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Strategic Communication: An Experimental Investigation*

Katharina Eckartz†, Christiane Ehses-Friedrich ‡

March 12, 2014

Abstract

In this paper we attempt to compare theoretically and experimentally three models of strategic information transmission. In particular we focus on the models by Crawford & Sobel (1982), Lai (2010) and Ehses-Friedrich (2011). These three models differ in the information that the receiver possesses and the sender's knowledge about these information. Lai, 2010 introduce a partially informed decision maker into Crawford & Sobel's model. Ehses-Friedrich (2011) makes the decision maker's knowledge public knowledge. The experiment replicates the results of earlier experimental studies (Dickhaut *et al.*, 1995, Cai & Wang, 2006, Wang *et al.*, 2010): on the one hand experts usually give a too truthful advice, they *overcommunicate*. On the other hand the decision makers rely too much on the received information. Moreover, communication as well as payoffs decrease with increasing preference differences. We find that when decision makers are privately informed the messages from the expert to the decision maker are less precise than in the baseline setting. In the public information treatment, the communication is less biased. In all treatments, however, the messages are more precise than theoretically predicted.

Keywords: Experiment, Strategic Information Transmission, Cheap talk, Communication

JEL Classification: C92, C72, D82, D83

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1 Introduction

In everyday life we often make decisions under uncertainty, i.e. while not knowing or being unsure which consequences our decision will have. Many of these decisions, as well as the resulting consequences, involve not only the decision maker but also other agents. In this paper we will focus on a situation in which an agent faces a decision while having no or only imperfect information about the state of the world. The agent is not sure which action to take and therefore consults an expert before making his decision. The expert, in turn, is influenced by the agent's decision.

A classical example is a person who experiences some physical pain and consults a doctor to get some advice on which treatment to choose. Similarly, imagine your car breaks down and you contact the garage to have the car fixed. On a level that effects more people, one can think of a policy maker who has to implement a policy to reach a certain goal like environmental protection. As a policy maker she is usually not an environmental expert and will have to contact experts to evaluate the impacts of potential policies.

In the ideal world, the preferences of the decision maker and the expert are perfectly aligned, i.e. one particular action is utility-maximising for both agents and both agents are aware of these conditions. In such a case, the expert should give truthful advice to the decision maker and the decision maker should follow this advice and choose the proposed action. These conditions, however, are rarely met in reality; often a conflict of interest between the decision maker and the expert exists: the doctor might want to give the patient a treatment which gives him a higher revenue (or lower costs). Yet, this treatment is not necessarily optimal for the patient, be it cost- or health-wise.[1] Similarly, the garage might exaggerate the car's damage or propose a solution which generates higher earnings. These two examples demonstrate that, even without considering higher levels of reasoning, the advised action might not be optimal to the agent.

If we introduce higher levels of reasoning, the expert's advice may be even more distorted. Take again the example of the environmental specialist who is advising the policy maker. The goal of the environmental specialist is to give advice such that environmental protection is highest. When giving his advice the expert is aware that the policy maker has to meet many diverse interests and, thus, the expert fears that the policy maker will choose a policy which will just lead to minimum protection. To reach a better environmental protection the expert might exaggerate the situation and, thereby, push the politician in a direction of higher protection. The politician herself might adjust her response as she might expect a distorted advice. Adding more levels of reasoning can result in a very distorted advice on the side of the expert and to increasingly neglecting the advice on the side of the decision maker.

The introduced examples all assume that the decision maker has no knowledge

[1] The doctor-patient relationship is a good example for countries in which the patient has to pay the costs of medical treatment herself. For countries with a public health insurance system without additional contributions you might interpret the scenario as the physical costs of treatment: the patient would feel better with a different treatment.

at all about the situation at hand and the message from the expert is the only signal she can use in the decision making process. In many real life situations the decision maker will, however, have some basic knowledge about the subject of her decision. Having a broken window in your car, chances are high that you will know that usually you can replace the glass separately without having to replace bigger parts of the car body. If the decision maker is completely uninformed she can acquire some basic knowledge before taking her decision. During this process she is limited by her own mental capacity as well as by the available time to acquire the needed knowledge. Now, when the decision maker approaches an expert and he gives his advice, it could make a difference whether he is informed about the (relevant) knowledge of the decision maker. Suppose that the expert has a good estimate about the decision maker's knowledge (consider, for example, a doctor who knows his patient is a nurse) or that the decision maker, hoping for a better outcome, decides to reveal her knowledge to the expert.

These examples set the stage for our research in which we will investigate stylised versions of these settings. We will analyse how the communication from the expert to the decision maker changes as a) the decision maker has some relevant knowledge herself and b) as the expert is informed about the decision makers' knowledge. We will concentrate on the communication, but we will also look at the decision makers' reactions and at the resulting payoffs.

Since it is pretty hard, if not impossible, to examine these questions with field data, we decided to conduct an experimental study. This study is based on three theoretical models which try to capture simplified versions of the earlier introduced scenarios (Crawford & Sobel, 1982, Lai, 2010 and Ehses-Friedrich, 2011). We attempt to compare the three models experimentally and analyse the impact of the decision maker's knowledge and the impact of the expert's knowledge about this. The paper is organised as follows: Section 2 gives an overview about the relevant literature. In Section 3.1 the three theoretical models of strategic information transmission which form the basis of this study are introduced. Subsequently, we derive the experimental hypotheses (3.2) and introduce the experimental design (3.3). In Section 4 we present our analysis. Finally, we conclude.

2 Literature

2.1 Theoretical literature

Strategic information transmission is a topic that has been vastly investigated in theory, mostly based on Crawford & Sobel (1982), *Crawford & Sobel* henceforth. Their model consists of two agents: one agent possesses information about the state of the world and the other agent has to make a decision ("to *take an action*") which influences both agents. The outcome depends on the state of the world and on the agent's decision. The agent who has to make the decision, referred to as the *decision maker* or the *receiver*,[2] consults the informed agent, whom we will

[2] In the experiment we will call her player B.

refer to as the *expert* or the *sender*,[3] to gather some information before making her decision. The expert has the possibility to transmit information ("to *send a message*") to the decision maker and thereby influence the decision maker's decision and, consequently, his own outcome. The model includes a strategic component as the preferences of the expert and the decision maker are assumed to be not aligned. Both agents are aware that the preferences differ. Crawford & Sobel show that the expert communicates some information and the closer preferences are, the more information is transmitted. However, full information transmission is not possible, unless the preferences are perfectly aligned.

Extensions to this basic model have been made in different directions: increasing the number of senders and/or receivers, changing the number of communication stages, and introducing informed receivers, to name a few. The related experimental economic literature will be discussed separately in Section 2.2.

In the introduction we motivated why it is plausible to assume an informed decision maker. Therefore, in this study we focus on models that extend the Crawford & Sobel and introduce a partially informed decision maker. The basic question these models try to answer is, how information on the decision maker's side affects communication and how it influences the utility of both agents. Lai (2010), Ehses-Friedrich (2011), Chen (2009), and de Barreda (2012) model an informed decision maker based on the Crawford-Sobel model. These models differ in the informative signal that the decision maker receives and in the expert's awareness of the decision maker's information. Ehses-Friedrich is the only of these studies who makes the decision maker's knowledge public knowledge.[4]

We investigate experimentally the theoretical predictions of these models and focus on two questions: what is the impact of the decision maker's own information and the expert's knowledge about this information on the transmitted information, on the decision maker's decision and, consequently, on the resulting payoffs? We will, therefore, consider models that model the decision maker's information similarly. In particular, we will rely on the basic model of Crawford & Sobel (1982) as a baseline. The private information model that we will consider is Lai (2010) (as of now *Lai*) and the public information model that we will consider is Ehses-Friedrich (2011) (as of now *Ehses-Friedrich*). The predictions of the models that use alternative modelling of the private information, Chen (2009) and de Barreda (2012), are similar to the ones by Lai.

The left part of Table 1 summarises how the three models by Crawford & Sobel, Lai, and Ehses-Friedrich differ in their knowledge-structure. Depending on the nature of the knowledge, the models give different equilibrium predictions for messages sent, actions taken as well as the resulting payoffs. Figure 1 illustrates the setting. The preference difference is displayed as a dotted line in the figure. Dashed lines represent information which distinguish the three models that we will focus on. These characteristics will constitute the treatments of the experiment (Section 3.3). In Section 3.1 the models will be introduced more formally

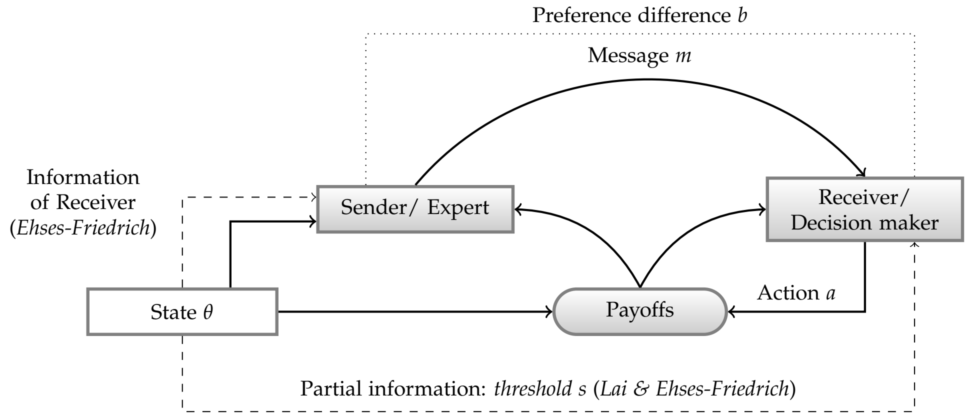
[3]In the experiment we will call him player A.

[4]Remember from the introduction that the expert might either observe certain characteristics of the decision maker and, from these, infer her knowledge or that the decision maker herself might reveal her knowledge to the expert, hoping to get a better advice.

Table 1 The knowledge-structure in the three models

	knowledge sender	knowledge receiver	treatment
Crawford & Sobel	perfect & private	none	NoInfo
Lai	perfect & private	imperfect & private	PrivateInfo
Ehses-Friedrich	perfect & private	imperfect & public	PublicInfo

Figure 1 Illustration of the underlying structure



and detailed. There, we will also introduce the short forms of the variables that are already included in Figure 1.

2.2 Experimental literature

The related research in experimental economics has on the one hand focused on testing predictions of the basic model by Crawford & Sobel. On the other hand, a substantial body of research has examined simplified versions of the sender-receiver game with completely opposed preferences, focussing on lying. First, we will discuss the studies which are closest related to our research, namely studies that focus on the basic Crawford & Sobel setting. Second, we will give an overview about experiments that examine extensions of the basic model. Subsequently, we will also cover the literature that relies on a setting with completely opposed preferences. We include the latter studies as lying aversion is discussed as a reason for overcommunication, which was observed in earlier studies and which we will discuss in the next paragraph. Moreover, this literature takes a prominent role in the experimental economic literature. Finally, the experimental literature on beauty contests will be introduced to illustrate the concept of level-k thinking.

Experiments testing Crawford & Sobel's implications The first study that experimentally examined Crawford & Sobel's sender-receiver model was Dickhaut, McCabe & Mukherji (1995). The authors focus on how the size of the preference difference between the two agents influences messages and actions. As preferences diverge, messages get less informative and the difference between states and actions increases. Receivers' payoffs decrease as preferences diverge. Cai & Wang (2006) follow a similar approach with some differences in the experimental design. Moreover, in their analysis they do not only focus on aggregate effects but also look at the individual level. They find that average payoffs are close to the most informative equilibrium. When looking at the individual level they find both overcommunication and overtrusting, i.e. senders' messages are more informative than predicted by the most informative equilibrium and receivers rely more on the messages than predicted. The third, and most recent paper, by Wang, Spezio & Camerer (2010) tries to understand the mechanisms underlying participants' behaviour in the sender-receiver game by using eye-tracking and pupil-dilation techniques. While the authors replicate Cai & Wang's findings of overcommunication, they also show that senders focus mainly on their own payoffs and that pupils dilate more, the more deceptive the sent message is. The authors interpret these findings as being an indication of the cognitive difficulty of sending deceptive messages. In the experimental design section (3.3) we will discuss the designs of these three studies in relation to our design. In particular, we will stress where the designs are similar and where they differ.

Experiments with extensions of the basic setting A number of related experimental studies are a bit more distant from our study. First of all, Vincent Crawford (1998) gives a structured overview about communication experiments involving cheap talk. Our study falls in his category of "signalling private information with a common language." Battaglini & Makarov (2011) analyse a strategic information transmission game with multiple audiences based on the model of cheap talk by Farrell & Gibbons (1989) with only two states of the world. Lai, Lim & Wang (2011) test a model with a 2x2 state space focussing on multidimensional cheap talk. They compare settings with one sender to settings involving two biased senders. Lai & Lim (2012) focus on a situation in which decision making can be delegated to the expert. They find "under-delegation" as subjects have a belief that the expert will be overcommunicating, which is actually consistent with the experts' behaviour. Minozzi & Woon (2012) analyse communication competition in a strategic information transmission game involving two senders with private information about their preferences. They find that subjects seem to be averse to lying, however this is crowded out over time.[5]

Experiments with completely opposed preferences A large body of experimental literature on sender-receiver games focuses on truth-telling and lying, also discussed as deception. The focus is in particular on lying aversion.[6] Usually, this literature relies on simplified versions of the sender-receiver game with only 2 states of the world and, consequently, also only 2 different possible messages and actions. In these settings the preferences of the senders and receivers are usually assumed to be completely opposed. Often the settings are based on cheap-talk

[5]The study uses a very large state-action space and the focus is not only on lying aversion, therefore we include it already in this paragraph.

