Global Games and Ambiguous Information: An Experimental Study*

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Abstract

This paper considers a global game with ambiguity-averse players, where the variance of noise terms in private signals may be unknown, and it examines comparative statics results with respect to information quality in the laboratory. Suppose that one of the actions is a safe action yielding a constant payoff and it is a risk dominant action. The experimental results show that low quality of information makes less subjects choose the safe action, whereas ambiguous quality of information makes more subjects choose the safe action. These results are consistent with theoretical predictions based upon a Bayesian Nash equilibrium where players have the maxmin expected utility preferences.

JEL classification: C72, C92, D82.

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1 Introduction

In games with incomplete information, more precise information is not necessarily beneficial to all players (Hirshleifer, 1971; Morris and Shin, 2002). An example is a global game (Carlsson and van Damme, 1993). A global game has a unique strategy surviving iterated elimination of interim-dominated strategies in which the probability of a risk dominant action goes to one as the variance of noise terms in private signals goes to zero. Thus, when a risk dominant equilibrium is inefficient, high quality of information increases the probability of inefficient coordination failure (Metz, 2002; Morris and Shin, 2004).

In this paper, we examine another type of information quality in global games, ambiguous quality, which refers to unknown precision of private signals. As demonstrated by the Ellsberg Paradox (Ellsberg, 1961) and related experimental findings,[1] decision makers distinguish between risk (known probabilities) and ambiguity (unknown probabilities), and may display aversion to ambiguity, which cannot be rationalized by Savage's subjective expected utility. Models of ambiguity aversion include the maxmin expected utility model (Gilboa and Schmeidler, 1989), the Choquet expected utility mode (Schmeidler, 1989), and the smooth model of ambiguity aversion (Klibanoff et al., 2005) among others.[2]

The purpose of this paper is to test the effect of ambiguous quality of information on the probability of coordination failure by laboratory experiments in a global-game setting and compare it with that of low quality of information.

Our model is built on the global game model of creditor coordination (Morris and Shin, 2004). Two players have collateralized debt and decide whether or not to roll over the debt. When a player rolls over the debt, he receives 1 if the underlying project is successful and 0 otherwise. When a player does not roll over the debt, he receives a constant value 0.6 of the collateral, which is chosen so that not to roll over the debt is risk dominant. The outcome of the project depends upon the number of players to roll over the debt and the state of fundamentals $\theta \in \mathbb{R}$. If $\theta < 0$, the project necessarily fails; if $\theta > 1$, it necessarily succeeds; if $0 < \theta < 1$, it succeeds if and only if both players roll over the debt. A player does not know the true value of θ but observes a noisy private signal $x_i = \theta + \varepsilon_i$, where ε_i is a noise term. Coordination failure refers to an inefficient outcome in which the project fails because players do not roll over the debt in spite of the fact that it would succeed if they rolled over the debt, i.e., $0 < \theta < 1$.

We compare the probabilities of coordination failure in the following three cases. In the first case, the precision of private signals is high, which we call high quality of information. This case is a benchmark. In the second case, the precision of private signals is low, which we call low quality of information. In these two cases, players know the true precision. In the third case, however, players do not know the precision of private signals; instead, they know that the precision takes values in a given closed interval containing the low

[1] See, for example, the surveys of Machina and Siniscalchi (2014) and Hey (2014).

[2] See a recent survey by Gilboa and Marinacci (2013).

and high precision, which we call ambiguous quality of information.

In our theoretical prediction, we assume that each player has the maxmin expected utility (MEU) preferences introduced by Gilboa and Schmeidler (1989) and elaborated by Gajdos et al. (2008).[3] That is, a player evaluates his action in terms of the minimum interim expected payoff to the action, where the minimum is taken over the set of posteriors. If the set of posteriors is a singleton, then the MEU preferences are reduced to the standard expected utility preferences. This model is regarded as a multiple-priors global game introduced by Ui (2015). As shown by Ui (2015), there exists a unique strategy surviving iterated elimination of interim-dominated strategies, where a player rolls over the debt if and only if his privates signal is greater than some cutoff point. Thus, coordination is more likely to fail when the cutoff is larger.

The following comparative statics results hold. First, the cutoff is larger under ambiguous quality of information because an ambiguity-averse player exhibits strong preferences for an outcome with a constant payoff.[4] Next, the cutoff is smaller under low quality of information because the probability of a risk dominant action goes to one as the variance of noise terms in private signals goes to zero. Therefore, ambiguous quality of information and low quality of information have the opposite effects.

In our experiments to test the above comparative statics results, we ran several treatments under between subjects design, varying information quality among ambiguous quality, low quality, and high quality, and compare the frequencies of actions. Our findings are summarized as follows. More subjects choose not to roll over the debt under ambiguous quality of information than high quality of information, whereas less subjects choose not to roll over the debt under low quality of information than high quality of information, which is consistent with the comparative statics results that the cutoff is larger under ambiguous quality of information and smaller under low quality of information. Therefore, ambiguous quality of information and low quality of information also have the opposite effects in our experimental results.

Using the logit model, we can estimate the cutoff for each quality of information and compare it with the theoretical cutoff. We find that the estimated cutoffs are substantially smaller than the theoretical cutoffs. In our model, the theoretical cutoffs are obtained by infinitely many times of elimination of interim-dominated strategies. It requires infinitely many hierarchies of beliefs, but subjects are not so sophisticated, which may explain the discrepancy between the estimated cutoffs and the theoretical cutoffs.

On the bases of this observation, we calculate alternative theoretical cutoffs using a nonequilibrium model of level-k thinking.[5] More specifically, we incorporate the MEU

[3]Gajdos et al. (2008) axiomatize MEU preferences when a set of priors is given as objective information, which is the case in our model.

[4]This fact is well noticed since the notable example of Dow and Werlang (1992). They study a model of portfolio selection with the CEU preferences, and show that a decision maker strictly prefers a safe asset to a risky asset in an interval of prices, and that larger ambiguity implies a larger interval, explaining the role of ambiguity in portfolio inertia.

[5]Level-k models have so far been applied to many games, and have succeeded in explaining a number

preferences into a coordination game under level-k thinking, which is introduced by Kneeland (2012). Each player has a bounded depth of reasoning determined by his cognitive type. $L0$ (level 0) types are nonstrategic; their behavior is exogenously given. $L1$ (level 1) types best respond to $L0$ types. For each $k \geq 1$, Lk (level k) types best respond to Lk-1 (level $k-1$) types. In our multiple-priors model as well as in the single-prior model of Kneeland (2012), Lk's best response is to roll over the debt if and only if his privates signal is greater than some cutoff point.

We compare Ln's cutoffs and the estimated cutoffs. The estimated cutoffs with high or ambiguous quality are between $L3$'s and $L4$'s cutoffs, and the estimated cutoff with low quality is between $L1$'s and $L2$'s cutoffs. Thus, there exists Ln's cutoff that is close to the estimated cutoff for each quality of information. However, if each subject with each quality of information is supposed to have the same level, the prediction of level-k thinking is not necessarily consistent with our experimental results. In fact, for each n, Ln's cutoff with not only ambiguous quality but also low quality is greater than Ln's cutoff with high quality. In other words, ambiguous quality of information and low quality of information have the same effect, which contradicts our main finding that they have the opposite effects. Nonetheless, we cannot draw any decisive conclusion because our experiments are not designed to test the level-k thinking of subjects.

