilibrium outcome, and the *distributional inefficiency*, which is measured by the divergence between the expected outcome and the legislature's ideal policy.[3] A key finding in Gilligan and Krehbiel (1989) is that, compared to the open rule, the closed rule is more informationally efficient (the restrictive-rule principle) but less distributionally efficient (the distributional principle). Krishna and Morgan (2001) have questioned this finding too, highlighting that these results are not a feature of all equilibria: there exists at least one 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 achieve the maximal possible distributional efficiency. Our experimental evidence clearly supports Gilligan and Krehbiel's (1989) distributional principle. Regarding the restrictive-rule principle, however, we do not find evidence that the closed rule is more informationally efficient than the open rule. Overall,

[3]Gilligan and Krehbiel (1989) adopt a slightly different terminology for distributional (in)efficiency: a rule that in our terminology is more distributionally efficient is a rule that in their terminology has a better distributive consequence.

we find that the distributional principle dominates the restrictive-rule principle and so the legislature's payoff is higher under the open rule than under the closed rule.

It is intuitive to expect that with multiple informed committee members sending recommendations to the legislature, we should obtain more informed decisions since increasing the number of experts should not hurt even if they are biased: a conjecture that we call the *heterogeneity principle*. This property is, however, not supported by our data: for both levels of bias, we do not find any statistically significant difference in the legislature's welfare between the open rule with two members and that with one member. This surprising result is due to an interesting behavioral phenomenon that has not been previously documented and that we call the *confusion effect*. In an open rule scenario with one committee member, when the legislature receives the recommendation, the recommendation tends to be followed. Since a committee member'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. In an open rule scenario with two committee members, when the legislature receives two conflicting recommendations, the legislature tends to "freeze" and ignore both of them. This leads to situations in which the policy incorporates no information about the environment. This phenomenon is indeed consistent with the way Gilligan and Krehbiel (1987) construct out-of-equilibrium behavior, but it goes well beyond explaining how beliefs are constructed out of equilibrium since it seems prevalent on the equilibrium path.

Section 2 reviews the literature. In Section 3, we present the theoretical framework and discuss the main predictions of the informational theory. In Section 4, we describe the experimental design and procedures. We report findings from our main experimental treatments in Section 5. Section 6 covers the robustness treatments. Section 7 concludes.

2 Literature Review

In the literature on legislative committees, we can distinguish four leading theories: the informational theory, the distributive theory, the majority-party cartel theory, and the bicameral rivalry theory.[4] The informational theory sees committees as institutional arrangements through which information is aggregated either within committees in a unidimensional policy environment (Gilligan and Krehbiel 1987; 1989; Krishna and Morgan 2001), which is the environment we consider, or from different committees in a multidimensional policy environment (Battaglini 2002; 2004). The distributive theory instead sees legislative committees as an institutional tool for the allocation of resources in congress (e.g., Weingast and Marshall 1988; Shepsle and Weingast 1995). Redistribution often requires commitment in order to maintain "promises"; allocating powerful positions in a committee is a way to assure such commitment power and make promises in bargaining credible. In the majority-party theory, legislative committees are an institutional tool through which party leadership imposes discipline: appointments of party loyalists to committees are not only a way for parties to control the legislative agenda, but also a reward system to promote congressmen who are orthodox to the party line (e.g., Cox and McCubbins 1993). Finally, in the bicameral rival theory, committees help to protect congress from outside influences through generating "hurdles" that make it difficult for outsiders to maneuver a bill through the legislature by buying off legislators' consent with campaign contributions or bribes (e.g., Diermeier and Myerson 1999).

A significant empirical literature has been devoted to comparing these theories. Our work differs from previous work in two ways. First, previous research has focused on comparing different theories of very different natures, such as the informational and the distributive. In our work, we focus on the informational theory. We test the predictions of

[4]See Groseclose and King (2001), from whom we are taking this classification, for an in-depth recent discussion of these theories.

Gilligan and Krehbiel (1989) and compare its insights with subsequent work focusing on how information aggregation occurs in the U.S. Congress. Second, as mentioned above, previous works testing the informational theory do not aim at directly studying the behavioral implications of the theory, rather, at testing indirect hypotheses. To our knowledge, our paper is the first experimental test of Gilligan and Krehbiel (1989) and more generally of models of communication comparing the open and the closed rules.

Our study also contributes to the experimental literature on cheap-talk games. The focus of this literature has been on games with one sender and one receiver communicating in a unidimensional environment. 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), and Wang, Spezio, and Camerer (2010). Besides their focus on the one-sender environments, these experiments also differ from ours in that they do not study how communication changes between the open and the closed rules. A common finding of this literature is overcommunication, in which the observed communication is more informative than is predicted by the most informative equilibria of the underlying game. We also observe overcommunication in our one-sender benchmark treatments, and the observation affects our evaluation of the heterogeneity principle.

A handful of recent studies depart from the one-sender-one-receiver environment. Motivated by Battaglini (2002), Lai, Lim, and Wang (2015) and Vespa and Wilson (2016) experiment on two-sender games with multidimensional state spaces. In contrast to our negative finding on the heterogeneity principle, Lai, Lim, and Wang (2015) find in a simple multidimensional setting that receivers make more informed decisions with two senders than with one. Vespa and Wilson (2016) find that senders exaggerate in the direction of their biases, a feature that is also observed in our data. Since the logic of multidimensional cheap-talk games is very different from the logic of their unidimensional counterparts, the findings in these papers are otherwise not directly comparable to ours. Moreover, these studies do not study how communication is affected by the different legislative rules, which is the main focus of our paper.

The two-sender game studied by Minozzi and Woon (2016), which also features a unidimensional state space, is perhaps closest to our environment. They obtain evidence that receivers average senders' exaggerating messages, a finding that is also obtained by us. Their setting differs from ours in that there is an additional dimension of private information about the senders' biases. Most importantly, as with the papers discussed above, Minozzi and Woon (2016) also do not study how communication changes with different legislative rules.[5]

3 The Model

3.1 The Set-Up

We sketch the model on which our experimental design is based. 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 (informed committee members), Sender 1 (S_1) and Sender 2 (S_2), and a receiver (the median voter of a legislature). The two senders each send a message (a recommendation or a potentially binding proposal) to the receiver. Based on the messages, the receiver (R) determines the action (the policy) to be adopted, $a \in A \subseteq \mathbb{R}$. The senders privately observe the state of the world, θ, commonly known to be uniformly

[5] Battaglini and Makarov (2014) depart from the one-sender-one-receiver environment by experimenting on games with one sender and two receivers.

distributed on $\Theta = [0, 1]$. 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.[6] Sender i's ideal action is $a_i^*(\theta) = \theta + b_i$, while the receiver's ideal action is $a^*(\theta) = \theta$; 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 reveals θ to both senders. Second, the two senders send messages to the receiver independently and simultaneously. Third, the receiver chooses an action.

The set of available actions for the receiver varies under different legislative rules. Two rules 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. Under the open rule, the receiver is free to choose any action $a \in A$ after receiving the messages, which are recommendations. Under 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; the receiver's choice is therefore restricted by Sender 1's message, a binding proposal in case the *status quo* is not chosen, while Sender 2's message remains a recommendation or a pure informational speech. As a benchmark, we also consider the model of a *homogeneous committee*, a case of the open rule with one sender. This is equivalent to the cheap-talk model of Crawford and Sobel (1982) and, in the context of legislative rules, the model of Gilligan and Krehbiel (1987).

[6]Our set-up is slightly different from that in Gilligan and Krehbiel (1989) (e.g., 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 otherwise theoretically equivalent set-up as we view it as providing a more intuitive experimental environment for subjects.

3.2 Equilibrium Predictions

Two papers that have studied the perfect Bayesian equilibria (hereafter equilibria) of the game specified above are Gilligan and Krehbiel (1989), who present the pioneering analysis, and Krishna and Morgan (2001), who present an alternative analysis based on different selections of equilibria. The informative equilibria characterized in the two papers commonly bring out some interesting features of the legislative rules. At the same time, the equilibria selected by Krishna and Morgan (2001) have different informational properties from those of Gilligan and Krehbiel (1989). Their equilibria, therefore, not only serve as the theoretical benchmark of our experiment but also provide an important motivation for our study, which is to assess the empirical validity of the different equilibrium characterizations.[7]

The equilibrium predictions can be divided into two groups. The first group covers the basic insights of the informational theory, which are common to the equilibria in both papers. The first result in this group is the *outlier principle*:

Result 1. *In both Gilligan and Krehbiel (1989) and Krishna and Morgan (2001), the receiver's equilibrium expected payoff is non-increasing in the bias b:*

(a) under the open rule, the receiver's payoff is strictly decreasing in $b \in \left(0, \frac{1}{4}\right]$ *in Gilligan and Krehbiel (1989) and is constant for* $b \in \left(0, \frac{1}{4}\right]$ *in Krishna and Morgan (2001); and*

(b) under the closed rule, the receiver's payoff is strictly decreasing in $b \in \left(0, \frac{1}{4}\right]$ *in both Gilligan and Krehbiel (1989) and Krishna and Morgan (2001).*

Table 1 summarizes the equilibrium expected payoffs under the two legislative rules for $b \in (0, \frac{1}{4}]$. The central question of the informational theory is how much information can

[7] To our knowledge, no other equilibria have been characterized for this game since Gilligan and Krehbiel (1989) and Krishna and Morgan (2001). Given this, studying the empirical validity of the equilibria in these papers seems both natural and a necessary first step.

Table 1: Equilibrium Expected Payoffs for $b \in (0, \frac{1}{4}]$

<table>
<tr><th></th><th colspan="4">Heterogeneous Committee</th><th>Homogeneous Committee</th></tr>
<tr><th></th><th colspan="2">Gilligan and Krehbiel (1989)</th><th colspan="2">Krishna and Morgan (2001)</th><th>Crawford and Sobel (1982)/ Gilligan and Krehbiel (1987)</th></tr>
<tr><th></th><th>Open Rule</th><th>Closed Rule</th><th>Open Rule</th><th>Closed Rule</th><th>Open Rule</th></tr>
<tr><td>R</td><td>$-\frac{16b^3}{3}$</td><td>$-\frac{16b^3}{3} - b^2(1-8b)$</td><td>$0$</td><td>$-\frac{4b^3}{3}$</td><td>$-\frac{1}{12N(b)^2} - \frac{b^2[N(b)^2-1]}{3}$</td></tr>
<tr><td>S_1</td><td rowspan="2">$-\frac{16b^3}{3} - b^2$</td><td>$-\frac{16b^3}{3}$</td><td rowspan="2">$-b^2$</td><td rowspan="2">$-\frac{4b^3}{3} - b^2$</td><td rowspan="2">$-\frac{1}{12N(b)^2} - \frac{b^2[N(b)^2+2]}{3}$</td></tr>
<tr><td>S_2</td><td>$-\frac{16b^3}{3} - 4b^2(1-4b)$</td></tr>
</table>

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

be transmitted under different legislative rules. Given that information is transmitted from the informed senders to the uninformed receiver, the receiver's payoff provides the relevant yardstick and welfare criterion to gauge information transmission outcomes.[8] Krishna and Morgan (2001) construct a fully revealing equilibrium under the open rule, in which the receiver's payoff is at the maximal possible level of zero and is therefore independent of b. In all the other cases, information transmission is imperfect, and the receiver's payoff varies with b.

Another result common to the equilibria in both papers is the *heterogeneity principle*: the presence of multiple senders with heterogeneous preferences allows the receiver to extract more information. In online Appendix A, we prove:

Result 2. *For $b \in (0, \frac{1}{4})$, compared to the case where there is only one sender under the open rule, the receiver is strictly 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).*

The second group of predictions reveals the divergence between Gilligan and Krehbiel

[8]We nevertheless note that the comparative statics in Result 1 (and in the upcoming Result 2) applies to the senders as well. For reference and comparison, Table 1 also includes the senders' expected payoffs and the payoffs in the case of a homogeneous committee.

(1989) and Krishna and Morgan (2001), which originate from different equilibrium selections, an issue that will be further discussed below. Here, we present the welfare implications of the different equilibria. Following Gilligan and Krehbiel (1989), we decompose the receiver's expected payoff into two components:

$$EU^R = -\underbrace{\mathrm{Var}(X(\theta))}_{informational} - \underbrace{(EX(\theta))^2}_{distributional}, \tag{2}$$

where $X(\theta) = a(\theta) - \theta$ is said to be the equilibrium outcome function.

The decomposition elucidates the comparisons of welfare by disentangling any welfare difference into differences in two measures of (in)efficiency. The first component, $\mathrm{Var}(X(\theta))$, represents *informational inefficiency*, which is the residual volatility in the equilibrium outcome. It measures information loss caused by the strategic revelation of information and is a loss shared by all three players. The second component, $(EX(\theta))^2$, represents *distributional inefficiency*, which measures the systematic deviation of the chosen action from the receiver's ideal. It is a zero-sum loss to the receiver that is distributed as gains to the senders given their different ideal actions. Note that if the receiver observed the state, both inefficiencies would be zero, which is the most efficient case; the negative variance and squared expectation are interpreted accordingly as informational and distributional *efficiencies*, where a less negative number represents a higher level of efficiency.

Gilligan and Krehbiel (1989) is the first to study the impacts of the legislative rules on informational and distributional efficiencies for heterogenous committees.[9] Their equilibrium analysis leads to the *restrictive-rule principle* and the *distributional principle*. We summarize these two principles together with a comparative statics on how the two efficiencies change with respect to $b \in (0, \frac{1}{4}]$:

Result 3. *In Gilligan and Krehbiel (1989), informational efficiency is greater under the*

[9]The corresponding analysis for homogenous committees is conducted by Gilligan and Krehbiel (1987).

closed rule than under the open rule (the restrictive-rule principle). Furthermore, the efficiency is decreasing in $b \in (0, \frac{1}{4}]$ under both rules. Distributional efficiency, on the contrary, is greater under the open rule than under the closed rule (the distributional principle): under the open rule $(EX(\theta))^2 = 0$ for all $b \in (0, \frac{1}{4}]$, while under the closed rule $(EX(\theta))^2$ is positive and increasing in $b \in (0, \frac{1}{4}]$

Based on a different equilibrium selection, in which the most informative outcome that can be supported by equilibrium behavior is selected for the two legislative rules, Krishna and Morgan (2001) obtain a different welfare conclusion:

Result 4. *In Krishna and Morgan (2001), informational efficiency is greater under the open rule than under the closed rule: under the open rule, full information revelation is possible for all $b \in (0, \frac{1}{4}]$, while even the most informative equilibrium under the closed rule is informationally inefficient. Distributional efficiency is the same under the open and the closed rules: in both cases $(EX(\theta))^2 = 0$ for $b \in (0, \frac{1}{4}]$.*

Table 2 exemplifies Results 3 and 4 by reporting the predicted values of $-\mathrm{Var}(X(\theta))$, $-\left(EX\left(\theta\right)\right)^2$, and the receiver's expected payoff for $b = 0.1$ and $b = 0.2$, the two bias levels we used in the experiment. It is useful to observe that, regardless of the equilibrium characterization or bias level, there is no distributional inefficiency under the open rule, as the receiver always chooses her optimal action given the information. Note also that with a fully revealing equilibrium constructed for the open rule, Krishna and Morgan (2001) predict that the receiver's expected payoff is higher under the open rule for both levels of bias. Gilligan and Krehbiel (1989), on the other hand, predict that the open rule yields a higher receiver's payoff only when the bias is low. These qualitative differences fuel the comparative statics for evaluating our experimental findings.

