Speculative Attacks and Financial Architecture: Experimental Analysis of Coordination Games with Public and Private Information*

Frank Heinemann[a], Rosemarie Nagel[b] and Peter Ockenfels[c]

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Abstract

Speculative Attacks are a coordination game with multiple equilibria if the state of the economy is common knowledge. With private information there is a unique equilibrium. This raises the question whether public information may be destabilizing by allowing for self-fulfilling beliefs. We present an experiment that imitates a speculative attacks model and compare sessions with public and private information. Our evidence suggests that there is no reason to belief that public information leads to self-fulfilling beliefs. Predictability of attacks is slightly higher with public than with private information, but prior probability of attacks is also higher with public information.

Statistical tests reject payoff dominance, risk dominance and maximin strategies as selection criteria. With public information subjects coordinate on equilibria somewhere between payoff dominant and risk dominant equilibrium. Reactions to parameter changes go into the directions predicted by risk dominance. Observed strategies can be explained by independent beliefs on other subjects attacking with a given probability.

Keywords: coordination game, global game, payoff dominance, private information, public information, risk dominance, strategic uncertainty, supermodular game.

JEL codes: C72, C 91, E 58.

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[a] Ludwig-Maximilians-Universität München.
[b] Universitat Pompeu Fabra, Barcelona.
[c] Goethe-Universität Frankfurt am Main.

1. Introduction

Transparency and the optimal way to disclose central bank information are among the main topics within the current discussion on financial architecture. Speculative attacks and market overreactions are often interpreted as evidence for systemic indeterminacy and instability. Recent theories attribute these instabilities to self-fulfilling beliefs caused by public information and suggest that stability can be increased by more sophisticated schemes of information disclosure. In this paper we present an experiment designed to test these theories.

Obstfeld (1996) models speculative attacks as a coordination game in which the expected payoff to speculating on devaluation depends positively on the amount of capital that follows the same strategy: A central bank pegs the exchange rate of its currency to some other currency or currency basket. A realignment is associated with fixed costs. Economic decisions by private agents depend on their expectations about future exchange rates. Agents who expect a devaluation sell the currency, they "attack" as we say. This increases supply and thereby raises costs for the central bank to maintain the peg. If a sufficient number of traders expects a devaluation, market pressure may raise costs of maintaining the peg above the costs of realignment. Here, the central bank devaluates its currency and traders' expectations are correct. If traders expect the exchange rate to hold, they do not sell the currency. Market pressure is lower and the rate can be sustained as expected. The model has multiple equilibria with self-fulfilling beliefs.

Applying the global games approach of Carlsson and van Damme (1993a,b), Morris and Shin (1998, 1999) have shown that there may be a unique equilibrium if traders have private instead of public information on the reactions of the central bank. Private information lets different traders hold different beliefs and reduces the degree of common knowledge. Public information is described as a statement that is common knowledge among traders. While Obstfeld assumes common knowledge of fundamentals and gets multiple equilibria, Morris and Shin (1998) get a unique equilibrium with private information on fundamentals. When agents get both, public *and* private information, uniqueness requires private information to be sufficiently precise when compared to public information (Morris and Shin, 1999). Public information may be destabilising when it leads to arbitrary and unpredictable outcomes. This has triggered a discussion on optimal mechanisms to release information to financial markets in order to prevent crises with self-fulfilling features.

In this paper we present an experiment that imitates the game structure of the speculative attack models by Obstfeld (1996) and Morris and Shin (1998). We compare sessions with public and private information and show in which respects behavior differs.

In all sessions, subjects coordinated their strategies in a way that an attack was successful, whenever the fundamental state was beyond some critical state. Critical states were surprisingly stable within a session and their variance across sessions was the same for both information conditions. Our evidence suggests that there is no difference in predictability that could be related to self-fulfilling features of the game with public information. Smith (1991) distinguished between common information and common knowledge. While public announcements may be common information, they need not become common knowledge. Strategic uncertainty is sufficient to create private beliefs even when information is public. For practical purposes, this tells us that the destabilizing effect of public information due to self-fulfilling beliefs may be less severe than theory suggests.

With public information, subjects rapidly coordinated on an equilibrium and achieved higher payoffs than with private information. With public information, we observed successful attacks at states where they did not occur with private information. In the model's interpretation this means that a commitment to provide public information increases the prior probability of devaluation. We conclude that transparency of the central bank may increase the probability of speculative attacks, but it does not reduce their predictability.

We also used the experiment to test the predictive power of various concepts to select among multiple equilibria. In the game with public information, different refinement criteria select different critical states (thresholds) beyond which attacks occur. In all sessions with public information we observed that subjects coordinated on thresholds somewhere between those associated with payoff dominant and risk dominant equilibrium. Observed thresholds were never close to the one associated with maximin strategies. Using treatments with different parameters, we observed that thresholds depend on exogenous parameters as predicted by comparative statics of the risk dominant equilibrium and by the theory of global games. We conclude that these concepts are able to predict the qualitative comparative statics of aggregate behavior in coordination games with strategic complementarities, even though we can reject their numerical predictions.

The theory of global games has been developed by Carlsson and van Damme (1993a,b) and Morris and Sin (2000). It embeds a coordination game with strategic complementarities in a stochastic environment, where the true game is selected randomly out of a class of possible games with differences in the payoff function. Applications have been used to explain speculative attacks (Morris and Shin, 1998), bank runs (Goldstein and Pauzner, 2000), liquidity crises (Morris and Shin, 2001; Hubert and Schäfer, 2001) and competition for order flow (Dönges and Heinemann, 2001). One line of theoretical research concentrates on the impact that different modes of releasing information have on uniqueness versus multiplicity of equilibria and thereby on stability of financial markets. Morris and Shin (1999) and Hellwig (2000) observed that uniqueness requires private information to be sufficiently precise when compared to public information. Heinemann and Illing (1999) showed that the probability of speculative attacks is reduced when precision of private information is increased. Metz (2001) observed that precisions of public and private information may have opposing effects on the probability of crises. While policy makers often claim that a more transparent policy increases financial stability[1], these results raise doubts by academic researchers who emphasize the endogeneity of default risks and the sensitivity with respect to the modes of information disclosure (Daníelson et al. 2001).

Previous experiments on coordination games with strategic complementarities carried out by Van Huyck, Battaglio and Beil (1990, 1991) have shown that with perfect information subjects coordinate rather quickly on an equilibrium between maximin strategies and payoff dominant equilibrium. Efficiency depends on group size and experience. While groups of two players coordinate on the payoff dominant equilibrium even in unfavorable set-ups, groups of 14 to 16 players reach the payoff dominant equilibrium only after experiencing efficient coordination in other treatments. Cabrales, Nagel and Armenter (2000) tested the global game approach by comparing otherwise equal treatments with common (=public) and private information on a payoff relevant parameter. They found no significant difference in behavior between the two information scenarios. In both cases subjects converged to coordination on the equilibrium of the private information game, which (in their experiment) coincides with maximin strategies and with the risk dominant equilibrium.

Chapter 2 of this paper explains the speculative attacks model that underlies our experiment. Chapter 3 lays out the experimental design. Chapter 4 derives theoretical predictions for the game used in our experiment. In Chapter 5 we analyze aggregate data and show that with public information speculative attacks are more likely, but there is no evidence for attacks being less predictable. Individual strategies are analysed in Chapter 6 to test the predictive power of various equilibrium refinements. Chapter 7 compares results to previous experiments and concludes the paper.

2. Speculative Attacks as a Coordination Game

Speculative attacks on a currency peg can be modelled as a coordination game with strategic complementarities as in Obstfeld (1996). He shows that the existence of multiple equilibria depends on underlying fundamentals: If the fundamental state of the economy is really bad, a devaluation is inevitable, even if nobody attacks. If the shadow exchange rate is far below the peg, maintaining the peg is associated with an unsustainable outflow of reserves. Here, there is a unique equilibrium in which all agents expect devaluation and sell the currency. If fundamentals are sound, there is not enough capital around to enforce a devaluation, or the peg is so close to the shadow rate that maximal rewards from a speculative attack are too small to cover transaction costs. Here, it is irrational to attack. It is only in intermediate situations, in which beliefs may be self-fulfilling.

[1] See BIS (2001) for a recent call for more transparency in order to avoid banking crises.

Morris and Shin (1998) use a reduced version of this model to show that there is a unique equilibrium if there is only private information on the fundamental state of the economy. They consider a game in which an infinite number of small traders $i \in [0,1]$ can decide whether to attack or not. The fundamental state is denoted by θ. If the proportion of attacking traders exceeds a hurdle function $a(\theta)$, the attack is successful and each attacking trader receives a reward $R(\theta) - T$. Otherwise, attacking agents loose transactions costs T. Assuming $a' > 0$ and $R' < 0$, larger θ is interpreted as a better state of the economy. At states above $\overline{\theta} = R^{-1}(T)$ a speculative attack is unrewarding because it does not cover transaction costs even if successful. Here, it is a dominant strategy not to attack. At states below $\underline{\theta} = a^{-1}(0)$ devaluation cannot be avoided. Assuming $\underline{\theta} < \overline{\theta}$, it is a dominant strategy to attack at states below $\underline{\theta}$. With common knowledge of θ, there are two equilibria in pure strategies with all or none of the agents attacking at all intermediate states $\theta \in [\underline{\theta}, \overline{\theta}]$.

Morris and Shin assume that fundamental state θ has a uniform distribution with sufficiently large support to include $\underline{\theta}$ and $\overline{\theta}$. Traders get private signals x^i that are random with independent uniform conditional distribution in $[\theta - \varepsilon, \theta + \varepsilon]$, where ε is sufficiently small. Now, each trader expects other traders to receive higher or lower signals than her own with equal probability. Common knowledge of the state is replaced by an equilibrium condition, at which agents compare expected returns from successful attack, weighted with the probability of success, with transaction costs that they have to pay with certainty. Morris and Shin (1998) prove that there is a unique equilibrium with thresholds x^* and θ^*, such that a trader attacks if and only if she receives a signal below x^*, and the attack is successful if and only if $\theta < \theta^*$.

Heinemann (2000) has shown that these thresholds converge to the unique solution of $(1 - a(\theta))\, R(\theta) = T$ for $\varepsilon \to 0$. The limit point for diminishing variance of private signals θ_0^* is independent from other assumptions on the probability distributions (Frankel, Morris and Pauzner, 2000). Limit point θ_0^* follows the intuition of risk dominance, introduced by Harsanyi and Selten (1988) for 2-player games[2]. In general, it is characterized by some kind of Laplacian beliefs: As Morris and Shin (2000) point out, θ_0^* is the optimal threshold of a trader who beliefs that the proportion of other traders who choose to attack has a uniform distribution in [0,1]. Henceforce, we refer to threshold θ_0^* as the 'Laplacian belief equilibrium' of the game with common knowledge.

Another, naïve way to define Laplacian beliefs in this game is to assume that each player believes other traders to attack independently with probability ½. In a game with infinitely many agents this leads each player to expect that exactly half of all agents attack. Hence an attack is expected to be successful if and only if $a(\theta) \leq 1/2$.

[2] With decreasing variance of signals, the equilibrium of the private information game converges to the risk dominant equilibrium for 2-player games, but not for general games with more than two players (Carlsson and van Damme, 1993a,b).

A best reply to such beliefs is to attack if and only if $\theta \leq \min\{\bar{\theta}, a^{-1}(1/2)\}$. We refer to this point as the 'naïve Laplacian belief equilibrium'.

In our experiment, we avoided any connotation that might be associated with "speculation" or "attacking". Therefore, we asked subjects to choose between two actions A and B. In order to avoid negative payoffs, Action A was introduced as secure alternative, yielding a positive and constant payoff that may be interpreted as avoided costs of a speculative attack T. Action B was the risky action, yielding a payoff of Y, if the number of subjects choosing B exceeds a hurdle function $a(Y)$ with $a' < 0$, and zero otherwise. Thus, we reversed the order of states, higher Y being worse states of the economy in which subjects might gain higher payoffs. This reversal was done to ease subjects' understanding of the game.