Previous experimental studies on global games support each of the nonequilibrium and equilibrium models. As argued by Kneeland (2012), the nonequilibrium model explains the experimental findings of Heinemann et al. (2004), which is the seminal work on experimental global games. Heinemann et al. (2004) compare a global game with private signals and a game with the same payoff functions in which players are informed of the true state as public signals. They find that subjects in both games switch actions at some cutoff points of public or private signals. In the game with public signals, however, players do not switch actions in any equilibrium, whereas Lk's best response is to switch actions at some cutoff point. Thus, the finding of Heinemann et al. (2004) in the case of public signals is consistent with the prediction of the nonequilibrium model.

On the other hand, Heinemann et al. (2004) demonstrate that the estimated cutoff with private signals is closer to the theoretical cutoff predicted by iterated elimination of interim-dominated strategies than the estimated cutoff with public signals, which deviates towards the payoff-dominant equilibrium. Thus, the finding of Heinemann et al. (2004) in the case of private signals is consistent with the prediction of the equilibrium model.

The experimental findings of Anctil et al. (2010) are also consistent with the prediction of the equilibrium model. Anctil et al. (2010) consider a single-prior creditor coordination game, which is the same as our game except the information structure, and find that more subjects choose not to roll over the debt under higher quality of information even if the resulting outcome is inefficient. Because not to roll over the debt is a risk dominant

of anomalous behaviors found in the laboratory (Stahl and Wilson, 1995; Nagel, 1995; Ho et al., 1998; Camerer et al., 2004; Costa-Gomes et al., 2001; Costa-Gomes and Crawford, 2006; Kawagoe and Takizawa, 2009, 2012). See Crawford et al. (2013) for a survey.

action, subjects are more likely to choose a risk dominant action under higher quality of information, which is consistent with the prediction of the equilibrium model but not with that of the nonequilibrium model.

Though Anctil et al. (2010) and this paper obtain similar results on the comparison of low quality and high quality, there are two important differences between the two papers. First, our focus is the effect of ambiguous quality of information, which is not discussed in Anctil et al. (2010). Next, the information structure of Anctil et al. (2010) is quite different from that of global games, whereas our setting completely conforms to standard global games. Thus, testing the hypothesis on higher quality of information in our setting is of independent interest.

In the setting of Anctil et al. (2010), each player receives a private signal taking three values, low, medium, and high. Players receiving the low and high signals have dominant actions, not to roll over the debt and to roll over the debt, respectively. Players receiving the medium signal have no dominant action, allowing multiple equilibria. In the ex post stage, however, one of the actions can be dominant with a small probability. When this probability is zero, information is said to be perfectly precise; when this probability is larger, information is said to be less precise. Anctil et al. (2010) compare high quality of information and low quality of information: under high quality of information, each action is ex post dominant with the same small probability; under low quality of information, to roll over the debt is ex post dominant with a larger probability, whereas not to roll over the debt is ex post dominant with the same small probability. Thus, the medium signal of low quality conveys information favorable to rolling over the debt, while that of high quality conveys information neutral to each action. Anctil et al. (2010) find that most subjects receiving the medium signal of low quality choose to roll over the debt, whereas most subjects receiving that of high quality choose not to roll over the debt. That is, most subjects choose to roll over the debt when they have information favorable to this action.[6]

In contrast to the setting of Anctil et al. (2010), a private signal in our setting takes continuous real numbers, resulting in a unique equilibrium. In addition, and more importantly, the probability distribution of noise terms is symmetric, and thus both low quality of information and high quality of information are neutral to each action. In spite of that, more players choose to roll over the debt under low quality of information, which is the hypothesis of standard global games. Our result provides more direct evidence on this hypothesis than that of Anctil et al. (2010). Combining it with the other result on

[6]To explain this finding, Anctil et al. (2010) consider another game with the same payoff function in which players receive a common public signal generated by the same probability distribution as that of a private signal in the original game. Since players have common information, the interim game is reduced to a complete information game in terms of the expected payoffs. Anctil et al. (2010) show that, in the complete information game when players receive the medium signal, to roll over the debt is risk dominant under low quality of information, and not to roll over the debt is risk dominant under high quality of information. The fining of Anctil et al. (2010) shows that subjects always choose a risk dominant action in this sense.

ambiguous quality of information under the same setting, we find that ambiguous quality of information and low quality of information can have the opposite effects on the probability of coordination failure, which is our contribution.

The rest of the paper is organized as follows. In Section 2, other related literature is discussed. Then, we introduce our model and present the theoretical prediction in Section 3. We explain our design of experiments and report the experimental results in Section 4. Section 5 concludes.

2 Related literature

A growing number of papers have studied global games experimentally since the seminal work of Heinemann et al. (2004). One of the earlier papers is Cabrales and Nagel (2007). They find that the behavior of the subjects converges to the theoretical prediction after enough experience has been gained and test the hypothesis that this behavior can be explained by learning. Duffy and Ochs (2012) estimate and compare the cutoff points of global games and the corresponding dynamic games. The global game models of currency attacks (Morris and Shin, 1998) are studied by Taketa et al. (2009) and Shurchkov (2012), and the global game models of bank runs (Rochet and Vives, 2004; Goldstein and Pauzner, 2005) are studied by Klos and Strater (2008).

In contrast, only a few attempts have been made to study strategic interaction under ambiguity empirically, and they focus on auctions.[7] Salo and Weber (1994, 1995) are the first to report experiments on auctions under ambiguity. They study the first price auctions in which bidders have the CEU preferences. A recent and more elaborate study is Chen et al. (2007). They analyze the first price and second price auctions in which bidders have the α-MEU preferences (Ghirardato et al., 2004), allowing both ambiguity aversion and ambiguity loving, and empirically show that bids in the first price auctions are lower with the presence of ambiguity, which suggests that bidders are ambiguity loving.

On the theoretical side of strategic interaction under ambiguity, there is a small but growing literature, which started in auction theory. The seminal works of Salo and Weber (1995) and Lo (1998) incorporate the CEU and MEU preferences into sealed bid auctions with independent private values, respectively. Recent studies on auctions under ambiguity include Bose et al. (2006) and Turocy (2008) among others. Bose and Renou (2014) incorporate ambiguity into mechanism design where agents have MEU preferences and demonstrate that it is possible to implement social choice functions that are not implementable by using a standard mechanism without any ambiguity.

The issue of higher order ambiguous beliefs is also important, which appears in the form of iterated elimination of interim-dominated strategies in multiple-priors global games. To explore this issue, general models have been discussed. Epstein and Wang (1996) and Ahn (2007) introduce type spaces analogous to Mertens and Zamir (1985):

[7] For market experiments under ambiguity, early works includes Camerer and Kunreuther (1989) and Sarin and Weber (1993).

Epstein and Wang (1996) construct type spaces consisting of hierarchy of preferences, which include the MEU and CEU preferences, and Ahn (2007) constructs type spaces consisting of hierarchy of multiple beliefs. Kajii and Ui (2005) introduce a class of incomplete information games in which players have the MEU preferences. This class of incomplete information games conforms to the models of Epstein and Wang (1996) and Ahn (2007), and includes multiple-priors global games of Ui (2015) and the auction models of the above mentioned papers except Chen et al. (2007). To study the implication of common knowledge under ambiguity, Kajii and Ui (2009) study the agreement theorem (Aumann, 1976) and the no trade theorem (Milgrom and Stokey, 1982) in a multiple-priors model, which is elaborated by Martins-da-Rocha (2010).

3 Model

3.1 Payoffs and information

We consider a two-player and uniform-distribution version of the global game of Morris and Shin (2004)[8] and incorporate the MEU preferences. This game is a special case of global games with multiple-priors studied by Ui (2015).[9]

Two creditors, who are players of the game, hold collateralized debt. They must decide whether to roll over the debt (action R) or not (action N). A player who rolls over the debt receives 1 if an underlying investment project is successful, and receives 0 otherwise. A player who does not roll over the debt receives the value of the collateral λ. Whether or not the project is successful depends on the number of players to roll over the debt and the state of fundamentals θ. When $\theta < 0$, the project always fails, and when $\theta > 1$, the project always succeeds. On the other hand, when $0 \leq \theta \leq 1$, the project succeeds if and only if both players roll over the debt. The payoff structure is summarized as follows.