We turn to review the key difference in the equilibrium constructions of the two papers,

Table 2: Predicted Efficiencies and Receiver's Expected Payoff

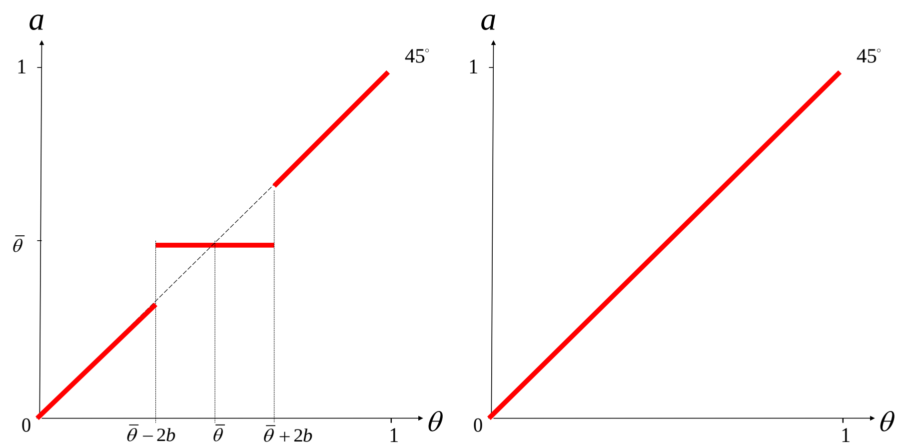
Theory	Informational Efficiency $-\text{Var}(X(\theta))$	Distributional Efficiency $-(EX(\theta))^2$	Receiver's Expected Payoff	Informational Efficiency $-\text{Var}(X(\theta))$	Distributional Efficiency $-(EX(\theta))^2$	Receiver's Expected Payoff
	$b = 0.1$					
	Open Rule			Closed Rule		
GK (1989)	-53.33×10^{-4}	0	-53.33×10^{-4}	-37.33×10^{-4}	-36.00×10^{-4}	-73.33×10^{-4}
KM (2001)	0	0	0	-13.33×10^{-4}	0	-13.33×10^{-4}
	$b = 0.2$					
	Open Rule			Closed Rule		
GK (1989)	-426.67×10^{-4}	0	-426.67×10^{-4}	-170.67×10^{-4}	-16.00×10^{-4}	-186.67×10^{-4}
KM (2001)	0	0	0	-106.67×10^{-4}	0	-106.67×10^{-4}

Note: GK (1989) and KM (2001) stand for, respectively, Gilligan and Krehbiel (1989) and Krishna and Morgan (2001). Informational and distributional *efficiencies* are measured by, respectively, the negative numbers $-\text{Var}(X(\theta))$ and $-(EX(\theta))^2$. The corresponding *inefficiencies* are thus measured by the absolute magnitudes of the variances and the squared expectations.

which leads to the contrasting welfare conclusions.[10] Consider first the open rule. If the senders' messages agree, the receiver infers that both senders are telling the truth and adopts her corresponding ideal action; when the messages disagree, beliefs cannot be derived by Bayes' rule, and an arbitrary out-of-equilibrium belief has to be assigned. This is where the two papers differ.

Gilligan and Krehbiel (1989) choose a particularly simple out-of-equilibrium belief: they essentially assume that the disagreeing messages convey no information. Consequently, the receiver's optimal action following message disagreements is her *ex-ante* optimal action under the uniform prior, $\frac{1}{2}$, which is independent of the messages. The "threat" of this action is sufficient to induce the senders to reveal the state when it is sufficiently low ($\theta \leqslant \overline{\theta} - 2b$) or sufficiently high ($\theta \geqslant \overline{\theta} + 2b$). When instead $\theta \in \left(\overline{\theta} - 2b, \overline{\theta} + 2b\right)$, no information is revealed, and the action is constant at $\frac{1}{2}$. This equilibrium construction is illustrated in Figure 1(a).

[10]See also Krehbiel (2001) for a discussion. Readers who are not interested in a theoretical discussion of the differences between the two equilibrium constructions can skip the reminder of this section in the first reading.



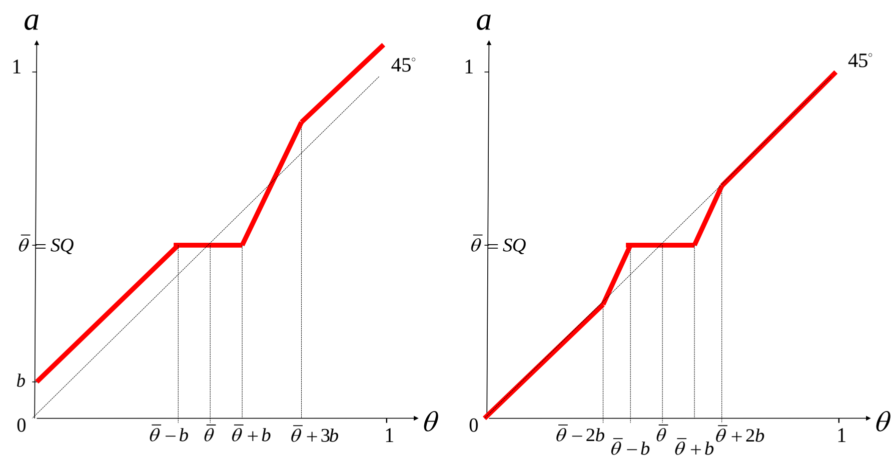
(a) Gilligan and Krehbiel (1989) (b) Krishna and Morgan (2001)

Figure 1: Equilibrium Action under Open Rule

Krishna and Morgan (2001) exploit the freedom in choosing out-of-equilibrium beliefs, designing a mechanism that optimally punishes deviations. The more complex specification, in which out-of-equilibrium actions are now functions of the disagreeing messages, allows them to construct a fully revealing equilibrium, which is illustrated in Figure 1(b).

Consider next the closed rule. If the senders' messages agree with each other, the receiver follows Sender 1's message, the proposed bill. Otherwise, the bill is rejected in favor of the *status quo* action. Accordingly, different specifications of out-of-equilibrium beliefs have no impact on actions in the case of disagreements. The consequential difference between Gilligan and Krehbiel (1989) and Krishna and Morgan (2001) lies in what they consider to be agreements.

Gilligan and Krehbiel (1989) define an agreement to exist when Sender 1's and Sender 2's messages differ by b, i.e., when $m_1 - m_2 = b$. Based on this definition, they construct an equilibrium in which Sender 1 manages to exploit his proposing power to impress a bias on the equilibrium outcome so that $(EX(\theta))^2 > 0$. While Sender 1 proposes his ideal action for a large number of states, there also exists a range, $\left(\overline{\theta} + b, \overline{\theta} + 3b\right)$, for which Sender 1 proposes a "compromise bill." From Sender 1's perspective, the threat of



(a) Gilligan and Krehbiel (1989) (b) Krishna and Morgan (2001)

Figure 2: Equilibrium Action under Closed Rule

disagreement from Sender 2 is particularly strong for $\theta \in \left(\bar{\theta} + b, \bar{\theta} + 3b\right)$. For these states, Sender 1 compromises, i.e., not proposing his ideal action, in order to make Sender 2 indifferent between his proposed bill and the *status quo*. Sender 2 supports the bill under the indifference, and the receiver adopts the bill accordingly. This equilibrium construction is illustrated in Figure 2(a).

Krishna and Morgan's (2001) definition of agreement requires the two messages to completely coincide, i.e., $m_1 - m_2 = 0$. Based on this definition, they construct an equilibrium where Sender 1 cannot impress a bias on the outcome so that $(EX(\theta))^2 = 0$, which is also the case under the fully revealing equilibrium they construct for the open rule. They also show that no closed-rule equilibrium can achieve full revelation. Compromise bills are also a feature of their equilibrium, but they are proposed by Sender 1 for two disconnected, symmetric ranges of states, $\left(\bar{\theta} - 2b, \bar{\theta} - b\right)$ and $\left(\bar{\theta} + b, \bar{\theta} + 2b\right)$. This equilibrium construction is illustrated in Figure 2(b).

4 Experimental Design and Procedures

We designed a laboratory environment that is faithful to the theoretical environment, subject to limitations imposed by the experimental software z-Tree (Fischbacher 2007). We implemented the state, the message, and the action spaces with intervals $[0.00, 100.00]$ that contained numbers with two-decimal digits.[11] Subjects' preferences were induced to capture the incentives of the quadratic payoffs in (1).

There were six main treatments, which are summarized in Table 3. We implemented two bias levels, $b = 10$ ($b = 0.1$ in the model) and $b = 20$ ($b = 0.2$ in the model) for each of the following legislative rules: the open rule with two senders, the closed rule with two senders, and the open rule with one sender.[12] The bias levels were chosen so that they provided reasonable variation within the realm of the theoretical predictions. A random-matching protocol was used in the main treatments. The senders in the main treatments sent messages that were points in the message spaces. We also conducted robustness treatments that used fixed matchings or interval messages.[13] A between-subject design was used in all treatments.

The experiment was conducted in English at The Hong Kong University of Science and Technology. A total of 320 subjects participated in the main treatments and 233 in the robustness treatments. Subjects had no prior experience in our experiment and were recruited from the undergraduate population of the university. Upon arriving at the

[11] One difference between our design and the model is that the action space in our design coincides with the state space. The bounded action space slightly changes the theoretical predictions of Gilligan and Krehbiel (1989). For example, in Figure 2(a), the equilibrium action under the closed-rule becomes flat when it reaches the upper bound.

[12] Our focus is on the two-sender cases. The open-rule-one-sender treatments were included only as a benchmark. The case of closed rule with one sender is first analyzed by Gilligan and Krehbiel (1987), who allow for an information-acquisition decision by the sender not modeled in the current environment.

[13] The distinction between point messages and interval messages is for the closed-rule treatments. In the original closed-rule setup of Gilligan and Krehbiel (1989), Sender 2 makes a speech in the form of "the state is in $[a, b]$." To maintain design consistency with the open-rule treatments, we adopted point messages for the closed-rule main treatments and explored the interval messages as robustness treatments.

Table 3: Main Treatments – Random Matching and Point Message

	Two Senders (Heterogeneous Committees)	Single Sender (Homogeneous Committee)
Open Rule	*O-2* 2 Treatments: $b = 10, 20$ Each Treatment: 4 Sessions Each Session: 5 Random Groups of 3 No. of Subjects: $2 \times 4 \times 5 \times 3 = 120$	*O-1* 2 Treatments: $b = 10, 20$ Each Treatment: 2 Sessions Each Session: 2 Matching Divisions Each Matching Division: 5 Random Groups of 2 No. of Subjects: $2 \times 2 \times 2 \times 5 \times 2 = 80$
Closed Rule	*C-2* 2 Treatments: $b = 10, 20$ Each Treatment: 4 Sessions Each Session: 5 Random Groups of 3 No. of Subjects: $2 \times 4 \times 5 \times 3 = 120$	

laboratory, subjects were instructed to sit at separate computer terminals. Each received a copy of the experimental instructions. The instructions were read aloud using slide illustrations as an aid. In each session, subjects first participated in one practice round and then 30 official rounds.

We illustrate the instructions for treatment *O-2* with $b = 20$.[14] At the beginning of each session, one third of the subjects were randomly assigned as Member A (Sender 1), one third as Member B (Sender 2), and one third as Member C (the receiver). These roles remained fixed throughout the session. Subjects 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 $[0.00, 100.00]$. This state variable was revealed (only) to Members A and B. Both members were presented with a line on their screen. The line extended from -20 (i.e., $0-b$)

[14] The full instructions for *O-2* with $b = 20$ can be found in online Appendix C, which also contains the instructions for *C-2* with $b = 20$.

to 120 (i.e., $100 + b$). The state variable was displayed as a green ball on the line. Also displayed was a blue ball, which indicated the member's ideal action.[15]

Members A and B then each sent a message to the paired Member C. The decisions were framed as asking them to report to Member C the state variable. 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 was displayed on the line, which indicated the chosen message. The members could adjust their clicks, and the finalized messages were then displayed simultaneously on a similar line on Member C's screen as a green (Member A's message) and a white (Member B's message) balls. Member C then chose an action in two decimal places from the interval $[0.00, 100.00]$ by clicking on the line, where a red ball was displayed indicating the action. Member C could adjust the action until the desired choice was made.

A round was concluded by Member C's input of the action choice, after which a summary for the round was 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 earnings 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 an exchange rate of 10 ECU = 1 HKD.[16] A session lasted for about one and a half hours. Subjects on average earned, counting both the main and the robustness treatments, HKD$123.2 (≈US$15.8) including a show-up fee.

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

[16] The number of ECU a subject earned in a round was determined by a reward formula that induced quadratic preferences. Refer to the sample instructions in online Appendix C for details.

5 Experimental Findings: Main Treatments

In Section 5.1, we report the observed information transmission outcomes *separately* for the open-rule and the closed-rule main treatments with two senders (*O-2* and *C-2*). The outcomes are evaluated by the correlations between state and action, the receivers' payoffs, and the two measures of efficiencies. In Section 5.2, we *compare* the receivers' payoffs and the efficiencies under the two legislative rules. We also bring in the findings from the one-sender treatments (*O-1*) for comparison. In Section 5.3, we analyze the behavior of sender-subjects and receiver-subjects in treatments *O-2* and *C-2*.

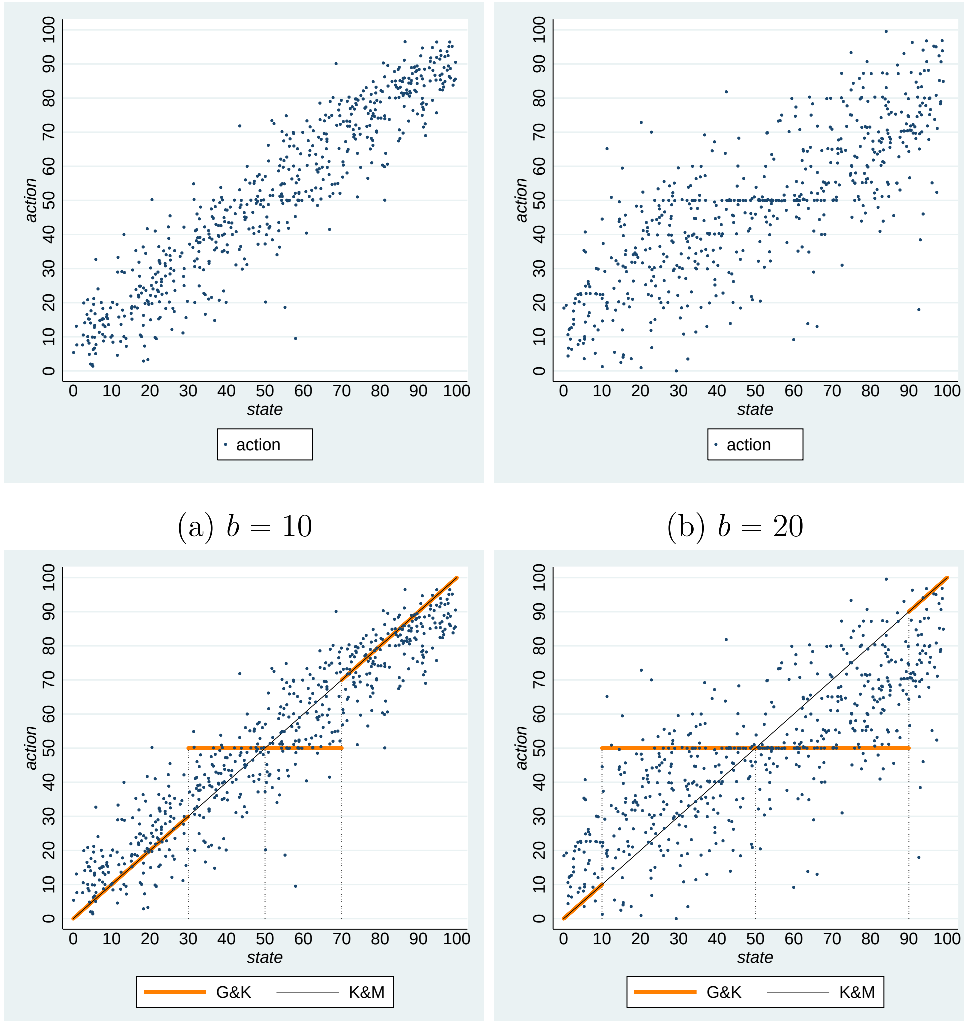
5.1 Information Transmission Outcomes: Open Rule and Closed Rule with Two Senders

Treatments O-2. Figure 3 presents the relationships between realized states and chosen actions in the open-rule treatments with two senders, *O-2*.[17] Two features of the data are apparent. First, there are positive correlations between state and action, which indicate that information is transmitted as predicted by the equilibria in both papers. Second, there is, especially for $b = 20$, a range of intermediate states around 50 for which the pooling action 50 is chosen, which is reminiscent of Gilligan and Krehbiel's (1989) equilibrium.

Table 4 reports estimation results from random-effects GLS models, which provide formal evaluations of these observations.[18] Gilligan and Krehbiel's (1989) equilibrium predicts

[17] Figures 3(a)–(b) present the data points for, respectively, the treatments of $b = 10$ and $b = 20$. For ease of comparison with the theoretical predictions, Figures 3(c)–(d) include the equilibrium relationships between state and action as predicted by Gilligan and Krehbiel (1989) (G&K) and Krishna and Morgan (2001) (K&M). The upcoming Figure 4 follows a similar presentation format.