[6]Many subjects prefer to tell the truth even when it is against their own financial interest.

experiments.[7]

In one of the first studies Gneezy (2005) examined the role of consequences on lying behaviour. He shows that subjects' willingness to lie is higher, the higher the associated gains for themselves, and, the lower the harm to the other subject. Gneezy's observations are reinterpreted by Hurkens & Kartik (2009). They argue that the observations are consistent with a situation in which there are two types of subjects: one type that never lies and the other type that only lies when he prefers the outcome of lying over the outcome of truth-telling.

Sánchez-Pagés & Vorsatz (2007) discuss how overcommunication can be explained as a "tension between normative social behaviour and incentives for lying" (p. 86).[8] They observe the presence of a set of morally consistent people. Once those are excluded from the analysis the excessive truth-telling vanishes. In a second study, Sánchez-Pagés & Vorsatz (2009) aim to distinguish between a preference for truth-telling and an aversion to lying by allowing the participants to remain silent. They find, amongst others, a "positive correlation between the probability of being truthful and the probability of remaining silent". Peeters, Vorsatz & Walzl (2008) examine the effect of possibilities to reward and find that receivers trust more when rewards are given, but senders do not send more truthful messages.

Sutter (2009) takes a wider perspective as to what can be classified as deception. He discusses whether truth-telling can be classified as deception if the sender expects the receiver to mistrust the message. Sutter finds evidence for this claim in his data. Recently, Erat & Gneezy (2012) focused on white lies.[9] They observe "pure lie aversion" in a significant fraction of their subjects. These subjects are even reluctant to tell a Pareto white lie, a lie that makes both the sender and the receiver of the message better off. Thus, these studies offer a number of potential explanations why we can observe truth telling and overcommunication.

Beauty contests & level-*k* models Strategic information transmission can take many steps of reasoning. The research on beauty contests, going back to Keynes, 1936, and first implemented experimentally by Rosemarie Nagel (1995), focusses purely on these steps of reasoning. Nagel makes the observation that behaviour which differs a lot from the game-theoretical benchmark might in fact be rational when taking into account the levels of reasoning, by employing one more level of reasoning than the believed level of reasoning of the counterpart. Nagel finds that about 80% of the participants are of level of reasoning type 0-3.[10] After this, Duffy & Nagel (1997) show that the proximity to the Nash-Equilibrium depends

[7] In cheap-talk experiments the setting is such that messages can be send and may be informative, however they have no direct effect on the players' payoffs. Thus, lying is costless.

[8] By behaving strategically people disrespect the social norm of truth-telling, therefore moral reasons might be the cause for the observed truth-telling. Sánchez-Pagés & Vorsatz (2007) argue that previous studies leave it open whether overcommunication is caused by social preferences.

[9] The authors talk about white lies as "lies that help others" (Erat & Gneezy, 2012, p.2). The study includes a larger set of states and actions. Payoffs are determined by whether the state and the action match.

[10] Level 0 players would randomly pick a number in the 0-100 interval, while a level 3 player would best-respond to a level 2 player.

also on the target-measure used.[11] Recently, Schnusenberg & Gallo (2011) show in a repeated setting that cognitive ability is only important in the first rounds, in later rounds learning dominates. Models taking into account these different levels are discussed as level-k models.

In this section we gave an overview about the related experimental literature. While a number of studies examined Crawford & Sobel's implications experimentally, no study analysed the influence of an informed receiver in a strategic information transmission setting. This is what we will do in this study. In addition, we also look at situations in which the expert is aware of the decision maker's knowledge. In particular, we will consider settings with partly aligned preferences. Therefore, our study differs, both in research goal as well as the experimental design, from the studies on lying aversion and is most similar to the studies which we discussed first in this section (Dickhaut *et al.*, 1995, Cai & Wang, 2006 and Wang *et al.*, 2010).

3 Experiment

3.1 The sender-receiver models

Crawford & Sobel (1982) analyse in their paper "Strategic information transmission" a sender-receiver game in which the sender (the expert) is completely informed, whereas the receiver (the decision maker) has no information about a state of the world. The preferences of the sender and the receiver are not completely aligned. The authors give an equilibrium description for a class of utility functions[12] and show that the closer the preferences of both actors are, the more information is transmitted. However, full information transmission is not possible as long as preferences are not perfectly aligned.

To gain some intuition of the theoretical background and the equilibrium description, consider the following functions which were introduced by Crawford & Sobel and which are used in most of the theoretical extensions to their model for comparative analysis: $U^d = -(a-\theta)^2$ for the decision maker's payoff and $U^e = -(a-\theta-b)^2$ for the expert's payoff. Let us look at the components of these functions: the *action (a)* is the decision that the decision maker takes. The second term, $\theta \in [0,1]$ (uniformly distributed), describes the state of the world about which the expert is fully informed. In Crawford & Sobel's model the decision maker has no information about the actual size of θ. The third term, b, measures the difference in preference between the two agents.[13] It is defined to be $b > 0$. Both agents are aware of the existence and size of this preference difference.

[11] For example, when the target-measure is dependent on the median, as compared to the mean, more behaviour is in line with the Nash-Equilibrium.

[12] For the conditions that have to be met in the general equilibrium analysis we refer to their paper.

[13] b is an abbreviation for the "preference bias". We will refer to it as the difference in preferences or b. It should not be confused with the "message bias" which we will introduce in Section 3.3 and which we will refer to as *bias*.

To illustrate the impact of the preference difference, note that the utility of the decision maker is maximised when he chooses an action that matches the state ($a = \theta$). In contrast, the utility of the expert is maximised when the decision maker chooses an action that equals the state plus the preference difference parameter ($a = \theta + b$). Thus, unless $b = 0$, a conflict of interest between the two actors exists. Since the theories, however, assume b to be positive, the action that the expert prefers is always higher than the action that maximises the utility of the decision maker.

Crawford & Sobel show that in equilibrium the expert partitions the state space. The information he transmits to the decision maker is the interval that contains the state of the world. The partitioning is independent of the state of the world and in equilibrium the expert has no incentives to deviate to another interval which does not contain the true state of the world. Crawford & Sobel, furthermore, proof the existence of a multiplicity of equilibria and argue to focus on the most informative equilibrium for comparative analysis. The most informative equilibrium becomes less informative as the preferences diverge. This means that the communicated partition becomes less precise.[14]

The partial information on the decision maker's side in Lai (2010) and Ehses-Friedrich (2011) are also modelled as a partitioning of the state space $[0, 1]$. For example, before consulting the expert the decision maker receives a signal that reveals whether $\theta \in [0, s]$ or $\theta \in [s, 1]$. Here s is the threshold that the decision maker knows. In this case communication constitutes an additional partitioning. These models investigate how the receiver's information influences the partitioning. Lai and Ehses-Friedrich differ in the extent to which the expert is aware of the information that the decision maker possesses: in Lai this information is private to the decision maker while in Ehses-Friedrich this information is public knowledge (Table 1). Both papers, Lai and Ehses-Friedrich take Crawford & Sobel as their benchmark and analyse how the communicated equilibrium partition changes in comparison.

While in Lai the communicated equilibrium partition of the expert always becomes less precise and can only be outweighed by the decision maker's own information, the communicated equilibrium partition in Ehses-Friedrich becomes in most cases more precise. When the communication is less precise, the loss can always be outweighed by the decision maker's own information. For direct comparisons of communication both papers use the quadratic loss function as introduced by Crawford & Sobel.

In this study we rely on the utility functions that are displayed in Equations 1 and 2. These functions are close to the specific functions that are used in the literature and also fit in the general class of functions analysed in the theoretical papers.

[14]This means the intervals of the partition are less equal or there are fewer intervals.

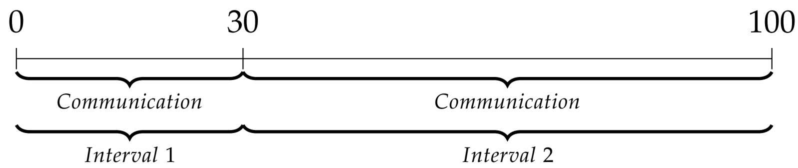
$$U^d = 50 - 100 \left| \frac{a - \theta}{100} \right|^{1.4} \tag{1}$$

$$U^e = 50 - 100 \left| \frac{a - (\theta + b)}{100} \right|^{1.4} \tag{2}$$

U^d represents the utility of the decision maker, U^e the utility of the expert. In the experiment the measurement unit of these utility-functions is "experimental currency units" (ECU). For the state of the world θ we use all integers in the space $[0, 100]$, a scaled version of $[0, 1]$, which is used in the theories. A detailed discussion follows in Section 3.3. Similarly, we restrict the action a to be an integer in the interval $[0, 100]$. Finally, we assume the preference parameter b, which defines the difference in preferences, to be a positive integer.

Example The following example is based on our specific utility functions (Eq. 1 & 2) and meant to illustrate the predictions in the three models using a particular set of parameters. Every graph illustrates the communicated partitions (*Communication*), where applicable the decision makers knowledge (*DM's info*), and the resulting equilibrium partitions (*Interval*).

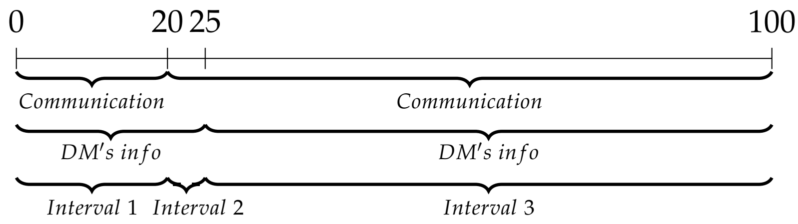
Suppose that the preference difference parameter b equals *10*, then in Crawford & Sobel the expert chooses the partition $[(0, 30); (30, 100)]$:[15]



When the state θ falls into the lower interval the expert will communicate this interval to the decision maker, else he will communicate the higher interval. Since the decision maker does not possess private information the communicated intervals are identical with the equilibrium partitions.

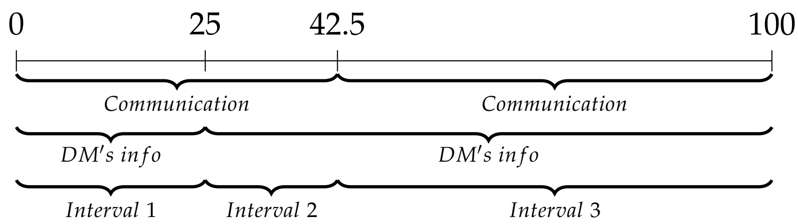
Now, consider an informed decision maker. She is *privately* informed whether the state is above or below her *threshold* s of *25*. The equilibrium partition is:

[15]In equilibrium the expert has to be indifferent between actions chosen in the lower interval and actions chosen in the upper interval at the boundary state. This means he is indifferent between $-a_{low} + (\theta + b)$ and $a_{high} - (\theta + b)$. With a uniform distribution a decision maker would choose 15 in the first interval and 65 in the second interval. So the indifference condition yields 30 for the boundary state. For all states in the lower interval the expert strictly prefers the lower action and for all states in the upper interval he strictly prefers the higher action. For more details about the computations of those equilibria we refer you to the respective theoretical papers.



In this case the communicated partition is independent of the decision maker's information. In fact, it has to be independent of it, as the decision maker's information is private to herself. Depending on the sent message, the decision maker can identify which of the three resulting intervals contains the state θ. Compared to the intervals in the previous scenario, in a setting with a privately informed decision maker, the communicated interval-lengths are less equal. This implies that fewer information is transmitted. It depends on the decision maker's knowledge whether she can outweigh this loss or not. In the displayed case, with a known threshold s of *25*, the decision maker does not gain much from the message and is even worse off compared to the uninformed case.

If the information of the decision maker is *public* and her threshold s is *25*, as before, then the expert communicates an interval having a boundary of *42.5*:[16]



This figure illustrates that in the example with public information the communication is more precise as the transmitted intervals are more equal. Taking into account also the decision maker's own information results in an additional partition. The resulting partition is more precise than before. Note that, even when the expert is aware of the decision maker's information, the model does not necessarily predict the expert to partition the state space into three intervals. A communicated partition into two intervals with a boundary of *42.5* is a sufficient equilibrium condition. Here the communication is more precise than in the other two settings and the expected utilities based on the communicated information increase. In addition, the decision maker's own information further increases her expected utility.