$\theta < 0$	R	N	$0 \leq \theta \leq 1$	R	N	$1 < \theta$	R	N
R	0, 0	0, λ	R	1, 1	0, λ	R	1, 1	1, λ
N	λ, 0	λ, λ	N	λ, 0	λ, λ	N	λ, 1	λ, λ

We assume $1/2 < \lambda < 1$. Thus, in the game with $\theta < 0$, N is a dominant strategy, and in the game with $\theta > 1$, R is a dominant strategy. In the game with $0 \leq \theta \leq 1$, there are two equilibria, (R, R) and (N, N). The former is Pareto dominant, and the latter is risk dominant.

The state θ is uniformly distributed over $[-\delta, 1+\delta]$ with $\delta > 0$. Player i does not directly observe θ, but observes a private signal $x_i = \theta + \varepsilon_i$, where ε_i is uniformly distributed over $[-d, d]$ with $0 < d \leq \min\{\delta, 1\}$. A strategy assigns either action R or action

[8] They assume a continuum of players and normal distributions.

[9] Ui (2015) considers a general class of multiple-priors global games with a continuum of players and proposes a procedure to obtain a unique equilibrium. Using the procedure, he shows that players exhibit strong preferences for an action yielding a constant payoff.

N to each realization of a private signal. We consider a class of strategies called switching strategies: the switching strategy with cutoff $k \in \mathbb{R}$ assigns action R to private signals greater than k and action N to private signals less than or equal to k.

Players know λ and δ, but do not know d. Instead, they know that $d \in D$, where $D \subsetneq \mathbb{R}_{++}$ is a compact set with $\min D > 0$ and $\max D \leq \min\{\delta, 1\}$. In addition, we assume that players have the MEU preferences with prior-by-prior updating.[10] That is, players evaluate their action in terms of the minimum interim payoffs, where the minimum is taken over $d \in D$. We interpret D as a measure of information quality in the following sense: if $D = \{d\}$ and $D' = \{d'\}$ with $d > d'$, then information quality D is lower than information quality D'; if $D \supsetneq D'$, then information quality D is more ambiguous than information quality D'.

More specifically, the preference relation is determined as follows. Consider player i who observes a private signal x_i and expects that player $j \neq i$ follows the switching strategy with cutoff k. When d is the true parameter, the expected payoff to action R is

$$\pi_d(k, x_i) \equiv \Pr_d[(0 \leq \theta \leq 1 \text{ and } \theta + \varepsilon_j > k) \text{ or } (\theta > 1) | \theta + \varepsilon_i = x_i].$$

Because player i has the MEU preferences, he prefers action R to action N if and only if

$$\min_{d \in D} \pi_d(k, x_i) \geq \lambda.$$

Let $b(k)$ be the value of a private signal such that player i observing $x_i = b(k)$ is indifferent between action R and action N; that is, $b(k)$ satisfies

$$\min_{d \in D} \pi_d(k, b(k)) = \lambda. \tag{1}$$

Then, player i prefers action R if $x_i \geq b(k)$, and prefers action N if $x_i \leq b(k)$, because $\pi_d(k, x_i)$ is increasing in x_i and so is $\min_{d \in D} \pi_d(k, x_i)$. This implies that the switching strategy with cutoff $b(k)$ is the best response to the switching strategy with cutoff k.

3.2 Equilibria

Let k be such that $b(k) = k$, or equivalently,

$$\min_{d \in D} \pi_d(k, k) = \lambda. \tag{2}$$

Then, the switching strategy with cutoff k is the best response to itself. This implies that a strategy profile in which both players follow this strategy is an equilibrium. Because the equation (2) has a unique solution as the next lemma shows, such an equilibrium is unique.

[10] In prior-by-prior updating, each player updates each prior in his set of priors to obtain the set of posteriors. This updating rule for multiple priors is also called the full Bayesian updating rule. For papers suggesting, deriving, or characterizing the full Bayesian updating rule in various settings, see Fagin and Halpern (1990), Wasserman and Kadane (1990), Jaffray (1992), Sarin and Wakker (1998), Pires (2002), Epstein and Schneider (2003), and Wang (2003) among others.

Lemma. *Suppose that* $1/2 < \lambda < 5/8$. *Then, the equation* (2) *has a unique solution given by*

$$k(D) \equiv \max_{d \in D} 1 + d(2\sqrt{2\lambda - 1} - 1).$$

Proof. Observe that the conditional joint distribution of (θ, ε_j) given a private signal $x_i \in [0,1]$ is the uniform distribution over $[x_i - d, x_i + d] \times [-d, d]$. Thus, by standard calculation of integration, we can obtain $\pi_d(k,k)$ for $k \in [0,1]$ as follows:

$$\pi_d(k,k) = \begin{cases} 1/2 - (d-k)^2/(8d^2) & \text{if } 0 \leq k \leq d, \\ 1/2 & \text{if } d < k < 1-d, \\ 1/2 + (k+d-1)^2/(8d^2) & \text{if } 1-d \leq k \leq 1. \end{cases} \tag{3}$$

Solving $\pi_d(k,k) = \lambda$ for $k \in [0,1]$, we have

$$k = f(d) \equiv 1 + d(2\sqrt{2\lambda - 1} - 1).$$

In fact, we can verify $f(d) \in (0,1)$ by the assumption $1/2 < \lambda < 5/8$. Note that $\pi_d(k,k) > \lambda$ if and only if $k > f(d)$, and $\pi_d(k,k) < \lambda$ if and only if $k < f(d)$, since $\pi_d(k,k)$ is increasing in k.

We show that $\max_{d \in D} f(d)$ is a unique solution of (2). If $k > \max_{d \in D} f(d)$, then $\pi_d(k,k) > \lambda$ for all $d \in D$, and thus $\min_{d \in D} \pi_d(k,k) > \lambda$. If $k < \max_{d \in D} f(d)$, then $\pi_d(k,k) < \lambda$ for some $d \in D$, and thus $\min_{d \in D} \pi_d(k,k) < \lambda$. Because $\min_{d \in D} \pi_d(k,k)$ is continuous in k, $\max_{d \in D} f(d)$ is a unique solution of (2). □

The equilibrium in which both players follow the switching strategy with cutoff $k(D)$ is a unique equilibrium in the following stronger sense. We omit the proof because the argument is the same as that of Carlsson and van Damme (1993).

Proposition. *Suppose that* $1/2 < \lambda < 5/8$. *Then, the switching strategy with cutoff* $k(D)$ *is the unique strategy surviving iterated elimination of interim-dominated strategies.*

Consider the case with $D = \{d\}$, in which our game is reduced to a standard global game. We write $k(d)$ for the equilibrium cutoff instead of $k(\{d\})$ with some abuse of notation. Note that $\lim_{d \to 0} k(d) = 1$. This implies that when the noise is very small, a risk dominant equilibrium (N, N) is a unique outcome when $0 \leq \theta \leq 1$, which is Pareto dominated by (R, R).

We have the following comparative statics result on the equilibrium cutoff $k(D)$.

Proposition. *Suppose that* $1/2 < \lambda < 5/8$. *If* $d' < d$, *then* $k(d) < k(d')$. *If* $\min D < d < \max D$, *then* $k(d) < k(D)$.