[18] We employ two major empirical strategies to analyze different variables. For the relationships between state and action, we use subject-level data. For each of the treatments *O-2* and *C-2*, a total of 20 decision groups (20 subjects of each role) participated in 30 rounds of decisions, which translate into a panel data set of 600 observations. Since the decisions made by a subject over the 30 rounds are likely to be correlated, we use random-effects regressions to account for the repeated observations at the subject level (our between-subject treatment design makes random effects more appropriate than fixed effects). "GLS" refers to



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

(c) $b = 10$ (with Predictions) (d) $b = 20$ (with Predictions)

Figure 3: Relationship between State and Action: Treatments *O-2*

that the correlation between state and action decreases from $\frac{3\sqrt{65}}{25} = 0.9674$ for $b = 10$ to $\frac{\sqrt{61}}{5\sqrt{5}} = 0.6985$ for $b = 20$. The fully revealing equilibrium of Krishna and Morgan (2001) predicts, on the other hand, that the correlation is invariant to changes in bias and equal to one. While the observed positive correlations are broadly in line with both predictions, the estimated coefficients reported in columns (1) and (3) of Table 4, in which we regress a on θ,

"feasible generalized least squares," which employs estimated covariance matrix (using the OLS residuals) to account for observations with unequal variance and/or correlation. For payoffs and efficiency measures, in which our interest is in the comparative statics, we use session-level data and perform non-parametric tests.

Table 4: Random-Effects GLS Regression: Treatments *O-2*

	$b = 10$		$b = 20$	
	(1)	(2)	(3)	(4)
Constant	7.282***	7.333***	18.21***	14.63***
	(0.807)	(0.904)	(1.157)	(2.054)
θ	0.851***	0.851***	0.598***	0.655***
	(0.0127)	(0.0132)	(0.0192)	(0.0293)
pooling_interval	–	−0.501	–	5.783*
	–	(2.645)	–	(2.463)
$\theta \times$ *pooling_interval*	–	0.0091	–	−0.0988*
	–	(0.0504)	–	(0.0386)
No. of Observations	600	600	600	600

Note: The dependent variable is action a. *pooling_interval* is a dummy variable for $\theta \in [50 - 2b, 50 + 2b]$. Standard errors are in parentheses. *** indicates significance at 0.1% level, ** significance at 1% level, and * significance at 5% level.

indicate that our data are more qualitatively consistent with Gilligan and Krehbiel (1989). Echoing the comparative statics, the coefficients decrease from 0.851 for $b = 10$ to 0.598 for $b = 20$ with non-overlapping 95% confidence intervals $[0.826, 0.876]$ and $[0.560, 0.635]$.

We further examine our data in light of a distinguishing feature of Gilligan and Krehbiel's (1989) equilibrium: the existence of a "pooling interval," $[50 - 2b, 50 + 2b]$, for which action 50 is chosen. Given the values of biases in our treatments, this generates the following prediction: the range of θ for which $a = 50$ is chosen extends from $[30, 70]$ for $b = 10$ to $[10, 90]$ for $b = 20$. In line with the comparative statics, Figures 3(a)–(b) reveal that there is a stronger cluster of actions at 50 for $b = 20$ than for $b = 10$; quantitatively, the frequencies of actions in $[49.5, 50.5]$ are 4% for $b = 10$ and 10.67% for $b = 20$. Apart from the comparative statics, these frequencies themselves provide supplementary evidence for the pooling intervals. As a benchmark for comparison, the observed frequencies of states in $[49.5, 50.5]$ are 1.17% for $b = 10$ and 0.5% for $b = 20$. Comparing the two sets of frequencies suggests that disproportionately many actions chosen in a close neighborhood of

50 are chosen when the state is not close to 50.

Columns (2) and (4) of Table 4 report estimation results from an extended regression model, in which we include a dummy variable for states in $[50-2b, 50+2b]$ ($pooling\_interval$) and an interaction term ($\theta \times pooling\_interval$). For $b = 20$, the statistically significant coefficient of $pooling\_interval$ is 5.783 and that of $\theta \times pooling\_interval$ is -0.0988. Taken together, the positive and the negative signed coefficients indicate that the fitted line for states in $[50 - 2b, 50 + 2b]$ has a greater intercept and a smaller slope compared to the fitted line for all states. This provides further evidence that the behavior for states in $[50 - 2b, 50 + 2b]$ is qualitatively different from the rest in the direction predicted by Gilligan and Krehbiel (1989). No statistically significant coefficients are obtained for $b = 10$.

We summarize these findings:

Finding 1. *In treatments O-2, receivers' actions are positively correlated with the state. The correlation decreases as the bias level increases, as predicted by Gilligan and Krehbiel's (1989) equilibrium. Further in line with Gilligan and Krehbiel (1989), there is evidence of pooling action chosen for a range of intermediate states around 50, especially for* $b = 20$.

Informational efficiency and receivers' payoffs allow us to further differentiate the two papers in terms of their different comparative statics regarding the outlier principle.[19] Gilligan and Krehbiel (1989) predict that a higher bias translates into a higher variance in the equilibrium outcome, i.e., a drop in informational efficiency, and, with no change in distributional efficiency, a lower receiver's payoff. On the other hand, Krishna and Morgan's (2001) fully revealing equilibrium predicts that informational efficiency does not change with the bias.

[19]Both predict that distributional efficiency does not change for the levels of bias we consider.

Table 5: Observed Efficiencies and Receivers' Payoffs

Session / Matching Group	Inform. Efficiency $-\mathrm{Var}(X(\theta))$	Distrib. Efficiency $-(EX(\theta))^2$	Receivers' Payoffs	Inform. Efficiency $-\mathrm{Var}(X(\theta))$	Distrib. Efficiency $-(EX(\theta))^2$	Receivers' Payoffs	Inform. Efficiency $-\mathrm{Var}(X(\theta))$	Distrib. Efficiency $-(EX(\theta))^2$	Receivers' Payoffs
					$b = 10$				
		O-2			*C-2*			*O-1*	
1	−100.80	−0.03	−100.83	−95.31	−54.37	−149.68	−82.61	−5.50	−88.10
2	−121.40	−0.58	−121.97	−55.62	−38.54	−94.16	−131.35	−17.30	−148.65
3	−70.41	−1.02	−71.43	−88.63	−47.84	−136.46	−205.85	−1.15	−207.00
4	−80.89	−2.56	−83.45	−109.36	−35.07	−144.43	−78.58	−14.14	−92.73
Mean	−93.37	−1.05	−94.42	−87.23	−43.95	−131.18	−124.60	−9.52	−134.12
					$b = 20$				
		O-2			*C-2*			*O-1*	
1	−280.71	−5.18	−285.89	−339.51	−49.16	−388.67	−335.38	−10.50	−345.43
2	−243.57	−8.30	−251.87	−304.11	−73.42	−377.53	−518.19	−7.64	−525.83
3	−398.26	−0.07	−398.33	−331.11	−22.20	−353.31	−334.95	0.00	−334.95
4	−280.55	−12.96	−293.51	−329.26	−25.19	−354.45	−320.90	−5.21	−326.11
Mean	−300.77	−6.63	−307.40	−326.00	−42.49	−368.49	−377.36	−5.84	−383.08

Note: Informational and distributional *efficiencies* are measured by, respectively, the negative numbers $-\mathrm{Var}(X(\theta))$ and $-(EX(\theta))^2$. The corresponding *inefficiencies* are thus measured by the absolute magnitudes of the variances and the squared expectations. Receivers' payoffs are calculated as $[-\mathrm{Var}(X(\theta)) - (EX(\theta))^2]$.

The first set of columns in Table 5 reports the observed efficiencies and receivers' payoffs in treatments *O-2*. The data support Gilligan and Krehbiel's (1989) comparative statics. An increase in the bias from $b = 10$ to $b = 20$ significantly lowers the informational efficiency: the average $\text{Var}(X(\theta))$, which measures inefficiency, increases from 93.37 to 300.77 ($p = 0.0143$, Mann-Whitney test).[20] It also results in a lower distributional efficiency, although the difference is not significant: the average $(EX(\theta))^2$, which measures inefficiency, increases from 1.05 when $b = 10$ to 6.63 when $b = 20$ ($p = 0.1$, Mann-Whitney test). Finally, the average receivers' payoff, which is calculated as $[-\text{Var}(X(\theta)) - (EX(\theta))^2]$, is significantly lower when the bias is higher: the average payoff decreases from -94.92 when $b = 10$ to -307.4 when $b = 20$ ($p = 0.0143$, Mann-Whitney test).[21]

We summarize these findings:

Finding 2. *In treatments O-2, an increase in the bias from* $b = 10$ *to* $b = 20$ *leads to:*

(a) a statistically significant decrease in receivers' average payoff, a finding consistent with Gilligan and Krehbiel (1989) but not with Krishna and Morgan (2001);

(b) a statistically significant decrease in informational efficiency, a finding consistent with Gilligan and Krehbiel (1989) but not with Krishna and Morgan (2001); and

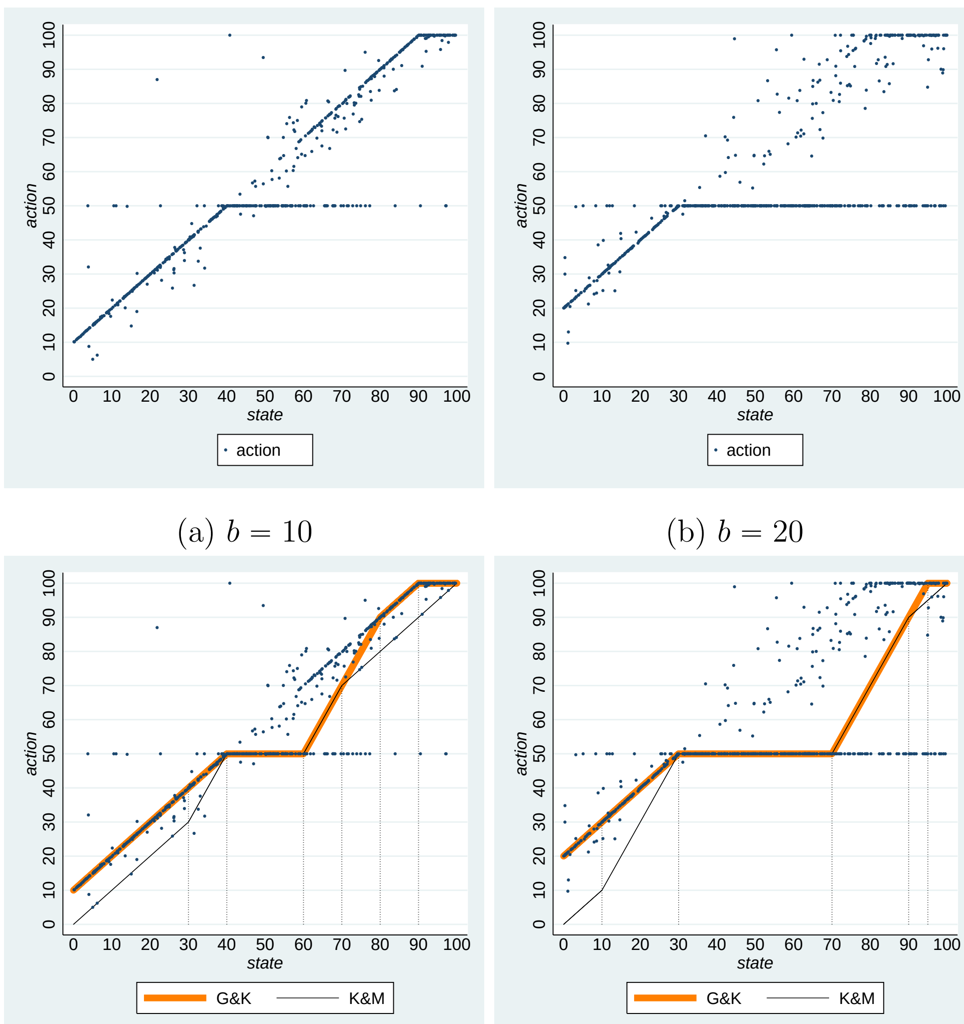
(c) no statistically significant change in distributional efficiency, a finding consistent with both Gilligan and Krehbiel (1989) and Krishna and Morgan (2001).

Treatments C-2. Figure 4 presents the relationships between realized states and chosen actions in the closed-rule treatments, *C-2*. We first note that the observations are less noisy compared to those from *O-2*, which should not be surprising given that under the

[20] Unless otherwise indicated, the p-values reported for non-parametric tests are from one-sided tests.

[21] In reporting receivers' payoffs, we follow the decomposition in (2) by using the observed $[-\text{Var}(X(\theta)) - (EX(\theta))^2]$. In the experiment, in order to provide subjects with proper rewards with minimal chance of zero payments, the actual payoffs are linear transformations of the reported payoffs. Refer to the sample instructions in online Appendix C for details regarding subjects' reward formula.

closed rule receivers have less freedom in their action choices, which are now binary. Three features of the data emerge from the figures. First, as predicted by both Gilligan and Krehbiel (1989) and Krishna and Morgan (2001), the *status quo* action of 50 is chosen for intermediate states. Second, Sender 1's ideal action is chosen for more "extreme" states, which is consistent with Gilligan and Krehbiel (1989). Third, and this is not predicted by either equilibrium, there is evidence of mixing behavior for certain high states.



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

(c) $b = 10$ (with Predictions) (d) $b = 20$ (with Predictions)

Figure 4: Relationship between State and Action: Treatments *C-2*

Both Gilligan and Krehbiel (1989) and Krishna and Morgan (2001) predict that the *status quo* action is chosen for $[50-b, 50+b]$. Out of this range, their predictions start to differ. A distinguishing difference is that, for a sizable set of states outside $[50-b, 50+b]$, Gilligan and Krehbiel (1989) predict that Sender 1's ideal action, $a_1^*(\theta) = \min\{\theta + b, 100\}$, is chosen, whereas Krishna and Morgan (2001) predict that the receiver's ideal action, $a^*(\theta) = \theta$, is instead chosen. For $b = 10$, the frequencies with which the receivers take the *status quo* 50, Sender 1's ideal $a_1^*(\theta) \pm 0.5$, or their own ideal $a^*(\theta) \pm 0.5$ are, respectively, 21.17%, 60.5%, and 3%; for $b = 20$, the corresponding frequencies are 44.33%, 37%, and 2.33%. While the different frequencies of the *status quo* across the bias levels do not differentiate the two equilibria, the drastic differences between the frequencies of Sender 1's ideal action and of the receiver's ideal action clearly support Gilligan and Krehbiel (1989). Note also that the combined frequencies of the *status quo* and Sender 1's ideal action account for more than 80% of the observations.

Distributional efficiency provides another measure that differentiates the two equilibrium characterizations with respect to their predictions on whose ideal action is chosen. Gilligan and Krehbiel (1989) predict that the receiver, who often takes Sender 1's ideal action, bears distributional inefficiency, i.e., $(EX(\theta))^2 > 0$. Krishna and Morgan (2001), on the other hand, predict that $(EX(\theta))^2 = 0$ as the receiver is able to take her ideal action. Table 5 indicates that the observed efficiencies support Gilligan and Krehbiel (1989): the average $(EX(\theta))^2 = 43.95$ for $b = 10$ and $(EX(\theta))^2 = 42.49$ for $b = 20$, which are both significantly greater than 0 ($p = 0.0625$, the lowest possible p-value for four observations from the Wilcoxon signed-rank tests).

Comparing Figures 4(a) with 4(c) and 4(b) with 4(d) further reveals that actions are chosen for the "right" states as predicted by Gilligan and Krehbiel (1989). Deviations from the prediction occur, however, for states in $[60, 80]$ for $b = 10$ and for states in $[75, 100]$ for $b = 20$. In both cases, mixing behavior is observed. In the former, concentrations of actions at 50 and Sender 1's ideal actions are observed; in the latter, concentrations of actions at

50 and 100 are observed.

Despite the unpredicted mixing behavior, our analysis so far points to Gilligan and Krehbiel's (1989) equilibrium as being able to better organize the closed-rule data. To further evaluate the precise prediction of their equilibrium, we estimate piecewise random-effects GLS models, with "breakpoints" dividing the state space $[0, 100]$ according to the state-action relationship predicted by their equilibrium. The bold lines in Figures 4(c)–(d) illustrate the segments adopted in the regressions. Table 6 reports the estimation results.