3. Experimental Design

Sessions were run at a PC pool of the economics department in the University of Frankfurt and in the LEEX at Universitat Pompeu Fabra, Barcelona, from November 2000 until June 2001. In Frankfurt students were invited to participate by e-mails to all students with an e-mail account at the department of business and economics and via leaflets and posters at various places in the university. In order to participate, they replied by e-mail or phone. In Barcelona students were notified via posters within the university and signed up on a list at the door of the laboratory. In both places, most of the participants were business and economics undergraduates. The procedure during the sessions was kept the same throughout all sessions at both places, besides the languages (German and Spanish, respectively). All sessions were computerised, using a program done with z-tree (Fischbacher, 1999). Students were seated in a random order at PCs. Instructions (see Appendix A) were then read aloud and questions were answered in private. Throughout the sessions students did neither communicate nor see others' screens.

We ran 13 sessions with common information (CI) and 12 sessions with private information (PI, see Table 1). At each session there were 15 participants. For two sessions with CI we invited subjects that had previously participated in other sessions. In total, we had 345 participating students.

Each session consisted of two stages with 8 independent rounds in each stage. In each round subjects were given 10 independent situations, in each of which they had to decide between two alternatives (A or B).

For each situation, state Y was randomly selected from a uniform distribution in the interval [10, 90]. In sessions with CI players were informed about Y. In sessions with PI each subject received a private signal. Signals X^i were randomly selected from a uniform distribution in the interval [Y – 10 , Y + 10] for each player, separately.

A subject who chose A got a payoff of T with certainty. The two stages of each session differed by the payoff that was paid for alternative A. In half of all sessions we started with T=20 and switched to T=50 in the second stage. In other sessions we reversed the order. The payoff for B was Y, if at least $a(Y) = 15(80 - Y)/Z$ subjects chose B, zero otherwise. The formula was given in the instructions, but also explained via an example and a table (see Appendix A). In four sessions we applied Z=100, in the others Z=60. Table 1 gives an overview of different sessions. Rules of the game including the structure of uncertainty were common information among subjects of each session.

Z	Secure payoff T	Location	Experienced subjects	Number of sessions with public information	Number of sessions with private information
100	First 20 / then 50	Frankfurt	No	1	1
100	50 / 20	Frankfurt	No	1	1
60	20 / 50	Frankfurt	No	1	2
60	20 / 50	Barcelona	No	3	3
60	50 / 20	Frankfurt	No	2	2
60	50 / 20	Barcelona	No	3	3
60	20 / 50	Frankfurt	Yes	1	
60	50 / 20	Frankfurt	Yes	1	
Total number of sessions				13	12

Table 1. Session overview.

For each period, the secure payoff for decision A (being either 20 or 50) was always shown on top of the screen. This was followed by a table: The left hand side displayed state Y in the CI condition or private signal X^i in the PI condition for each of the ten situations. At the right hand side, subjects had to decide between A and B by clicking at either of two boxes. There was no presetting. Decisions could be changed until subjects clicked at an OK-button at the lower end of the screen.

Once all players had completed their decisions in one round, they were informed for each situation about Y, how many people had chosen B, whether decision B was successful or not, their individual payoff and their cumulative payoff over all 10 situations within the period. Furthermore they were reminded of their own signals (in PI-condition) and their own choices. Other information of other players were withhold. After all players had left the information screen a new period started and information of previous periods could not be revisited.[3] Subjects were allowed to take notes and many of them did.

[3] Within the decision phase a descending clock at the top of the screen indicated the time left. However, at the time limit subjects were only reminded to make their decision with no other consequence. In the information phase reaching the time limit meant that the screen vanished and the next period started. Time limits were originally set to 180 seconds for a decision phase and 150 seconds for the information phase. After many students showed signs of boredom in the first sessions with CI, we reduced time limits in the second treatment of sessions with CI by 30 seconds.

At the end of each session we asked participants to fill in a questionnaire (via computer) asking for their personal data and also four questions about their behavior and whatever comments they had regarding the experiment.

Once completed the questionnaire, each person was paid in private converting their total points into DM and Pesetas, respectively. In sessions with Z=100: 250 ECU = 1 DM. In sessions with Z = 60: 200 ECU = 1 DM = 70 Ptas.

Average payment per subject varied across sessions from 34 to 44 DM in Frankfurt and from 2380 to 3140 Pesetas in Barcelona[4]. Session length was between 90 and 120 minutes.

4. Theoretical Predictions

While the original speculative attacks model assumes an infinite number of traders, the experiment had n = 15 subjects interacting in each game. In this section we describe theoretical predictions for the game used in the experiment. Thereby, we give a generalization of the speculative attacks model to a finite number of traders. Figure 1 shows the hurdle to success of action B and the payoffs.

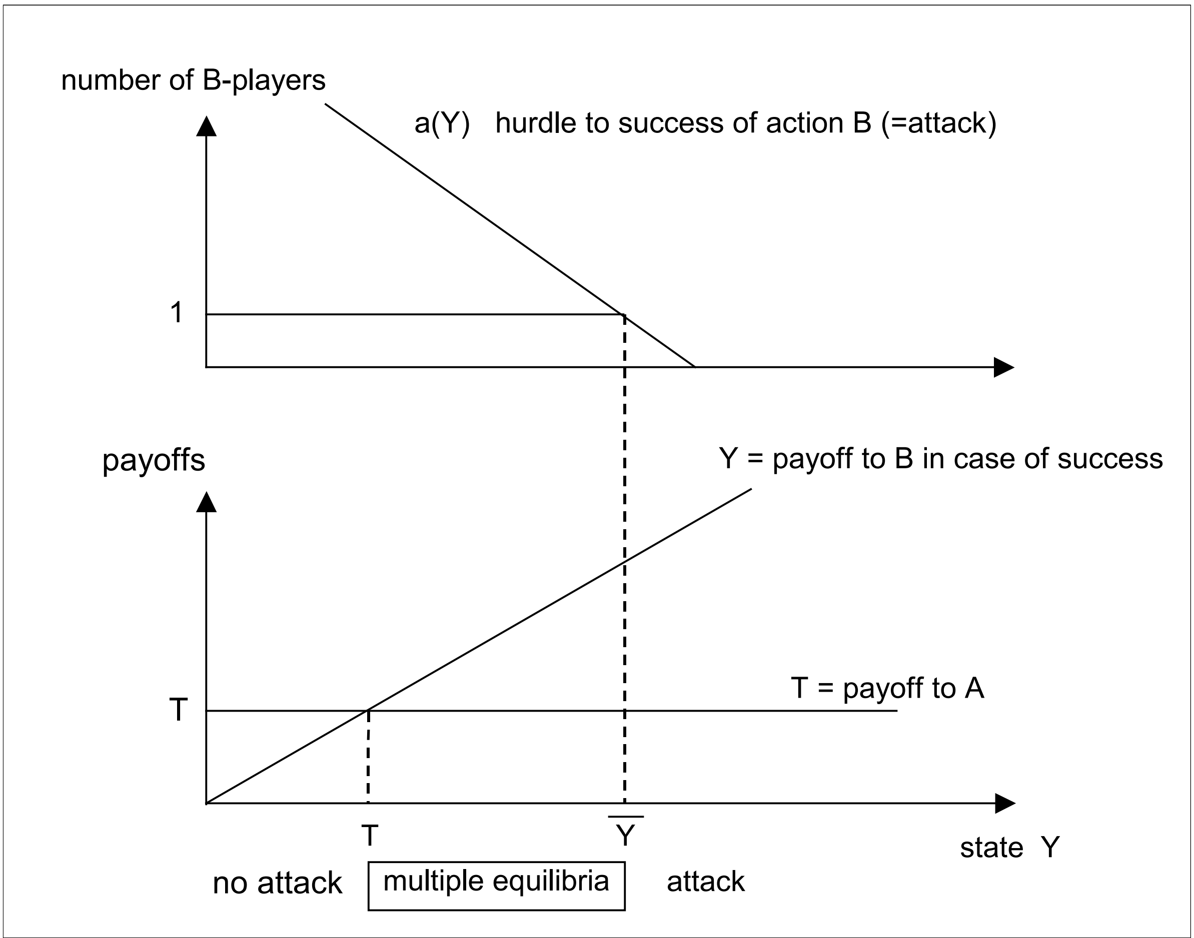

Figure 1. The speculative attack game. If at least a(Y) traders attack, attacking traders receive a payoff Y-T. Otherwise they loose T.

[4] Average payoffs in Euro varied from € 17.50 to € 22.50 in Frankfurt and from € 14.30 to € 18.90 in Barcelona.

If state Y is common information (CI), the game has multiple equilibria for some Y. We can distinguish three regions for Y.

(i) If $Y < \underline{Y} = T$, payoffs from action B are always smaller than those from action A. Therefore, all choosing A is an equilibrium in dominant strategies and it is also Pareto optimal.

(ii) If $Y > \overline{Y} = a^{-1}(1) = 80 - Z/n$, a single agent choosing B is sufficient for success. Therefore, all choosing B is an equilibrium in dominant strategies and also Pareto optimal.

(iii) If $\underline{Y} < Y < \overline{Y}$, there are two Nash equilibria in pure strategies: Either all players choose A (a single agent deviating to B is not successful) or all players choose B and get a higher payoff than at A.

Refinement criteria define different thresholds at which players switch from A to B.

The payoff dominant equilibrium, recommend by Harsanyi and Selten (1988), prescribes to choose B, if and only if $Y > T$. Thus, the threshold associated with payoff dominance is T.

The maximin strategy prescribes to choose action B if and only if success does not depend on other subjects' decisions. Thus, the agent should choose B if and only if $Y > \overline{Y}$.

In the game with private information (PI), there is a unique equilibrium with a threshold X^*, such that a risk neutral player with signal X^* is indifferent between choosing A or B provided that all other players choose B if and only if they receive signals above X^*. At state Y the probability of getting reward Y for action B is given by the probability that at least $a(Y)-1$ out of the other $n-1$ players get signals above X^* and choose B. This can be described by the binomial distribution. The probability that a single player gets a signal above X^* at state Y is $(Y - X^* + \varepsilon)/(2\varepsilon)$. Denoting the round-up of $a(Y)$ by $\hat{a}(Y)$, expected utility of an agent choosing B is

$$U_B(X^*) = \int_{X^*-\varepsilon}^{X^*+\varepsilon} Y \ \mathrm{prob}\left(\#\left\{j \neq i \,|\, X^j > X^*\right\} \geq a(Y) - 1 \,\middle|\, Y\right) \mathrm{d}Y$$

$$= \int_{X^*-\varepsilon}^{X^*+\varepsilon} Y \left[1 - Bin\left(\hat{a}(Y) - 2, n-1, \frac{Y - X^* + \varepsilon}{2\varepsilon}\right)\right] \mathrm{d}Y,$$

where Bin is the cumulative binomial distribution. The equilibrium threshold signal X^* is defined by $U_B(X^*) = T$. In the game with PI there is no threshold state that divides successful from failed attacks. For states in an ε-surrounding of X* the number of attacking agents and success of an attack depend on the random draws of individual signals.

In the game with common information, the global game approach selects the "Laplacian belief equilibrium". It is the equilibrium of the game with private information as ε converges to 0. Alternatively, it can be defined using the specific belief structure. In the limit, each agent believes the proportion of other players choosing B to be uniformly distributed in [0,1]. With this belief, the probability of success at state Y is $1-\frac{\hat{a}(Y)-1}{n}$. At the equilibrium threshold state Y^*, an agent is indifferent between A and B. This threshold is the unique solution to $Y\left[n-\hat{a}(Y)+1\right]=nT$.

The risk dominant equilibrium, as defined by Harsanyi and Selten (1988) differs slightly from the Laplacian belief equilibrium for $n>2$. Here, each player acts as if she believes that other players believe that the probability of success has a uniform distribution in [0,1]. Its threshold is given by the solution to $Y\left[1-Bin\left(\hat{a}(Y)-2,\, n-1,\, 1-T/Y\right)\right]=T$.

The threshold of the "naïve Laplacian equilibrium" is given by the state at which an agent is indifferent, who beliefs that other players attack independently with probability ½. It is given by the solution to $Y\left[1-Bin\left(\hat{a}(Y)-2,\, n-1,\, ½\right)\right]=T$.

Table 2 comprises theoretical equilibrium thresholds for our different treatments. If the signal or state received by a player is below the threshold, then she should choose A. If the signal or state is above the threshold, she should choose B.

	Treatments			
	T=20, Z=100	T=20, Z=60	T=50, Z=100	T=50, Z=60
Payoff dominant equilibrium of CI game	20	20	50	50
Maximin equilibrium of the CI game	73.33	76.00	73.33	76.00
Unique equilibrium of PI game	32.36	41.84	60.98	66.03
Laplacian belief equilibrium of CI game	33.33	44.00	60.00	64.00
Risk dominant equilibrium of CI game	34.55	44.00	62.45	67.40
'naïve' Laplacian belief equilibrium of CI game	33.07	48.00	51.48	56.00

Table 2. Theoretical equilibrium thresholds.