Proof. Note that $k(d)$ is strictly decreasing in d and $k(D) = \max_{d \in D} k(d) = k(\min D)$. This implies the proposition. □

According to this proposition, ambiguous quality of information makes more players choose a safe action yielding a constant payoff, which is action N. This is a consequence of ambiguity-averse player's strong preferences for an outcome with a constant payoff. On the other hand, high quality of information makes more players choose a risk dominant action, which is action N. This paraphrases the result that a risk dominant equilibrium is a unique outcome when the noise is very small.

For example, assume that $\lambda = 0.6$, and consider low quality $D_L = \{0.3\}$, high quality $D_H = \{0.2\}$, and ambiguous quality $D_A = \{0.1, 0.3\}$. By Proposition 3.2,

$$k(D_L) < k(D_H) < k(D_A). \tag{4}$$

4 Experiments

We considered the game in the previous section with $\lambda = 0.6$ and $\delta = 0.3$ and examined the comparative statics results (4) in the laboratory. In conducting our experiment, however, we multiplied every number of payoffs and signals by ten in order to avoid any decimal fraction. Thus, the state θ is uniformly distributed over $[-3, 13]$ and the payoff structure is as follows.

$\theta < 0$

	R	N
R	0, 0	0, 6
N	6, 0	6, 6

$0 \leq \theta \leq 10$

	R	N
R	10, 10	0, 6
N	6, 0	6, 6

$10 < \theta$

	R	N
R	10, 10	10, 6
N	6, 10	6, 6

We compared low quality $D_L = \{3\}$, high quality $D_H = \{2\}$, and ambiguous quality $D_A = \{1, 3\}$, where (4) remains true.

4.1 Design and procedures

The experiment was conducted at Future University Hakodate in October and December 2009. We have totally three sessions, as summarized in Table 1. In each session, 30 subjects were recruited via our electronic mailing list. All subjects were students of computer science department. Only a few of them knew game theory, and none of them knew global games.

[Table 1]

The experiment was programmed and conducted by z-tree software (Fischbacher, 2007). At the beginning of each session, subjects randomly drew PC terminal numbers. Subjects were seated in front of the corresponding terminals and given printed instructions, which were also read aloud by an experimenter.[11] In order to prevent any communication including eye contact between subjects, each terminal was separated by partitions. Each session consisted of two experiments, Experiments 1 and 2, which had the same payoff structure and different information structures. Experiment 1 was designed for practice and common to all sessions. In order to prevent any repeated game

[11]The instruction we used in Session A is given at the end of this paper.

effect, each experiment was run under complete random matching procedures; that is, each subject was faced with the same subject only once.

In Experiment 1, there were three rounds, and a subject was informed of θ in each round. It gave subjects an opportunity to learn the payoff structure as well as the experimental procedures. Subjects were also asked to complete a questionnaire to test their understanding of the payoff structure, which was checked by an experimenter.

In Experiment 2, we basically followed the procedures of Heinemann et al. (2004). There were 25 rounds, and a subject was informed of a private signal $x_i = \theta + \varepsilon_i$ in each round, where ε_i is uniformly distributed over $[-d, d]$. A subject was also informed that d took some value contained in D. When D was not a singleton, a subject knew neither the true d nor the way d was chosen from D.

In each session, d and D were set as follows. In Session L, $D = D_L$, and in Session H, $D = D_H$, where subjects were informed of $d = 2$ or $d = 3$ respectively, and it was the same for all rounds. In Session A, $D = D_A$, where subjects were informed of neither the true value of d nor the way d was chosen from D_A. The true value of d was randomly and independently determined in each round with probability 0.6 for $d = 3$.

Each session lasted for about an hour. Points earned in Experiment 2 were paid to subjects in cash with the conversion rate 1 point = 15 JPY. Points earned in Experiment 1 were not paid because this experiment was designed for practice. The average reward was 2334 JPY (approximately 1 USD = 93 JPY when the experiment was conducted).

4.2 Results

We examine aggregate data from all rounds (750 decisions per session) and test the comparative statics results (4), which predict that the relative frequency of action N in Session L is the lowest and that in Session A is the highest.

Table 2 lists the number of subjects choosing action N (the safe action) in each round and each session. Table 3 lists the observed relative frequencies of action N in all rounds and its theoretical predictions, i.e., the probabilities of the event that a private signal is less than the theoretical cutoff. The observed relative frequency is substantially smaller than its theoretical prediction in each session.[12] However, the observed comparative statics results are consistent with the prediction; that is, the relative frequency in Session L is the lowest and that in Session A is the highest in both observed values and the theoretical prediction (4).

[Table 2]

[Table 3]

Using the paired t-test and the Wilcoxon matched-pairs signed-ranks test, we find that the difference of the relative frequencies of action N in all rounds between each

[12] In fact, the null hypothesis that both are the same is rejected (binomial test, 1% significant level).

pair of sessions is statistically significant. The test results are summarized in Table 4. The difference of the relative frequencies of action N between Sessions L and H and that between Sessions H and A are both significant at 5% level in each test. Given the test results together with the observed comparative statics results, we conclude that our experimental results support the theoretical prediction (4).

[Table 4]

To find how players' decision depends upon private signals, we estimate the following logit model that predicts the probability of action N in each round and each session:

$$\Pr[\mathrm{N}|d_1, d_2, x, t] = f(\beta_0 + \beta_1 d_1 + \beta_2 d_2 + \beta_3 x + \beta_4 t),$$

where $f(z) = \exp(z)/(1 + \exp(z))$ is a logistic function, d_1 and d_2 are dummy variables, x is a private signal, and t is the number indicating the round ranging from 1 to 25. The construction of the dummy variables is shown in Table 5. If subjects' behavior is consistent with the theoretical prediction (4), the probability of action N for each x and t must be the lowest in Session L and the highest in Session A; that is,

$$\Pr[\mathrm{N}|0, 0, x, t] < \Pr[\mathrm{N}|1, 0, x, t] < \Pr[\mathrm{N}|1, 1, x, t],$$

or equivalently, $\beta_1, \beta_2 > 0$.

[Table 5]

The estimation result is summarized in Table 6. The coefficient β_1 is not significant, but β_2 is significant at 5% level (one-tailed t-test). The other coefficients are also significant (one-tailed t-test, $p < 0.001$). Figure 1 depicts the graph of $\Pr[N|d_1, d_2, x, t]$ for each session as a function of a private signal x in rounds $t = 1$ and $t = 25$.

[Table 6]

[Figure 1]

The estimated values of β_1 and β_2 are positive, and β_2 is significantly different from zero, but β_1 is not. This suggests that

$$\Pr[\mathrm{N}|0, 0, x, t] \leq \Pr[\mathrm{N}|1, 0, x, t] < \Pr[\mathrm{N}|1, 1, x, t].$$

That is, the probability of action N is the highest in Session A, although the probabilities can be the same in Sessions L and H. This confirms the robustness of the effect of ambiguous quality of information, which is different from that of low quality of information even if $\beta_1 = 0$.

Because $\beta_3 < 0$, the probability of action N is decreasing in x like the switching strategy. Because $\beta_4 > 0$, the probability of action N is increasing in t, which can be understood as experience effects. Although we adopted completely random matching procedure following Heinemann et al. (2004), data in each round is not necessarily independent.