Table 6: Random-Effects GLS Regression: Treatments *C-2*

	$b = 10$	$b = 20$
	(1)	(2)
Constant	11.11***	21.50***
	(0.795)	(2.148)
θ	0.967***	0.969***
	(0.0193)	(0.123)
interval_middle	19.63**	18.01***
	(6.839)	(4.654)
$\theta \times$ *interval_middle*	−0.497***	−0.664***
	(0.135)	(0.147)
interval_high	−25.20**	−0.954
	(9.296)	(12.86)
$\theta \times$ *interval_high*	0.281*	−0.249
	(0.133)	(0.196)
interval_top	86.90*	210.4
	(35.01)	(162.9)
$\theta \times$ *interval_top*	−0.974**	−2.464
	(0.370)	(1.674)
No. of Observations	600	600

Note: The dependent variable is action a. *interval_middle* is a dummy variable for $\theta \in (50-b, 50+b]$. *interval_high* is a dummy variable for $\theta \in (50+b, \min\{50+3b, 95\}]$. *interval_top* is a dummy variable for $\theta \in (\min\{50+4b, 95\}, 100]$. Standard errors are in parentheses. *** indicates significance at 0.1% level, ** significance at 1% level, and * significance at 5% level.

The coefficients of θ and the intercept terms show the estimated relationships between state and action in the "baseline" segments, $[0, 40)$ and $(80, 90]$ for $b = 10$ and $[0, 30)$ for

$b = 20$. Gilligan and Krehbiel's (1989) equilibrium predicts that Sender 1's ideal action, $a_1^*(\theta) = \min\{\theta + b, 100\}$, is chosen for states in these intervals. The statistically significant estimates support the prediction. First, the estimated intercepts for $b = 10$ and $b = 20$ are, respectively, 11.11 and 21.5, which are in the neighborhoods of the biases. Second, the coefficients of θ for $b = 10$ and $b = 20$ are, respectively, 0.967 and 0.969, which are close to one. Taken together, these indicate that the fitted lines for the baseline segments start around the corresponding bias levels and have slopes close to one.

Interpretations for the segment dummies are similar to those for treatments *O-2*. For each segment, the coefficients indicate how the fitted line for the segment "tilts" relative to the baseline case: a positive (negative) coefficient of the dummy indicates that the fitted line has a greater (smaller) intercept, and a positive (negative) coefficient of the dummy's interaction with the state indicates that the fitted line has a greater (smaller) slope. For brevity, we note without discussing each case in detail that column (1) in Table 6 shows that, for $b = 10$, the statistically significant coefficients are all signed in ways that are qualitatively consistent with Gilligan and Krehbiel's (1989) prediction about the orientations of the different segments. For $b = 20$, column (2) indicates, however, that statistically significant coefficients are obtained only for the middle segment. This echoes that the "anomalous" mixing behavior for higher states is more prevalent for $b = 20$.[22]

We summarize the above findings:

Finding 3. *In treatments C-2,*

(a) Sender 1's ideal action is chosen for more extreme states, $\theta \in [0, 40) \cup (60, 100]$ for $b = 10$ and $\theta \in [0, 30) \cup (75, 100]$ for $b = 20$;

[22] Table B.1 in online Appendix B reports estimation results from including additional segment dummies that capture the prediction in Krishna and Morgan (2001) as illustrated in Figures 2(a) and 4(c)–(d). The additions yield only insignificant estimates, suggesting that Krishna and Morgan's (2001) prediction does not improve upon Gilligan and Krehbiel's (1989) in organizing our data.

(b) the status quo action 50 *is chosen for intermediates states,* $\theta \in [40, 60]$ *for* $b = 10$ *and* $\theta \in [30, 75]$ *for* $b = 20$*; and*

(c) there is evidence of mixing between Sender 1's ideal action and the status quo for some of the extreme states, $\theta \in [60, 80]$ *for* $b = 10$ *and* $\theta \in [75, 95]$ *for* $b = 20$

Overall, the observed relationships between state and action and distributional efficiencies are more consistent with Gilligan and Krehbiel (1989) than with Krishna and Morgan (2001), whose prediction about the receiver's ideal action being chosen is rarely observed.

Gilligan and Krehbiel (1989) and Krishna and Morgan (2001) both predict that a higher bias translates into a lower informational efficiency and a lower receiver's payoff. Table 5 shows that these common predictions are supported: when the bias increases from $b = 10$ to $b = 20$, the average $\mathrm{Var}(X(\theta))$, which measures informational inefficiency, increases from 87.23 to 326, and the average receivers' payoff decreases from -131.18 to -368.49 ($p = 0.0143$ in both cases, Mann-Whitney tests).

For distributional efficiency, Gilligan and Krehbiel (1989) predict that a higher bias translates into a lower efficiency, whereas Krishna and Morgan (2001) predict invariance. There is no significant difference between the average $E(X(\theta))^2$ at the two bias levels, which are 43.95 for $b = 10$ and 42.49 for $b = 20$ (two-sided $p = 0.8857$, Mann-Whitney test). While the finding of no difference supports Krishna and Morgan's (2001) comparative statics *considered in isolation*, the positive numbers are, as analyzed above, in line with Gilligan and Krehbiel (1989). Especially since the former's comparative statics rests on Sender 1's inability to impress a bias on actions—the opposite of what we observe—the absence of difference in observed distributional efficiencies does not appear to be a finding that corroborates Krishna and Morgan's (2001) equilibrium.

We summarize these findings:

Finding 4. *In treatments C-2, an increase in the bias from $b = 10$ to $b = 20$ leads to:*

(a) a statistically significant decrease in receivers' average payoff, a finding consistent with both Gilligan and Krehbiel (1989) and Krishna and Morgan (2001);

(b) a statistically significant decrease in informational efficiency, a finding consistent with both Gilligan and Krehbiel (1989) and Krishna and Morgan (2001); and

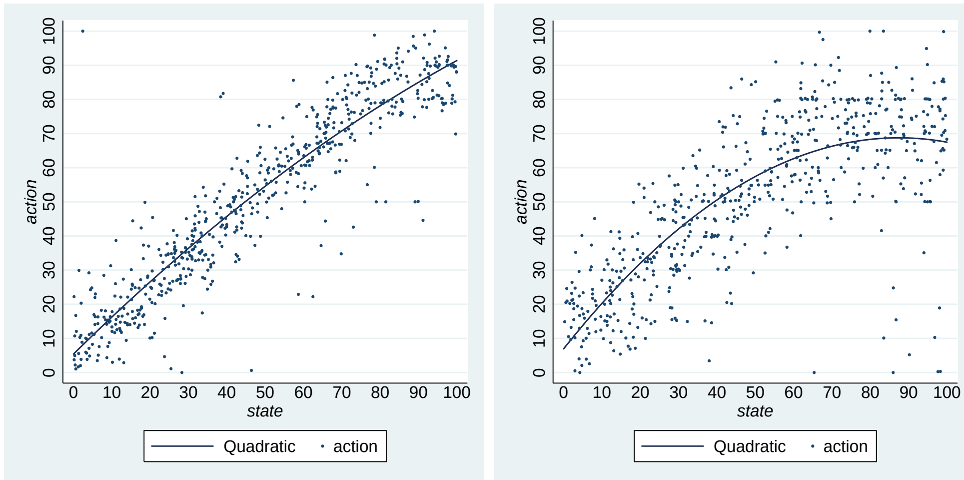
(c) no statistically significant change in distributional efficiency.

5.2 One-Sender Treatments and Welfare Comparisons

Treatments O-1. Figure 5 presents the relationships between realized states and chosen actions in the open-rule treatments with one sender, *O-1.* For both levels of bias, there is clear evidence of positive correlations between state and action. Some evidence of pooling exists, however, for states near the upper ends, especially for $b = 20$.

The open rule with one sender is equivalent to the one-sender cheap-talk model of Crawford and Sobel (1982). They show that in the presence of misaligned interests all equilibria are partitional: the sender partitions the state space and partially transmits information by revealing only the element of the partition that contains the true state. While we do not observe this equilibrium property, which would be a subtle property when expected from subjects, we observe some evidence of pooling: for $b = 20$, there is a cluster of actions around 80 chosen for states in more or less $[60, 100]$.

As an attempt to formally pick up this data feature, we estimate a random-effects GLS model that allows for a quadratic relationship. Columns (1) and (2) in Table 7 confirm that, for both $b = 10$ and $b = 20$, the estimated relationships between state and action are quadratic, which are also illustrated in Figure 5. To provide evidence that this is peculiar to the one-sender case, qualitatively different from the observations with two senders, we



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

Figure 5: Relationship between State and Action: Treatments *O-1*

Table 7: Random-Effects GLS Regression: Treatments *O-1* (and *O-2* for Comparison)

	O-1		*O-2*	
	$b = 10$	$b = 20$	$b = 10$	$b = 20$
	(1)	(2)	(3)	(4)
Constant	5.401***	6.931***	7.375***	19.07***
	(1.330)	(1.998)	(1.207)	(1.792)
θ	1.107***	1.414***	0.846***	0.549***
	(0.0587)	(0.0809)	(0.0523)	(0.0805)
θ^2	−0.00247***	−0.00808***	5.26E-05	0.000471
	(0.000571)	(0.000772)	(0.000500)	(0.000774)
No. of Observations	600	600	600	600

Note: The dependent variable is action a. Standard errors are in parentheses. *** indicates significance at 0.1% level, ** significance at 1% level, and * significance at 5% level.

estimate the same specification for treatments *O-2*. Columns (3) and (4) indicate that no similar quadratic relationships are obtained in these cases.

A common finding in the experimental literature on one-sender communication games is *overcommunication*: the observation of communication that is more informative than is predicted by the most informative equilibria of the underlying game. Given that all equilibria are partitional, our finding that state and action are, despite the quadratic relationships, positively correlated along the whole state space suggests that overcommunication is also observed in our treatments *O-1*.

Welfare Comparison between O-2 and O-1. The heterogeneity principle, which holds for both Gilligan and Krehbiel's (1989) and Krishna and Morgan's (2001) equilibria, predicts that the open rule with two senders yields a higher receiver's payoff than does its one-sender counterpart. The payoff-dominance is derived from a higher informational efficiency in the two-sender case, as there is no distributional inefficiency under any open-rule equilibrium given that the receiver chooses her optimal action given the information.

The heterogeneity principle does not hold with statistical significance under either level of bias. Table 5 shows that, for $b = 10$, the average receivers' payoff is -94.42 in *O-2*, which is higher than the -134.12 in *O-1* but without statistical significance, and, for $b = 20$, the payoff is -307.4 in *O-2*, which is again higher than the -383.08 in *O-1* but without statistical significance ($p \geqslant 0.1$ in both cases, Mann-Whitney tests).

Comparing the two measures of efficiencies further dissects the absence of payoff differences. For $b = 10$, both informational and distributional efficiencies are higher in *O-2* than in *O-1*. However, only the latter is statistically significant: informational inefficiencies are 93.37 in *O-2* and 124.6 in *O-1* ($p = 0.2429$, Mann-Whitney test); distributional inefficiencies are 1.05 in *O-2* and 9.52 in *O-1* ($p = 0.0286$, Mann-Whitney test). For $b = 20$, informational efficiency is higher in *O-2* but distributional efficiency is higher in *O-1*. Both differences are, however, insignificant: informational inefficiencies are 300.77 in *O-2* and 377.36 in *O-1*, and distributional inefficiencies are 6.63 in *O-2* and 5.84 in *O-1* ($p \geqslant 0.1$ in both cases, Mann-Whitney tests). Since the magnitudes of distributional efficiencies are exceedingly smaller relative to those of informational efficiencies, the statistically insignificant comparisons of the latter drives the insignificant comparisons of receivers' payoffs. We summarize:

Finding 5. *Under the open rule, having an additional sender does not significantly increase receivers' payoffs relative to the case when there is only one sender.*

An interesting phenomenon, which we call the *confusion effect*, may account for why having two senders does not significantly improve informational efficiency. When the two senders' messages do not coincide, receivers may choose to ignore them due to confusion. Making their decision without relying on any information, receivers then take their *ex-ante* optimal action 50, as is prescribed by Gilligan and Krehbiel (1989) for out-of-equilibrium behavior. On the other hand, with only one sender, receivers rarely ignore the messages, which is evident in the observed overcommunication. The confusion effect under two senders combined with the overcommunication under one sender results in no significant difference in informational efficiencies across the two cases.

The observation that receivers choose 50 more often when facing two senders than when facing one sender can be seen by comparing Figure 3 with Figure 5. To formally evaluate the difference, we estimate a random-effects probit model, regressing a dummy variable for $a \in [49.5, 50.5]$ on the state and a dummy variable for treatments *O-1*. Table 8 shows that, for both $b = 10$ and $b = 20$, actions in a close neighborhood of 50 are less frequently obtained with one sender, although only the case for high bias is statistically significant. We summarize:

Finding 6. *Under the open rule, the receiver's ex-ante optimal action* 50 *is chosen more often with two senders than with one sender, indicating a reduction in information transmission with two senders.*

Finding 6 suggests that there may be an implicit cost in increasing the number of senders that has not been recognized in the theoretical literature: the occurrence of disagreeing messages, recognized in the theory only as out of equilibrium, may be so prevalent in practice that it reduces welfare by inducing the receiver to shut down updating.

Table 8: Random-Effects Probit Regression: Open-Rule Treatments

	$b = 10$	$b = 20$
	(1)	(2)
Constant	-2.229***	-1.453***
	(0.295)	(0.174)
θ	0.00231	0.00156
	(0.00336)	(0.00219)
one_sender	-0.619	-0.528**
	(0.347)	(0.193)
No. of Observations	1200	1200

Note: The dependent variable is a dummy variable for $a \in [49.5, 50.5]$. *one_sender* is a dummy variable for treatments *O-1*. Standard errors are in parentheses. *** indicates significance at 0.1% level, ** significance at 1% level, and * significance at 5% level.

Welfare Comparison between C-2 and O-1. The heterogeneity principle also covers the closed rule, where both Gilligan and Krehbiel (1989) and Krishna and Morgan (2001) predict that the receiver's payoff (and informational efficiency) is lower under the open rule with one sender. They, however, differ in terms of distributional efficiency: since the Sender 1 in Gilligan and Krehbiel's (1989) equilibrium impresses a bias on action, according to them the closed rule would be less distributionally efficient than the open rule with one sender; Krishna and Morgan (2001), on the other hand, predict that they are the same.

The heterogeneity principle again does not hold with statistical significance. Table 5 shows that, for $b = 10$, the average receivers' payoff is -131.18 in *C-2*, which is slightly higher than the -134.12 in *O-1*, and, for $b = 20$, the payoff is -368.49 in *C-2*, which is higher than the -383.08 in *O-1* but without statistical significance ($p \geqslant 0.6571$ in both cases, Mann-Whitney tests).

Distributional efficiencies are significantly higher in *O-1* than in *C-2*, which is consistent with Gilligan and Krehbiel (1989): the inefficiencies are, for $b = 10$, 9.52 in *O-1* and 43.95 in *C-2*, and, for $b = 20$, 5.84 in *O-1* and 42.49 in *C-2* ($p = 0.0143$ in both cases, Mann-

Whitney tests). The prediction common to both papers on informational efficiency is observed but without statistical significance: informational inefficiencies are, for $b = 10$, 87.23 in *C-2* and 124.6 in *O-1*, and, for $b = 20$, 326 in *C-2* and 377.36 in *O-1* ($p \geqslant 0.2429$ in both cases, Mann-Whitney tests). The insignificant dominance of informational efficiency under the closed rule is further offset by the dominance of distributional efficiency under the open rule with one sender, resulting in even smaller payoff differences than are observed in the comparison between *O-2* and *O-1*. We summarize:

Finding 7. *Receivers' payoffs are higher under the closed rule with two senders than under the open rule with one sender, but the differences are not statistically significant.*

The confusion effect also appears to be at work under the closed rule. Given that the *status quo* action coincides with the receiver's *ex-ante* optimal action, receivers in treatments *C-2* may also choose to ignore disagreeing messages and take action under the prior. Figures 4(c)–(d) indeed show that action 50 is chosen more often than is predicted. The *status quo* action is chosen for some states for which equilibria prescribe full or partial revelation, indicating that less information is transmitted than is predicted. This, together with the overcommunication observed in treatments *O-1*, contributes to Finding 7.

Welfare Comparison between O-2 and C-2. We conclude this subsection by addressing the choice between the open rule and the closed rule with two senders, the fundamental policy question behind the informational theory. Gilligan and Krehbiel (1989) predict that the open rule is more distributionally but less informationally efficient than the closed rule. Krishna and Morgan (2001) predict that the open rule is as distributionally efficient as the closed rule but more informationally efficient. Their difference in terms of payoffs is more delicate, in which Krishna and Morgan (2001) predict that receivers' payoffs are always higher under the open rule whereas Gilligan and Krehbiel (1989) predict that this is the case only for $b = 10$.