Comparing the three examples, least communication takes place with private information. Similarly, expected utilities are also lowest with private Information. When the decision maker is uninformed, her expected utility equals *42* ECU.[17]

[16]With public knowledge of the decision maker's information, the expert's partitioning of the state space depends on b and the decision maker's knowledge.

[17]The decision maker's expected utility before communication takes place is $EU^d = 50 - 100\sum_{i=1}^{N}\int_{g_{i-1}}^{g_i}\left|\frac{a-\theta}{100}\right|^{1.4} f(\theta)d\theta$ where g_i represents the boundaries of the partition, N is the number of intervals and $g_0 = 0$ and $g_N = 1$.

Relying on Equations 1 and 2, a privately informed decision maker with a boundary of *25* has an expected utility of *41.75* ECU, whereas a decision maker whose information is known by the expert has a utility of *44.01* ECU. In all three settings the expected utilities of the sender are smaller than the expected utilities of the receiver, but the senders' utilities are ranked in the same order. With similar preferences the expected utilities of the two players are alike, the larger the preference difference, the more the expected utilities diverge.

3.2 Hypotheses

The experimental hypotheses will cover a range of measures: senders' communication, receivers' actions and both actors' payoffs. We base our predictions, where possible, on the explicit predictions of the theoretical models. In the remaining cases we calculate predictions for our set of experimental parameters and base our predictions on these calculations. Table 2 gives a qualitative overview about the treatment-specific predictions relating to communication and expected utility.

To analyse the experts' communication, three potential measures are indicative: the message precision, the message bias and the correlation between the state and the expected value of the sent message. In the following we will address them one by one. First, *message precision* refers to the *lengths* of the sent intervals. The longer a sent interval, the less information is transmitted. Table 3 shows the predicted lengths of the sent intervals. Second, to get an estimate of *what* is communicated, we will rely on the expected value of the transmitted intervals (ev_{int}). The distance between this ev_{int} and the state θ will be referred to as the *message bias*. We will focus on this measure, in particular, in the analysis (Section 4). In addition, Table 4 shows the predicted correlation between the state θ and the expected value of the sent interval ev_{int}. A higher correlation is indicative of more communication. The drawbacks of this measure are that it requires variation on ev_{int} and that it does not capture the difference between ev_{int} and the state θ.

All displayed predictions are based on the specific parameters that were chosen for this experiment. These parameters were chosen to capture the whole potential range of scenarios. Based on the displayed predictions, as well as on the general underlying models, we identify the experimental hypotheses.[18]

All three models predict the communication to decrease as the preferences diverge. This effect is illustrated in Table 3: the predicted length of the sent interval increases, the more the preferences diverge, i.e as b increases. Since the theoretically predicted equilibrium partitions are independent of the the state θ (see Section 3.1), the lengths of the sent intervals are also independent of θ.[19] Moreover, Table 4 also shows that the predicted correlation between the state and the

[18] In Appendix B we display the equilibrium conditions for the specific models that we compare in this study.

[19] To get an intuition, assume that the expert and decision maker partition the state space *before* the realisation of the state of the world, even though this is not a necessary condition for the equilibrium. Therefore, the partitioning depends only on the size of b and, if the expert is aware of it, the information structure of the decision maker (i.e. the size of s). The expert communicates the interval which contains the true state of the world.

expected value of the sent message is expected to decrease as b increases. In our experiment PrivateInfo is a special case as for b=15 all randomly chosen states are located within the same communicated experimental interval [5,100]. Thus, the expected value of the interval is constant and no correlation can be calculated. Constructing a similar set of parameters and including one state that is smaller than the lower border of the interval [5,100] demonstrates that also here the correlation is decreasing. Have a look at the bottom part of Table 4 for more details. These observations lead us to the first experimental hypothesis:

Hypothesis 1a - Communication: b effect
Independent of the treatment, communication is predicted to decrease as the preference difference b increases.

Lai compares his model with the model of Crawford & Sobel and shows that in his own model the expert gives a less informative advice than in CS. Table 3 illustrates this prediction: with our experimental parameters, on average the interval length is predicted to be longer than in CS.

Hypothesis 1b: Communication in PrivateInfo
In PrivateInfo less communication than in NoInfo is predicted.

Ehses-Friedrich also compares her model to the model of Crawford & Sobel. She identifies conditions under which more communication is predicted. In particular, the communication depends on the combinations of b and the decision maker's threshold s, which we introduced in Section 3.1.

Since our experiment is designed to cover different potential cases, our average results do not always represent the theoretical predictions. In our experiment this is the case for PublicInfo. The model by Ehses-Friedrich predicts that, aggregated over all cases, communication is more precise. For the specific experimental parameters that were selected for this experiment, however, slightly less communication than in NoInfo is predicted. The lower part of Table 3 displays the predicted lengths of all b-s-combinations that are possible in this experiment. When the threshold is at s=14, for example, communication is always more precise than in CS. The general pattern in Ehses-Friedrich is that small thresholds result in, in relation to the other treatments, more information transmission even for relatively high differences in preferences. Cases with higher thresholds yield no communication improvement. However, the lower b, the higher the threshold s must be to lead to less communication.

Hypothesis 1c: Communication in PublicInfo
For PublicInfo it depends on the specific setting how much communication is predicted. Aggregated over all experimental parameters, slightly less communication than in NoInfo is predicted.

For very large preference differences no communication is predicted, however, the threshold as of which no communication is predicted, differs between the treatments. In NoInfo the threshold is at $b = 25$, in PrivateInfo it is at $b = 16.67$ and

Table 2 Predictions

	communication	expected utility (EU)
Crawford & Sobel	baseline	baseline
Lai	always less communication	sometimes higher EU
Ehses-Friedrich	theoretically more communication	always higher EU

Table 3 Predicted length of the sent intervals

	b				
Treatment	10	15	20	40	All
NoInfo	56.67	65	83.33	100	76.25
PrivateInfo	65	95	100	100	90
PublicInfo - All	56	85.42	90.12	100	82.89
PublicInfo - s=14	54.33	57.67	61	100	68.25
PublicInfo - s=50	48.33	100	100	100	87.08
PublicInfo - s=71	61.5	94.5	100	100	89
PublicInfo - s=81	59.83	89.5	99.5	100	87.21

in PublicInfo it is at $b = max(\frac{s}{4}, \frac{100-s}{4})$. No communication does not mean that no message is sent but that the message is meaningless, a so called "babbling equilibrium"; the sent message covers the whole message space, in our case [0,100]. Consequently, the predicted correlation between the expected value of the sent interval and θ should be zero.[20]

For simplicity we will focus in this study only on the settings which predict no communication irrespective of the receivers' knowledge.

Hypothesis 1d: No Communication

In all treatments, no communication is predicted at b=40. In addition, in PrivateInfo no communication is predicted with b=20.[21]

All three models focus on comparing messages and payoffs. The receivers' behaviour is only implicitly analysed. Nevertheless, we will follow the previous experimental studies and concentrate on the response of the receivers' behaviour, which can be thought of as "trusting", to changes in b. We will analyse this "trusting" as the correlation between senders' messages and receivers' actions.

Hypothesis 2: receivers' decisions

In all treatments the correlation between the expected value of the message and the action ("trusting") decreases with b.

[20]Technically, here the expected value of the sent interval is constant at 50. A correlation between a vector of constants and a vector of variables is not calculable. However, if one adds an error term ϵ to (at least) one element of the vector of constants it can be shown that $Cor \to 0$ as $\epsilon \to 0$. Hence, in practice we follow previous studies and interpret the correlation as being equal to zero.

[21]For completeness: PublicInfo, in addition, predicts no communication in the scenarios b=15 & s=50 and b=20 & s={50,71}. In all other cases communication is predicted.

Table 4 Predicted information transmission (correlation between θ & ev_{int})

b	NoInfo	PrivateInfo	PublicInfo
10	0.85	0.76	0.86
15	0.76	*0.45**	0.47
20	0.41	0	0.4
40	0	0	0

*The predicted correlation for PrivateInfo (b=15) is based on an experimental parameter set in which in period 21 the original value of θ (θ=6) is substituted by θ=4. This modification is only done here for illustrative purposes.

Table 5 Predicted payoffs

Receiver

	b				
Treatment	10	15	20	40	All
NoInfo	42.41	40.43	37.68	34.21	38.68
PrivateInfo	44.17	42.12	41.33	41.33	42.24
PublicInfo	44.83	43.15	41.59	41.33	42.72

Sender

	b				
Treatment	10	15	20	40	All
NoInfo	40.85	37.12	32.63	17.48	32.02
PrivateInfo	42.28	38.53	35.49	20.33	34.16
PublicInfo	42.9	39.4	35.67	20.33	34.58

The models focus on (expected) utilities, which cannot be measured directly but which can be approximated by the experimental payoffs. Therefore, we will focus on experimental payoffs in the following. Table 5 displays in the upper part the average expected payoffs of the receivers and in the lower part those of the senders, all split by b and treatment.

Hypothesis 3: Expected payoffs
In all treatments, the expected payoffs of both players decrease as the preference difference increases. Comparing the treatments, payoffs are predicted to be: $PublicInfo \geq PrivateInfo > NoInfo$.[22]

3.3 Design

Set-up Our experimental set-up divides the subjects into *senders* (labelled *"participant A"*) and *receivers* (labelled *"participant B"*). These roles are fixed throughout the whole experiment.[23] We apply a random strangers-matching protocol in 16-person matching groups. The experiment consists of 24 rounds. It is designed

[22]On the disaggregate level, in most of the b-s-combinations the expected payoffs are also ordered $PublicInfo \geq PrivateInfo$.

[23]We followed Cai & Wang, 2006 in the labelling. In their design roles were not fixed, however.

between-subjects, consisting of three treatments which represent the three earlier introduced models. Like Cai & Wang (2006) the experimental goal was framed as finding a "secret number", which corresponds to state θ. As introduced in Section 3.1, the theories assume a continuous state space over the interval [0,1]. To approximate this continuity and facilitate comprehensibility, the state- , message-, and action-space was scaled to all integers in the interval [0,100].[24] This "blown-up" space is intended to be more intuitive to understand for the participants compared to a $[0, 1]$ space with two decimal places. The earlier studies (Dickhaut *et al.*, 1995, Cai & Wang, 2006 and Wang *et al.*, 2010) all used discrete spaces with a small number of four to five states and four to nine possible actions.[25] Thus, the more fine-grained state space is a novel feature of our study. We thereby give participants the possibility to differentiate their messages. Moreover, this representation is closer to the theoretical models. In addition, this fine-grained state space allows us to distinguish in our analysis between message precision and message bias.

The experimental protocol is the same in all treatments, senders are first informed about the size of θ on the experimental screen. Second, they send a message to the receiver. Messages in our experiment can consist of either a point or an interval. Moreover, after they send the message, senders have to guess which action the decision maker will take.[26]

The receiver sees exactly the sent number/interval[27] (unlike Cai & Wang, 2006, but like Dickhaut *et al.*, 1995). We do this as we do not want to introduce an additional layer of uncertainty to the experiment. Subsequently, the receiver takes an action by choosing an integer between 0 and 100 from the action space. After every round, feedback on the true state, the chosen action, and the corresponding payoffs is provided. In total the experiment consisted of 24 rounds.