To see the effects of t in more detail, we calculate estimated cutoffs as follows. When a private signal is equal to the equilibrium cutoff, a player is indifferent between the two actions. On the basis of this observation, we regard $c(d_1, d_2, t) \in \mathbb{R}$ satisfying

$$\Pr[\mathrm{N}|d_1, d_2, c(d_1, d_2, t), t] = 1/2$$

as an estimated cutoff in round t, which is calculated as

$$c(d_1, d_2, t) \equiv -(\beta_0 + \beta_1 d_1 + \beta_2 d_2 + \beta_4 t)/\beta_3.$$

We list the estimated cutoffs in the first and the last rounds and the theoretical predictions in Table 7. The estimated cutoffs in the last round is closest to the predicted cutoffs because it is increasing in t. In other words, the experience effects make players' behavior closer to the theoretical prediction. However, there is still a substantial gap between the estimated cutoffs in the last round and the predicted cutoffs.[13]

[Table 7]

In our model, the predicted cutoffs are obtained by infinitely many times of iterated elimination of interim-dominated strategies. It requires infinitely many hierarchies of beliefs, but subjects are not so sophisticated, which may explain the discrepancy between the estimated cutoffs and the predicted cutoffs.

Motivated by the above observation, we compare the estimated cutoffs with theoretical cutoffs based upon level-k thinking. Each player has a bounded depth of reasoning determined by his cognitive type. We assume that $L0$ types choose action R with probability 0 if $x_i < 0$, with probability x_i if $x_i \in [0, 10]$, and with probability 1 if $x_i > 10$. In the model of level-k thinking, Ln types best respond to Ln-1 types for each $n \geq 1$. Then, Ln's best response to Ln-1 is the switching strategy with cutoff $b^{n-1}(\lambda)$, where $b(\cdot)$ is given by (1) for each $n \geq 1$ (see Appendix B).

We list Ln's cutoff for $n \in \{1, 2, 3, 4, 5, 6\}$ in Table 7. For each round and each session, there exists $n \geq 0$ such that the estimated cutoff is very close to Ln's cutoff. Moreover, Ln's cutoff in Session A is the largest for each n, which is consistent with our experimental result. However, Ln's cutoff in Session L is also the largest for each n and the same as that in Session A, which is not consistent with our experimental result.

On the other hand, to test level-k thinking by laboratory experiments, we should use only the first round data. However, because $\theta = 0.2$ in the first round, each private signal is close to zero, thus making most subjects choose action N. In fact, 27 out of 30 subjects in Sessions L and H and 25 out of 30 subjects in Session A choose action N (see Table 2). Moreover, the difference of the relative frequencies between them (i.e. 27/30 and 25/30) is not statistically significant (Fisher's exact test, $p = 0.706$).

To summarize, although level-k thinking may explain the estimated cutoff in each session separately, it cannot say much about the observed comparative statics results in our experiment.

[13] In fact, the hypothesis that both are the same is rejected by Wald test in each session.

4.3 Predictions under ambiguity

To study what subjects think about d when they make decisions, we conducted another experiment, Session P. This session is the same as Session A except the prediction stage: subjects were asked to answer their predictions of d and their confidences in them before they chose their actions in each round, which follows Chen et al. (2007).[14] In this session, we set $D = D_A = \{1, 3\}$ with the same sequence of d as that of Session A, of which subjects were not informed. Subjects were asked to answer their subjective probability of $d = 1$ by an integer percentage and the confidence in it by one of the following five categories: not confident, slightly confident, moderately confident, fairly confident, and very confident.

Our finding is that, when subjects are asked to answer their predictions, not only their predictions but also their behaviors are not always consistent with ambiguity aversion.

To find the relationship between a prediction and a private signal, we first estimate a regression model where the dependent variable is a subjective probability and the independent variable is a private signal. The estimation result is summarized in Table 8. We find that the estimated coefficient of a private signal is insignificant. This suggests that observed private signals have no effect on predictions.

[Table 8]

Thus, it is enough to focus on aggregate data. The histogram in Figure 2 depicts the relative frequencies of subjective probabilities of $d = 1$. The bar from 41% to 50% is the highest.[15] That is, many subjects thought that both cases would occur equally likely. Such a neutral prediction which is independent of a private signal is inconsistent with ambiguity aversion.

[Figure 2]

Correspondingly, subjects' behavior is also inconsistent with ambiguity aversion. The relative frequency of action N is 0.628 in Session P, which is significantly smaller than 0.664 in Session A, and close to 0.623 in Session H where $d = 2$ (see Table 3). This implies that subjects were not necessarily ambiguity averse in Session P because ambiguity aversion must result in stronger preferences for action N.

The above result suggests that the prediction stage made subjects less ambiguity averse not only in their predictions but also in their behaviors. We have no conclusive explanation for this. One reason might be that the procedure we employed in the prediction stage was not incentive compatible. In other words, subjects might have answered our question as if a prediction and a decision were separated. Without any incentive, it is natural for a subject to assume that the two events occur equally likely if there is no prior knowledge

[14] The following procedures were firstly developed by Curley et al. (1989), as Chen et al. (2007) introduced in their paper.

[15] 50% is both the mode and the medium of subjective probabilities. The average is 45%.

about probabilities.[16] Furthermore, once a subject had made such a neutral prediction, he might have made a decision consistent with this prediction. This is just one casual explanation. To study the relationship between subjects' perception under ambiguity and ambiguity-averse behavior in a strategic environment, we have to develop a more sophisticated procedure in the future research.

5 Concluding remarks

In our experiment, we study the relationship between information quality and coordination failure in a creditor coordination game where "not to roll over" is a risk dominant action. We find the different roles of ambiguous quality and low quality: a credit crisis (less efficient outcome) is more likely to occur by ambiguous quality, whereas it is less likely to occur by low quality. This finding gives an empirical evidence to support the result of Ui (2015) on ambiguous quality of information and the standard comparative statics result of global games on low quality of information.

On the effect of low quality of information, Anctil et al. (2010) obtain a similar result. However, as argued in the introduction, the model of Anctil et al. (2010) is not a global game in the sense of Carlsson and van Damme (1993). In addition, low quality of information in Anctil et al. (2010) convey information favorable to an efficient outcome. Thus, their finding does not necessarily give an empirical evidence to support the standard comparative statics result of global games. In this sense, our finding on the effect low quality of information is of independent interest.

Our experimental finding leads us to the following policy implication: we can decrease the probability of a credit crisis by reducing ambiguity. One way to reduce ambiguity is to provide creditors with more information about the probability distribution. For example, when the authorities forecast the state of the economy, it is more helpful to publish not only central tendencies but also ranges. In line with this discussion, many central banks have begun to express their views about the likely future path of the economy more openly including both central tendencies and ranges. Examples include the fan charts of Bank of England, which reveal the Bank's subjective probability distribution for the future paths of CPI inflation and GDP growth.

Our experimental study has demonstrated that higher order ambiguous beliefs matter in global games. We adopt global games in order to give an empirical evidence to support the result of Ui (2015). However, to explore the role of ambiguous information under strategic interaction in the laboratory, a simpler game would be more appropriate for the following reason. To solve global games, subjects must iteratively eliminate dominated strategies infinitely many times, but they are not so rational, which may explain the discrepancy between the predicted cutoffs and the estimated cutoffs in our experiment. Thus, possible future research includes an experimental study of a Bayesian game with ambiguous information which subjects can solve by a finite number of iterations.

[16] This conforms to the so-called principle of indifference (insufficient reason).

Appendix

A Instructions

Instructions to participants varied according to different treatments. We present here an English translation of the instruction for Session A. At other sessions, instructions were adapted accordingly.

General information

This is an experiment on economic decision-making. You do not need to have any knowledge of economics. If you follow the instructions given below and make an appropriate choice, then you will earn a considerable amount of money in cash.

Please observe the following rules during the experiment. (i) Turn off your cellular phone. (ii) Refrain from talking. (iii) Eye contact and exchanging signs with your neighbors are forbidden. (iv) If you have any questions during the experiment, raise your hand quietly.

Experiment 1

In this experiment, you make a decision repeatedly with different partners, who are randomly chosen. You are never paired with the same partner more than once. The outcome of your decision-making depends on both your choice and your partner's choice. There are three decision-making situations. One of them is randomly chosen, and the outcome is determined by both your choice and your partner's choice.