Gilligan and Krehbiel's (1989) distributional principle is confirmed with clear evidence. Table 5 shows that distributional inefficiency are, for $b = 10$, 1.05 in *O-2* and 43.95 in *C-2*, and, for $b = 20$, 6.63 in *O-2* and 42.49 in *C-2* ($p = 0.0143$ in both cases, Mann-Whitney tests). The comparisons of informational efficiencies are less clear cut and also insignificant. The closed rule is more informationally efficient for $b = 10$, but the opposite is observed for $b = 20$. Both comparisons are statistically insignificant: informational inefficiencies are, for $b = 10$, 93.37 in *O-2* and 87.23 in *C-2*, and, for $b = 20$, 300.37 in *O-2* and 326 in *C-2* ($p \geqslant 0.1714$ in both cases, Mann-Whitney tests).

As in the other cases, informational efficiencies drive the payoff comparisons. However, in the case of $b = 10$, the dominance of the open rule over the closed rule in distributional efficiency involves a 40-times difference, resulting in at least marginally significantly higher receivers' payoffs under the open rule. For $b = 10$, the average receivers' payoffs are -94.42 in *O-2* and -131.18 in *C-2* ($p = 0.0571$, Mann-Whitney test). For $b = 20$, the payoffs are -307.4 in *O-2* and -368.49 in *C-2* ($p = 0.1714$, Mann-Whitney test). The fact that the distributional-principle effect dominates the restrictive-rule-principle effect with statistical significance for the low but not the high bias weakly favors Gilligan and Krehbiel (1989).

We summarize these findings:

Finding 8. *Comparison of receivers' welfare between treatments O-2 and C-2 gives the following findings:*

(a) for both $b = 10$ and $b = 20$, distributional efficiency is significantly higher under the open rule than under the closed rule;

(b) for both $b = 10$ and $b = 20$, informational efficiency under the open rule is not significantly different from that under the closed rule; and

(c) receivers' payoffs are significantly higher under the open rule than under the closed

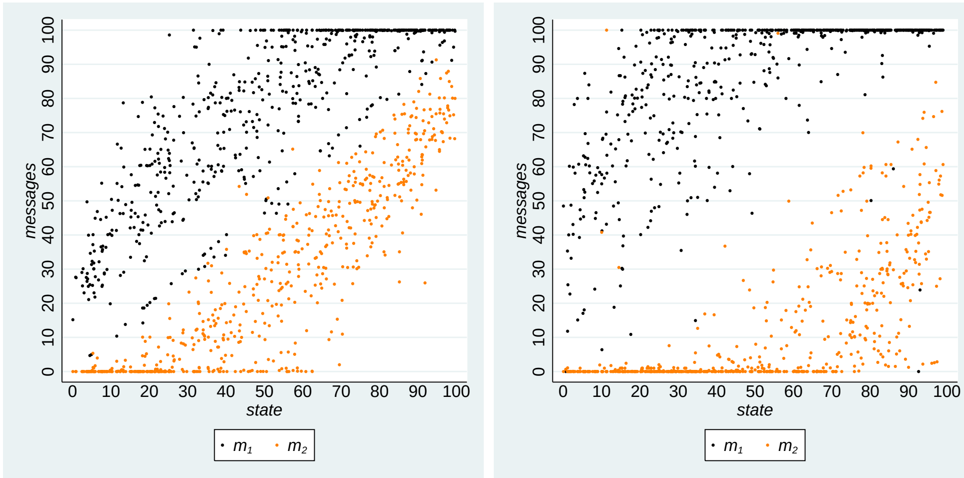
rule only for $b = 10$.

5.3 Senders' and Receivers' Behavior in Two-Sender Treatments

We turn to the observed behavior of senders and receivers in treatments *O-2* and *C-2*. An issue with *O-2* is that the open-rule model is a cheap-talk game. Since cheap-talk messages acquire meanings only in equilibrium, we may have equilibria where the same outcome is achieved with very different messages. Nevertheless, the qualitative patterns of the observed messages, combined with receivers' responses, should provide an informative picture about the nature of subjects' interactions. For *O-2*, we therefore focus on highlighting some interesting qualitative properties in the data. The issue is relatively minor for *C-2*. Because the messages from Sender 1 have a binding property under the closed rule, their exogenous meanings are used in equilibrium. In this case, we compare the observed proposals more directly with the theoretical predictions.

Treatments O-2. Figure 6 presents the relationships between realized states and senders' messages in *O-2*. For both levels of bias and for both senders, messages are positively correlated with the state. The two senders send different messages, where $m_1 > \theta > m_2$ in more than 95% of the observations. The distances between m_1 and m_2 widen when b increases: the average distances are 47.66 for $b = 10$ and 74.7 for $b = 20$.

The positive correlations indicate that messages reveal information. The larger distances between m_1 and m_2 with a higher level of bias are qualitatively consistent with a common property of the equilibrium strategies in the two papers. Senders' behavior does not otherwise quite resemble the strategies in either equilibrium. In our environment, a fully revealing (monotone) strategy by a sender requires him to send truthful messages. While for $b = 10$ there are observed cases of truthful messages by Senders 1, they disappear for $b = 20$, inconsistent with Krishna and Morgan's (2001) full revelation by a sender



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

Figure 6: Relationship between State and Message: Treatments *O-2*

irrespective of the bias level.[23]

The fact that $m_1 > \theta > m_2$ in almost all observations indicate that senders "exaggerate" in the directions of their biases. They, however, frequently exaggerate beyond their ideal actions, $a_1^*(\theta) = \min\{\theta + b, 100\}$ for Sender 1 and $a_2^*(\theta) = \max\{0, \theta - b\}$ for Sender 2. For $b = 10$, the frequencies of m_1 within $a_1^*(\theta) \pm 0.5$ and of m_2 within $a_2^*(\theta) \pm 0.5$ are, respectively, only 10.83% and 12.83%. The corresponding frequencies increase to 84.66% and 91.17% when the ranges are extended for m_1 to include up to $4b$ above $a_1^*(\theta)$ and for m_2 to include up to $4b$ below $a_2^*(\theta)$. For $b = 20$, the corresponding increases are from 19.67% for m_1 and 17% for m_2 to, respectively, 91.5% and 94.5% when the ranges are extended up to $3b$ above or below the ideal actions.

Related to this tendency to "overexaggerate" is the frequent use of boundary messages 0 and 100. Consider the benchmark where the senders recommend their ideal actions. Under our bounded spaces, we would then see message 0 sent by Senders 2 only for $\theta \in [0, b]$

[23]Observed truthful messages refer to those state-message pairs on (or very close to) the 45-degree line in Figure 6, in which the messages reveal the true states or equivalently indicate the receiver's ideal actions. For $b = 10$, 6% of Sender 1's messages are within ± 0.5 of the true states. For Senders 2, the frequency is only 0.5%. For $b = 20$, the frequencies are at most 0.5% for both senders.

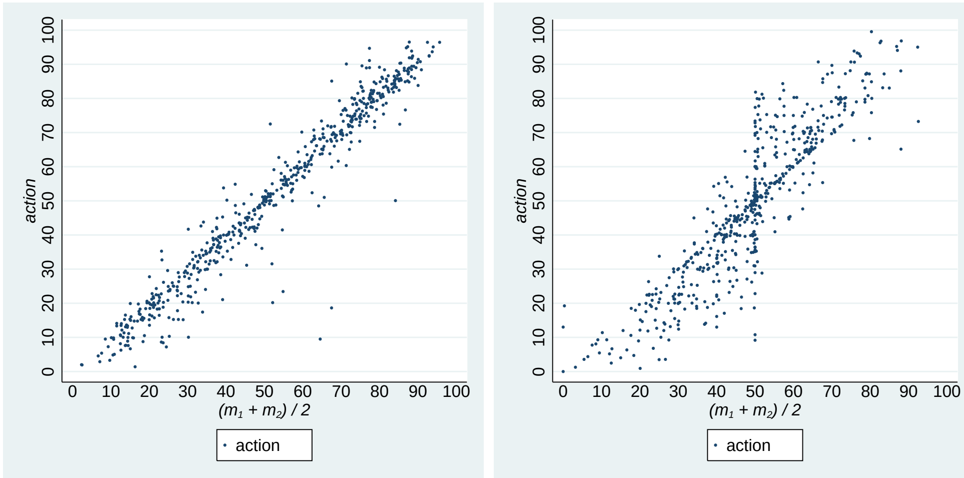
and message 100 sent by Senders 1 only for $\theta \in [100 - b, 100]$. Figure 6 reveals, however, that the boundary messages are sent more often than this. When $b = 10$, message 0 is sent by Senders 2 for states below 60, and message 100 is sent by Senders 1 for states above 40. When $b = 20$, the ranges extend to below 70 for message 0 and to above 20 for message 100. The boundary messages are used as pooling messages, which suggests that information is sometimes not transmitted for the intermediate states. This further points to inconsistency with Krishna and Morgan's (2001) equilibrium. The loss of information for intermediates states is more consistent with Gilligan and Krehbiel's (1989) equilibrium, but the randomized messages for intermediate states in their equilibrium are replaced by pooling boundary messages in the laboratory.

Turning to receivers' behavior, our first observation is that the senders' pooling behavior for intermediate states identified above is consistent with the information transmission outcome, reminiscent of Gilligan and Krehbiel's (1989) equilibrium (Finding 1 and Figure 3(b)).[24] The endogenous uses of messages are a particularly important issue for analyzing receivers' behavior.[25] The aggregate behavior depicted in Figure 6 suggests that, when at least one of the senders' messages is not a boundary message, taking an action that equals the average of Sender 1's and Sender 2's messages should provide a good prediction for the optimal action. On the other hand, when both messages are boundary messages, the average of the messages, i.e., 50, is consistent with a range of states.

Figure 7 presents receivers' actions as functions of average messages. The qualitative difference between the data patterns in Figures 7(a) and 7(b) provides evidence that receivers are responding to the fact that, in the case of $b = 20$, a message-average of 50 is

[24] Section B.2 in online Appendix B provides additional analysis to demonstrate that the equilibrium construction in Krishna and Morgan (2001) is not supported by receivers' observed responses to messages.

[25] While the implied meaning of the message pair in a round for a group certainly differs from that in another round for another group, given the limited space we focus on analyzing aggregate behavior. Note that since random matching is used for these treatments, a subject is effectively playing against a population, which makes average behavior of the other roles highly relevant for one's decisions.



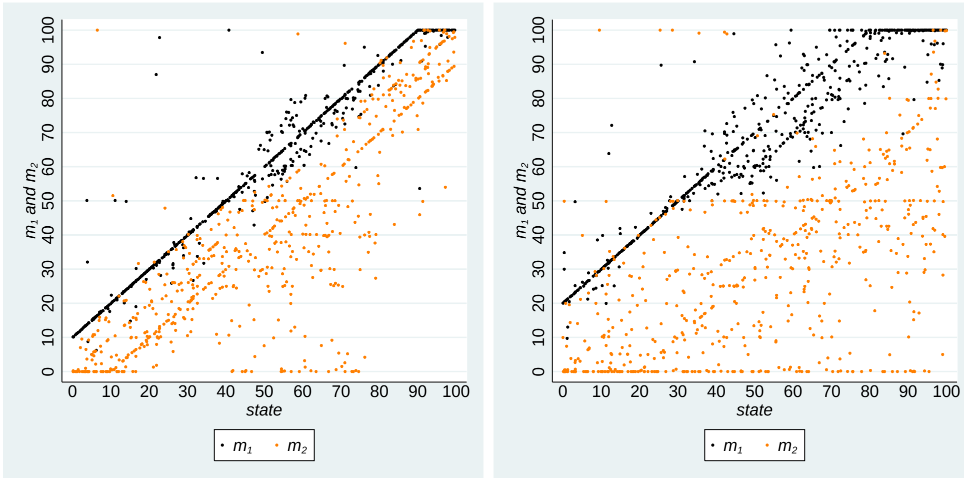
(a) $b = 10$ (b) $b = 20$

Figure 7: Action as a Function of Average Message: Treatments *O-2*

consistent with a wider range of states given that senders send boundary messages more frequently under the higher bias.

Treatments C-2. The key difference between the closed-rule equilibria in Gilligan and Krehbiel (1989) and Krishna and Morgan (2001) is that, in a large number of states, the Sender 1 in the former proposes his ideal action whereas that in the latter proposes the receiver's ideal action. They also differ with respect to compromise bills. In Gilligan and Krehbiel (1989), they are proposed for relatively high states; in Krishna and Morgan (2001), they are proposed for both relatively high and low states.

Figure 8 presents the relationships between realized states and senders' messages in *C-2*. The data clearly favor Gilligan and Krehbiel (1989). Senders 1 frequently propose their ideal action $a_1^*(\theta) = \min\{\theta + b, 100\}$. The frequencies of m_1 within $a_1^*(\theta) \pm 0.5$ are 70.16% for $b = 10$ and 53.33% for $b = 20$. In contrast, the frequencies of m_1 within $\theta \pm 0.5$ are around 3% for both levels of bias. Deviations from proposing $a_1^*(\theta)$ are also observed for higher but not lower states.



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

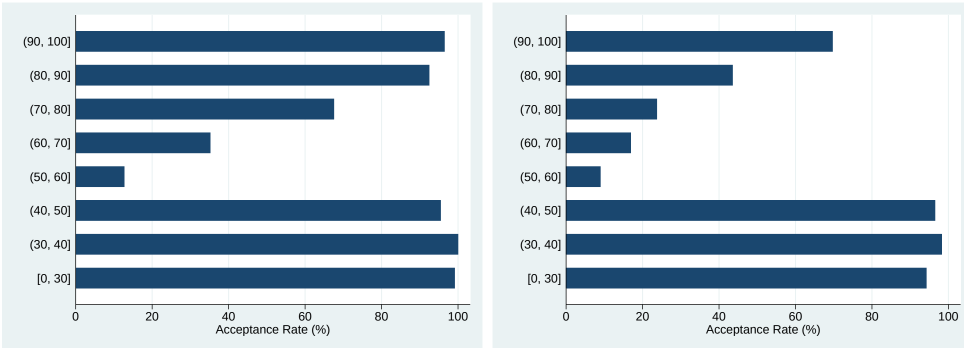
Figure 8: Relationship between State and Message: Treatments *C-2*

Figure 9 presents receivers' adoption rate of m_1. For both levels of bias, receivers adopt close to 100% of the time when $m_1 < 50$, reject more than 50% of the time when $m_1 \in [50, 50 + 2b]$, and adopt in the majority of the cases again when $m_1 > 50 + 2b$. For $b = 10$, the adoption rate rises back to near 100% when $m_1 > 90$.

The close-to-100% adoption rate happens when, for both $b = 10$ and $b = 20$, $m_1 \notin [50, \min\{50 + 4b, 100\}]$. We illustrate that this is a best response consistent with Gilligan and Krehbiel's (1989) equilibrium by examining the relevant incentive conditions. Given that Sender 1 recommends his ideal action, i.e., $m_1(\theta) = \theta + b < 100$, as is more or less observed, Senders 2 prefer m_1 over the *status quo* if and only if

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

Thus, for $m_1 \notin [50, \min\{50 + 4b, 100\}]$, not only Senders 1 but Senders 2 also prefer m_1 over the *status quo* 50. There is therefore no incentive for them to generate disagreements.



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

Figure 9: Receivers' Adoption Rate of Proposals from Senders 1: Treatments *C-2*

Note further that receivers adopt m_1 if and only if

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

Expecting that the two senders have no incentive to generate disagreements when $m_1 \notin [50, \min\{50 + 4b, 100\}]$, receivers adopting these proposals irrespective of the speeches from Senders 2 therefore constitutes a best response.

By a similar argument, the low adoption rate for $m_1 \in [50, 50 + 2b]$ can also be shown to be a best response consistent with Gilligan and Krehbiel's (1989) equilibrium. For m_1 in this range, it is impossible for the two senders to reach an agreement, because their preferences are misaligned. Expecting this, receivers rejecting $m_1 \in [50, 50 + 2b]$ and taking the *status quo* irrespective of the speeches from Senders 2 is a best response. The high adoption rate for $m_1 \in (50 + 2b, \min\{50 + 4b, 100\})$ remains unaccounted for. As can be seen in Figure 8, however, some of the m_1 observed in this range are compromise bills closer to the *status quo*, which may explain their high adoption rate.