5. Aggregate Results

In all sessions, subjects chose B with success at high values of Y. In the interpretation this means that attacks are successful at bad states of the economy. At lower values of Y (good states of the economy) attacks are not successful. We relate the states at which attacks are successful to exogenous conditions and show that speculative attacks are more likely with common than with private information. To be more precise, the average threshold state beyond which attacks are successful is lower with common information (CI). Therefore, with CI it is more likely that a randomly drawn state falls into the region where successful attacks occur. While theory is not able to predict at which states attacks occur with CI, in the experiment predictability was higher with common than with private information. There is no evidence for indeterminacy caused by self-fulfilling beliefs. In addition, with CI subjects achieved better coordination and could better predict at which states an attack was rewarding. Hence, with CI efficiency losses due to prediction failures are lower than with private information .

5.1. Thresholds to Successful Attacks

In all sessions, subjects tended to choose A for low signals or states and B for high signals or states. In consequence, the total number of players, who chose B, was rising with rising Y. Combining the data from all 8 rounds of one treatment, we find treatment specific thresholds from which on action B (attack) is likely to be successful.

In most sessions with common information (CI) subjects coordinated on thresholds that clearly divided successful from failed attacks. These thresholds were surprisingly stable during each treatment, so that even combined data from all 8 periods of one treatment show a clear separation of states at which action B was rewarding from those, where it was not in 24 out of 26 cases. Often these thresholds can be identified as one of the steps of the hurdle function $\hat{a}(Y)$. An example is shown in Figure 2.

In most sessions with private information (PI) there is an overlap of states with successful and failed attacks. Because random signals may deviate from the state by 10 units on the Y-scale, success or failure of an attack at any given state is unpredictable even if all individual strategies are known. At low states an attack may occur just because many subjects got much higher signals or reverse. In addition, the lack of common information hinders subjects to coordinate on the same strategy. With 15 subjects however, aggregate results are fairly predictable and even with PI, combined data of all periods of one treatment show complete separation of states with successful and failed attacks in 9 out of 24 cases. In all other sessions, such as shown in Figure 3, we have an interval of states where some attacks failed and others succeeded.

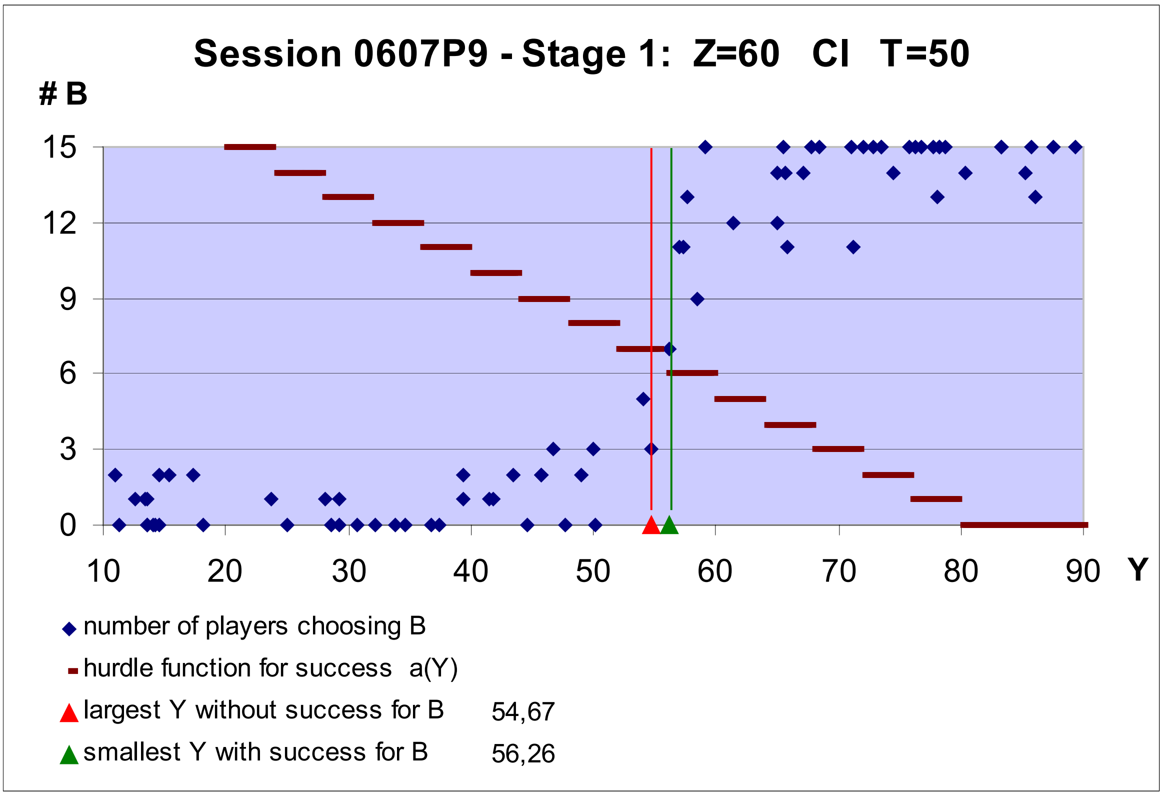

Figure 2. Combined data from all eight periods of one stage of a session with common information. There are 80 Y-values drawn in one stage. Dots indicate the associated number of subjects, who chose B. The step function is the minimal number of B-players needed for getting a reward at B. Two lines indicate the highest state, up to which action B always failed, and the lowest state, from which on B was always successful. In this example there is complete separation of states with failed and successful attacks.

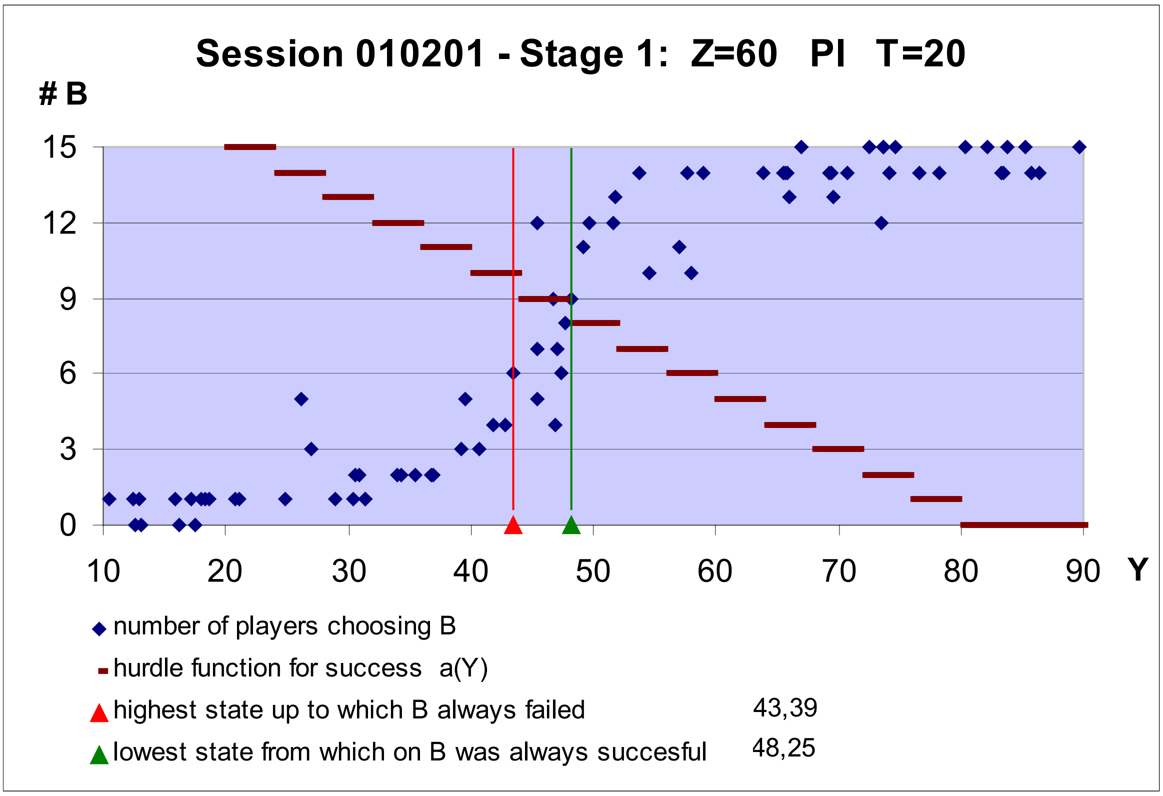

Figure 3. Combined data from all eight periods of one stage of a session with private information. In this example states with successful and failed attacks overlap.

Tables 3 and 4 give an indication of the states where action B was successful in different sessions. For each treatment, we give an interval from the highest state, up to which action B always failed, to the lowest state, from which on action B was always successful. A star indicates treatments, where states with successful and failed attacks can be clearly divided. In other sessions there were states within this interval with both outcomes. We use the midpoint of the interval to measure how thresholds depend on exogenous conditions. The width of the interval gives us a measure of predictability of attacks. Although it does also depend on random numbers, we can use it to ask how the information condition influences predictability within a session.

Sessions with Common Information					Thresholds to success	
Session	Z	Location	Experience	Order	T = 20	T = 50
001206	100	Frankfurt	no	20/50	33.08 – 33.40 *	52.57 – 53.62 *
010131	100	Frankfurt	no	50/20	18.35 – 21.51 *	49.59 – 50.74 *
010207	60	Frankfurt	no	20/50	40.47 – 46.67	55.98 – 56.68 *
010321b	60	Frankfurt	no	50/20	35.12 – 38.07 *	50.67 – 52.17 *
010530b	60	Frankfurt	no	50/20	31.14 – 35.54 *	47.03 – 51.74 *
0531PB	60	Barcelona	no	20/50	39.96 – 40.74 *	51.98 – 52.71 *

0606PA	60	Barcelona	no	20/50	39.34 – 41.61 *	49.95 – 53.62 *
0608PE	60	Barcelona	no	20/50	47.17 – 48.24 *	52.08 – 55.48 *
0607P9	60	Barcelona	no	50/20	31.50 – 42.44	54.67 – 56.26 *
0614L9	60	Barcelona	no	50/20	44.37 – 45.70 *	53.29 – 53.56 *
0614P9	60	Barcelona	no	50/20	39.01 – 41.35 *	50.28 – 51.87 *
010516b	60	Frankfurt	yes	20/50	32.15 – 36.36 *	55.83 – 56.69 *
010516a	60	Frankfurt	yes	50/20	30.75 – 32.86 *	49.83 – 51.05 *

Table 3. Thresholds to success in sessions with common information. A star indicates treatments, where states with successful and failed attacks can be clearly divided.

Sessions with Private Information					Thresholds to success	
Session	Z	Location	Experience	Order	T = 20	T = 50
001115	100	Frankfurt	no	20/50	29.74 – 34.11	51.68 – 54.25
001207	100	Frankfurt	no	50/20	26.85 – 27.06 *	51.90 – 53.35 *
010201	60	Frankfurt	no	20/50	43.39 – 48.25	56.35 – 60.05
010321a	60	Frankfurt	no	50/20	47.23 – 52.79	54.70 – 56.60
010523	60	Frankfurt	no	50/20	43.26 – 46.03 *	53.82 – 58.25
010530a	60	Frankfurt	no	20/50	46.69 – 51.21	54.91 – 55.24 *
0529	60	Barcelona	no	20/50	41.91 – 45.61	47.33 – 56.20
0530L1	60	Barcelona	no	50/20	35.22 – 41.52	52.47 – 55.44
0530PE	60	Barcelona	no	20/50	43.14 – 49.34 *	47.80 – 51.60 *
0607L6	60	Barcelona	no	50/20	39.80 – 41.88	49.90 – 54.43 *
0606L8	60	Barcelona	no	20/50	43.67 – 46.19	57.38 – 59.67 *
0608LA	60	Barcelona	no	50/20	35.66 – 40.48	55.09 – 57.54 *

Table 4. Thresholds to success in sessions with private information. A star indicates treatments, where states with successful and failed attacks can be clearly divided.