A decision-making situation is represented by the following payoff tables. In viewing them, you should regard yourself as player I and your partner as player J.

Payoff Table 1
($-3 \leq X < 0$)

I\J	A		B	
A	I	J	I	J
	0	0	0	6
B	I	J	I	J
	6	0	6	6

Payoff Table 2
($0 \leq X \leq 10$)

I\J	A		B	
A	I	J	I	J
	10	10	0	6
B	I	J	I	J
	6	0	6	6

Payoff Table 3
($10 < X \leq 13$)

I\J	A		B	
A	I	J	I	J
	10	10	10	6
B	I	J	I	J
	6	10	6	6

In each decision-making situation, players I and J choose alternatives A or B without knowing the partner's choice. Player I chooses A or B in row, and player J chooses A or B in column. The outcome is represented at the intersection of the two choices. The number in the left hand is player I's payoff and that in right hand is player J's payoff. For example, in Payoff Table 1, if player I chooses A and player J chooses B, then the intersection is the following. Thus, player I earns 0 and player J earns 6.

I	J
0	6

A random number X determines which payoff table is used. It is uniformly distributed over the interval $[-3, 13]$. Thus, any value in this interval can be chosen equally likely. If the value of $X < 0$, then Payoff Table 1 is used. If $0 \leq X \leq 10$, then Payoff Table 2 is used. If $X > 10$, then Payoff Table 3 is used.

In Experiment 1, the value of X is informed to you before you make a decision, and it is common to all participants.

The procedure of Experiment 1, which we call a round, is summarized as follows.

Step 1 Your partner is determined.

Step 2 The value of X is chosen and informed to you.

Step 3 You and your partner choose alternatives A or B.

Step 4 Payoffs for you and your partner are determined.

When you complete one round, you start a new round with a new partner and the new value of X.

On your computer screen, you have quizzes which test your understanding of the payoff tables. Please answer each of them.

Experiment 1 is practice for learning experimental procedures and operating your computers. The payoffs earned in this experiment is not paid to you. Please read the instructions on your computer screen carefully, and start your decision-making.

Experiment 2

The procedure of Experiment 2 is basically the same as that of Experiment 1. That is, a random number X determines which payoff table is used. It is uniformly distributed over the interval $[-3, 13]$. Thus, any value in this interval can be chosen equally likely. If the value of $X < 0$, then Payoff Table 1 is used. If $0 \leq X \leq 10$, then Payoff Table 2 is used. If $X > 10$, then Payoff Table 3 is used. In each payoff table, players I and J choose alternatives A or B without knowing the partner's choice.

The difference is that, in Experiment 2, X is *not* informed to you before you make a decision. Instead, you are informed of another random number Y.

A random number Y is the sum of X and R (i.e. $Y = X + R$), where R is also a random number following a uniform distribution. The value of R is chosen from either $[-1, 1]$ or $[-3, 3]$. That is, in the former case, any value in $[-1, 1]$ can be chosen equally likely, and in the latter case, any value in $[-3, 3]$ can be chosen equally likely. A certain rule determines which interval is used. Possibly, $[-1, 1]$ is always chosen, or $[-3, 3]$ is always chosen. Of course, a mixture of both is also possible. But not only the chosen interval but also the choosing rule are not informed to you before decision-making.

Note that the value of Y you receive might be greater than or less than the value of X. Of course, both might be equal.

In each round, the value of X and the interval of R are common to all participants. But R is determined independently for you and your partner. Thus, your value of Y is different from your partner's. Note that what is informed to you is not the value of R but the value of Y (the sum of X and R).

If $-3 \leq Y \leq 13$, you are informed of Y. But if $Y < -3$ or $Y > 13$, you are not informed of Y. In these cases, you are informed that $Y < -3$ or $Y > 13$ respectively.

The figure at the bottom of this instruction depicts the relationship between X and Y. In this figure, your Y is less than your partner's Y. Of course, the other cases are also possible. In any case, you cannot know the value of your partner's Y.

From the value of Y you receive, you have to guess X, your partner's Y, and your partner's choice. Then, you choose alternatives A or B. After making a decision, the value of X is revealed, and then your payoff is determined by the corresponding payoff table.

The procedure of Experiment 2, which we call a round, is summarized as follows.

Step 1 Your partner is determined.

Step 2 The interval of R, $[-1, 1]$ or $[-3, 3]$, is determined, which is not informed to you. The rule to determine the interval is also not informed to you.

Step 3 The value of X is chosen, which is not informed to you.

Step 4 The value of $Y = X + R$ is chosen and informed to you.

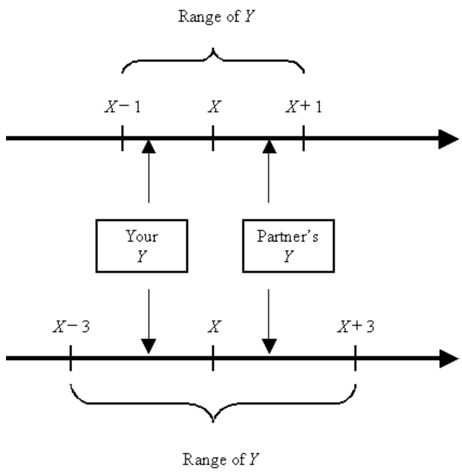
Step 5 You and your partner choose alternatives A or B.

Step 6 The value of X is revealed.

Step 7 Payoffs for you and your partner are determined.

When you complete one round, you start a new round with a new partner and the new values of X and R. You repeat a round 25 times.

After finishing all rounds, you will be paid in cash proportional to the sum of your payoffs. The conversion rate is 15 JPY for a point.



B Comparative statics with level-k thinking

In this appendix, we incorporate level-k thinking into a game in Section 3.1.

Assume that $L0$ types choose action R with probability 0 if $x_i < 0$, with probability x_i if $x_i \in [0,1]$, and with probability 1 if $x_i > 1$. When an $L1$ type observes a private signal $x_i \in [\max D, 1-\max D]$ and d is the true parameter, the expected payoff to action R is equal to the conditional probability that the opponent chooses R, i.e., $E_d[x_j|\theta+\varepsilon_i = x_i] = x_i$. Having the MEU preferences, he prefers action R to action N if and only if

$$\min_{d\in D} E_d[x_j|\theta+\varepsilon_i = x_i] = x_i \geq \lambda,$$

which implies that the switching strategy with cutoff λ is $L1$'s best response to $L0$. For each $n \geq 1$, Ln types best respond to Ln-1 types. Thus, Ln's best response to Ln-1 is the switching strategy with cutoff $b^{n-1}(\lambda)$, where $b(\cdot)$ is given by (1). We write $\bar{k}(n,D) = b^{n-1}(\lambda)$ for the cutoff of Ln types.

We have the following comparative statics result on the cutoff $\bar{k}(n,D)$, where $\bar{k}(n,d)$ denotes $\bar{k}(n,\{d\})$ with some abuse of notation.