6 Robustness Treatments

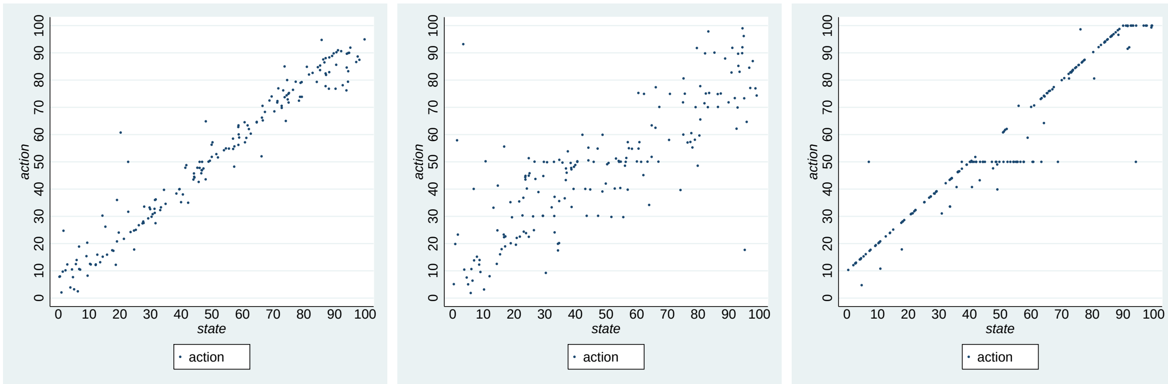
We consider two treatment variations for robustness checks. The first replaces the random matchings used in the main treatments with fixed matchings (F). In our two-sender treatments, equilibrium play requires the coordination of three parties, each faces a large number of choices. A fixed-matching protocol, which provides repeated interactions with the same partners, may facilitate better convergence to an equilibrium. The second variation concerns only the closed rule, in which we replace the point messages used in the main treatments for Senders 2 with interval messages (while keeping the random matchings). The interval messages (I) are explored according to the original setup in Gilligan and Krehbiel (1989).[26] The two variations result in four additional sets of treatments (each with the same two bias levels): one for the open-rule with two senders (*O-2-F*), one for the open-rule with one sender (*O-1-F*), and two for the closed-rule with two senders (*C-2-F* and *C-2-I*). A total of 233 subjects participated in these treatments.[27]

Figure 10 presents the relationships between realized states and chosen actions in the six robustness treatments with two senders. The qualitative patterns of the data from the main treatments are similarly observed. Table 9 further summarizes how well Findings 1–8 are preserved in the robustness treatments. There are no qualitative changes in any of the findings; e.g., no statistically significant comparisons with opposite conclusions are obtained. There are "quantitative changes," where the statistical significance of a result changes from significant to insignificant or vice versa.

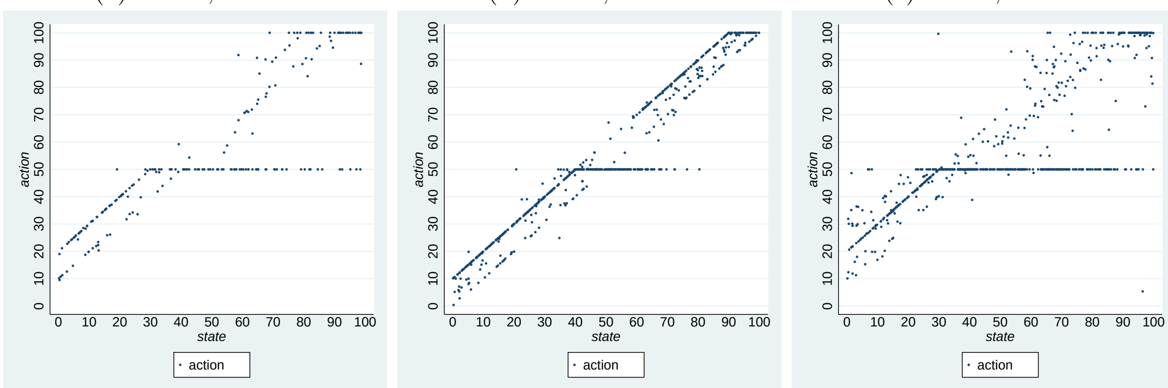
Take Finding 7 for treatments *C-2-I* as an example. Table B.6 in online Appendix B and Table 5 show that, for $b = 10$, the average receivers' payoff is -75 in *C-2-I*, which is significantly higher than the -134.12 in *O-1* ($p = 0.0143$, Mann-Whitney test), and,

[26]The interval messages are implemented in the laboratory by allowing Member B to click on the message line twice to pinpoint the interval they intend as a message.

[27]Table B.2 in online Appendix B provides details about these robustness treatments.



(a) *O-2-F*, $b = 10$ (b) *O-2-F*, $b = 20$ (c) *C-2-F*, $b = 10$



(d) *C-2-F*, $b = 20$ (e) *C-2-I*, $b = 10$ (f) *C-2-I*, $b = 20$

Figure 10: Relationship between State and Action: Robustness Treatments with Two Senders

for $b = 20$, the payoff is -351.22 in *C-2-I*, which is higher than the -383.08 in *O-1* but without statistical significance ($p = 0.1$, Mann-Whitney test).[28] Note that in Finding 7, which compares the main treatments *C-2* with *O-1*, the higher payoffs under the closed rule are not statistically significant for both levels of bias. Since only a subset of the comparisons supporting the finding changes in statistical significance for the robustness treatment (when $b = 10$), we characterize this as a "partial quantitative change." We find that all quantitative changes to our findings are partial in this sense. In addition, more than half of the findings have no changes. Overall, our findings from the main treatments

[28] A way to interpret this finding is that information transmission may work well in a heterogeneous committee with moderate bipartisanship, where the members' biases, though opposite, are moderate in magnitudes.

Table 9: Comparisons of Findings between Main and Robustness Treatments

	O-2-F	*O-1-F*	*C-2-F*	*C-2-I*
No Change	Finding 2			
			Finding 4	Finding 4
	Finding 6	Finding 6		
		Finding 7	Finding 7	
			Finding 8	
Partial Quantitative Change	Finding 1			
			Finding 3	Finding 3
	Finding 5	Finding 5		
				Finding 7
				Finding 8

Note: "No Change" refers to the cases where all the qualitative and quantitative (in the sense of statistical significance) aspects of the main-treatment findings are preserved in the robustness treatments. "Partial Quantitative Change" refers to the cases where a subset of the comparisons or estimates supporting a particular finding changes in statistical significance in the robustness treatments.

survive well in the robustness treatments.[29]

7 Conclusion

In this paper, we have provided the first experimental investigation of the informational theory of legislative committees with heterogeneous members. We have focused on two legislative rules: the open rule, in which the legislature is free to choose any action, and the closed rule, in which the legislature is restricted to choose between a committee member's proposal and an exogenous *status quo*.

We find that, even in the presence of conflicts, legislative committee members help improve the legislature's decisions by providing useful information. We obtain clear evidence in support of two key predictions: the outlier and the distributional principles, which concern how the legislature's welfare varies with the committee members' biases and with the

[29]The data analysis supporting the conclusion in Table 9 can be found in Section B.3 in online Appendix B.

legislative rules. While we obtain no statistically significant evidence for the restrictive-rule principle, we find that the open rule, as predicted, leads to more favorable decisions by the legislature when the members' biases are less extreme. Overall, our findings support the predictions of Gilligan and Krehbiel's (1989) equilibria.

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The Informational Theory of Legislative Committees: An Experimental Analysis

Marco Battaglini Ernest K. Lai Wooyoung Lim
Joseph Tao-yi Wang

Online Appendices (Not Intended for Publication)

Appendix A – Proof of Result 2

Since the receiver's expected payoff in Krishna and Morgan's (2001) equilibrium is higher than that in Gilligan and Krehbiel's (1989) under a given legislative rule, it suffices to show that the receiver's payoffs in Gilligan and Krehbiel's (1989) open-rule (O) and close-rule (C) equilibria are higher than that under the open rule with one sender (CS):

Open Rule. We have that $EU_O^R(b) = -\frac{16b^3}{3} > -\frac{4b^2}{3}$ for $b \in (0, \frac{1}{4})$. There are three cases to consider: i) if $N(b) > 2$, then $EU_{CS}^R(b) = -\frac{1}{12N(b)^2} - \frac{b^2[N(b)^2-1]}{3} < -\frac{b^2[N(b)^2-1]}{3} < -\frac{8b^2}{3} < -\frac{4b^2}{3}$ for $b \in (0, \frac{1}{4})$; ii) if $N(b) = 2$, then $EU_{CS}^R(b) = -\frac{1}{48} - b^2 < -\frac{4b^2}{3}$ for $b \in (0, \frac{1}{4})$; and iii) if $N(b) = 1$, then $EU_{CS}^R(b) = -\frac{1}{12} < -\frac{4b^2}{3}$ for $b \in (0, \frac{1}{4})$.

Closed Rule. We have that $EU_C^R(b) = -\frac{16b^3}{3} - b^2(1-8b) > -\frac{1}{48}$, where the inequality follows from the fact that $\frac{dEU_C^R(b)}{db} < 0$ for $b \in (0, \frac{1}{4})$. There are two cases to consider: i) if $N(b) \leqslant 2$, then $EU_{CS}^R(b) < -\frac{1}{48}$ for $b \in (0, \frac{1}{4})$; and ii) if $N(b) > 2$, then $EU_{CS}^R(b) < -\frac{8b^2}{3} < -\frac{1}{48}$ for $b \in (0, \frac{1}{4})$.

Appendix B – Additional Data Analysis

B.1 Additional Regression Results for Treatments *C-2*

Table B.1: Random-Effects GLS Regression: Treatments *C-2*

	(1) $b = 10$	(2) $b = 20$
Constant	11.20***	20.53***
	(0.826)	(3.250)
θ	0.967***	1.179
	(0.0194)	(0.633)
interval_low	−4.579	1.778
	(11.49)	(5.383)
$\theta \times$ *interval_low*	0.121	−0.249
	(0.331)	(0.668)
interval_middle	19.65**	18.96***
	(6.847)	(5.227)
$\theta \times$ *interval_middle*	−0.500***	−0.874
	(0.135)	(0.638)
interval_high_1	2.869	−36.87*
	(23.83)	(17.73)
$\theta \times$ *interval_high_1*	−0.151	0.0204
	(0.367)	(0.669)
interval_high_2	−66.58	242.5
	(36.80)	(130.8)
$\theta \times$ *interval_high_2*	0.943	−2.751
	(0.523)	(1.423)
interval_top	87.34*	209.4
	(35.03)	(161.9)
$\theta \times$ *interval_top*	−0.980**	−2.653
	(0.371)	(1.778)
No. of Observations	600	600

Note: The dependent variable is action a. *interval_low* is a dummy variable for $\theta \in (50-2b, 50-b]$. *interval_middle* is a dummy variable for $\theta \in (50-b, 50+b]$. *interval_high_1* is a dummy variable for $\theta \in (50+b, 50+2b]$. *interval_high_2* is a dummy variable for $\theta \in (50+2b, \min\{50+3b, 95\}]$. *interval_top* is a dummy variable for $\theta \in (\min\{50+4b, 95\}, 100]$. Standard errors are in parentheses. *** indicates significance at 0.1% level, ** significance at 1% level, and * significance at 5% level.

Table B.1 reports the estimation results mentioned in footnote 22 in the main text, in which we include additional segment dummies (*interval_low* and *interval_high_2*) and their interactions with the state to capture Krishna and Morgan's (2001) prediction. The estimated coefficients of the four variables are all insignificant.

B.2 Additional Analysis of Receivers' Responses to Messages in Treatments *O-2*

As mentioned in footnote 24 in the main text, we further evaluate whether receivers' observed responses to messages are consistent with Krishna and Morgan's (2001) fully revealing equilibrium. Specifically, we explore the extent to which the relevant incentive conditions that guarantee full revelation are satisfied by our data.

In equilibrium, action $a(m_1(\theta), m_2(\theta)) = \theta$ is induced by message pair $(m_1(\theta), m_2(\theta))$ for all $\theta \in \Theta$. Denote the actions induced pursuant to Sender 1's and Sender 2's deviations in an arbitrary state θ by, respectively, $a(\tilde{m}_1, m_2(\theta))$ and $a(m_1(\theta), \tilde{m}_2)$, where $\tilde{m}_1 \neq m_1(\theta)$ and $\tilde{m}_2 \neq m_2(\theta)$. Note that $\tilde{m}_i$, $i = 1, 2$, can itself be a message used in equilibrium in $\tilde{\theta} \neq \theta$, but $(\tilde{m}_1, m_2(\theta))$ and $(m_1(\theta), \tilde{m}_2)$ are out-of-equilibrium message pairs unexpected in equilibrium.

There is no incentive to deviate from the fully revealing equilibrium if the following two inequalities are satisfied:

$$\text{Sender 1:} \; -b^2 \geqslant -[a(\tilde{m}_1, m_2(\theta)) - (\theta + b)]^2, \text{ and} \tag{B.1}$$

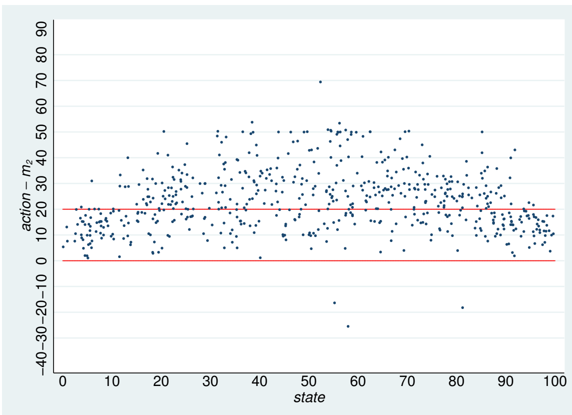
$$\text{Sender 2:} \; -b^2 \geqslant -[a(m_1(\theta), \tilde{m}_2) - (\theta - b)]^2. \tag{B.2}$$

for all $\theta \in \Theta$ and all $\tilde{m}_1, \tilde{m}_2 \in M$. Condition (B.1) guarantees that Sender 1 has no incentive to deviate when Sender 2 reveals θ. Condition (B.2) guarantees the same for Sender 2. Rearranging (B.1) and (B.2) gives the following that can be readily applied:

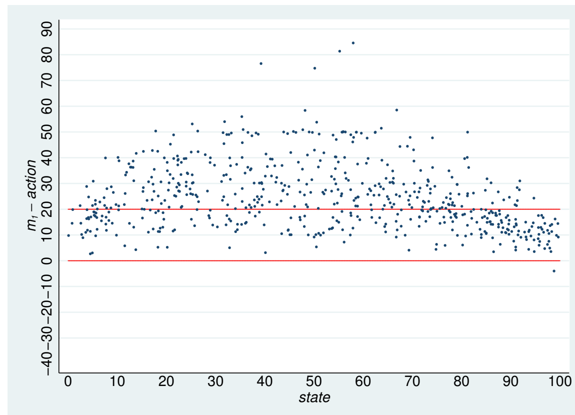
$$\text{Sender 1:} \; a(\tilde{m}_1, m_2(\theta)) - m_2(\theta) \notin (0, 2b), \text{ and} \tag{B.3}$$

$$\text{Sender 2:} \; m_1(\theta) - a(m_1(\theta), \tilde{m}_2) \notin (0, 2b). \tag{B.4}$$

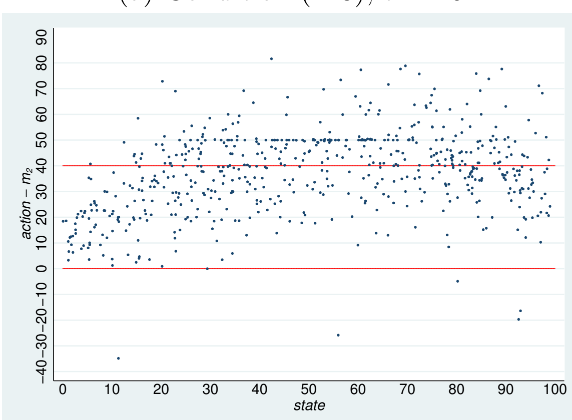
Applying Conditions (B.3) and (B.4) to our data says that, if in a state the observed distances $a - m_2$ and $m_1 - a$ are in $(0, 2b)$, then receivers' responses are inviting deviations in that state. Krishna and Morgan's (2001) equilibrium construction requires (B.3) and (B.4) to be satisfied in all states in order to achieve a message-contingent optimal punishment of deviations. Figure B.1 shows that the conditions are respected for about half of the states only and for states that are closer to 50. Receivers' observed responses to messages fall short of punishing deviations as stipulated by Krishna and Morgan's (2001) construction.