5.2. Probabilities of Successful Attacks

The higher the threshold to success, the smaller is the probability that a randomly selected state falls into the region, where subjects succeed to play B. This is interpreted as a lower prior probability of speculative attacks that enforce a devaluation. From tables 3 and 4 it is obvious that the threshold is higher in treatments with a high payoff for the secure action (T=50) than in treatments with T=20. In the interpretation this means that opportunity costs of an attack reduce the probability of devaluation.

According to the theory of global games, the mean threshold to success should only depend on T and Z. Table 5 contains a statistic of midpoints of the intervals of indeterminacy as a measure of thresholds to success that can be compared to theoretical predictions in table 2. For sessions with common information Laplacian belief and risk dominant equilibria seem to be good approximations for T=20, but payoff dominant and 'naïve' Laplacian belief Equilibria fit better for T=50. Mean thresholds rise from left to right column as the theory of global games predicts.

Treatment	T=20, Z=100	T=20, Z=60	T=50, Z=100	T=50, Z=60
Sessions with CI				
Mean threshold to success	26.59	41.73	51.63	52.78
Standard deviation	9.4	5.9	2.1	2.2
(Number of sessions)	(2)	(9)	(2)	(9)
Sessions with PI				
Mean threshold to success	29.44	44.16	52.80	54.74
Standard deviation	3.5	4.0	0.2	2.8
(Number of sessions)	(2)	(10)	(2)	(10)

Table 5. Observed mean thresholds to success from sessions with inexperienced subjects. Numbers in brackets indicate number of observations.

In sessions with a high hurdle function (Z=60) the threshold tends to be higher than in sessions with a low hurdle (Z=100). In treatments with T=20 the average difference is 14. In treatments with T=50, the effect of the hurdle function is less than 2 units. This is partially due to the non-linear payoff function. Qualitatively, reactions to the hurdle function are in line with predictions of the theory of global games. In the interpretation by Morris and Shin (1998) and Heinemann (2000) the effect of the hurdle function means that capital controls reduce the probability of successful attacks.

For a systematic analysis of the influence of information and other controls variables on mean thresholds we use linear regressions (see Appendix B.1). To control for the non-linearity in the payoff function, our regressions include an interaction variable TZ that equals one if and only if T=50 and Z=60. Regression 1 shows that T and Z explain 82% of all data variation. Regression 2 shows that information, location, and the order of treatments increase this to 89%.

With common information thresholds tend to be 2.45 units lower than with private information. This difference is numerically small, but significant at 2%. Given the stochastic framework used for our experiment, a commitment to provide public information at any state increases the prior probability of devaluation by 3.1%[5].

[5] Since states have a uniform distribution on [10,90], a reduction of the threshold by 2.45 increases the probability of states exceeding the threshold by 2.45 / 80 = 3.1%

In sessions with private information, thresholds were higher in Frankfurt than in Barcelona. In sessions with common information it was the other way round, but not significant (see Regressions 3 and 4).

Surprisingly, thresholds tend to be higher in sessions, where we started with a low payoff for the secure action (T=20) than in sessions, where we started with a high payoff (T=50). Originally we expected the opposite result. With numerical inertia, the threshold for T=20 should be higher after a treatment with T=50 than in a session that starts with T=20. After a treatment with T=20 the threshold for T=50 should be lower than in a session that starts with T=50. But, we observe thresholds in treatments with T=20 to be lower after a treatment with T=50 by some 5 units. In treatments with T=50 thresholds are about 1 unit higher, when they were preceded by a treatment with T=20.[6] There are different possible explanations: The order effect could be due to subjects having more trust in the ability of the group to coordinate after observing coordination close to T (in treatments with T=50), where the hurdle to success a(Y) requires a smaller number of players. A formal way to express this is suggested by answers in the questionnaire. Many subjects report that they played B for all signals or states that were some increment δ^i above T, where δ^i is sometimes stated as being 10 or 20 and gradually adjusted with experience. The order effect is consistent with a numerical inertia in these increments δ^i. After observing a threshold close to T=50, subjects may have been driven to try attacks at states close to T=20 in the second stage. Subjects who start with T=20 do not get that close to the payoff dominant equilibrium, because here, the hurdle is higher. Taking their experience to the second stage when T=50, they are more cautious than subjects who start with T=50.

5.3. Predictability of Attacks

Here, we ask whether there is any difference in predictability of thresholds that could be related to the information condition. Comparing the standard deviations of average thresholds in Table 5 above shows that the information condition has no big impact on the dispersion of observed thresholds among otherwise equal treatments. This impression is supported by separate regressions of thresholds for both information conditions. In sessions with common information 91% of all data variation can be explained by the other controlled variables (see Regressions 3). In sessions with private information other controlled variables explain 93% of data variation (see Regression 4). However, the standard deviation of residuals is 2.84 in sessions with common and 4.63 in sessions with private information. If thresholds have a normal distribution, they can be predicted within an interval of four standard deviations with a probability of 95%. We see clearly that this interval is larger with private than with common information.

Even though thresholds are fairly predictable for both scenarios, there may be differences in predictability within a session. This can be measured by the width of the interval between the highest state, up to which action B always failed, and the lowest state, from which on action B was always successful. Table 6 indicates

[6] The difference in the numerical impact that the order of treatments has on thresholds for T=20 and T=50, respectively, is accounted for by the interaction variable TO in the regressions.

average width of these intervals. They tend to be wider for a steep hurdle function (Z=60) and also for private information. Note that the average distance between two neighbouring states is 0.99.[7]

Treatment	T=20, Z=100	T=20, Z=60	T=50, Z=100	T=50, Z=60
Sessions with CI Average width of the interval of indeterminacy	1,74	3,59	1,10	2,02
Sessions with PI Average width of the interval of indeterminacy	2,29	4,43	2,01	3,53

Table 6. Average width of the interval between the highest state, up to which action B always failed and the lowest state, from which on action B was always successful.

On average over all treatments with common information the interval for which there is no clear indication of whether attacks fail or succeed has width 2.55. In treatments with private information its width is 3.68 on average. Regressions 5 and 6 (Appendix B.2) show that this difference in information conditions is just on the edge to significance at a 10%-level. If this difference is real, private information increases the range of states for which we cannot predict whether an attack is successful or not by 1.13. Accordingly, with PI the probability that a state falls into this region rises from 3.2% to 4.6%.

In fact, this method underestimates predictability in CI-conditions and overestimates it in PI-conditions. In sessions with CI subjects consciously coordinate on a common threshold. In at least 18 out of 26 treatments with CI, we have the impression that subjects coordinated on a step of the hurdle function. With a high degree of coordination the probability that an attack is successful at any state below the given interval (or fails at a state above it) is zero. With random signals in the PI setting, this probability is inevitably positive. Thus, with private information predictability is even lower than the width of the interval indicates.

We conclude that predictability of an attack given some history is also higher with common than with private information, because with CI subjects coordinate on a threshold that is fairly observable. Without a history of group behavior predictability of the mean threshold to success is about the same for both information conditions.

With public information the central bank has more control on the beliefs of traders than if they get private information from other sources. Uncontrolled information reduces the ability of the central bank to predict an attack. This loss in predictability that is modelled by the random nature of private information in our experiment outweighs the loss of predictability that might occur with public information due to self-fulfilling beliefs. The results of our experiment indicate that both effects are small when the number of traders is sufficiently large. For games with fewer players, both

[7] With 80 values of Y, independently drawn from a uniform distribution on [10,90].

effects might gain importance and it is an open question which one is bigger with fewer subjects.

5.4. Coordination Failures

If subjects coordinate on a common threshold in sessions with common information, at each state either all or no subject chooses B. When their behavior is fully coordinated, they never regret any decision. Of course, coordination takes time and during convergence of individual strategies, we observe a decreasing number of decisions that subjects could have regretted in the information phase. There are two possible situations in which a subject could regret her decision: (i) she chose B when B was not rewarding, (ii) she chose A, when choosing B would have given a higher reward. These situations should not occur, if a subject could predict whether an attack will be successful or not. The total number of cases where subjects could regret their decisions give us a measure for their ability to predict whether an attack will be successful or not.

Figure 4 shows the average number of decisions where a subject could have improved her payoff by deciding differently. In sessions with common information this number has a clear trend to decrease over time. Reason is that subjects learn to coordinate on a common threshold. The change of treatment in period 9 cancels the agreement and leaves subjects to find a new coordination point. In sessions with private information the number of regrettable decisions is decreasing after the first two periods and bounces around 1.0 for the remaining periods. With private information there are more regrettable decisions than with common information from the second round of a treatment onwards. This tells us that subjects can better predict the outcome with CI. This is mainly due to randomness of signals. Random nature of signals in the PI-condition leads to an expected number of regrettable decisions of about 0.6-0.7, even if all subjects played the same threshold strategy. Given that attacking without success leads to an efficiency loss, the lower number of unsuccessful attacks is another argument in favour of common information.

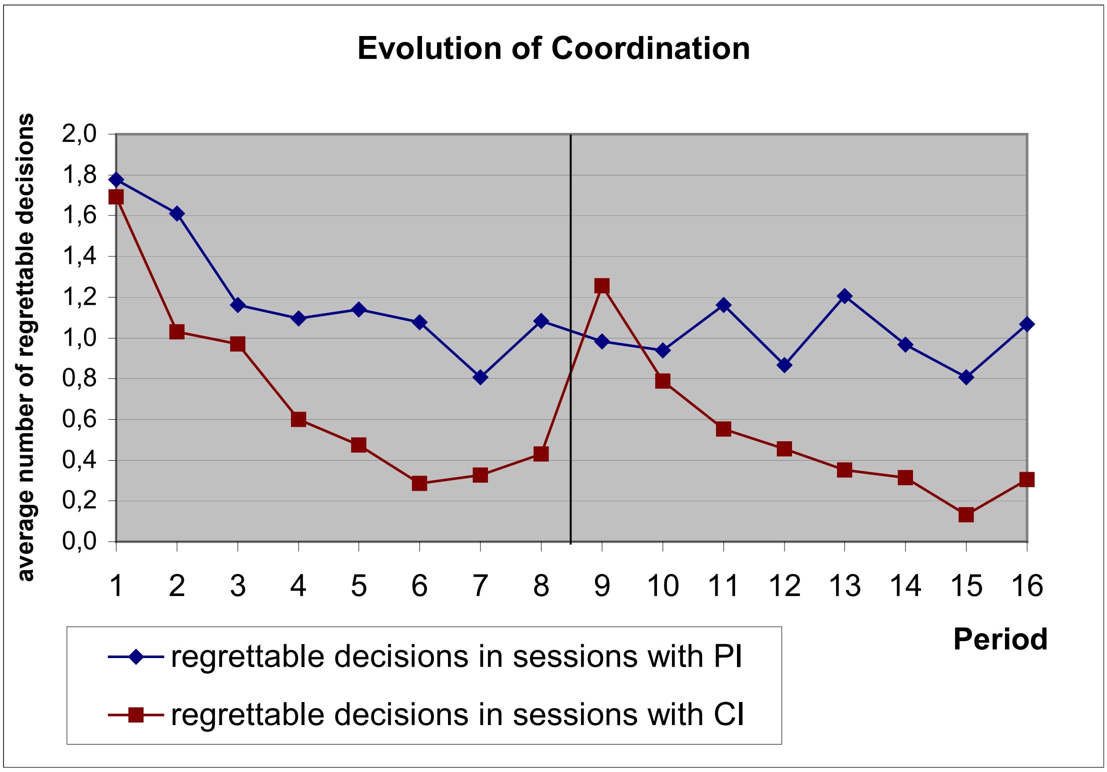

Figure 4. Average number of situations in which a subject could have achieved a higher payoff by a different decision.

6. Individual Strategies

Strategic uncertainty lets subjective beliefs differ even when all subjects share the same information. Subjects are aware of strategic uncertainty and react by playing threshold strategies. The mean of individual thresholds within a session is predictable with a surprising precision.

Common knowledge of the payoff function leads to multiple equilibria and therefore to unpredictability of attacks. But, common information is not sufficient for common knowledge. Subjective beliefs differ unless coordination is achieved. Once coordination is achieved, the coordination point is self-enforcing. We find that the distribution of individual thresholds does not change systematically after the first three periods. Using the data of the last four periods of each treatment, we estimate mean individual thresholds with logistic regressions. We use these estimates to test the predictive power of various refinement concepts.