In contrast to the three closely related experiments by Dickhaut *et al.*, Cai & Wang, and Wang *et al.*, the potential experimental payoffs can be displayed as graphs. Both, the senders and the receivers, can use a tool in the experimental software to draw payoff-curves for different possible states, and thereby visualise the potential payoffs of both players in separate graphs. We hope that this representation fosters participants' understanding of the setting. In particular in comparison to payoff-tables which have been used in previous studies, we expect the graphs to facilitate understanding of the underlying mechanisms, to visualise the payoff differences, and to ease perspective-taking of both players. Consequently, it might be easier to think more strategically. Participants can draw curves for all possible parameters, however at most three different curves are visible at the

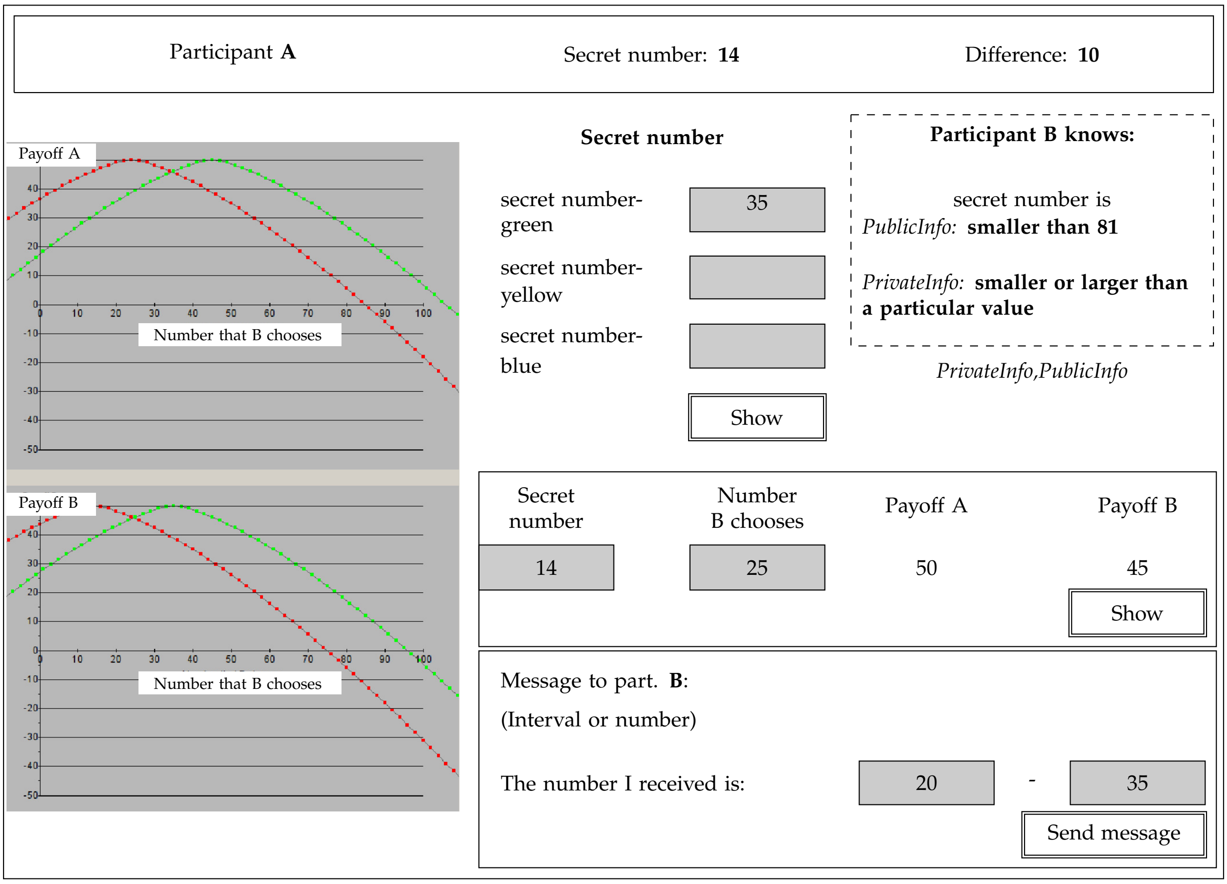
[24]This is equivalent to using all two decimal numbers with two decimal places in the [0,1] interval.

[25]Only Minozzi & Woon (2012), in a different setting, use a quasi-continuous space using integers between -100 and 100.

[26]This guess was not monetarily incentivised and was included to get an indication which actual message the senders wanted to send. In contrast to Cai & Wang (2006) and Dickhaut *et al.* (1995) who always assumed a uniform distribution over intervals, we can see how the self-reported guess relates to ev_{int} of the sent interval and the true state θ.

[27]A message consisting of a single number was displayed as "Message: 60 - 60" to the receiver.

Figure 2 Screen Sender



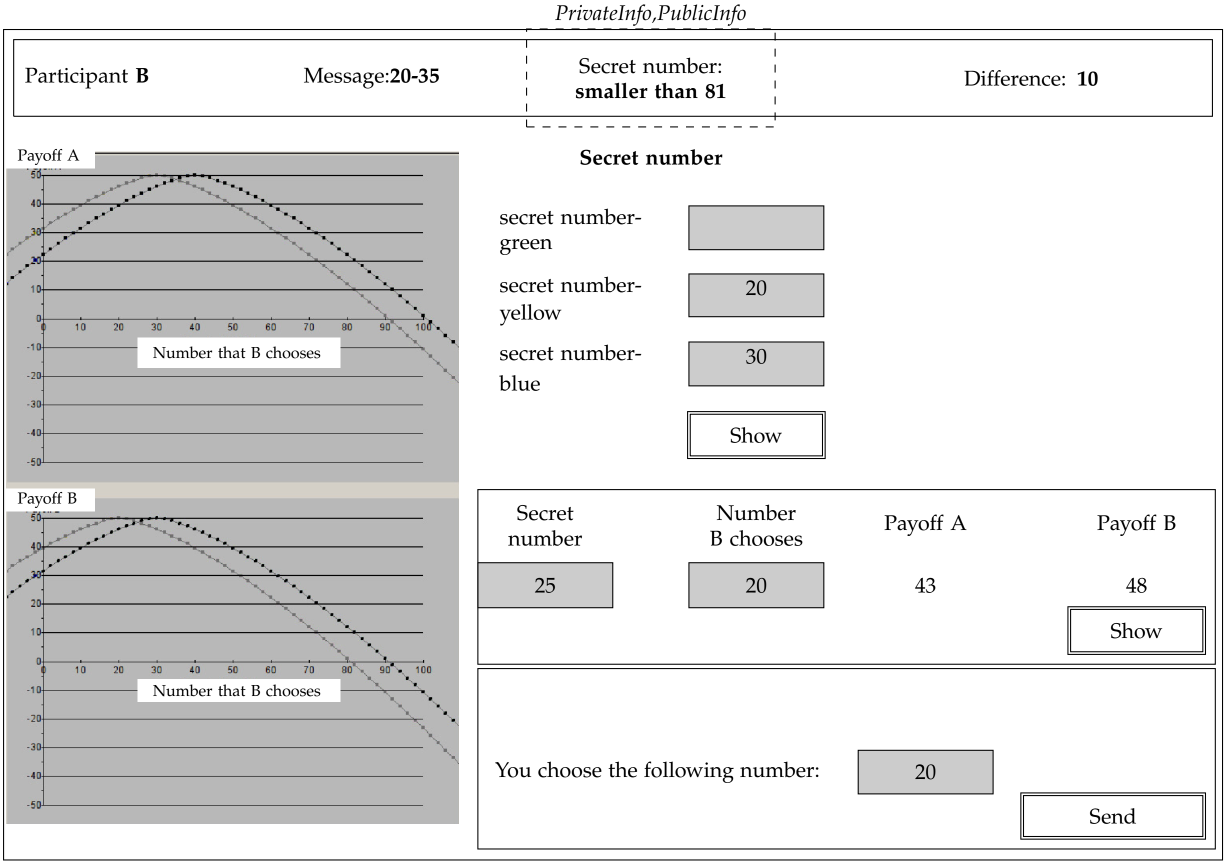
The right curves are the *green* curves, the left are the *red* ("true") ones.

same time.[28] The "true" payoff curves, corresponding to the secret number, are only displayed to the senders. The receivers can never be sure whether the curve they look at represents the true payoff curve or not. Additionally, both players have access to a payoff calculator, in which they can calculate the payoffs for different choices of the receivers as a function of specific states.[29] Figures 2 and 3 display the experimental screens of the senders and the receivers, respectively. Dotted lines represent treatment-specific information.

Treatments The three experimental treatments (Table 1) differ in the receiver's information and the expert's knowledge about these information. *NoInfo* is the baseline treatment representing the Crawford & Sobel setting in which the receiver does not receive information about the state. In the *PublicInfo* treatment (representing Ehses-Friedrich) both players learn that the secret number is below or above a specific value (for example "smaller than 81"). In this treatment the receiver's information is public knowledge.[30] In the *PrivateInfo* treatment, the sender is only informed that the receiver learns that the true state is above or

[28]The curves were shown in different colours to ensure comparability between the two graphs.
[29]The sender could use a calculator to learn the true payoffs for different choices of the receiver.
[30]To ensure public knowledge this information was read out aloud at the beginning of each round.

Figure 3 Screen Receiver



The right curve are the *blue* curves, the left are the *yellow* ones.

below a "particular value" but he does not know the exact threshold.

Experimental parameters Table 6 displays the experimental parameters. The states were selected by a random draw from a uniform distribution between 0 and 100. We restricted the information structures (the thresholds s) to four values that were selected from a random draw. To cover the whole range of possible values we divided the interval into four groups (0-25,26-50,51-75,76-100) and randomly selected one value for each group.[31] Additionally, this experiment is restricted to four different bias parameters which were selected to map the different possible predictions. The very high parameter, b=40, was included because no communication is predicted in all treatments. Thus, it allows to check for overcommunication. The subject pool was split into two groups: one group faces preference differences of 10 or 20 (b_{low}), in the other group the sizes of b are 15 and 40 (b_{high}).[32] All combinations of receivers' thresholds and states are the same in all three treatments and for both groups of high and low bs. The order of scenarios was randomised once and then kept constant across all sessions to ensure comparability.

[31] In a similar setting Minozzi & Woon (2012) also divided the state space before sampling their shifiting-parameters S.

[32] We had to make a trade-off between the length of the experiment and budget-constraints and hence split the participants pool into two groups.

Table 6 Parameters in the experiment

Period	state	s	b_{low}	b_{high}	Period	state	s	b_{low}	b_{high}
1	89	71	10	15	13	62	71	10	15
2	14	81	10	15	14	18	81	20	40
3	91	71	20	40	15	48	81	20	40
4	23	50	10	15	16	42	14	20	40
5	46	50	10	15	17	74	50	10	15
6	52	50	20	40	18	75	50	20	40
7	10	14	10	15	19	11	50	20	40
8	84	14	20	40	20	38	81	10	15
9	59	14	10	15	21	6	71	10	15
10	7	71	20	40	22	53	71	20	40
11	86	81	10	15	23	12	14	20	40
12	90	14	10	15	24	90	81	20	40

3.4 Conducting the experiment

The experiment was conducted in the end of 2011 in the experimental economic laboratories of the Max-Planck-Institute of Economics and the Friedrich-Schiller-University in Jena.[33] After subjects came to the lab, they received the experimental instructions.[34] Subsequently, subjects went at their own speed through a tutorial which was presented on the computer screen using E-nstructions (Schmelz, 2010). This tutorial walked the participants through the information which they would see on the experimental screens. Amongst others, it explained graphically the preference difference parameter b.[35] We designed this tutorial as intuitive and extensive as possible to make sure that the participants understand the experiment.[36] Afterwards, subjects went through two trial rounds without interaction and feedback, the first round as a sender and the second round as a receiver. In between the trial rounds and the start of the experiment, subjects were answering control questions. The experiment took between 1.5 hours and 2 hours 20 minutes.[37] Most sessions were completed within 2 hours.[38] The experiment was programmed in z-Tree (Fischbacher, 2007).

Participants accumulated earnings in ECU during the experiment which were converted into Euro at the end of the experiment with a conversion rate of 100 ECU = 1.75 Euro. The earnings were dependent on the receivers' decisions as well as

[33]Sessions 1 to 5 were conducted in the large laboratory of the Max-Planck-Institute, sessions 6 and 7 in the smaller University-laboratory.

[34]The experimental instructions can be found in Appendix A. The original instructions were in German.

[35]In the experimental instructions b was named U, relating to the German Word for difference "Unterschied". For simplicity we will continue to refer to it as b here. In Cai & Wang (2006) this parameter is called d.

[36]We tested the understandability of the experiment in a pilot experiment in the video laboratory of the Max-Planck-Institute of Economics in Jena.

[37]Due to time constraints we had to stop the first session after 20 rounds.

[38]Subjects needed between 20 and 30 minutes of the experimental time to complete the introductory part.

the state θ. Additionally, subjects received a show-up fee of 2.50 Euro. Subjects were privately paid out in cash at the end of the experiment. In total 220 subjects were participating in the experiment, 32 of those participated in pilot experiments.[39] The first pilot experiment was used to check and improve the understandability of the experiment and to calibrate the conversion rates. The second pilot experiment was used as a test.[40]

4 Results

This analysis is guided by the experimental hypotheses developed in Section 3.2.[41] In a large part we will rely on mixed effects regressions which allows us to account for the subject- and group-specific heterogeneity.[42]

Hypotheses 1a-d are hypotheses about the senders' communication. There are three measures of *communication* that we can analyse in this experiment: first *message precision*, operationalised as the length of the sent intervals, which we also used when we derived the hypotheses in Section 3.2. A second interesting measure is the *bias* of the communicated information. For this, communication is operationalised as the distance between the expected value of the sent interval ev_{int} and the state θ. The third measure is the correlation between θ and ev_{int}. Furthermore, some of the theoretical literature (e.g. Ehses-Friedrich and de Barreda, 2012) focus on the so-called "communication effect" to quantify differences in the communication in terms of hypothetical payoffs.[43] This measure is highly, theoretically as well as empirically, related to the measures of communication which we use. For completeness we also calculated the communication effect and report the comparisons of the hypothetical payoffs in Appendix 7. Since the results go qualitatively in the same direction as our measure for the bias in the communication, we will not discuss it separately.

To analyse hypotheses 1a-c, we will estimate the following mixed effects regression.

$$\text{Communication} = \sum_{\text{Treat.}} \beta_{\text{Treat.}} \cdot d_{\text{Treat.}} + \epsilon_{\text{group}} + \epsilon_{\text{subj.}} + \epsilon_{\text{subj.},t} \tag{3}$$

Communication in this regression is measured either as the message *precision* or as the message *bias*. The regression includes fixed effects for the experimental

[39] In one session we had to reduce the matching group size to 14 due to excessive non-show-ups. Table 8 in the Appendix gives an overview.

[40] After the second pilot non-binding time-limits were introduced into the software.