Proposition. *Suppose that* $1/2 < \lambda < 1$*. If* $d' < d$ *and* $\bar{k}(n,d) \leq 1-d$*, then* $\bar{k}(n,d') < \bar{k}(n,d)$*. If* $\min D < d < \max D$ *and* $\bar{k}(n,D) < 1-\max D$*, then* $\bar{k}(n,d) < \bar{k}(n,D)$*.*

Proof. We solve (1) assuming $b(k) \leq 1-\max D$. Because $\pi_d(k,x_i)$ is increasing in x_i and $\pi_d(k,k) = 1/2$ if $k \in [d, 1-d]$ by (3), we must have $b(k) > k$ because $\lambda > 1/2$. If $k \leq x_i \leq k+2d$, we get

$$\pi_d(k,x_i) = 1 - \left(d - (x_i-k)/2\right)^2/(2d^2) \geq 1/2$$

by standard calculation of integration. We can verify that $\pi_d(k,x_i)$ is decreasing in d, which implies that $\max D = \arg\min_{d\in D} \pi_d(k,x_i)$. Solving (1), we have

$$b(k) = k + 2\left(1-\sqrt{2(1-\lambda)}\right)\max D.$$

This implies that

$$\bar{k}(n,D) = b^{n-1}(\lambda) = \lambda + 2(n-1)\left(1-\sqrt{2(1-\lambda)}\right)\max D,$$

which establishes the lemma because $1-\sqrt{2(1-\lambda)} > 0$. □

According to this proposition, if the cutoff point is not too large, ambiguous quality of information makes more players choose a safe action yielding a constant payoff, which is action N. This is a consequence of ambiguity-averse player's strong preferences for an outcome with a constant payoff. Low quality of information makes more players choose a risk dominant action, which is action N. To see the intuition, recall that an action is risk dominant if it is a best response when the opponent chooses an action completely at random, i.e., with a probability 1/2 for each action. This implies that a risk dominant action is more likely to be a best response when a player is more uncertain about the opponent's action under lower quality of information.

For example, assume that $\lambda = 0.6$, and consider low quality $D_L = \{0.3\}$, high quality $D_H = \{0.2\}$, and ambiguous quality $D_A = \{0.1, 0.3\}$. Then,

$$\bar{k}(n, D_H) \leq \bar{k}(n, D_L) = \bar{k}(n, D_A),$$

where strict inequality holds if $n \geq 2$. This result is inconsistent with our experimental findings.

References

Ahn, D., 2007. Hierarchies of ambiguous beliefs. J. Econ. Theory 136, 286–301.

Anctil, R. M., Dickhaut, J., Johnson, C., Kanodia, C., 2010. Does information transparency decrease coordination failure? Games Econ. Behav. 70, 228–241.

Aumann, R. J., 1976. Agreeing to disagree. Ann. Statist. 4, 1236–1239.

Bose, S., Ozdenoren, E., Pape, A., 2006. Optimal auctions with ambiguity. Theoretical Econ. 1, 411–438.

Bose, S. Renou, L., 2014. Mechanism design with ambiguous communication devices. Econometrica 82, 1853–1872.

Cabrales, A., Nagel, R., 2007. Equilibrium selection through incomplete information in coordination games: an experimental study. Exper. Econ. 10, 221–234.

Camerer, C., Ho, T.-H., Chong, J. K., 2004. A cognitive hierarchy theory of one-shot games. Q. J. Econ. 119, 861–898.

Camerer, C., Kunreuther, H., 1989. Experimental markets for insurance. J. Risk Uncertainty 2, 265–300.

Carlsson, H., van Damme, E., 1993. Global games and equilibrium selection. Econometrica 61, 989–1018.

Chen, Y., Katuscak, P., Ozdenoren, E., 2007. Sealed bid auctions with ambiguity: theory and experiments. J. Econ. Theory 136, 513–535.

Costa-Gomes, M., Crawford, V. P., 2006. Cognition and behavior in two-person guessing games: an experimental study. Amer. Econ. Rev. 96, 1737–1768.

Costa-Gomes, M., Crawford, V. P., Broseta, B., 2001. Cognition and behavior in normal form games: an experimental study. Econometrica 69, 1193–1235.

Crawford, V. P., Costa-Gomes, M. A., Iriberri, N., 2013. Structural models of nonequilibrium strategic thinking: theory, evidence, and applications. J. Econ. Lit. 51, 5–62.

Curley, S. P., Young, M., Yates, F. F., 1989. Characterizing physician's perceptions of ambiguity. Med. Dec. Making 9, 116–124.

Dow, J., Werlang, S., 1992. Uncertainty aversion, risk aversion, and the optimal choice of portfolio. Econometrica 60, 197–204.

Duffy, J., Ochs, J., 2012. Equilibrium selection in static and dynamic entry games. Games Econ. Behav. 76, 97–116.

Ellsberg, D., 1961. Risk, ambiguity, and the Savage axioms. Quart. J. Econ. 75, 643–669.

Epstein, L. G., Schneider, M., 2003. Recursive multiple priors. J. Econ. Theory 113, 1–31.

Epstein, L. G., Wang, T., 1996. "Beliefs about beliefs" without probabilities. Econometrica 64, 1343–1373.

Fagin, R., Halpern, J., 1990. A new approach to updating beliefs. In: Bonissone, P. P., Henrion, M., Kanal, L. N., Lemmer, J. F. (Eds.), Uncertainty in Artificial Intelligence 6. Elsevier, New York, pp. 317–325.

Fischbacher, U., 2007. z-Tree: Zurich toolbox for ready-made economic experiments. Exper. Econ. 10, 171–178.

Gajdos, T., Hayashi, T., Tallon, J.-M., Vergnaud, J.-C., 2008. Attitude toward imprecise information. J. Econ. Theory 140, 27–65.

Ghirardato, P., Maccheroni, F., Marinacci, M., 2004. Differentiating ambiguity and ambiguity attitude. J. Econ. Theory 118, 133–173.

Gilboa, I., Marinacci, M., 2013. Ambiguity and the Bayesian paradigm. In: Acemoglu, D., Arellano, M., Dekel, E. (Eds.), Advances in Economics and Econometrics: Tenth World Congress vol. 1. Cambridge University Press, pp. 179–242.

Gilboa, I., Schmeidler, D., 1989. Maxmin expected utility with a non-unique prior. J. Math. Econ. 18, 141–153.

Goldstein, I., Pauzner, A., 2005. Demand-deposit contracts and the probability of bank runs. J. Finance 60, 1293–1327.

Heinemann, F., Nagel, R., Ockenfels, P., 2004. The theory of global games on test: experimental analysis of coordination games with public and private information. Econometrica 72, 1583–1599.

Hey, J. D., 2014. Choice under uncertainty: empirical methods and experimental results. In: Machina, M., Viscusi, W. K. (Eds.), Handbook of the Economics of Risk and Uncertainty. North-Holland, pp. 809–850.

Hirshleifer, J., 1971. The private and social value of information and the reward to inventive activity. Amer. Econ. Rev. 61, 561–574.

Ho, T.-H., Camerer, C., Weigelt, K., 1998. Iterated dominance and iterated best response in experimental "p-beauty contests". Amer. Econ. Rev. 39, 649–660.

Jaffray, J.-Y., 1992. Bayesian updating and belief functions. IEEE Trans. Syst. Man Cybern. 22, 1144–1152.

Kajii, A., Ui, T., 2005. Incomplete information games with multiple priors. Japanese Econ. Rev. 56, 332–351.

Kajii, A., Ui, T., 2009. Interim efficient allocations under uncertainty. J. Econ. Theory 144, 337–353.

Kawagoe, T., Takizwa, H., 2009. Equilibrium refinement vs. level-k analysis: an experimental study of cheap-talk games with private information. Games Econ. Behav. 66, 238–255.

Kawagoe, T., Takizwa, H., 2012. Level-k analysis of experimental centipede games. J. Econ. Behav. Organ. 82, 548–566.

Klibanoff, P., Marinacci, M., Mukerji, S., 2005. A smooth model of decision making under ambiguity. Econometrica 73, 1849–1892.

Klos, A., Strater, N., 2008. Global games and demand-deposit contracts: an experimental study of bank runs. Working paper.

Kneeland, T., 2012. Coordination under limited depth of reasoning. Working paper.