Refinements are models of belief formation that define theoretical predictions for thresholds based on plausible assumptions on beliefs over beliefs. Disaggregate data give us a good impression of the validity of these assumptions. Individual strategies follow changes of payoff relevant parameters in the same direction as Laplacian beliefs, risk dominance and 'naïve Laplacian beliefs'. But, numerical tests based on the data of our experiment reject all three theories. We can also reject payoff dominance, although it is a good predictor if the number of players needed for success at this equilibrium is sufficiently small. The maximin criterion is clearly off the case.

With private information, mean thresholds of individual strategies are higher than with common information. In sessions with CI observed mean thresholds are strictly between payoff dominant and risk dominant equilibrium in all sessions. With PI mean thresholds are lower than predicted by the unique equilibrium in treatments with T=50, where the hurdle is low. Strategic uncertainty adds to stochastic signals, but subjects did not behave as if they belief that signals are distributed with a variance larger than it actually is. Neither can the behavior in sessions with CI be explained by differences in subjective posterior beliefs on the state as is suggested by the theory of global games.

Strategic uncertainty can be measured by parametric models of believe formation. In sessions with common information, mean thresholds are close to optimal thresholds of subjects who attribute probability $^2/_3$ to any other player choosing B when they get the critical signal.

6.1. Threshold Strategies

As one should expect, subjects tended to choose A for low signals or states and B for high signals or states. Since subjects chose between A and B in 10 different situations each period, we are able to infer whether or not they used threshold strategies. We say that a subjects' behavior was consistent with existence of a threshold, if the highest signal or state for which the subject chose A was smaller than the lowest signal or state for which this subject chose B. Most subjects' behavior was consistent with existence of a threshold from second round onwards, although the threshold may have changed over time as subjects gained experience about behavior of others. Some subjects chose the same action for all signals/states in some rounds, even if this action was dominated by the other for some signals/states. E.g. some subjects chose B when they should have known that $Y < T$. In most sessions, subjects who chose dominated actions in some rounds were the same as subjects whose behavior was inconsistent with a threshold after the second round. We call a subject's behavior 'rational' if her or his behavior was consistent with existence of a threshold and did not exhibit any dominated actions. Table 7 shows the average number of subjects who behaved 'rational' for each round. Sessions are distinguished by location, information, and subjects' experience. In total 92% of all strategies were consistent with undominated thresholds.

Location	Barcelona	Barcelona	Frankfurt	Frankfurt	Frankfurt
Information	Private	Common	Private	Common	Common
Experience	no	no	no	no	yes
No. of sessions	6	6	6	5 [8]	2
Round 1	11.50	9.67	11.00	11.00	12.50
Round 2	12.50	11.67	12.83	14.00	14.50
Round 3	12.83	12.33	14.17	13.60	15.00
Round 4	12.50	13.00	14.33	14.60	15.00
Round 5	13.50	13.33	13.83	14.20	14.00
Round 6	13.67	13.83	14.33	14.40	15.00
Round 7	14.00	13.83	14.67	14.40	15.00
Round 8	14.00	14.00	14.50	14.40	15.00
Round 9	12.83	13.17	14.33	14.20	14.00
Round 10	14.00	13.33	14.50	14.00	15.00
Round 11	13.83	14.17	14.67	14.60	15.00
Round 12	14.17	13.67	14.17	14.40	15.00
Round 13	14.33	14.50	14.50	14.80	15.00
Round 14	14.50	14.50	14.50	15.00	14.50
Round 15	14.00	14.67	14.33	15.00	14.50
Round 16	14.50	14.67	14.00	15.00	14.50
Average	13.54	13.40	14.04	14.18	14.59

Table 7: Average number of subjects, whose behavior was consistent with undominated threshold strategies. The total number of subjects was 15 in each session.

We could not find any significant difference in the proportion of threshold strategies between sessions with common and private information, nor between different treatments (see Regression 7 in Appendix B.3). In Barcelona the number of 'rational' subjects appears to be significantly smaller than in Frankfurt, when we use a simple Regression. Here, the location dummy is significant at the 5%-level and can explain 23% of the data variation (see Regression 8 in Appendix B.3). We do not have an explanation for this difference. Table 3 shows, however, that in first and final rounds the difference between locations was small.

Two sessions with subjects, who had participated in one of the other sessions before (experienced subjects), showed a higher proportion of threshold strategies than sessions with subjects, who participated for the first time. However, the selection of subjects, who agreed to participate a second time, is endogenous, and figures must be compared with caution.

In the first round the number of inexperienced subjects behaving 'rational' varied between sessions from 5 to 14 with an average of 10.78. In the second round, after they received information about their achieved payoffs and about aggregate behavior of other subjects, the number of 'rational' subjects varied from 10 to 15. The average increased to 12.70. Some subjects seemed to need first feedback to understand the advantage of threshold strategies. The number of 'rational' subjects tended to increase over time, although with the change of treatment in round 9, we

[8] Because of computer problems one session with common information in Frankfurt stopped after 13 rounds, another one lost data of round 16.

observed this number to drop, especially in Barcelona. This may be due to confusion stemming from the parameter change. In the last four rounds we observed that in all sessions at least 13 out of 15 participants behaved 'rational'. Figure 5 plots the percentage of 'rational' subjects from all sessions with inexperienced subjects for each round.

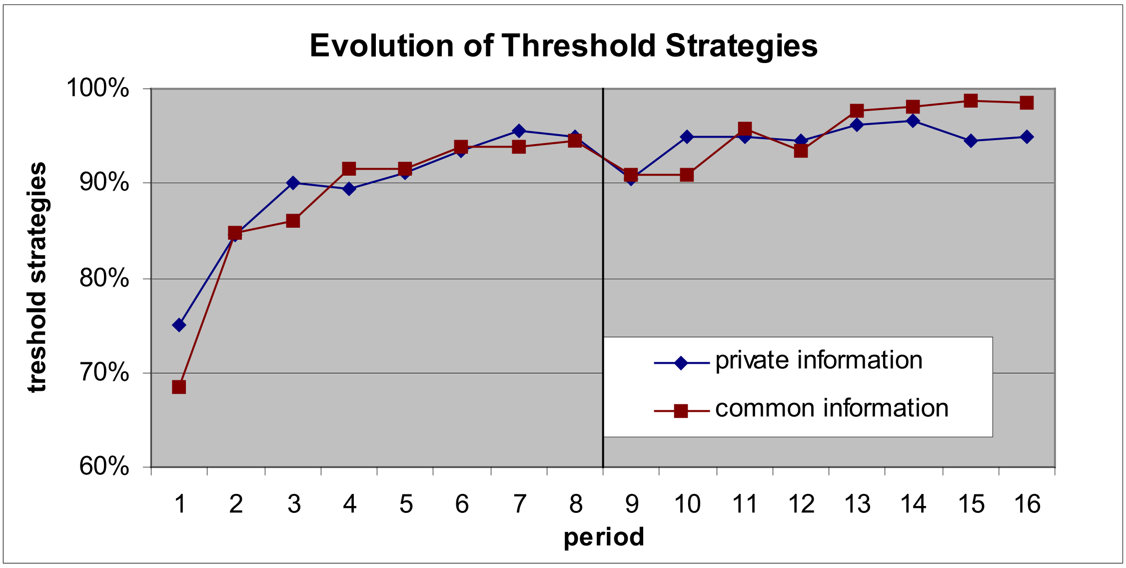

Figure 5. Percentage of subjects, whose behavior was consistent with undominated threshold strategies.

On one hand it is not surprising that most participants seem to have played threshold strategies: The hurdle for success of B is decreasing in Y, the payoff to B in case of success is increasing. Common sense tells us that we should choose B for high states and A for low states or signals. On the other hand, deductive reasoning needs very strong assumptions to get this result: In games with private information, theory predicts threshold strategies but requires common knowledge of the game structure. As we know from other experiments by Stahl and Wilson (1994) and Nagel (1995), real subjects fail to reason more than at most 3 layers of beliefs over beliefs. In games with common information non-threshold strategies may even occur in Nash equilibria.

The strength of threshold strategies lies in their robustness. If a subject expects others to play threshold strategies or randomize, her or his best response is a threshold strategy. Even though other strategies might form an equilibrium in common knowledge games, the best response to any reasonable belief deviating from common knowledge is a threshold strategy. As there is strategic uncertainty at least in the first rounds of a treatment, threshold strategies are a natural way to play. Once a sufficient number of subjects plays threshold strategies, the best response is again a threshold strategy. Other strategies may be an equilibrium under common knowledge, but they are not robust against even slightest deviations from common knowledge.

6.2. Mean Thresholds of Individual Strategies

During the first three periods of a session subjects adjust to playing threshold strategies with different thresholds. We estimate the distribution of thresholds for each session using a logistic regression. Estimates based on single periods do not show much variation after the first three period of each treatment. This is in line with a general impression that the distribution of individual thresholds does not change much after the first periods. Therefore, we can improve the quality of estimates by combining data of the last four rounds of each treatment. Results are logistic distributions that may be interpreted as estimated probabilities for subjects choosing B conditional on state Y or signal X, respectively. Figure 6 and 7 give an impression of the data fit obtainable by logistic regressions. The cumulative logistic distribution is given by $prob(B) = \frac{1}{1+\exp(a-bx)}$. The mean is $\frac{a}{b}$, standard deviation is $\frac{\pi}{\sqrt{3}\,b}$.

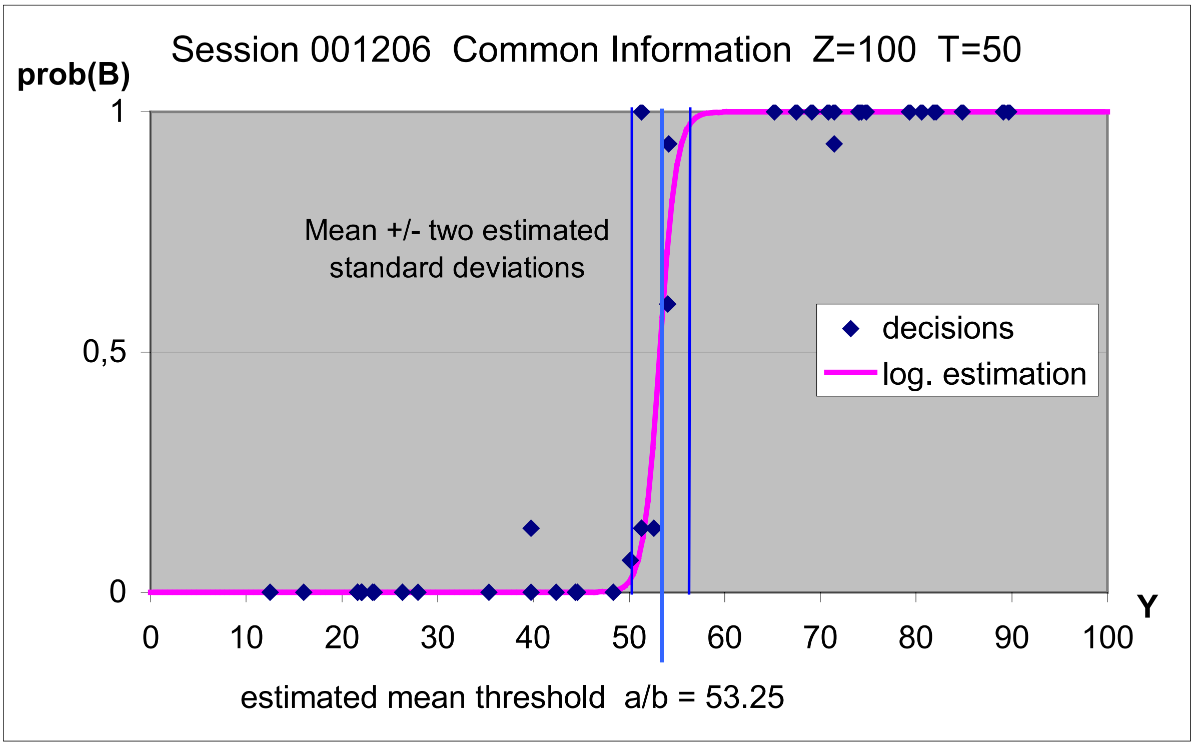

Figure 6. Data and logistic estimation of probability to choose B during the last for rounds of a treatment with common information. There are 40 data points indicating the proportion of subjects who chose B at the respective states Y. The displayed treatment was the one with the smallest estimated standard deviation in subjects' behavior.