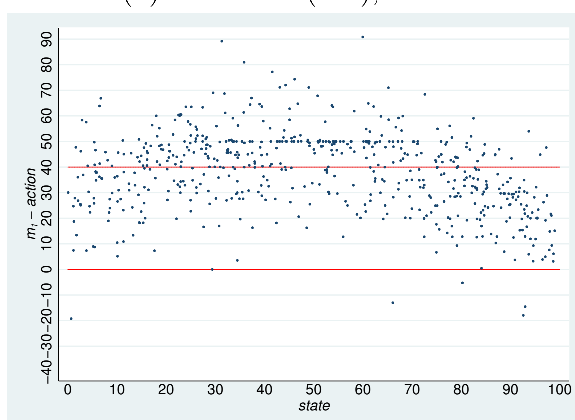
(a) Condition (B.3), $b = 10$



(b) Condition (B.4), $b = 10$



Condition (B.3), $b = 20$



Condition (B.4), $b = 20$

Figure B.1: Distance between Action and Message: Treatments *O-2*

B.3 Robustness Treatments

Table B.2: Robustness Treatments

	Two Senders (Heterogeneous Committees)	Single Sender (Homogeneous Committee)
Open Rule	*O-2-F* Fixed Matching Point Message 2 Treatments: $b = 10, 20$ Each Treatment: 1 Session Each Session: 6 Fixed Groups of 3 No. of Subjects: $2 \times 1 \times 6 \times 3 = 36$	*O-1-F* Fixed Matching Point Message 2 Treatments: $b = 10, 20$ Each Treatment: 1 Session Each Session: 9/10 Fixed Groups of 2 No. of Subjects: $(9 + 10) \times 2 = 38$
Closed Rule	*C-2-F* Fixed Matching Point Message 2 Treatments: $b = 10, 20$ Each Treatment: 1 Session Each Session: 6/7 Fixed Groups of 3 No. of Subjects: $(6 + 7) \times 3 = 39$ *C-2-I* Random Matching Interval Message 2 Treatments: $b = 10, 20$ Each Treatment: 4 Sessions Each Session: 5 Random Groups of 3 No. of Subjects: $2 \times 4 \times 5 \times 3 = 120$	

Table B.2 provides details about the eight robustness treatments. In the following, we provide data analysis to support the conclusion from the comparisons of the findings between the main and the robustness treatments summarized in Table 9 in the main text.

Finding 1. Columns (1), (2), (4), and (5) in Table B.3 show that the correlation between state and action in treatments *O-2-F* decreases in the bias as is observed in main treatments *O-2*. However, the estimated coefficients of the dummy variable *pooling_interval* and its interaction with the state are not statistically significant. Although Figure 10(b) in the main text shows that, similar to *O-2* with $b = 20$, there is a cluster of actions around 50 that is more concentrated than the clusters at the other actions, the regression does not pick up the effect quantitatively, perhaps because of the comparably few number of observations. These account for the "partial quantitative change" of Finding 1.

Table B.3: Random-Effects GLS Regression: Treatments *O-2-F* and *O-1-F*

	O-2-F						*O-1-F*	
	$b = 10$			$b = 20$			$b = 10$	$b = 20$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	6.471***	6.853***	5.460***	16.52***	17.40***	18.62***	6.389**	9.204**
	(0.882)	(0.975)	(1.289)	(2.008)	(3.543)	(3.182)	(2.08)	(3.202)
θ	0.886***	0.881***	0.948***	0.653***	0.643***	0.532***	1.064***	1.437***
	(0.015)	(0.0155)	(0.06)	(0.0358)	(0.0358)	(0.147)	(0.0716)	(0.141)
θ^2	–	–	−0.0063	–	–	0.00119	−0.00220**	−0.00821***
	–	–	(0.000586)	–	–	(0.0014)	(0.000687)	(0.00134)
pooling_interval	–	−4.616	–	–	−1.389	–	–	–
	–	(3.388)	–	–	(4.439)	–	–	–
$\theta \times$ *pooling_interval*	–	0.0861	–	–	0.0192	–	–	–
	–	(0.0656)	–	–	(0.0723)	–	–	–
No. of Observations	180	180	180	180	180	180	270	300

Note: The dependent variable is action a. *pooling_interval* is a dummy variable for $\theta \in [50-2b, 50+2b]$. Standard errors are in parentheses. *** indicates significance at 0.1% level, ** significance at 1% level, and * significance at 5% level.

Finding 2. Table B.6 reports the observed efficiencies and receivers' payoffs in the robustness treatments. In treatments *O-2-F*, an increase in the bias from $b = 10$ to $b = 20$ leads to: i) a significant increase in the average $\text{Var}(X(\theta))$ from 44.49 to 283.48 ($p = 0.0076$, Mann-Whitney test), ii) an insignificant increase in the average $(EX(\theta))^2$ from 1.17 to 1.47 ($p = 0.197$, Mann-Whitney test), and iii) an significant decrease in the average receivers' payoff from -45.66 to -284.94 ($p = 0.0076$, Mann-Whitney test). These account for the "no change" of Finding 2.

Finding 3. The data patterns in Figures 10(c)–(f) in the main text for treatments *C-2-F* and *C-2-I* are highly similar to those in Figures 4(a)–(b) for main treatments *C-2*. Table B.6 show that, for *C-2-F*, the average $(EX(\theta))^2 = 50.77$ for $b = 10$ and $(EX(\theta))^2 = 60.60$ for $b = 20$ and, for *C-2-I*, $(EX(\theta))^2 = 27.80$ for $b = 10$ and $(EX(\theta))^2 = 55.11$, which are all significantly greater than 0 ($p \leqslant 0.0625$ in all four cases, Wilcoxon signed-rank tests).[1] Table B.4 reports estimation results from piecewise random-effects GLS models, which corresponds to Table 6 in the main text for *C-2*. For *C-2-F*, there are a few changes in the significance of the estimates. There is also one change for *C-2-I*. These account for the "partial quantitative change" of Finding 3 for the two robustness treatments.

Finding 4. Table B.6 shows that an increase in the bias from $b = 10$ to $b = 20$ leads to: i) significant increases in the average $\text{Var}(X(\theta))$ from 50.29 to 235.03 in *C-2-F* and from 47.20 to 296.11 in *C-2-I* ($p \leqslant 0.0143$ in both cases, Mann-Whitney tests), ii) no significant

[1] The p-value of 0.0625 is the lowest possible value for four observations (treatments *C-2-I*) from the Wilcoxon signed-rank test.

Table B.4: Random-Effects GLS Regression: Treatments *C-2-F* and *C-2-I*

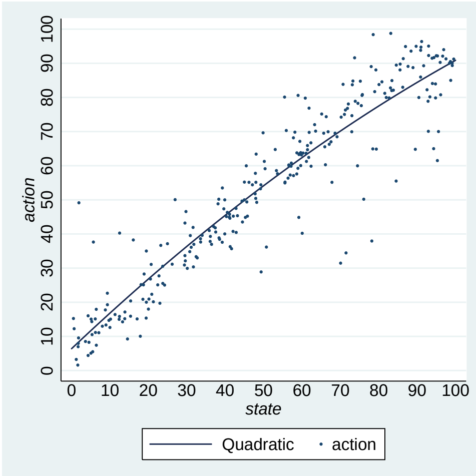
	C-2-F		*C-2-I*	
	$b = 10$	$b = 20$	$b = 10$	$b = 20$
	(1)	(2)	(3)	(4)
Constant	9.778***	15.77***	8.925***	22.23***
	(1.091)	(3.094)	(0.558)	(2.268)
θ	0.991***	1.097***	0.973***	0.913***
	(0.0236)	(0.193)	(0.0122)	(0.117)
interval_middle	24.15**	9.494	26.56***	10.68***
	(8.867)	(7.434)	(4.624)	(4.088)
$\theta \times$ *interval_middle*	−0.636***	−0.490*	−0.656***	−0.456***
	(0.135)	(0.147)	(0.0933)	0.135
interval_high	−42.76**	18.60	−47.84***	−35.45**
	(13.27)	(22.07)	(5.918)	(13.05)
$\theta \times$ *interval_high*	0.592*	−0.525	0.622***	0.181
	(0.191)	(0.327)	(0.0847)	(0.195)
interval_top	52.19	−201.8	80.03**	−101.3
	(43.89)	(294.4)	(25.55)	(161.8)
$\theta \times$ *interval_top*	−0.629	1.703	−0.867**	0.82
	(0.464)	(3.03)	(0.27)	(1.661)
No. of Observations	180	210	600	600

Note: The dependent variable is action a. *interval_middle* is a dummy variable for $\theta \in (50 - b, 50 + b]$. *interval_high* is a dummy variable for $\theta \in (50 + b, \min\{50 + 3b, 95\}]$. *interval_top* is a dummy variable for $\theta \in (\min\{50 + 4b, 95\}, 100]$. Standard errors are in parentheses. *** indicates significance at 0.1% level, ** significance at 1% level, and * significance at 5% level.

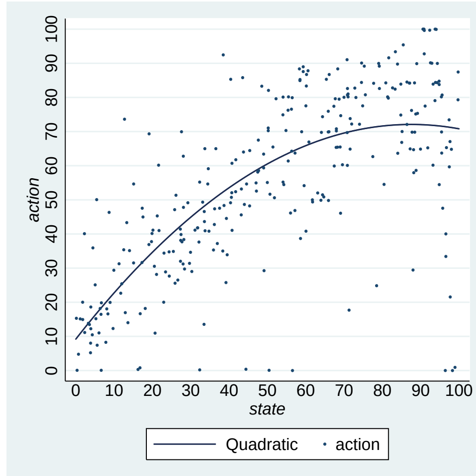
changes in the average $E(X(\theta))^2$ from 50.77 to 60.6 in *C-2-F* and from 27.8 to 55.11 in *C-2-I* (two-sided $p \geqslant 0.3429$ in both cases, Mann-Whitney tests), and iii) significant decreases in the average receivers' payoff from −101.06 to −295.63 in *C-2-F* and from −75 to −351.22 in *C-2-I* ($p \leqslant 0.0143$ in both cases, Mann-Whitney tests). These account for the "no change" of Finding 4 for the two robustness treatments.

Finding 5. Table B.6 shows that, for $b = 10$, the average receivers' payoff is −45.66 in *O-2-F*, which is significantly higher than the −111.33 in *O-1-F* ($p = 0.044$, Mann-Whitney test), and, for $b = 20$, the payoff is −284.94 in *O-2-F*, which is higher than the −500.76 in *O-1-F* but without statistical significance ($p = 0.1838$, Mann-Whitney test). The statistically significant comparison for $b = 10$ accounts for the "partial quantitative change" of Finding 5.

Finding 6. Figure B.2 presents the relationships between realized states and chosen actions in treatments *O-1-F*. The estimation results reported in columns (7) and (8) in Table B.3 confirm that the similar quadratic relationships seen in treatments *O-1* are also



(a) $b = 10$



(b) $b = 20$

Figure B.2: Relationship between State and Action: Treatments *O-1-F*

Table B.5: Random-Effects Probit Regression:
Open-Rule Robustness Treatments

	$b = 10$	$b = 20$
	(1)	(2)
Constant	−1.728***	−1.192***
	(0.283)	(0.284)
θ	−0.00391	−0.0033
	(0.00456)	(0.00412)
one_sender	−0.0276	−1.014**
	(0.251)	(0.332)
No. of Observations	450	480

Note: The dependent variable is a dummy variable for $a \in [49.5, 50.5]$. *one_sender* is dummy variable for treatments *O-1-F*. Standard errors are in parentheses. *** indicates significance at 0.1% level, ** significance at 1% level, and * significance at 5% level.

observed in *O-1-F*. Table B.5 shows that the same kind of results as those reported in Table 8 in the main text are also obtained from the probit regressions: actions in a close neighborhood of 50 are less frequently obtained with one sender, but only the case with $b = 20$ is statistically significant. This accounts for the "no change" of Finding 6.

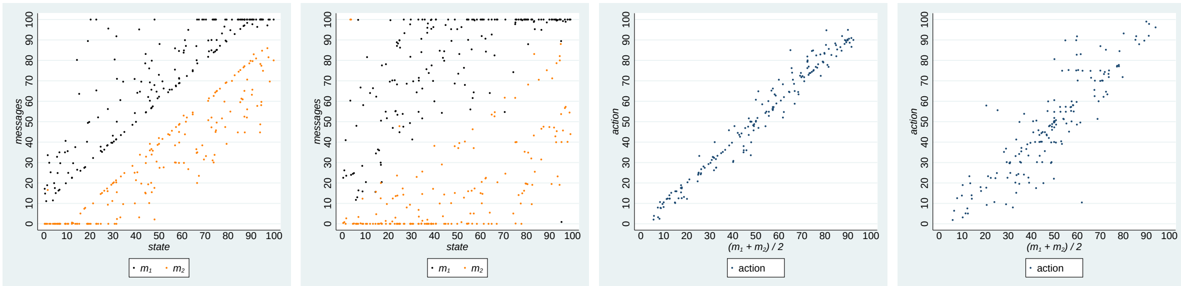
Finding 7. Table B.6 shows that, for $b = 10$, the average receivers' payoff is -101.06 in *C-2-F*, which is higher than the -111.33 in *O-1-F* but without statistical significance, and, for $b = 20$, the payoff is -295.63 in *C-2-F*, which is again higher than the -500.76 in *O-1-F* but without statistical significance ($p \geqslant 0.2681$ in both cases, Mann-Whitney tests). These account for the "no change" of Finding 7 for *C-2-F* and *O-1-F*. The "partial quantitative change" for *C-2-I* is reported in the main text as an example.

Finding 8. For distributional inefficiencies, Table B.6 shows that, for $b = 10$, the average $(EX(\theta))^2$ is 1.17 in *O-2-F*, which is significantly lower than the 50.77 in *C-2-F*, and, for $b = 20$, the average $(EX(\theta))^2$ is 1.47 in *O-2-F*, which is again significantly lower than the 60.6 in *C-2-F* ($p \leqslant 0.0023$ in both cases, Mann-Whitney tests). For informational inefficiencies, for $b = 10$, the average $\text{Var}(X(\theta))$ is 44.49 in *O-2-F*, which is lower than the 50.29 in *C-2-F* but without statistical significance, and, for $b = 20$, the average $\text{Var}(X(\theta))$ is 283.48 in *O-2-F*, which is higher than the 235.03 in *C-2-F* but without statistical significance ($p \geqslant 0.2226$ in both cases, Mann-Whitney tests). For receivers' payoffs, for $b = 10$, the average payoff is -45.66 in *O-2-F*, which is significantly higher than the -101.06 in *C-2-F* ($p = 0.0325$, Mann-Whitney test), and, for $b = 20$, the payoff is -284.94 in *O-2-F*, which is higher than the -295.63 in *C-2-F* but without statistical significance ($p = 0.5822$, Mann-Whitney test).

For treatments *C-2-I*, since random matchings are used, the comparison should be made to main treatments *O-2*. For distributional inefficiencies, Table 5 in the main text and Table B.6 show that, for $b = 10$, the average $(EX(\theta))^2$ is 1.05 in *O-2*, which is significantly lower than the 27.8 in *C-2-I*, and, for $b = 20$, the average $(EX(\theta))^2$ is 6.63 in *O-2*, which is again significantly lower than the 55.11 in *C-2-I* ($p = 0.0143$ in both cases, Mann-Whitney tests). For informational inefficiencies, for $b = 10$, the average $\text{Var}(X(\theta))$ is 93.37 in *O-2*, which is significantly higher than the 47.2 in *C-2-I* ($p = 0.0143$, Mann-Whitney test), and, for $b = 20$, the average $\text{Var}(X(\theta))$ is 300.77 in *O-2*, which is higher than the 296.11 in *C-2-I* but without statistical significance ($p = 0.5571$, Mann-Whitney test). For receivers' payoffs, for $b = 10$, the average payoff is -94.42 in *O-2*, which is lower than the -75 in *C-2-I* but without statistical significance, and, for $b = 20$, the payoff is -307.4 in *O-2*, which is higher than the -351.22 in *C-2-I* but again without statistical significance ($p = 0.1$ in both cases, Mann-Whitney tests).

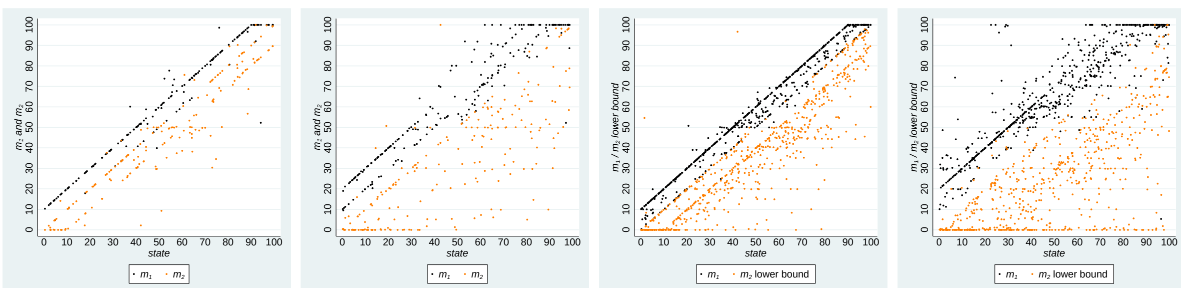
The two sets of comparisons with changes in statistical significance in the latter account for the "no change" of Finding 8 for *O-2-F* and *C-2-F* and the "partial quantitative change" for *C-2-I*.