[41] We used the statistical software R (R Development Core Team, 2012) for the analysis.

[42] Since we have repeated observations of every participant, the experimental observations cannot be assumed to be independent. OLS, however, requires uncorrelated error-terms. Mixed effect models allow to account for this design in the regression. In our experiment we have repeated observations of every subject in matching groups with feedback and can also account for the matching group in the regression.
The p-values and confidence intervals were bootstrapped using the "mcmcsamp" function in the lme4-package (Bates *et al.*, 2012) in R with 5000 replications.

[43] For Lai's model we can calculate the predicted communication effect.

treatments. Moreover, since we have repeated observations of the individual participants that make their decisions in fixed matching groups, we include a random effect for the individuals, $\epsilon_{\text{subj.}}$, as well as a random effect for the matching group, ϵ_{group}. We included the latter term to capture potential differences between the matching groups. The last term, $\epsilon_{\text{subj.},t}$, is the residual. The regression results are displayed graphically in Figure 4. The figure shows the estimates with 95% confidence intervals. The upper two graphs show the estimates for each level of b, using message *precision* in the top graph (4.2) and message *bias* in the middle graph (4.2). The bottom graph (4.3) shows the estimates for the data aggregated over all levels of b.

Remember that we had two experimental groups which only differed on the levels of b that they faced. The first experimental group faced $b \in \{10, 20\}$, the second group faced $b \in \{15, 40\}$ (see Section 3.3 under the heading of *Experimental parameters*). We account for this in the graphical analysis by examining both experimental groups separately: vertical comparison between the figures in Figure 4 is a *within* group comparison. The graphical analysis is supported by the regression results which are reported in Appendix D.3. The estimation results for message precision are displayed in Table 13, those for the bias in the communicated information are displayed in Table 14.[44] These regressions use the experimental data pooled over all levels of b. We will occasionally use regression results to support our analysis.

H1a-c hypothesise a directional effect. Testing against the one-sided alternative would thus be justified. Nevertheless, we will rely on two-sided p-values as those are more conservative.

Hypothesis 1a: Communication: *b* effect In this hypothesis we analyse whether communication decreases with increasing preference differences. To analyse the effect of b in the different treatments, the relevant comparisons in Figure 4 are the vertical comparisons *within* every treatment.

Starting with message precision, in PrivateInfo the length of the sent intervals in group 2 ($b_{15,40}$) seems to be indeed significantly longer with increasing preference differences between the two parties. The results in NoInfo do not show a significant relation between the length and b. The effect in PublicInfo is in-between the two treatments, a small increase can be observed in group 1 ($b_{10,20}$). The regression results reveal that the effect is highly significant for PrivateInfo ($\beta_{\text{PrivateInfo}\cdot\text{b}} = 0.2$ in Table 13) and only significant at 10% level in PublicInfo.[45] In all treatments the length of the sent intervals is much shorter than theoretically predicted (Table 25). Observing overcommunication is in line with earlier experimental evidence.

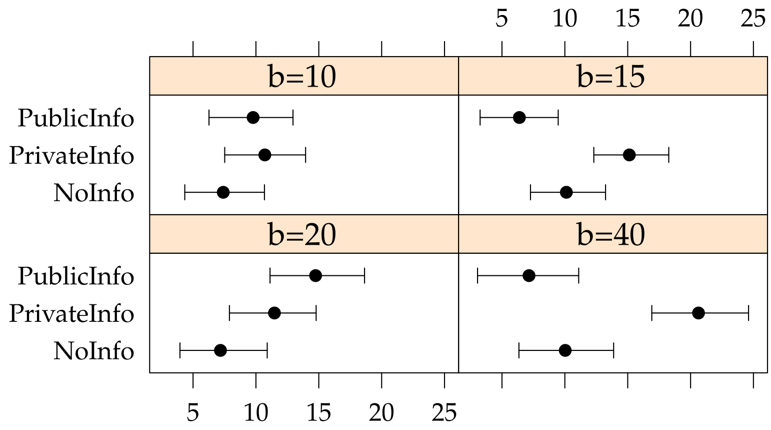
Turning to the bias in the communication, the figures show clearly that in both groups the message bias is higher when the preference difference b is higher. This

[44] One session had to be stopped early. To account for potential differences, we replicate the regressions using only the data of the first 20 instead of all 24 rounds. The regression results are reported in Section D.2 in the Appendix. While the sizes of the coefficients differ slightly, the main results will not be affected. Possible differences will be mentioned.

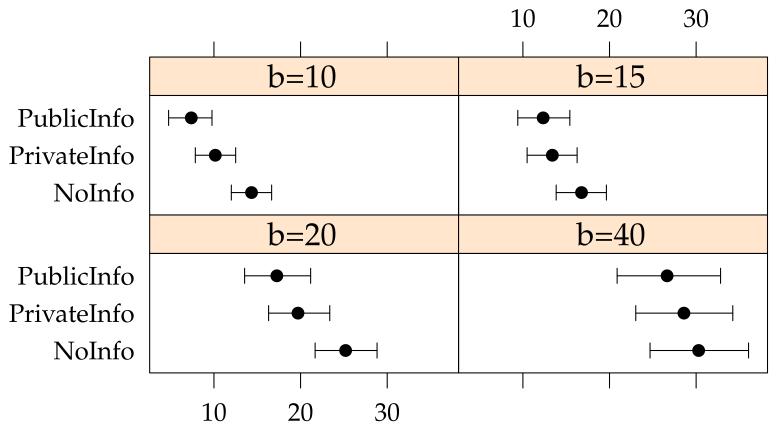
[45] This effect is larger and its significance is higher when one considers only the restricted data set of the first 20 rounds (Appendix D.2).

Figure 4 Communication estimates (Equation 3)

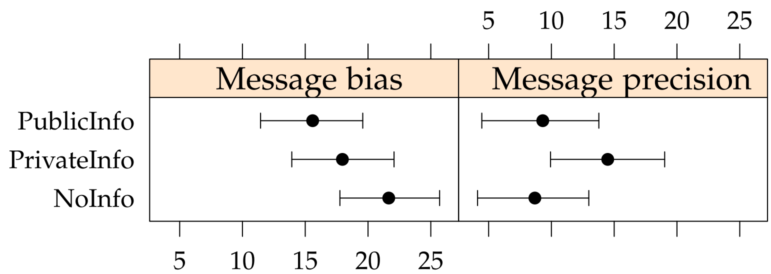
4.1 Message precision (length of the sent intervals)



4.2 Message bias (ev_{int}-θ)



4.3 Aggregated over b



Estimates with 95% confidence intervals.

Table 7 Observed correlations

	b	Cor(θ,ev_{int})	Cor(ev_{int},a)	Cor(θ,a)
NoInfo	10	0.96	0.93	0.9
	15	0.85	0.86	0.73
	20	0.87	0.84	0.77
	40	0.2	0.42	0.12
	all	0.7	0.74	0.65
PrivateInfo	10	0.96	0.94	0.94
	15	0.94	0.88	0.89
	20	0.88	0.84	0.84
	40	0.65	0.58	0.74
	all	0.84	0.8	0.85
PublicInfo	10	0.93	0.94	0.91
	15	0.92	0.89	0.84
	20	0.85	0.86	0.84
	40	0.63	0.67	0.68
	all	0.81	0.83	0.82

All correlations are significant at 1% significance level.

In the Appendix Table 10 shows an extended table in which we also include the correlations with the senders' guess of the receivers' behaviour.

effect is confirmed by the regression on the pooled data set (Table 14), all three interaction terms ($\beta_{\text{Treat.}\cdot\text{b}}$) are significantly different from zero, the size of the marginal effect of b is about 0.6.

Cai & Wang rely on correlation tables in their analysis. Similarly, the first column of Table 7 displays the correlation between the expected value of the communicated interval and θ. In line with the theoretical prediction this correlation is decreasing in b.

These observations are in line with the theoretical prediction: less is communicated with higher preference differences. In PrivateInfo the interval length is increasing in b and at the same time the distance between the communicated information and θ increases with b. Consequently, the correlation between θ and the message decreases in b.

Hypothesis 1b: Communication in PrivateInfo This hypothesis deals with the communication in PrivateInfo in comparison to the communication in NoInfo. To analyse this hypothesis, we compare the behaviour aggregated over all levels of b between PrivateInfo and NoInfo. The regression results over the aggregated data are displayed in Figure 4.3.

Starting again with message precision, the right part of Figure 4.3 shows that the sent intervals in PrivateInfo are longer than in NoInfo (p=0.06).[46] This in line with the theoretical predictions. The left part of the same figure shows that the message bias, the distance between the expected value of the sent message and θ,

[46] The regression results of the underlying regressions are reproduced in Section D.1.

is smaller in PrivateInfo than in NoInfo, however this difference is not statistically different.

Hypothesis 1c: Communication in PublicInfo Here the focus is on the communication in PublicInfo in comparison to the communication in PrivateInfo. The right part of Figure 4.3 does not show a significant difference between the lengths of the sent messages in PublicInfo and NoInfo on an aggregate level. The expected values of the sent intervals, however, are significantly closer to θ in PublicInfo than in NoInfo (left part of Figure 4.3). This is in contrast to the theoretical predictions for the specific parameter set we used in this experiment. However, the smaller message bias is in line with the general theoretical predictions.

Hypothesis 1d: No Communication In this hypothesis we focus on the cases where no communication (a so-called "babbling equilibrium") is predicted irrespective of the receivers' knowledge structure. Table 7 shows that in those four cases (all Treatments b=40 and PrivateInfo b=20) the expected values of the sent messages are correlated with the states. This correlation is significantly higher than zero, which is in contrast to the theoretical predictions. In PublicInfo and PrivateInfo this correlation is relatively high, while in NoInfo it is rather low. Hence, similar to the previous experimental studies (Cai & Wang, 2006 and Wang *et al.*, 2010), we find communication also in the cases where no communication is predicted. Overcommunication is even higher when the decision maker is partially informed.

Hypothesis 2: receivers' decisions Based on the theoretical background we expect that the correlation between the actions of the decision makers and the state decreases with increasing preference differences. We follow again the method of Cai & Wang (2006) and concentrate on the correlations displayed in the second column of Table 7. This column displays the correlation between the expected value of the sent interval ev_{int} and the action a of the receiver, i.e. the number that she chooses. In line with the expectation, the correlation is decreasing with the size of b.

Except for when b=40 the observed correlations are on remarkably high levels. Recall from Hypothesis 1d that the sent messages should contain no meaningful content when the preference differences are high. Therefore, since the receivers are aware of the high preference difference, we would not expect the receivers to rely on the messages when the preference difference is too high (i.e. in the cases discussed in Hypothesis 1d, e.g. all treatments when b=40). Still, in contrast to these expectations, when b equals 40 the correlation is significantly higher than zero.

To analyse hypothesis 3 we will rely on the following mixed effects model. As before, individual and group specific random effects are included in the regression. The regression is estimated separately for senders and for receivers. Figure 5 displays graphically the estimates with 95% confidence-intervals. The upper two graphs show the estimation results for every level of b for the senders and the receivers, respectively. Like in the analysis of Hypothesis 1 the *within* group comparisons can be seen by vertically comparing the estimates. Additionally, the bottom graph in Figure 5 displays the aggregated payoffs for both player types.[47]

$$\text{Payoff} = \sum_{\text{Treat.}} \beta_{\text{Treat.}} \cdot d_{\text{Treat.}} + \epsilon_{\text{group}} + \epsilon_{\text{subj.}} + \epsilon_{\text{subj.},t} \qquad (4)$$

Hypothesis 3: Payoffs We are interested in the effects of b and the treatments on the payoffs (in ECU) of the experimental participants. Looking at Figures 5.1 and 5.2 and comparing the estimates within each treatment between the low and high levels of b (vertical comparison), we can see that the estimates in the lower boxes ($b_{20,40}$) are to the left of the estimates in the upper boxes ($b_{10,15}$). This means that the payoffs, irrespective of the player type, are negatively influenced by b in all treatments. The regression results reveal, moreover, that this effect is smaller in the information treatments.

To examine whether the payoffs, aggregated over all levels of b, differ between the three treatments, Figure 5.3 shows that on the aggregated level the payoffs in the information treatments are higher than NoInfo. Receivers in PrivateInfo receive significantly more payoffs than in NoInfo, the other differences are not significantly different. Moreover, in line with the theoretical predictions, the payoffs of the senders are smaller than those of the receivers.