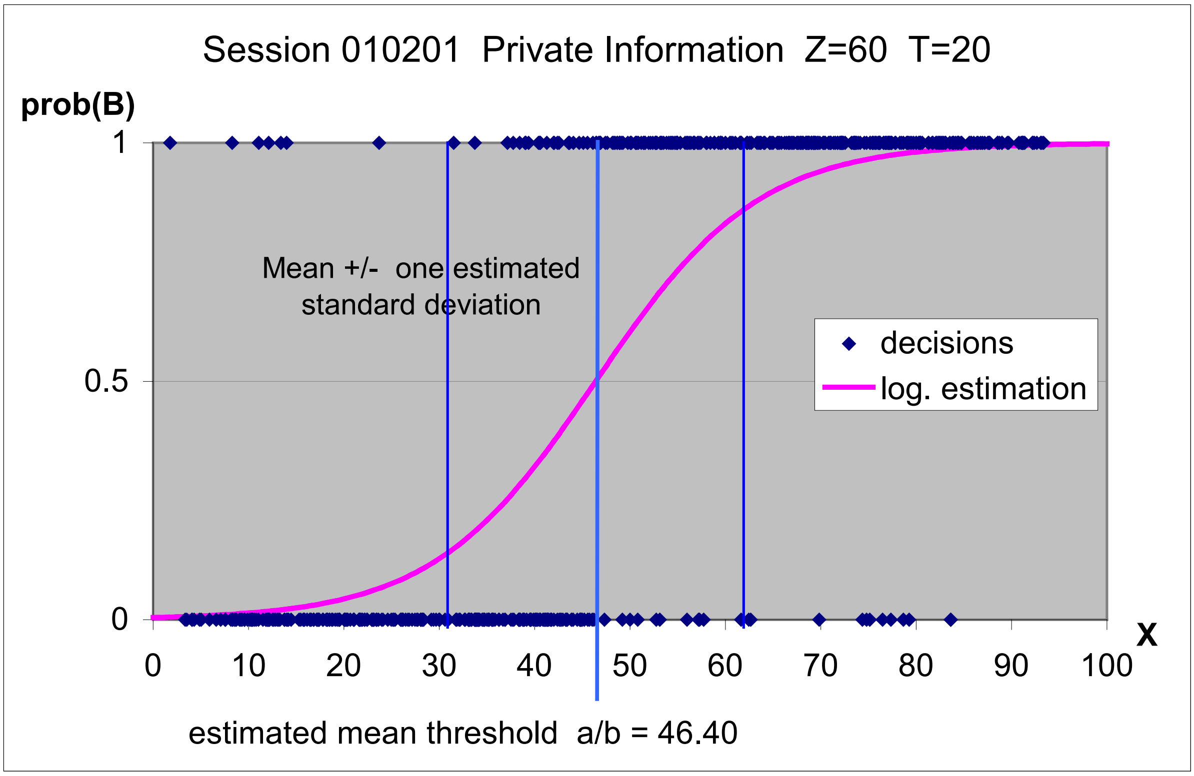

Figure 7. Data and logistic estimation of probability to choose B during the last for rounds of a treatment with private information. There are 600 data points indicating subjects' decisions for A or B at the respective signals X^i. The displayed treatment was the one with the largest estimated standard deviation in subjects' behavior.

Detailed results of logistic regressions (based on decisions in the last four rounds of each treatment) for all sessions and treatments are displayed in Appendix B.4. Table 8 gives a summery statistic of estimated mean thresholds a/b and estimated standard deviations $\frac{\pi}{\sqrt{3}\,b}$ of individual thresholds for distinguished treatments.

Treatment	T=20, Z=100	T=20, Z=60	T=50, Z=100	T=50, Z=60
Sessions with CI				
Average estimated mean of individual thresholds	26.30	37.84	52.96	52.56
Average estimated standard deviation	5.30	7.94	5.71	7.56
Sessions with PI				
Average estimated mean of individual thresholds	29.76	41.95	55.22	57.02
Average estimated standard deviation	8.81	10.05	9.46	9.77

Table 8. Average estimated means and standard deviations of individual thresholds to action B in sessions with inexperienced subjects.

Similar to the analysis of thresholds to successful attacks in Chapter 5.2, we run linear regressions using the controlled variables to explain mean and dispersion of individual thresholds. Appendix B.4 displays results for two of these regressions. Regression 9 shows significant influence on the estimated mean threshold (a/b) by the parameters of the payoff function T and Z, by the information scenario, and by the order of treatments. All of these effects are very similar to their influence on the threshold to success that we discussed above. The information condition has an even stronger impact on the mean of individual thresholds than on the critical state to success. Note, that the mean of individual thresholds depends on the behavior of subjects with extreme strategies, while the threshold state to success does not.

Non-parametric tests also show a significant difference between sessions with different information and order of treatments. Here, we had to use separate tests for each T. While information and order of treatments were significant at 5% in Mann-Whitney-Tests for both T-values, information failed to be significant at 5% for Kolmogoroff-Smirnov-Tests.

Regression 10 shows that dispersion of individual thresholds as measured by the standard deviations of the logistic distributions is significantly larger with private than with common information. It is also larger in sessions starting with T=20 than in the second stage of a session that had started with T=50. The standard deviation of individual thresholds within a session is another measure of coordination. The higher this standard deviation is, the less are subjects' decisions coordinated. Hence, common information improves the ability of subjects to coordinate their strategies.

When we include sessions with experienced subjects, we observe that experience lowers the mean threshold by about 3.1. But, with only four data points for experienced subjects, this difference fails to be significant. The dispersion of individual thresholds is about 4.8 smaller in sessions with experienced subjects. This difference is large and significant. Thus, experience with coordination games increases the ability of subjects to coordinate.

6.3. Testing Equilibrium Theories

Theoretical equilibrium concepts that have been introduced in Chapter 4 above define different threshold states or signals where subjects switch to the risky action. In this section we ask whether observed behavior is in line with any of the theoretical equilibrium concepts.

We have seen already that there is some dispersion in individual strategies that should not occur in equilibrium, because in theoretical equilibria all subjects follow the same strategy. But, even if individual strategies differ, refinement theories might succeed in describing the average behavior of individuals or the aggregate outcome of dispersed individual behavior. Here, we test the hypothesis that the means of individual thresholds as derived by logistic regressions in Chapter 6.1 are either of the theoretically predicted equilibrium thresholds. Appendix C exhibits precise results of these tests.

The hypothesis that subjects play Maximin strategies can be most clearly rejected, as all estimated mean thresholds were far below the thresholds associated with Maximin strategies.

The hypothesis that subjects play the payoff dominant equilibrium in sessions with common information is rejected at the 1% level if we jointly use data from treatments with T=20 and T=50. However, for T=50 estimated thresholds came rather close to the payoff dominant equilibrium and using data from treatments with T=50 only, the p-value for rejection is at 4%.

The hypotheses that subjects play the Laplacian belief or the risk dominant equilibrium could be rejected at a p-level of 1%. A look at Table 15 (Appendix B.4) reveals that estimated mean thresholds have been below these equilibria in *all* treatments with common information.

The hypotheses that subjects play the 'naïve' Laplacian belief equilibrium could be rejected for all data with Z=60 and for all data with T=20. For data with T=50, the p-value was at 6.8% and did not allow to reject this hypothesis.

The hypothesis that subjects play the unique equilibrium in games with private information was rejected at the 1% level when we used all data from sessions with Z=60. However, for data from treatments with T=20, we could not reject this hypothesis. In fact, it seemed a pretty good predictor here. A look at the data reveals that estimated thresholds are distributed around equilibrium for treatments with private information and T=20, while they are clearly below equilibrium for all treatments with T=50.

In Chapter 6.2 above, we pointed out that thresholds were higher for higher T or lower Z. This is actually another reason to reject payoff dominance or minimax strategies, because the payoff dominant equilibrium does not depend on Z and the minimax strategy does not depend on T. The other theoretical equilibria follow these parameter changes in the observed direction.

Finally, we use revealed thresholds from Table 3 above, and count, how often they are in a neighbourhood of various theoretical equilibria. Results of this heuristic procedure are summarized in Table 9. The success rate indicates the percentage of treatments from sessions with CI and inexperienced subjects, in which the intervals of indeterminate behavior overlap with a neighborhood of 2 around theoretical equilibria.

Equilibrium	All 22 observations	T=20 only (11)	T=50 only (11)
Payoff dominant equilibrium	32%	9%	55%
Laplacian belief equilibrium	18%	36%	0
Risk dominant equilibrium	18%	36%	0
'naïve' Laplacian belief equil.	36%	27%	45%
Maximin Strategy	0	0	0
neither of the above	27%	45%	9%

Table 9. Success rates of theoretical equilibrium thresholds +/– 2. Percentage points do not add to 100, because intervals overlap.

While observed behavior came rather close to payoff dominance in treatments with T=50, risk dominance and the global game solution (Laplacian beliefs) were a better approximation to behavior for T=20. Reason might be the higher number of subjects needed for success at low values of Y.

Surprisingly, 'naïve' Laplacian beliefs did not bad in this comparison. We can even do better, if we replace the belief that other players choose B with probability ½ by higher probabilities. If each player beliefs that each other player chooses B with probability p, the best response is a threshold Y, solving $Y\left[1 - Bin\left(\hat{a}(Y) - 2, n-1, p\right)\right] = T$. If we take p = 2/3, we get equilibrium thresholds and according success rates as displayed in Table 10.

Parameters	Z=100, T=20	Z=60, T=20	Z=100, T=50	Z=60, T=50
Best response threshold to p=2/3	23.515	40.00	50.035	52.00
Success cases	0 out of 2	6 out of 9	1 out of 2	7 out of 9
Success rate	54%		73%	

Table 10. Best response thresholds to belief that other players choose B with probability 2/3 and success rates of these thresholds +/– 2.

The overall success rate of thresholds that are a best response to p = 2/3 is 64%. The success rate does not change for p ∈ [0.6, 0.68] and is lower for any p outside this interval. In F-tests the hypothesis that subjects play a best response to p=2/3 could not be rejected, while all the other theoretical equilibria could (see Appendix C). However, this is not a fair test, as we did not plan to test this equilibrium beforehand, but rather arrived at it endogenously.

Thresholds, associated with a best response to subjects believing that others choose B with probability p=2/3 can explain observed behavior in sessions with common information very well. This might be an artifact of our experiment and might just hold for sessions with Z=60. But, it might also be possible that optimising the success rate by choosing a proper p, and explaining those p-values by parameters of the game, opens a way to measure strategic uncertainty in two-action-games.

7. Comparison with Previous Experiments and Conclusions

Previous experiments on coordination games with strategic complementarities have shown that we should distinguish between two kinds of coordination: Coordination on *an* equilibrium and coordination on the *efficient* equilibrium. Comparing our results with those of Van Huyck, Battaglio und Beil (1990, 1991), we find some similarities and some clarifications:

- As in their experiment, we find a fast convergence towards an equilibrium in sessions with common information.
- Groups of 14 – 16 did never succeed to reach an equilibrium better than maximin-strategies in the experiment of Van Huyck et al. (1990), where all members were needed to coordinate for this purpose, while in two-player-games coordination on the payoff dominant equilibrium was achieved even when subjects were matched randomly for each decision situation. In our experiment, we never observed an equilibrium that needed coordination of more than 12 out of 15 subjects. When coordination of eight subjects was necessary to reach the efficient equilibrium (Z=60, T=50), the groups achieved coordination at equilibria, where 6-8 B-players were needed.
- In the median treatments of Van Huck et al. (1991), behavior always converged to an equilibrium determined by the median of the first round, hinting at extremly strong inertia effects in this sort of games. In our game, it should be easier to observe changes in the equilibrium played, because of random draws and continuous strategy space. Even so, in 24 out of 26 treatments with common information, we did not observe the threshold for success of action B to move. In only two sessions, there was a slight change of the threshold between the first and some later period of a treatment.
- A change of treatment and associated experience with coordination, led subjects to play more efficient equilibria in Van Huyck et al. (1991). We observed similar effects, but the increase in efficiency was not significant. Experience lowered dispersion of individual thresholds and thereby reduced coordination failures.
- Van Huyck et al. found that subjects coordinate on equilibria that are somewhere between the payoff dominant equilibrium and maximin-strategies. However, in their game there is no difference between risk dominant and maximin-strategies. In our experiment, all observed equilibria in sessions with common information were between the payoff dominant and the risk dominant equilibrium and far .off maximin strategies.