Finally, Figures B.3–B.5 present senders' and receivers' behavior in the robustness treatments analogous to Figures 6–9 in the main text.



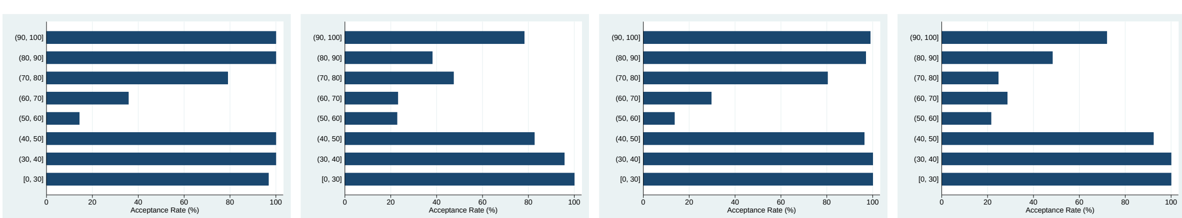
(a) State-Message, $b = 10$ (b) State-Message, $b = 20$ (c) Average Message-Action, $b = 10$ (d) Average Message-Action, $b = 20$

Figure B.3: Relationship between State and Message and Action as a Function of Average Message: Treatments *O-2-F*



(a) *C-2-F*, $b = 10$ (b) *C-2-F*, $b = 20$ (c) *C-2-I*, $b = 10$ (d) *C-2-I*, $b = 20$

Figure B.4: Relationship between State and Message: Treatments *C-2-F* and *C-2-I*



(a) *C-2-F*, $b = 10$ (b) *C-2-F*, $b = 20$ (c) *C-2-I*, $b = 10$ (d) *C-2-I*, $b = 20$

Figure B.5: Receivers' Adoption Rate of Proposals from Senders 1: Treatments *C-2-F* and *C-2-I*

Table B.6: Observed Efficiencies and Receivers' Payoffs: Robustness Treatments

Session / Fixed Group	Informa. Efficiency $-\text{Var}(X(\theta))$	Distrib. Efficiency $-(EX(\theta))^2$	Receiver Payoffs	Informa. Efficiency $-\text{Var}(X(\theta))$	Distrib. Efficiency $-(EX(\theta))^2$	Receiver Payoffs	Informa. Efficiency $-\text{Var}(X(\theta))$	Distrib. Efficiency $-(EX(\theta))^2$	Receiver Payoffs	Informa. Efficiency $-\text{Var}(X(\theta))$	Distrib. Efficiency $-(EX(\theta))^2$	Receiver Payoffs
	$b = 10$											
	O-2-F			*C-2-F*			*C-2-I*			*O-1-F*		
1	−16.51	0.00	−16.51	−24.19	−63.23	−87.42	−42.20	−27.29	−69.49	−13.15	−29.58	−42.73
2	−6.27	−0.12	−6.39	−129.21	−4.57	−133.78	−49.48	−30.16	−79.64	−11.65	−8.02	−19.66
3	−50.81	−0.18	−51.00	−76.49	−66.77	−143.26	−52.76	−22.91	−75.67	−112.76	−20.05	−132.80
4	−5.55	−0.17	−5.71	−35.76	−42.45	−78.21	−44.38	−30.83	−75.21	−40.59	−2.77	−43.36
5	−151.07	−6.53	−157.60	−18.52	−71.77	−90.28	–	–	–	−131.49	−31.35	−162.84
6	−36.72	−0.02	−36.74	−17.60	−55.82	−73.42	–	–	–	−21.94	−0.04	−21.98
7	–	–	–	–	–	–	–	–	–	−171.29	−1.20	−172.49
8	–	–	–	–	–	–	–	–	–	−119.05	−31.95	−151.00
9	–	–	–	–	–	–	–	–	–	−227.66	−27.47	−255.13
Mean	−44.49	−1.17	−45.66	−50.29	−50.77	−101.06	−47.20	−27.80	−75.00	−94.40	−16.94	−111.33
	$b = 20$											
	O-2-F			*C-2-F*			*C-2-I*			*O-1-F*		
1	−322.62	−0.26	−322.88	−178.32	−46.00	−224.31	−449.08	−31.08	−480.13	−85.97	−7.24	−93.21
2	−313.39	−6.07	−319.46	−217.13	−137.10	−354.24	−287.98	−13.68	−301.66	−341.35	−10.82	−352.17
3	−406.42	−2.10	−408.53	−514.78	−1.91	−516.69	−190.54	−118.33	−308.87	−527.44	−0.01	−527.45
4	−207.05	−0.14	−207.19	−222.24	−109.98	−332.22	−256.85	−57.36	−314.21	−4.95	−99.81	−104.77
5	−425.66	−0.21	−425.87	−135.03	−43.87	−178.90	–	–	–	−574.22	−40.10	−614.33
6	−25.73	−0.02	−25.75	−138.75	−31.53	−170.28	–	–	–	−149.33	−0.13	−149.45
7	–	–	–	−238.93	−53.84	−292.77	–	–	–	−1044.45	−15.93	−1060.38
8	–	–	–	–	–	–	–	–	–	−891.23	−4.46	−895.69
9	–	–	–	–	–	–	–	–	–	−210.98	−6.80	−217.78
10	–	–	–	–	–	–	–	–	–	−985.04	−7.38	−992.42
Mean	−283.48	−1.47	−284.94	−235.03	−60.60	−295.63	−296.11	−55.11	−351.22	−481.49	−19.27	−500.76

Note: Informational and distributional *efficiencies* are measured by, respectively, the negative numbers $-\text{Var}(X(\theta))$ and $-(EX(\theta))^2$. The corresponding *inefficiencies* are thus measured by the absolute magnitudes of the variances and the squared expectations. Receiver payoffs are calculated as $[-\text{Var}(X(\theta)) - (EX(\theta))^2]$.

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 C.1: 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.

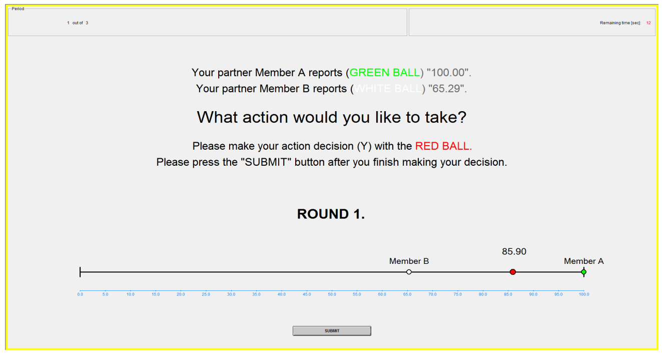


Figure C.2: Member C's Screen

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 $X+20 = 45$.) 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 $100 - \frac{[\mathbf{10}]^2}{50} = 98$ 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 $100 - \frac{[\mathbf{20}]^2}{50} = 92$ 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 $100 - \frac{[\mathbf{30}]^2}{50} = 82$ 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 C.1 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 $100 - \frac{[\mathbf{10}]^2}{50} = 98$ 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 $100 - \frac{[\mathbf{20}]^2}{50} = 92$ ECU.

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 C.1: Your earnings

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 $100 - \frac{[\mathbf{30}]^2}{50} = 82$ 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 C.1 provides an elaborate example regarding your earning and the distance between your ideal action and the action taken by Member C.

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 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 $b = 20$

INSTRUCTION

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

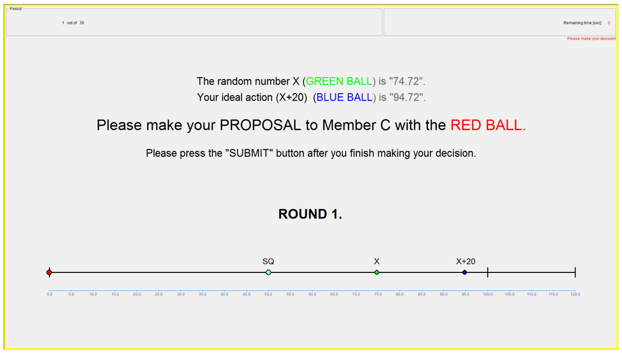
In each round and for each group, the computer will randomly select a number with two decimal places from the range $[0.00, 100.00]$. Each possible number has equal chance to be selected. The selected number will be revealed to Member A and Member B. Member C, without seeing the number, will have to 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

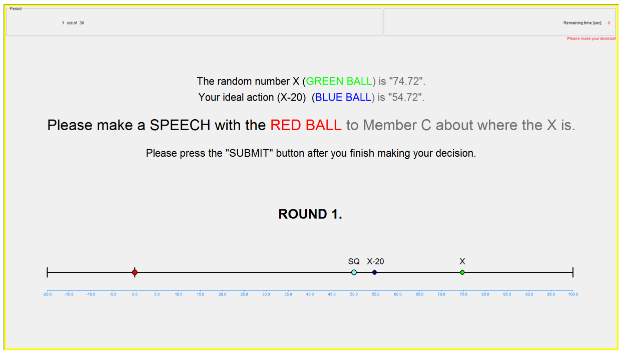
You will be presented with a horizontal line on your screen. The left end of the line represents 0.00 and the right end 120.00. You will see a green ball on the line, which represents the randomly selected number X. There is another blue ball that represents your "ideal action," which is equal to $X + 20$. 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 C.3: 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 clicking on the line. A red ball, which represents your speech, 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 speech.

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 a red ball, 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.

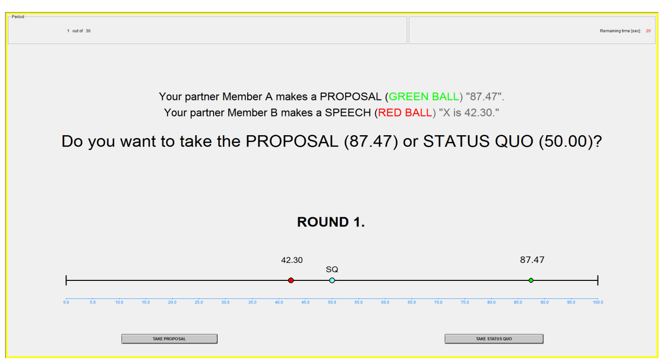


Figure C.4: Member C's Screen

<u>Your Reward in Each Round</u>

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,

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

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 10." 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 $100 - \frac{[\mathbf{10}]^2}{50} = 98$ 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 10." 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 $100 - \frac{[\mathbf{20}]^2}{50} = 92$ 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 10." 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 $100 - \frac{[\mathbf{30}]^2}{50} = 82$ 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 C.2 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 10." 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 $100 - \frac{[\mathbf{10}]^2}{50} = 98$ ECU.
2. Member A makes a proposal "40" and Member B makes a speech "'X is 10." 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 $100 - \frac{[\mathbf{20}]^2}{50} = 92$ ECU.
3. Member A makes a proposal "50" and Member B makes a speech "'X is 10." 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 $100 - \frac{[\mathbf{30}]^2}{50} = 82$ 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 C.2 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 C.2: 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 – Level-k Models

As a supplementary, non-equilibrium analysis of our experimental environment, we construct two level-k models, one for the open rule with two senders and one for the closed rule with two senders. As the anchoring point of the model, we assume, following the convention in the level-k literature on communication games, 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' recommendations or proposals.[2] 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 $a(m_1, m_2) = \overline{m} = \frac{m_1+m_2}{2}$.[3] 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 $k = 1, \ldots, K$, best responds to level-k Sender $j \neq i$ and level-$(k-1)$ receiver, while level-k receiver best responds to level-k senders.[4] 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, $k = 1, \ldots, K$, 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

[2] The 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; Crawford and Irreberri 2007a; 2007b) and the theoretical work on lying aversion (e.g., Kartik 2006; Kartik, Ottaviani, and Squintani 2007).

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

[4] Unlike 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's (2010) 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.

takes action $a = \overline{m} = 30$. 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.[5]

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

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

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 $\overline{m} = 30 < 50$, and the receiver takes $a = 30 - 10 = 20$. Level-1 Sender 2 sends $m_2 = 0$ only for $\theta \leqslant 60$. 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 $\overline{m} > 50$, 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 $\overline{m} = 50$, combining the two messages the receiver believes that $\theta \in [40, 60]$ (note that Sender 1 sends $m_1 = 100$ only for $\theta \geqslant 40$). 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 $m_2(\theta) = \max\{2(\theta - 2b) - 100, 0\}$.[6] Given these level-2 senders' strategies, the best-responding level-2 receiver then

[5]For the bias parameters we adopt in the experiment, the detailed cases of level-1 senders' strategies are:

for $b = 10$, $m_1(\theta) = \begin{cases} 100, & \theta > 40, \\ 2(\theta + 10), & \theta \leqslant 40, \end{cases}$ and $m_2(\theta) = \begin{cases} 0, & \theta < 60, \\ 2(\theta - 10) - 100, & \theta \geqslant 60; \end{cases}$

for $b = 20$, $m_1(\theta) = \begin{cases} 100, & \theta > 30, \\ 2(\theta + 20), & \theta \leqslant 30, \end{cases}$ and $m_2(\theta) = \begin{cases} 0, & \theta < 70, \\ 2(\theta - 20) - 100, & \theta \geqslant 70. \end{cases}$

Under these strategies and the level-0 receiver's action rule, Sender 1 obtains his ideal action for $\theta \leqslant 50 - b$, and Sender 2 obtains his for $\theta \geqslant 50 + b$. 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.

[6]For our adopted bias parameters, the detailed cases of the strategies are:

discounts or adds on the average messages by $2b$:

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

Higher level players' strategies are similarly derived by iterating on these best-responding processes.[7]

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.[8]

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for $b = 10$, $m_1(\theta) = \begin{cases} 100, & \theta > 30, \\ 2(\theta + 20), & \theta \leqslant 30, \end{cases}$ and $m_2(\theta) = \begin{cases} 0, & \theta < 70, \\ 2(\theta - 20) - 100, & \theta \geqslant 70; \end{cases}$

for $b = 20$, $m_1(\theta) = \begin{cases} 100, & \theta > 10, \\ 2(\theta + 40), & \theta \leqslant 10, \end{cases}$ and $m_2(\theta) = \begin{cases} 0, & \theta < 90, \\ 2(\theta - 40) - 100, & \theta \geqslant 90. \end{cases}$

Under these strategies and the level-1 receiver's action rule, Sender 1 obtains his ideal action for $\theta \leqslant 50 - 2b$, and Sender 2 obtains his for $\theta \geqslant 50 + 2b$. Note that even though for $\theta \leqslant 50 - 2b$, 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 $\theta \geqslant 50 + 2b$. 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 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.

[7] In particular, level-k senders' strategies, $k = 3, \ldots, K$, are $m_1(\theta) = \min\{2(\theta + kb), 100\}$ and $m_2(\theta) = \max\{2(\theta - kb) - 100, 0\}$. Note that for $k \geqslant \frac{50}{b}$, 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, $k = 3, \ldots, K$, the on-path response rule is

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

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

[8] Given 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:

for $b = 10$, $m_1(\theta) = \begin{cases} 100, & \theta > 90, \\ \theta + 10, & \theta \leqslant 90, \end{cases}$ and $m_2(\theta) = \begin{cases} 0, & \theta < 10, \\ \theta - 10, & \theta \geqslant 10; \end{cases}$

for $b = 20$, $m_1(\theta) = \begin{cases} 100, & \theta > 80, \\ \theta + 20, & \theta \leqslant 80, \end{cases}$ and $m_2(\theta) = \begin{cases} 0, & \theta < 20, \\ \theta - 20, & \theta \geqslant 20. \end{cases}$

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 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 $m_1(\theta) = \min\{\theta+b, 100\}$.[9] Any $m_2 \in [0, 50) \cup (100 - b, 100]$ will satisfy these requirements.[10] 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.[11] 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

[9]Recall that level-2 Sender 1 best responds to level-2 Sender 2 and level-1 receiver.

[10]Note 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 $b \geqslant 12.5$, $50 + 2b \geqslant 75 \geqslant 100 - 2b$, 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.

[11]Specifically, for $b \geqslant 12.5$, level-2 receivers choose (for $\theta \in [0, 50 - b]$, $(50 - b, 50 + b)$, $[50 + b, \min\{50 +$

m_2 will induce 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.[12] 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.

$3b, 75+b\})$, and $[\min\{50+3b, 75+b\}, 100]$, respectively)

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

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)

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

[12]Note 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.

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