Lo, K. C., 1998. Sealed bid auctions with uncertainty averse bidders. Econ. Theory 12, 1–20.

Machina, M. J., Siniscalchi, M., 2014. Ambiguity and ambiguity aversion. In: Machina, M., Viscusi, W. K. (Eds.), Handbook of the Economics of Risk and Uncertainty. North-Holland, pp. 729–807.

Martins-da-Rocha, V. F., 2010. Interim efficiency with MEU-preferences. J. Econ. Theory 145, 1987–2017.

Mertens, J.-F., Zamir, S., 1985. Formulation of Bayesian analysis for games with incomplete information. Int. J. Game Theory 14, 1–29.

Metz, C. E., 2002. Private and public information in self-fulfilling currency crises. J. Econ. 76, 65–85.

Milgrom, P., Stokey, N., 1982. Information, trade and common knowledge. J. Econ. Theory 26, 17–27.

Morris, S., Shin, H. S., 1998. Unique equilibrium in a model of self-fulfilling currency attacks. Amer. Econ. Rev. 88, 587–597.

Morris, S., Shin, H. S., 2002. Social value of public information. Amer. Econ. Rev. 92, 1521–1534.

Morris, S., Shin, H. S., 2004. Coordination risk and the price of debt. Europ. Econ. Rev. 48, 133–153.

Nagel, R., 1995. Unraveling in guessing games: an experimental study. Amer. Econ. Rev. 85, 1313–1326.

Pires, C. P., 2002. A rule for updating ambiguous beliefs. Theory Dec. 53, 1573–7187.

Rochet, J.-C., Vives, X., 2004. Coordination failures and the lender of last resort: was Bagehot right after all? J. Europ. Econ. Assoc. 2, 1116–1147.

Salo, A., Weber, M., 1994. First-price sealed-bid auctions: an experiment on probabilistic risk. Universität Mannheim Working Paper.

Salo, A., Weber, M., 1995. Ambiguity aversion in first-price sealed-bid auctions. J. Risk Uncertainty 11, 123–137.

Sarin, R., Wakker, P., 1998. Dynamic choice and nonexpected utility. J. Risk Uncertainty 17, 87–119.

Sarin, R., Weber, M., 1993. Effects of ambiguity in market experiments. Manage. Sci. 39, 602–615.

Schmeidler, D., 1989. Subjective probability and expected utility without additivity. Econometrica 57, 571–587.

Shurchkov, O., 2013. Coordination and learning in dynamic global games: experimental evidence. Exper. Econ. 16, 313–334

Stahl, D., Wilson, P., 1995. On player's models of other players: theory and experimental evidence. Games Econ. Behav. 10, 218–254.

Taketa, K., Suzuki-Löffelholz, K., Akikawa, Y., 2009. Experimental analysis on the role of a large speculator in currency crises. J. Econ. Behav. Organ. 72, 602–617.

Turocy, T., 2008. Auction choice for ambiguity-averse sellers facing strategic uncertainty. Games Econ. Behav. 62, 155–179.

Wang, T., 2003. Conditional preferences and updating. J. Econ. Theory 108, 286–321.

Wasserman, L. A., Kadane, J. B., 1990. Bayes' theorem for Choquet capacities. Ann. Statist. 18, 1328–1339.

Ui, T., 2015. Ambiguity and risk in global games. Working paper, Hitotsubashi University. `http://wakame.econ.hit-u.ac.jp/~oui/ggmp.pdf`

Table 1: Summary of treatments in each session

Name	# of subjects	Information quality
Session L	30	$D_L = \{3\}$ (low)
Session H	30	$D_H = \{2\}$ (high)
Session A	30	$D_A = \{1, 3\}$ (ambiguous)

Table 2: The number of action N

Round	θ	Session L	Session H	Session A
1	0.2	27	27	25
2	7.1	13	12	15
3	11.7	8	5	8
4	-1.7	29	30	29
5	2.9	16	22	24
6	10.7	7	5	9
7	5.9	13	13	18
8	4.4	14	16	24
9	1.5	23	27	25
10	8.6	10	10	13
11	9	10	13	15
12	3.4	23	23	26
13	6	15	16	17
14	9.1	11	11	10
15	11.9	4	5	6
16	-2.1	30	30	30
17	11.3	3	5	6
18	2.4	26	28	29
19	-1.7	30	29	29
20	7.4	14	17	15
21	-2.9	29	30	30
22	1.6	26	26	29
23	4.6	18	21	26
24	-0.7	30	30	30
25	8.9	10	16	10
Total		439	467	498

Table 3: The relative frequency of action N in aggregate data

	Session L	Session H	Session A
Observed	0.585	0.623	0.664
Predicted	0.792	0.799	0.806

Table 4: The paired t-test and the signed-ranks test

	L vs. H	H vs. A	L vs. A
t-value of the paired t-test	-2.565^{*}	-2.154^{*}	-3.970^{**}
z-value of the signed-ranks test	-2.379^{*}	-2.146^{*}	-3.411^{**}

Note: * indicates 5% significance level; ** indicates 1% significance level.

Table 5: Dummy variables

	Session L	Session H	Session A
d_1	0	1	1
d_2	0	0	1

Table 6: The logit model

	Coefficient	S. E.	z-value	p-value
β_0	2.066	0.166	12.43	0.000
β_1	0.214	0.135	1.59	0.112
β_2	0.302	0.137	2.21	0.027
β_3	-0.376	0.016	-23.39	0.000
β_4	0.028	0.008	3.54	0.000
LL	-1001.159			
Pseudo R^2	0.328			

Note: Each p-value is of one-tailed z-test .

Table 7: Estimated cutoffs and theoretical cutoffs

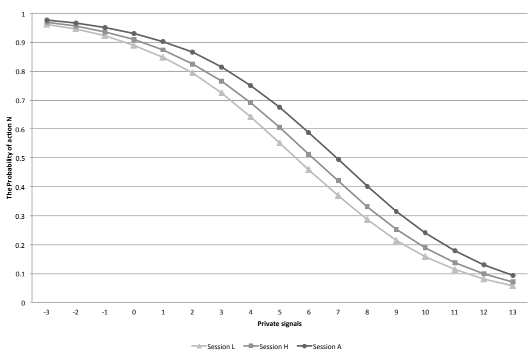
	Session L	Session H	Session A
Estimated			
$t = 1$	5.57	6.14	6.94
$t = 25$	7.36	7.93	8.73
Predicted	9.68	9.79	9.89
$L1$'s cutoff	6.00	6.00	6.00
$L2$'s cutoff	6.63	6.42	6.63
$L3$'s cutoff	7.27	6.84	7.27
$L4$'s cutoff	7.90	7.27	7.90
$L5$'s cutoff	8.53	7.69	8.53
$L6$'s cutoff	9.17	8.11	9.17

Table 8: The estimation result

	Coefficient	S. E.	t-value	p-value
Constant	45.253	1.379	32.820	0.000
Private signal	−0.032	0.203	−0.157	0.875

Figure 1: The estimated probability of action N

(a) $t = 1$



(b) $t = 25$

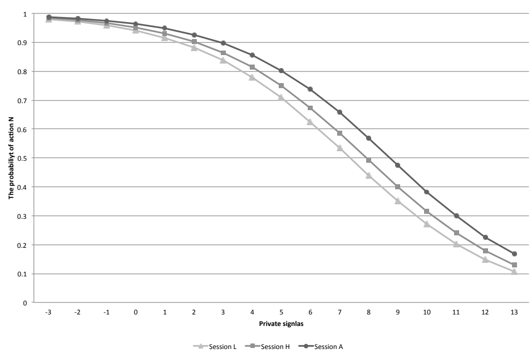


Figure 2: A subjective probability of $d = 0.1$