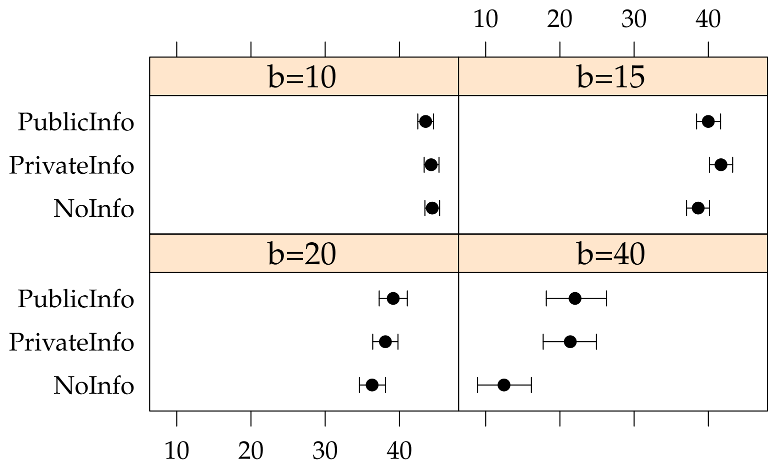
In the analysis we so far relied on the observed measures of communication: the message bias (difference between the expected value of the sent message and the state) and the message precision (length of the sent interval). In addition, we analysed the correlation of the ev_{int} with θ. In the experiment we also asked the senders to state which action they expected the decision maker to take after they sent the message. We will not go into detail here, but there are two things that can be observed: the correlation between the self-reported expectations and the expected value of the sent interval is high, even though it is decreasing with b. The second observation is that senders expect the decision makers to take an action that is lower than the expected value of the sent interval. This observation is not surprising if the senders understand the basic underlying dynamics of the experiment. In Appendix C (Table 10 and Figure 6) we display descriptively the relation between the two variables.

Cai & Wang (2006) devote a part of their study to behavioural type analysis. Our experiment was not designed to investigate this topic. As a result we have too few observations per person with high enough bs to properly answer such questions. In addition, in PrivateInfo and PublicInfo we cannot identify whether a subject is influenced by his level of reasoning or by the experimental information. When we use all available data and try to classify subjects into behavioural types, the average fitting rate is at maximum 60%. Consequently, we will disregard questions of type analysis in this study.

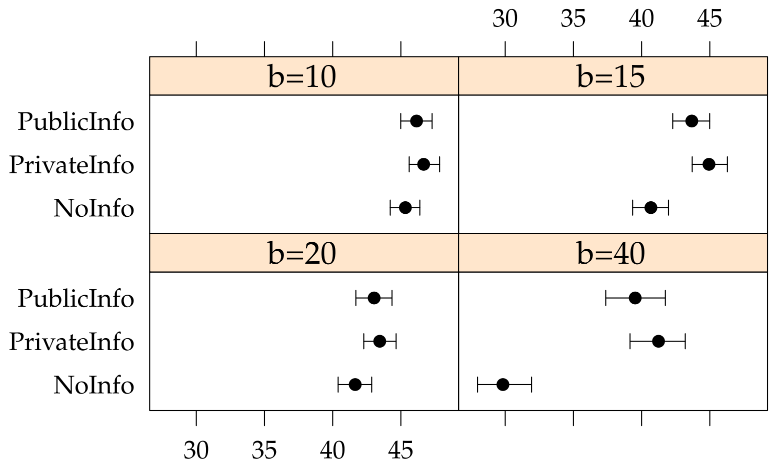
[47]The estimation results are displayed in Appendix D.3 in Table 15. Moreover, as a robustness-check we report the regression results over the first 20 rounds in Appendix D.2.

Figure 5 Payoff estimates (Equation 4)

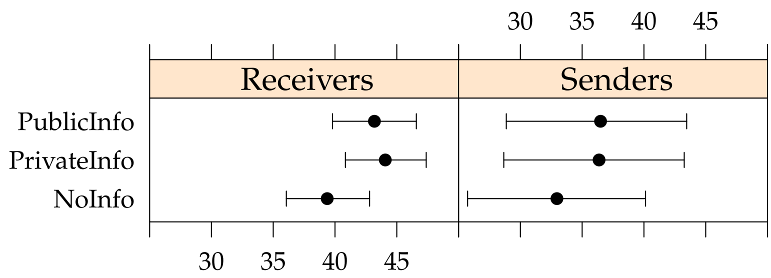
5.1 Senders



5.2 Receivers



5.3 Aggregated over *b*



Estimates with 95% confidence intervals.

5 Discussion

In this paper we compared experimentally three theoretical models of strategic information transmission. First, we will describe and discuss the comparison of our experimental results with the theoretical predictions. Subsequently, we will discuss behavioural differences between the treatments.

Like the previous experimental studies, in all treatments we find evidence of the prediction by Crawford & Sobel (1982) that the more the preferences of the two players diverge, the less is communicated. This is especially true when we analyse the *bias* in the communication. Also, the players' payoffs decrease with increasing preference differences.

Also in line with earlier results, senders overcommunicate and decision makers rely too much on the received messages. Correlations between the states and the expected values of the sent messages are on similarly high levels in all treatments. When the preference difference between the two players is too high (e.g. in all treatments when the preference difference parameter b=40), the theory predicts no communication, irrespective of the treatment. Still, we observe a correlation between the communicated information (expected value of the sent interval) and the state that is significantly higher than zero.

The theoretical models assume that subjects partition the state space and therefore the theoretical predictions correspond, in particular, to the observed length of the sent intervals. When we compare the observed message *precision* with their theoretical predictions, we observe that in all treatments the sent messages are much shorter than theoretically predicted. In particular, many subjects send message that only contain one particular state. Two reasons for this behaviour seem plausible. First, it might be that the subjects partition the state space but their partitioning is more fine-grained than theoretically predicted. Alternatively, it might be that subjects do not partition the state space as assumed in the theoretical models. Possibly they base their message entirely on the observed state and send a (small) interval that, depending on the size of the preference difference, is either close to the true state or more distant.

Let us now turn to comparing the treatments. Starting with message *precision*, we can observe treatment differences: in PrivateInfo the communicated intervals are, in line with the theoretical prediction, longer than in NoInfo. In PublicInfo the lengths of the communicated intervals are not significantly different from those in NoInfo. Then, if we take the expected value of the sent interval as a proxy for the communicated information, the transmitted information in the information treatments PrivateInfo and PublicInfo is closer to the real state than in NoInfo. This lower bias is in line with the theoretical predictions in PublicInfo, however, it is in contrast to the theoretical predictions in PrivateInfo. The marginal effect of the preference difference parameter b on the distance between the expected value of the sent interval and the state is about 0.6 in all treatments. Thus, the senders communicate less biased information in both PrivateInfo and PublicInfo and, moreover, the senders do not fully adjust the content (i.e. the expected value) of their sent message to increasing preference differences.

We discussed the overcommunication when no communication is predicted already above. When b equals 40 we observe the biggest differences between the three treatments: while the correlation between θ and ev_{int} is relatively low in NoInfo, it is higher than 0.6 in PublicInfo and PrivateInfo. This means that as soon as the decision maker is partially informed, in a situation when no (meaningful) communication is predicted, we observe subjects to transmit meaningful information, irrespectively of whether or not the expert is aware of *what* the decision maker knows.

To summarise, it depends on the measure and the specification whether we observe differences between the information treatments and the baseline. In the cases where a difference is observable, the communication and payoffs are better in the two information treatments (PrivateInfo and PublicInfo) than in NoInfo. The only exception is PrivateInfo in which the message precision is worse than in the other two treatments.

So far we relied entirely on the theoretically predicted behaviour as a benchmark. This literature does not, however, take behavioural aspects into account. There are a few behavioural aspects that we would like to discuss briefly. First of all, Wang *et al.* (2010) observe that subjects' pupils dilate more the more deceptive their sent message is. The authors interpret this observed pupil dilation as an indication of the cognitive difficulty of sending deceptive messages. With our experimental set-up we tried to allow subjects to understand the experimental dynamics better. In particular, we tried to facilitate perspective-taking. Moreover, our tutorial before the experiment put high emphasis on illustrating the meaning of the preference difference parameter b. Still, even if one fully understands the dynamics of the situation, it might be difficult to send deceptive messages. The observed overcommunication could be an indication for this.

The overcommunication might, however, also result from subjects' lying aversion. Some studies, which we discussed in Section 2.2, found a significant fraction of subjects to be averse to lying. These subjects will send informative messages not because they find it difficult to be deceptive but because they want to communicate truthfully. The effects of lying aversion would be expected to be symmetric in all treatments. Yet, it might be that (some) subjects are not lying averse per se but rather afraid of being detected lying by the decision maker. Detection of lying is only possible in the information treatments and this could contribute to the less biased messages which were sent in PrivateInfo and PublicInfo.

The senders' behaviour might also be motivated by fairness or leadership considerations. Assume that a sender would want to compensate the decision maker for the difference in information possession and therefore transmit more information; we would expect that this would lead to comparatively less information transmission in the information treatments where this information disparity is not present. This is, however, not what we observe. Thus, while we cannot exclude that equality or leadership considerations are contributing to the observed overcommunication, in particular in NoInfo, they cannot account for the observed treatment differences.

6 Conclusion

In this paper we compared experimentally the three models of strategic information transmission by Crawford & Sobel (1982), Lai (2010) and Ehses-Friedrich (2011). The latter two models are extensions of the model by Crawford & Sobel. The three models differ in the information that the two agents possess. While in the baseline setting by Crawford & Sobel the two agents do not possess information, Lai introduces a privately informed decision maker. Ehses-Friedrich makes the receivers' information public. Our experimental treatments were designed to capture the essential features of these three models.

In our experimental design we use a message and action space which is more fine-grained than the state space that was used in the earlier experimental economic studies by Dickhaut *et al.*, 1995, Cai & Wang, 2006 and Wang *et al.*, 2010. We thereby give participants the possibility to differentiate their messages. Moreover, this representation is closer to the theoretical models. Finally, it allows us to distinguish in our analysis between message precision and message bias.

First of all, we can reproduce the earlier experimental evidence of overcommuniation and overtrusting in all three treatments. Looking at those cases when no communication is predicted, overcommunication and overtrusting are especially noticeable. Looking at the two distinct measures of communication, another finding that all three treatments have in common is that the sent messages are much more precise than theoretically predicted. Amongst others, this is due to the fact that the theories assume partition equilibria in which senders' partition the state space in one to three partitions; in the experiment, however, a large share of the sent messages are very short or even single numbers. Yet, in the PrivateInfo-treatment, representing Lai's model, the sent messages are longer than in the other two treatments. Focusing on the bias, in PublicInfo, representing the setting by Ehses-Friedrich, the transmitted information is significantly closer to the true state than in NoInfo. In PrivateInfo the messages are also less biased than in NoInfo but this difference is not significantly different.

Let us go back to the questions that motivated this research. First, focussing on the advice that a decision maker gets, is it beneficial for the decision maker to be (partially) informed? Second, how does the expert's knowledge about the decision maker's knowledge influence his advice? In this study we observed that when subjects' behaviour differs between the three treatments, the two treatments that include an informed decision maker (PrivateInfo and PublicInfo) led to better results in terms of message precision, -bias and payoffs, than the NoInfo treatment – the only exception being that subjects in PrivateInfo sent longer intervals than in NoInfo. Still, the communicated interval lengths in PrivateInfo were much shorter than theoretically predicted. The latter observation is in line with Lai's prediction. In contrast to his predictions, however, communication in PrivateInfo was less biased than in NoInfo. Finally, like the earlier experimental studies, this research suggests that the best outcomes for both players will be reached when the preference difference is small.

If we want to transfer these results to the "real world" and to the examples that we started with in the introduction, we want to stress here that the experimental setting was very stylised. Thus, it is a question for further research to examine whether similar results can be observed in settings that are closer to "real world" settings. If external validity is given, this research shows that it is (with the exception of message precision) beneficial for a decision maker to be partially informed. For "real life" this suggests that decision makers should consider acquiring some basic information about the decision to take before consulting an expert. Moreover, to get a more precise advice the decision maker should reveal to the expert that she possesses some basic knowledge. Based on the experimental results we would, moreover, suggest to reveal the knowledge fully. Nevertheless, information acquisition is a balancing of costs and benefits. In this study we focused on the potential benefits. For future research we suggest to examine the relation between costs and benefits of information acquisition. It might still be that information acquisition in some cases is prohibitively costly. In addition, it would be interesting to analyse the feasibility of informing the expert about the decision maker's knowledge.

References

Bates, D., Maechler, M. & Bolker, B. (2012). *lme4: Linear mixed-effects models using S4 classes*, R package version 0.999999-0.

Battaglini, M. & Makarov, U. (2011). *Cheap talk with multiple audiences: An experimental analysis*, Economic Theory Center Working Paper 012-2011, Princeton University, Department of Economics.

Cai, H. & Wang, J.T.Y. (2006). Overcommunication in strategic information transmission games. *Games and Economic Behavior*, *56*(1), pp. 7–36.

Chen, Y. (2009). Communication with two-sided asymmetric information. *Available at SSRN 1344818*.

Crawford, V. (1998). A survey of experiments on communication via cheap talk. *Journal of Economic Theory*, *78*(2), pp. 286–298.

Crawford, V.P. & Sobel, J. (1982). Strategic information transmission. *Econometrica*, *50*, pp. 1431–51.

de Barreda, I.M. (2012). *Cheap talk with two-sided private information*, mimeo, Nuffield College, University of Oxford.

Dickhaut, J.W., McCabe, K.A. & Mukherji, A. (1995). An experimental study of strategic information transmission. *Economic Theory*, *6*(3), pp. 389–403.