In a previous experiment on global games Cabrales, Nagel and Armenter (2000) did not find any difference in behavior between sessions with common and private information. However, their stage game had only five possible states and signals and might have been too discrete to discover the subtle effects of information. In our game, with a continuous space for states and signals, we observed that with common information, coordination of agents was much better than with private information. In addition, the average threshold, and thus, the prior probability of failure of the risky action, was significantly higher with private information. On the other hand, we did not find any significant difference in the proportion of subjects using threshold strategies or in the dispersion of achieved mean thresholds across different sessions with equal conditions.

This leads us to conclude that the destabilizing effects of public information, due to existence of multiple equilibria, may be less severe than theory predicts. However, public information does change the threshold, and might therefore increase the probability of successful speculative attacks. In liquidation games as Hubert and

Schäfer (2000) or Morris and Shin (2001), the probability of inefficient liquidation should be lower with common than with private information, for the same reason.

The current discussion on the optimal modes of information disclosure concentrates on the multiplicity of equilibria associated with public information. Our experiment suggests that this may be a subordinate effect. The major effect might be that public information reduces strategic uncertainty and thereby leads players to coordinate on an equilibrium with a higher payoff. Efficiency (from the players' viewpoint) may be desirable for some coordination games, e.g. to avoid inefficient liquidation. For others, it may be the opposite. In order to avoid speculative attacks, a central bank should minimize expected gains from speculation. Hence, our experiment suggests that a commitment to provide public information (transparency) raises the prior probability of successful speculative attacks.

In our view, strategic uncertainty is the major force that drives subjects to play threshold strategies, explains the low variation of observed equilibria in common information games, and also explains most of the comparative statics. We think that the deviation of observed behavior in sessions with private information from Nash-equilibrium into the direction of 'naïve' Laplacian beliefs might also be due to strategic uncertainty that must be added to exogenous uncertainty in these games. Even though we could reject all pre-selected equilibrium concepts, the concepts that considered both, possible gains from coordination as well as the hurdle to achieve these gains, did best in predicting observed comparative statics. In particular, the equilibrium that we called 'Laplacian belief equilibrium', introduced by Carlsson and van Damme (1993a) and Morris and Shin (2000) as limiting equilibrium of global games for diminishing uncertainty of private information, combines the advantages to exhibit comparative statics as we observed them *and* to be easy to calculate. Risk dominance is difficult to calculate in some games, because the tracing procedure may be quite complicated. The 'naïve' Laplacian belief equilibrium fails to react to changes in the payoff function apart from those tried in our experiment, and lacks a theoretical justification.

In our experiment actual behavior in common information settings was restricted by payoff dominance on one side and risk dominance or 'Laplacian beliefs' on the other side. More research needs to be done to explain how strategic uncertainty interferes with these selection criteria. We believe it to be possible to measure the degree of strategic uncertainty that is associated with different games. Going into this direction could help explaining patterns of behavior in multiple equilibrium games and appears to be a promising task for future research.

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Appendix A. Instructions

Instructions to participants varied according to different treatments. Here, we present an English translation of instructions for a session with private information, Z=60 and starting with T=20 in full length. For the other sessions instructions were adapted accordingly.

General information

Thank you for your participation in an economic experiment, in which you have the chance to earn money. We ask you not to communicate from now on. If you have a question, then raise your hand, and one of the instructors will come to you.

You are one of 15 persons, who interact with another. The rules are the same for all participants. The experiment consists of 2 stages with 8 independent rounds in each stage. In each round you will receive 10 independent situations, in each of which you have to make a decision (A or B).

Rules of the first stage (the two stages differ only by the payoff for decision A):

Decision situation:

For each situation a number called Y is selected randomly from the interval 10 to 90. This number is the same for all participants. All numbers in the interval [10, 90] have the same probability to be drawn. When you make your decision, you will *not* know the drawn number Y.

However, each participant will receive a hint number for the unknown number Y. This hint number is randomly selected from the interval [Y-10, Y+10]. All numbers in this interval have the same probability to be drawn. Hint numbers of different participants are drawn independently from the same interval

On basis of your hint number you can decide in each situation between two different decisions: A or B.

<u>If you decide for A</u>, then an amount of 20 ECU (Experimental Currency Unit) is credited to your account. This amount is the same for all rounds of the first stage and for all participants (in the second stage the amount is raised to 50 ECU).

<u>If you decide for B</u>, then your payoff depends on how many participants select the same decision B and also depends on how large is the unknown number Y. Decision B is the more successful, the more participants decide for B and the larger the number Y is. If the number of participants who decide for B is at least $20 - Y/4$, then each participant, who decided for B, receives the amount of Y ECU. A more exact explanation of this formula is given with the help of an example and the table at the end of the instructions. If fewer participants decided for B, then those choosing B receive zero ECU.

Once all participants made their 10 decisions for the 10 games, a round is terminated. (Remember there are 8 rounds in each of the two stages)

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Information after each round

Each participant will be informed after each round for each of the 10 games on

(1) the number Y,
(2) how many participants decided for A or B,
(3) the own payoff and also the total sum of the own payoffs over all 10 games.

Example:

The number of participants is 15. The payoff for A is always 20. The unknown number Y, which was drawn, is 48,65.

The hint numbers drawn for the fifteen participants are: 38.89, 45.24, 42.67, 56.40, 52.92, etc.

The participant with the hint number 38.89 knows that Y is between 28,89 and 48,89, the participant with the hint number 45.24 knows that Y is between 35,24 and 55,24, etc.

Six participants decide for A, nine participants decide for B.

The participants, who chose A, receive 20 ECU.

In order to receive a positive payoff for B, at least 20-48.65/4 = 7.84 (remember the formula (20-y/4)) participants have to decide for B (that is 8 or more). Since 9 participants selected B, each of them receives Y = 48.65.

For the calculation of the minimum number of the participants needed such that payoff for B is positive see attached table:
Since Y = 48.65, the number of participants must be 8 in order to get a positive payoff for decision B.

Note: You don't know the true value of Y, but you receive a hint number, which is an approximation of Y. Therefore you cannot exactly determine, how many players must select B, in order to get a positive payoff.

For the calculation of the minimum number of participants who have to choose B in order to get a positive payoff for B:

Participants who choose B, receive a positive payoff, only if at least 20-Y/4 participants choose B.

In the right hand column you find the minimal number of participants and in the left column the according intervals for Y.

If the unknown number Y is in the interval, (Note: Y is between 10 and 90)	Then at least … of the 15 participants (including yourself) have to select B, in order to get a positive payoff
20,00 bis 23,99	15
24,00 bis 27,99	14
28,00 bis 31,99	13

32,00 bis 35,99	12
36,00 bis 39,99	11
40,00 bis 43,99	10
44,00 bis 47,99	9
48,00 bis 51,99	8
52,00 bis 55,99	7
56,00 bis 59,99	6
60,00 bis 63,99	5
64,00 bis 67,99	4
68,00 bis 71,99	3
72,00 bis 75,99	2
76,00 bis 90,00	1

Instructions for PC:

Each round is divided into a decision phase and into an information phase. During the decision phase the screen shows the current round in the heading line (period). The second line informs you about the sure payoff for decision A. The following table shows your hint number for each game in the left column. In the right column you must click which decision you want to select. Once you decided for all 10 games, you must press the red OK button. As long as you have not pressed the red button, you can still modify your decisions. When exceeding the time limit you are reminded to make your decisions.

When all participants have pressed the OK-button, the decision phase of a round is terminated and the information phase begins. The display in the information phase indicates line by line for each situation of this round the true value Y, the number of players, who decided for B, your own decision, and the change of your account balance. After the time limit the next round starts. In addition you can leave the information phase beforehand through the gray OK button. After leaving the information screen you have no more possibility to inform yourself about passed decisions.

Questionnaire:

At the end of the experiment (after the second stage) we ask you to fill out a questionnaire. The personal data asked for are treated strictly confidential and used for research purposes only.

Payoffs:
Also at the end of the experiment the ECUs you have obtained are converted into DM [Pesetas] and paid in cash. 1 ECU corresponds to 0,5 Pfennig [3.5 Pesetas], so that 200 [100] ECU are converted to 1 DM [35 Pesetas].

In Sessions with common information, the first part of the description of the decision situation was replaced by

For each situation a number called Y is drawn randomly from the interval 10 to 90. This number is the same for all participants. All numbers in the interval [10, 90] have the same probability to be drawn.

On the basis of your this number you can decide in each situation between two different decisions: A or B.

The remaining text was adapted to common information accordingly.

In sessions that started with T=50, we only changed these parameters.

Appendix B: Regression Results

Appendix C lays out regression results on which various statements in the main text of the paper are based. We use linear regressions to explain the average number of subjects, whose behavior is consistent with an undominated threshold strategy, for the thresholds to success and predictability of attacks and to explain the summery statistics of individual behavior obtained by logistic regressions for each session and treatment. For these regressions, we use only the data from sessions with inexperienced subjects. Explaining variables are the control variables of our experiment. Table 11 explains the variables.

Name	Nature	Definition	
T	dummy	0: payoff for secure action T=20	1: T=50
Z	dummy	0: session with Z=100	1: session with Z=60
TZ	dummy	0: if T=20 or Z=100	1: if T=50 and Z=60
Loc(ation)	dummy	0: session in Barcelona	1: session in Frankfurt
Info(rmation)	dummy	0: session with common information	1: session with private information
Ord(er)	dummy	0: session starting with T=50	1: session starting with T=20
TO	dummy	0: if Order=0 or T=20	1: if Order=1 and T=50
Rat(ionality)	number	Average (per session) number of subjects whose behavior is consistent with an undominated threshold strategy	
Y*	number	Mean between highest state up to which all attacks failed and lowest state from which on all attacks succeeded in all 8 periods.	
ΔY*	number	Distance between the two states defining Y*	
a	number	Results from logistic estimation on basis of last four period	
b	number	Results from logistic estimation on basis of last four periods	
Mean	number	a / b = estimated mean threshold	

Table 11. Variables used in linear regression.

B.1. Thresholds to Success

Threshold states Y* from which on an attack is likely to occur depend on various of the exogenous conditions.

Regression 1: $Y^* = \gamma_0 + \gamma_1 T + \gamma_2 Z + \gamma_3 TZ + u$.

Regression 2: $Y^* = \gamma_0 + \gamma_1 T + \gamma_2 Z + \gamma_3 TZ + \gamma_4 Loc + \gamma_5 Info + \gamma_6 Ord + \gamma_7 TO + u$.

Regression 3-4: $Y^* = \gamma_0 + \gamma_1 T + \gamma_2 Z + \gamma_3 TZ + \gamma_4 Loc + \gamma_6 Ord + \gamma_7 TO + u$.

No.	Data source (number of observations)	Explaining variables: estimated coefficients γ_i (t-values)								R^2 Adj. R^2
		Intercept	T	Z	TZ	Loc	Info	Ord	TO	
1	All treatments (46)	28.01 (14.57	24.20 (8.90)	14.37 (6.79)	-12.78 (-4.27)					0.82 0.81
2		22.88 (11.12)	26.34 (10.92)	15.30 (8.23)	-12.89 (-5.26)	1.35 (1.27)	2.45 (2.63)	5.10 (3.87)	-4.29 (-2.31)	0.89 0.87
3	Treatments with CI (22)	25.24 (8.01)	27.30 (7.47)	13.12 (4.57)	-12.99 (-3.49)	-1.65 (-0.97)		6.00 (2.93)	-4.51 (-1.57)	0.91 0.87
4	Treatments with PI (24)	23.55 (10.04)	25.33 (8.90)	17.05 (7.87)	-12.73 (-4.41)	3.95 (3.29)		3.87 (2.54)	-3.96 (-1.84)	0.93 0.90

Table 12. Regressions explaining thresholds to success.

B.2. Width of the Interval with Indeterminate Outcomes

The difference between the lowest state, from which on all attacks succeeded, and the highest state, up to which all attacks failed, has no clear relation to exogenous conditions. If any, the information condition is on the edge to significance at 10%. But, note that it explains only 6% of data variation.

Regression 5: $\Delta Y^* = \delta_0 + \delta_1 T + \delta_2 Z + \delta_3 TZ + \delta_4 Loc + \delta_5 Info + \delta_6 Ord + u$.

Regression 6: $\Delta Y^* = \delta_0 + \delta_5 Info + u$.