Duffy, J. & Nagel, R. (1997). On the robustness of behaviour in experimental 'beauty contest' games. *The Economic Journal*, *107*(445), pp. 1684–1700.

Ehses-Friedrich, C. (2011). *Expert communication to an informed decision maker*, mimeo, Max-Planck-Insitute of Economics.

Erat, S. & Gneezy, U. (2012). White lies. *Management Science*, *58*(4), pp. 723–733.

Farrell, J. & Gibbons, R. (1989). Cheap talk with two audiences. *The American Economic Review*, *79*(5), pp. 1214–1223.

Fischbacher, U. (2007). z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, *10*(2), pp. 171–178.

Gneezy, U. (2005). Deception: The role of consequences. *American Economic Review*, *95*(1), pp. 384–394.

Hurkens, S. & Kartik, N. (2009). Would I lie to you? On social preferences and lying aversion. *Experimental Economics*, *12*(2), pp. 180–192.

Keynes, J.M. (1936). *The general theory of interest, employmentand money*, London: Macmillan.

Lai, E.K. (2010). *Expert advice for amateurs*, mimeo, Department of Economics, Lehigh University.

Lai, E.K. & Lim, W. (2012). Authority and communication in the laboratory. *Games and Economic Behavior*, *74*(2), pp. 541–560.

Lai, E.K., Lim, W. & Wang, J.T.Y. (2011). *Experimental implementations and robustness of fully revealing equilibria in multidimensional cheap talk*, mimeo, Department of Economics, Lehigh University.

Minozzi, W. & Woon, J. (2012). Lying aversion, lobbying, and context in a strategic communication experiment. *Journal of Theoretical Politics*, forthcoming.

Nagel, R. (1995). Unraveling in guessing games: An experimental study. *The American Economic Review*, *85*(5), pp. 1313–1326.

Peeters, R., Vorsatz, M. & Walzl, M. (2008). Rewards in an experimental sender–receiver game. *Economics Letters*, *101*(2), pp. 148–150.

R Development Core Team (2012). *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria, ISBN 3-900051-07-0.

Sánchez-Pagés, S. & Vorsatz, M. (2007). An experimental study of truth-telling in a sender–receiver game. *Games and Economic Behavior*, *61*(1), pp. 86–112.

Sánchez-Pagés, S. & Vorsatz, M. (2009). Enjoy the silence: An experiment on truth-telling. *Experimental Economics*, *12*(2), pp. 220–241.

Schmelz, K. (2010). E-nstructions: Using electronic instructions in laboratory experiments. *Jena Economic Research Papers*, p. 047.

Schnusenberg, O. & Gallo, A. (2011). On cognitive ability and learning in a beauty contest. *Journal for Economic Educators*, *11*(1), pp. 13–24.

Sutter, M. (2009). Deception through telling the truth?! Experimental evidence from individuals and teams. *Economic Journal*, *119*(534), pp. 47–60.

Wang, J.T.y., Spezio, M. & Camerer, C.F. (2010). Pinocchio's pupil: Using eyetracking and pupil dilation to understand truth telling and deception in sender-receiver games. *The American Economic Review*, *100*(3), pp. 984–1007.

A Instructions

Welcome and thank you for participating in this experiment. Please read the following instructions carefully. If you have questions now or at a later point, please raise your hand. We will then come to your seat and answer your question in private.

This experiment will take about 2 hours. We ask you to turn off your mobile phone now. During the experiment the communication with other participants and the usage of aids is not allowed.

In this experiment there are two types of participants: participant **A** and **B**. Which of the roles you will take will be randomly decided at the beginning of the experiment and will be fixed throughout the whole experiment. Your role will be displayed to you on your screen. This experiment consists of 24 rounds. In each of these rounds you will be randomly matched with another participant who will take the other role.

At the beginning of each round a randomly drawn secret number will be shown to participant **A**. This number is always an integer between 0 and 100. Participant **B** receives:

- *no information about the secret number* [NoInfo]
- *every round a value and knows whether the secret number is larger or smaller than that particular value. Participant* ***A*** *does not receive information about this value.* [PrivateInfo]
- *every round a value and knows whether the secret number is larger or smaller than that particular value. Participant* ***A*** *sees this information on his own screen as well.* [PublicInfo]

After participant **A** has received the secret number, he sends a message to participant **B** "the number I received is between ... and ...." When he wants to send a single number to participant **B**, he fills in only the first box, when wants to send him an interval, he fills in both boxes. Note that in the latter case, the first number may not be larger than the second number. Subsequently, participant **B** selects a number. This number determines, together with the secret number, the payoff of both participants.

Before participants make their decision, both participant **A** as well as participant **B** can use a graphical interface to display the payoffs of both players depending on the number chosen by participant **B**.

Payoffs:

- The payoff of participant **B** is the higher, the closer the chosen number is to the secret number. It is highest when **B** chooses exactly the secret number.

- The payoff of participant **A** is the higher, the closer the chosen number is to the secret number + the "difference U" (see next point). It is highest when **B** chooses "secret number + difference U".
- The difference U between the actual number and the higher number will be displayed on the screen at the beginning of each round. The difference U is always positive.
- Calculating the payoffs:[48]
  - participant **A**:

$$U^d = 50 - 100 \left| \frac{chosen\ number - (secret\ number + U)}{100} \right|^{1.4}$$

  - participant **B**:

$$U^e = 50 - 100 \left| \frac{chosen\ number - secret\ number)}{100} \right|^{1.4}$$

To illustrate the experiment and the payoffs, please turn now to the tutorial displayed on your screen. To move forward and backward in the tutorial, please use the scroll device of your mouse.

The experiment will end with a short questionnaire. Before the experiment is started you will go through 2 trial rounds on the computer, once in the role of participant A and once as participant B. The trial rounds will end with a few control questions. Please answer those questions accurately.

During the experiment all payments will be displayed in ECU and at the end the earnings of all rounds will be added. The conversion rate is 1 ECU=0.0175 Euro, i.e. 100 ECU=1.75 Euro. In addition you will be paid 2.50 Euro show-up fee.

[48] The vertical lines in the formulas are called "absolute value bars" and mean that the value in between the bars will always be positive. Thus, when "chosen number - secret number" = -15, the formula will be in the end: 50-100*0.15$^{1.4}$.

B Equilibrium conditions

- $EU^d = 50 - 100\sum_{i=1}^{N} \int_{g_{i-1}}^{g_i} \left|\frac{a-\theta}{100}\right|^{1.4} f(\theta)d\theta$
- $EU^e = 50 - 100\sum_{i=1}^{N} \int_{g_{i-1}}^{g_i} \left|\frac{a-(\theta+b)}{100}\right|^{1.4} f(\theta)d\theta$

where $g_0 = 0$ and $g_N = 100$ and $g_0 = 0 < g_1 < \cdots < g_{N-1} < g_N = 100$

N describes the number of intervals, which could range from 1 to 4 in our experiment. The boundaries g_i are either the communicated boundaries or the own threshold s.

Under the assumption of a uniform distribution, the chosen action is always $a = \frac{g_{i-1}+g_i}{2}$. The own information of the receiver s is always given in the experiment. The communicated boundaries depend on the own information s, the parameter b, and the underlying model.

For the following cases, we concentrate on the expected utility of the receiver, as the senders formula differs only by parameter b.

1. No information:
   NoInfo for $b = 40$
   $EU^d = 50 - 100 \int_0^{100} \left|\frac{a-\theta}{100}\right|^{1.4} f(\theta)d\theta$

2. No communication but own information:
   PrivateInfo for $b = 40$ and for $b = 20$
   PublicInfo for $b = 40$ and for $b = 20$ if $20 \leqslant s \leqslant 80$ and $b = 15$ if $40 \leqslant s \leqslant 60$
   $$EU^d = 50 - 100\left(\int_0^s \left|\frac{a-\theta}{100}\right|^{1.4} + \int_s^{100} \left|\frac{a-\theta}{100}\right|^{1.4}\right) f(\theta)d\theta$$

3. Communication of two intervals but no own information:
   NoInfo for $b = 20$, $b = 15$ and $b = 10$. Boundaries: $\bar{\theta} = 50 - 2b$
   $$EU^d = 50 - 100\left(\int_0^{\bar{\theta}} \left|\frac{a-\theta}{100}\right|^{1.4} + \int_{\bar{\theta}}^{100} \left|\frac{a-\theta}{100}\right|^{1.4}\right) f(\theta)d\theta$$

4. Communication of two intervals and own information:

   (a) PrivateInfo for $b = 15$ and $b = 10$ and $s > \bar{\theta}$.[49] Boundaries: $\bar{\theta} = 50 - 3b$. PublicInfo for $b = 20$ if $s > 80$, $b = 15$ if $s > 60$ and $b = 10$ if $s \geqslant 60$. Boundaries: $\bar{\theta} = \frac{s}{2} - 2b$

   $$EU^d = 50 - 100\left(\int_0^{\bar{\theta}} \left|\frac{a-\theta}{100}\right|^{1.4} + \int_{\bar{\theta}}^{s} \left|\frac{a-\theta}{100}\right|^{1.4} + \int_s^{100} \left|\frac{a-\theta}{100}\right|^{1.4}\right) f(\theta)d\theta$$

   (b) PrivateInfo for $b = 15$ and $b = 10$ and $s < \bar{\theta}$. Boundaries: $\bar{\theta} = 50 - 3b$. PublicInfo for $b = 20$ if $s < 80$, $b = 15$ if $s < 40$ and $b = 10$ if $s \leqslant 40$. Boundaries: $\bar{\theta} = \frac{1+s}{2} - 2b$.

   $$EU^d = 50 - 100\left(\int_0^{s} \left|\frac{a-\theta}{100}\right|^{1.4} + \int_{s}^{\bar{\theta}} \left|\frac{a-\theta}{100}\right|^{1.4} + \int_{\bar{\theta}}^{100} \left|\frac{a-\theta}{100}\right|^{1.4}\right) f(\theta)d\theta$$

5. Communication of three intervals and own information:
   PublicInfo for $b = 10$ if $40 < s < 60$. Boundaries: $\bar{\theta}_1 = \frac{s}{2} - 2b$ and $\bar{\theta}_2 = \frac{1+s}{2} - 2b$

$$EU^d = 50 - 100\left(\int_0^{\bar{\theta}_1} \left|\frac{a-\theta}{100}\right|^{1.4} + \int_{\bar{\theta}_1}^{s} \left|\frac{a-\theta}{100}\right|^{1.4} + \int_s^{\bar{\theta}_2} \left|\frac{a-\theta}{100}\right|^{1.4} + \int_{\bar{\theta}_2}^{100} \left|\frac{a-\theta}{100}\right|^{1.4}\right) f(\theta)d\theta$$

[49] The case where $s = \bar{\theta}$ equals our second equation. However, in our experiment this case could not occur.

C Descriptive statistics

Table 8 Number of participants

	Session							
	1	2	3	4	5	6	7	Total
NoInfo		32				16	16	64
PrivateInfo			32		32			64
PublicInfo	32			28				60

Table 9 Mean length of the sent intervals - Player A

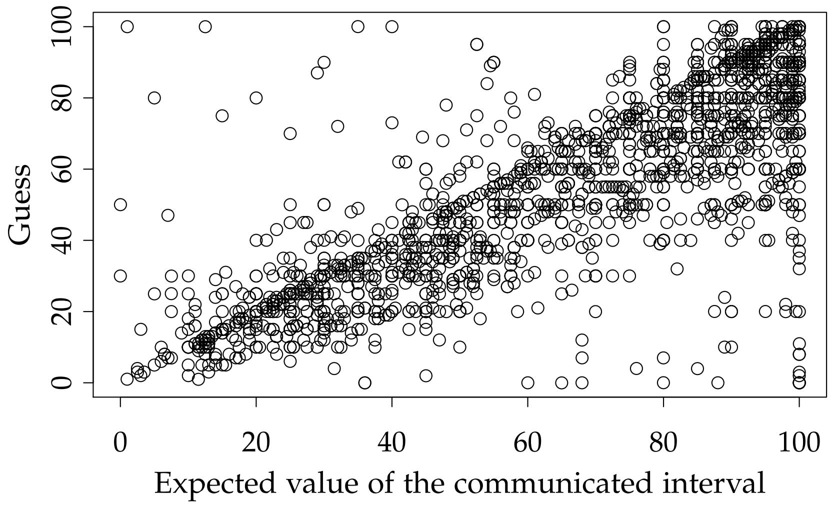
	b						
Treatment	10	15	20	40	mean	min	max
NoInfo	7.4	10.12	7.18	10.03	8.68	0	100
PrivateInfo	10.71	15.13	11.47	20.63	14.49	0	100
PublicInfo	9.79	6.39	14.79	7.22	9.55	0	95

Table 10 Observed correlation between ev_{int} and θ

	b	Corr (ev_{int},*guess*)	Cor(θ,M) M=ev_{int}	Cor(θ,M) M=*guess*	Cor(M,a) M=ev_{int}	Cor(M,a) M=*guess*	Cor(θ,a)
NoInfo	10	0.9	0.96	0.93	0.93	0.86	0.9
	15	0.8	0.85	0.86	0.86	0.68	0.73
	20	0.69	0.87	0.77	0.84	0.66	0.77
	40	0.28	0.2	0.33	0.42	0.23	0.12
	all	0.68	0.7	0.74	0.74	0.63	0.65
PrivateInfo	10	0.97	0.96	0.97	0.94	0.92	0.94
	15	0.93	0.94	0.94	0.88	0.86	0.89
	20	0.9	0.88	0.94	0.84	0.81	0.84
	40	0.76	0.65	0.73	0.58	0.59	0.74
	all	0.9	0.84	0.89	0.8	0.8	0.85
PublicInfo	10	0.95	0.93	0.97	0.94	0.93	0.91
	15	0.95	0.92	0.91	0.89	0.88	0.84
	20	0.9	0.85	0.93	0.86	0.87	0.84
	40	0.65	0.63	0.75	0.67	0.68	0.68
	all	0.87	0.81	0.89	0.83	0.85	0.82

guess is the senders' reported guess about the receivers' behaviour.

Figure 6 Jitter-plot of ev_{int} plotted against the senders' *guess*



Guess is the senders' reported guess about the receivers' behaviour.

Table 11 Receivers' observed payoffs

	b				
Treatment	10	15	20	40	All
NI	45.33	40.68	41.65	29.83	39.37
PrivateInfo	46.67	44.94	43.45	41.24	44.07
PublicInfo - All	46.16	43.66	43.04	39.53	43.19
PublicInfo - s=14	45.24	44.71	42.46	37.16	42.65
PublicInfo - s=50	45.42	44.53	44.38	41.47	43.95
PublicInfo - s=71	47	43.68	42.51	38.41	42.9
PublicInfo - s=81	47.13	41.73	42.51	40.68	43.15

Table 12 Senders' observed payoffs

	b				
Treatment	10	15	20	40	All
NoInfo	44.42	38.63	36.32	12.47	32.96
PrivateInfo	44.27	41.7	38.11	21.4	36.37
PublicInfo - All	43.53	39.99	39.16	22.04	36.45
PublicInfo - s=14	41.78	38.29	34.41	8.62	31.68
PublicInfo - s=50	42.84	39.53	42.09	27.33	37.95
PublicInfo - s=71	43.46	38.73	37.62	24.3	36.03
PublicInfo - s=81	46.04	43.18	41.89	26.78	39.98

D Supplementary regressions

D.1 Underlying regressions of the segplots

$$Y = \beta_0 + \sum_{\text{Treat.}} \beta_{\text{Treat.}} \cdot d_{\text{Treat.}} + \sum_{\text{Treat.}} \beta_{\text{Treat}\cdot\text{b}} \cdot d_{\text{Treat.}} \cdot b + \epsilon_{\text{group}} + \epsilon_{\text{subj.}} + \epsilon_{\text{subj.},t} \quad (5)$$

The estimation baseline is NoInfo.

Table 13 Estimation of Eq. 5,
Y = *communication*: message precision (length of the sent intervals)

	β	σ	t	p value	95% conf	interval
(Intercept)	8.75	2.36	3.7	0.0002	4.12	13.4
PublicInfo	-1.16	3.39	-0.343	0.7317	-7.81	5.48
PrivateInfo	1.39	3.35	0.414	0.6787	-5.18	7.95
NoInfo:b	-0.00303	0.04	-0.0757	0.9396	-0.0815	0.0754
PublicInfo:b	0.0835	0.044	1.9	0.0579	-0.0028	0.17
PrivateInfo:b	0.205	0.0397	5.16	0.0000	0.127	0.283

Table 14 Estimation of Eq. 5,
Y = *communication*: message bias (ev_{int} - θ)

	β	σ	t	p value	95% conf	interval
(Intercept)	9.07	1.97	4.6	0.0000	5.2	12.9
PublicInfo	-6.37	2.85	-2.24	0.0253	-12	-0.788
PrivateInfo	-4.76	2.79	-1.71	0.0882	-10.2	0.712
NoInfo:b	0.592	0.0626	9.46	0.0000	0.469	0.715
PublicInfo:b	0.618	0.0673	9.18	0.0000	0.486	0.75
PrivateInfo:b	0.642	0.0614	10.5	0.0000	0.522	0.763

Table 15 Estimation of Eq. 5, Y = *payoffs*

1. Receiver

	β	σ	t	p value	95% conf	interval
(Intercept)	48.9	1.08	45.5	0.0000	46.8	51.1
PublicInfo	-1.75	1.54	-1.14	0.2565	-4.78	1.27
PrivateInfo	-1.26	1.49	-0.843	0.3995	-4.18	1.67
NoInfo:b	-0.451	0.0357	-12.6	0.0000	-0.521	-0.381
PublicInfo:b	-0.193	0.0373	-5.17	0.0000	-0.266	-0.12
PrivateInfo:b	-0.17	0.0332	-5.12	0.0000	-0.235	-0.105

2. Sender

	β	σ	t	p value	95% conf	interval
(Intercept)	55	1.48	37.1	0.0000	52.1	57.9
PublicInfo	-4.05	2.17	-1.87	0.0613	-8.3	0.192
PrivateInfo	-2.02	2.1	-0.962	0.3364	-6.15	2.1
NoInfo:b	-1.04	0.0525	-19.8	0.0000	-1.14	-0.936
PublicInfo:b	-0.696	0.0587	-11.9	0.0000	-0.811	-0.581
PrivateInfo:b	-0.783	0.0525	-14.9	0.0000	-0.886	-0.68

$$Y = \beta_0 + \sum_{\text{Treat.}} \beta_{\text{Treat.}} \cdot d_{\text{Treat.}} + \epsilon_{\text{group}} + \epsilon_{\text{subj.}} + \epsilon_{\text{subj.},t} \tag{6}$$

The estimation baseline is NoInfo.

Table 16 Estimation of the Eq. 6,
Y = *communication*: message precision (length of the sent intervals)

	β	σ	t	p value	95% conf	interval
(Intercept)	8.68	2.31	3.76	0.0002	4.15	13.2
PublicInfo	0.63	3.29	0.191	0.8482	-5.82	7.08
PrivateInfo	5.8	3.3	1.76	0.0786	-0.664	12.3

Table 17 Estimation of Eq. 6,
Y = *communication*: message bias (ev_{int}- θ)

	β	σ	t	p value	95% conf	interval
(Intercept)	21.6	2.11	10.3	0.0000	17.5	25.8
PublicInfo	-6.06	2.98	-2.03	0.0425	-11.9	-0.205
PrivateInfo	-3.69	2.91	-1.27	0.2047	-9.38	2.01

Table 18 Estimation of Eq. 6, Y = *payoffs*

1. Receiver

	β	σ	t	p value	95% conf	interval
(Intercept)	39.4	1.76	22.3	0.0000	35.9	42.8
PublicInfo	3.81	2.52	1.51	0.1299	-1.12	8.75
PrivateInfo	4.7	2.5	1.88	0.0605	-0.209	9.61

2. Sender

	β	σ	t	p value	95% conf	interval
(Intercept)	33	3.55	9.28	0.0000	26	39.9
PublicInfo	3.54	5.01	0.706	0.4800	-6.28	13.4
PrivateInfo	3.41	5.04	0.677	0.4982	-6.46	13.3

D.2 Regressions over rounds 1-20

Table 19 Estimation of Eq. 5,
Y = *communication*: message precision (length of the sent intervals)

	β	σ	t	p value	95% conf	interval
(Intercept)	8.84	2.42	3.66	0.0003	4.1	13.6
PublicInfo	-1.69	3.41	-0.495	0.6208	-8.38	5
PrivateInfo	0.962	3.36	0.287	0.7744	-5.62	7.54
NoInfo:b	0.0196	0.0446	0.44	0.6601	-0.0679	0.107
PublicInfo:b	0.122	0.0456	2.67	0.0076	0.0324	0.211
PrivateInfo:b	0.247	0.0447	5.52	0.0000	0.159	0.335

Table 20 Estimation of Eq. 5,
Y = *communication*: message bias (ev_{int}- θ)

	β	σ	t	p value	95% conf	interval
(Intercept)	7.42	1.93	3.84	0.0001	3.63	11.2
PublicInfo	-6.15	2.77	-2.22	0.0264	-11.6	-0.723
PrivateInfo	-4.03	2.71	-1.48	0.1379	-9.35	1.29
NoInfo:b	0.65	0.0643	10.1	0.0000	0.524	0.776
PublicInfo:b	0.699	0.0666	10.5	0.0000	0.569	0.83
PrivateInfo:b	0.675	0.0651	10.4	0.0000	0.548	0.803

Table 21 Estimation of Eq. 5, Y = *payoffs*

1. Receiver

	β	σ	t	p value	95% conf	interval
(Intercept)	48.1	1.07	44.8	0.0000	46	50.2
PublicInfo	0.0694	1.51	0.046	0.9633	-2.89	3.03
PrivateInfo	1.01	1.51	0.669	0.5035	-1.95	3.98
NoInfo:b	-0.385	0.0388	-9.93	0.0000	-0.461	-0.309
PublicInfo:b	-0.25	0.037	-6.75	0.0000	-0.322	-0.177
PrivateInfo:b	-0.264	0.0361	-7.3	0.0000	-0.334	-0.193

2. Sender

	β	σ	t	p value	95% conf	interval
(Intercept)	53.1	1.5	35.3	0.0000	50.2	56.1
PublicInfo	-2.61	2.12	-1.23	0.2180	-6.77	1.54
PrivateInfo	-1.21	2.12	-0.572	0.5674	-5.36	2.94
NoInfo:b	-0.919	0.0573	-16	0.0000	-1.03	-0.806
PublicInfo:b	-0.667	0.0573	-11.6	0.0000	-0.779	-0.555
PrivateInfo:b	-0.713	0.055	-13	0.0000	-0.821	-0.605

Table 22 Estimation of the Eq. 6,
Y = *communication*: message precision (length of the sent intervals)

	β	σ	t	p value	95% conf	interval
(Intercept)	9.24	2.34	3.95	0.0001	4.65	13.8
PublicInfo	0.386	3.35	0.115	0.9083	-6.18	6.95
PrivateInfo	5.6	3.35	1.67	0.0948	-0.971	12.2

Table 23 Estimation of Eq. 6,
Y = *communication*: message bias (ev_{int}- θ)

	β	σ	t	p value	95% conf	interval
(Intercept)	20.7	2.08	9.91	0.0000	16.6	24.7
PublicInfo	-5.09	2.94	-1.73	0.0841	-10.9	0.686
PrivateInfo	-3.51	2.93	-1.2	0.2308	-9.25	2.23

Table 24 Estimation of Eq. 6, Y = *payoffs*

1. Receiver

	β	σ	t	p value	95% conf	interval
(Intercept)	40.2	1.57	25.6	0.0000	37.1	43.3
PublicInfo	2.83	2.22	1.27	0.2032	-1.53	7.18
PrivateInfo	3.49	2.27	1.54	0.1240	-0.957	7.93

2. Sender

	β	σ	t	p value	95% conf	interval
(Intercept)	34.4	3.55	9.68	0.0000	27.4	41.4
PublicInfo	2.49	5.01	0.497	0.6191	-7.33	12.3
PrivateInfo	2.99	5.04	0.593	0.5531	-6.89	12.9

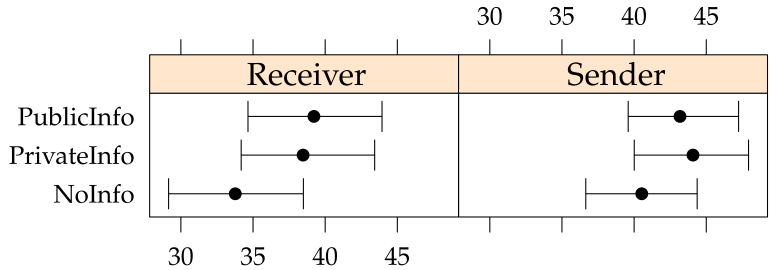
D.3 Additional analysis

$$\text{Int. length}_{\text{obs.}} - \text{int. length}_{\text{pred.}} = \sum_{\text{Treat.}} \beta_{\text{Treat.}} + \epsilon_{\text{group}} + \epsilon_{\text{subj.}} + \epsilon_{\text{subj.},t} \qquad (7)$$

Table 25 Estimation of eq. 7, observed - predicted interval lengths

	β	σ	t	p value	95% conf	interval
NoInfo	-67.6	4.73	-14.3	0.0000	-76.9	-58.3
PublicInfo	-74.1	4.74	-15.6	0.0000	-83.4	-64.8
PrivateInfo	-75.5	4.79	-15.8	0.0000	-84.9	-66.1

Figure 7 "Communication effect"



Hypothetical $EU(ev_{\text{int.}}) = \sum_{\text{Treat.}} \beta_{\text{Treat.}} \cdot d_{\text{Treat.}} + \epsilon_{\text{group}} + \epsilon_{\text{subj.}} + \epsilon_{\text{subj.},t}$
Estimate with 95% confidence intervals.