No.	Data source (number of observations)	Explaining variables: estimated coefficients δ_i (t-values)								R^2 Adj. R^2
		Intercept	T	Z	TZ	Loc	Info	Ord	TO	
5	All treatments (46)	1.81 (1.25)	-1.00 (-0.59)	1.96 (1.50)	-0.73 (-0.42)	-0.02 (-0.02)	1.11 (1.69)	-0.66 (-0.72)	-1.08 (-0.83)	0.21 0.06
6		2.55 (5.33)					1.12 (1.70)			0.06 0.04

Table 13. Regressions explaining the width of the interval of indeterminate outcomes.

B.3. Threshold Strategies

In all sessions, the number of subjects, whose behavior is consistent with an undominated threshold strategy, tends to increases over time. The average differs across sessions. Regression 7 shows that the information condition is not significant. Regression 8 shows that there may be a significant difference in behavior of subjects from Barcelona and Frankfurt.

Regression 7: $\text{Rat} = \beta_0 + \beta_1 Z + \beta_2 \text{Loc} + \beta_3 \text{Info} + \beta_4 \text{Ord} + u$.

Regression 8: $\text{Rat} = \beta_0 \qquad + \beta_2 \text{Loc} + u$.

No.	Data source (Number of observations)	Explaining variables: estimated β-coefficients (t-values)					R^2 Adjusted R^2
		Intercept	Z	Location	Information	Order	
7	All sessions (23)	13.39 (51.43)	0.33 (0.82)	0.50 (1.64)	-0.04 (-0.14)	0.18 (0.69)	0.27 0.11
8	All sessions (23)	13.47 (76.69)		0.63 (2.48)			0.23 0.19

Table 14. Regressions explaining the average number of subjects, whose behavior is consistent with undominated threshold strategies.

B.4. Logistic Estimation of Individual Thresholds

Table 15 gives statistical information on individual behavior for all sessions and treatments.

1	2	3	4	5	6	7	8	9	10	11	12
session	Z	location	Exper-ience	Infor-mation	order	T	Average number of 'rational' subjects	Parameter estimation a	b	Estimated mean a/b	Estimated standard deviation
001115	100	Frankf.	no	PI	20/50	20	14.25	4.78	0.146	32.75	12.43
						50	14	10.54	0.185	56.91	9.79
001207	100	Frankf.	no	PI	50/20	50	14.5	10.63	0.199	53.53	9.13
						20	14.875	9.35	0.349	26.77	5.19
001206	100	Frankf.	no	CI	20/50	20	14	8.96	0.271	33.03	6.68
						50	14.75	62.18	1.168	53.25	1.55
010131	100	Frankf.	no	CI	50/20	50	13.625	9.67	0.184	52.66	9.87
						20	14.6	9.04	0.462	19.57	3.93

010201	60	Frankf.	no	PI	20/50	20	13.5	5.43	0.117	46.40	15.50
						50	13.625	7.48	0.124	60.21	14.59
010321a	60	Frankf.	no	PI	50/20	50	12.375	7.67	0.131	58.45	13.82
						20	14.125	7.05	0.151	46.62	11.99
010523	60	Frankf.	no	PI	50/20	50	14	12.75	0.210	60.75	8.64
						20	14.875	10.18	0.246	41.42	7.38
010530a	60	Frankf.	no	PI	20/50	20	13.625	7.42	0.167	44.59	10.89
						50	14.75	14.86	0.247	60.10	7.34
010207	60	Frankf.	no	CI	20/50	20	14.375	8.18	0.212	38.52	8.54
						50	14.625	24.74	0.434	56.96	4.18
010321b	60	Frankf.	no	CI	50/20	50	12.5	7.60	0.166	45.75	10.92
						20	14	9.27	0.285	32.57	6.38
010530b	60	Frankf.	no	CI	50/20	50	14.625	13.19	0.280	47.16	6.49
						20	14.875	4.90	0.154	31.90	11.82
0529LN	60	Barcel.	no	PI	20/50	20	12.375	7.80	0.183	42.72	9.93
						50	13	7.79	0.144	54.07	12.60
0530L1	60	Barcel.	no	PI	50/20	50	13.875	12.62	0.234	54.00	7.76
						20	14.5	9.26	0.255	36.28	7.11
0530P3	60	Barcel.	no	PI	20/50	20	11.375	7.48	0.167	44.77	10.85
						50	14.375	13.41	0.262	51.19	6.93
0607L6	60	Barcel.	no	PI	50/20	50	13.5	9.47	0.173	54.73	10.48
						20	14	9.63	0.252	38.25	7.20
0606L8	60	Barcel.	no	PI	20/50	20	13.75	7.51	0.173	43.48	10.51
						50	14.125	12.24	0.238	59.87	7.62
0608LA	60	Barcel.	no	PI	50/20	50	13.5	13.01	0.229	56.83	7.92
						20	14.125	6.94	0.198	35.02	9.15
0531PB	60	Barcel.	no	CI	20/50	20	12.5	6.44	0.165	38.93	10.97
						50	13.25	9.67	0.193	50.16	9.41
0607P9	60	Barcel.	no	CI	50/20	50	12.5	15.78	0.289	54.55	6.27
						20	14.625	9.33	0.249	37.50	7.29
0606PA	60	Barcel.	no	CI	20/50	20	14.25	18.99	0.472	40.24	3.84
						50	14.875	33.32	0.618	53.88	2.93

0614L9	60	Barcel.	no	CI	50/20	50	11.375	9.05	0.164	55.16	11.05
						20	14.25	12.21	0.288	42.36	6.29
0608PE	60	Barcel.	no	CI	20/50	20	12.375	6.11	0.149	41.14	12.21
						50	12.875	9.88	0.173	57.30	10.51
0614P9	60	Barcel.	no	CI	50/20	50	13.25	15.09	0.290	52.08	6.26
						20	14.625	16.30	0.436	37.41	4.16
010516b	60	Frankf.	yes	CI	20/50	20	14.375	12.18	0.370	32.94	4.91
						50	14.625	19.87	0.346	57.38	5.24
010516a	60	Frankf.	yes	CI	50/20	50	14.625	57.50	1.146	50.19	1.58
						20	14.75	16.04	0.516	31.08	3.51

Table 15. The first row is the session number. The next five rows give session specific conditions. Row 7 indicates the treatment specific payoff to action A. Row 8 gives the average number of subjects per period, whose behavior was consistent with undominated threshold strategies. Rows 9 and 10 are results of logistic regressions based on data of the last four periods of each treatment. Rows 11 and 12 show the estimated mean and standard deviation of individual thresholds, calculated from estimates a and b.

The closer the estimated mean a/b came to the payoff for the secure action T, the closer came subjects towards the payoff dominant equilibrium. A low estimated standard deviation indicates a high degree of coordination across subjects within the last periods of a treatment.

B.5. Mean and Dispersion of Individual Thresholds

Estimated mean thresholds of subjects during the last four periods of a treatment depend on exogenous conditions in a similar way as thresholds to success.

Regression 9: $a/b = \alpha_0 + \alpha_1 \mathrm{T} + \alpha_2 \mathrm{Z} + \alpha_3 \mathrm{TZ} + \alpha_4 \mathrm{Loc} + \alpha_5 \mathrm{Info} + \alpha_6 \mathrm{Ord} + \alpha_7 \mathrm{TO} + \mathrm{u}$

Estimated standard deviation of individual thresholds during the last four periods of a treatment is larger for private than for common information. The impact of other exogenous variables is less evident.

Regression 10: $\pi/(b\sqrt{3}) = \nu_0 + \nu_1 \mathrm{T} + \nu_2 \mathrm{Z} + \nu_3 \mathrm{TZ} + \nu_4 \mathrm{Loc} + \nu_5 \mathrm{Info} + \nu_6 \mathrm{Ord} + \nu_7 \mathrm{TO} + \mathrm{u}$

No.	Data source (number of observations)	Explaining variables: Coefficients (t-values)								R^2 Adj. R^2
		Intercept	T	Z	TZ	Loc	Info	Ord	TO	
9	All treatments (46)	22.75 (10.28)	27.70 (10.68)	12.50 (6.25)	-11.25 (-4.27)	0.77 (0.68)	3.84 (3.82)	5.17 (3.65)	-3.29 (-1.65)	0.90 0.89
10		2.97 (1.67)	2.53 (1.21)	2.95 (1.83)	-0.96 (-0.45)	1.49 (1.62)	2.29 (2.84)	2.90 (2.54)	-4.00 (-2.48)	0.36 0.24

Table 16. Regressions explaining mean and dispersion of individual thresholds.

Appendix C. Testing Equilibrium Theories

Here, we test whether the means of individual thresholds can be explained by any theory of equilibrium selection in games with CI or by the unique equilibrium in games with PI. We describe the test procedure in detail for tests of the payoff dominant equilibrium. The payoff dominant equilibrium depends on T, but not on Z. Using all 22 data from CI sessions with inexperienced subjects, we use the model $Mean_j = \alpha + \beta T_j + u_j$, with T_j being the numerical payoff to the secure action instead of the dummy variable defined in Table 11 above. The payoff dominant equilibrium predicts $\alpha = 0$ and $\beta = 1$. Thus our null Hypothesis is $H_j^0 = T_j$. Estimated coefficients are $\hat{\alpha}$=24.486 and $\hat{\beta}$= 0.563. The test statistic is defined by $F = \frac{\sum_j (Mean_j - H_j^0)^2 - \sum_j \hat{u}_j^2}{\sum_j \hat{u}_j^2} \cdot \frac{m-k}{k}$, where m is the number of observations and k is the number of regressors in the model. The distribution of the test statistic is assumed to be $F \sim F(k, m-k)$. Let $\Phi(F,k,m-k)$ be the value of the cumulative F-distribution at F. We reject Hypothesis H^0, if $\Phi(F,k,m-k)$ < 5%.

Tables 17 and 18 summarize the results of tests of various equilibrium concepts. Note, that maximin strategies do only depend on Z. Other theoretical equilibria depend on both, T and Z. Here, we test hypotheses accordingly using either all data with the same Z or all data with the same T.

Hypothesis	Data from CI sessions with inexperienced subjects	m	Model	k	$\Phi(F,k,m-k)$	Result
Payoff dominant equilibrium	All	22	$Mean_j = \alpha + \beta T_j + u_j$	2	0.000	Reject
	T=20	11	$Mean_j = \alpha + u_j$	1	0.000	Reject
	T=50	11	$Mean_j = \alpha + u_j$	1	0.040	Reject
Laplacian belief equilibrum	Z=60	18	$Mean_j = \alpha + \beta T_j + u_j$	2	0.000	Reject
	T=20	11	$Mean_j = \alpha + \beta Z_j + u_j$	2	0.005	Reject
	T=50	11	$Mean_j = \alpha + \beta Z_j + u_j$	2	0.000	Reject
Risk dominant equilibrium	Z=60	18	$Mean_j = \alpha + \beta T_j + u_j$	2	0.000	Reject
	T=20	11	$Mean_j = \alpha + \beta Z_j + u_j$	2	0.004	Reject
	T=50	11	$Mean_j = \alpha + \beta Z_j + u_j$	2	0.000	Reject

'naïve' Laplacian belief equilibrium	Z=60	18	$Mean_j = \alpha + \beta T_j + u_j$	2	0.000	Reject
	T=20	11	$Mean_j = \alpha + \beta Z_j + u_j$	2	0.000	Reject
	T=50	11	$Mean_j = \alpha + \beta Z_j + u_j$	2	0.068	Accept
Best response to belief that others play B with probability 2/3	Z=60	18	$Mean_j = \alpha + \beta T_j + u_j$	2	0.252	Accept
	T=20	11	$Mean_j = \alpha + \beta Z_j + u_j$	2	0.309	Accept
	T=50	11	$Mean_j = \alpha + \beta Z_j + u_j$	2	0.542	Accept
Maximin Strategy	All	22	$Mean_j = \alpha + \beta Z_j + u_j$	2	0.000	Reject

Table 17. F-tests for selection criteria in sessions with common information.

Hypothesis	Data from PI sessions (inexperienced subjects)	m	Model	k	$\Phi(F,k,m-k)$	Result
Private information equilibrium	Z=60	20	$Mean_j = \alpha + \beta T_j + u_j$	2	0.000	Reject
	T=20	12	$Mean_j = \alpha + \beta Z_j + u_j$	2	0.682	Accept
	T=50	12	$Mean_j = \alpha + \beta Z_j + u_j$	2	0.000	Reject

Table 18. F-tests for equilibrium in sessions with private information.